Thera Bank
Loan Offer Classification

Question

Can we reduce costs of marketing campaigns?

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Can we increase conversion rate on personal loans we offer?

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Can we increase conversion rate on personal loans we offer?

Can we use our data to predict which of our existing customers will accept a personal loan?

Machine Learning Solution

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- Insightful - Observe which customers are likely to accept an offer and which aren’t
- Strategic - Proactively market to the correct segment of customers

Current Process

- Compile information on all existing customers
- Send loan offer to all customers
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Issues

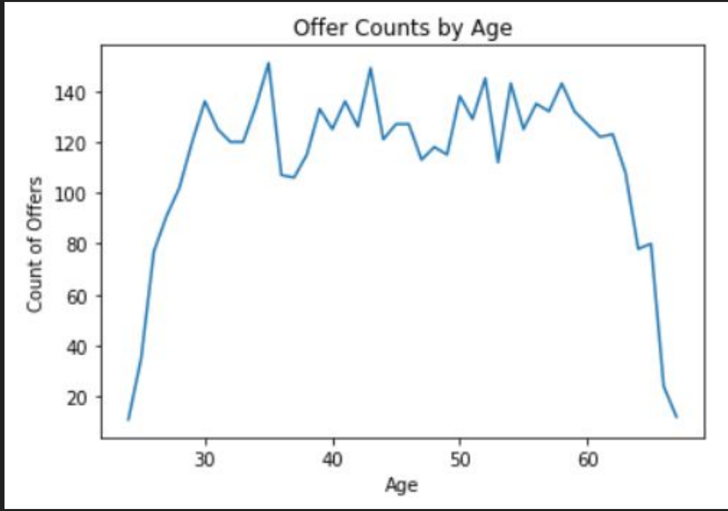
- High costs with sending to all of our customers
- Data is not driving marketing decisions

Data

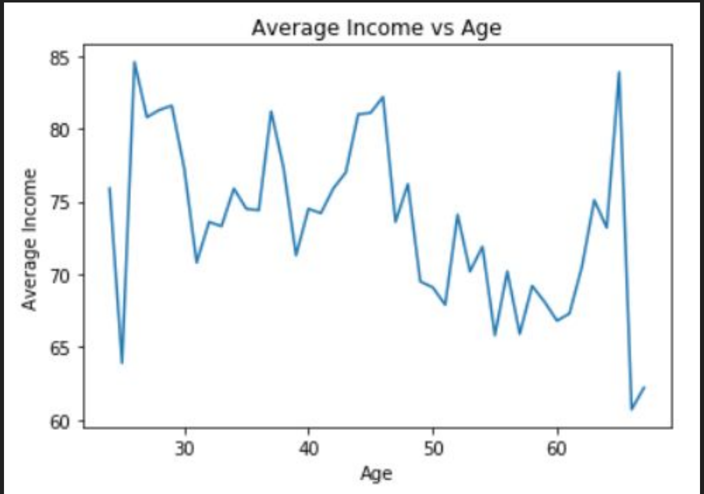
- Marketing campaign from last year (5,000 loan offers made)
- Details on age, number of years working, income, level of education, etc.
- Ignores zip code and observations with negative years of work experience

Analysis

Approx 100-140 offers were made for each age between 30 and 60

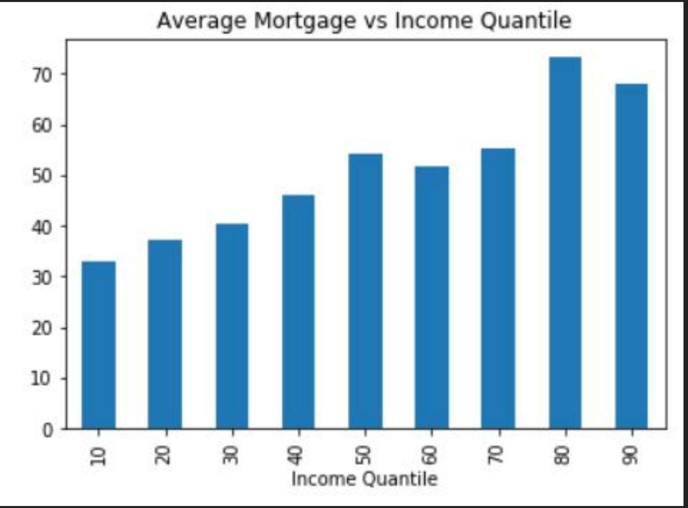


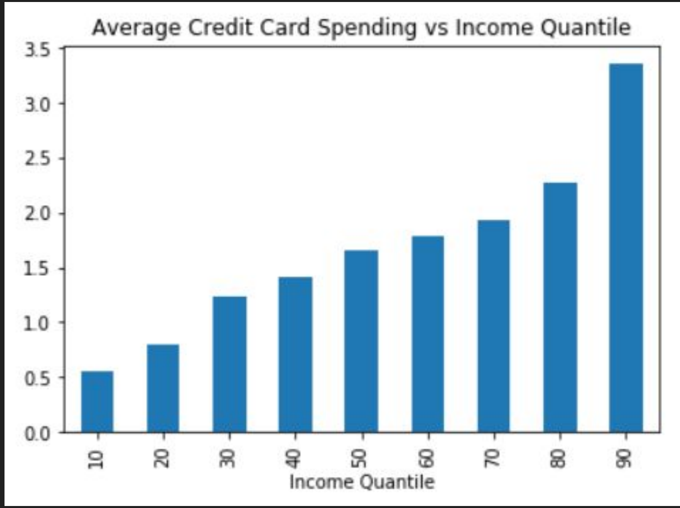
Large variability in income by age



Analysis

- Higher income customers have larger mortgages and credit card spending





Model

- Predict whether or not customer will accept or reject loan offer
- Gradient boosting with hyperparameter tuning
  - Learning rate
  - Number of estimators

Model

- Data is split with 75% being used for training and 25% for testing
- Data is scaled appropriately
- To address class imbalance, synthetic observations are incorporated into the model

Results

After hyperparameter tuning, training set performs with 99.1% accuracy

```
param_grid = {'learning_rate':[0.05, 0.1, 0.25, 0.5, 0.75, 1], 'n_estimators':[25, 50, 75, 100, 150, 200, 250]}
gb_cv = GridSearchCV(GradientBoostingClassifier(random_state = 5), param_grid = param_grid)
gb_cv.fit(X_train_res, y_train_res)
print("Best Score:" + str(gb_cv.best_score_))
print("Best Parameters: " + str(gb_cv.best_params_))
```

```
Best Score:0.991314449752181
Best Parameters: {'learning_rate': 1, 'n_estimators': 75}
```

Results

- When applied to testing set, we correctly identify 1,216 observations out of 1,237.
- Of the 107 accepted loan offers, model correctly identifies 99 (92.5%)
- Conversion rate of offers made increases to 88.4% (99/112)

	0	1
0	1117	8
1	13	99

Conclusion

- Classifying responses reduces costs and increases conversion
    - Loan offers sent to approximately 9% of customers
    - Conversion rate increases to 88.4%
- Opportunities for improvement - update data on existing customers, incorporate cost function into score optimizing