CELENT

CASE STUDY

COMMONWEALTH BANK: PERSONALIZED ENGAGEMENT AT SCALE

WINNER OF CELENT MODEL BANK 2020 AWARD FOR CUSTOMER ENGAGEMENT

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April 2020

CASE STUDY AT A GLANCE

FINANCIAL INSTITUTION	Commonwealth Bank of Australia (CommBank)
INITIATIVE	Adaptive Models in Customer Engagement Engine
SYNOPSIS	CommBank's Customer Engagement Engine (CEE) program facilitated a shift away from product and campaign-based marketing to deliver customer journeys powered by data insights applied in real time and at scale. Every customer engagement triggers a call into the CEE, which renders a "next best conversation" recommendation in 150 to 300 milliseconds. Through CEE, CommBank has transformed the way it manages customer relationships, creating a truly unique capability with hundreds of AI Adaptive Models (ADMs) scanning huge data sets spanning customer demographics, behaviours and product holdings to ensure that CommBank has the right conversation with the right customer at the right time, in the right channel.
TIMELINES	• CEE project start: 2015 • Branch and contact center rollout complete: September 2016 NetBank (online banking) fully enabled: December 2016 Mobile Banking fully enabled: February 2017 Push notifications enabled: June 2017 • April 2018: ADMs turned on for learning in digital channels • June 2018: Phase I introduced 4 ADMs into live scoring (test and learn) • Feb. 2019: Phase II extended ADMs to all eligible Next Best Conversations in digital channels
KEY BENEFITS	• Demonstrable improvement in customer satisfaction • Step change improvement in AI model management capacity • Up to 66% uplift in click-through rates • Up to 60x click through rate in top decile compared to bottom decile in some of the bank's most predictive models
KEY VENDORS	Pegasystems

CELENT PERSPECTIVE

- Commonwealth Bank received a Celent Model Bank 2018 award for Customer Engagement for its Customer Engagement Engine (CEE) implementation. This 2020 award recognizes the bank's ongoing refinement and expanded utilization of CEE and its demonstrable expertise in deploying AI at scale across all points of customer engagement. CommBank achieves this by operationalizing the use of ML-powered adaptive statistical models to dramatically improve its model management capacity.

- Operationalizing the use of customer data to form actionable insights that inform the customer conversation in real time, across all touchpoints, is a rarity. Commonwealth Bank has not only arrived, it sets the bar. In so doing, it has effectively broken the tension between personalization and scaling.

DETAILED DESCRIPTION

Introduction

Commonwealth Bank is a leading provider of integrated financial services. It provides retail, business, and institutional banking, and wealth management products and services. One in three Australians, 17.4 million customers, call CommBank their main financial institution. Customer focus — and therefore, the ability to scale personalization — is the overarching priority of the bank's strategy.

Table 1: Commonwealth Bank Snapshot

THROUGH 2019	COMMONWEALTH BANK OF AUSTRALIA
YEAR FOUNDED	1911
ASSETS	$962 billion
GEOGRAPHICAL PRESENCE	HQ: Sydney, AU
EMPLOYEES	48,238 employees in 11 countries
OTHER KEY METRICS	1,172 branches across Australia and New Zealand 3,963 ATMs – most in Australia 7 million digital / 5.6 million mobile customers 7.4 million digital customer logons daily
RELEVANT TECHNOLOGIES	Pegasystems Customer Decision Hub Pega Marketing Pega Adaptive Decision Manager Internally built CRM system

Source: Commonwealth Bank of Australia

CommBank's vision is to "improve the financial wellbeing of customers and communities." This is more than a tagline for the bank and its nearly 50,000 employees. Rather, it expresses a broadly held philosophy and underlying value that underpins the bank's strategy and investments. Here are three examples of how CommBank executes this vision. All three examples utilize its Customer Engagement Engine (CEE) and occur automatically at scale.

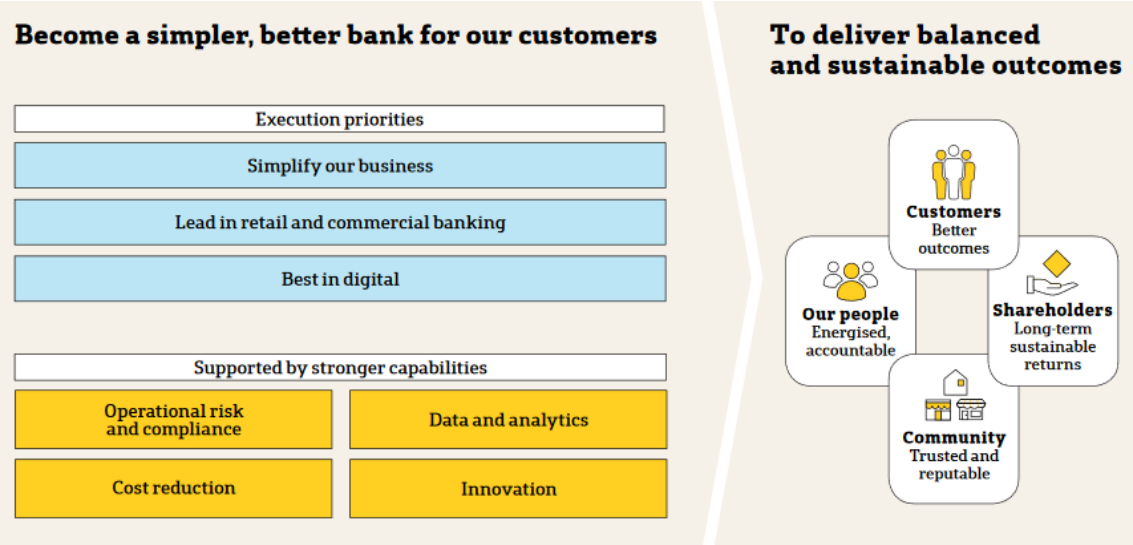
1. **Smart Alerts**: In the last year CommBank sent its customers over 20 million smart alerts, which have helped customers avoid unnecessary fees by alerting them to overdrawn accounts and missed credit card payments. For example, rather than hitting customers with a fee for missing a payment deadline, CEE is used to send proactive digital notifications to guide them toward making an on-time payment.

2. **Natural Disaster Impact Mitigation (or similar)**: The engine has also allowed CommBank to rapidly contact those customers who are eligible for the bank's assistance packages when bushfires or other natural disasters hit. By reaching out proactively in affected areas, CommBank can be there for its customers when needed most.

3. **Benefits Finder**: CEE integrated with CommBank's mobile banking app is using AI to provide recommendations to customers on more than 180 government benefits and rebates for which they may be eligible. This is done automatically as customer attributes are deduced from interaction history.

Error! Reference source not found. from the bank's 2019 annual report summarizes how CommBank translates its customer-centric vision and core values into growth opportunities and ultimately financial performance.

Figure 1: Commonwealth Bank Puts Customers First



Source: Commonwealth Bank of Australia

Opportunity

CommBank migrated to Pegasystems Customer Decision Hub (CDH) as the platform for CEE to replace disparate technologies and create a single decision-making engine for customer conversations across all channels. CDH is a customer relationship management "brain" that combines adaptive, machine learning analytics, and real time decision-making, enabling CommBank to deliver relevancy and personalization to customers at every touchpoint. CommBank's CEE implementation is documented in a previous case study, *Commonwealth Bank: Customer Engagement Engine, Winner of Celent Model Bank 2018 Award for Customer Engagement*, April 2018. To summarize, CEE was first implemented for front line staff in the branch and contact center, followed by its NetBank (2016), SMS and mobile banking channels (2017). It now is live across 19 points of customer engagement, including email, SMS, push notifications, ATM and direct mail.

CommBank's original and continued investment in its Customer Engagement Engine is being driven by the simple idea that the organization should be aligned to deliver superior customer engagement, resulting in the best customer experience possible — at scale. Practically, this involves ensuring that each customer point of contact results in the right conversation to ensure the right message is conveyed or the right offer extended. If done well, this would ensure the best possible level of customer service. This concept is institutionalized at CommBank by the term "Next Best Conversations" or NBCs. Many times, the next best conversation is not a sales pitch, but a simple "Thank you," "Happy birthday" or a reminder that a bill is coming due.

Each NBC can be thought of as a one-to-one communication, spanning multiple products and services, collectively designed to support a diverse set of business goals such as acquisition, retention, cross sell, and compliance, but stringently prioritised against each other — to ensure CommBank consistently engages customers with the most relevant NBC possible. Unlike traditional marketing campaigns, NBCs are customer, channel, and context aware. Supporting CommBank's broad product line and diverse customer base required a large and evolving number of NBC options.

As the number of NBC options and CEE-enabled customer interaction points grew, CEE served up exponentially increasing numbers of Next Best Conversations, now exceeding 20 million per day.

Choosing the optimum NBC for each customer interaction is not trivial. Practically, it requires CEE to dynamically prioritize available NBCs based on a complex set of interdependent variables. In conducting this prioritisation, CEE needed highly predictive statistical models (e.g., likelihood to take up a home loan) so it could rank the available NBCs for each customer interaction based on relevance. While the use of statistical models in driving customer contact already existed, the capability required highly repetitive, manual, and time-consuming work.

> *"Each model took CommBank's Data Science team four weeks to build as we had to source the data, create the label files identifying what we wanted to predict and then run a number of iterations of the model through R or Python — that's all before we looked at model deployment. We were staring into 25 years of Data Science effort to get to enterprise scale."*
>
> *Richard Nesbitt, Head of Data Science & Modelling*

To continue to grow the number of NBCs and keep them effective, CommBank needed an automated modelling framework with superior predictive power and minimal human intervention. Enter ADMs.

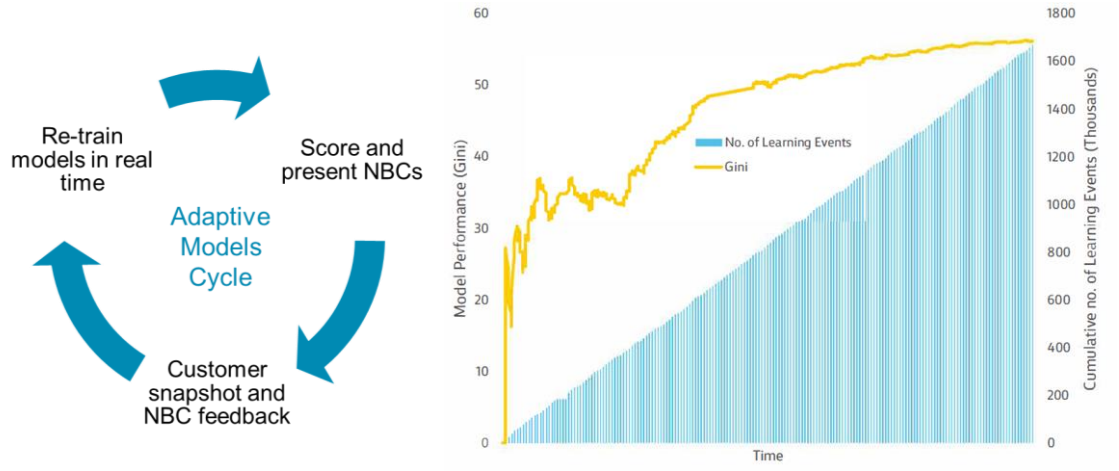
Solution

Adaptive Models (ADMs) in CEE are CommBank's implementation of Pegasystems' Adaptive Decision Manager technology. As its name implies, Adaptive Models use contextual information and adaptive learning to continually optimize their predictive ability as they are utilized in production. As models are fed additional contextual information (a change of address, for example), and encounter new interactions, they get more and more precise — leading to higher success rates. Since the rate of learning is a function of the number of interactions exposed to the ADMs, CommBank's CEE "learning curve" has steadily improved alongside the growth in NBC volume. Here's how it works:

1. An ADM instance is set up in CEE with defined parameters that set the level of granularity in which ADM models are partitioned. ADMs are currently set at NBC, channel, and location levels, meaning the NBC served to any given customer can vary depending on CommBank's understanding of that customer's channel preferences and utilization.
2. Interactions are recorded at a rate of over 20 million per day. Once a set number of interactions (learning events) is recorded for a given combination of parameters, a model will be estimated, using all the predictors set up to be used.
3. Each time a further number of interactions is observed, the model will be re-estimated.
4. Each time a call is made to CEE that requires scores to be calculated, CEE will calculate in real time the ADM score for the customer and relevant NBC, using the most up-to-date version of the ADM and predictor data available in CEE at that time. This ADM score is then used to choose which NBC to present to the customer.

Any NBC presented will result in further learning events for the ADM to learn from and re-estimate on, continually improving the ADM's predictive ability over time (Figure 2). The graph on the right highlights the learning path of one ADM over time, showing a significant jump in predictive power after just a couple of days of learning. The predictive power then more gradually improves as the number of learning events increases.

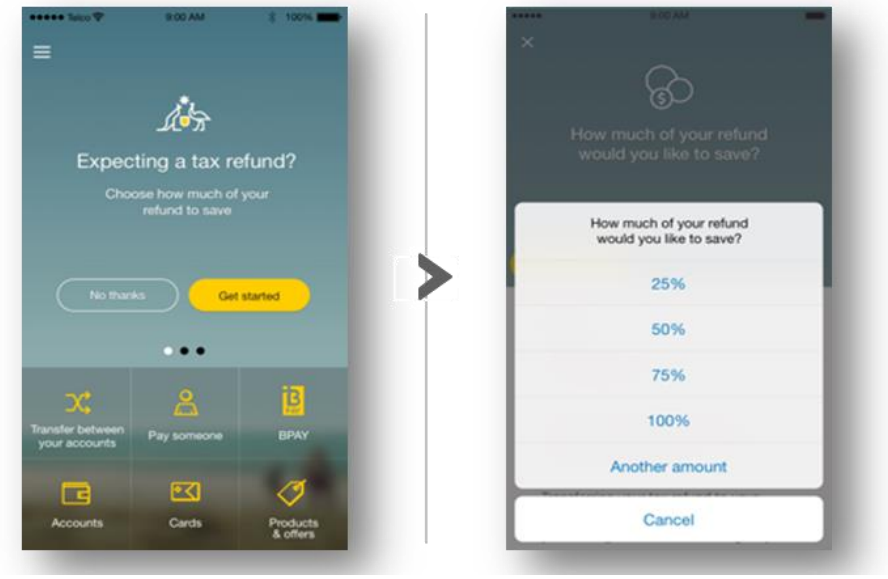
Figure 2: CommBank's Adaptive Models Are Self-Learning



Note: A gini coefficient or index is the measure of predictive power of a model and how well it can differentiate a group of customers, in this case how likely someone is to respond to a conversation. The score is between 0–100 and the closer to 100 the better.
Source: Commonwealth Bank of Australia

CommBank began by running hundreds of ADMs in learning mode in a staging environment and model incubator. Once the models were demonstrably stable and safely learning in the right way from the right data, they were tested in production. Once the bank was satisfied that the ADMs were stable and effective, it exposed its entire inventory of ADMs to live customer interaction data. There are currently 291 digital adaptive models in production and driving the prioritisation of NBCs. To manage this large number of models, CommBank set up a monitoring framework that tracks how well the models are predicting. This has allowed CommBank to better differentiate which conversations are most relevant and helpful at a given point in time. Naturally this has resulted in an uplift in positive customer response rates (click-through rates). NBCs are usually action-oriented, so clicks correlate to customers engaging and taking the recommended action. Not all NBCs are designed for immediate response, however. Some are tuned for other outcomes that can happen considerably later than the initial customer clicks. Figure 3 illustrates one such example.

Figure 3: One NBC Anticipates Tax Refunds and Invites Proactive Savings



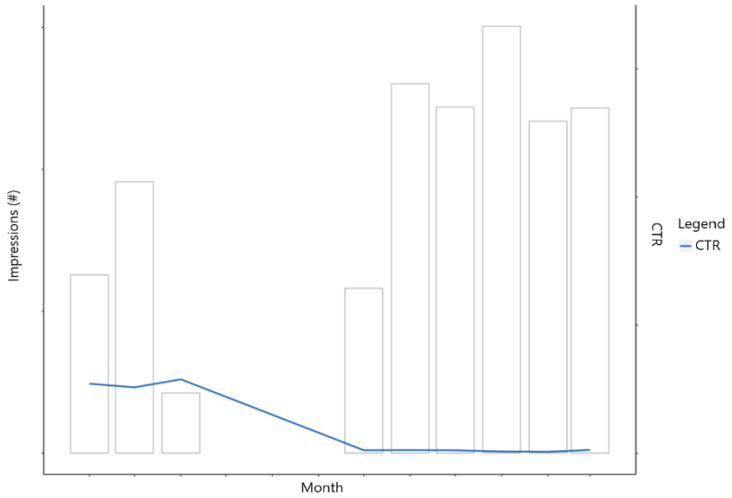
Source: Commonwealth Bank of Australia

Like the click-through rate in digital channels, contact center and branch staff can flag whether a conversation resonated positively or negatively with a customer. This direct staff feedback allows the ADMs to learn in the same way they learn from direct customer response. CommBank also very closely monitors qualitative feedback received from front line staff and the customers they serve, to make sure it is providing a continually excellent customer experience.

Model build, monitoring and management is run by CommBank's Retail Data Science & Modelling unit comprised of data scientists and modelling professionals who are embedded across the retail bank to deliver AI-driven applications and deploy machine learning solutions to solve complex problems at scale. The core team responsive for the implementation of adaptive models is a cross-functional delivery scrum made up of engineers, data scientists, digital product owners and Pegasystems specialists.

CommBank's Data Science team's attention has now shifted from manual model building and testing, to building increasing numbers of self-learning statistical models for other purposes across the bank. To manage this effectively, CommBank created automated model reporting to provide alerts for any shifts in the models. One example is tracking the alignment between the predicted and actual click-through rate of each NBC. If the difference breaches a specific threshold, automated alerts are sent out to trigger a review. Changes in NBC effectiveness can occur when the type of customer eligible for a conversation changes and the findings from the models are then no longer relevant. The reporting framework includes both daily alerts for early detection of issues and more comprehensive monthly reporting. Figure 4 illustrates.

Figure 4: Model Effectiveness Is Not Static and Must Be Monitored



Source: Commonwealth Bank of Australia

The bank has already identified 25 cases of material changes in individual NBCs which the models are scoring. What would have previously been weeks of effort to re-train models is now almost trivial. CommBank can improve the performance of stale models by resetting them and letting them re-learn from fresh data at the click of a button. These 25 models are now re-learning automatically on newer data, saving the bank a further year of manual effort!

Results, Lessons Learned, and Future Plans

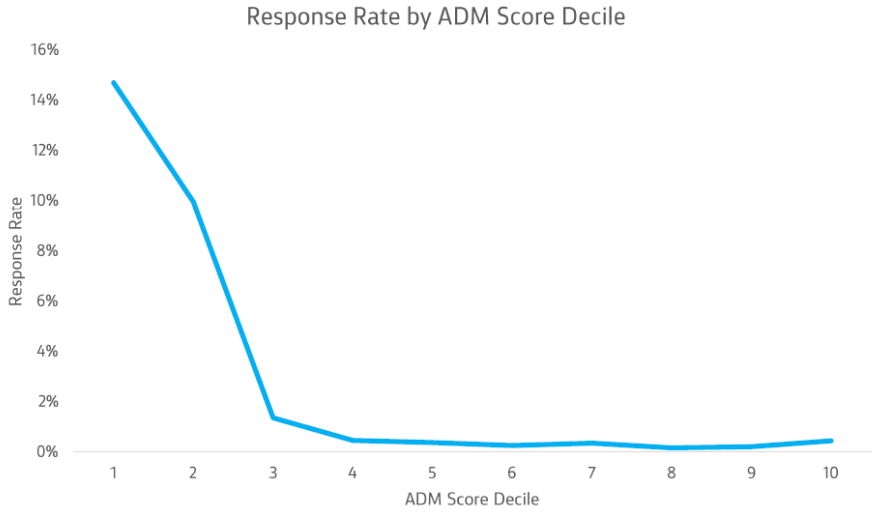
The time and cost savings of adaptive models compared to manual model management is manifest. But, more compelling in Celent's view is the collective result of the speed and scale advantages brought by CommBank's arsenal of ADMs. Said simply, many highly predictive models are required to deliver personalized and relevant customer engagement at scale. It is the net effect of many models over time that produces sustainable improvements in customer experience. Toward this end, CommBank developed 560 models in total, with 291 in production

thus far. In aggregate, the ADMs have learned from 678 million customer interactions representing 157 billion data points. This has resulted in:

- Up to 66% uplift in click-through rates.
- Up to 60x click-through rate in top decile compared to bottom decile in some of the bank's most predictive models.

Figure 5 highlights the power of using ADMs in prioritising NBCs. In this example the top three deciles (roughly 30% of customer interactions) of the ADM show a strong response rate from customers compared to the larger customer population. Therefore, this conversation will be prioritised to customers with similar attributes. Conversely, since the ADM identifies that this NBC is not relevant to the bottom seven deciles, CEE will not show this conversation to customers like them.

Figure 5: This ADM Shows Dramatic Response Rate in Top 3 Deciles



Source: Commonwealth Bank of Australia

In addition to CommBank's ability to automate model management at scale, its use of ADMs provides additional opportunities to enhance customer experience and business value, including:

- By shedding light on the profile of customers who are likely to click on given messages, ADMs effectively automate A/B tests for collateral, messaging, or offers to customers with different score profiles, optimising NBC performance and customer experience with far less staff effort.
- The ability to choose an optimal advertising or offer placement based on customers' likelihood to click through accomplishes two objectives. First, it improves offer effectiveness for the bank. It also improves CX by ensuring that messages from CommBank are highly relevant.
- New offers, communications, and messages get to market faster and are personalized for each customer.
- Introducing dynamic impression capping. By taking into account how often a particular message has been displayed to each customer, CommBank drives a more contextual and personalised experience. Previously, caps were determined by manual rules,

whereas now the machine independently picks how often to display each message to a given customer.

Lessons Learned

Setting up this capability was complex; the analytics is intimately connected to the production system in which the framework runs, and its resiliency. As a result, a dedicated cross-team scrum along with broader, early buy-in across the bank is crucial for success.

Another finding was that ADMs allowed CommBank to operate more aggressively in the market without increasing risk. ADMs permitted the bank to move from running lengthy experiments toward faster rollouts with shorter experimentation periods.

Future Plans

To further leverage its investment in CEE and ADMs, CommBank is developing additional functionality such as driving hyper-personalisation by using ADMs to do rapid collateral experimentation and selection to allow them to show the right customers the right image that resonates best with them. Additionally they are focussed on enabling ADMs across the remaining channels connected to CEE.

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