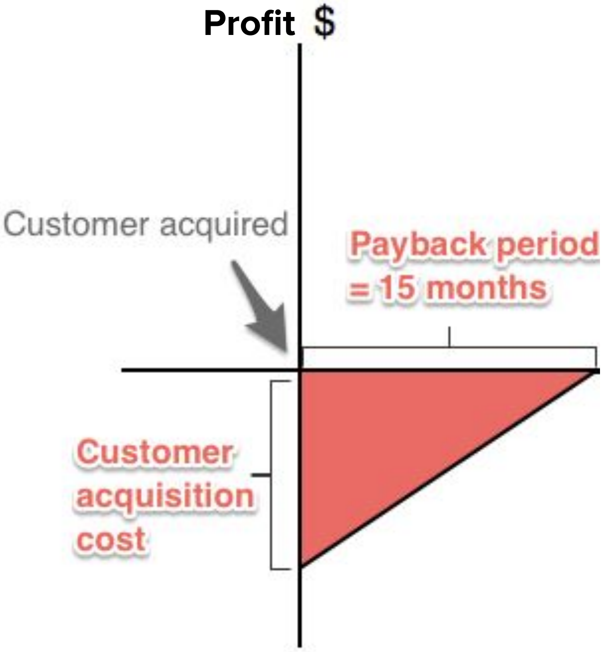
Predicting Cross-Sold Customers

Andrew Smith

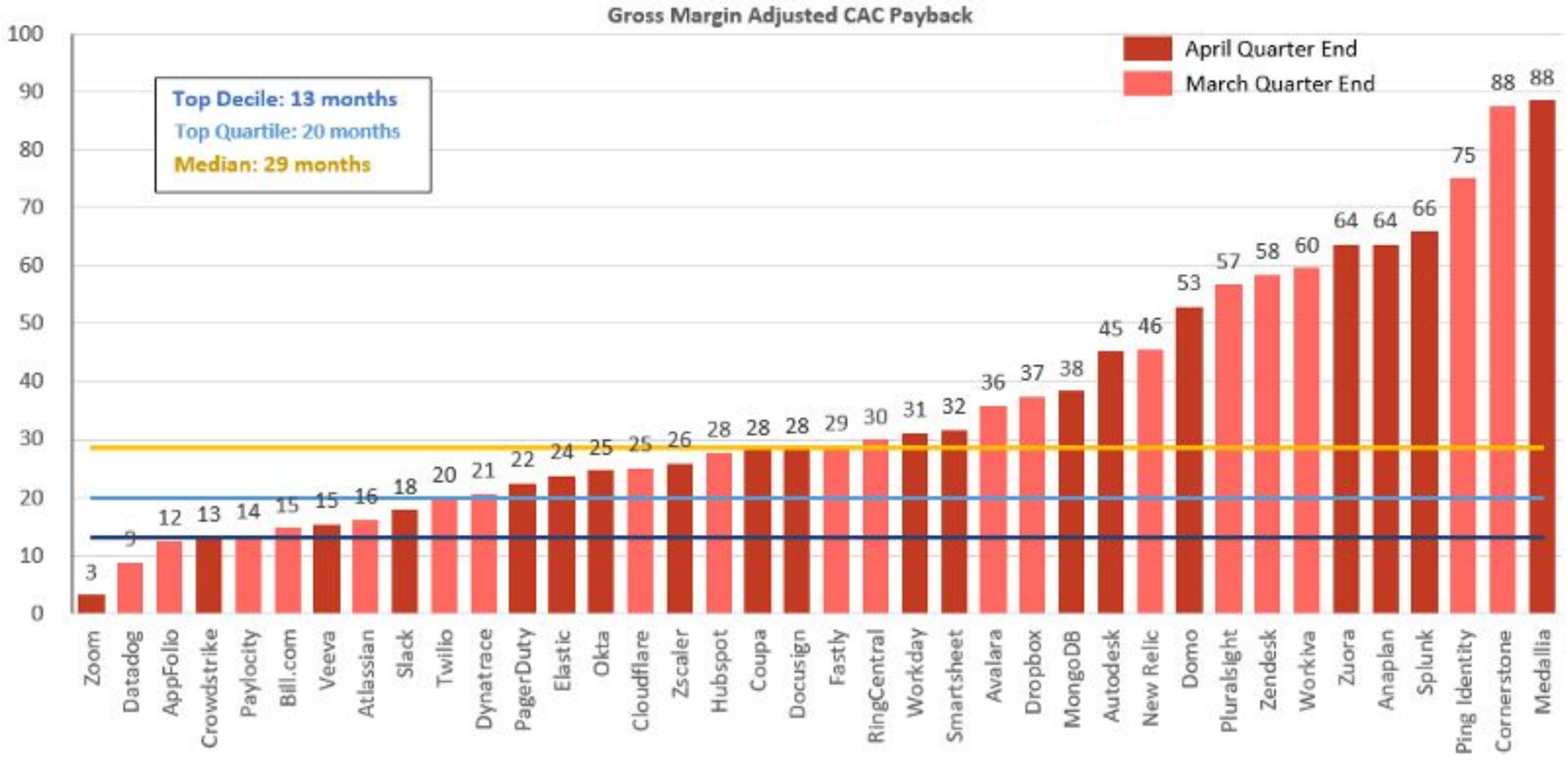
Goals

- Predict whether an existing health insurance customer will be cross-sold car insurance

Cross-Selling = Profitable Growth



Payback Distribution



Use Case

- Give special attention to these customers to try to ensure they are cross-sold and ignore customers with a low probability of conversion
    - Dynamic Pricing (discounts to select customers)
    - Pushed Marketing Campaigns
    - More attention by the sales team

- Key Metric of Interest:
    - F2 Score - places less weight on precision with more weight on recall
    - Having a wider funnel of cross-sell customers is best

Tools

Modelling / Cleaning / Viz

pandas

scikit learn

Imbalanced Learn

seaborn

Data Sources & Data Description

- Data sources:
  - Kaggle Dataset, 381,109 rows
- Key variables:
  - Labels:
    - 0 (not cross-sold) / 1 (cross-sold)
  - Features *(9)*:
    - Gender
    - Age
    - Drivers License (Y/N)
    - Region Code
    - Previously Insured (Y/N)
    - Vehicle Age
    - Annual Premium
    - Policy Sales Channel
    - Vintage (Days as customer)

Model Workflow

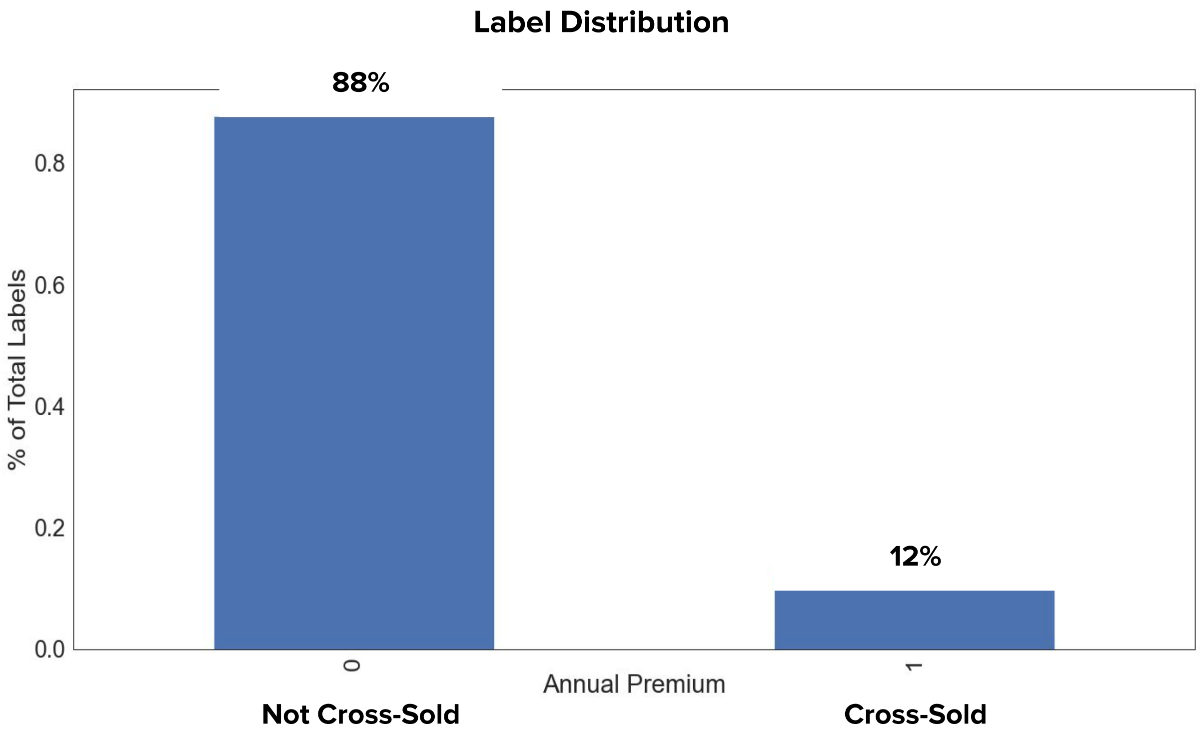
1. Baseline Models
2. Sampling Methods on Baseline Models w/ Parameter tuning
3. Feature Engineering
4. Random Bagging Methods

Baseline Models

Model	F2	Accuracy	Precision	Recall	Notes
Logistic Regression	**61.1%**	75.7%	31.1%	80.6%	Threshold of 0.2
Categorical Naiive Bayes	**46.1%**	78.3%	29.4%	53.7%	Categorical Only
KNN (n_neighbors = 5)	**16.7%**	85.3%	30.2%	15.0%	Various K's tested
Random Forest	**9.1%**	87.2%	39.3%	7.7%	--
XG Boost (Binary Logistic)	**0.7%**	87.8%	53.1%	0.6%	Optimizied for error
Gaussian Naiive Bayes	**0.3%**	87.7%	25.7%	0.2%	Continuous Only

** Represent test Scores after a train, test, val split*

Baseline Models



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Baseline Models w/ Imbalance Sampling and Hyperparameter Tuning

Model	F2	Accuracy	Precision	Recall	Notes
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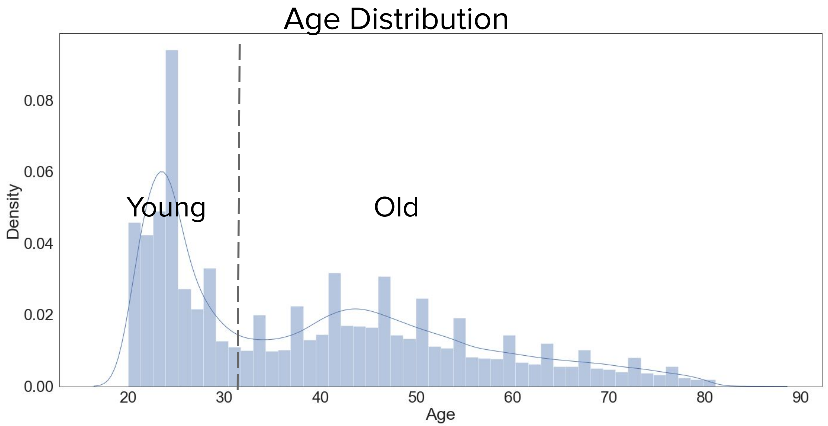
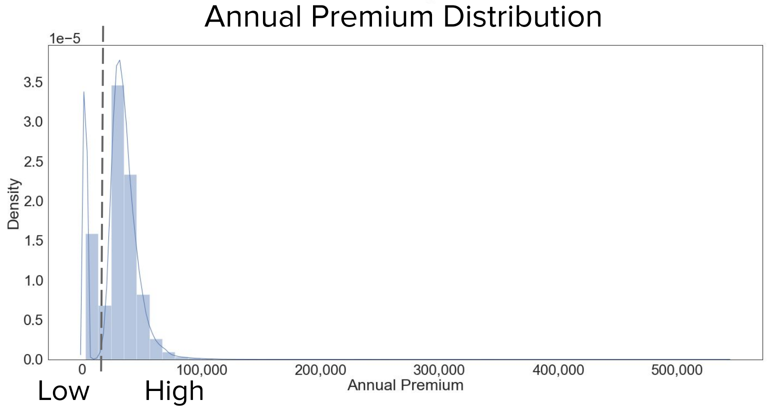
Feature Engineering

Categorical Variables





Interaction Terms

Age **X** Vintage
Young **X** Large Premium
Vehicle Damage **X** Vehicle Age
Gender **X** Age

No impact on top model (logistic regression)

Model Workflow

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Undersampling Bagging Methods

Model	F2	Accuracy	Precision	Recall	Notes
Balanced Random Forest	**60.1%**	72.9%	28.8%	82.4%	Undersampling bagging
Balanced Bagging Classifier	**55.7%**	76.0%	30.2%	71.1%	Undersampling bagging

** Represent test Scores after a train, test, val split*

Top Model: Logistic Regression *(threshold = 0.2)*

61%	**81%**	**75%**
F2 Score	Recall	Accuracy

Confusion Matrix

Actual \ Predicted	No Cross-Sell	Cross-Sell
No Cross-Sell	**True Positives** (Predicted no cross-sell and actual is no cross-sell) **498,896**	**False Negatives** (Predicted cross-sell and actual is no cross-sell) **16,984**
Cross-Sell	**False Positives** (Predicted no cross-sell and actual is cross-sell) **1,701**	**True Negatives** (Predicted cross-sell and actual is cross-sell) **7,641**

Top Features

Vehicle Damage
2.64

Policy Sales Channel 26
1.45

Region Code 28
1.44

Converted from log odds

Model Weakness / Next Steps

- Low precision
- Request further features
- Discuss types of anonymous sales channels / regions to posit more features
- Speak with domain experts to brainstorm further features
- Try ensembling

Questions
?

Appendix: Feature Pairplot