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CONTENTS

*Editorial***Dr. A. S. Ramasastrri**

Research Articles

1. SOA maturity influence on digital banking transformation 01
Alan Megargel, Venky Shankararaman, Terence Fan Ping-Ching
2. The rise of machine learning and robo-advisors in banking 28
Chaman Lal Sabharwal
3. Sustainable co-training of mixture-of-experts for credit scoring of
borrowers in social lending 44
Jae-Min Yu, Sung-Bae Cho

Practitioners' Perspective

4. BIAN – PNC open APIs for banking 65
**Mark Grobaker, Arashdeep Kaur, Chaitanya Kommuru,
Wenting Tao, Pallavi Thakur, Hans Tesselaar**
5. A robust framework for implementing technology controls amidst
extreme disruption 79
Subramanian Annaswamy

Dr. A. S. Ramasastrri

In the past decade, disruptive technologies have shrunk the world leading to location-agnostic production and consumption of services. This has transformed the banking industry to a great extent, altering the way the business is conducted.

Banks have created digital infrastructure to offer various solutions like mobile banking, e-wallets and virtual cards, for successfully fulfilling the changing needs of the modern-day customer. Wholesale banking is also catching on this trend of designing and delivering the right mix of products and services to corporate customers, harnessing digital technologies.

Banks have adopted the SMAC technologies – Social, Mobile, Analytics and Cloud – very innovatively. While the SMAC technology developments will continue to be exploited by banks, there are several new technologies emerging in the realm of quantum computing, high-speed networks, biometrics, machine learning, robotics and smart wearables.

Among them, the four key technologies that we consider to be having a great impact on banking are FABS – Five G, Artificial Intelligence, Blockchain and Smart things. We feel that in the next decade, banking will witness a continued trend of reinventing itself, riding on FABS in addition to SMAC. Each of these technologies has potential to challenge the present banking sector and change it to the benefit of all stakeholders.

These trends are highlighted in the three research articles in the current journal. In his article titled “The Rise of Machine Learning and Robo-advisors in Banking”, Chaman Lal Sabharwal highlights the use of robo-advisors, which relies heavily on the machine learning techniques. “Sustainable Co-training of Mixture-of-Experts for Credit Scoring of Borrowers in Social Lending” by Jae-Min Yu and Sung-Bae Cho is an illustration of the use of semi-supervised learning in an important area of banking like credit scoring. Alan Megargel, et al., in their article “SOA Maturity Influence on Digital Banking Transformation” discuss how Service-Oriented Architecture (SOA) is clearly an enabler for digital banking.

The two contributions from practitioners are on open APIs and Framework for Technology Controls. Hans Tesselaar, et al., present the perspective of “BIAN on

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Open APIs for Banking”. Subramanian Annaswamy discusses in detail a “Robust Framework for Implementing Technology Controls Amidst Extreme Disruption.”

I am sure the banking technology related research and practice across the world presented through the journal will keep enhancing, both in breadth and depth, as we move on.

Dr. A. S. Ramasastry
Editor-in-Chief

SOA maturity influence on digital banking transformation

Alan Megargel¹ · Venky Shankararaman¹ · Terence Fan Ping-Ching²

Abstract Digital Banking is an evolution of online banking, where the banks attempt to further enhance customer experience by integrating digital technologies such as mobile technology, social media and analytics. Traditional banks have the highest barriers to entry into the digital banking market due to the presence of legacy core banking systems. These legacy systems while still high performing and reliable, are inflexible to change and are not easily integrated to the modern application systems needed for delivering digital banking services across multiple online banking channels. One solution that is widely adopted in the industry to overcome this obstacle is the implementation of a Service-Oriented Architecture (SOA). In this paper, we investigate the relationship between three factors, namely a bank's technology infrastructure, IT governance processes, SOA maturity, and their impact on time-to-market (T2M) of digital banking products and services. Our research study is achieved through surveys and case study interviews conducted with the chief technologists from eight banks operating in Asia. A key conclusion from our study is that SOA maturity plays a very important role in enhancing a bank's capability towards digital banking transformation. In order to move towards higher levels of SOA maturity, we make three recommendations – establishing an SOA centre of excellence, implementation of a well-architected Enterprise Service Bus (ESB), and adoption of an ESB framework and toolkit.

Keywords: Digital Banking · FinTech · Legacy Systems · Service-Oriented Architecture · SOA · SOA Maturity · SOA Centre of Excellence · IT Governance

1 Introduction

“Digital Banking – a new concept in the area of electronic banking, which aims to enrich standard online and mobile banking services by integrating digital technologies, for example, strategic analytics tools, social media interactions, innovative payment solutions, mobile technology and a focus on user experience.”
[18]

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There is no standard definition of digital banking, however, the above definition encompasses most of the concepts discussed in the literature. Digital Banking is seen as an evolution from what was previously referred to as e-banking or online banking, with more focus on customer experience.

Digital Banking, which mostly falls within the boundary of retail banking as an industry, is shaped by “five competitive forces” [20] – 1) Customers are becoming increasingly more sophisticated, expecting personalized banking services to be delivered to them at anytime of the day across any channel; 2) Substitutes such as “FinTech” and other IT firms are providing non-bank alternative financial services such as payments, marketplace lending, and crowdfunding; 3) Entrants along with substitutes are more agile than traditional banks, have lower barriers to entry in terms of regulatory controls and legacy infrastructures, and are in fact defining the standards for Digital Banking; 4) Incumbents who are traditional banks are urgently pursuing digital strategies in order to salvage their diminishing market shares, but are severely inhibited due to their existing inflexible monolithic legacy systems; and 5) Suppliers such as technology vendors have relatively limited banking domain knowledge, and their further offerings of ‘commercial-off-the-shelf’ applications will not help traditional banks to unravel their legacy architectures.

Ironically, it is the incumbent traditional banks which have the highest barriers to entry into the digital banking market. Legacy core banking systems, which are inflexible to change, are at the “heart” of the problem, and replacing an existing core banking system on a live bank would be analogous to performing a heart transplant on a runner during a race. Bank management is essentially about managing risk, and the impact of a failed core banking system “transplant” is too high for most of the bank managers to consider it as a viable option. Therefore, core banking system replacements are rare as many banks are still using legacy mainframe technologies built in the 1970s. These legacy systems, while still high-performing and reliable, are inflexible to change and are not easily integrated to the modern application systems needed for delivering digital banking services across multiple online banking channels. The literature reveals universally that the solution for overcoming this obstacle is to implement a Service-Oriented Architecture (SOA) whereby the functionality of underlying legacy systems can be exposed as reusable services which are easily consumed by digital banking channels.

The SOA style of architecture is proven to be more flexible, enabling banks to become more agile, with improved time-to-market delivery of new products and services across multiple channels [25]. There is much written about the benefits of SOA in banking, as well as the lessons learned from failed SOA implementations. Banks that implement SOA well, are in the best position to compete in the digital banking market. However, many banks have either failed to realize the benefits of an SOA, or have not yet invested in it.

In this paper, we define a set of propositions which identify and explain the barriers to entry into digital banking for traditional banks, who are intent on protecting their market share against FinTech substitutes. Through surveys and case study interviews conducted with the chief technologists from various banks, a descriptive analysis of digital banking strategies and implementation challenges is provided, which reveals

that SOA maturity has an influence on digital banking transformation. The rest of the paper is organized as follows. In Section 2, we review related literature in digital banking and SOA. In Section 3, we define and explain the three propositions. Section 4 presents the methodology adopted for evaluating the propositions. In Section 5, we present an analysis of the results of the evaluation. Section 6 summarizes the key findings and the implications for senior management. In Section 7, we present the conclusions from our work.

2 Literature review

2.1 Digital banking: response to fintech substitutes

Many traditional banks are urgently pursuing “digital” strategies in order to compete directly with FinTech firms [26]. “Digital Banking” is a buzzword used by many traditional banks in an attempt to position themselves alongside FinTech firms. Anecdotally, some banks have simply renamed their existing “self-service channels architecture” to “digital architecture”. But it’s not that simple. Traditional banks have high barriers to enter into this new digital industry currently led by FinTech firms.

Much is written about digital banking – its evolution, its drivers, trends in the industry, threats from new entrants, and what banks now must do to survive in this digital age. There exists some degree of urgency for banks to accelerate their digitization agendas, driven by a number of factors including: the proliferation of mobile phones, changing consumer habits and preferences towards interacting via digital media, online comparison sites where consumers can share experiences across different banking products and services, demand for 24/7 availability of banking services, and competition from non-bank alternative solutions such as marketplace lending and crowdfunding platforms [6].

A 2015 survey revealed that 72% of bank executives felt their bank only had a fragmented strategy for dealing with digital innovation, and that their legacy infrastructure was the main inhibitor [26]. Legacy monolithic core banking systems are inflexible to change, and are not easily integrated to the modern technology required for digital banking [6]. In order to enable the level of agility required to meet rapidly evolving business requirements, banks will inevitably reach a “point of no return” whereby they will need to break apart their monolithic core banking systems into smaller and more flexible modules [6]. In order to achieve a modular architecture, banks will need to invest in a Service-Oriented Architecture (SOA) which enables the rapid assembly and reuse of “digital assets” [7].

2.2 SOA as an enabler of digital banking

Service-Oriented Architecture (SOA) is clearly an enabler for digital banking. While, in most cases, the SOA literature does not refer directly to digital banking, there is much written on the benefits of SOA as it applies to “e-Banking” or “Online Banking”, which are the precursor terminologies used for digital banking. The benefits of e-Banking include: faster transaction speed as compared to branches,

flexibility of banking anytime of the day, better control by customers over their accounts, and lower interest rates as banks pass on cost savings to their customers [2].

An empirical study was conducted on a European Bank with over 1000 branches and over 15,000 employees to determine the impact of SOA on the success of e-Banking, and the results showed a significant positive impact in terms of: a) financial benefits – increased revenues / decreased expense; b) agility to quickly assemble new processes through reuse of existing services; c) improved business-IT alignment; d) improved ROI through service reuse; e) reduced time to market of products and services; f) reduced cost of development through service reuse; g) improved overall reusability of IT assets; h) easier system integration; and i) reduced unscheduled downtime [2].

The business value to be achieved from an SOA investment are – improved business agility and reduced cost as a result of service reuse. However, there are both technical and organizational challenges to overcome [5, 17]. The technical challenges of SOA adoption include: a) the complexity of deciding “the right level of granularity of services”, and b) the complexity of mapping the message level details of legacy systems that are not well-documented [5]. However, once the complexity of service granularity and message mapping are resolved, the overall integration complexity can be reduced through the implementation of an Enterprise Service Bus (ESB) design pattern [5]. Governance is another challenge, as achieving SOA business value requires establishment of clear roles and responsibilities that cut across organization boundaries, compliance to standards, enforcement of policies, and fulfilment of service level agreements [16].

2.3 SOA case studies in banking

Most of the banks are still using legacy systems which are inherently inflexible to change and therefore, with the ability to expose functionality of legacy systems as reusable services, the business case potential for SOA in this industry is generally high [19]. Banks generally do not reveal details of their technology architecture or related internal inefficiencies to the public, therefore the number of case studies in this area is limited, and those that exist are anonymous.

Empirical case studies on two large well-established European Banks referred to anonymously as “Central Europe Bank” and “Northern Europe Bank”, reported significant positive benefits from the SOA adoption in both the case studies [3]. Salient points from the study include: a) services that expose functionality of legacy systems are reusable and also hide the complexity of the underlying system; b) services can efficiently execute composite transactions; c) reusable services “are a source of strategic value”; d) reusable services enable agile development of systems; e) an architecture board decides on the funding of new services; f) policies enforce the reuse of existing services; and g) “SOA invokes an unfamiliar concept that raises barriers to adoption” [3].

Another set of case studies were conducted on the SOA adoption at two large banks in Switzerland, with results indicating that exposing legacy system functionality as reusable services – a) improves business agility and time-to-market; b) reduces cost

through service reuse; and c) requires strong architecture governance processes [23]. Similar results were found from studies conducted on a “Large European Bank” and a “Large UK Bank” [8], as well as a “Large Netherlands Bank” [14], and a “Large South East Asia Bank” [27].

2.4 SOA maturity models

SOA implementation in complex organizations such as banks typically span several years [8], and many organizations find it useful to periodically benchmark their SOA maturity in terms of technical implementation, which includes service design, deployment, performance, and reuse; as well as organizational processes which includes architectural decision-making, funding, and benefits realization [9, 12]. There are no pervasive or standard SOA maturity models in the market. However, many of them are founded on and/or extended from the Capability Maturity Model Integration (CMMI) developed by Carnegie Mellon University, which consists of five stages of maturity as follows: 1) “initial” – reusable software components, 2) “managed” – standardization of data and resources, 3) “defined” – support of business processes, 4) “qualitatively managed” – enterprise service architecture, 5) “optimized” – adaptive architecture [9, 10].

There are studies which compare the various SOA maturity models, including: a) Service Integration Maturity Model (SIMM), b) Sonic SOA Maturity Model (SOAMM), c) IT Service Capability Maturity Model, d) Web Services Maturity Model, e) Enterprise SOA Maturity Model, f) IBM Service Integration Maturity Model, g) Combined SOA Maturity Model (CSOAMM), and h) The Open Group Service Integration Maturity Model (OSIMM) [9, 15]. The various SOA maturity models typically layer organizational (non-technical) dimensions such as “benefits & metrics”, “methodology” and “governance” across the five CMMI maturity stages [10, 21]. None of the related studies revealed any research instrument such as a survey which can be operationalized.

3 Barriers to entry for digital banks

3.1 Propositions

A theoretical model of digital banking barriers to entry is given in Figure 1 below. Time-to-market (T2M), represented as the dependant variable in the model, is a measure of traditional banks’ agility to deliver new innovative digital banking products and services to the market. The barriers to entry, represented as the independent variables in the model, are the inhibitors which are keeping banks from achieving their digital banking time-to-market objectives. The three main inhibitors, which we expect to verify through data collection, are: a) legacy technology infrastructure which is inflexible to change; b) organizational complexity and challenges around technology decision-making; and c) lack of technical knowledge around web services standards and SOA best practices. We propose that banks’ assessed level of SOA maturity will have a moderating effect on these inhibitors as predictors of digital banking time-to-market.

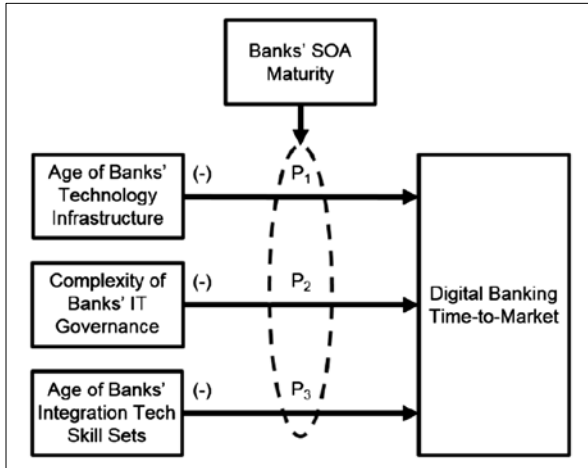


Fig. 1 Theoretical model of digital banking barriers to entry

The following set of propositions are illustrated in the above model as P1-P3.

3.1.1. Proposition 1

P1 – The age of banks’ technology infrastructure has a negative influence on bank’s time-to-market of digital banking products and services. This causal relationship is reduced as banks’ SOA maturity increases.

Rationale – The “age” of technology infrastructure, in this case, is a means to determine the degree to which a technology is considered to be “legacy”. An IBM mainframe developed in the 1970s, for example, would be considered as a legacy technology infrastructure when hosting a core banking system in the current era. Legacy core banking systems are monolithic (all-in-one functionality) rather than modular (separate integrated components), and they use outdated and often proprietary (non-standard) integration protocols. Legacy systems are therefore “brittle” (inflexible to change). The literature reveals universally that the solution for overcoming this obstacle is to implement an SOA whereby the functionality of underlying legacy systems can be exposed as reusable services, enabling the agile development of new innovative products and services. We propose that legacy systems are a barrier to entry (inhibitor) for banks’ intent on pursuing their digital banking strategies, and the effect of this inhibitor is reduced as the SOA maturity of banks increases. To explore this proposition, a common SOA maturity model will be used to assess each bank in the study.

3.1.2. Proposition 2

P2 – The complexity of banks’ IT governance processes has a negative influence on bank’s time-to-market of digital banking products and services. This causal relationship is reduced as banks’ SOA maturity increases.

Rationale – As a natural consequence of a growing bank, organizations tend to become “siloed”, with each business unit having its own dedicated technology and operations functions. The downside effect of this organizational model is that bank-wide technology decision making becomes more complex, and agility suffers in terms of time-to-market of new innovations. As a means to control complexity, banks strive to establish enterprise-wide technology standards and IT architecture standards such as SOA, as well as governance processes to enforce those standards. An effective and mature SOA implementation is one that bridges the gap across organizational silos, aligns to the overall business strategy of the bank, and enables the bank to be agile in terms of time-to-market of new product and service innovations. We propose that complex technology decision-making processes are a barrier to entry (inhibitor) for banks’ intent on pursuing their digital banking strategies, and the effect of this inhibitor is reduced as the SOA maturity of banks increases.

3.1.3. Proposition 3

P3 – The age of banks’ integration technology skillsets has a negative influence on bank’s time-to-market of digital banking products and services. This causal relationship is reduced as banks’ SOA maturity increases.

Rationale – The “age” of integration skillsets, in this case, is a means to determine the degree to which technical knowledge about application integration protocols is outdated. File Transfer Protocol (FTP) developed in the 1970s, for example, is used for bulk transfer of data files between applications on a batch processing schedule. Technical knowledge about FTP would be considered as outdated in the context of digital banking whereby application systems are integrated on-demand in real-time using modern web services standards. For banks’ technology architects and developers, learning and understanding about how to use modern web services standards, is perceived to be difficult. We propose that the lack of knowledge about modern integration technology is a barrier to entry (inhibitor) for banks’ intent on pursuing their digital banking strategies, and the effect of this inhibitor is reduced as the SOA maturity of banks increases.

4 Method

We conducted an “explanatory study” [22, 31] to establish the causal relationship between banks’ organizational and technological complexities and banks’ time-to-market of digital banking innovations. Following a deductive research approach, a set of propositions were deduced based on the practice-based banking and SOA industry experience of the authors. Therefore, expert opinion (“theory”) that the barriers to entry (inhibitors) for digital banking are: legacy technology, complex decision-making processes, and outdated skillsets. Banks tend not to expose (make publically known) their internal inefficiencies due to reputation risk, and the only realistic means to collect data about these inefficiencies is through selected bank’s anonymous participation in a multiple case study research project [4, 31]. A mixed methods approach is appropriate for case study based research [28], combining both qualitative and quantitative methods.

The constructs of our propositions, which are highly technical and have bank-wide implications, require us to include the senior-most technology staff as participants in our case study. Typical chief technologist roles which match this requirement are: Chief Technology Officer, Chief Information Officer, Chief Innovation Officer, Chief Architect, Chief Strategist. It was difficult to approach and seek time from these chief technologists. Our realistic aim was to secure participation from three to five banks in Asia. After approaching 12 banks, we were able to secure participation from eight of them.

In order to make the case study participation process more efficient, we included a pre-interview survey to be followed by an interview with the chief technologist (the participant). Our survey questions were grouped into sections to cover the following areas:

- Digital Banking Maturity
- Technology Architecture
- IT Governance
- Core Competencies/Skills
- SOA Maturity

Multiple case studies follow a “replication design”, rather than a “sampling design” typically used in surveys [31]. “Literal replication logic” is used in our multiple case study design whereby individual cases are selected which predict similar results [31]. Our multiple cases (banks) are analogous to multiple experiments whereby we expect the findings to be replicated across each experiment. We present ‘no-rival theory’ of barriers to entry for digital banks, therefore, “theoretical replication logic” which predicts contrasting results is not considered in our multiple case study design [31].

The typical criteria for determining sample size is irrelevant, because sampling logic is not used in multiple case study designs, and hence the judgment for determining the number of cases is discretionary [31]. For a straightforward theory

like ours which does not require a high degree of certainty, “two or three literal replications” (cases/banks) would be sufficient [31]. We included eight banks.

Data collected from each case study was written up in individual case reports, one for each bank. Once all individual case studies were complete, a consolidated cross-case report was written. The cross-case consolidated data was then analysed using quantitative and qualitative methods [22, 28], cross-case conclusions were drawn, and arguments were made to declare the propositions as accepted.

All eight banks that participated, labelled as “Bank A” through “Bank H” in the following sections, are operating in Asia, but are not necessarily headquartered in Asia. Headquarters of five out of these eight banks are in Asia-Pacific, two in Europe and one in the US.

5 Results and analysis

The case study data from the eight participating banks is summarized in Table 1 given below. For each variable of our theoretical model illustrated in Figure 1 above, an assessment is given on a Likert Scale. Then to facilitate analysis of the relationships between variables, they are segregated into two groups, for example: Low to High SOA Maturity, and Simple to Complex IT Governance.

Table 1 Summary of case study assessment data

Likert scores for each variable (theme)								
Bank	A	B	C	D	E	F	G	H
Time to Market	5.25	4.75	4.50	4.00	4.50	5.25	3.00	4.25
Core Banking System	5.00	2.50	2.00	2.00	4.00	1.50	3.50	2.50
IT Governance	4.00	4.00	3.20	3.80	4.20	3.60	4.80	4.20
Core Compencies	4.75	4.75	4.50	5.00	5.00	5.75	4.75	4.25
SOA Maturity	4.90	3.70	2.90	2.80	3.30	5.10	2.40	2.80

Themes segregated into 2 groups based on clusters of Likert scores								
Bank	A	B	C	D	E	F	G	H
Time to Market	Short	Short	Long	Long	Long	Short	Long	Long
Core Banking System	Modern	Legacy	Legacy	Legacy	Modern	Legacy	Modern	Legacy
IT Governance	Complex	Complex	Simple	Simple	Complex	Simple	Complex	Complex
Core Compencies	Weak	Weak	Weak	Strong	Strong	Strong	Weak	Weak
SOA Maturity	High	High	Low	Low	Low	High	Low	Low

5.1 Time-to-market

Time-to-market of digital banking capability, the dependent variable in our theoretical model illustrated in Figure 1, is assessed based on the criteria and rationale provided in Table 2 below. These criteria involve large-scale change scenarios which have implications and dependencies on the overall flexibility of banks’ architecture.

Table 2 Time-to-market assessment criteria

Assessment Criteria	Rationale, Implications on Architecture
<p>The length of time taken to introduce (buy or build, and deploy) a full-featured internet banking channel, assuming that funding is not a constraint.</p>	<ul style="list-style-type: none"> • If an Internet Banking channel exchanges information via on-demand reusable services as opposed to pass-through messages or scheduled batch interfaces, the implementation time will be faster, even in the presence of a legacy core banking system. Pass-through messages and batch interfaces are less likely to be reusable. • The implementation time will improve as the percentage of required services’ availability increases. A 100% availability would be the best case, otherwise missing services would need to be developed. • The implementation time will be faster if the internet banking channel conforms to the common requirements of existing services, as opposed to imposing channel specific constraints.
<p>The length of time taken to introduce (buy or build, and deploy) a real-time inbound marketing engine for delivering personalized cross-sell offers targeted to specific customers, assuming funding is not a constraint.</p>	<ul style="list-style-type: none"> • If the rules that trigger real-time inbound marketing offers are managed centrally by a business rules management system (BRMS) as opposed to hard-coded rules embedded in a channel, and the BRMS exposes those rules as reusable decision services, the implementation time will be faster. • A BRMS-driven marketing engine implies that real-time business events (customer interactions) are captured via a pre-existing enterprise service bus (a collection of reusable services), i.e. an SOA is implemented before a BRMS.
<p>The length of time taken to introduce (buy or build, and deploy) an interactive personal finance robo-advisor, assuming funding is not a constraint.</p>	<ul style="list-style-type: none"> • If the mathematical rules and algorithms that govern the dialog with customers are managed centrally by an automated advisory

	<p>platform as opposed to hard-coded algorithms embedded in a channel, and the advisory platform exposes its functionality as reusable advisory services, the implementation will be faster.</p> <ul style="list-style-type: none">• A centrally managed advisory platform implies that current and historical customer behaviour information is accessible via a pre-existing enterprise service bus (a collection of reusable services), i.e. an SOA is implemented before an advisory platform.
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5.2 SOA maturity

The case study survey data reveals that SOA maturity has a positive influence on banks’ time-to-market of digital banking capability. Across the eight banks, we looked for cross-case similarities in the grouping of our independent variables as provided in Table 1 above, namely, core banking systems (CBS) which can be legacy or modern, IT governance (simple/complex), and core competencies (weak/strong), where time-to-market capability differs as influenced by SOA maturity. For example, Banks D and F both have legacy core banking systems, simple IT governance, and strong core competencies. What differs is that Bank D with a low SOA maturity has a long time-to-market, and Bank F with a high SOA maturity has a short time-to-market. These cross-case similarities are also present for Banks H and B, as well as Banks G and A, as illustrated in Figure 2 below.

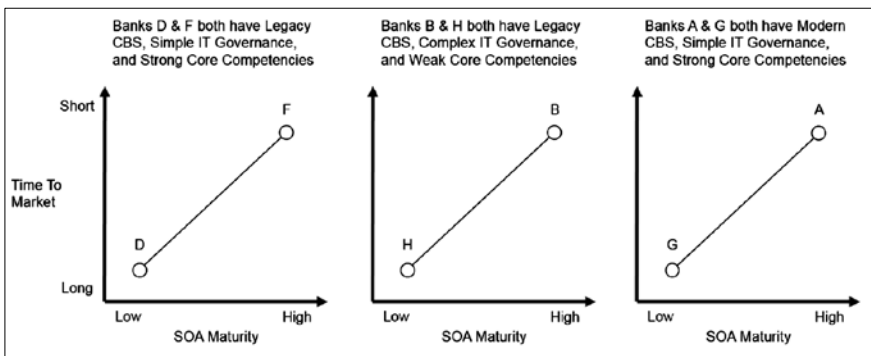


Fig. 2 SOA maturity influence on time-to-market

SOA maturity, the moderating variable in our theoretical model illustrated in Figure 1, is assessed based on the criteria and rationale provided in Table 3 below. These criteria draw from the common findings identified from our literature review in section 2.4: SOA Maturity Models.

Table 3 SOA assessment criteria

Assessment Criteria	Rationale, Implications on Architecture
<p>The extent to which reusable services are deployed, for example, “getAccountBalance”, which is developed once and reused by multiple banking applications.</p>	<ul style="list-style-type: none"> • Reusable services are the building blocks of an SOA which can be quickly assembled and orchestrated to implement complex business logic. • Implementing new business logic using existing services is faster and more cost-effective than developing business logic from scratch for each new set of requirements. • Banks, which embrace service reuse as an architectural principle, are more likely to improve time-to-market of digital banking capability as service reuse rates increase.
<p>The extent to which an Enterprise Service Bus (ESB) is implemented which can be managed centrally as a deployed collection of reusable services.</p>	<ul style="list-style-type: none"> • An ESB implementation implies that application integration (via services) is managed centrally, rather than distributed across each integration end-point. • The time-to-market and cost benefits of service reuse can be better assured using a central management model of an ESB rather than a distributed model.
<p>The extent to which reusable services provide an intermediate layer of abstraction that essentially decouples the service consumer from the service provider such that the service consumer need not know the data format or transport protocol used by the service provider.</p>	<ul style="list-style-type: none"> • Services which decouple the service consumer from the service provider via data abstraction are more likely to be reusable, as compared to services which tightly couple application systems via pass-through messages. • A services layer that provides decoupling through abstraction improves architectural flexibility. In that, it is technically possible for a service provider system (such as a core banking system) to be completely replaced (or decomposed into microservices) without requiring any code changes on the service consumer systems.
<p>The extent to which the service schema, the data format exposed to the service</p>	<ul style="list-style-type: none"> • Data abstraction at the services layer can be better managed (by a

<p>consumers, is aligned to the enterprise data model.</p>	<p>data architect) if it aligns to a common data model, such as an enterprise data model.</p> <ul style="list-style-type: none">• Service schemas which are managed and aligned to a common data model, as the basis for data abstraction at the services layer, are more likely to be reusable.
<p>The effectiveness of the SOA Centre of Excellence (or Competency Centre) which enforces bank-wide SOA principles, policies, best practice guidelines, and standards.</p>	<ul style="list-style-type: none">• The success of an SOA is better assured with an effective SOA Centre of Excellence (COE), which can be measured in terms of bank-wide service reuse rate and cost avoidance due to service reuse.• Centrally managing/guiding the design of services for optimal reusability, as well as making available and maintaining a bank-wide service catalogue, will better ensure service reuse and thereby improve time-to-market of digital banking capability.
<p>The extent to which bank-wide service reuse rate, and cost avoidance due to service reuse, are published (internally).</p>	<ul style="list-style-type: none">• If the cost avoidance of service reuse as a measure of SOA success is published (internally), the bank-wide adoption of SOA will be better assured.• Publishing the success of SOA in financial terms (cost avoidance) will dissuade internal opponents of SOA from bypassing the ESB with point-to-point integration.
<p>The extent to which service reuse cost avoidance figures are included in all project funding proposals which involves application development.</p>	<ul style="list-style-type: none">• The financial discipline of including cost avoidance figures (due to service reuse) in all project funding proposals will better ensure bank-wide service reuse.• As project managers get their cost avoidance figures from the SOA COE, use of existing services will be tracked, and new reusable services will be designed as required.
<p>The extent to which both design time and runtime governance tools are implemented, for managing and</p>	<ul style="list-style-type: none">• SOA design time governance tools:<ol style="list-style-type: none">a) make service design documentation and service contracts available to application

<p>monitoring bank-wide usage of SOA assets.</p>	<p>developers, b) manage service schemas and service templates, and c) manage service lifecycles.</p> <ul style="list-style-type: none"> • SOA runtime governance tools: a) manage service access/authorization, and b) monitor service usage. • The effective usage of this tools will better assure service reuse, and thereby improve time-to-market capability.
<p>The percentage of core banking functionality, required by channels, which is exposed as reusable services via an ESB.</p>	<ul style="list-style-type: none"> • As the percentage of required core banking functionality exposed as reusable services increases, architectural flexibility improves, assuming that the services layer provides decoupling through abstraction. Ultimately, a flexible architecture enables the replacement of applications systems with minimal impact.
<p>The degree to which an ESB enables a complete replacement of the core banking system without making any changes to any channel application (e.g. Teller, Internet Banking, etc.).</p>	<ul style="list-style-type: none"> • This is the “acid test”. If a bank is technically able to replace its core banking system (CBS) (at least as a thought experiment) without impacting any of its channels, then it can be said that – a) all of the core banking services are reusable, b) the services layer completely decouples the channels from the CBS through data abstraction, and c) the bank has the option to decompose its core banking functionality into microservices.

5.3 Age of banks’ technology infrastructure

As revealed in the literature, legacy core banking systems are inflexible to change and inhibit banks’ agility to deliver digital innovation quickly to the market [6, 11, 26]. It is also established that SOA is an enabler which can provide a more flexible and agile architecture, by exposing the underlying functionality of legacy core banking systems as reusable services [1, 2, 17, 30].

Of the eight banks interviewed, five of them (Banks B, C, D, F and H) have IBM mainframe-based (Z/OS, OS/390, AS/400) core banking systems that are on an average greater than 20 years old, two of them (Banks E and G) have more modern

client/server-based core banking systems that are between 11 and 20 years old, and one (Bank A) has a new client/server-based core banking system that is less than five years old. None of the eight banks have implemented a modular core banking system implemented as separately deployable microservices, although Bank F is actively working towards that goal.

From the case study survey data, we looked for cross-case similarities in IT governance (simple/complex) and core competencies (weak/strong) in order to isolate the impact of core banking systems on time-to-market, and to see if SOA maturity has any influence on this relationship. Banks A, B, G, and H, all have complex IT governance and weak core competencies. Bank A has a modern core banking system and also has a short time-to-market as expected based on common wisdom. However, a low SOA maturity has a negative influence on time-to-market for Bank G, which also has a modern core banking system, as illustrated in Figure 3 below.

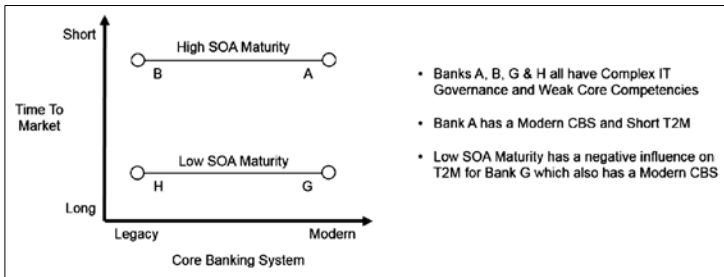


Fig. 3 Core banking systems impact on time-to-market

Table 4 Core banking system assessment criteria

Assessment Criteria	Rationale, Implications on Architecture
Core banking system (CBS) architecture classification.	<ul style="list-style-type: none"> • Legacy mainframe-based systems which use dumb terminals for human interaction and pre-internet era proprietary machine interfaces, are difficult to integrate to and inflexible to change, and therefore, score lower on our Likert scale. • Client/Server-based systems which use network-distributed “intelligent terminals” are more likely to use modern integration standards, and are more modular and flexible to change, and therefore, score higher than legacy systems on our Likert scale. • Modular systems with separately deployed server-side components

	(or microservices) provide the most flexible architecture whereby new banking processes can be quickly assembled using reusable services, and therefore, score the highest on our Likert scale.
Number of years since the initial deployment of the current CBS.	<ul style="list-style-type: none"> • Systems which were deployed pre-internet era, including mainframes and some client/server-based systems, are more likely to use proprietary machine interfaces which are difficult to integrate and inflexible to change, and less likely to have modernization support from vendors. Therefore, older systems score lower on our Likert scale.

Bank A, having the newest (< 5 years) and the most modern core banking system, had the highest Likert score (5.25) for time-to-market capability as expected, with the added benefit of a new SOA implementation, which if managed well should enable continued high time-to-market capability going forward. They have exposed nearly 100% of their core banking functionality required by their retail banking channels as reusable services.

Banks C, D, and E, understand the benefits of reusable services, but are challenged to expose some of the business logic embedded within their older legacy core banking systems (CBS). As such, some of their digital banking solutions are stand-alone, having implemented separate equivalent business logic external to their CBS. This external stand-alone business logic is less likely to be reusable.

Bank F has the oldest (> 30 years) legacy core banking system. In the absence of an SOA they would likely have the poorest time-to-market capability. However, they also had the highest Likert score (5.10) for SOA maturity. They have overcome the challenges of exposing embedded business logic from their legacy CBS as reusable services, and they have a high degree of service reuse which enables a more flexible architecture and improved business agility to quickly deliver innovative digital solutions to the market. Along with Bank A (having the newest CBS), Bank F also had the highest Likert score (5.25) for time-to-market capability.

A general observation across all of the eight cases is that banks that ranked lower in terms of age/legacy of their CBS and ranked lower in terms of SOA maturity, also ranked lower in terms of time-to-market capability. This shows evidence that legacy systems are indeed an inhibitor for digital banking.

Another observation is that banks with legacy systems tend to rank higher in terms of time-to-market capability if they also ranked higher in terms of SOA maturity. Bank F shows the strongest evidence of this, as they have the oldest legacy CBS, while also

having the highest SOA maturity of any of the participants, and this combination puts them on par with Bank A (newest CBS) in terms of time-to-market capability. Therefore, based on our quantitative and qualitative analysis, we have a strong argument in support of proposition P4 – *The age of Banks’ technology infrastructure has a negative influence on Bank’s time-to-market of digital banking products and services. This causal relationship is reduced as Banks’ SOA maturity increases.*

5.4 Complexity of banks’ IT governance

IT Governance can be defined as “[s]pecifying the decision rights and accountability framework to encourage desirable behaviour in the use of IT” [29], including managing and monitoring IT investments and benefits. Where “desirable behavior” involves enterprise-wide control of IT investments, it has been found in one study across multiple financial institutes that “IT governance mechanisms conspired to discourage innovation” [29].

Large IT investments proposed by one business unit – even if the intended benefit spans the enterprise – require buy-in from other business units before funding can be approved. The larger the organization is, the more complex these technology decision-making processes become. An effective Enterprise Architecture (EA) practice is one that is able to exert bank-wide influence over architectural direction, and is able to attain buy-in across multiple business units in the support of large IT investments [24].

If we look at large IT investments from a buy vs. build vs. assemble perspective, implementing new solutions using a ‘buy (off-the-shelf) or build (from scratch)’ approach can be assumed to be more costly than using an assemble (reuse) approach. Assembling new solutions by reusing existing services in a SOA and by leveraging existing enterprise platforms such as Business Process Management (BPM), Business Rules Management System (BRMS) and Enterprise Data Warehousing (EDW) will not only require less capital investment, but will also shift IT governance focus more towards managing and monitoring the benefits of existing IT assets anchored around a SOA. With a mature SOA in place that provides agility and reuse, the impact of complex IT governance processes on the time-to-market of new innovative digital banking solutions should be reduced.

From the case study survey data, we looked for cross-case similarities in core banking systems (legacy/modern) and core competencies (weak/strong) in order to isolate the impact of IT governance on time-to-market, and to see if SOA maturity has any influence on this relationship. Banks C and H both have legacy core banking systems and weak core competencies, as illustrated in Figure 4 below. However, neither bank has a short time-to-market, hence, it is indeterminate if IT governance has any impact, at least based on the case study survey data.

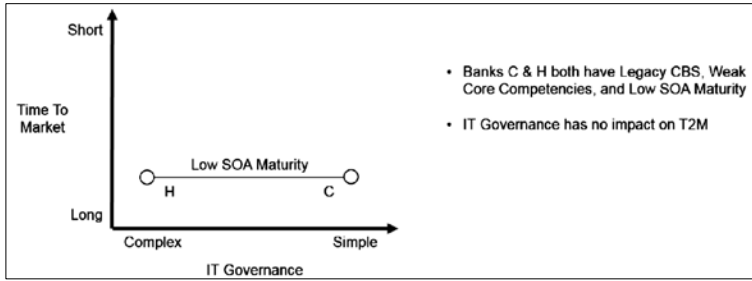


Fig. 4 IT governance impact on time-to-market

Our assessment of bank’s IT governance processes takes into consideration – the level of influence enterprise architecture has on technology investments, and the level of financial discipline that is practiced in managing the benefits of technology investments. Our assessment of IT governance complexity in relation to time-to-market capability is based on the criteria and rationale provided in Table 5 below:

Table 5 IT governance assessment criteria

Assessment Criteria	Rationale, Implications on Architecture
<p>The effectiveness of the enterprise architecture practice, whereby Enterprise Architects have a bank-wide sphere of influence over their respective architecture domains and are able to set bank-wide architecture direction.</p>	<ul style="list-style-type: none"> It is proposed that the time-to-market of digital banking capability is better achieved in the presence of a mature SOA. The benefits of an SOA are more likely to be achieved if there is bank-wide adoption. The bank-wide adoption of SOA is typically inhibited by organizational constraints and lack of senior management buy-in. An effective enterprise architecture practice is one that is able to bridge the gaps between organizational “silos”. If an Enterprise Architect with domain authority over SOA has a bank-wide sphere of influence, and is able to set bank-wide direction, then SOA adoption is better assured, and thereby the time-to-market of digital banking capability is improved.
<p>The extent to which technology standards are enforced bank-wide (as opposed to allowing different technology standards for each business unit).</p>	<ul style="list-style-type: none"> The enforcement of technology standards is intended to reduce the Total Cost of Ownership (TCO) of technology assets in the bank, by –

	<p>a) reducing the number of difference vendor licenses; and b) reducing the number of different skillsets required to support the technology.</p> <ul style="list-style-type: none">• If the technology enabling digital banking capability, including SOA, is standardized bank-wide, then the financial benefits of digital banking is better assured.
<p>The degree to which technology investments are considered for bank-wide usage, i.e., a multi-purpose technology that can support different business processes, and can be leveraged across different business units.</p>	<ul style="list-style-type: none">• Enterprise platforms such as BPM, BRMS, EDW, and SOA (ESB) are intended to support multiple business processes across different business units, e.g.; BPM can be used to manage loan origination and trade settlement business processes.• Enterprise Architects who are able to influence and direct the multipurpose use of these platform technologies, at the point of technology investment (funding) and beyond, are able to better assure bank-wide TCO goals.
<p>The extent to which actual financial benefits (increased revenue or reduced cost) of each technology investment are tracked, and are re-evaluated periodically.</p>	<ul style="list-style-type: none">• The business case proposals for funding technology investments include the expected financial benefits, including Return on Investment (ROI).• The financial discipline to track and periodically re-evaluate the actual financial benefit of technology investments will aid in managing technology lifecycles, and thereby better assuring TCO goals.
<p>The extent to which technology investments are customer experience-driven, as a means to gain competitive advantage.</p>	<ul style="list-style-type: none">• Digital banking strategies are centred on improving customer experience, to protect or gain market share.• Considering customer experience, leveraging design thinking techniques, before making technology investments, will better assure digital strategy outcomes.

Banks G and H were assessed to have the most rigorous IT governance processes with Likert scores of 4.80 and 4.20 respectively, and were also assessed as having the

poorest time-to-market capability with Likert scores of 3.00 and 4.25 respectively. This supports the idea that rigorous IT governance mechanisms can discourage innovation [29]. Bank E was also assessed as having highly rigorous IT governance processes with a Likert score of 4.20, but was ranked higher relative to Bank G and Bank H in terms of time-to-market with a Likert score of 4.50 – the difference being that Bank E was assessed as having a relatively more mature SOA in place. Bank F, being the largest bank in the study, traditionally had highly complex IT governance processes. However, they were also ranked the highest in terms of time-to-market, the difference being that they were assessed as having the highest level of SOA maturity.

Bank G has a highly rigorous IT governance process which is effective in managing and monitoring its IT investments globally, yet, they have not invested in a bank-wide SOA implementation, and therefore, they do not have a flexible architecture which can accelerate time-to-market at lower costs. In contrast, Bank F has recently decentralized its IT governance processes, effectively relaxing its global control of IT investments and have already achieved a high level of SOA maturity which enables a relatively faster time-to-market at a lower cost.

If complex and rigorous IT governance processes inhibit innovation in terms of time-to-market, then we can observe from our study that SOA maturity helps to overcome this barrier. The quantitative analysis of our case study survey data, summarized in Figure 4 above, does not provide empirical evidence, but our cross-case qualitative analysis of the interview comments and observations provides partial support of proposition *P5 – The complexity of Banks' IT governance processes has a negative influence on Bank's time-to-market of digital banking products and services. This causal relationship is reduced as Banks' SOA maturity increases.*

5.5 Age of banks' integration technology skillsets

In order to compete in this digital age, banks must transform themselves to become more like technology firms [13, 26], and move away from the traditional branch-based, account-centric style of banking. Becoming digital has implications on how applications integrate. Traditionally, applications integrate mostly via File Transfer Protocol (FTP) under a scheduled batch process, meaning that transactions are batched up and posted overnight rather than in real-time. Digital banking requires real-time transaction processing, and therefore banks' technology staff need to acquire a new set of core competencies around modern integration standards, technologies, and tools.

From the case study survey data, we looked for cross-case similarities in core banking systems (legacy/modern) and IT governance (simple/complex) in order to isolate the impact of modern integration technology related core competencies/skills on time-to-market capability, and to see if SOA maturity has any influence on this relationship. Both banks C and D have legacy core banking systems and simple IT governance, as illustrated in Figure 5 below. However, neither banks have a short time-to-market, so it is indeterminate whether or not core competencies has any impact, at least based on the case study survey data.

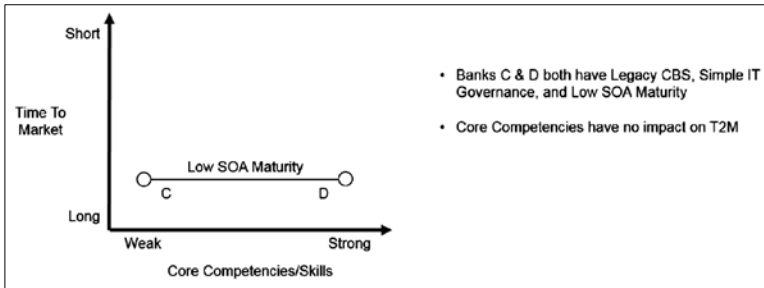


Fig. 5 Core Competencies impact on time-to-market

Software development capability, and integration technology related core competencies/skills, in relation to time-to-market capability are based on the criteria and rationale provided in Table 6 below:

Table 6 Core competencies assessment criteria

Assessment Criteria	Rationale, Implications on Architecture
The strength of the bank’s software development capability, to support in-house or outsourced application development.	<ul style="list-style-type: none">• To compete in this digital age, banks must transform themselves into technology firms.• Increasingly, digital banking capability cannot be provided by COTS systems, rather the capability must be developed within the architectural constraints of each bank, and with agility in order to gain time-to-market advantages.
The degree to which software developers understand XML, XSD, Xpath and other standards, and know how to use model-driven development tools.	<ul style="list-style-type: none">• Increasingly, model-driven development tools are used to support the rapid development of software applications, including the complex business logic within BPM executable processes and SOA services.• Modeling tools typically import/export and manipulate data formats that are compliant with industry standards and are supported by multiple technology vendors.
The degree to which software developers understand the current web services industry standards (e.g. SOAP, WSDL) ratified by W3C.	<ul style="list-style-type: none">• Model-driven SOA development and testing tools comply with web services industry standards. These GUI-driven tools enable the rapid

	<p>development of complex business logic without writing any code. Service consumer code can be automatically generated by importing the WSDL provided by a SOAP service.</p> <ul style="list-style-type: none"> • Architectural styles like REST are less likely to be supported by automated code generators, because there are no industry standards for tools vendors to comply with.
<p>The degree to which software developers understand the common enterprise integration patterns, e.g. synchronous request-reply, publish-subscribe, etc.</p>	<ul style="list-style-type: none"> • SOA services inherently implement the synchronous request-reply message exchange pattern. • Banks which are still implementing an EAI style of integration will typically use asynchronous fire-and-forget or pub-sub messaging patterns. • For a bank to transition to SOA, understanding of both modern standards as well as legacy standards is needed.

Bank H had the lowest Likert score (4.25) for core competencies/skills related to modern integration standards. Even though they were assessed relatively high in terms of IT governance processes (see previous section), the bank still mostly employs a message-oriented EAI style of integration, and have not yet embraced SOA, which is likely contributing to their relatively low time-to-market ranking as compared to other banks. Bank H also typically outsources their application development rather than employing in-house developers.

In contrast, Bank F had the highest Likert score (5.75) for integration technology-related core competencies/skills. They have embraced SOA globally, and do most of their application development in-house. They are very strong in their understanding and implementation of modern integration standards. Despite being ranked relatively low in terms of IT governance processes (see previous section), their high level of SOA maturity likely contributes to their high time-to-market ranking as compared to other banks.

Except for Banks C and H, most of the banks in this study were assessed relatively high in their understanding and adoption of modern integration technology. Other than for the contrast between Banks H and F, there is not a strong indication that integration technology core competencies is a factor in determining time-to-market capability, and it is unclear from the data that SOA maturity has a moderating effect on this causal relationship. The quantitative analysis of our case study survey data, summarized in Figure 5 above, does not provide empirical evidence, but our cross-case qualitative analysis of the interview comments and observations and contrast between Banks H

and F, provides partial support of proposition *P6 - The age of Banks' integration technology skillsets has a negative influence on Bank's time-to-market of digital banking products and services. This causal relationship is reduced as Banks' SOA maturity increases.*

6 Discussion

As a result of the individual case study interviews, surveys and analysis of the data collected, we could identify and explain the barriers to entry (inhibitors) for digital banks who are intent on protecting their market share against the FinTech substitutes. Based on the common observations gathered across the individual case studies, we then recommended what actions banks should take in order to overcome these challenges. The barriers to entry are summarized as follows:

Legacy systems – Banks that rank lower in terms of age/legacy of their core banking system (CBS) and rank lower in terms of SOA maturity, also tend to rank lower in terms of time-to-market capability. This shows evidence that legacy systems are indeed an inhibitor for digital banking. Banks which find it difficult to carve out business logic embedded within their CBS also tend to implement pass through messages which expose the underlying CBS interface directly, without any data abstraction, leading to tight coupling between systems and ultimately an inflexible architecture. To work around tight coupling between systems, some banks implement digital banking innovations as stand-alone solutions that bypass the CBS entirely. Banks which suffer from an inflexible architecture due to tight coupling between systems, also tend to implement significant percentages of their application interfaces as batch-mode bulk data transfers rather than on-demand services required by digital banking. Banks with legacy systems tend to rank higher in terms of time-to-market capability if they also rank higher in terms of SOA maturity.

Complex IT governance processes – Banks which have rigorous IT governance processes are effective in managing and monitoring their IT investments globally. However, banks which take a 'buy (off-the-shelf) or build (from scratch)' approach to solution development, even in the presence of a strong enterprise architecture practice, are challenged to attain buy-in across business units for large capital investments, thereby inhibiting time-to-market capability. In contrast, banks which take an "assemble" (reuse) approach to solution development leveraging a bank-wide SOA implementation, even in the absence of an enterprise architecture practice, tend to have accelerated time-to-market capability at lower costs.

Lack of integration technology skillsets – Most of the banks in our study were assessed relatively highly in their understanding of modern integration technology standards. However, not all banks that rank highly in this category had effective SOA implementations. Regardless of any in-house integration technology related skillsets, some banks tend to outsource their application development, including integration components, while other banks tend to develop their applications in-house. The banks which outsource their development also tend to maintain a significant percentage of batch-mode data transfers rather than on-demand services. The banks which were

assessed highly for their integration technology skillsets and also develop applications in-house, also rank higher in terms of SOA maturity and time-to-market capability.

6.1 Management implications

SOA centre of excellence – The two highest ranked banks in terms of time-to-market capability both have an effective SOA Centre of Excellence (CoE) which enforces bank-wide SOA principles, policies, best practice guidelines, and standards. The other six banks were assessed as having a poor or non-existent SOA CoE, with the highest Likert item score being “Somewhat Disagree” to the question “Your bank has an effective SOA Centre of Excellence (or Competency Centre) which enforces bank-wide SOA principles, policies, best practice guidelines, and standards. Some of the banks had a SOA CoE in place previously, but then later disbanded this functional group due to various reasons, including: change in management, loss of funding, and lack of senior management support. Without an effective SOA CoE in place, the ongoing success of an SOA implementation is at risk.

SOA framework and governance tools – Referring to the preview of two paragraphs, if the banks with disbanded SOA CoE’s had the financial discipline to track and publish (internally) their cost avoidance due to service reuse, then they would likely not have lost senior management support and would not have been disbanded. It all comes down to service reuse rate and cost avoidance due to service reuse as the most important metrics to manage. What some of these banks seem to be lacking is a well-architected ESB (Enterprise Service Bus) framework and runtime governance tools for controlling and monitoring service usage, and design-time governance tools for managing service lifecycles and making reusable services available to application developers.

SOA competencies – From our study, it is clear that an effective SOA implementation seems to be a key factor in overcoming the barriers to entry for digital banking. Using modern integration technology to develop services is easy. To design services for optimal reuse, and to ensure that services are indeed reused, and to ensure that the benefits of service reuse is realized, is difficult. Banks are complex, and to develop SOA competencies entails a long learning curve, several years in many cases. If banks want to compete in this digital age, then they will need a flexible architecture like an SOA which will enable rapid time-to-market capability. Some of the banks in this study could have benefitted early on from a pre-packaged set of banking industry standard services, an ESB framework, a set of runtime and design-time governance tools, and best practice guidelines.

7 Conclusion

In this paper, we evaluated three propositions which identify and explain the barriers to entry for digital banks. The evaluation is achieved through multiple case studies conducted across eight banks operating in Asia, involving an interview and pre-interview survey with the chief technologist at each bank.

The outcome of our propositions is summarized in Table 7 below. Proposition P₁ is supported by the case study survey data and interview comments. Propositions P₂ and P₃ are not supported by the quantitative analysis of case study survey data; however, they are partially supported by the cross-case qualitative analysis of interview comments and observations.

Table 7 Outcome of Propositions (P₁ - P₃)

P ₁	The age of banks' technology infrastructure has a negative influence on bank's time-to-market of digital banking products and services. This causal relationship is reduced as banks' SOA maturity increases.	Supported
P ₂	The complexity of banks' IT governance processes has a negative influence on bank's time-to-market of digital banking products and services. This causal relationship is reduced as banks' SOA maturity increases.	Partially Supported
P ₃	The age of banks' integration technology skillsets has a negative influence on bank's time-to-market of digital banking products and services. This causal relationship is reduced as banks' SOA maturity increases.	Partially Supported

The important observations from our cross-case analysis are: a) SOA maturity is directly related to the time-to-market of digital banking capability; b) a more modern core banking system improves time-to-market capability, however, this can be negated by a lower SOA maturity; and c) as long as SOA maturity is high, improved time-to-market capability can be achieved even in the presence of a legacy core banking system.

A key conclusion from our study is that SOA maturity plays a very important role in enhancing a bank's capability to deliver digital banking transformation. In order to move towards higher levels of SOA maturity, we make three recommendations –

establishment of an SOA centre of excellence, implementation of a well-architected Enterprise Service Bus (ESB), and adoption of an ESB framework and toolkit.

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Glossary

1. **Business Process Management (BPM):** A discipline at the intersection between management and IT, encompassing methods, techniques and tools to represent, model, design, analyse, enact, and control business processes involving humans, organizations, applications, and documents.
2. **Business Rules Management System (BRMS):** Software suite that helps to define, execute and monitor decision logic that is used by other applications.
3. **Enterprise Data Warehousing (EDW):** This includes all the tools and methodologies for developing a unified database that stores the required business information that is accessible by different divisions across the company.
4. **Enterprise Application Integration (EAI):** Deals with technologies and methodologies that enable the integration of applications residing within an enterprise.
5. **Enterprise Service Bus (ESB):** An architecture pattern where reusable business services are exposed using enterprise standard semantics and standard transport protocols.
6. **FinTech:** Firms that are non-bank software technology companies that provide alternative financial services over the internet.
7. **Message-Oriented Middleware (MOM):** A software platform that provides the means to transport messages between business applications using a number of interaction patterns.
8. **Service Oriented Architecture (SOA):** An architectural approach for designing and building applications that tie services together and are defined by industry standard interfaces (e.g. Web Service Description Language).

The rise of machine learning and robo-advisors in banking

Chaman Lal Sabharwal ¹

Abstract Machine Learning (ML) is a branch of artificial intelligence. A learning algorithm is an algorithm that supports the technology to simulate the human learning process. Computers execute algorithms to facilitate temporal and spatial efficiency for knowledge extraction from large volume of data. Computers are used in all aspects of life, one aspect is financial industry of which banking is a major part. Financial institutions are now increasingly leaning on machine learning to devise new business opportunities, deliver customer services and even detect banking fraud as it is taking place. Deep learning is a branch of machine learning that produces efficient algorithms to model high-level data. These new technologies utilize complex techniques inspired by genetics. The future software applications include NLP processing and analysis of text-based business reports, and intelligent algorithms with intuitive graphical user interface. The financial industry stores vast amounts of data from transaction data to customer data. This volume is likely to increase in the future, and the financial sector is increasingly looking to make the most of such data. In 2016, there was a lot of talk in the industry about the potential for deploying machine learning and over the last two years, this is aptly taking off in the mainstream in finance and banking. But the noise and behavioral elements inherent in raw financial data often require non-standard machine learning solutions, possibly yet to be developed. The full potential of machine learning in finance is still to be explored. We present an intuitive, practical and non-mathematical view of the impact of machine learning. This paper shows how machine learning is going to be used in financial sector in the future.

Keywords: Machine Learning · Robo-advisors · Finance · Banking · Cyber Security · Fraud Prevention

1 Introduction

Computer is a machine, and an algorithm is a process to accomplish a task. A learning algorithm is an algorithm that supports the technology to simulate the human learning process. Machine learning is a collection of learning algorithms. Humans build computers, design algorithms, and create software (program, debug, optimize) to implement algorithms. Computers are used to execute algorithms to facilitate temporal and spatial efficiency for knowledge extraction from large volume of data. Computers are ubiquitous in all aspects of life, one aspect is financial industry, and banking is a major part of it.

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Machine learning is a branch of artificial intelligence and has become a craze in the technology industry, with computers learning to complete tasks without being directly programmed to do so. Deep learning, a branch of machine learning, which has now become mainstream, produces efficient algorithms to model high-level data. For example, in 2016, there were many machine learning pilots and trials in the industry, with acquisitions of machine learning startups by tech giants [01].

Machine learning is an amalgamation of concepts from various fields: mathematics and statistics, information theory and electrical engineering, computer graphics and robotics, psychology and cognitive science, software engineering and graph theory, etc. [02]. Machine learning originated in engineering, then it was used in psychology and increasingly used in data mining, later it found its way into medicine, radiology, biometrics, forecasting of natural hazards, meteorology [03]. Machine learning has been successfully used in businesses like NetFlix for movies, Amazon for book sales, ticket purchasing by airline industries. Insurance companies are beginning to use machine learning for sales and retaining customers [04]. Machine learning is now a technical greenhorn nuance in finance and banking industry.

Financial institutions are now increasingly leaning on machine learning to devise new business opportunities, deliver customer services and even prevent banking frauds as it is taking place. In modern days, for portfolio management and credit risk analysis, machine learning plays a prominent part in all aspects of banking. Funds are increasingly migrating towards true artificial intelligence models that can not only analyze large volumes of data, but also continue to improve themselves. These new technologies utilize complex techniques including deep learning, a form of machine learning called Bayesian networks, and evolutionary computation, which is inspired by genetics [05]. The future software applications are intelligent algorithms with intuitive user-friendly graphical user interface. The idea of interface is that it gives a visual interpretation of what the algorithm is doing. The implication is transparency of outcome as some parameters are calibrated [24]. This machine learning algorithm ethics explain what and how it is performing instead of being just a 'black-box'. The algorithms include NLP processing and analysis of text-based business reports, machine learning, deep learning and reinforcement learning.

The financial sector is renowned for the vast amounts of data it holds – from transaction data to customer data, and everything in between. This volume is likely to increase in the future, and the finance sector is increasingly looking to make the most of the data that it holds. This has been largely analyzed using statistical analysis tools, however, the challenge is sifting through such a wealth of data efficiently in a timely fashion. In 2016, there was a lot of hype in the industry about the potential for deploying machine learning and over the last two years this is aptly taking off in the mainstream finance and banking. But the noise and behavioral elements inherent in raw financial data often require non-standard machine learning solutions, possibly yet to be developed. The full potential of machine learning in finance is still to be explored [06]. This paper details how machine learning is going to be used in financial sector in the future.

The paper is organized as follows: Section 2 glances through the background of banking and need for machine learning; section 3 is about machine learning and its

use in banking industry; section 4 highlights advantages of machine learning in banking; section 5 explains the impact of machine learning and use cases; section 6 is about machine learning opportunities in finance followed by conclusion in section 7.

2 Banking technology background

In 1959, Bank of America pioneered the use of computers in banking industry. During the contemporary times in banking, computers are used for managing amazingly large volume of accounts accurately and efficiently, analyzing profits and losses, and performing risk analysis. In addition, computers are used for electronic fund transfers, network security systems, malware security, and fraud prevention. For example, direct deposit is a simple instance of an electronic transaction. Banks have extended electronic transaction capabilities through the automated teller machines (ATMs), the internet via cellular phones, laptops, and landline (is becoming extinct). Most of the electronic transactions are performed remotely. Web based banking systems use a dedicated server through the bank secure network system keeping records of transaction patterns.

Computers are used to control ATMs dispensing money to account holders, requests from customers and all money transactions, etc., and to monitor the camera-controlled video (CCTV) of the events. For security, remotely controlled cameras are used to ensure that no one steals money, a proactive way to deter the robbers. Computer algorithms are proficient to confirm personnel and customer identity verification remotely and instantaneously. Knowledge-driven banking has benefitted secure e-banking. The list of applications of computers used in the financial industry is endless [07].

2.1 Banking business requirements

Since the customers are getting sophisticated, banks have to provide state-of-the-art excellent service. It has become the cornerstone for business communities to provide efficient service [08]. Computers have revolutionized the banking sector as never envisioned before. The computing technology has two aspects:

Software

- Electronic transactions software
- Encryption requirement
- Dedicated server
- Web-based secure banking

Hardware

- During 1960s, it was mainframe and punched cards, cables connectivity, which is now obsolete
- Currently, in 2018, smartphone, iPad, and laptop are in vogue. Wireless provides faster and instant feedback.

2.2 Account management and customer management

Account management is the genesis and backbone of all banking information systems. Besides accurate and efficient transactions, computers are used in various banking

service roles. Banking software is used to perform all transactions through a centralized database. Customer Relations Management (CRM) software is used to store and manage information for customers, e.g. contact info, accounts, and other related perspective financial data in one central location. For any bank, the main objective of a CRM is customer acquisition and retention, marketing and accomplishing the bank objectives. It is used to monitor customer handling with dignity and give the customers the attention they need to track transactions [07].

2.3 Underwriting insurance and claims

Machine learning can support automating large volumes of underwriting in auto, home, commercial, life and group insurance sectors. In the future, machine learning will enhance modeling, highlighting key considerations for human decision-makers that may otherwise have gone unnoticed. It's also predicted that advanced AI will enable personalized underwriting by company or individual, taking into account unique behaviors and circumstances. Enhanced underwriting may leverage not only machine learning for data mining, but also wearable technology and deep learning facial analyzers. For example, Lapetus, a startup, wants to utilize selfies to accurately predict life expectancy. These types of nuanced, real-time risk analyses will enable not only more accurate customer pricing, but also early detection of risks. With regards to claims, machine learning can also help insurance companies improve customer data accuracy and create faster payout recommendations [09].

For example, the human underwriters can be easily succoured by robo-underwriters. This leads to reducing a large number of positions in insurance industry. Since large banks are publicly traded insurance firms that have stockpiles of live data, the machine learning algorithms can be trained continuously. Presently robo-systems used by big corporations will soon become a norm and will be available freely [10].

2.4 Robo-technology

Robo-advisor is not a human being or a mechanical robot, but an ecosystem. The term 'robotics' originates from engineering where robots (machines) are used for heavy duty jobs in manufacturing. The robots can operate in hazardous environments as required in military. Robots do not get angry at ill-informed customer, do not demand pay raises, do not form unions to go on strike, do not get tired, do not get dozy on the job, etc. Figure 1 shows a robot-advisor, compliments of google digital nirvana images.



Fig. 1 Digital nirvana is in the eyes of banking consumers

The 'robo-advisor' is a very recent popular software for providing service to the customers. From robo-advisors, the user can get confidential advice by providing login information about the account, e.g. name, password and additional information for double authentication (like instantaneous phone call or text message with special code, etc.). The user can then key in the desired information parameters and get instant advice without the need of human advisor.

In finance, a robo-advisor is a computer with interactive financial software supported with user-friendly graphical user interface to calibrate portfolios in response to the need and risk tolerance of the user. The robo investing software allows you to consistently calibrate and customize your online investing to meet your long-term financial goals and your short-term investment strategy. Since the robo-system is built on the training from thousands of related customers, this advice is more unbiased than the human advisor. The top robo-advisors are also responsible for consistently rebalancing the portfolio. As compared to human advisors who are subjective, error-prone and time-consuming, robo-advisors are objective, more accurate, fast, effective, and work around the clock.

Financial advisors offer the same services, but cannot do so with the same regularity as robo-advisors do. The difficulty with these devices is that robo-advisors are not sentimental, whereas, stock market fluctuates on timely sentiments also in addition to actual data. Human advisors can provide sentimental advice that robo-advisors do not. Thus, robo-advisors and traditional financial advisors can co-exist [11].

Robo-advisors are digital platforms that provide automated, algorithm-driven financial planning services with virtually no human interaction as shown in Figure 1. It is expected that capabilities in the future will evolve into more advanced offerings such as automatic asset shifts and expanded coverage across alternative asset classes like real estate. For example, in Wealth Management industry, current robo-advisor handles total assets under management (AUM) that is only \$10 billion of industry's \$4 trillion assets (far less than 1% of all managed account assets). A Business Insider study estimates that this figure will rise to 10% by 2020 [05].

All in all, robo-advisors are flooding the market with their online investment opportunities. There are some case studies for comparing the robo-advisors [12], [13]. In the next section, we will consider the attributes of the robo-advisors for machine learning algorithms.

2.5 Telemarketing

Telemarketing is another area actively exploring and exploiting the use of robo-advisors to induce customers to open accounts and make long-term deposits. It eliminates need for call centers. Since robo-advisor can perform repetitive tasks, it can serve as a chatbot-like live chat. Unlike people who may ask the customer for the contact info to get back to the customer later, the chatbot has immediate answers. In the past, there were text-oriented "chatboxes" where a live human being was interacting with the user.

With the advent of high speed computing power, the present and the future of banking appears promising. Machine learning uses natural language processing (NLP) and the use cases for training the chatbots. The early users of chatbots are likely to have an edge over banks using archaic manual query processing or digging in webpages to search for the required information. Future chatbots that are voice-oriented are beginning to appear as chatbots are in vogue.

3 Machine learning and banking

The AI algorithms have their roots in 1970s when computers were in mainframe era. Machine learning is mostly linear algebra and statistics, for example, face identifications is eigenfaces that is based on linear algebra singular value decomposition (SVD). In 1960s, computer-vision designed algorithms to locate ears, eyes, mouse, nose in photographs, with no knowledge that eigenface technology will find its way into security applications.

Alexnet was designed in 2002, one of the most popular softwares. It is an image recognition program trained on 1.3 images of 1000 different objects. It was first published in 2012 for research community. If a new image does not fit in, it can be retrained efficiently on additional data instead of from scratch. Nowadays, there is a hype on deep learning. Deep learning is simply neural networks with a large number of inner layers.

In finance, machine learning is used to make fast trading decisions. These days with the high volume of banking data, the quantitative nature of real-time transactions, accurate and efficient processing is of paramount importance. High frequency trading (HFT) is a norm. Due to the availability of high-speed computing power, machine learning algorithms are ubiquitous in applications than ever in the past [14]. Machine learning devices are an integral part of financial ecosystems whether it is portfolio management, risk analysis, loan approval or fraud prevention [09].

For portfolio risk analysis, one needs to understand how these tools work and how to calibrate relevant parameters to make most out of these. Unfortunately, there are few tech-savvy users of the tools who are knowledgeable about the intricacies of the algorithmic techniques. As an educated bank advisor, it is necessary to understand the basic techniques and basics of techniques to grasp the application usability and its calibration parameter implications. Thus, knowledge of inner workings of algorithms and their parameters is desirable to use machine learning intelligently, to understand the implications of parameter calibration for impact on desired output.

Machine learning applications for banking are useful for finance in general. The modern banks not only manage the money, but they also provide additional services including, brokerage activities, insurance underwriting, loans, etc. Thus, there are several ways machine learning can be used – portfolio management, fraud detection and prevention, automated trading systems.

Banking is different from stock market. In finance, hedge funds are different from mutual funds. Some robo-advisors are public while some algorithms are considered proprietary for hedge funds. For more details on algorithms used by hedge fund managers, see [15]. A recent study performed by investment research firm Eurekahedge tracked the performance of 23 hedge funds from 2010-2016, and found that AI-savvy managed funds outperformed those managed by more traditional quants and generalized hedge funds.

3.1 Bank related algorithm features

Here we discuss the features of robo-advisors for comparison of best performers in 2017 and 2018. To characterize the data, the term feature, attribute, predictor, parameter, variable, characteristic, context, are synonymous and interchangeably used in the literature. Machine learning algorithm transforms one set of data features into another set of output data latent variables. For banking, it transforms the historical marketing data into future prediction data by means of Tradebot (Tradebot is based in Missouri, USA); whereas decision tree based fraud detection application transforms transaction data to binary data whether the transaction is fraudulent or genuine. Captterra company provides free service and lists custom product features and customer reviews to build the list for comparisons of readily available robo-advisors [13]. The robo-advisors were evaluated on the following parameters: Platform Deployment, Functionality Support for Brokerage, Core Banking, Credit Union, Investment Banking, Online Banking, Private Banking and Retail Banking. QwikDial meets the maximum requirements.

Nerdwallet is another business that ranks the robo-advisors on their overall functionality, fees, pros and cons. For finance, robo-advisors Wealthfront and Betterment are the two best overall standouts in their 2018 ranking [16]. Others are listed in order of ranks – Wealhsimple: for socially responsible investors; Ellevest: for portfolio mix; Vanguard Personal Advisor Services: for access to a financial advisor and portfolio mix; Schwab Intelligent Advisory: for access to a financial advisor. FutureAdvisor and Wealthfront were the two best robo-advisors in 2017 due to their low cost investments, account minimums, streamlined interfaces, and outstanding features. The portfolio comparison attributes were investments in exchange-traded funds (ETFs), index funds and features diverse investment management through constant, tax-efficient rebalancing [17]. FutureAdvisor prides itself as an award-winning investment advisory firm with an investment council team of savvy finance experts. FutureAdvisor brags about holistic low-fee index funds, diversification, wealth management, and tax efficiency. Wealthfront focuses on a core set of investment products, including:

- Individual accounts
- Joint accounts
- Trust accounts
- Traditional IRA
- Roth IRAs & SEP IRAs
- 401(k) rollovers
- 529CollegeSavingsPlan
- For more details on six-point strategy see [17]
- 401(k) advice
- Holistic approach
- Tax-loss harvesting
- Consistent monitoring
- Expert advice
- Tax-efficient methods

Retirement Planning is a free service to evaluate customer funds, offers sound recommendations, and provide custom advice to improve the portfolio and holdings. This includes nine simple steps and real-time updates. As a free service, this makes FutureAdvisor a best robo-advisor for cost-efficient retirement planning.

Investment Management is not free to use, there is an annual fee that covers the following services:

- Comprehensive portfolio management
- 24/7 online investment managers
- Easy-to-navigate dashboard and FutureAdvisor app
- Accountability as fiduciary
- Professional advice
- Automatic algorithms to monitor for opportunities

Personal Capital Accountant is free and ranks one. Free service is available in the US only, and is expected to be available to other countries also. One inconvenience

encountered with it is that, one cannot download it for using it as a standalone robo-advisor.

3.2 Cybersecurity

Online investment companies are cropping up everywhere, but it is not clear as to which ones are legitimate? How do we proactively ensure that a brokerage service is fiduciary or fraudulent? Cybersecurity, computer security or IT security is the protection for computer systems from theft of or damage to their hardware, software or electronic data, as well as from disruption or misdirection of the services they provide [18].

3.2.1. Risk management

Since more and more consumer data is accessible online due to availability of fast computing power coupled with petabyte disk space, relatively large (big) data is at a greater security risk. The goal of machine learning algorithms is: (1) to avoid false positives (false alarms) and (2) reduce false negatives (missed cases). The precision metric for false alarm or false positives uses the frequency that non-risky transaction should not be falsely flagged as risky, whereas the sensitivity metric measures missed cases or is false negative, which means risky transaction should not be flagged as safe, clearly outliers should be detected, not declared normal [19]. An overall accuracy measure is called an F-metric. Using these measures, the machine learning and deep learning algorithms learn the fraud patterns and learn to protect data.

3.2.2. Fraud detection and prevention management

Traditional methods of fraud detection include computers analyzing structured data against a set of rules. However, this type of analysis requires a lot of additional effort including domain knowledge. It produces many false positives. While a linear model can handle 20-30 features, deep learning technology can control thousands of predictor attributes. For example, consider the payment giant PayPal and its advanced fraud protocols. PayPal has been able to boost security by leveraging deep learning technology. In fact, PayPal's fraud is relatively low at 0.32% of revenue, a figure far better than the 1.32% average that the merchants face [05]. The modern fraud detection deep learning algorithms outperform humans and are becoming more sophisticated that learn continuously with incoming streaming data. But input data has to be accurate. As the security can be breached on several fronts, genuine learning algorithms devoid of overfitting will be necessary in the future.

Example, telemarketing machine learning is used in a Portugese retail bank and predicts success of telemarketing for acquiring long-term deposits in a bank [03]. Data is collected from 2008-2013; it relates to client, product, and social economic features. It consists of 150 attributes, data was reduced to 22 latent features for determining the success of the telemarketing. There are tons of machine learning algorithms, as shown

in Figure 2[14], out of which four machine learning data mining models were selected for this study[13]: logistic regression (LR), decision trees (DT), neural nets (NN), support vector machines (SVM). On comparing data mining models LR, DT, NN, SVM several studies showed different classification performances [03]. For reality check, the experiments [03] showed that first two methods LR and DT are easier to understand, while the other two NN and SVM are complex, they provide more accurate predictions. Area under the receiver operating characteristic (ROC) curve (AUC) metric was used.

In this instance, NN turned out to be the best. It is not surprising that there is an increasing interest in deep learning and data mining these days. Examples, [03] used data-driven model for modeling bank telemarketing success, call duration time was one of the attributes. The data from Iran bank consisted of 22,427 customers from January to July 2006. The customers, who purchased the product, were indeed influenced by telemarketing [03].

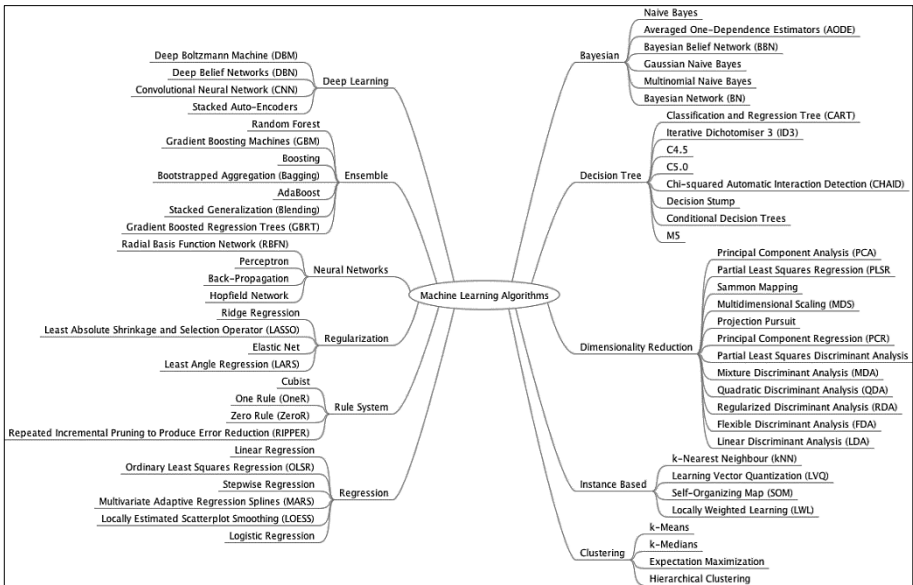


Fig 2. Mindmap of learning algorithms [14]

4 Recompenses of technology in banking

The banks use computers to allow customers to do transactions remotely and securely, around the clock. Banks, brokerage industry, credit card companies, and other businesses use smartphones and computers to do business transactions electronically [07]. Online banking has become a fad these days for numerous reasons. Advances in technology are replacing traditional banks with virtual banks, internet banks. For example, Discover credit card company already provides internet e-checking and savings accounts similar to traditional banks. The bank employees as well as customers have quick access to most update account information. The customers have

the flexibility to avoid going to a physical location for face-to-face communication. This saves travel time, and travel expense leading to comfortable and cost-effective banking. Also, internet banking has lower costs than traditional banks. For example, online banks pay higher interest rate and charge lower loan fees. Money changes hands electronically and remotely when the customer makes transactions. Even the telephone answering machines are automated to answer frequently asked queries. For example, decision tree algorithms aid in routing the queries to the proper respondent. There is a wide variety of banking software, free apps, for customers to use on smartphones as well as laptops.

Most of the companies assume big data to make big changes to their industries before the end of the decade otherwise believing their companies might fall behind [21]. There's plenty of big data in every industry, especially banking and financial services. Not only efficiency, but also financial regulatory requirements mandate that every customer interaction must be retained. Except for dispensing cash from ATMs, every customer interaction automatically generates the necessary electronic record. The financial organizations and banks are using this data to generate business insights. These businesses perform data analytics in real-time to drive immediate decision-making. For example, some of the most common use cases where banks and finance industries are deploying big data analytics are:

- *Fraud Detection/Prevention:* Banks and finance industries use analytics to detect fraudulent interactions from legitimate business transactions. By applying data analytics and machine learning, they define attributes for normal and abnormal activity based on a customer's history and use them to detect the unusual behavior indicating fraud. The algorithmic analysis systems detect irregular activity and suggest immediate actions, such as blocking such transactions, which stops fraud before it occurs and improves profitability.
- *Security:* Whatever the applications, security is of paramount importance. To create secure banks, networks have to be made secure in several ways. Some of the methods for implementing security are to avoid robots to access information, use biometric features, double authentication via presenting, question and verify the correctness of the answers, e.g. presenting images, ask the user to identify images with a specific feature, a phone call, text with a message code.
- *Compliance and Regulatory Requirements:* The Dodd-Frank Act, enacted after the 2008 financial crisis, requires documentation of the details of every trade for trade surveillance that recognizes abnormal trading patterns. For this reason, financial services businesses operate under a tight regulatory framework, which requires significant levels of monitoring and reporting.
- *Promotional Marketing:* Banks are working to change from product-centric to customer-centric businesses. In order to achieve such transformation, it is better to understand their customers through clustering. For example, big data analytics enables them to cluster customers into distinct groups which are defined by data attributes customer demographics, daily transactions, interactions with online and telephone customer service systems, and external data, such as the value of their

houses, value of car, type of employment, etc. They target customers according to their groups with common values in their promotions and marketing campaigns.

- *Focused Marketing-Sentiment Analysis:* One step beyond promotional marketing is dedicated marketing, which targets customers based on understanding of their individual characteristics, income and buying habits. While structured information is in records, financial services firms can also incorporate unstructured data from the customers' social media profiles in order to create a fuller picture of the customers' needs through customer sentiment analysis. Once those needs are understood, big data analysis can create a credit risk assessment in order to decide whether or not to go ahead with a transaction, e.g. extend credit card limit, loan approval.
- *Risk Management:* Financial firms manage their customer risk through analysis of complete customer portfolios. The algorithmic trading manages risks against historical data. Big data analysis can support real-time alerting if a risk threshold is surpassed. The financial firms that have implemented big data projects are already enjoying a competitive advantage. Due to both regulatory requirements and the perceived value of big data analytics, financial organizations will continue to implement big data analytics projects.

The implementation of these ideas requires increased investments in data center technology as well as increased hiring of quants with big data skills. For value-added resellers, understanding their use cases will lead to additional opportunities to sell big data products and services.

5 Impact of machine learning on banks use cases

Machine Learning (ML) is currently on the verge of having the biggest impact on the banking industry. There are different kinds of machine learning used for different purposes. For example, supervised learning will be used to make trend-based predictions using sample data; unsupervised learning will be used to identify relationships between a large number of variables; deep learning systems will undertake tasks that are hard for people to define but easy to perform; reinforcement learning will be used to choose a successive course of actions to maximize the final reward.

Some interesting points on machine learning in finance are highlighted [22]. Five largest banks of the USA are investing in machine learning for efficiency in their workflows [20]. There are many examples of banks that are embracing machine learning in their workflow. The Machine Learning Natural Language Processing (NLP) is used for updating the text records in the Customer Relations Management (CRM) system, efficient customer self-service portals, electronic and mobile interaction and transaction management, and up-to-date predicting the stock market trends in order to ensure successful trading.

The financial giants like JPMorgan Chase, Wells Fargo, Bank of America, Citibank and the US Bank indicate that machine learning is the way the industry should evolve for banking services in the future. These five leading banks of the US are taking the machine learning incredibly seriously. Each bank has its own financial services robo-system, e.g. JPMorgan Chase COiN; Wells Fargo AI Enterprise Solutions System; Bank of America the virtual assistant Erica; Citibank FeedzAI; and US Bank AI Innovation group with Machine Learning and AI.

JPMorgan Chase has a proprietary ML algorithm, namely, Contract Intelligence (COiN). It is used to reduce the computation time to analyze the business correspondence documentation and extract the important information from it. This tool enables the bank to process thousands of documents in seconds instead of hours. Because of its fruitful outcome, the bank is actively exploring the ways to apply it in other daily operations. JPMorgan Chase is a leader in investment banking. Another initiative from JPMorgan Chase is called the Emerging Opportunities Engine. It is used to analyze the transactions and find the customers who are most likely to engage in follow-up trading. It has been applied in Equity Capital Markets, and is now making its way to other markets, including the Debt Capital trading. The bank also invests heavily in the development of their proprietary virtual chat assistant. This will help save billions in wages while providing top-notch customer support 24/7.

Wells Fargo AI Enterprise Solutions team applies their effort to providing increased connectivity to the company's payment and benefits solutions system to provide the excellent services to the corporate banking customers resulting in an AI-powered chatbot for the company's Facebook messenger. This virtual assistant is also used for resetting the password and providing the account details. It eliminated the previous system that required the customers to fill in several pages of forms, thus becoming a seamless dialogue that took mere minutes instead of hours.

Bank of America was amongst the first financial companies to provide mobile banking to its customers 10 years ago. They introduced Erica, the virtual assistant, positioned as the world's most prominent payment and financial service innovation, due to leveraging cognitive messaging and predictive analytics. By integrating the AI assistant, Erica, into their mobile banking solution, Bank of America aims to free up their routine transactions customer support centers for dealing with more complicated cases faster, thus drastically improving the overall customer experience.

Citibank FeedzAI invests on financial services and cybersecurity. FeedzAI uses machine learning algorithms to analyze huge volumes of big data real-time and alert the financial institutions of alleged fraud cases at once. FeedzAI concentrates on using data science to identify and demolish fraudulent attempts in various avenues of financial activities, including online and mobile banking.

US Bank concentrates on developing conversational interfaces and chatbots to augment the customer service. For example, the deep learning algorithm is expected

to be able to help answer rarely asked questions much more quickly. These are just tools to help humans to be more productive, not a mastermind to replace them.

Since machines are best-equipped to make trading decisions in the short and medium term, the banks will need to hire excellent data scientists who are finance-savvy. These people will be needed to acquire, clean, and assess the data; they need to understand big data. They won't need to be a machine learning expert, but will need to be an excellent quant and an excellent programmer [22].

6 Opportunities

Machine learning is transforming the financial industry in their approach to creating, producing and delivering services. Some people can be intimidated by words like machine learning and artificial intelligence, because it involves a lot of mathematics and statistics. We have seen the sci-fi thrillers like *The Matrix*, *The Terminator* and *Ex Machina* that have mythologized AI as a threat in disguise. On a practical side, we hear about "robots" displacing jobs in manufacturing. Even in the financial industry, robo-advisors have generated much anxiety, causing distress for money managers and investment firms. This type of strategic calculus definitely adds up, and data analytics can be a bit intimidating [23].

In practice, however, machine learning isn't formidable. Financial industry will find that if they use machine learning and advanced analytics, it will complement human services, not replace them. There is an opportunity to combine the power of both sentimental human intelligence and machine speed/space intelligence. They will co-exist as an efficient ecosystem.

The reason is that by analyzing data collected from previous rendezvous, a data-driven machine learning platform can quickly predict, with amazing accuracy, which features are most effective from a variety of attributes: financial objectives, risk profile, products used/offered, geographic region, etc. When AI-powered platforms pull in data from all touchpoints and product lines, they allow managers across the organization to see what marketing materials are working. This capability further refines the overall content experience, while providing opportunities for collaboration among interdepartmental teams. These hyper-relevant recommendations shorten sales cycles and enhance the entire client experience.

On a practical side, when AI is used to uncover what works best and when, it results in a system that is both automated and scalable. It not only radically streamlines how you bring on board new customers, it compresses the time necessary to bring new employees on board and get them up to a productive level. AI makes it easier to bring new bankers up to speed, so that they can start managing their relationships quickly and with more efficiency. This allows banks to scale their hiring more aggressively than otherwise possible, further broadening the avenues for increased revenue generation. Knowing that they are working off a proven content blueprint that

generates results, new relationship managers come out of the gate with both the tools and the confidence to succeed from day one.

From manual menial tasks to regulatory compliance to almost every facet of banking operations, including marketing client services, the industry is being propelled forward by machine learning. Machine learning complements employees' work, delivers meaningful value to clients, improves the overall experience, and returns value to their investments.

7 Conclusion

We have briefly described how machine learning comes into play in the finance industry, in particular banking. The dimension and scope of financial service is considerably different in response to competitiveness, degree of internationalization, innovation, and emerging trends. We are witnessing the society which is becoming paperless, cashless, scan and go, no checks, no bank drafts, instant update, no physical credit card debt cards. The businesses design unique features to attract customers and implement them to outperform their peers to compete in the international market.

Robo-advisor is not a threat, but a tool to assist humans to work more efficiently. Machine learning tools are used to extract knowledge from larges piles of data and serve clients efficiently. The combination of human and robo-advisors forms an ecosystem. Robo-advisors can also be used to train both the employees and managers to get on board quickly and work more efficiently.

Future banking security is of paramount importance. User ID, password, double authentication may no longer be necessary. Smart phones have capabilities of speaker phones for voice recognition, keyboards for thumb press (like key press), cameras for face recognition, iris eye movement (to distinguish between two similar faces, in the case of twins or not), and other biometric information. India is the first country to have uniform identification Aadhaar card – much more informative than social security card in the USA.

There is no work or information on how sentiment analysis is going to be used in banking. It is worth exploring as part of biometric information for fraud detection. The current predictions (supervised learning) depend on the past performances, to predict future trend from the social media, news trends, etc. Partly, it is in practice in an ad hoc manner. Machine learning may be used to formalize it. Although machine learning is already in use in thousands of companies around the world, most big opportunities have not yet been tapped.

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Sustainable co-training of mixture-of-experts for credit scoring of borrowers in social lending

Jae-Min Yu¹ · Sung-Bae Cho¹

Abstract Of late, social lending has been so popular that several services for it are provided based on credit scoring with a variety of personal aspects that affect an individual's credit. The factors that are not considered in traditional banks might be more influential than the conventional scoring. Loan requisition can be registered continuously, anytime, by whoever wants loan through social lending. At the same time, large-scale unlabeled data are increasing. Labeling data is expensive. In this paper, with focus on these characteristics, we present a global-local co-training algorithm for mixture-of-experts to exploit the unlabeled data for accurate credit scoring. We conducted experiments with dataset from the Lending Club to evaluate the accuracy based on the reliability of unlabeled dataset. To show the usefulness of the proposed method, we compared the performance with other machine learning methods such as Naive Bayes, logistic regression, decision tree and SVM, and analyzed the confusion matrix. A series of repetitive experiments revealed the quantitative superiority in various characteristics.

Keywords: Social Lending · Credit Scoring · Co-training · Mixture-of-experts

1 Introduction

Social lending, also called as peer-to-peer lending, is proliferating. It is a platform enabling individuals to borrow or lend, without a bank as the financial intermediary. Recently, the credit scoring model has been extensively studied for the evaluation of loan admission with the rapidly growing financial industry [1]. It is basis on which social lending is developed with the number of new users accelerating over time to satisfy the increasing worldwide demand for financial platforms and personal loans. However, the investment of lenders in the loan is not protected generally from governments. In terms of principal guarantee, social lending differs from bank deposit.

The core problem is whether social lending can approve lending to borrowers or not [2]. This problem can be considered as binary classification (good or bad) from the point of machine learning. Most of the loan datasets consist of biased instances [3]. This can be explained by poverty of default cases in the midst of plenty of normal customer cases. Biased dataset belonging to one of the classes can be regarded as

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imbalanced. Classification problem of imbalanced dataset occurs in both credit scoring and intrusion detection.

Another problem in social lending is the lack of systematic means/methods to check if repayments from borrowers are made duly on time. We consider this kind of data as unlabeled dataset (Loan requisition can be registered continuously anytime by whoever needs loan in social lending. Simultaneously, large-scale unlabeled data is increasing). Labeling all of this data costs high. Most of the real social lending data is unlabeled due to non-repayment.

Table 1 shows the statistics of the Lending Club data in terms of different classes. Except for fully paid and charged off, the rest of the classes mean in progress. That is, fully paid class means that borrowers repay principal in due date, whereas charged off class means that borrowers did not repay. About 74% of dataset consists of unlabeled data including late within 31-120 days, late within 16-30 days, loan in grace period and loan in current. This can support the approach of semi-supervised learning that uses both labeled and unlabeled datasets to enhance the performance of loan default classification.

Table 1 The statistics of the lending club data (2013-2014)

Classes	No. of loans	Percent of loan	Amount (\$)	Percent of amount
Charged off	13,350	5.67%	200,700,075	5.73%
Late in 31-120 days	4,974	2.11%	76,178,175	2.17%
Late in 16-30 days	783	0.33%	12,539,600	0.35%
In grace period	1,928	0.81%	30,711,275	0.87%
Current	162,337	68.96%	2,452,472,400	70.06%
Fully paid	52,023	22.10%	727,834,325	20.79%

Table 2 Matured loans of lending club data (2013-2014)

Matured loans	No. of loans	Percent of loan	Amount (\$)	Percent of amount
Charged off	13,350	20.42%	200,700,075	21.61%
Fully paid	52,023	79.57%	727,834,325	78.38%

The social lending data have a problem against the conventional classification method. We can see that the number of normal borrowers is larger than that of defaulted borrowers in Table 2. If the number of data with a class is abnormally high and we use a simple accuracy as metrics, machine learning algorithms tend to classify most of the data as the majority class for reducing the probability of misclassification. In this case, other minor class dataset can be considered as an important class [4]. This problem could cause to reduce the performance of machine learning classifiers. If we apply these situations to social lending, we could not find defaulted borrowers (minority) among normal borrowers (majority). Also, imbalanced dataset has a difficult problem to determine accurate classification boundary.

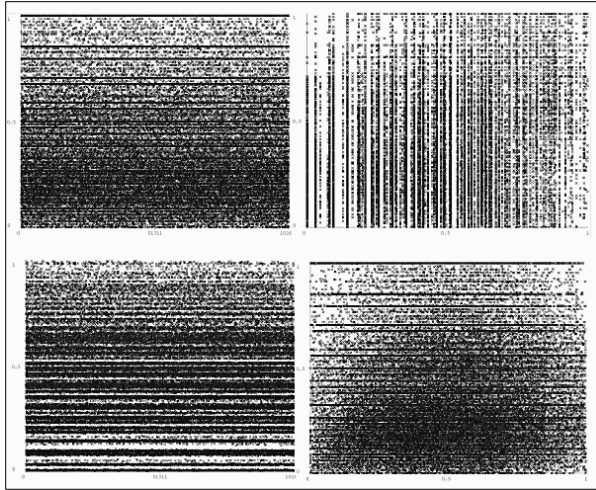


Fig 2. Distribution of the lending club dataset

2 Background

2.1 Learning issue on imbalanced data

In case of imbalanced data, the models such as artificial neural network and decision tree should consider the relative difference on classes because they tend to ignore minor class during classifying major class accurately [7]. Breiman et al. showed that minor class can be classified as major class (misclassification) when classifying imbalanced data [8].

To reduce the total misclassification, classifier learns major data more, to increase the correct classification of major class. Therefore, minor class can be classified as major class. Many studies have been performed to overcome this imbalanced data problem [9]. Table 3 shows the related works of learning imbalanced data. Oversampling extracts minor class by duplication for total dataset. Undersampling extracts less major class compared to total dataset. The mixture-of-experts is good at dealing with imbalanced data.

Table 3 Related works of learning imbalanced data

Author	Method
Chen et al. [10]	Oversampling extracts minor class dublicately for total dataset
Kubat et al. [11]	Undersampling which extracts major class, less compared to total dataset
Cardie et al. [12]	Learning method which gives a weight to minor class
Grzymala et al. [13]	Method which gives a weight to learning rule
Joshi et al. [14]	Method which boost minor class
Veropoulos et al. [15]	Gives penalty to each class
Kotsiantis et al. [16]	Utilizes mixture of experts to deal with imbalanced data

2.2 Co-training

Co-training is an approach of multi-view semi-supervised learning proposed by Blum [17]. A classifier becomes better when the features used follow the two assumptions: Each feature is appropriate for its problem space, and two features in a class are conditionally independent. Co-training is based on two learning models for different feature sets with each other. The models are independently learned, and enlarge the opponent's data instances while iteratively predict the unlabeled data instances. Originally, co-training was used for classifying web pages and has been applied to a variety of problems [18], [19].

Co-training is often compared with another conventional method of semi-supervised learning, called as Expectation-Maximization (EM) [20]. Because of a concrete model assumption problem, co-training is recently preferred to the EM algorithm [21], and it can be used for learning the mixture-of-experts at the semi-supervised scheme. Although the co-training algorithm needs two independent feature sub-spaces, these are difficult to split feature space into two sub-spaces in the real world. To overcome it, Goldman proved that two models trained with different methods become two independent feature sets [22].

2.3 Mixture-of-experts

The mixture-of-experts is a class of probabilistic models [5], [23]. It consists of several experts that manifest conditional probabilistic processes, and a gating network of combining the experts. The operational rationale in the mixture-of-experts is that each expert constructs a conditional model to cover a part of input space, while the gating network determines the weights of each expert to form an ensemble.

Due to the power of divide-and-conquer, it can transform the non-linearly separable problem into a set of the linearly separable problems. Figure 3 illustrates these characteristics with a radial decision boundary that was approximated by several linear decision boundaries. The linear decision boundaries are mapped to the localized regions in the whole space. This principle states that complex problems can be better-solved by decomposing them into smaller tasks. The mixture-of-experts assumes that separate processes are in the underlying process of generating the data. Modelling these processes is conducted by the experts, while the decision for the process is modelled by the gating network.

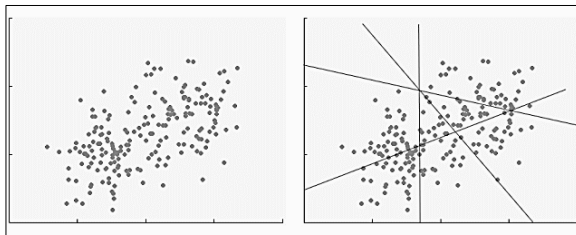


Fig 3. Non-linearly separable boundary estimated by several linearly separable boundaries

2.4 Prediction of financial data

Several researchers have studied the credit score by machine learning methods such as neural networks (NN) [24], [25], decision tree (DT) [26], support vector machine (SVM) [27], and case-based reasoning (CBR) [28]. They are different from the statistical approaches that assume a specific distribution of dataset. Table 4 shows the relevant research, each of which confirms the superiority to the statistical methods for credit scoring [29]. Similar to the credit scoring problem, many researchers have worked out the financial problems in general with machine learning methods. Min used SVM for predicting bankruptcy to verify the explanatory power and stability of the method [30]. Tsai presented a hybrid method of four different models and showed the superiority of the combination of machine learning and clustering algorithms with the dataset from a Taiwan bank [31]. In spite of the good performance, the previous works did not fully exploit the characteristics in the financial data. The co-training of mixture-of-experts are novel for the credit scoring problem.

Table 4 Relevant works of machine learning for financial data

Author	Problem	Data	Method
Min, et al [30]	Bankruptcy prediction	Corporate financial information	SVM
Li, et al [32]	Customer loan assessment	Customer financial information	SVM
Choudhry, et al [33]	Stock market forecasting	Customer credit information	GA and SVM
Tsai, et al [31]	Credit scoring	Customer credit information	EM and DT, EM and NB
Omidi, et al [34]	Forecasting stock prices	Stock price information	Neural Network
Milad, et al [1]	Risk evaluation	Social lending information	Random Forests
Zang, et al [35]	Risk evaluation	Social lending information	Neural Network
Emekter, et al [36]	Risk evaluation	Social lending information	Logistic Regression
Bitvai, et al [37]	Credit rating	Social lending information	Bayesian Non-Linear Regression
Byanjankar, et al [38]	Risk evaluation	Social lending information	Neural Network
Serrano-Cinca, et al [39]	Credit rating	Social lending information	Decision Tree
Zhang, et al [40]	Risk evaluation	Corporate financial information	Long Short-Term Memory
Huo [41]	Credit rating	Customer credit information	Logistic Regression, Neural Network

3 Proposed method

3.1 Semi-supervised learning for credit scoring

The semi-supervised approach is required to classify personal information in P2P environment. With the collection of the personal data, it is time-consuming for people to classify all of these borrowers. Personal requests to borrow money are always created as nature of social lending. Because these tasks have high labelling cost, we need to learn model through minor classified user information.

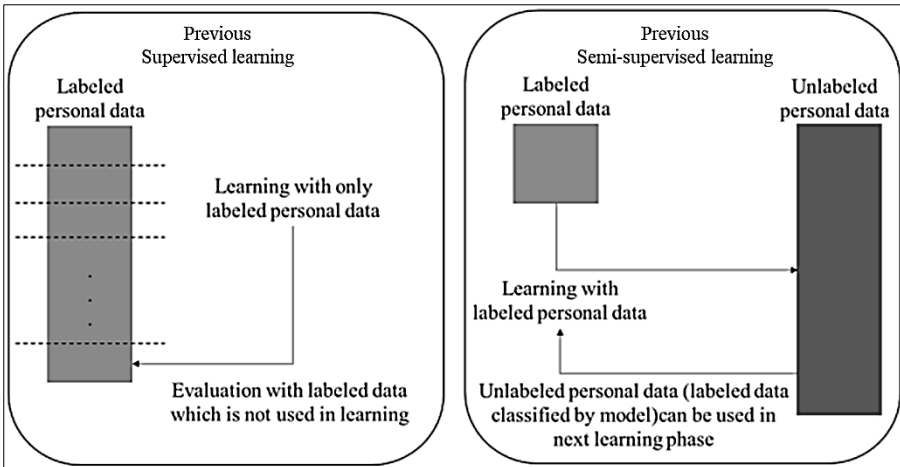


Fig 4. Semi-supervised approach for credit scoring

To predict credit scoring, previous studies proposed the methods based on supervised learning mostly. However, sample dataset is different from parent population in real social lending. In Figure 4, the classifier has a possibility to learn classification standard of other environment which is different from the real world. Therefore, we propose a semi-supervised approach to learn minor labeled personal data and major unlabeled personal data simultaneously.

3.2 Co-training with global and local perspectives

At first, local experts should be constructed in the separate space of dataset and then the mixture-of-experts model determines the credit scoring. When we divide the whole space into several sub-spaces, the data instances in each sub-space are similar with each other. The local experts become specialists to separate the similar patterns in a part of entire personal data. We use the k-means algorithm to make the clusters. Figure 5 describes the whole process of the co-training with global and local perspectives that were originally proposed at our previous study [42].

Figure 6 illustrates the algorithm based on this structure for predicting defaults. It can adopt the global and local views for the classification problem simultaneously.

Because it is not easy to divide the features of data instances according to each view, we use different learning algorithms for each model.

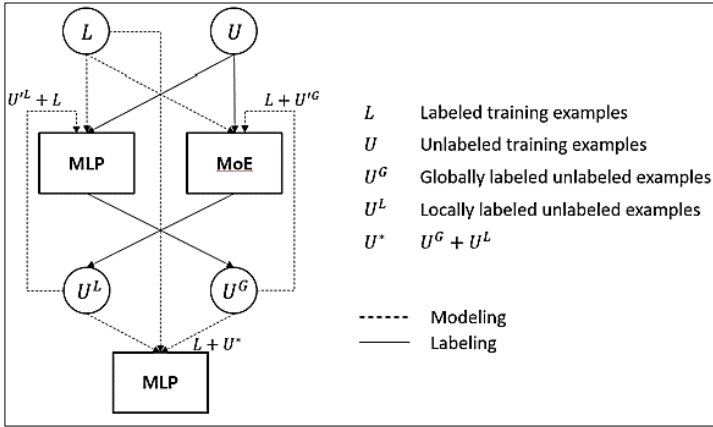


Fig 5. The overall procedure of the proposed learning method

Inputs:

- Threshold e .
- Labeled data L .
- Unlabeled data U .
- Multi-layer perceptron M_G
- Mixture-of-experts $M_L = (\mu_1, \mu_2, \dots, \mu_N, g)$

Initialization:

Generate two sets of training instances $L_G \leftarrow L$ and $L_L \leftarrow L$.

Do while L_G and L_L are not the same with the previous iteration:

- Train M_G and M_L with L_G and L_L .
- Predict U with M_G and M_L .
- Get instances that the confidence degree of M_G is higher than M_L and add them to U^L .
- Get instances that the confidence degree of M_L is higher than M_G and add them to U^G .
- Sort U^L and U^G in descending order of confidence.
- For each class C
 - Select N instances in U^L which have higher confidence than threshold e Add them to L_L with label C .
 - Select N instances in U^G which have higher confidence than threshold e
 - Add them to L_G with label C .
 - Remove the selected data instances in U, U^L and U^G .

Output:

- The predicted labels of unlabeled instances.
- Multi-layer perceptron M_G and mixture-of-experts M_L .

Fig 6. The co-training algorithm used in this paper

The mixture-of-experts utilizes various experts focusing on their own fields. Social lending information that is able to decide credit evaluation consists of various attributes. In order to evaluate the credit of borrowers, various attributes should be recognized accurately. Fifty-four attributes are inserted to the mixture-of-experts as input value. Gating network determines the reflection degree of opinions of experts based on the input value. The output of gating network $G(x)$ can be defined as equation (1) for input value x . The final output vector $O(x)$ of combining outputs of N -experts is calculated by the following equation (2).

$$G(x) = \{g_1(x), g_2(x), g_3(x), \dots, g_N(x)\} \quad (1)$$

$$O(x) = G(x)E(x)^T = \sum_{i=1}^N g_i(x)e_i(x) \quad (2)$$

$$\text{where } E(x) = \{e_1(x), e_2(x), e_3(x), \dots, e_N(x)\}$$

Among these combined opinions, the highest value is chosen as the result through the above process. Local experts and gating network were implemented by using multilayer perceptrons. In order to train gating network, the expected output about specific input value x is calculated by the accuracy of each expert. Before calculating the accuracy for each expert, the error of expert i for x can be defined as equation (3). Figure 7 shows the structure of mixture-of-experts in the proposed co-training.

$$Err_i(x) = \sum_t |e_i^t(x) - y^t| \quad (3)$$

where y is the correct vector corresponding to input value x . $e_i^t(x)$ and y^t means the values of $e_i(x)$ and y at time t . After the normalization using minimum error and maximum error of each expert, the accuracy of an expert is calculated by equation (4).

$$Acc_i(x) = 1 - \frac{Err_i(x) - \min_k Err_k(x)}{\max_k Err_k(x) - \min_k Err_k(x)} \quad (4)$$

$$y_g^t = Acc_t(x) (t = 1, 2, 3, \dots, N) \quad (5)$$

Finally, the expected output vector y of gating network for x can be defined as equation (5). Gating network is learned based on the backpropagation algorithm using total training data instances and expected output vector.

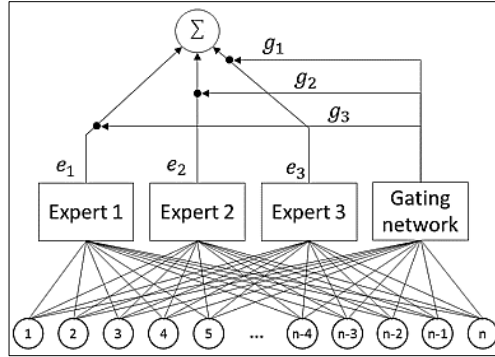


Fig 7. Structure of mixture-of-experts

Generally, it is important to carefully predict the labels of unlabeled instances when we have insufficient data for the local experts, because of the imperfect characteristics and poor performance of the models. The proposed method compares the two confidences from M_G and M_L to minimize the degradation caused from imperfection. After initial training with the data for credit scoring, the models get labeling only when the confidence of a model is higher than the other. The data samples which pass the criteria are added to the set of U^L or U^G .

After the added samples are sorted in descending order of the confidence, N samples in each class with the highest confidence are chosen. By picking the data instances with high confidence, the local experts can be improved for the prediction performance. The training process stops when L_G and L_L are the same; in other words, the proposed method continues learning iteratively until additional data instances for L_L and L_G are not left.

In the proposed co-training method, the two models are based on the multilayer perceptron trained with backpropagation algorithm. They are trained repeatedly using gradient descent with the error function of given data instances from its opponents. Newly added data instances from the global model are used for learning the other model, local experts, at the next iteration and for the local experts are vice versa. In the following equations, E_L and E_G indicate the error functions of the additional labeled samples for the two models, respectively.

$$E_G = \|O_G - f_G(x)\| \tag{6}$$

$$E_L = \left\| O_L - \sum \pi_i f_{Li}(x) \right\| \tag{7}$$

where O_L is an output vector of the local experts and $f_G(x)$ is an output vector of the global model. In equation (7), an error function of a local expert, O_G , means, an output of the global model, and π_i is an output of gating network in the i th local experts, and $f_{Li}(x)$ is an output of the i th local experts. In particular, O_G can be altered with an output function of the global model in the previous step, $f'_G(x)$, and an output function of the local experts in the previous step, $\sum \pi'_i f'_{Li}(x)$ can be replaced with O_L as shown in the equations.

$$E_L = \left\| f'_G(x) - \sum \pi_i f_{Li}(x) \right\| \quad (8)$$

$$E_G = \left\| \sum \pi_i f'_{Li}(x) - f'_G(x) \right\| \quad (9)$$

The co-training method stops when the current and previous errors are the same, but it is not easy to satisfy the condition. In this paper, we set the maximum number of iterations for training process to that of added training instances for each model. The number of samples for training each model $N(L_L)$ and $N(L_G)$ are determined with the confidence degree.

3.3 Measuring confidence degrees

As a detailed method of semi-supervised learning, we classify unlabeled data as each class using the proposed models learned with minor labeled data. Among these classified data, we select the data with higher confidence and give these data to labeled dataset. Each classifier can model with updated dataset again. In the process of data selection with higher confidence, we collect the prediction score or probability of each data for each classifier. Selection method based on the probability is applied. If the probability of each classifier is the same as Table 5, this data can be classified as bad class with the highest probability.

Table 5 Data example for classification (probability-based)

Classifier	Prob. (bad class)	Prob. (good class)
MLP	0.24	0.76
Mixture-of-expert	0.89	0.11

For determining the confidence value, we set $\text{confidence}(w, x)$ as an original confidence of the input x for the model w – $\text{confidence}(w, x)$ can be changeable with the learning methods. In this paper, the models are implemented with multilayer perceptron whose outputs can be evaluated by a measure of confidence as follows:

$$\text{confidence}(w, x) = \{w(x) | \text{output vector of } w \text{ for } x\} \quad (10)$$

The number of data in local experts is smaller than that in global model, because the original data was split into several sub-data for the local experts. As the data instances for some classes do not exist within sub-spaces even if the original problem space covers the whole classes, the mixture-of-experts may have a higher bias. Since the experts cannot be trained with all the classes, it can output unrelated values about missing classes at the local experts. In order to overcome these problems, the training instances in certain class should be confirmed whether they exist or not, before calculating a confidence of the model. The following equations show the modified confidence degrees for class C .

$$confidence(M_G, x, C) = \begin{cases} M_{G,C}(x), & \text{if } N_{M_G,C} > 0, \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

$$confidence(M_L, x, C) = \sum_{i=1}^N g_i confidence(\mu_i, x, C) \quad (12)$$

$$confidence(\mu_i, x, C) = \begin{cases} \mu_{i,C}(x), & \text{if } N_{\mu_i,C} > 0, \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

where μ_i is the i th local experts, g specifies a gating network, and $M_{G,C}(x)$ and $\mu_{i,C}(x)$ denote the outputs of M_G and μ_i for class C . g_i is an output of g for the i th local experts and $N_{M_G,C}$ and $N_{\mu_i,C}$ are the numbers of training data samples for class C for M_G and μ_i .

4 Experiments and Results

4.1 Social lending dataset

The social lending dataset comes from the Lending Club, and consists of personal and financial variables, indicators of wealth, and variables specific to the loan as shown in Table 6. The data contains approximately 400K people, and consist of 56 attributes including one dependent variable. The data was collected between January 2012 and September 2015.

Table 6 Description of the lending club dataset

Section	Variable	Description
Variables specific to the loan	Loan amount	The listed amount of the loan applied for by the borrower.
	Term	The number of payments on the loan.
	Purpose	A purpose provided by the borrower for the loan request.
	Interest rate	Interest rate on the loan.
	Installment	The monthly payment owed by the borrower if the loan originates.
Indicators of wealth	Home ownership	The home ownership status provided by the borrowers.
	Annual income	The self-reported annual income provided by the borrower.
Personal and financial variables	Employment length	Employment length in years.
	Debt to income	A ratio of the borrower's total monthly debt payments on the total debt obligations.
	Delinquency	The number of delinquency in the borrower's credit file for the past two years.
	Inquiry	The number of inquiries in past six months.

	Total account	The total number of credit lines currently in the borrower’s credit file.
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Credit scoring is performed by the proposed method that classifies the criteria such as good or bad credit of the client. The proposed method uses a lot of variables which can be acquired from information of client including both unlabeled and labeled ones. After learning with events (loan) that have already occurred and the results (payment or delinquent), we evaluate the credit scoring in a way asking whether this client can repay or not. The purpose of analysis of data is to evaluate credit of clients.

4.2 Reliability test

First, we conducted the experiments for evaluating the accuracy according to the reliability of unlabeled dataset. We divide the labeled dataset into unlabeled data (U) and labeled data (L) intentionally to check the accuracy of unlabeled dataset. The number of instances of labeled data is 45,304. The number of instances of unlabeled data is 15,102. The dataset ratio is 75 (labeled): 25 (unlabeled).

Table 7 shows the confusion matrix of unlabeled dataset with respect to the reliability threshold. We conducted experiments with two semi-supervised classifiers (the proposed method and self-training) and confirmed that higher reliability led to higher accuracy of dataset. Instances of data used in this experiment are reduced in case of higher reliability. However, the accuracy of used dataset can increase as shown in Figure 8.

Table 7 Confusion matrix of unlabeled dataset based on reliability

Reliability	Dataset	TP	TN	FP	FN
The proposed method					
0.99	8,413	7,556	423	362	72
0.95	11,335	9,543	912	714	166
0.90	12,229	9,971	1,178	840	240
0.85	13,137	10,643	1,180	1,083	231
0.80	13,629	10,697	1,468	1,091	373
Self-training					
0.99	8,648	7,791	404	58	395
0.95	12,965	10,621	1,017	1,093	234
0.90	13,116	10,626	1,205	1,058	227
0.85	14,168	10,912	1,592	1,212	452
0.80	14,131	10,775	1,685	1,125	5,476

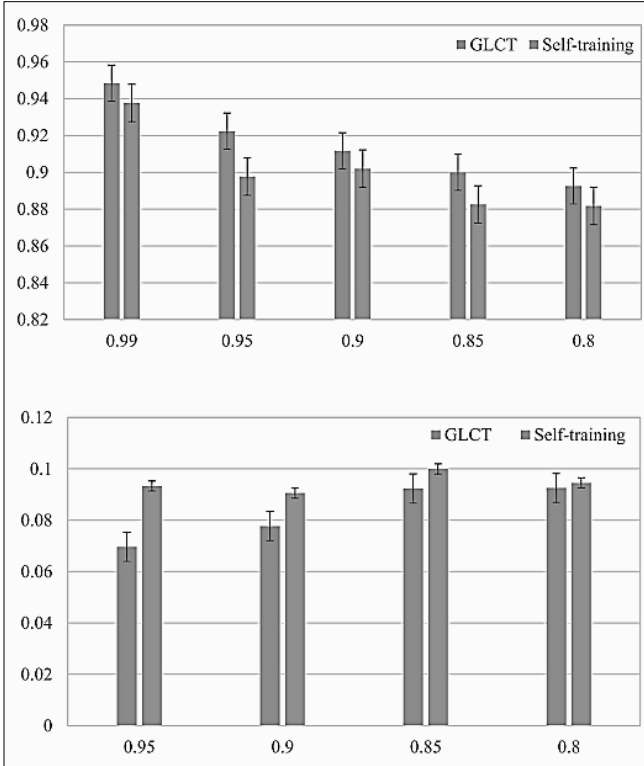


Fig. 8 Accuracy (top) and false positive rate (bottom) for U*

4.3 Quantitative analysis

Next, we present the experiments to evaluate the usefulness of predicting the default in social lending. We chose k-means clustering algorithm for obtaining training data for the mixture-of-experts with three experts. The parameters used are as follows: the number of hidden nodes in the multilayer perceptron is 10, the learning rate is 0.3, and the number of cluster is 3. In the initial step, the labeled data samples are used for training, and then the unlabeled data samples are labeled based on the previous model.

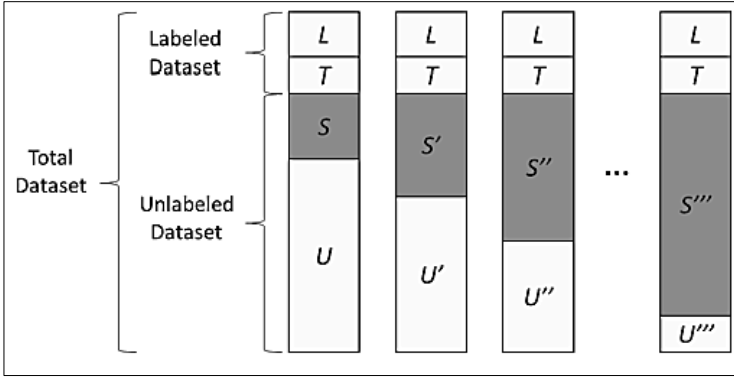


Fig. 9 Distribution of dataset

Labeled data used for experiment is the Lending Club 2014 dataset. The number of training samples is 52,857, and that of test samples is 22,651. The unlabeled data (U) used is also taken from Lending Club 2014 dataset. The number of samples is 161,121. Ratio of the selected unlabeled data is decile. It ranges from 10% to 30% as shown in Figure 9. Additionally, we conducted experiment with the whole unlabeled dataset. Each sample according to the dataset ratio is below 10% (16,011), 20% (32,022), 30% (48,033), and 100% (160,121).

Figure 10 shows the result with the unlabeled dataset ratios. We can confirm that utilizing unlabeled dataset leads to higher accuracy. However, when utilizing all of unlabeled dataset, it does not guarantee improvement in performance in semi-supervised learning. We compared with another conventional semi-supervised learning to show the usefulness of the proposed method. Figure 11 shows the result compared with self-training. We can confirm that the proposed method had better performance than the other semi-supervised learning.

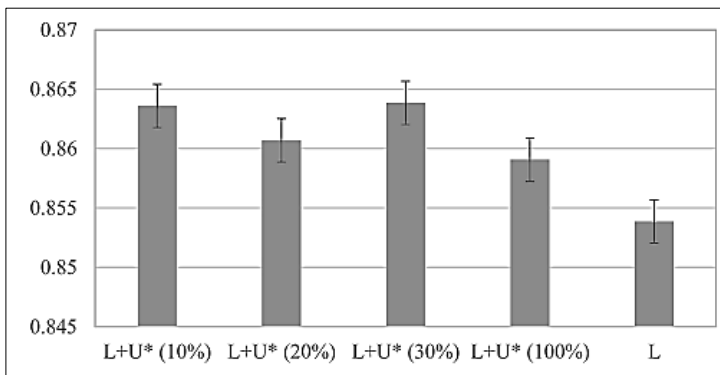


Fig. 10 Comparison of accuracies according to the unlabeled dataset ratios

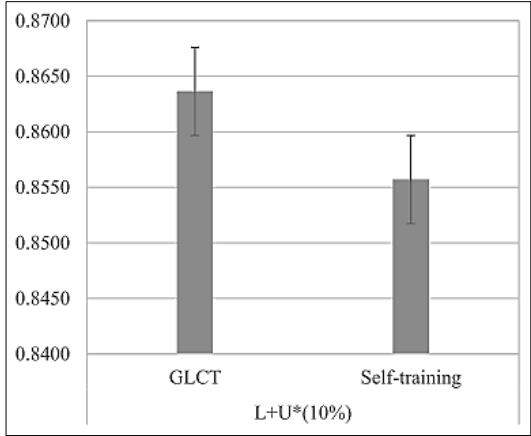


Fig. 11 Comparison of accuracies with self-training

4.4 Comparing with other machine learning methods

We compared the performance against other machine learning methods such as Naive Bayes, logistic regression, decision tree, and SVM. The number of training data used in other machine learning methods is 52,857, and that of test data is 22,651. In the experiment, we used unlabeled dataset additionally, and the number of unlabeled data becomes 16,011. Figure 12 shows higher accuracy of the proposed method compared with other machine learning methods. To confirm the qualitative results, we plotted ROC curve for all the methods. The proposed method was the best with the highest AUC value as shown in Figure 13.

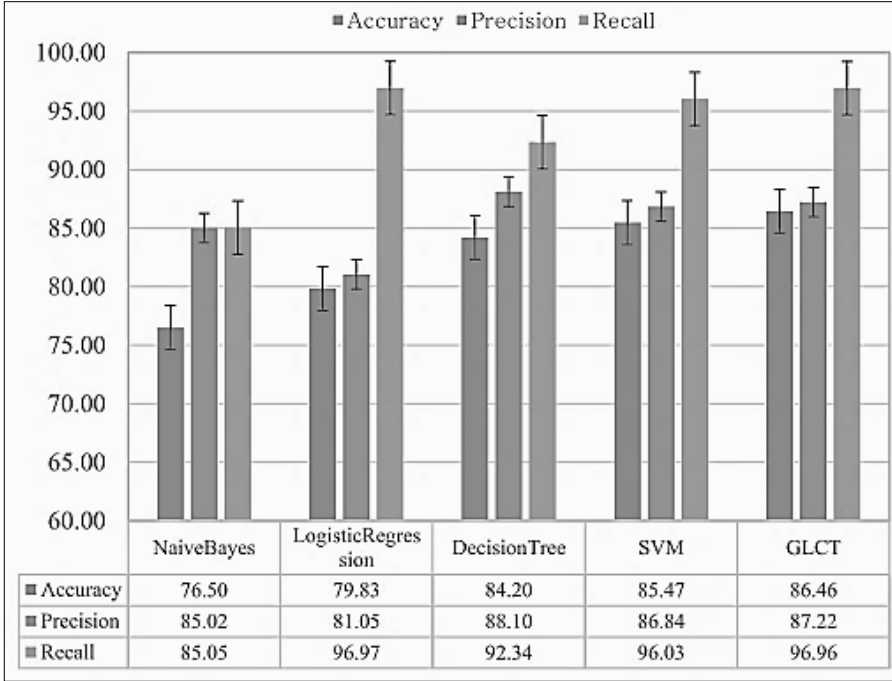


Fig. 12 Comparison with other machine learning methods

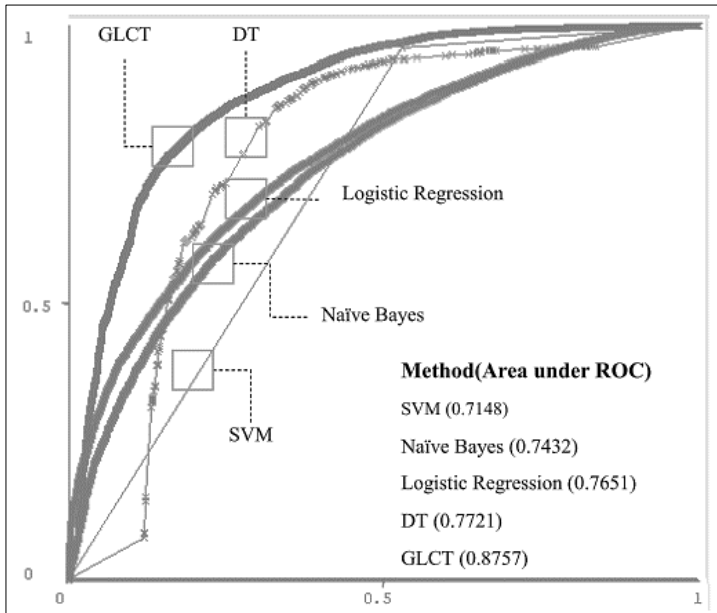


Fig. 13 ROC curve with other machine learning methods

5 Conclusion and future work

Identifying potential default borrower is important for maintaining the sustainability of social lending market. To predict the default of borrowers, financial features such as the number of delinquent accounts, debt-to-income ratio and so on are used. A large scale of unlabeled data from people in the world can be one of the main characteristics in financial data. In this paper, we incorporate a co-training algorithm based on mixture-of-experts for distinguishing default borrowers in social lending, and use the world's largest social lending platform, Lending Club's, publicly available dataset. The experiment was conducted with the ratio of labeled data. We obtained the quantitative results evaluated on various aspects through a series of iterative experiments, confirming the usefulness of the proposed method.

In the future, we will conduct additional experiment to validate reliability. Another research direction can be the integration with the social media dataset to get better default prediction. There exists a large dataset that borrower characteristics can be identified by, such as Twitter and Facebook. The data from social media have a great potential to improve the method with higher accuracy for predicting borrower's default by integrating with the social lending data.

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BIAN – PNC open APIs for banking

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Abstract This paper demonstrates a working proof-of-concept for open APIs in banking, in compliance with the European Commission's PSD2 (Payment Service Directive) financial regulation document. This proof-of-concept was implemented within PNC Bank, a US-based financial services institution. PNC Bank is headquartered in Pittsburgh and operates in 19 states and the District of Columbia with 2,459 branches and 9,051 ATMs. The aim of this paper is to help and encourage other groups within banking, and the broader financial services space, to build on these efforts, and ensure PSD2 compliance at their respective institutions.

Keywords: BIAN · Payment Service Directive · APIs (Application Programming Interface) · Enterprise Architecture

1 Introduction – BIAN in practice

The Banking Industry Architecture Network (BIAN) model fits with PNC views enterprise architecture (EA) at PNC. The organisation brought a business perspective to enterprise architecture. To PNC, technology is not just a collection of servers and software, but rather a set of technical solutions that are aligned to specific business capabilities and functions.

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1.1. Adding the business view

To begin with, the bank looked at every application that existed in its portfolio and mapped it to the aligned BIAN service domains (specific business functions) in its EA management tool. This gave it a clear view of systems that was providing similar or overlapping capabilities, which could be optimised, while also creating a consistent and replicable way to evaluate proposed new solutions for our application portfolio.

1.2. Creating a bank on a page

PNC created a business-driven “bank on a page” heat map, using BIAN’s M4 model, to show what areas were suffering from obsolescence and compliance issues. As the bank moved forward, it aligned risk and project portfolio views to the same bank on a page overview. Using BIAN’s framework, the bank can move its core platforms into a componentised framework, which allows it to manage transformations in logical steps that are aligned with the overall business strategy.

1.3. Positioning for disruptive industry change

Defining the banks’ technology into capabilities in this way also sets it up for future innovation. The proliferation of FinTech is setting new expectations with new business models that sometimes compete directly with banks. PNC evolved its core banking capabilities into a componentised framework that will allow it to embrace evolving business expectations and customer demands. The search for innovation partnerships becomes easier when you are no longer tied to the past era’s monolithic application approaches. PNC is exploring open banking APIs, for example, in a collaborative project with BIAN and Carnegie Mellon University.

By aligning to the BIAN framework, the bank is assured that its enterprise architecture can continuously adapt to new market and technology demands.

2 Project objectives

2.1 Objective 1: Comply with PSD2

The first goal of the project was created a working proof-of-concept for open APIs for banking, in compliance with Payment Service Directive (PSD2). PSD2 is a financial regulation document that applied to banks and financial institutions in the European Union. This regulation published on January 13, 2016, was effective for banks from January 13, 2018. The reason for PSD2 to have banks create these APIs is to allow third parties to use them for easy interaction with the banks. There are two primary usecases required by PSD2. Banks should enable third parties to: (1) submit peer-to-peer payments to the bank, and (2) check account balances. Both of these capabilities are enabled via openly accessible APIs. Per PSD2 requirements, no fees should be charged to third parties for these services. Details on PSD2 is found in a whitepaper published by Deutsche Bank [1].

2.2 Objective 2: Demonstrate a solution built on BIAN, IFX, and PNC

The second goal of the project was to use principles from BIAN and Interactive Financial Exchange (IFX) to build a solution. This solution was built to interact with PNC, but could be adapted to any bank. BIAN provided architectural principles designed to guide technology implementations at financial institutions. IFX provides a messaging standard, again, designed specifically for financial institutions. BIAN and IFX were interested in producing a prototype to show how their standards, designed specifically for financial applications, could be combined to produce a functioning product. PNC is a top-ten US bank and a partner with BIAN in several initiatives and offered to make a test environment accessible to the CMU development team.

We used BIAN frameworks at a high level to guide the implementation of a message exchange. The messages themselves would be structured according to the IFX format as given in Figure 1. We chose the scenarios to be modelled, based on the requirements of PSD2, which has been discussed below.

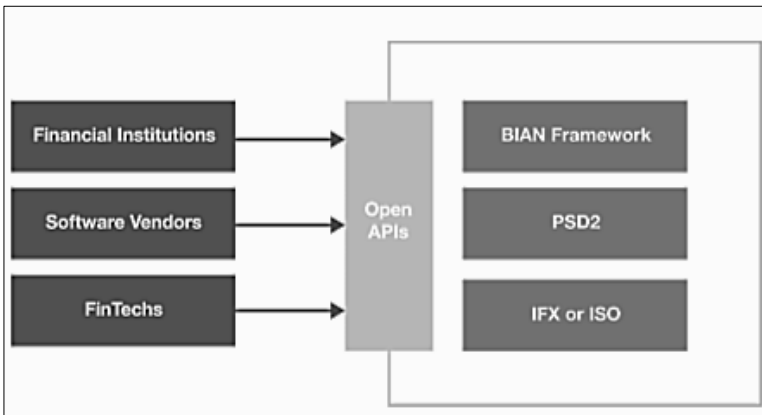


Fig. 1 Left: Sample parties interacting with open APIs. Right: Standards used to structure the messages to be returned from the bank, in this case, PNC Bank

3 Project methodology

3.1 PSD2 usecases

We began by examining the usecases of PSD2. Per PSD2, banks should enable third parties to: (1) submit peer-to-peer payments to the bank, and (2) check account balances. We developed the following diagrams to model these usecases.

The Figure 2, depicts a peer-to-peer payment model. In this case, Ben Roethlisberger wants to make a payment to Amazon. (Since we were working from Pittsburgh, our usecases involved star players from the Pittsburgh Steelers!) Ben has an account in PNC, and Amazon has an account in Chase. In order to initiate the payment, Ben fills a third party provider (TPP) form to request a payment to be sent.

In this case, Venmo is the TPP. Venmo then sends a message to PNC requesting the transfer. PNC transfers the money to Chase, and the funds are now available for Amazon to access. Payment could just have been as easy as from Ben to another consumer, rather than from Ben to a business. Either one would qualify for this PSD2 usecase of sending a payment.

Incidentally, services like Venmo do not currently exist in Europe for payments between EU countries. Even in the US, Venmo works by using the ACH system, which takes up to 3-5 days for processing. Usage of open APIs would enable instantaneous transfers. The area in the dotted box is the one focussing on the prototype; that is, we developed the messaging between the TPP and the bank.

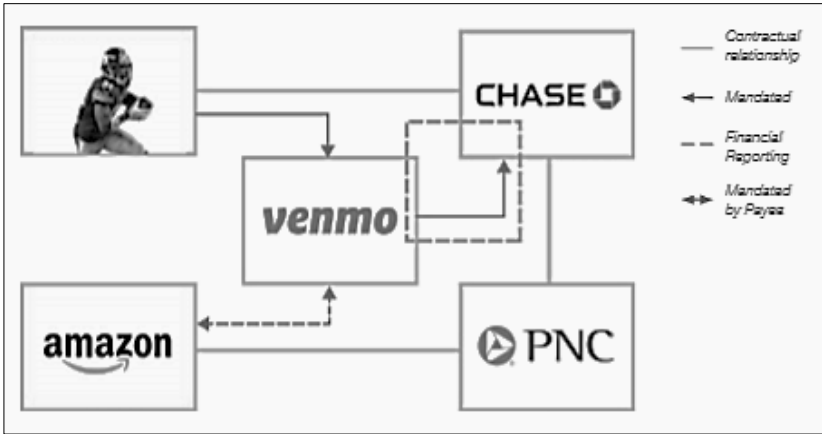


Fig. 2 Peer-to-peer payment, the first usecase specified in PSD2. Ben Roethlisberger sends payment to Amazon

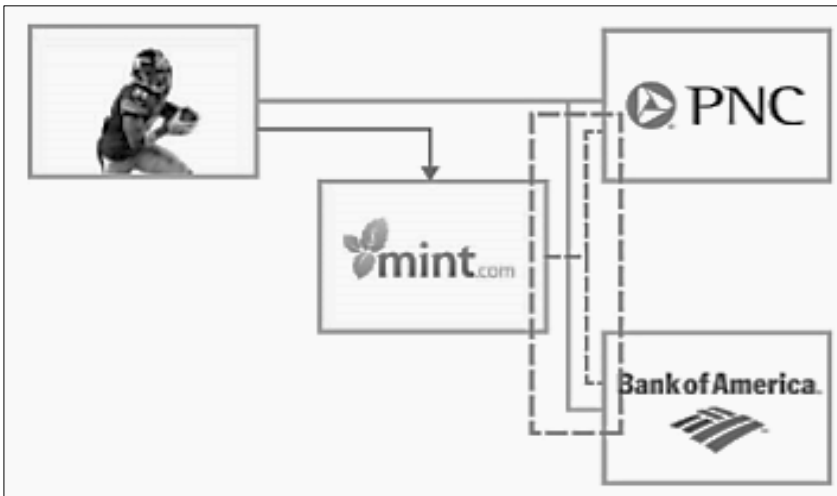


Fig. 3 Check account balances, second usecase specified in PSD2. Antonio Brown gets his balances from PNC and Bank of America

Figure 3 shows a model of checking account balances across multiple banks. In this case, Antonio Brown requests his TPP, Mint, to monitor balances from his two accounts, PNC and Bank of America. Mint would automatically generate balance requests to PNC and Bank of America on a regular basis (daily or more frequently, depending on the TPP configuration). The banks then responds to this message by providing their respective balances to Mint. (Services such as Mint do not currently exist in Europe.)

3.2 BIAN’s contribution

Guy Rackham, a BIAN Lead Architect, referred us to the architectural document he helped produce. One of the main components of the Semantic API How-to Guide is the Semantic API Selection Framework, which is shown below in Figure 4. The framework helps the developer or architect to “ask all right questions” that need to be asked before developing a solution. This framework proved helpful in structuring a solution to the needs of PSD2.

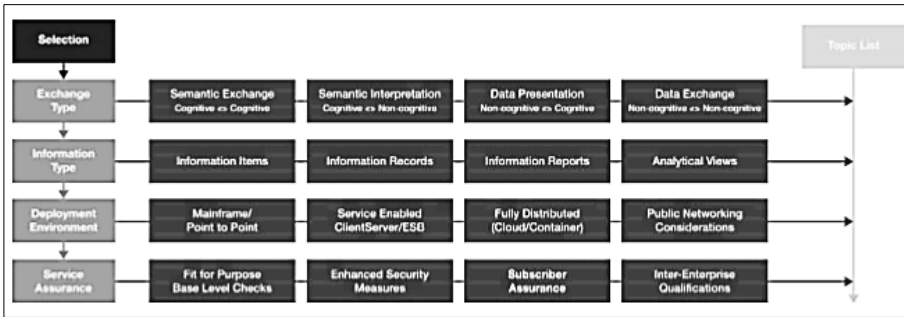


Fig. 4 BIAN’s semantic API selection framework

In order to carryout the usecases of PSD2: send payment and check balance, a PSD2-specific guidance has been provided. The steps taken is as shown in the diagram below Figure 5.

8.7.1.1 — Payment Add Request <PmtAddRq>

The Payment Add message allows a client to schedule a single payment, where the amount is input by the customer or from a presented bill. The Payment Add message may reference an existing payee or add a new one, by specifying the information within <RemitInfo> <PayeeInfo>. If the Payment service provider supports <CustPayeeId>, the client must specify an existing <CustPayeeId> or include the <CustPayeeInfo> aggregate, but not both. Whether or not the Payment service provider supports <CustPayeeId>, the <CustPayeeInfo> aggregate may specify an existing standard payee or create a new fully specified or transfer payee. It is not possible to modify an existing payee within an Add Payment message. The customer may modify a payee via <CustPayeeModRq>.

See the matching response message **PmtAddRs**

Datatype: Aggregate

Tag	Type	Usage	Description/Context notes
begin Aggregate			
begin block			
RqID	UUID	Required	Request Identifier. Sent by a client as a universally unique identifier for the message. Used to correlate responses with requests.
MsgHdr	Aggregate	Optional	Message Request Header aggregate.
AsyncRqID	UUID	Optional	Asynchronous Request Identifier. Sent by a client to retrieve a response that was asynchronously generated by a server, generally in the case where the response would have taken too long to build and be able to be sent synchronously. For more information, see Status .
CustId	Aggregate	Optional	Customer Identification Aggregate. This is the identifier of the user for whom the request is being issued. This element is required if the owner of the object(s) specified in the request is not the user specified in <SignonRq>. For example, if a CSR or SP issues the request on behalf of the user, then <CustId> is required, and must contain the value of the user whose request is being issued.
end block			
begin block			
PmtInfo	Aggregate	Required	Payment Information Aggregate
DupChkOverride	Boolean	Optional	Duplicate Check Override Flag. When set to True, requests that the server not perform duplicate checking if any is normally performed. The client is affirming that this is a new payment being added.
end block			
end Aggregate			

Fig. 5 PmtAddRq screenshot from IFX BMS website

As shown in the send payment case, shown in Figure 6 below, the consumer (PSU, the payment service user) first registers the TPP (third party provider). Then he requests the TPP to send a payment. The TPP authenticates itself with the bank, and finally instructs the bank to make the payment.

3.3 Peer-to-peer payment

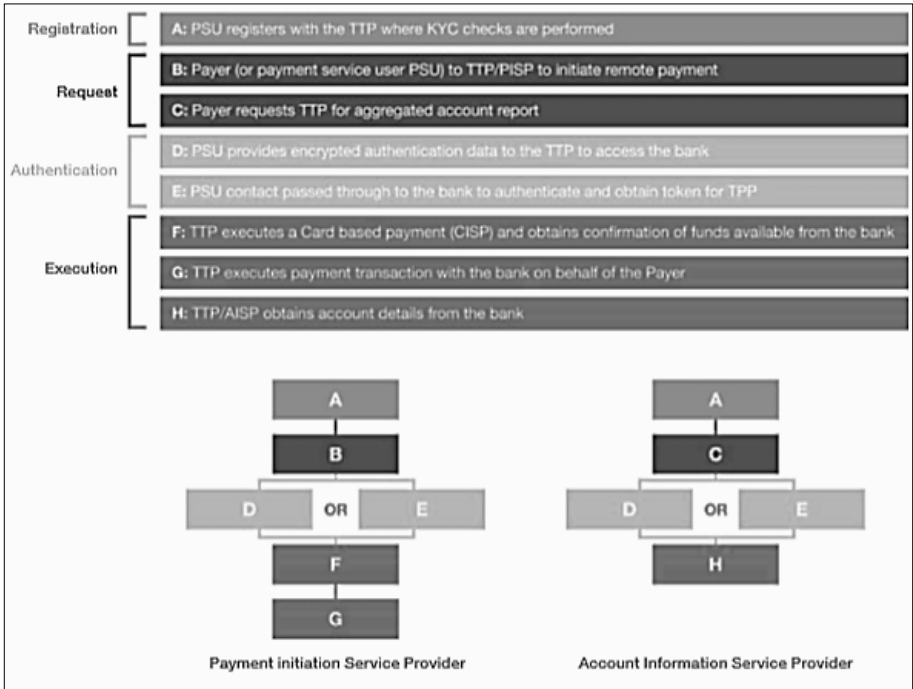


Fig. 6 PSD2 usecases: peer-to-peer payment (left), and check balances (right)

In the check balances case, once again the PSU first registers with the TPP, and then asks the TPP to check balances. After authentication, the TPP retrieves the balances from the bank. Of these steps, it is necessary to determine which would be in or out of scope of the project. The registration would be out of scope, as that pertains to user registration for the TPP only (your login credentials for Venmo, Mint, etc.). However, the request, authentication, and execution would all relate to the project and had potential scope.

Furthermore, we mapped all these steps from PSD2 using the BIAN Semantic API How-to Guide. The results of this exercise shown in the appendix (Figures 9-11). Let us now understand more about the kind of messages sent, especially in the execution step. We turned to IFX to learn more about the messaging format they could offer.

3.4 IFX Messages for PSD2

Rich Urban, president of IFX, indicated the right IFX message formats to be applied in each of the usecases. For sending a payment, IFX message called PmtSendRq is used, which would be acknowledged by the PmtSendRs message. In terms of checking balance, using the BalInqRq message was acknowledged by BalInqRs.

All IFX documentation is available on the IFX website. The most important part of the website is BMS (business messaging specification). The BMS section of the site has thousands of available message specifications.

The JSON for these messages has been downloaded and removed the optional fields which were not required.

3.5 Comparing IFX and ISO

In compare and contrast of IFX and ISO, both are standards to be used by financial institutions for sending messages, most commonly payment messages.

ISO's 20022 standard is currently used worldwide with prominent contributors like SWIFT and VISA. ISO 20022 includes eight parts: ISO 20022-1 through ISO 20022-8. These parts describe the metamodel, UML profile, XML schema etc., for the messages. IFX promotes messages that are sent in XML or JSON. There is also built-in capability to generate a swagger document for these message structures. IFX can contain ISO elements, if desired. Based on our experience in this project, IFX messages are defined and organized in a way which is easy to read/understand.

3.6 Interacting with PNC

After working with BIAN and IFX to understand their frameworks, standards, and message formats, we began to collaborate more closely with PNC. In order to test the APIs being developed, it was necessary to simulate sending and receiving of messages to/from other systems in the bank.

PNC had already set up an environment, called the API store, which had some open APIs. These open APIs did not generate IFX compliant messages. Rather, they returned data in a flat format as part of a RESTful exchange. For example, a request

will return details about that card number, if it exists in the data. While interacting and testing these APIs using “Postman”, a freely available tool, Postman enabled us to create HTTP requests to APIs in the PNC API store. (Note that the API store is not used in daily business operations yet at the PNC Bank. Right now it is a sandbox area where PNC is exploring how it could deploy open API solutions in production.)

3.7 Solution architecture

As shown earlier in figures 2 and 3, the focus the work was on the interaction between the TPP and the bank. If we “zoom in” on this relationship, there are a few steps that need to happen in the communication.

As shown in this Figure 7, first a third party provider (TPP) would initiate a payment using the RESTful API that we have built (“API” in the figure). Once the payment is submitted to the API, the API first looks up additional data from other PNC systems (steps 2 and 3). Once that data has been retrieved, it makes a call to the Bank Payment System to make the payment.

Finally, the bank payment system returns a response to the API (step 5). The API, in turn, reads this message, and uses it to generate a JSON IFX compliant message (step 6). The message will be the `PmtSendRs` or the `BallnqRs`. In the implementation stage, the `PmtSendRq` and `BallnqRq` were not used. However, the bank might want to use these messages when communicating with internal payment systems.

The appropriate message was generated and sent back to the TPP. What we gain by doing this is that now, the TPP can expect a consistently formatted response message when it interacts with any bank. Furthermore, the bank can also choose to archive these response messages, which may be useful for historical or reporting purposes.

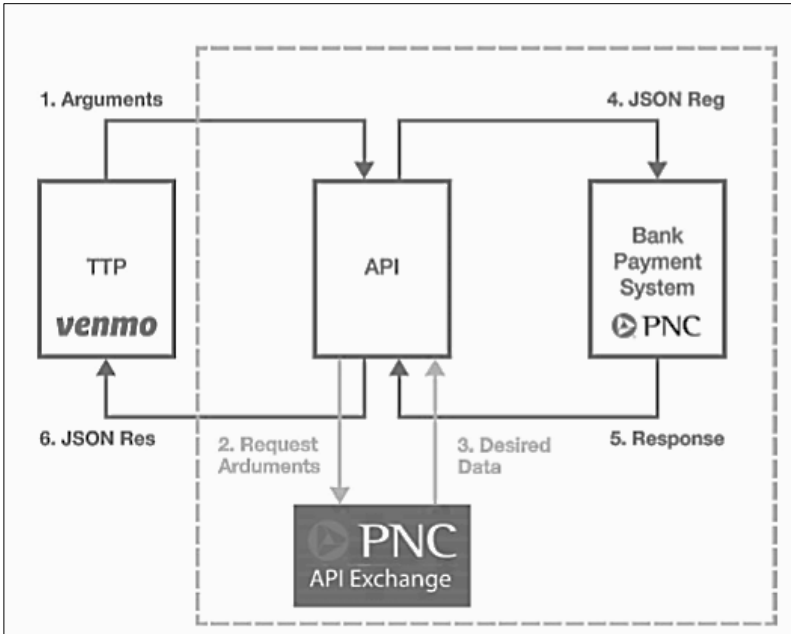


Fig. 7 Message Architecture of TPP, API, and Bank Systems

4 Implementation

4.1 Introduction and file description

All the code is available on Git³. The API has been developed and deployed on the local machines during the development phase of the project. The PNC team’s Virtusa consultants helped us to set-up the proper IDE and development environment to work with the PNC API store.

One advantage of this design is that BankInfo, for example, can be used consistently in many different contexts. Several different IFX messages may contain BankInfo. By having a BankInfo object, we can enforce that it must contain the same five fields everywhere it is used. Now, wherever BankInfo is used, it must have this consistent definition. BankInfo and other objects are then converted into the appropriate JSON structure when they are used.

4.2 Choice of HTTP method for RESTful API

For the APIs, an appropriate HTTP method had to be chosen to correspond to the operation. BIAN’s API How-to Guide is a useful resource for this task. The Figure 8

³ <https://github.com/chinthakadd/cmu-bian-starter>

below shows a mapping between action terms and the corresponding HTTP method. This is used to perform mappings for the two usecases.

BIAN How-To Guide Semantic APIs

		ACTION TERMS	Description	Applicable REST Verbs
Initialise & Register	Actions to set-up, establish a new control record instance	Register	Record the details of a newly identified entity	PUT; POST
		Initiate	Begin an action including any required initialization tasks	PUT; POST
		Activate	Commence/open an operational or administrative service	PUT; POST
		Create	Manufacture and distribute an item	PUT; POST
Invocation & Execution	Actions to access/update/influence an established instance	Configure	Change the operating parameters for an operational capability	PUT; PATCH
		Update	Change the value of some (control record) properties	PUT; PATCH
		Record	Capture transaction or event details against managed activity	PUT; PATCH
		Execute	Execute a task or action on an established facility	PUT; PATCH
		Evaluate	Perform a check, trial or evaluation	GET
		Provide	Assign or allocate resources or facilities	PUT; PATCH
		Authorise	Allow the execution of a transaction/activity	PUT; POST
		Request	Request the provision of some service	GET
Maintain & Analyze (delegation only – no action terms apply)		Terminate	Conclude, complete activity	DELETE
Report & Notify	Actions to extract details & subscribe to updates	Notify	Provide details against a predefined notification agreement	Managed using event frameworks
		Retrieve	Return information/report as requested	Managed using event frameworks

Fig. 8 Action term to HTTP verb mapping

Mapping for PSD2 usecases:

- Send payment: For this, we need to “Create” a message to send a payment, so we used the HTTPPUT operation.

The steps involved are:

- Step 1: This will take a PUT request, based on the input in the RequestBody
- Step 2: Create objects for the response message
- Step 3: Prepare elements needed to make call to API Store
- Step 4: Make call and store the response
- Step 5: Format response into IFX format, using objects created above
- Step 6: Note that formatting of this message (e.g. which objects to include) is based on IFX message specification.
- Check balance: For this operation, we need to “Request” a balance, so we use the HTTP GEToperation.

The steps involved are:

- Step 1: Responds to a GET request, and reads in the variables in the URL path
- Step 2: Create objects for the response message
- Step 3: Prepare elements needed to make call to API Store
- Step 4: Make call and store the response
- Step 5: Format response into IFX format, using objects created above

- Step 6: Note that formatting of this message (e.g. which objects to include) is based on IFX message specification.

4.3 Using our APIs

The APIs has been run locally and ways of interacting with them via the Swagger UI is explained. The code automatically generates a Swagger UI, since it was built with the Spring framework. The user can submit data to each of these endpoints and examine the response messages. Of course, a TPP would also be able to send data to these endpoints without having to use the Swagger UI. The API was also deployed to the PNC API store, where the interface is different, but with the same functionality.

5 Conclusion

In this paper, we have shown that the BIAN and IFX frameworks can be applied successfully to comply with PSD2 requirements in order to enable third parties to send payments and check balances. As the banking industry will be required to build new functionality (open APIs) to comply with PSD2 requirements, it is an ideal time to coalesce around a standard method for doing so. Messages with the IFX format are well-suited to send response messages to the TPP, as well as messages from one bank to another. When a TPP submits a send payment request, it could receive back a standard IFX compliant message from whichever bank it interacts with. The bank, in turn, could send an IFX message from the payee bank to the payer bank to provide details for the money transfer.

5.1 Lessons learned

This paper required us to collect information from different stakeholders, and determine the type of solution they were asking for. We also had to acquaint with the previous work that had been done by other standards bodies such as BIAN, IFX, and the European Commission (which produced PSD2).

5.2 Future work

- **Standardize which IFX fields the TPP should be required to submit**

The TPP is required to submit many of the fields needed to produce the IFX response message. In reality, a number of these fields can and should be retrieved from within the bank's own systems. For example – branch name. The TPP would not know this, but the bank would. However, some of this data was not easily available from the API Store available. It is suggested that the industry leaders determine the fields that are required from the TPP, and the fields that could be supplied by the bank. If feasible, this classification could even be included with the IFX standard itself.

- **Which parties should create an IFX message (TPP, bank, or both)**

Industry leaders should also determine which parties need to create an IFX message. It is currently not clear if the TPP would be required to submit an IFX-formatted message, or if just the banks should communicate using this standard. We believe the TPP could be asked to format its message in a specific way, but there may be concern about putting that burden on the TPPs. Furthermore, the industry should define whether banks should use IFX for messages to other systems within the same bank (e.g. PNC to PNC) and to other banks (e.g. PNC to Chase) or not.

- **Develop context-specific guidelines for message formats**

Consider that there are three distinct messaging contexts: TPP-bank, intra-bank, and bank-to-bank. To use real names as examples: Venmo-PNC, PNC-PNC, and PNC-Chase. In our work, it became clear that each of these contexts would have different expectations in terms of what information would be sent or received. We recommend incorporating this distinction into either BIAN or IFX standards. “Message context” seems to be an important topic that a PSD2 solution much take into account.

- **Review required/optional fields in IFX**

In its documentation, IFX has marked fields in the messages as either required or optional. Based on the needs discovered during further implementation work, these required/optional fields should be updated appropriately. For example, if a field currently marked as optional is discovered through discussion and implementation to be required, then this should be updated in IFX documentation.

- **Develop process to lookup necessary fields within bank**

The banks will need to develop a process to look up the relevant information from within their systems to populate IFX fields not provided by the TPP. We used other APIs to communicate within the bank. However, depending on the implementation, the bank in question may just be able to look up for the necessary information from a database table. In such a case, interaction with an API may not be required since the data is internally available.

- **Build solution for messages between banks**

We have not worked on the messaging from one bank to another. However, for performing payment transaction between users of different banks, such a message would be required. We recommend formatting this message in an IFX format. The ‘PmtSendRq’ message may be the appropriate message to use in this case. Another possibility would be to send data between banks in the message body of an HTTP PUT or GET (a RESTful API). However, since banks will likely be familiar with

IFX and to avoid a long message body, it may be preferable to send messages between banks in IFX formats.

- **Implement authentication step of PSD2 (OAuth)**

We have also not implemented the authentication step required in PSD2 as an OAuth implementation would eventually be necessary to implement PSD2. As the work required would be fairly intensive, it was deemed out of scope for our project. We did create a prototype of what the OAuth interaction might look like, and we included this as part of the UI shown in our demo. However, we opted not to include this in our code submission as it was just for simple demonstration purposes.

Appendix

Mapping of PSD2 steps to BIAN’s semantic API selection framework:

Standard Interface Type	Payer to TPP/PSF to initiate remote payment	PSU provides encrypted authentication data to the TPP to access the bank	TPP/ASP obtains account details from the bank	TPP Executes payment transaction with the bank on behalf of payer
Exchange Type	Exchange Type	Exchange Type	Exchange Type	Exchange Type
Conversation (any media)	Conversation (any media)	Conversation (any media)	Conversation (any media)	Conversation (any media)
Interactive data extract	Interactive data extract	Interactive data extract	Interactive data extract	Interactive data extract
Data capture form	Data capture form	Data capture form	Data capture form	Data capture form
Interactive design presentation	Interactive design presentation	Interactive design presentation	Interactive design presentation	Interactive design presentation
Data Publishing	Data Publishing	Data Publishing	Data Publishing	Data Publishing
Transaction exchange	Transaction exchange	Transaction exchange	Transaction exchange	Transaction exchange
File transfer	File transfer	File transfer	File transfer	File transfer
Information Type	Information Type	Information Type	Information Type	Information Type
Information items	Information items	Information items	Information items	Information items
Data elements	Data elements	Data elements	Data elements	Data elements
Information forms	Information forms	Information forms	Information forms	Information forms
Data records	Data records	Data records	Data records	Data records
Narrative log (any media)	Narrative log (any media)	Narrative log (any media)	Narrative log (any media)	Narrative log (any media)
Recording (any media)	Recording (any media)	Recording (any media)	Recording (any media)	Recording (any media)
Analysis	Analysis	Analysis	Analysis	Analysis
Deployment Environment	Deployment Environment	Deployment Environment	Deployment Environment	Deployment Environment
User interface	User interface	User interface	User interface	User interface
Data exchange interface	Data exchange interface	Data exchange interface	Data exchange interface	Data exchange interface
Session management	Session management	Session management	Session management	Session management
Service directory	Service directory	Service directory	Service directory	Service directory
Service exchange	Service exchange	Service exchange	Service exchange	Service exchange
Encapsulation	Encapsulation	Encapsulation	Encapsulation	Encapsulation
Security assurance	Security assurance	Security assurance	Security assurance	Security assurance
Service Assurance	Service Assurance	Service Assurance	Service Assurance	Service Assurance
Base level CIA	Base level CIA	Base level CIA	Base level CIA	Base level CIA
Base level auditability	Base level auditability	Base level auditability	Base level auditability	Base level auditability
Enhanced CIA	Enhanced CIA	Enhanced CIA	Enhanced CIA	Enhanced CIA
Enhanced auditability	Enhanced auditability	Enhanced auditability	Enhanced auditability	Enhanced auditability
Authenticate/authorized	Authenticate/authorized	Authenticate/authorized	Authenticate/authorized	Authenticate/authorized
Appropriate	Appropriate	Appropriate	Appropriate	Appropriate
Aligned/qualified/coordinated	Aligned/qualified/coordinated	Aligned/qualified/coordinated	Aligned/qualified/coordinated	Aligned/qualified/coordinated

Fig. 9 PSD2 usecase: send payment

Standard Interface Type	Payer requests TPP for aggregated account report	PSU provides encrypted authentication data to the TPP to access the bank	TPP/ASP obtains account details from the bank
Exchange Type	Exchange Type	Exchange Type	Exchange Type
Conversation (any media)	Conversation (any media)	Conversation (any media)	Conversation (any media)
Interactive data extract	Interactive data extract	Interactive data extract	Interactive data extract
Data capture form	Data capture form	Data capture form	Data capture form
Interactive design presentation	Interactive design presentation	Interactive design presentation	Interactive design presentation
Data Publishing	Data Publishing	Data Publishing	Data Publishing
Transaction exchange	Transaction exchange	Transaction exchange	Transaction exchange
File transfer	File transfer	File transfer	File transfer
Information Type	Information Type	Information Type	Information Type
Information items	Information items	Information items	Information items
Data elements	Data elements	Data elements	Data elements
Information forms	Information forms	Information forms	Information forms
Data records	Data records	Data records	Data records
Narrative log (any media)	Narrative log (any media)	Narrative log (any media)	Narrative log (any media)
Recording (any media)	Recording (any media)	Recording (any media)	Recording (any media)
Analysis	Analysis	Analysis	Analysis
Deployment Environment	Deployment Environment	Deployment Environment	Deployment Environment
User interface	User interface	User interface	User interface
Data exchange interface	Data exchange interface	Data exchange interface	Data exchange interface
Session management	Session management	Session management	Session management
Service directory	Service directory	Service directory	Service directory
Service exchange	Service exchange	Service exchange	Service exchange
Encapsulation	Encapsulation	Encapsulation	Encapsulation
Security assurance	Security assurance	Security assurance	Security assurance
Service Assurance	Service Assurance	Service Assurance	Service Assurance
Base level CIA	Base level CIA	Base level CIA	Base level CIA
Base level auditability	Base level auditability	Base level auditability	Base level auditability
Enhanced CIA	Enhanced CIA	Enhanced CIA	Enhanced CIA
Enhanced auditability	Enhanced auditability	Enhanced auditability	Enhanced auditability
Authenticate/authorized	Authenticate/authorized	Authenticate/authorized	Authenticate/authorized
Appropriate	Appropriate	Appropriate	Appropriate
Aligned/qualified/coordinated	Aligned/qualified/coordinated	Aligned/qualified/coordinated	Aligned/qualified/coordinated

Fig. 10 PSD2 usecase: check account balances

Process mapping for steps

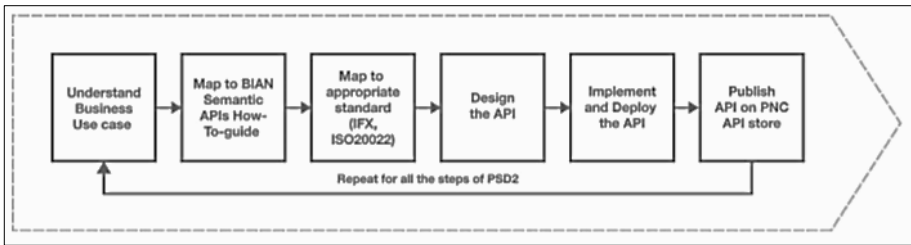


Fig. 11 Business process for building solutions to the different steps of PSD

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A robust framework for implementing technology controls amidst extreme disruption

Subramanian Annaswamy¹

Abstract This paper presents a practitioner's approach to addressing technology control issues, especially in the financial services industry. In an era of extremely disruptive technologies, organisations are increasingly vulnerable to complex control issues, which requires creative problem solving. This paper provides a model for control professionals to address emerging risks in a reliable manner. The article presents the industry best practices and experiences of experts in IT audit of some of the leading financial services firms.

Keywords: Big Data · Compliance · Controls · Continuous Auditing · Continuous Monitoring · Cyber Risks · Big Data · GDPR · Sheltered Harbor

1 Introduction

In the last few years, there has been a seismic shift in the technology landscape across a number of industries, including the financial services. Disruptive innovations in the financial sector [1] include profoundly impactful changes, such as big data, robotic process automation (RPA), and machine learning. Although these technologies have significantly improved the functional and technical capabilities, correspondingly, a new class of technology control issues have also emerged. As a result, the organisations are increasingly finding it difficult to adhere to industry best practices, organisational policies as well as regulatory obligations.

This article provides a practitioner's perspective on how to address emerging control concerns by using a flexible approach based on a general framework. The approach outlined will enable financial services firms to maintain a controls-conscious culture. As a result, emerging risks can be meaningfully addressed through a combination of thoughtful instrumentation and appropriate management oversight.

2 The changing technology landscape and how it is indeed different this time

When we speak of disruptive technologies, we sometimes hear a dismissive refrain from control professionals: "we will tackle this challenge just as we have done in the past". The sceptics also assert that several so-called disruptive technologies sometimes never see the light of the day, so why bother with every change. This is an oversimplification and it may indeed be a lot different this time. For the control

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professionals (e.g., IT risk, technology management, IT auditors) industry studies, such as the annual ISACA Protiviti survey for IT Audit best practices [2], identify the core trends that are worthy of further research from a risk remediation perspective. Here are some of the big trends driving the industry presently:

- **The pursuit of digitization** – The relentless pursuit of digitization by organisations, large and small, has resulted in a fundamental transformation of business processes. The main beneficiary of such efforts is the end user who now increasingly expects an improved user experience, especially on mobile platforms. The obvious risk is sensitive data manifesting via various channels, including mobile platforms.
- **Creation of a data-driven business organisation** – Several large organisations are undertaking a data-centric approach to their organisational transformation. Microsoft, for instance, transformed itself by establishing four shared services groups: Data, Data Science, Change Management and Business Intelligence. The idea was to promote the widespread use of common data, reports, algorithms, and processes across the firm [3].
- **Agile practices** – A truly disruptive innovation in the industry is the introduction of agile practices. There are several types of Agile methodologies, such as Kanban, Scrum and Lean Development. We will use the term “agile” here more generically [4]. Although first pioneered by the software industry to deliver software timely and to meet specifications, agile methodology has now gone mainstream across several industries. This methodology is, “a well-developed holistic system engineered to overcome more than a dozen common barriers to successful innovation,” according to Bain and Co. [5]. As illustrated by Bain and Co. [6], Agile methods have resulted in the tripling of success rates in software development projects. These successes do come at a price: one of the core values of Agile is based on delivering working prototypes over excessive documentation. Therein lies the reservations of the control professionals over Agile practices as documentation is often regarded as a proxy for the controls themselves.
- **Continuous delivery** – One of the key tenets of Agile workflow adoption is the concept of continuous delivery. Today, the technology industry has generally embraced the idea of small incremental functional rollouts in Agile projects as the *de facto* standard. This approach is the diametrical opposite of the traditional waterfall delivery model that resulted in a large-scale delivery at the end of monolithic phase of a project. A related idea is the concept of DevOps, which brings in development and support staff under one common organisation. In the era of continuous delivery and DevOps, the question of how to continuously improve controls remains a valid concern.
- **Cyber risks and privacy** – Last, but certainly not the least, is the extreme focus on cyber risks and privacy, which is interrelated to some extent. As the industry moves into big data, data capture and aggregation becomes prolific, so does the issue of protecting sensitive data. Added to this, is the increased regulatory expectations around protection of private data. The EU General Data Protection Regulation (GDPR) [7] that came into effect in May 2018 is the latest regulation to focus on protection of private data. This regulation imposes stiff penalties for inadequate safeguards or breaches of private data in

Europe. Additionally, increasing cyber incidents and exploits have also focused the industry's attention on safeguarding technology assets. The digitization efforts only make organisations more vulnerable to the cyber hazards as more assets now reside on electronic platforms. Industry initiatives in North America such as Sheltered Harbor [8], are aimed at improving cyber resiliency for the entire financial sector. Controls needed to address cyber risks and privacy are now at the forefront of implementation programs in many organisations, given the nature and extent of these risks.

At a gathering of the leading IT audit directors in North America last year [9], the above factors were named as key drivers in the industry for which the assurance professionals are somewhat unprepared. Paradoxically, it is also acknowledged that the very people who are expected to deliver on the above changes may also be the ones who are most resistant to change (i.e., the middle managers).

3 We do have a silver bullet, sort of...

Like all the revolutionary changes, tackling the present challenges will require forethought, leadership and a rubric that may improve the chances of success. So, is it possible to stay ahead of the curve to address the most egregious of the control problems? Certainly. The big idea is to leverage some of the very technologies that are causing the disruption and to improve data gathering for monitoring compliance.

Once it is clear what controls are required or need enhancing, it should be easy to look for control signatures – the metrics that could be measured to evaluate the strength of the controls. For instance, compliance to the adoption requirements of Agile can be monitored by the number of incremental releases using standard tooling by the development team. Such a metric is a useful measure of the teams' effectiveness in adopting Agile.

4 The ARM model for control uplift

We propose a general-purpose model for reliable and robust establishment of controls that will enable not only the implementation of a controls program, but help the organisation to stay current as technologies come and go. It is called the ARM model and it consists of three distinct phases that are somewhat sequential and yet cyclical in nature:

1. A – Assess
2. R - Remediate
3. M – Monitor

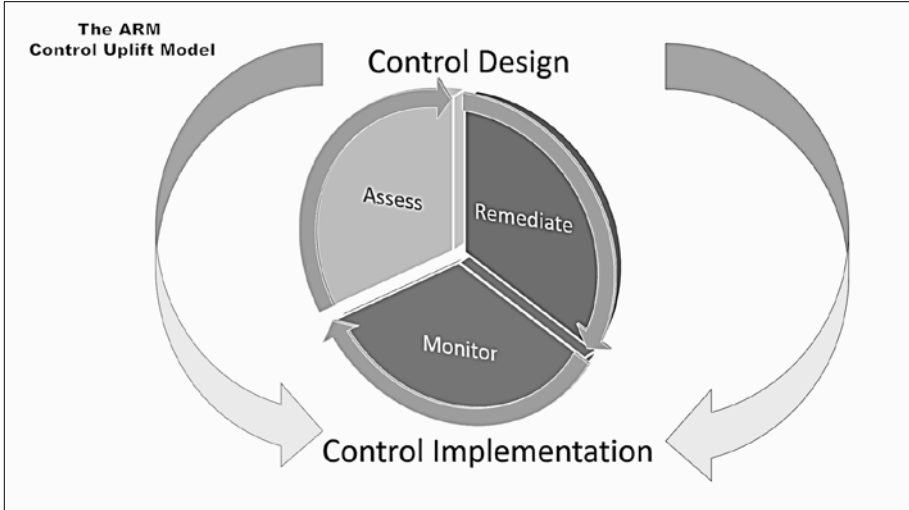


Fig. 1 ARM model of controls implementation

Credit scoring is performed by the proposed method that classifies the criteria such as good or bad in credit of client. The proposed method uses a lot of variables which can be acquired from information of client including both unlabeled and labeled ones. After learning from events (loan) that have already occurred and the consequences (payment or delinquent), the credit scoring evaluates if the client can repay or not. The purpose of analysis of data is to evaluate credit of clients.

The three phases of the ARM model are explained below:

- a. **A – Assess:** This inaugural phase of controls remediation requires assessing technology disruptors and evaluating the associated risks. It is during this early stage that the firm should start reviewing the controls that are to be created, modified or removed due to their staleness. Taken together, this is referred to as “control uplift”. The compliance metrics should be based on a robust identification of risks. Does the organisation have a process to assess and evaluate emerging technologies to identify the disruptors? Pay particular attention to upcoming deployments and pilot projects or Proof-of-Concepts (POCs) that are often harbingers of technology changes. Care should be taken to ensure that the new or modified controls cover the assets being impacted. For example, if an organisation is rolling out a machine learning-enabled application to assist in new account opening, the risks that may manifest as a result must be thought-through. In a “robo client account opening” scenario, a metric worth monitoring could be – the number of times the human operator did not override the machine learning’s suggestion (whether to open an account or not). In such a case, a control could be devised to seek data directly from the account opening process to be analyzed by the controls

monitoring program to measure and report the number of manual overrides on opening an account.

- b. **R - Remediate:** This is the phase when you actually implement the controls to remediate the emerging risks. By no means is this a simple undertaking. It is believed that auditing the state of controls through a constant evaluation is equally important (see continuous monitoring and continuous auditing below). In the list of tactics for implementing controls, (see Tactics below) there are several ideas on what controls is to be implemented as part of this phase.
- c. **M – Monitor:** The final phase of the control uplift effort should endeavor to maintain a state of compliance by constant monitoring. It goes without saying that there is no such thing called an ideal end state – controls have to continuously evolve with time. As technologies change, controls have to be revisited and modified as necessary. A robust control framework will enable the organisation to remain ready to take on the control challenges.

5 Tactics for implementing controls

As part of the ARM model, one needs to have a good repertoire of controls to be considered for implementation. In particular, it will be vital to ensure that the controls take direct feeds of data that cover the control signatures as explained earlier. Embedding continuous monitoring (CM) and continuous auditing (CA) into the controls efforts is recommended. The following considerations apply within the uplift efforts:

- a. **Structure controls to cover the control signatures** – Controls have to be designed to ingest data from the systems that represent the state of controls. Pay specific attention to end-to-end checks that enable you to draw an accurate conclusion on the overall state of controls. For example, as part of emerging regulatory expectations, financial regulators expect the ability to ‘drill down’ transactions from books and records back to point of capture (e.g., trading or banking systems). One should consider integrating and implementing data warehouses that can act as ‘reliable sources’ internally. One should also identify ‘golden sources’ of reference, market and transactional data, and question unorthodox sources of data. The use of end user computing (EUC), for instance, is often a source of doubt. Equally important is the need to adopt a common firm-specific or industry-adopted taxonomy of controls. Such a taxonomy enables consistent assessment and reporting of state of controls to management.
- b. **General controls remain relevant** – The new technologies have not obviated the need to test general controls although certain controls have become obsolete. Reconsider these common controls through the lens of new technologies being introduced:
 - i. Change Management (think of systemic disruption)
 - ii. Access and Entitlements (think of data privacy as well as migration risks in the production environment)

- iii. Disaster Recovery and Readiness (think financial ‘safety and soundness’ as evaluated by the regulators)
- iv. Enterprise Data Governance (think front-to-back and consider regulatory expectations on data governance).

Even an established control like entitlement need to be thought-through as technologies such as artificial intelligence bots, make an appearance. Such bots will typically have full access to production. Therefore, the question arises as to how to enforce segregation of duties for a bot, for instance?

- c. **Embed continuous monitoring and continuous auditing into control efforts:** Although Continuous Auditing (CA) and Continuous Monitoring (CM) are used interchangeably, these are quite distinct. CM is a mechanism to track management’s awareness and readiness around compliance of controls. CA, on the other hand, is a program to test the state of compliance ‘continuously’ (i.e., with sufficient frequency). In general, a CM program is easier to deploy than CA. That is because CA requires careful planning, a stable project team, and a steady list of tests. To the question, if we need to invest in both, answer is an emphatic ‘yes.’

6 Role of the three lines of defence in control uplift programs

Once the framework is defined, it should be decided as to who will be involved in the implementation of the control uplift program. In this process, three lines of defence [10] have a vital role to play. The first line (i.e., the business management) has the primary responsibility for the introduction of controls. The second line functions (i.e., risk oversight groups such as Compliance and Legal) have a role for establishing policies and procedures that assist in providing oversight over the first line. Finally, the third line is the independent assurance function, such as internal and external auditors, who have to independently report to the Board directly. How each of these three lines participate in the control uplift effort also depends on the structure of the organisation.

7 Bringing it all together

To get a program of control uplift started, support of management and execution of vision is essential to execute on it. One of the key questions that may come up in launching such programs is if it is worth doing it at all. This is where thought leadership and commitment to the controls agenda is essential. Let us remind ourselves of what the famous management guru Peter Drucker said: “There is nothing quite so useless, as doing with great efficiency, something that should not be done at all [11].” For the control professionals, this translates to pursuing those control initiatives that truly matter and doing so with complete commitment.

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Editorial

Dr. A. S. Ramasastrri

Research Articles

1. SOA maturity influence on digital banking transformation 01
Alan Megargel, Venky Shankararaman, Terence Fan Ping-Ching
2. The rise of machine learning and robo-advisors in banking 28
Chaman Lal Sabharwal
3. Sustainable co-training of mixture-of-experts for credit scoring of borrowers in social lending 44
Jae-Min Yu, Sung-Bae Cho

Practitioners' Perspective

4. BIAN – PNC open APIs for banking 65
Mark Grobaker, Arashdeep Kaur, Chaitanya Kommuru, Wenting Tao, Pallavi Thakur, Hans Tesselaar
5. A robust framework for implementing technology controls amidst extreme disruption 79
Subramanian Annaswamy