## **Fraud Detection**

## **Problem Framing:**

|  | Qualitative  | Quantitative   | Question  |
|--|--|--|---|
| Current State                                  | Increase in fraudulent<br>transaction => bad customer<br>experience => less<br>customers => less revenue<br>=> loss to the bank  | 10% fraudulent<br>transactions => 5%<br>less customers =><br>5% less revenue   | What is the average number of fraudulent transactions at present and what can be done about it in order to decrease them? |
| Objectives                                     | <ul> <li>Build a model that can detect fraudulent transactions</li> <li>Less fraud =&gt; better customer experience =&gt; increase revenue</li> </ul>  | Find and decrease the fraudulent transactions.   | How do we detect fraudulent transactions?   |
| Benefit/Cost<br>Tradeoff and<br>Prioritization | Errors -  TP - Fraud identified => customers protected => better user experience => more revenue to bank  FP - Valid transaction marked fraud => bad user experience => less revenue  FN - Fraud marked valid => Risk to customers' assets => bad user experience => Less revenue  TN - Valid transaction marked valid => no significant impact on revenue | cost-benefit matrix  c(TP) c(FP) c(FN) c(TN)  Improve the predictive model with one that yields a lower number of false positives AND a lower number of false negatives. In other words, improve the precision AND the recall. | What are the costs of errors/benefits of correct predictions and why?   |
| Constraints                                    | Can only afford very little FN rate and less FP rate   | At most 5% FN and<br>10% FP=> Customer<br>risk and better user<br>experience   | What are the acceptable risks/budgets and why?  |

| Benefit: significantly lesser fraudulent transactions => significantly better user experience => significantly more customers => significantly better revenue     Cost: very few false negatives => limited risk of bad user experience => limited risk of losing customers => limited risk to revenue | decrease in fraudulent transactions (from 20% to | What is the desired outcome benefits/costs) that we want to see and why? |
|--|--|--|
|--|--|--|

## Why ML

|  | qualitative   | quantitative   | question   |
|--|---|--|--|
| best non-ML<br>alternative<br>hypothesis | classify based on<br>amount or location of<br>transaction => too<br>many FP and FN =><br>more fraud and bad<br>user experience =><br>lesser customers =><br>loss of revenue | 50% FP 70% FN => not cleaning enough fraudulent transactions and causing more complaints for misclassifying genuine transactions as fraudulent => 5% revenue loss risk | What are the non-ML alternatives and why are they problematic? (pains/missed gains)? |
| ML value proposition hypothesis          | much fewer FP and<br>FN => better user<br>experience => more<br>revenue   | 10% FP 50% FN => 50% less fraud in expense of 1% bad engagements => 5% increase in revenue at the expense of 0.1% risk   | What are the advantages (pain relievers/gain creators) of ML solutions and why?      |
| ML feasibility hypothesis                | <ul> <li>data: labeled dataset of each person's bank history</li> <li>model: state of the art review suggests</li> </ul>  | <ul> <li>data: around five thousand samples</li> <li>model: state of the art claim solutions with 10% FP 20%</li> </ul>  | What data and models are good candidates and why?                                    |

| candidates<br>are available |  | promising<br>candidates<br>are available | FN |  |
|-----------------------------|--|--|----|--|
|-----------------------------|--|--|----|--|

## **ML Solution Design**

|        | choices   | metrics   | experiment  |
|--------|---|---|---|
| data   | (labeled) transaction data  | ● label imbalance   | <ul> <li>randomized         70/15/15         train/validation         /test split</li> </ul>  |
| model  | pr(fraud)   | AUCPR     (Precision     recall curve)  | <ul> <li>rule based heuristic</li> <li>tf-idf + logistic regression</li> <li>tf-idf + random forest</li> <li>BERT + logistic regression</li> <li>train these benchmark models using train data. validate and tune using validation data. select the model with best AUCPR on test data</li> </ul> |
| action | if Pr(fraud) ><br>threshold: auto take<br>down                            | <ul> <li>precision</li> <li>recall</li> <li>confusion</li> <li>matrix</li> </ul>  | choose a threshold to maximize the recall (estimated reward) subject to precision > 90%   |
| reward | <ul> <li>decrease in fraud</li> <li>cost of misclassificati on</li> </ul> | <ul> <li>% Decrease in fraud</li> <li>% Increase in daily active users</li> </ul> | A/B test  |