Improving Customer Service in Finance using Machine Learning

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Financial Firms

- Include banks, mortgage lenders, brokerage firms, credit companies
- Products: mortgages, loans, credit cards, bank accounts, financial services
- Very sales and marketing focused
- Handle sensitive consumer information
- Requires consumer to put their trust into the firms hands

Customer Service in Finance

- A lot of complaints due to service and products
- Employees have to balance service and sales
- Complaints filed directly to the firms but also CFPB, Consumer Financial Protection Bureau
- Customer churn do to bad experience
- Loss of time and money for both firms and consumers

Complaints

- For the most part, many complaints are handled appropriately by firms
- Employees trained in customer service
- Some complaints are not handled so well
- Filed online, in person, over the phone
- Stressful and emotional process

Problems to solve

- How can we predict difficult to handle consumer complaints in finance?
- What do these difficult complaints look like?
- If we can predict, what can be done to improve customer service?

Who can benefit?

Consumers

Financial Firms

UnionBank
RBS The Royal Bank of Scotland
WELLS FARGO
WACHOVIA
Capital One Bank
mb financial bank
citi
Commerce Bank
Deutsche Bank
TD Bank America's Most Convenient Bank®
usbank Five Star Service Guaranteed
Northern Trust
ABN·AMRO
JPMorganChase
FIRST TENNESSEE powering your dreams

Benefits

Save time and money for consumer and firms

Prevent customer churn

Being able to predict right away which complaints need special handling

Leverage results to improve internal customer service policies and procedures

Prevent mishandling of consumer information

The Data

- The data used to answer the previous question comes directly from the CFPB
- Contains over 1,200,000 complaints as of 5/20/2019
- Filed directly by consumers against various firms
- Data can be found https://data.world/cfpb/consumer-complaints

cfpb Consumer Financial Protection Bureau

Data Overview

Contains 18 columns

1,284,185 rows

Contains a feature for written complaint called 'consumer_complaint_narrative'

Complaints are those filed to CFPB and reflects just a sample of all complaints filed to financial firms since 2012

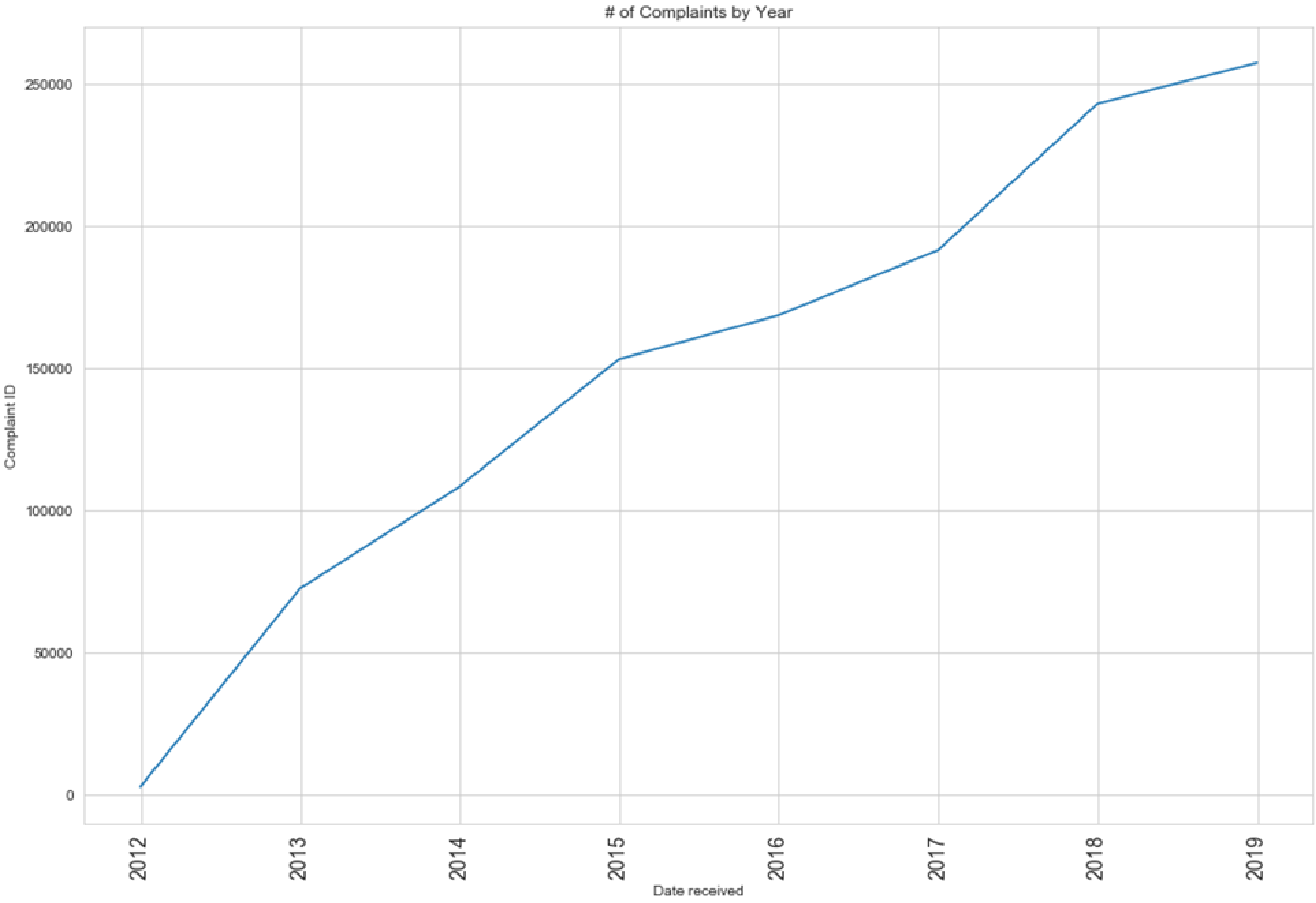
How do we predict the difficult complaints?

- Data contains a column called ‘timely_response’
- A timely response will be our indicator of whether our complaint was handled in an ‘appropriate’ manner or not
- ‘timely_response’ will be the predictor label for machine learning
- True or False

Defining an Appropriate Response

- Handled in time as defined by CPFB - 15 days
- Has value of True in data for ‘timely_response’
- True – assumes complaint handled as efficiently as it could
- Not responding in time possibly means complaint was not resolved, difficult to handle, or maybe ignored due to lack of concern

Exploratory Data Analysis



Complaints by year

- 2013 to 2014 up 149.53%
- 2014 to 2015 up 141.42%
- 2015 to 2016 up 110.09%
- 2016 to 2017 up 113.64%
- 2017 to 2018 up 126.90%
- 2018 to 2019 up 105.93%

Complaints By Year

- Number of complaints filed to CFPB at least doubles each year
- Increased partly due to ease of reporting and adoption of technology
- Worse yet, we can infer customer service is falling or that consumers are increasingly unhappy

of Complaints by Product

Top complaints based on chart

Mortgage: 278249

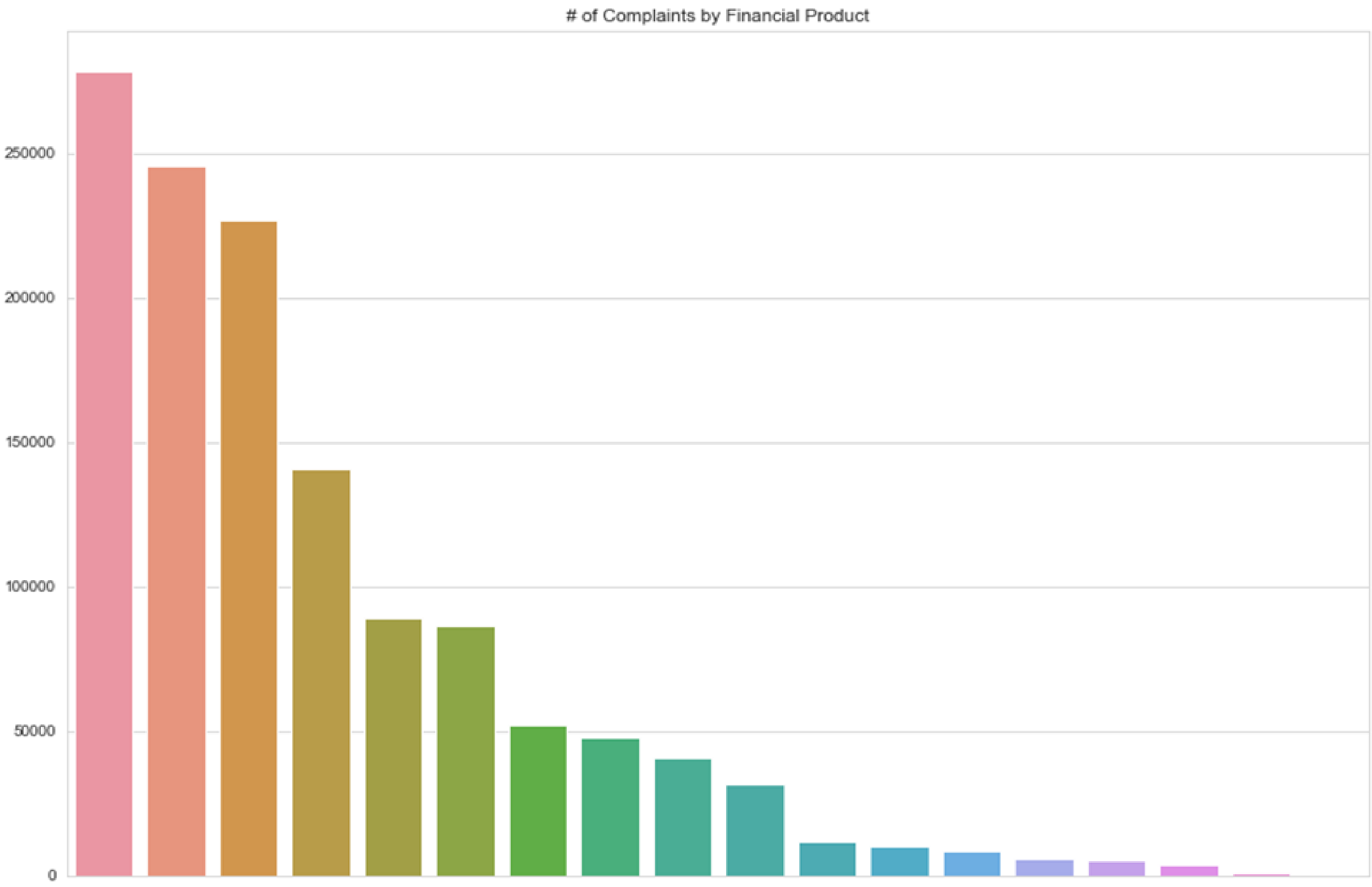
Debt collection: 245218

Credit Based Services: 226781

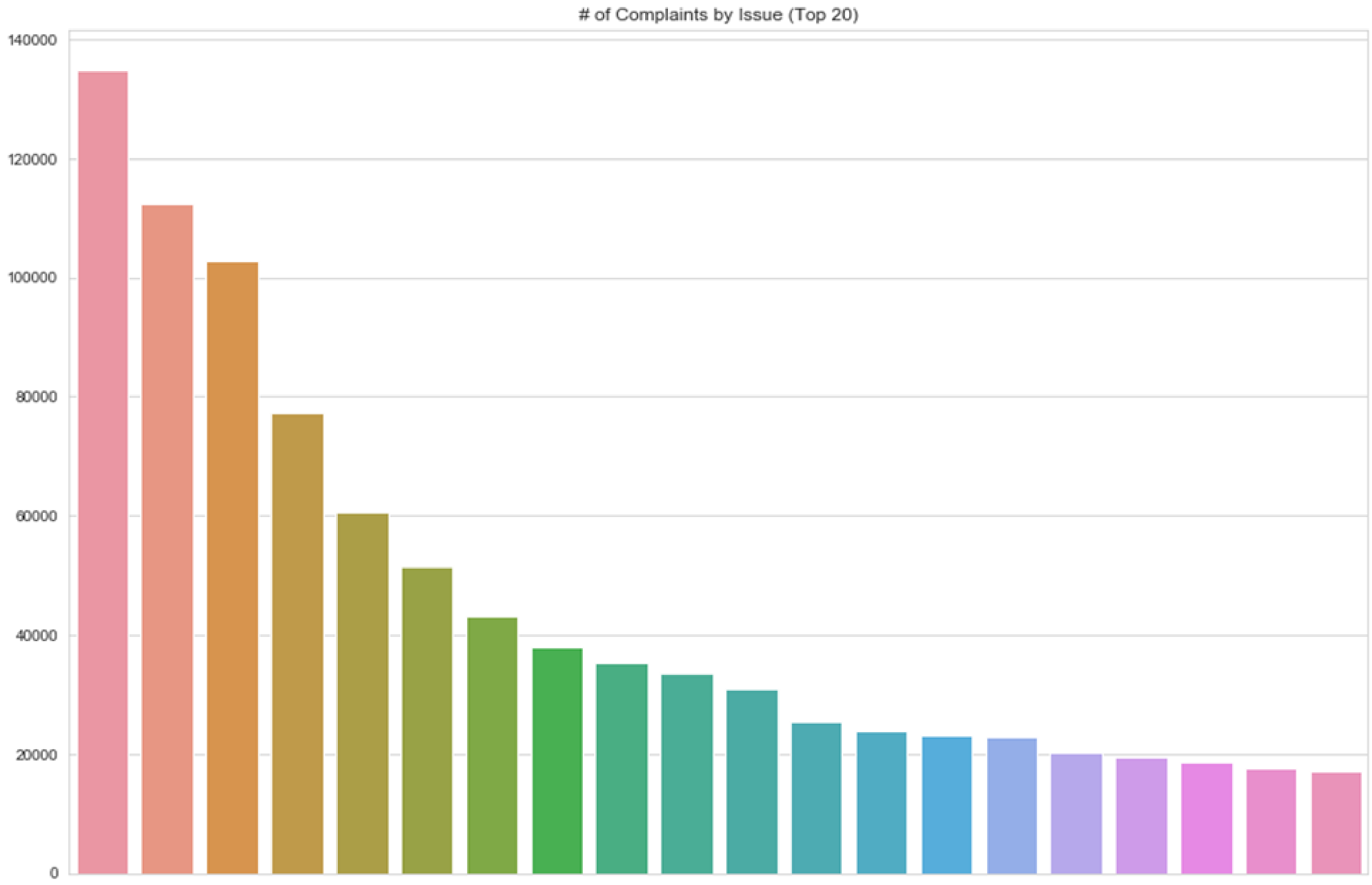
Credit reporting: 140432

Credit card: 89190

Bank account or service: 86206



of Complaints by Issue



- Incorrect information on your report: 134809
- Loan modification, collection, foreclosure: 112311
- Incorrect information on credit report: 102686
- Loan servicing, payments, escrow account: 77333
- Cont'd attempts collect debt not owed: 60687
- Problem with a credit reporting company's investigation into an existing problem: 51498
- Attempts to collect debt not owed: 43181
- Account opening, closing, or management: 37961
- Communication tactics: 35449
- Improper use of your report: 33441
- Disclosure verification of debt: 30800
- Managing an account: 25535
- Written notification about debt: 23766
- Trouble during payment process: 23188
- Deposits and withdrawals: 22851
- False statements or representation: 20278
- Managing the loan or lease: 19438
- Struggling to pay mortgage: 18682
- Dealing with my lender or servicer: 17630
- Application, originator, mortgage broker: 17229

Complaint Issues

Many issues seem to stem from how customer information in handled and reported

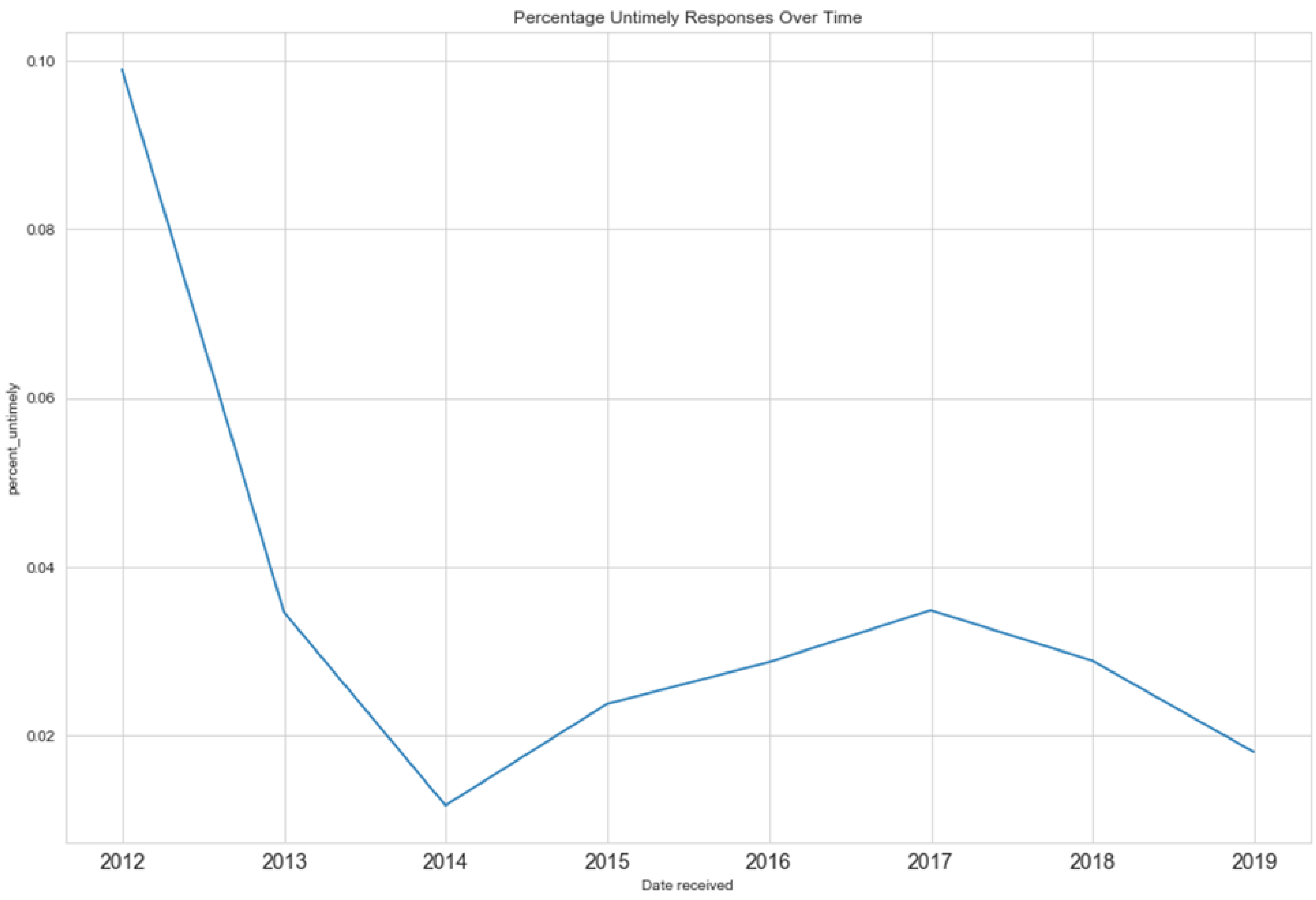
Red flag that employees need to be trained to handle consumer information

Could be a employees are in a rush to get sales and getting clients in and out of the seat as fast as possible

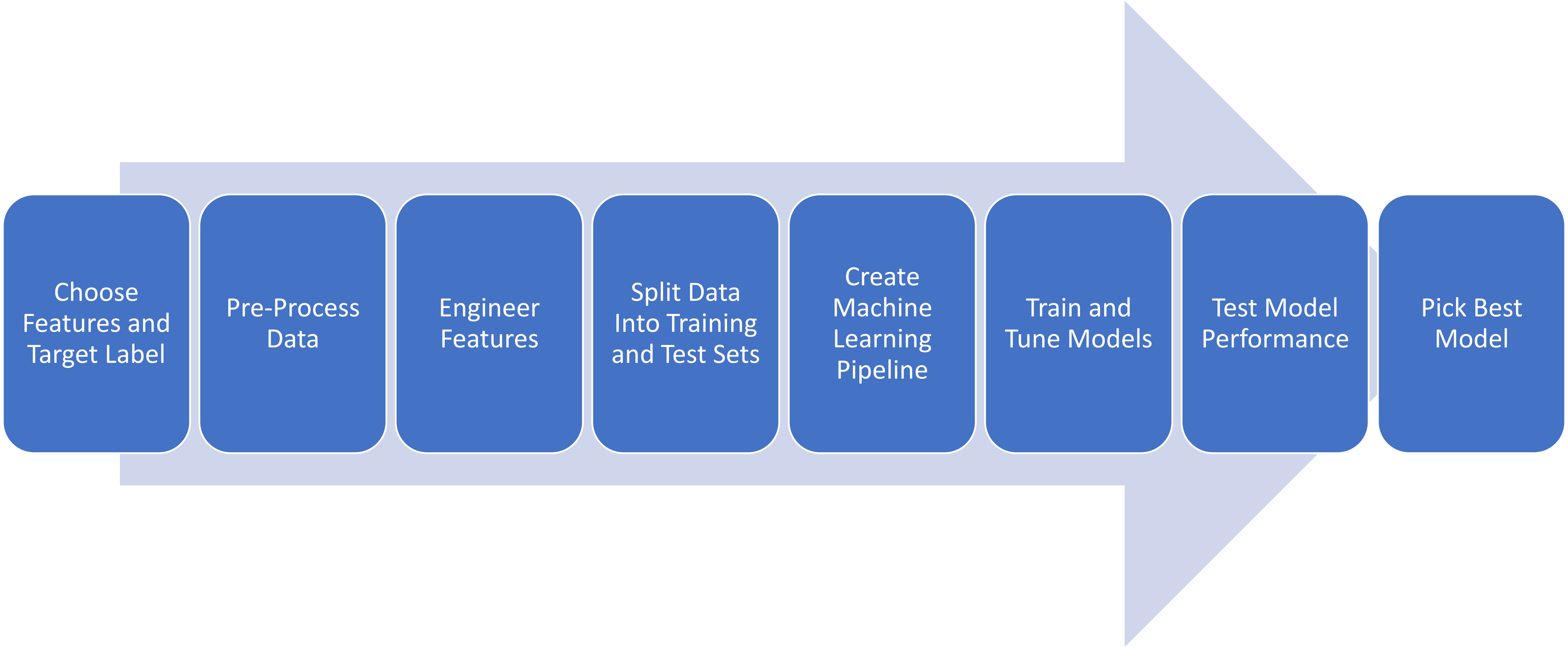
Entering wrong information can cause many problems for both parties

Percentage of Untimely Responses

- Based on the CFPB's data untimely responses have been decreasing since 2017
- Even a small percentage of complaints not appropriately responded to can cause 10s of millions of dollars in potential losses



Solving the Problem



Choosing Features and Labels

Features

- Product
- Sub Product
- Issue
- Sub Issue
- Consumer Complaint
- Company
- Submitted Via
- Sentiment Score (Engineered)

Prediction label

Timely Response → True or False

Pre-Processing Data

- Drop Columns with large amounts of missing data
- Remove irrelevant data columns
- Fill in missing values
- One hot encode categorical features
- Apply NLP techniques on written complaints

Natural Language Processing

- Remove ‘X’s that represents censored information
- Remove punctuation
- Remove extra white spaces
- Remove stop words that give little meaning – ‘of’, ‘is’
- Edit word lengthening – “hellllooo” -> “hello”
- Tokenize text – create a list of words
- Stemming – removing suffixes like “-ly” and “-ing”
- Lemmatize – get the root word, “ran”, “runs”, “running” -> “run”

Feature Engineering – Sentiment Score

Scored written complaints based on the ‘attitude’

Used sentiment analysis package called VADER from NLTK

Score between -1 and +1

More negative score means a negative attitude and vice versa

Machine Learning – Binary Classification

Logistic Regression

Random Forest

Gauge Model Performance

Accuracy is a bad measure ~97% of labels were True for timely responses

We want the model to accurately classify complaints that were not responded to appropriately - < 3% of the data

Instead use log loss, precision, recall, AUC

Why Log Loss?

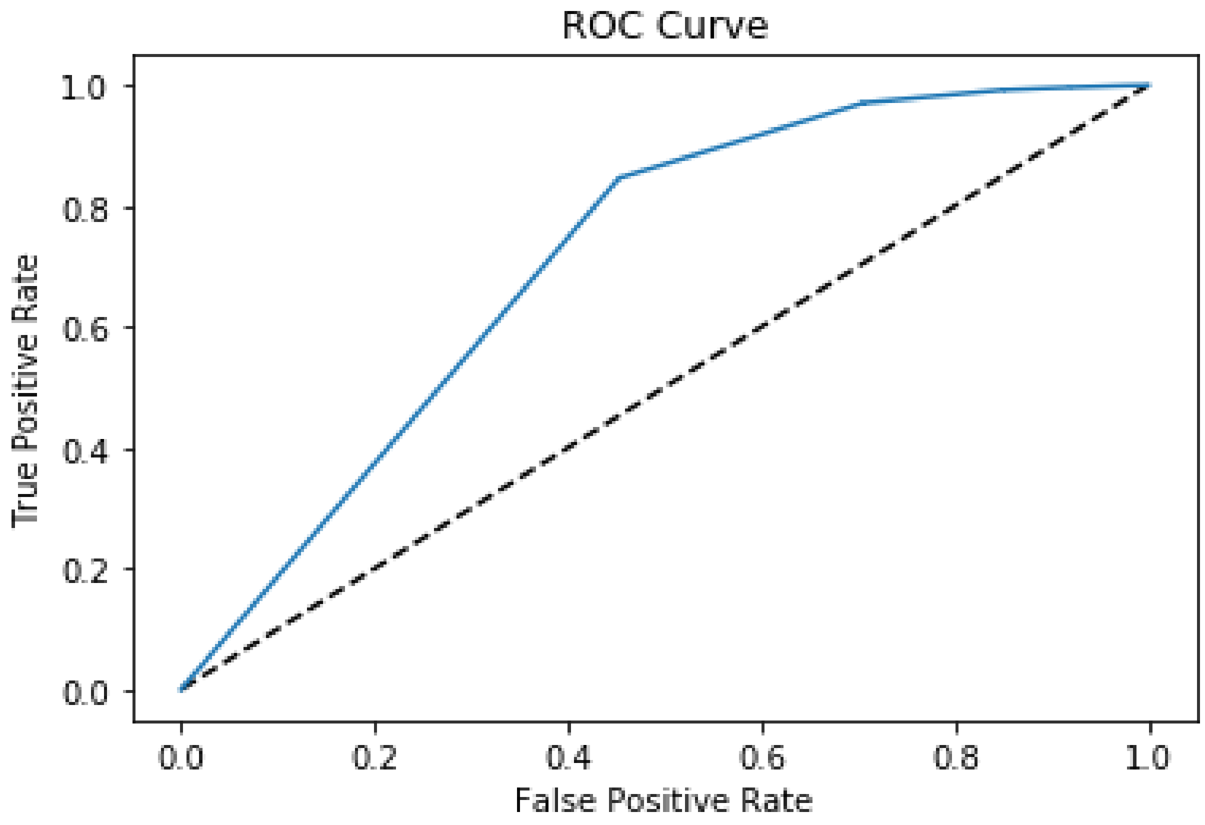
- If the model classifies label as True for all data, then still 97% accurate
- Log loss measure the error, want lowest score possible
- Log loss punishes incorrect predictions
- Ex) predicts True with 90% probability, but actually False – log loss 2.30
- Ex) predicts True with 50% probability, but False – log loss 0.69

Results of Base Model – Random Forest

Random Forest (Un-tuned)				
	Precision	Recall	F1-Score	Support
FALSE	0.44	0.05	0.08	2843
TRUE	0.97	1	0.98	93117

Log Loss	Accuracy	AUC
0.5128	0.9699	0.7124

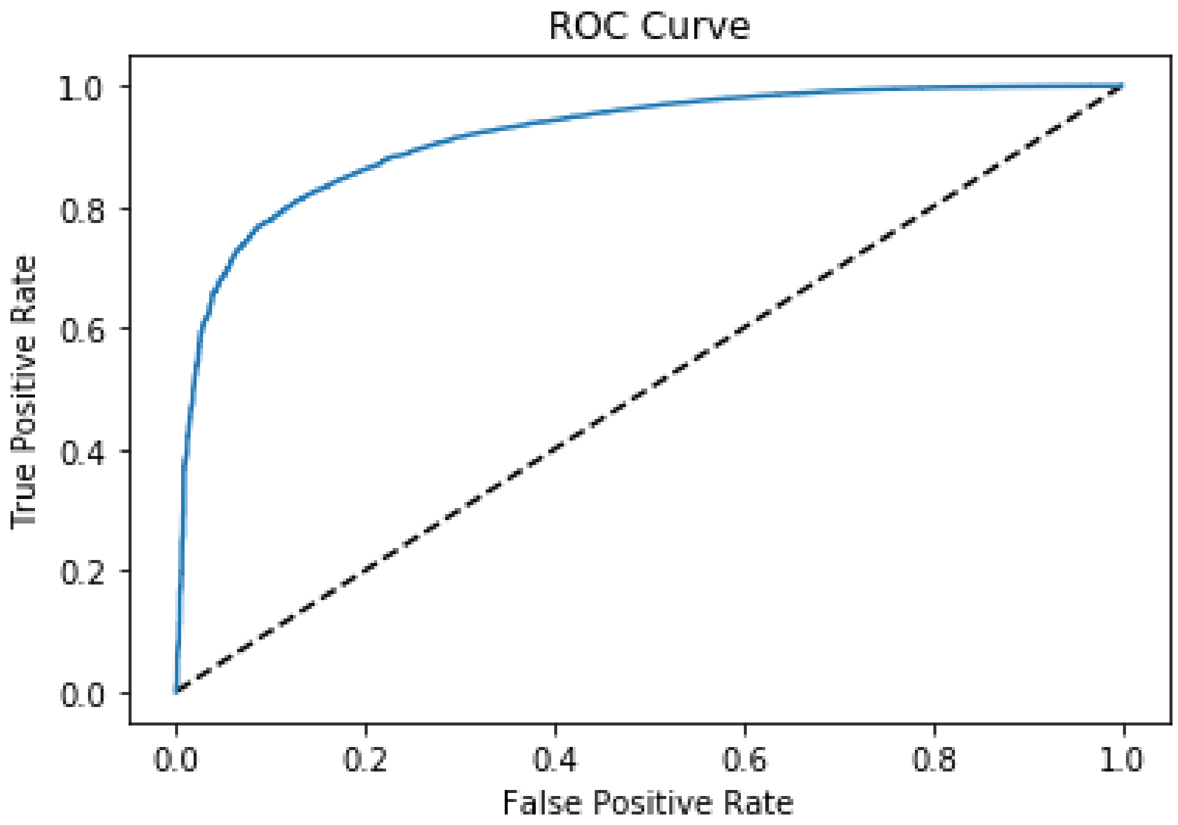
Currently the model predicts a False Label is False 44% of the time, but only correctly identifies 5% of all False labels.



Results of Best Model – Logistic Regression

Logistic Regression (Tuned Hyper Parameters, Lemmatization)				
	Precision	Recall	F1-Score	Support
FALSE	0.61	0.21	0.31	2843
TRUE	0.98	1	0.99	93117

Log Loss	Accuracy	AUC
0.5128	0.9731	0.9175



Currently the model predicts a False Label is False 61% of the time, and correctly identifies 21% of all False labels.

Notes on Model Performance

- Trained different versions of models with different NLP pre-processing such as with and without lemmatization
- Lemmatization showed better results than stemming
- Used Bag of Words model – analyzes based on token counts
- Adding sentiment score did not improve results
- Used grid search and randomized grid search to tune hyper parameters

Satisfied with results?

Better predictions are always better

Being able to identify 21% of hard to handle responses is still a win

Financial products are large dollar items

Failure to rectify some credit or debt complaints can ruin consumer lives

21% of difficult complaints from ~1,400,000 is still 7350 complaints identified

Some Math

- According to https://www.magnifymoney.com/blog/mortgage/u-s-mortgage-market-statistics-2018/, the average mortgage balance is $148,060
- According to CFPB data in this project: 5528 complaints that were not responded in an appropriate manner were mortgages
- Being able to identify 21% is 1160 complaints
- That’s a lot of money and risk to lose due to preventable customer churn

For a large bank that is: $148,060 X 1160 =
$171,749,600!!!

Business Use Cases

The exploratory data analysis itself has identified that many of these issues stem from mishandling of customer information. A company who sees similar patterns needs to rethink how employees are handling sensitive information. For example, bad credit reporting from mishandling information can cause a consumer to not be approved for a loan, that means a loss for the financial firm as well.

The classification model can be implemented on every written complaint sent to a firm. Any predictions of ‘difficult’ complaints for a certain product can be handed to a special team to prevent customer churn or better handle a difficult situation. These complaints should not be handled by less experienced employees. Special protocols and procedures can be put in place to handle any complaints tagged as ‘difficult’ by the model.

Looking Forward

Since NLP and sentiment analysis are not exact sciences, it would be a great exercise to see what improvements can be done to further preprocess the written complaints text

Finding better features to engineer for better performance

Trying out a larger variety of machine learning models

Thank You!

By: Justin Tsao

Find the full project and all the code here:

https://github.com/jltsao88/Improving_Customer_Service_Machine_Learning

Credit for images

- Slide 2 - https://due.com/blog/this-is-the-sad-truth-about-how-most-banks-make-money-and-what-you-can-do-about-it/
- Slide 3 - https://www.salesforce.com/ca/blog/2017/02/improve-customer-service.html
- Slide 4 - https://www.ratchetandwrench.com/articles/5045-dealing-with-customer-complaints
- Slide 6 - www.consumerphysics.com,