# What's next?





# A Cross-Business Recommendation Engine for FEMSA

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## Problem Statement

- FEMSA is one of Mexico's largest holding companies, and a key player in beverages and convenience in Latin America
- FEMSA's retail brand, Oxxo, has become the largest convenience store chain in Mexico
- FEMSA's digital wallet, Spin, provides financial services and products in store, where customers can pay their utility bills, buy phone topups, and make deposits
- FEMSA is now **shifting to an integrated ecosystem**, and as the company looks to generate synergies between businesses



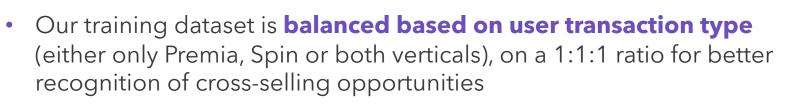
## Our Data



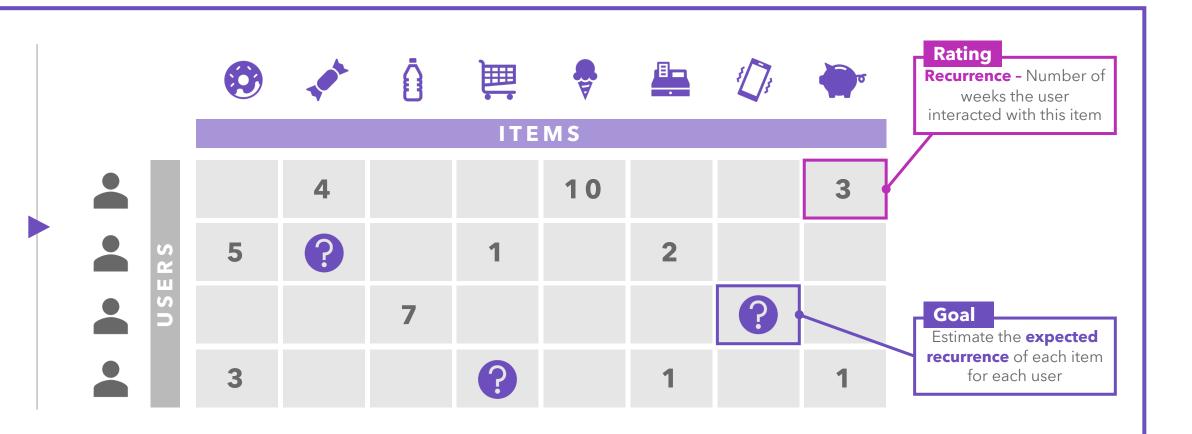








• We have **26 items from Oxxo**, including macro-categories as candy and groceries; and 20 items from Spin, including bill payments and deposits, among others



## Methodology

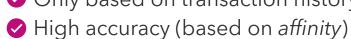


# **BASELINE MODEL**









✓ Fast training

Fast scoring



We tested the effectivity of our baseline model on **two** controlled settings, testing 8 categories on each, sending push notifications:





Check out our discounts in this item!



Product's ranking per user, mainly based on interactions rather than explicit feedback



**III.** Value gap analysis

Given the experiment results, we estimate the expected impact of deploying our Final Model, using "same predicted category" users



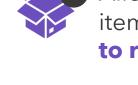
# FINAL MODEL

- Deep learning based
- Bilateral Variational Autoencoders Learns latent representations
- Fast training
- Scalable



The better the recommender system, less cross-selling occurs





of users and items

Allowing for previously seen items provides **less incentives** to recommend new items



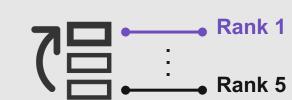
### **Similarity based Recommendations**

We identify **similarity groups** between *single-business* users and both-business users, mapping crosssell opportunities

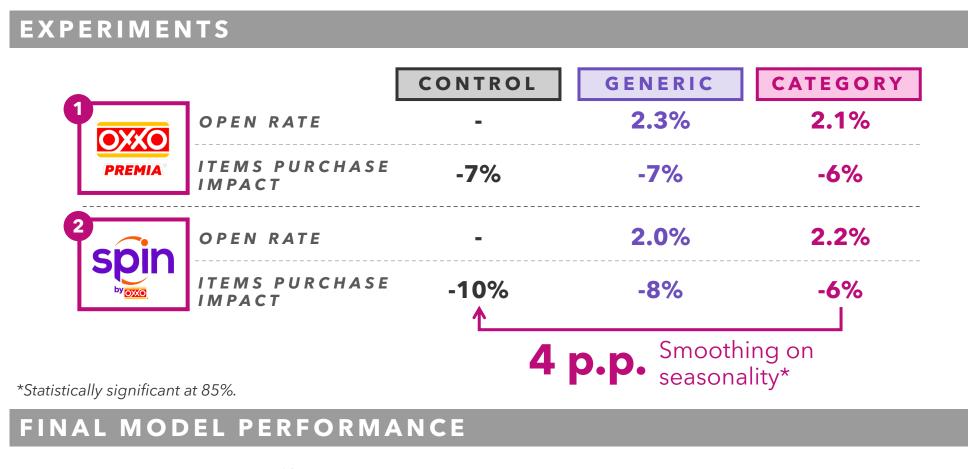


Stratified Recommendations

We order users based on their predictions; prioritizing higher ranked recommendations based on propensity



## Results



#### 14.24% 15% 10.53% 9.47% 10% 7.44% 5% **USERS** AVG. WITH NEW 0.02% 0.01% **CROSS-SELL**

Recall@1

## **VALUE GAP ANALYSIS**

Precision@1



CONTROL MODEL

SAR BiVAE Final Model (Post-processed BiVAE)





SHARE

5 p.p. Smoothing on seasonality

37%

ITEMS

# Business Impact

## **ASSUMPTIONS**

**5.2%** Purchased items impact

**1.5** USD/item on average

250k Customers/campaign

BASELINE MODEL **EXPECTED VALUE** 

► 108k USD/campaign

# NEW EXPECTED VALUE PER CAMPAIGN

**EFFICIENCY** CAPTURE

50%

**75%** 100%

**EXPECTED VALUE** (USD)

126k 134k 143k

# Next Steps



## **ARCHITECTURE**

- Pipeline development Smoothing postprocessing logics
- Improving data quality, for less sparse datasets and accurate modeling
- Application of additional business rules

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## **MODELLING**

- Testing users level features with hybrid model alternatives once there's less sparse data
- Testing user-level features in the postprocessing similarity matching



# **DEPLOYMENT**

- Additional testing opportunities
- Piloting once there's a proper architecture,
- Brainstorming further use cases for the Final Model