OneBankAssure [a pseudonym] sought to delight its customers by delivering new digital value propositions that exploited new data science and machine learning disciplines. The company created a new organizational unit focusing on these disciplines and funded many new use cases that leveraged them. This case describes the practices of this new unit and recounts the story of the development of one of the company’s successful machine learning use cases. To create fertile ground for the use of machine learning capabilities, the company was also making significant investments in training and culture change, so as to become a more data-driven and evidence-based organization.
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ONEBANKASSURE: CUSTOMER INTIMACY THROUGH MACHINE LEARNING

OneBankAssure (1BA) was a financial services firm that had been formed by the merger of two banks and an insurance company. By 2017, it had grown both organically and by acquisition to 16,000 employees who served more than 3.5 million customers.

The company faced challenges from Fintech companies, which used technology and automation to deliver a host of standalone financial services through easily accessible channels such as smartphones and the internet. To overcome this challenge, the company was aggressively pursuing the integration of banking and insurance products—“bank-insurance integration”—and creating new value propositions for customers. 1BA’s leaders had been persuaded that customers who availed themselves of multiple business lines and multiple channels were more profitable and more loyal. 1BA sought to be an omnichannel “one-stop shop” for financial services. Company leaders believed that they could bind customers to the company if they leveraged customer data across product lines and channels, developed customer intimacy, and offered new products and services valued by customers.

1BA’s goal was to become one of the top banks and insurers in its market.

How can we narrow the gap, so that the appetite for the Fintechs to challenge us in our market is small? Why would they come if there’s not much to grab? This is what we are working on.

FRED, VICE PRESIDENT OF STRATEGY, INSURANCE

Company leaders believed that learning from and leveraging company data was key to increasing revenues per customer and finding sources of new revenues.

Data and AI are the fuels that will make this happen.

ROBERT, DATA SCIENCE AND MACHINE LEARNING (DSML) STRATEGY EXECUTIVE

ONEBANKASSURE: STRATEGY AND STRUCTURE

1BA reached its customers through seven hundred fifty branches, as well as through mobile and web apps. Insurance products were sold to customers in bank branches and through four hundred tied agents. (A “tied agency” is an independent organization that sells only one company’s products.) 1BA’s operating model was a unified model, with common processes and shared data across its banking and insurance operations.

Among those reporting to the CEO were the heads of corporate functions (such as sustainability, human resources, strategy, marketing, finance, and risk), the heads of the two main business lines, and the head of innovation. The head of Data Science and Machine Learning (DSML)—a new unit offering applied data science and machine learn-

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1 This is an anonymous case about a real organization. Some identifying facts about the company and all the names have been altered.
ing modeling services to the business—also reported directly to the CEO. The head of innovation focused on digital transformation and oversaw the traditional IT service function. (See exhibit 1 for the 1BA organizational chart.)

The fusion of data-driven services and digital transformation was a key source of innovation for 1BA, and DSML in particular had been an area of strategic investment for the company.

The key element in our strategy is putting the customer at the center of our attention. We’ve been customer centric in the past, but today, and tomorrow, we need to do so proactively. And that’s why we need DSML. Each and every customer leaves data behind—in 1BA, in the outside world. DSML is going to translate that data into information, information that we will use to proactively fulfill customer needs. DSML is a translator, and a crucial one. DSML will be a key cornerstone of our future strategy.

CHIEF EXECUTIVE OFFICER

For this strategy to be successful, DSML needed to partner well with the IT unit, because IT was ultimately responsible for running the models and applications that DSML developed.

The Information Technology Unit at 1BA

1BA had a core banking and insurance engine that was relatively new, well designed, and well integrated, according to the head of IT and others. The company also had a new mobile development center of expertise that took care of the web and mobile channels. An IT committee set standards, such as for communications, networks, security, and API gateways. 1BA’s leaders considered the company’s transaction processing data and managerial information very good.

The IT staff comprised about 75% full-time employees and 25% contractors, the latter providing specialized skills and flexibility. The application development staff, having experimented with agile methods for several years, was standardizing its agile approach, moving from a project structure to a scrum leader structure, and setting maturity goals for scrum teams. IT leaders had established an Agile Competency Center to facilitate this change. In 2014, in anticipation of DSML’s distinct support needs, IT had hired an expert in DevOps and two new data architects who were expert in the kinds of tools that DSML used.

The IT organization had a reputation for being innovative. Indeed, the head of IT, Oliver, who reported to the head of innovation, fostered and encouraged innovation among the IT staff with free time, seed grants, innovation spaces, and recognition schemes. IT staff had pursued a number of digital innovation use cases, looking for clever ways to solve business problems with technologies such as blockchain, mobile devices, virtual reality, drones, and even game consoles.

Just because you’re in IT doesn’t mean you cannot think like a business person. In a digital world, IT is a business métier. Like insurance or asset management or payments, IT is part of the business.

OLIVER, HEAD OF IT

The CEO had brought Oliver from another part of the business to run IT and continued to work closely with him.

There is an unbelievably cooperative mindset between the business and IT. The business is not looking at IT as a supplier that will throw something over the wall. The business and IT have learned to speak each other’s languages. I know business. I speak more business language than I do IT language, and that helps in having the alignment with the business—and it’s all about the alignment.

OLIVER
THE DSML UNIT: FUELING THE UPTAKE OF MACHINE LEARNING

The CEO had created DSML in 2014 to jump-start the uptake of data-driven decision making at 1BA. He saw DSML as a strategic investment and promoted DSML throughout the company. He also invested aggressively in data scientists.

*We hired, through headhunters, some hotshots, some experts in this environment, and we also hired about thirty real mathematicians for modeling things.*

OLIVER, HEAD OF IT

DSML had a centralized structure. The two main DSML roles were data scientist and business integrator. The data scientists scoped projects, developed models, wrestled with data, and worked on data visualization. The business integrators liaised with the business functions, translated analytics and mathematics into business terms, managed projects, and helped use case owners prepare for rollout.

Prioritizing Investments in Use Cases

DSML investments were overseen by a steering committee that was chaired by the CEO and included the head of innovation, the head of IT, the head of DSML, and three top business executives. The committee met monthly for at least two hours to prioritize use cases and review use case outcomes. Reflecting 1BA’s transformation goals, the top priority of the committee was to drive revenue, the second to reduce risk, and the third to reduce costs.

Developing Use Cases

In 2014, DSML pursued three new use cases each quarter. By 2017, a staff of seventy-five was pursuing hundreds of use cases per year, 90% of which involved machine learning (ML) of some sort. The rest of DSML’s use cases entailed mainly data visualization or other data science approaches. Most of the ML models employed supervised learning approaches, but there was some use of unsupervised learning for anomaly identification. DSML’s portfolio included use cases related to fraud detection, robo-advising, credit scoring, process analytics, and customer service. In 2017, at the urging of 1BA’s head of strategy, DSML began to add artificial intelligence capabilities, such as natural language and image processing, for use cases involving chat bots and the extraction of content from emails, for example.

To manage development, DSML used a mix of agile and stage-gate principles. Initial ideas came from the business, and all use cases had a business owner.

*We don’t start with a solution. We don’t sit with a solution, a sledgehammer, waiting for a nail to come along. We start with the clear definition of the business question. We come from the problem domain to the solution. That’s why on some projects, the data science challenge is not so remarkable, but the business impact is always great.*

BENJAMIN, VICE PRESIDENT, DSML

Initial ideas were fleshed out by a team that included a use case owner, a business integrator, and a data scientist. After gathering some evidence in support of the idea, this team developed a one-page summary that addressed the financial, technical, and organizational feasibility of the idea and its potential value to 1BA. Based on this summary, the DSML Steering Committee might fund a three-month sprint project. During this sprint—and through additional three-month sprints, if needed—ML models and applications would be co-developed iteratively with business owners and key end users. They would work first to develop a valuable, relevant, and sustainable model that anticipated production and data flow issues, and then would flesh out its use environment (visualizations of model results, changes in business practices, etc.).
Models were often piloted more than once, capitalizing on actual use to surface problems with models or workflow early on, and earning gradual but steadfast user buy-in.

We stress piloting. We need that feedback to be able to improve the model, and to make sure that it will be useful for the end users when it’s deployed. And also so that if a model doesn’t work, we can make the decision not to deploy it. It doesn’t make sense to deploy something that’s not useful. It’s also important to get buy-in and build the motivation for change in the organization. Piloting is essential.

LAURA, BUSINESS INTEGRATOR, DSML

To close the loop on their funding decisions, the steering committee evaluated the results of pilots, and they ultimately granted permission for the business owner to commercialize successful pilots.

Using Co-Creation to Develop ML Applications That Are Actually Used

Every DSML use case was co-created by owners, users, data scientists, and business integrators. Co-creation of use cases was considered crucial at 1BA for three reasons: the use cases needed to achieve business goals; use cases involved exploiting new, poorly understood technology; and the company was using a process that was new to most of its business partners.

We are using co-creation on every DSML case. We sit with the business, as close as possible to them. It’s an iterative process. We slowly develop the full model and application. Using co-creation, we try to capture from the commercial teams their feel for the customer, their insights on what works and what doesn’t, and their daily process.

SOPHIA, CHIEF BUSINESS INTEGRATOR, DSML

A co-creation team developed a shared vocabulary and a shared knowledge base, so that team members could make decisions together. The technical experts listened and learned about the business domain, while also exercising some judgment about what they heard.

It’s finding a balance between what the end users are saying in their feedback and the bigger picture.

JACK, DATA SCIENTIST, DSML

At the same time, the business experts developed a higher level of understanding of how to develop an ML model, and how the model was going to fit—or not!—into their processes, work practices, and workflow. In addition, business participants often also had to learn about how agile projects unfold. At the start of a use case with a first-time owner, the DSML business integrator had to teach the business participants not just about ML but also about agile project management principles.

You have to manage their expectations in terms of what they can expect from each phase. It takes a lot of my effort to get the phase scope clear, to guard the scope, and just to explain scoping. And you have to be closely following up, making sure that everyone keeps looking in the same direction, and has the same understanding of what we will do, and what we can do, and what we cannot do, and what we will do in the next phase.

LAURA

The members of the DSML team were acutely aware that the technical quality of the models they built did not guarantee that the models would be successfully used. The team also knew that only DSML models that were used would achieve business goals.
It starts with data, but it doesn’t end there. Business has to take it, and business has to make it part of their operational world. If not, nothing happens. Now, we are much more sensitive to this need for organizational change and behavioral change from the first day of the project.

SOPHIA, CHIEF BUSINESS INTEGRATOR, DSML

Involving business owners and users at the very inception of each project and at every stage after that helped DSML members keep the “usage goal” front and center and to constantly visualize how users would actually use the application.

One lesson for me is definitely the importance of thinking really early, from the beginning, about the end result: How do they want to use it? What are they going to do with it? Where in the process will the model sit? Are you trying to automate a process or will the model be supportive? I want to be able to imagine someone using it.

LAURA, BUSINESS INTEGRATOR, DSML

Implementing ML Applications

Developing ML applications and running them in production required very different capabilities. The first required flexibility, agility, iteration, and quick prototyping, whereas the second required a stable, secure, and scalable technical and data environment. While Benjamin’s DSML team was responsible for the development of ML models and the ML applications in which they were embedded, Oliver’s IT organization was responsible for running those applications in 1BA’s IT production environment. This division of responsibilities had been enabled by clear discussions on who did what.

Since the beginning, we have had a good, clear discussion about our governance structure—who is responsible, who is accountable, who should be consulted, and who should be informed—for everything that has to be done. IT is accountable if something goes into production. We have SLAs and performance levels commitments we make to the business. We commit to having a disaster recovery processes, to having backups, to having all this security and everything else that we have for all the other applications. So every time we take in something, it becomes our accountability, and we have a whole process of adapting it and putting it in place, like we do for all the other applications.

OLIVER, HEAD OF IT

The division of responsibilities, interestingly, also aided cooperation between the DSML and IT teams. The DSML data scientists developed models with IT’s production requirements in mind. The IT team proactively observed the tools used by the DSML developers, and once a preponderance of developers were using a new tool, IT added it to the production environment. IT gave DSML developers laptops with the approved development tools and gave them access to data on the Hadoop servers. IT managed the frameworks for mobile and touchpad applications, and had created tiles where DSML could drop in information produced by DSML’s applications.

In the early days the IT team would refactor ML applications prior to putting them into production. When the DSML data scientists observed that IT was doing this, they began developing applications that for the most part didn’t need to be refactored. The IT team still tested all new applications in the production environment.

Applications that run in production must be embedded in our way of working, with releases, with performance management, with disaster recovery, with cybersecurity.

OLIVER
Overall, 1BA executives were satisfied that the relationship between the “model makers” and the “model runners” was working well.

_When I look at other companies and other banks, I think that one thing we do well is that we give model run enough importance, and I think that’s good._

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**OLIVER, HEAD OF IT**

That said, the interface was not always frictionless.

_The discussions we have around when “run” starts and when “make” stops can be difficult. It’s not always black and white. After we put a machine learning model into production, if we see that the results are not good anymore, then it has to go back to DSML._

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**OLIVER**

**Monitoring and Managing ML Applications**

ML applications had a number of components to them: the model itself, the data that it ran on, the model’s outputs, and the production environment. Effectively managing all of these could be complicated. IT was responsible to application owners for model run, i.e., for ensuring that applications ran to completion and securely, and that backup and recovery were taken care of. Regarding quality of inputs and outputs, the primary responsibility for managing ML applications belonged to the Bank-Insurance Marketing unit, which owned the underlying data. This freed up the DSML staff to work on new use cases (and lessened the model monitoring burden for IT staff). In addition, the use case owner was responsible for monitoring the model’s business results.

_It’s not just if the model is working correctly, but what the business results are. We tell the use case owner, “Now you must do a check every X months to see if the model is still aligned, because if we are quoting higher premiums for lower risk—or vice versa—we have an issue.” If this happens, the model needs to be retrained by DSML._

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**OLIVER**

DSML’s ML applications were designed to self-report a number of health indicators to different stakeholders. For use case owners, health indicators would focus on whether or not the business results were in line with company goals. For the data owners, health indicators might focus on whether the model’s recommendations fell within an expected range or whether new data had expected characteristics. For the IT unit, health indicators would show that the application had run to completion and used the expected resources. These health indicators helped stakeholders spot problems, but collectively monitoring ML applications in production remained a complex endeavor. It was important that the right people were monitoring the right parameters and that nothing slipped between the cracks. 1BA was still working out the kinks in the model management process. The company had plans to develop a dashboard that would summarize model metrics and make them more transparent.

**Accumulating Curated Data into a Data Platform**

1BA had valuable data assets—good transaction processing (or operating) data, good aggregated managerial information, and in particular, a customer data warehouse—but these were not sufficient to build ML models. ML models required data that could serve as proxies for unmeasured and immeasurable factors that shape customer behavior, such as willingness to pay, business goals, and implicit preferences. Operating data could sometimes serve as a proxy—such as using profitability as a proxy for willingness to pay. But selecting proxies from operating data required a sophisticated understanding about the data’s source and history, as well as its level of accuracy. Non-operating data, such as data owned by various individuals in the business or external data, often seemed like a better source of proxies, but in reality, both of these kinds of data could be just as error prone as and more
unfathomable than operating data. Moreover, data used to train an ML model needed to be far more granular than the data in most data warehouses. As a result, getting data was a challenge for ML modeling. In particular, a lack of metadata about operating data (which is usually not a problem for day-to-day operations) was a big stumbling block for DSML model developers, who needed metadata to interpret data or to choose among data sources. It is not surprising, then, that data used in ML models required significant additional curation, no matter how good the company’s operating data was.

*I think 80% of our time is really getting the data ready for the model. The modeling itself is not that difficult, to be honest. The data tends to be a huge challenge.*

JACK, DATA SCIENTIST, DSML

As a result, 1BA sought to leverage the large investments in data curation made by each use case team. Early on, the DSML team had begun building a curated, architected data platform of both internal and external data for multiple future ML use cases. For DSML, 1BA’s IT group created a Hadoop data lake to which the group ported, at DSML’s request, data from existing internal data sources—particularly related to customers—as well as external data sources, including financial data on companies. IT set up ETL\(^2\) routines to constantly refresh both kinds of data feeds. The data lake was formally owned by the Bank-Insurance Marketing data team. That team also used the data lake for reporting, analysis, and visualization.

It was expected that the extent of reuse of this data would increase and the time taken to curate data for a new project would decrease. A further benefit of the data platform was enabling the improvement of existing models when new data was made available.

*When we start a case, we ask, “Okay what can we reuse, potentially?” Then as we go along, we realize we need additional data. If we get interesting new data, we can add those to previous models, retrain, and restart again. In this way we move a model to a higher level. The models are gradually getting more mature.*

SOPHIA, CHIEF BUSINESS INTEGRATOR, DSML

1BA was also making an effort to collect some additional data with future ML applications in mind. Pop-ups nudged bank clerks to ask a customer in front of them about a key piece of missing data. Claims processors had been asked to document their reasoning behind decisions about claims to inform the development of future models.

**Monitoring the Value Created by the DSML Unit**

DSML keenly monitored the total value created by all of their initiatives. Benjamin, the head of DSML, spent most of his time working hand in hand with senior executives to evangelize the value potential of data science and machine learning. DSML distributed a confidential report quarterly to 1BA’s top executives that identified all the value the unit’s use cases had created for the company. The value figures were provided by the business. This report was treated as a highly confidential document.

**THE “INTELLIGENT CUSTOMER LEADS” USE CASE: A NEW IDEA FOR AN OLD PROCESS**

Referred to internally as the “IC Leads” use case, this application illustrated how 1BA was using internal bank and insurance data, external data, customer analytics, and machine learning to drive growth in revenue. The purpose

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\(^2\) ETL stands for Extract, Transform, and Load. It refers to automated processes that extract the desired data from its original data source; transform the data by changing its structure, format, aggregation level, or encoding to match the destination source; and then load it into the destination source.
of IC Leads was to drive additional revenue, particularly from SMEs, by providing high-quality leads to tied insurance agents. Each lead provided not only specific suggestions (e.g., “approach this customer about this product”) but also contextual information about the customer and the product.

The lead list says, “These are the customers and products where you have the highest chance for success. Target them first.”

ETHAN, IC LEADS OWNER, INSURANCE

Traditionally, agents had received many leads from 1BA, primarily from the Insurance Products Marketing organization. Often lead delivery outpaced agents’ ability to effectively follow up on them.

I ended up with a lot of lists that I didn’t really use, to be honest. To use them you have to fix up the data, and then you have to make selections from them.

MAX, TIED AGENCY OWNER

Further, they did not always trust the usefulness of the lead lists.

They always wanted to know, “Okay, but how did you create this lead list?” They were right to be doubtful of the quality. There were mistakes.

ETHAN

Typically, the agents had filtered the leads, using their own knowledge about their customers, as well as their own biases and preferences for what they wanted to sell, or to whom they wanted to talk that day.

Before IC Leads, maybe three employees sat together, went through a list, refining it. Then the manager looked at it. He removed leads, saying, “Not this guy, not this person, not this lady, because I know them, I called them last week.” And maybe they cross-checked against other sources.

STEVEN, PROFESSOR/CONSULTANT

Developing the Use Case

The IC Leads use case owner, Ethan, was an executive in the Insurance Products division. Together with a business integrator and a data scientist, Ethan developed an initial model to assess the feasibility of using ML, the availability of appropriate data, and the lift in revenue that might be gained. 1BA had rich information on its business customers, but that data had previously been used mainly for credit scoring by the bank, not for identifying sales leads for insurance.

We focused first on the SMEs. What data was available about them that we were not using yet? The model is based on information that the agents were not already using.

SOPHIA, CHIEF BUSINESS INTEGRATOR, DSML

Their one-page feasibility summary was approved by the steering committee for further development in a “pre-pilot” sprint with the involvement of four agents from different-sized agencies. The objective of this sprint was for DSML to quickly and iteratively work with the agents to co-create an ML model and application. The interactions among the agents, the data scientist, and the business integrator were intense. The first task was to check for overall model validity.
We took a very agile approach. I think we developed and presented quite a few models before we really had one where we said, “Okay, that’s it. Now we feel there will be a commercial advantage.”

ROBERT, DSML STRATEGY EXECUTIVE

The agents, who had been handpicked by the CEO, were eager to participate and to learn. And at first they were very excited to see that the ML model actually worked, but then they quickly got serious about how challenging it would be to achieve adoption.

It shifted from, “Yeah, we did it!” to something more like “Gee, this is another way of thinking, of working with the client. What do we say? How do we put it?”

SOPHIA, CHIEF BUSINESS INTEGRATOR, DSML

Integrating Model and Process

Once the validity of the ML model was clear, the team focused on how the model’s outputs would be used by the agents. The first concern was what information to show the agent and how to present it. IC Leads’ ML algorithm produced leads ranked by quality. An application around the algorithm applied business rules to select which leads to present to which agent, so as to focus agents’ attention on quality leads for SME customers.

The focus of the model on SME clients is something we know that we will do for years to come. It’s strategic. Beyond that, we’re using simple but clear business rules about which leads we show, how many leads we typically show, with what frequency we provide leads.

ETHAN, IC LEADS OWNER, INSURANCE

Leads were displayed in blocks, distinguishing ML-generated leads for sales to companies from those for sales to individuals. Referrals from the bank to an insurance agency—which was at the core of 1BA’s bank-insurance model—made up another block. Time-sensitive leads made up yet another block.

Say a customer of an insurance agent goes to our website to do a simulation for home insurance, and he stops midway. The insurance agent will receive a lead that says, “This customer cut off the simulation process for this product.” If the insurance agent is going to call that customer, he has to do that within several hours because if you wait a day, two days, three days, it’s useless. The client’s gone to somebody else’s website and finished the transaction.

ETHAN

Given the agents’ historical practice of passing over leads, a key issue was to convince the agents to actually follow up on the leads that IC Leads produced.

We cannot tell them what to sell. They have to be convinced. They have to see the added value of an approach like this. That’s a nice challenge.

ETHAN

At the same time, it was important to ensure that the agents continued to use their judgment.

With IC Leads, they need to combine our predictions with their double checks and post-processing to get the benefit of the human angle.

STEVEN, PROFESSOR/CONSULTANT

Thus, the team needed to envision how agents would use the leads and how they would interact with customers.
Luckily, in preparation for the rollout, the team brought three members of 1BA’s insurance product support team into the project. These support staff had traditionally assisted tied agents in two ways: by being product experts, and by coaching the agents in selling. The support staff immediately sensitized the use case team to the magnitude of change it was expecting from the agents.

Even though everybody is always saying it’s a big change, it’s an even bigger change for the people that are doing the work. The project team was gradually persuaded by the support staff that the team didn’t really appreciate what a big change it was going to be.

SOPHIA, CHIEF BUSINESS INTEGRATOR, DSML

The support staff helped the project team understand that it would have to help the agents approach the customer by suggesting new workflows and scripts.

The support staff found some mistakes, but more importantly, they said we had to write scripts, and we had to be sure that the agents were trained on the scripts. We had thought that if we just improved the quality of the leads, it would work easily. But we were also asking the agents to be more customer-centric. That was a shift we underestimated.

SOPHIA

The support staff developed scripts for the agents to help them approach customers with whom they might not have had a strong prior relationship.

They cannot simply tell the customer that they got a lead. They have to have another story. They have to have a good script on how to approach them.

ETHAN, IC LEADS OWNER, INSURANCE

To emphasize the importance of sales coaching, Ethan reorganized his support personnel. The support team had previously been organized by product line, since product expertise was the team’s main capability. With the implementation of IC Leads, the role of product expert was separated from the role of sales coach, and more resources were devoted to coaching.

They are coaching agents who need to understand the needs of the client, the customer journey. How do you contact customers? How do you do customer acquisition? How do you make that phone call? What do you say? Some of them are afraid to make that “cold prospect” phone call, so you show them, and then you say, “Okay, try it yourself.” That’s coaching.

ETHAN

Rolling Out, Championing, and Adoption

An initial limited rollout of IC Leads took the form of a standalone dashboard, showing a selection of leads for existing 1BA clients. Then in October 2016, 1BA rolled out a CRM system for the company and its tied agents. The IC Leads display was integrated into the CRM, so the two rolled out concurrently. Leads for an existing customer popped up for that customer’s agent. Leads for a certain territory went to the owner of the agency in that territory. The integration between the CRM system and IC Leads was helpful because agency owners and 1BA could use the CRM dashboards to track progress on leads: whether the customer was called, whether an offer was made, and what business resulted from an offer.

More than 80% of the agents adopted the tool almost immediately. A number of factors helped speed the adoption of IC Leads. For example, the agents involved in the project championed its benefits. A video produced to promote IC Leads to other tied agents included the following story from Max, one of the four agents on the
development team.

The leads that I have the most success with at our office are for [an employee insurance product]. IC Leads suggested a lead for this product at a very large firm, with approximately sixty employees, that already had coverage from a competitor. My business consultant and I paid them a visit and made them an offer. The competitor responded rather awkwardly, which was the last straw for the client, so they came to us for this as well as [other SME products]. Altogether, we’re talking [$125,000] in premiums. So that was a very successful lead, to be honest. And without IC Leads I would not have pursued it.

MAX, TIED AGENCY OWNER

Also, the normal set of pressures on agents to always sell more helped foster adoption. Notably, the coaches helped raise the level of adoption by tailoring their efforts to the varying needs of the agents. Moreover, the coaches were a key and continuing source of feedback to improve the system; the coaches alerted the DSML team to changes needed to make IC Leads more useful or easier to use.

There had been no incentive changes associated with IC Leads.

If they want to earn more money, they know they have to use the leads. It’s as simple as that.

ETHAN, IC LEADS OWNER, INSURANCE

But 1BA insurance was closely monitoring which agencies were using the leads and which were not. Future incentive links were a possibility.

Initial Outcomes

1BA closely monitored the quality of leads and revenues resulting from them. The results of IC Leads were considered excellent, especially because they addressed a number of 1BA’s strategic goals. IC Leads delivered 10,000 leads in its first year of operation. Twice as many leads were expected to be delivered in its second year of operation. IC Leads had helped the agents, who were always strapped for time, to prioritize their efforts and focus their attention on the right customers and the right products. Agents’ sales conversion rate had increased from 2% to 7% (industry average was about 3%) after less than a year of widespread use. The goal was to get to 9% or 10%.

That is a lot of new company customer acquisition, which is, for us, very important.3

ETHAN

IC Leads had strengthened the relationship between 1BA and its tied agents.

Our tied agents (and they are critical, believe me) consider IC Leads to be a brand for them, and they perceive IC Leads as something very important that helps them to achieve their goals.

ETHAN

Not surprisingly, 1BA’s overall attitude toward the use of ML had received a positive boost.

Other parts of the business are looking at Insurance as the example. “They did it, they made it work, so we have to do it, too.” Everybody wants to be on DSML’s agenda. It’s inspired them. It’s also created a little internal competition, to be better than Insurance was.

3 Benjamin, Vice President of DSML, says that IC Leads is not 1BA’s most valuable use case—other projects have yielded as much as eight times the revenue from IC Leads.
Managing the Model

IC Leads was a managed and evolving application. A working group led by Ethan was responsible for enhancements of the application’s business rules and the timing of model retraining. The business rules (such as which leads to present to which agents), which had been simple to start with, were being fine-tuned on the basis of feedback from agents and coaches. As the functionality of the application evolved, it was likely that these rules would get more complex and that some of them would be automated. The model’s algorithm was maintained in two ways. First, it was routinely retrained every quarter to incorporate new data, mainly from clients’ quarterly financial reports, but also to capture other changes in the underlying corpus of data about customers. Second, DSML periodically alerted the working group to the availability of other new, potentially relevant data that might suggest that the model be retrained. Based on this kind of input from DSML, the working group made minor updates to the model about six months into the rollout.

The ML model did not learn “on the fly.”

We have a feedback loop, but it’s quite basic. If an agent decides not to pursue a lead, or they stop pursuing it, they say why. They can select from a list of specific reasons, including “I prefer not to say” or “not on the list” (and then they write something). It’s very basic. The information is captured, but it does not feed back into the model automatically. We take it into account if and when they have new requirements, or if we think we need to retrain the model.

Extending IC Leads

Almost immediately upon roll out, the IC Leads team recognized that much of the data used to predict leads for existing company clients was also available on non-clients because the data came from their public financial statements. As a very quick first extension, the team developed an ML model to identify leads for cold prospects.

A new block which I’m very fond of is the “quick-starter guide.” There we provide information about new companies that have been established in the agent’s territory or have started new business activities. This information is publicly available, and we provide the agent with a lead within twenty-four hours. For the first insurer to contact this new company, the chance of success is high. If he’s the second, he can almost forget about it.

This valuable extension of IC Leads took far less time to implement than the initial version of IC Leads, for several reasons: much of the data was already curated and organized; the data scientists had learned how to develop a model that could be easily deployed to production; and most importantly, the case owner was actively managing the business side of the pilot and rollout, involving his coaches (rather than tied agents) in the pilot.

Ethan’s organization has matured in its abilities. They’ve learned from the past. They began to take ownership during the pilot, and that is a very good thing. When it was time to involve the agents, they selected the agents, they communicated with them, they gathered their feedback, and they provided feedback to us.
As of late 2017, IC Leads was generating leads on deep-selling, cross-selling, and upselling for existing clients, and for calling on new clients. Identifying customers that were likely to churn was slated to be the next extension.

*It’s in that churn area where we still have a lot of challenges. That’s something we are working on with DSML, and that’s really the next frontier.*

**ETHAN, IC LEADS OWNER, INSURANCE**

Achieving such an extension involved the technical challenge of developing a model that made good anticipatory predictions, ideally before the customer was fully conscious of their own dissatisfaction. Also, encouraging agent adoption of the extension would likely be culturally challenging; Ethan’s coaches would need to teach agents how to salvage customers on the brink of churning.

*They say, “Even if you can predict it, what then? What do I tell them? What do I say?”*

**ETHAN**

**CREATING A FERTILE GROUND AT 1BA FOR ML EXPLOITATION**

1BA’s leaders knew that in order to effectively exploit ML, the company as a whole had to be made into fertile ground for ML applications by increasing the company’s “ML Savvy.” 1BA’s CEO wanted the company’s culture to be more data driven and more customer centric than it was. Still, it was surprising to 1BA’s leaders that the technical challenges of the ML use cases had been so small in comparison to the cultural challenges. The head of DSML was acutely aware of this.

*The biggest challenge is the organization’s inability to absorb its own ideas, to embed a solution, to make it a natural process within the organization. There is no technological challenge. There is no data science challenge.*

**BENJAMIN, VICE PRESIDENT, DSML**

Benjamin’s partner in infusing ML into 1BA, Oliver, echoed Benjamin’s perspective.

*The technology is the easiest part. You find it on the market, you can find people with the skills. Developing the model is easy. Getting the culture of the company to accept it, embedding it into the standing organization and making it business as usual, that is the most difficult part. I can guarantee you, you don’t need mathematicians to do that—you need psychologists to do that.*

**OLIVER, HEAD OF IT**

Being exposed to internal use cases like IC Leads had gone a long way toward shaping 1BA business leaders’ expectations about what ML could do. The leaders’ motivation to learn more about ML had been heightened by exposure to Fintechs and by being approached by AI product companies with ideas and opportunities. To help both executives and line managers understand that data science and ML were now part of the playbook of business, and to make 1BA more ML Savvy, 1BA was doing four things: First, the CEO had signaled his strong commitment to data science. Second, he had funded training for the top executives that included a module on ML. Third, he had invested in the development of innovation roadmaps across the company. Fourth, he had made it clear that he expected all 1BA’s employees to have some digital literacy.

**1. Sending Clear Signals on Data Science**

1BA’s CEO had signaled his commitment to DSML in many ways. He made a video to explain his large investment
in DSML to the company. He made Benjamin, DSML’s leader, part of the top management team. He gave DSML a generous budget and blanket permission to hire experts externally. And he chaired the DSML Steering Committee.

DSML has the top’s attention. It’s a good signal. When you start with big data and machine learning, you have to start it from as high as possible in the organization, because otherwise it will not be taken seriously. And by taken seriously I mean in allocating budgets, resources, priorities, but also in using it.

OLIVER, HEAD OF IT

2. Teaching Top Executives About ML

In 2015, 1BA launched a “1BA University” initiative to create a more forward-looking, collaborative culture. 1BA’s Talent Development team designed a four-module instructional program for 1BA’s top three hundred executives that covered leadership, customer-centricity, bank-insurance integration, and digital transformation. Cross-functional cohorts of about twenty executives spent roughly a week on each module, which were taught a few months apart. Participants completed between-module assignments. The course rapidly became very popular, so HR sped up the rate at which it was starting new cohorts in order to get more people through the course more quickly.

The second module, on customer-centricity, included a half-day, hands-on game developed by DSML. Teams of executives competed against one another to identify and implement the most valuable use cases. Key lessons included the basics of predictive modeling and decision trees, dealing with poor data (the game incorporated real 1BA data), feature engineering, how use cases drove to 1BA’s bottom line, and how externalities (competitor moves or regulatory changes) shaped value creation. During three rounds of play they spent money on developing and running their use cases, and with luck, made and retained profits. The most profitable team won. The other half of the day was used to review how ML was already being applied at 1BA and for further discussion.

Other topics in the customer-centricity module included being proactive in addressing customer needs and being socially responsible. The game was well received.

The feedback we get is that most of them appreciate it a lot. And they adore the gamified aspects. Being able to beat their peers helps a lot.

STEVEN, PROFESSOR/CONSULTANT

3. Developing ML Innovation Roadmaps

Instead of waiting for managers at 1BA to “pull” for innovations from the bottom, the CEO had opted to orchestrate a “push” of innovations from the top. A transformation initiative under the head of innovation sought to connect “dreamers” with operational managers. Isabel, the leader of this initiative, facilitated the formation of small, self-organizing working groups of operational managers from different areas of 1BA. The "dreamers" Isabel wanted to connect with the operational managers were experts such as data scientists from the DSML team.

The charge for each working group was first to identify emerging technologies such as ML that were likely to change their area’s business model or business processes. Then the groups experimented with the emerging technologies, with the help of dreamers, to learn how new technologies might change their business. Eventually, each group developed a roadmap for applying relevant new technologies in its business area. The projects on the roadmaps flowed into various investment portfolios, including those of the IT group and the DSML team. Roadmaps were revised every six months. The success of this initiative was measured via both the number of realized use cases that made it from the roadmaps through commercialization and the development of overall innovation capabilities among 1BA’s operational managers.

We will be successful when the creation of those roadmaps has become a recurrent process in the
organization, and the operational managers are capable of taking an announcement about a new technology and knowing how it affects our business, our architecture, and everything. And they can pull in a group of people in five minutes and have a very good discussion and revise the roadmap. To me, that will be success.

ISABEL, MANAGER, TRANSFORMATION OFFICE

4. Cultivating Digital Literacy in Employees

Employees were encouraged to develop and sustain their work-related digital literacy through online training and certification programs, resulting in obtaining “Digital Driver’s Licenses.” This training initiative complemented a personal “sustainability assessment” initiative, under development in mid-2017, intended to alert employees to the skills they needed to “future-proof” their jobs. The assessment was planned to suggest a training program that would prepare employees with needed skills. Among the different digital licenses, the most basic took about a half day to acquire (if one did not opt to just take the test). That one covered 1BA’s various digital services (such as Outlook, SharePoint, and OneNote), digital collaboration, digital media (such as Twitter and Instagram), and 1BA’s mobile apps and platforms that instantiated the integrated bank-insurance concept.

It gives those who don’t feel confident in the digital area the opportunity to catch up, and for those who do feel very safe with digital usage, to check their knowledge. Interestingly, even people who get 100% on the test often go through the learning material.

AMELIA, MANAGER, TALENT DEVELOPMENT

There was a more advanced license for managers, and another one for technical experts.

MOVING FORWARD WITH MACHINE LEARNING

The IC Leads application had helped 1BA understand how to leverage the power of ML for strategic gains. Even more importantly, its success had generated enthusiasm and curiosity across the company about what else ML could do. IC Leads had spawned numerous ML use cases and applications. The CEO’s complementary effort to raise the company’s ML Savvy was creating a fertile ground in which ideas about how to use ML productively could blossom. A virtuous cycle between this fertile ground for new ideas and the actual implementation of many powerful use cases was producing great optimism within the company about the future of its ML journey.
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