# A Multi-Stakeholder Recommender System for Rewards Recommendations

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## ABSTRACT

Australia's largest bank, Commonwealth Bank (CBA) has a large data and analytics function that focuses on building a brighter future for all using data and decision science. In this work, we focus on creating better services for CBA customers by developing a next generation recommender system that brings the most relevant merchant reward offers that can help customers save money. Our recommender provides CBA cardholders with cashback offers from merchants, who have different objectives when they create offers. This work describes a multi-stakeholder, multi-objective problem in the context of CommBank Rewards (CBR) and describes how we developed a system that balances the objectives of the bank, its customers, and the many objectives from merchants into a single recommender system.

## CCS CONCEPTS

• **Information systems** → Recommender systems.

## KEYWORDS

Multi-Stakeholder Recommender System, Rewards Recommendation, Multi-Objective Optimization

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## 1 COMMBANK REWARDS

CBR is a program to reward customers when they shop at specific merchants. Offers are presented to customers through the CommBank App as shown in Figure 1. Offers are presented to customers in a specific order, who can view them and may choose to activate them. After customers spend with the merchant, they then automatically redeem the offer by receiving cashback into their accounts, effectively saving them money.

CBR is offered to millions of customers and hundreds of merchants. There are many challenges in building a recommender system for such a large scale prioritisation task, including offer constraints and special featured offers. However, in this work we will narrow the scope of the problem by addressing it as a more generalised multi-stakeholder, multi-objective problem where the goal is to maximise the satisfaction of the largest number of stakeholders possible.

## 2 MULTIPLE STAKEHOLDERS AND MULTIPLE OBJECTIVES

In a system like CBR, customers are not the only stakeholder and the objectives of other stakeholders are important to be taken into account [1, 2, 7, 11, 12]. For our rewards recommender, we have three types of stakeholders:

(1) *Customers* are eligible CBA Mastercard® cardholders who use their card to spend at merchants. By redeeming an offer, they will be receiving cashback into their account, hence saving money.[1] The customer objective is always to *save money*.
(2) *Merchants* are sellers and providers of services who ultimately want to sell more products or provide more services. However, their objectives in offering rewards may differ. For example, some offers have objectives that are aligned with increasing *brand awareness* while others may focus on *customer acquisition*.
(3) *The bank* positions the right offer to the right customer with an objective to maximise the usage of the rewards system ultimately making both merchants and customers satisfied.

Let us elaborate on each stakeholder's objectives. Customers are the most important players in this system, they define where they will spend their well-earned money. Offers need to be appealing enough for them to activate and claim it. Once redeemed, an offer

[1] CBA has returned more than $10 million in cashback to its customers in 10 months since CBR launch [8].


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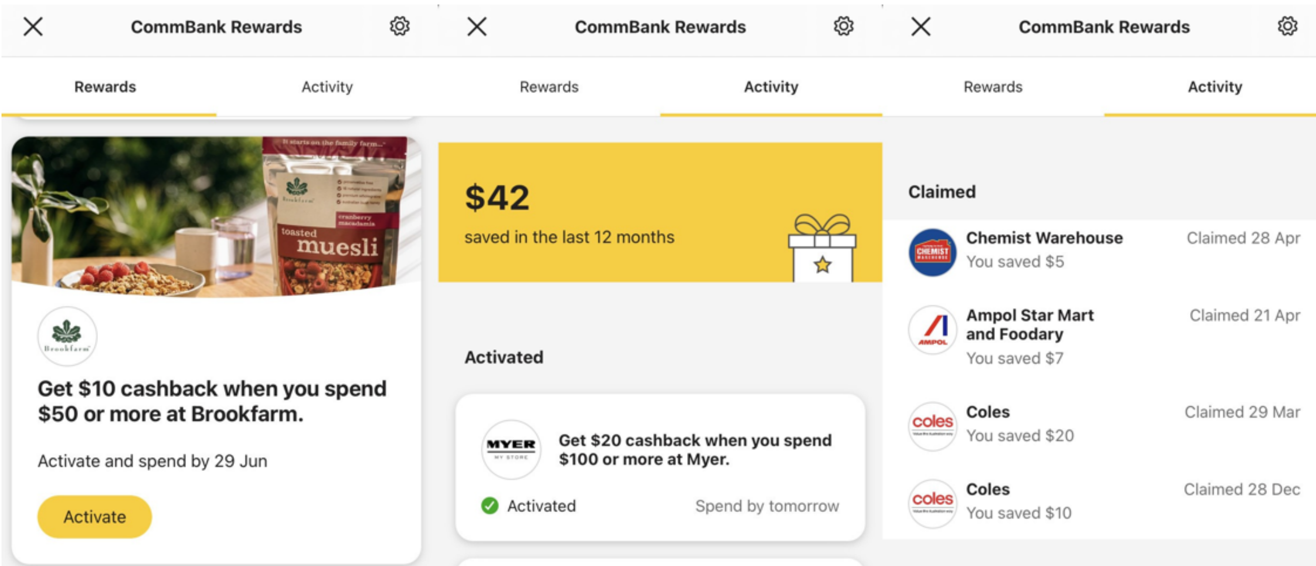


**Figure 1: CBR - Offers and Activity**

will trigger some cashback to be deposited to the customers account. Effectively, this is saving them money from their purchase at the merchant whose offer they have claimed. Therefore, the customer objective can be summarised as **Saving Money** (SM). In order to achieve this objective, customers try to maximise the amount of cashback they receive from offers. For offers to be claimed and for customers to achieve their objectives, offers need to be relevant and timely. Customers are unlikely to activate an offer for a petrol station if they do not own a car, and they are equally unlikely to claim if they have just filled up their tanks.

Merchants or offer providers have distinct objectives from one another. Not all merchants choose to offer rewards for the same reason. In order to more precisely describe the merchant's objective we use the notation $O^s_{c,m}$ where an offer $O$ for a customer $c$ by a merchant $m$ was in a specific status $s \in \{g, v, a, r\}$, which is given ($g$), viewed ($v$), activated ($a$) or redeemed ($r$). We use $C$ to denote the set of all customers and $M$ for the set of all merchants. For capturing spenditure events, or transactions, we use the following notation $T^{t,s}_{c,m}$ where a transaction $T$ happened between a customer and a merchant anywhere between the time of the offer and the time $t$ indicated. A negative $t$ such as $-3y$ indicates 3 years prior to the offer, while positive $t$ such as $4w$ indicate 4 weeks after the offer. The following list shows the distinct merchant objectives in CBR:

**Brand Awareness** (BA) is a set of marketing strategies that are used to help a merchant to keep its brand top of mind of potential and current customers. People are more likely to purchase from a known brand and it leads to more sales and profitability for the merchant [6]. Brand awareness is measured by whether a customer has seen a specific merchant offer. An individual recommendation is measured to be successful if the customer views the offer. Hence $O^v_{c,m} = 1$, while $O^{g-v}_{c,m} = 0$. That is, all offers that have been given to customers and not viewed $(g - v)$ have not met the objective. From a merchant perspective, they want to maximise Equation 1.

$$BA_m = \frac{\sum O^v_{c,m}}{\sum O^g_{c,m}}, \forall c \in C \tag{1}$$

**Customer Acquisition** (CA) is the collection of activities used to bring consumers down the marketing funnel from brand awareness to purchase decision. It aims to bring in new customers and expand the circle of customers for a merchant. Customer acquisition can also lead to establishing long-term connections [5]. Acquisition is measured by whether a new customer who has not spent money at a merchant within three years has then spent money at the merchant twelve weeks after an offer. We measure CA at an action state as shown in Equation 2.

$$CA^s_m = \sum T^{12w,s}_{c,m}, \forall c \in C | (T^{-3y,s}_{c,m} = 0) \text{ and } O^s_{c,m} \tag{2}$$

**Bring Back Customers** (BB) is winning back lapsed customers. Lapsed customers are defined as customers who were dormant for at least the past year. Tailored reward recommendation will incentivise previous customers to shop again with the merchant using discounts and cashbacks. In this objective, we focus on customers who have spent money prior at a specific merchant but have not done so in the last year. The BB goal is measured on each action state as shown in Equation 3.

$$BB^s_m = \sum T^{12w,s}_{c,m}, \forall c \in C | (T^{-1y,s}_{c,m} = 0) \text{ and } (\Sigma T^{-3y,s}_{c,m} > 0) \text{ and } O^s_{c,m} \tag{3}$$

**Customer Retention** (CR) is about keeping loyalty with its customers and gaining more value from the existing customer base. The benefit of customer retention is manifested through the common knowledge that "merchants have a way higher chance of selling to an existing customer rather than a new customer" and "it can cost much more to acquire a new customer than to keep an existing one" [5]. In this objective, we focus on ensuring known customers of a certain merchant keep transacting with that merchant. CR is measured as shown in Equation 4.

$$CR_m^s = \sum T_{c,m}^{12w,s}, \forall c \in C | (\Sigma T_{c,m}^{-1y,s} > 0) \text{ and } O_{c,m,s}^v \quad (4)$$

**Share of Wallet** (SW) is a marketing metric demonstrating what percentage of a customer's total expenses on a specified product or service goes to buying from a particular merchant in comparison with their competitors [3, 13]. For instance, if a person spends $400 per month on groceries and $100 of that amount is spent at a specific grocer, this grocer has a 25% share of wallet for that customer. To calculate share of wallet for each customer we calculate the proportion of all expenditure of customers for a merchant and for the merchants in the same merchant category code (MCC). SW is calculated as in Equation 5.

$$SW_m^s = \frac{\sum T_{c,m}^{12w,s}}{\sum \sum T_{c,n}^{12w,s}}, \forall c \in C, \forall n \in M | MCC_n \equiv MCC_m \quad (5)$$

For all objectives, except BA, the maximization problem involves trying to have a higher proportion of successful cases as customers progress towards the recommender action funnel. Objectives ($Obj_m^a$) should be proportinally higher for the set of redeemed ($r$) customers than for the set of activated ($a$) customers, which should be higher than the set of view ($v$) customers, which should be higher than the set of given and not view ($g-v$) customers. That is: $Obj_m^r/Obj_m^g > Obj_m^a/Obj_m^g > Obj_m^v/Obj_m^g > Obj_m^{g-v}/Obj_m^g$.

The bank's objective is to maximise the usage of the reward system ultimately delivering into the objectives of customers and merchants. It is in the bank's interests that all merchants objectives are met, while customers are also saving money. This ensures a fair marketplace without disadvantaging customers or merchants. The system's objective and the bank's objective is the same in this paper. This might not be the case for a generalised system where the marketplace owner could have dynamic objectives, for example, at different times they might want to preference different aspects of the marketplace.

## 3 MULTI-STAKEHOLDER, MULTI-OBJECTIVE RECOMMENDER

In our rewards recommender, we prioritise offers with customers by taking into account the objectives of all stakeholders. Our first step is the *creation of three distinctive datasets*, which are separated by time periods to avoid potential data leakage. These are training set (A) with 1 year of card transaction data, training set (B) with the subsequent 12 weeks of transaction data and testing set (C) with the following 12 weeks of transactions. These datasets comprise of billions of transactions between millions of customers coming from hundreds of millions of merchants. To simplify our system, we only used merchants who were associated with an offer, bringing down the magnitude of our problem to only a few hundred merchants, their customers and transactions.

Our *feature generation* step uses impression data and RFM (recency, frequency, and monetary) analysis [4], creating features from dataset A indicating whether a customer viewed an offer, how much was spent at a merchant, and how often and when the last transaction was made. We calculate from dataset B *target variables matrices* for each stakeholder's objective. That is, we calculate how much every customer has saved for each offer (customer objective) as well as how effective each customer is when measured against a specific merchant's objective. Please note that because merchant offers only have one assigned objective, the union of all merchant objective target variables has the same dimension as the customer objective matrix. All target values are normalised between 0 and 1, where 1 indicates the customer and the offer had the maximum effectiveness for an objective while 0 indicates it has the maximum opposite effect. A value of 0.5 indicates no effect.

By having features and target variables, we can train supervised *machine learning models*. We build an offer model that can predict how much customers will save based on their previous transactions. We also build models to predict how much each customer will help the offer achieve its objective. This creates two models per offer: one model that focuses on the customer objective and one that focuses on the merchant objective. We then generate two prediction matrices and devise a set of strategies to best achieve the bank's objective of maintaining both customers and merchants satisfied. In order to best position the offer to our customers we prioritised them based on the predicted customer and merchant's objectives. We have experimented with a few strategies to combine stakeholders objectives inclusive of using learning to rank on the optimal rankings from both target matrices.

## 4 SPEAKER BIO

**Dr. Luiz Pizzato** is an Executive Manager for the AI Labs team at Commonwealth Bank of Australia. He is an expert data scientist and AI leader with more than 20 years of technical experience in the area of Artificial Intelligence. He has a PhD in Computer Science. Luiz has an extensive list of peer-reviewed publications, including more than a dozen in the area of Recommender Systems. As part of his contributions, Luiz has defined the area of reciprocal recommenders [9, 10] with extensive applicability to people matching problems such as online dating and job search and talent recruitment.

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