Predicting Customer Default at Verizon

Team 3 Consulting, Fridays 9am-12pm

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Agenda

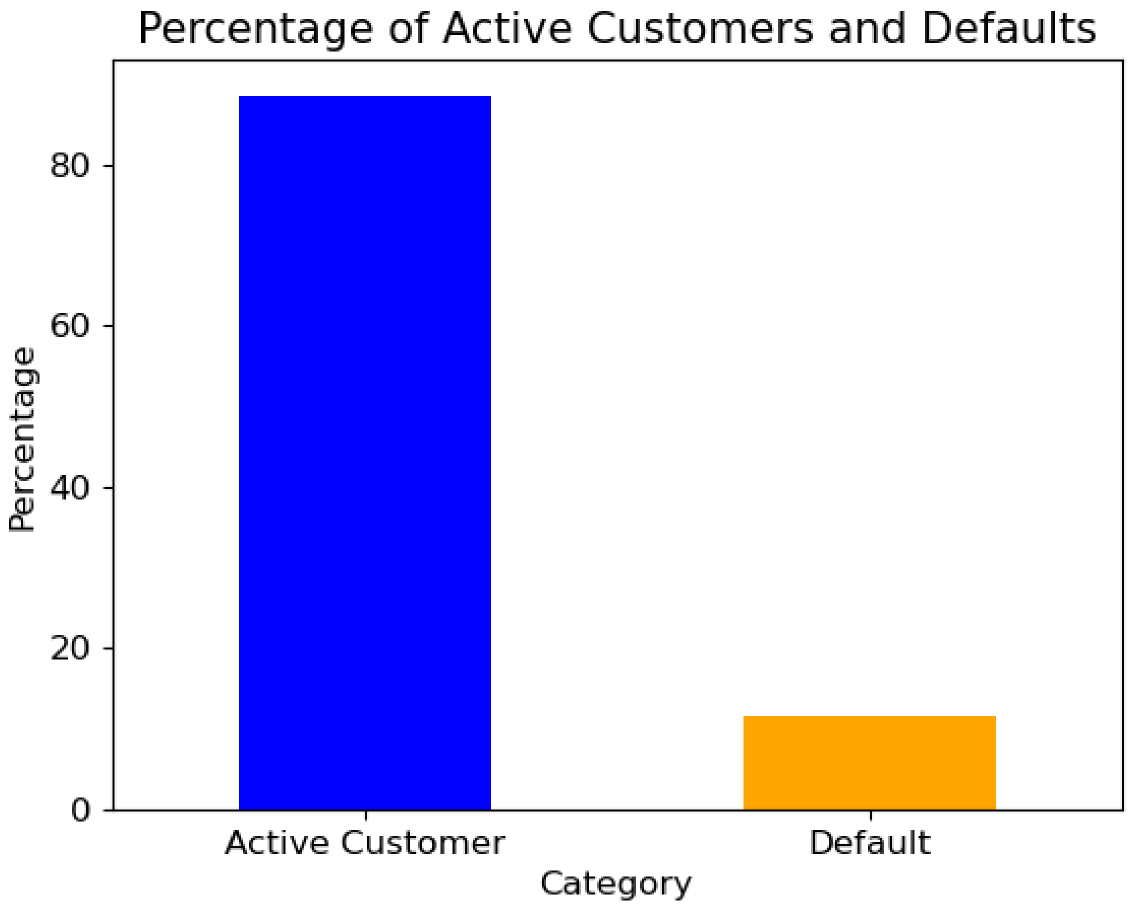
Problem Definition

Model Selection

Model Performance

Business Value

Currently, 12% of customers default on their contracts



Problem Definition → Model Selection → Model Performance → Business Value

Verizon needs to determine whether to grant contracts or not to maximize profit and minimize revenue loss

Profit Potential of Denied Contract / Would Pay

$250 per 36-month contract

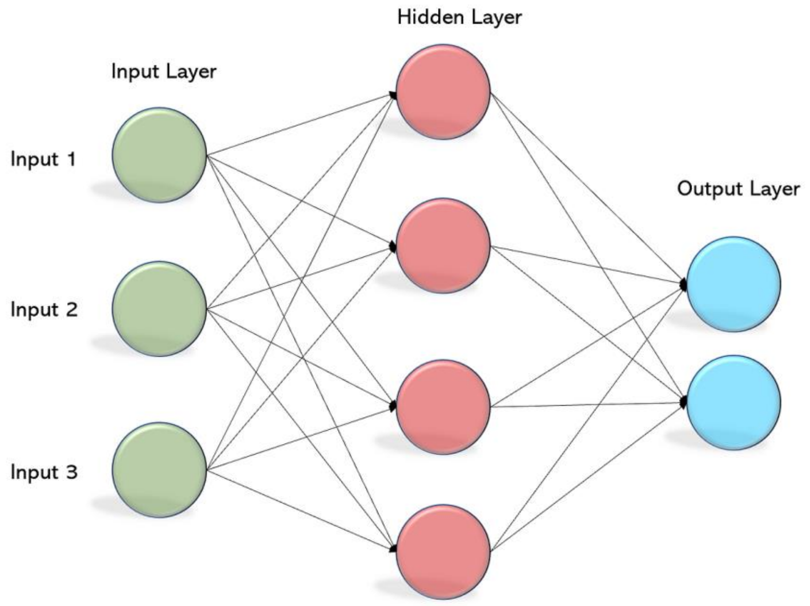
Revenue Loss From Defaulted Contracts

$1000 per customer

Verizon can use the Multi-layer perceptron (MLP) model to address its problem

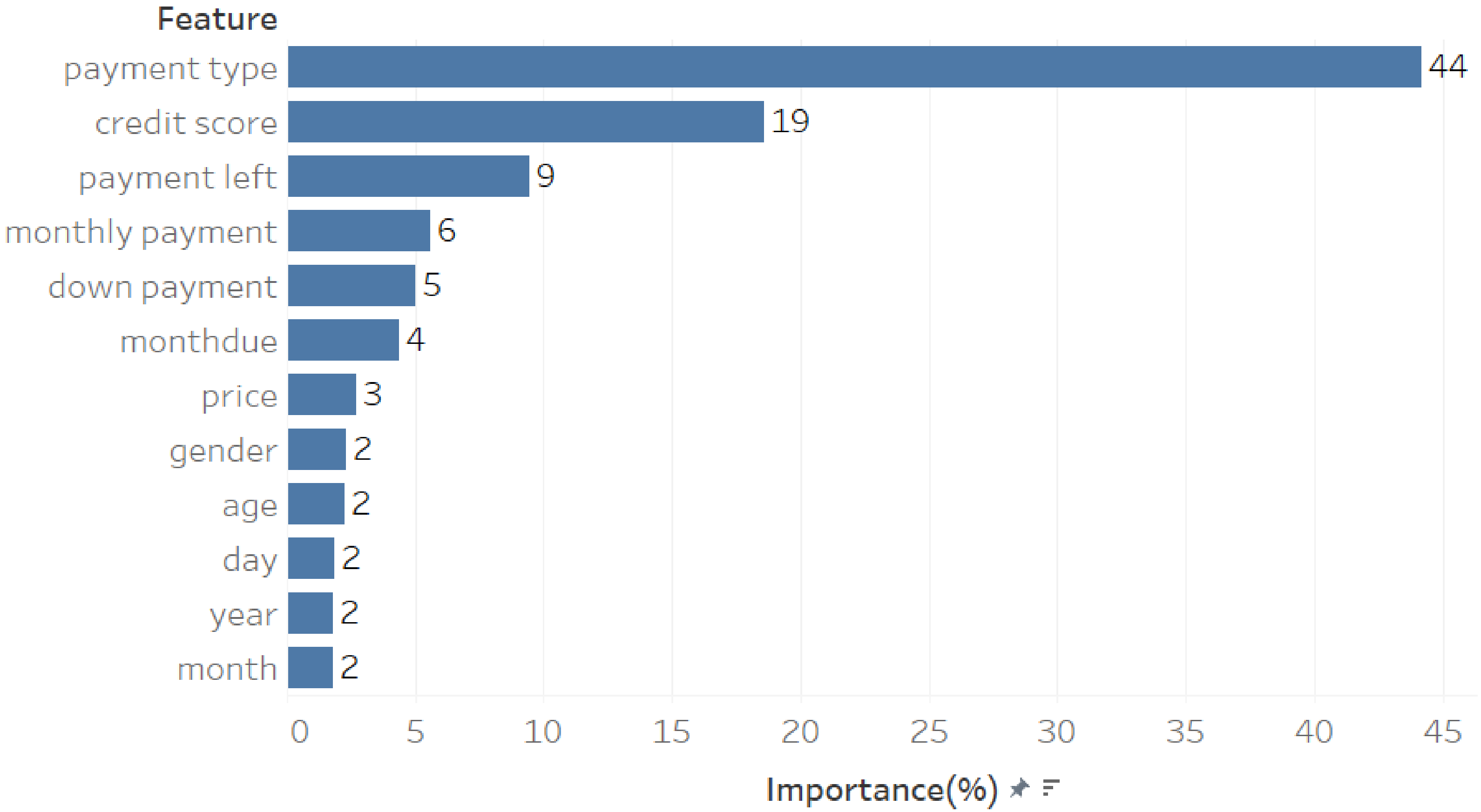
The MLP model would be a suitable choice:

- Good for classification problems
- Ability to handle "imbalanced data"
- Capable of modeling complex (non-linear) relationships in the data
- Adaptable to various data types, including structured data and sequences



Multi-layer perceptron

Payment type is the strongest predictor of default in the model



Problem Definition | Model Selection | **Model Performance** | Business Value

To assess the model, we look at the model's predictions compared to Verizon's historical data

	Customers who pays their bills	Customers who Default
Contract Accepted	80%	8%
Contract Declined	3%	9%

- Of the 12% of contracts that were declined, the model correctly identified that 75% of the customers defaulted.
- Of the 88% of contracts that were accepted, the model correctly identified that 91% of the customers would pay their bill

The business value of our model is approximately $200M per million applicants

	Customers who pays their bills	Customers who Default
Contract Accepted	**Profit Gained** 80% of 1M @ $250 $200,926,113	**Loss Incurred** 8% of 1M @ $1000 $84,356,750
Contract Declined	**Profit Missed** 3% of 1M @ $250 $5,737,870	**Loss Avoided** 9% of 1M @ $1000 $88,987,320

Value = Profit Gained + Loss Avoided – Loss Incurred – Profit Missed

= **$199,818,813 per million applicants**

Appendix

Why MLP is a suitable choice for the Verizon Case

Non-linear Relationships: MLPs are capable of modeling complex, non-linear relationships in the data. In the context of predicting customer defaults, relationships between customer attributes (e.g., age, gender, credit score) and default behavior are often not linear, making MLPs effective at capturing these intricate patterns.

Flexibility and Expressiveness: MLPs consist of multiple layers and neurons, allowing them to learn and represent a wide range of functions. This flexibility enables them to adapt to various data distributions and feature interactions, making them well-suited for the heterogeneous and multifaceted nature of customer data.

Scalability: MLPs can handle both small and large datasets efficiently. As Verizon's customer base grows, having a scalable model is crucial to accommodate increasing volumes of data without sacrificing predictive accuracy.

Model Performance comparisons

	MLP Classifier	XGBoost Classifier	Isolation Forest	OneClass SVM
Class	Supervised		Anomaly Detection	
Accuracy	0.90	0.89	0.59	0.57
Precision	0.59	0.51	0.04	0.05
Recall	0.69	0.79	0.130	0.15
F1 Score	0.65	0.62	0.07	0.07
ROC-AUC	0.94	0.94	0.37	0.45

Asymmetric Costs in the context of the MLP model for predicting customer defaults

- **True Positives (TP):**
  - These are cases where the model correctly identifies applicants who will default.
  - Action: When a TP occurs, Verizon can take steps to reject the applicant, preventing potential losses. The phone can be retained and possibly sold to other customers.
  - Model Focus: The model will be designed to have high sensitivity (recall) to capture as many true positives as possible while still maintaining reasonable specificity.

- **False Positives (FP):**
  - These are cases where the model incorrectly rejects applicants who would have honored their contracts.
  - Action: Verizon should aim to minimize false positives to prevent lost profits. Strategies could include providing alternative payment options or special offers to these applicants.
  - Model Focus: The model will be tuned to reduce the occurrence of false positives, possibly by adjusting the classification threshold.

Asymmetric Costs in the context of the MLP model for predicting customer defaults

- **True Negatives (TN):**
  - These are cases where the model correctly approves applicants who will make every payment.
  - Action: Verizon benefits from these customers as they are likely to generate profits over time. Special attention can be given to retaining and nurturing these customers.
  - Model Focus: The model will ensure that it correctly identifies these cases while allowing some flexibility for false negatives to avoid overly conservative decisions.

- **False Negatives (FN)**
  - These are cases where the model incorrectly approves applicants who will default.
  - Action: FN cases result in potential losses for Verizon, both in terms of missed monthly payments and the phone's unrecoverable or diminished value. Mitigating these losses is crucial.
  - Model Focus: While minimizing false negatives is important, it may require a balance with false positives. Setting the classification threshold too low to catch all potential defaulters could lead to too many false positives.