Final Project Report

Project: Bank Marketing (Campaign)

Data Glacier Virtual Internship

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Group Name: BRAVO

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Problem description:

ABC Bank wants to sell its term deposit product to customers and before launching the product they want to develop a model which helps them in understanding whether a particular customer will buy their product or not (based on customer's past interaction with bank or other Financial Institution).

The steps to solving this task include outlining the project, the initial data understanding and strategies to solve data problems, data cleansing and transformation, exploratory data analysis code, exploratory data analysis presentation and model recommendation, model selection and building, and presenting the final solution and code.

This presentation presents the final solution. We will be choosing a model that best accomplishes the task of predicting whether customers will buy the term deposit or not. This model can be used to analyze marketing segments to determine if increasing marketing efforts in those marketing segment is a good financial investment.

Model Development and Metrics

- We originally built and tested 22 models (11 without duration feature and 11 with duration feature)
- However the models with duration feature are limited in their scope because duration is not known before a call is performed. Therefore, they are discarded.
- To choose an ML model for this task requires knowledge of performance metrics.
- The relevant metrics are Precision, Recall, F1_score, auc_roc, and auc_pr.

Precision, Recall, and F1_score

Definitions:

- ➢ Precision: Proportion of true positive predictions among all positive predictions
- ➢ Recall: Proportion of true positive predictions among all positive cases
- ➢ False positives: Customers who did not buy the product and were incorrectly identified.
- ➢ False negatives: Customers who bought the product and were incorrectly identified.
- ➢ F1 score: Measures model accuracy considering both precision and recall equally and it is useful metric for imbalanced datasets (our dataset is imbalance).

Precision, Recall, and F1_score

Why is precision important?

- ➢ With marketing a term deposit product, it is important to correctly predict positive cases out of all the positive predictions because it prevents those that are not positive from being selected (False positives). When those that are not positive are predicted as buyers it wastes money and resources to market to them.

Why is recall important?

- ➢ It is also important to correctly predict positive cases out of all the positive cases because when those that are positive are not predicted positive (False negatives) there is a wasted opportunity to market to them.

Why is F1_score importance?

- ➢ Precision and Recall are important. Since F1_score fairly balances both precision and recall, F1_score is also important.

AUC_ROC (Area Under the Receiver Operating Characteristic Curve)

Definitions:

- ➢ True Positive Rate (TPR) (aka: Recall): Proportion of true positive predictions among all positive cases.
- ➢ False Positive Rate (FPR): Proportion of False positive predictions among all negatives cases.
- ➢ ROC curve: The graph of FPR and TPR for various threshold values.

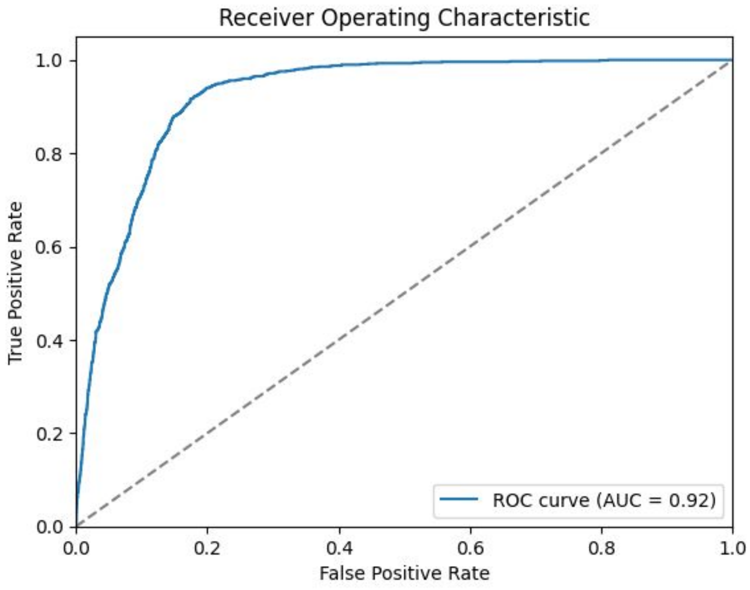
The decision threshold(the conceptual boundary that distinguishes one class from the other) is what determines the tradeoff of FPR and TPR. A model can be made with various decision thresholds. If you want to consider all the similarity thresholds similarly instead of choosing a single point on the curve corresponding to a decision threshold then you can take the area under the curve (AUC) of the ROC curve (AUC_ROC)

AUC_ROC (Area Under the Receiver Operating Characteristic Curve)

Importance:

- ➢ It values the model for all decision thresholds rather than just one.
- ➢ It is relatively robust to data imbalance.

ROC curve for Gradient Boosting Machine Model (GBM):



AUC_PR (Area Under the Precision Recall Curve)

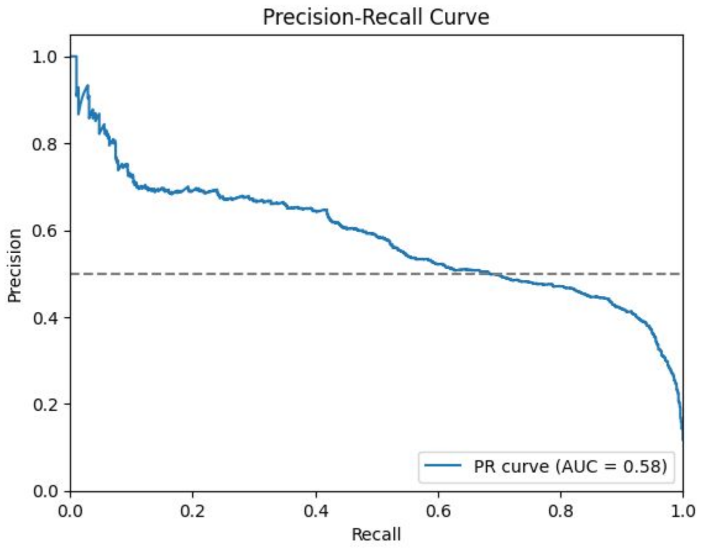
Definitions:

- ➢ PR curve: The graph of Recall and Precision for various threshold values.
- ➢ Recall and Precision (see previous definitions)

Similar to auc_roc the decision threshold(the conceptual boundary that distinguishes one class from the other) is what determines the tradeoff of Recall and Precision. A model can be made with various decision thresholds. If you want to consider all the thresholds similarly instead of choosing a single point on the curve corresponding to a decision threshold then you can take the area under the curve (AUC) of the PR curve (AUC_PR).

AUC_PR (Area Under the Precision Recall Curve)

PR curve for Gradient Boosting Machine Model (GBM):



Importance:

- ➢ It values the model for all decision thresholds rather than just one.
- ➢ It is extremely robust to data imbalance.
- ➢ Focus on the positive class (Buyers). We are marketing to the positive class.

Model Performance

Gradient Boosting Machine (GBM):

	RandomOverSampler	SMOTE
F1_score	0.588	0.525
Precision	0.445	0.564
Recall	0.864	0.491
auc_roc	0.924	0.920
auc_pr	0.582	0.560

Logistic Regression:

	Class Balancing	RandomOverSampler	SMOTE
F1_score	0.558	0.558	0.553
Precision	0.428	0.426	0.422
Recall	0.803	0.806	0.801
auc_roc	0.900	0.901	0.900
auc_pr	0.495	0.497	0.498

Support Vector Machine (SVM):

	Class Balancing	RandomOverSampler	SMOTE
F1_score	0.570	0.565	0.570
Precision	0.418	0.416	0.448
Recall	0.896	0.882	0.784
auc_roc	0.918	0.917	0.911
auc_pr	0.535	0.538	0.561

Random Forest:

	Class Balancing	RandomOverSampler	SMOTE
F1_score	0.577	0.579	0.540
Precision	0.470	0.474	0.525
Recall	0.749	0.746	0.556
auc_roc	0.913	0.912	0.910
auc_pr	0.566	0.565	0.551

- The columns are imbalancing techniques and the rows are ML metrics. Each inner cell is a metric score for a given combination of imbalance technique and metric.
- Class balancing via class weights is implemented on every model (except GBM), even when another imbalance technique is used.
- Class Balancing as a method means that only Class Balancing via weights was applied.

Chosen Model: Gradient Boosting Machine (GBM) classifier with Random Oversampling

- To enhance the effectiveness of marketing efforts, we developed a cutting-edge predictive model for ABC Bank. This model is designed to identify customers that are more likely to subscribe to the term deposit product. By focusing the resources on those high-potential customers, we aim to improve the campaign efficiency and reduce unnecessary costs.

- F1 Score and AUC-PR were used as key metrics to determine the best model because they provide better measures of performance for the minority class and address class balance. They are also critical because they take into account both false positives (wasting resources) and false negatives (missing potential subscribers) both of which we interested in.

- The dataset's imbalance, is addressed by Random Oversampling. This technique effectively balances by increasing the number of instances of the minority class. This technique helped the model better represent both classes during training, preserving the original data distribution.

GBM tradeoffs

- GBM has the highest scores for F1_score, auc_pr, and auc_roc making it an easy choice as the superior model.
- It doesn't achieve the highest precision and recall scores individually but having the highest F1 score compensates for these shortcomings
- GBM trades explainability for performance because it is a black box model. This is often the natural cost of a better performing model. Explainability is less important because we believe that applying the model directly on marketing segments leads to the most informed results rather than studying the predictors and potentially making over generalized judgements to target marketing segments.

Conversion Rates

- ➢ We can explore the Conversion rate using the Precision metric
- ➢ Conversion rate is the percentage of potential subscribers who actually sign up. It displays the efficiency with which our model converts forecasts into actual subscriptions.

For our model

- ➢ Current Precision: 44.5%

Business Translation

- ➢ Conversion Rate = Current Precision = 44.5 %

- ➢ About 45 clients who are expected to subscribe really do so out of every 100. This proves that the model is effective in identifying possible members.
- ➢ Therefore, a better precision means we're focusing our marketing on people who are more likely to buy, which leads to more subscriptions per dollar spent and better returns on our investment.

Enhanced customer acquisition

- ➢ Implementing our predictive model significantly enhances customer acquisition.
- ➢ With our dataset of 41188 contacts 4640 were the actual subscribers. This base rate represents the proportion of subscribers in the entire contact pool.

Our Model’s Performance:

- ➢ Truly predicted Subscribers = 0.864 (Recall) × 4640 ≈ 4004
- ➢ Total positive predictions : True Positives (TP) / Precision = 4004 / 0.445 ≈ 8991

With the Model: The conversion rate, 44.5 % which is the percentage of correctly predicted subscribers out of those predicted by the model

Without the Model: Using a non-targeted approach or random selection, the expected conversion rate based on the base rate is 11.3% (4,640 actual subscribers out of 41188 total contacts).

Business Impact

➢ **Enhanced Efficiency**

The model improves targeting by focusing on 8,991 predicted subscribers. This approach allows the bank to efficiently use its marketing budget by contacting only those likely to subscribe, unlike the current approach that contacts all customers without any expectation.

➢ **Reduced Wastage**

By concentrating on the customers who are most likely to subscribe, the approach optimizes the use of resources and boosts total marketing effectiveness.

Cost Reduction with the Model

- If the bank contacts each of the 41188 clients ,say at a cost of $2 then total cost would be $82,376

- **Implementation of our Model**: We identify 8,991 potential subscribers with a precision of 44.5% and a recall of 86.4% by using our predictive model. With 4,004 actual memberships, this targeted method costs only $17,982

- By using our model, the bank can maximizes resource usage while achieving considerable cost savings and improving marketing efficiency by focusing on high-potential consumers.

- This Targeted marketing can reduce the cost by 78.18% ,demonstrating Enhanced marketing efficiency.

Improved Return On Investment (ROI)

- ➢ The recall and precision value attained by the model have a significant influence in improving the measure of the profitability of the marketing campaign, calculated by comparing the revenue generated to the cost incurred.

Say if the bank has a revenue of $100 for each subscription:

- ➢ Without the predictive model expected
  Net profit is $464,000 - $82,376 = $381,624 (Total revenue -Total cost)
  ROI = 463%
- ➢ With the model
  Net profit would be $400,400 - $17,982 = $382,418 (For 4004 subscriptions)
  ROI = 2127%

- ➢ By using our Gradient Boost classifier model, the ROI increases significantly from 463% to 2127%. This means for every dollar spent on targeted marketing, the bank gets $21.27 in return, compared to $4.63 without the model, demonstrating that targeted marketing can be both cost-effective and profitable.

Customer Lifetime Value

- CLV is the total amount of money that is expected to be earned from a customer throughout their entire relationship with the bank.
- The F1 Score for our model indicates it is moderate at identifying potential subscribers. By accurately targeting these valuable individuals, we not only improve the marketing efficiency but also maximize Customer Lifetime Value. This means we can focus our efforts on those who will bring the most long-term revenue, ensuring resources are spent where they have the greatest impact.
- Consequently, employing this predictive model enable improved targeting, leading to better resource allocation. This enhances the revenue generated from each customer, thereby increasing Customer Lifetime Value (CLV).

Enhances Sales Funnel Optimization

- ➢ Sales Funnel Optimization for a Bank implies ensuring that the bank concentrates its efforts on the clients who are most likely to sign up for their services, helping to attract more customers and make better use of marketing resources.
- ➢ The AUC – PR value (0.582) of our model suggest it has a moderate ability to distinguish between leads that are likely to convert and those that are not.
- ➢ This helps bank in focusing sales efforts on leads, improving the efficiency of the sales funnel reducing time spent on less promising ones.
- ➢ Better lead prioritization will simplify the sales process, increasing conversion rates and overall sales efficiency.
- ➢ Optimizing the sales funnel contributes to maximizing the return on marketing and sales investments.

Deposit Volume

- Deposit Volume: Total amount of money deposited by customers.
- The F1_score on our test data indicates the model’s ability to discern buyers. The model is used to test samples of different marketing segments and determine if resources are well spent in that segment.
- Although the model detects buyers and is used to increase buyers, it can have an association with deposit volume because more buyers generally indicate larger deposit volume.
- However, there are situations where a large number of buyers does not mean increased deposit volume if everyone is making relatively low-level deposits.
- The F1_score also focuses on the positive classes which is critical to this association.
- However, it is hard to rely on because it does not directly predict amounts deposited.

Customer Retention:

- ➢ The combination of relatively high F1-Score and Recall on our test data indicates that the model can discern buyers relatively strongly and wastes little opportunity to classify the positive class when it is positive.
- ➢ The model can be applied to new data to find buyers with the effect of high F1-Score and Recall.
- ➢ High Recall indicates that there are less false negatives, which is good for customer retention because to maintain customer retention, more positive cases need to be correctly identified.

Market Share

- The auc_roc of our test data indicates the model’s ability to discern buyers and non-buyers in a more general case.
- The model can be tested on a sample for each market segment. Based on the proportion of buyers in the sample, the marketing segment can be prioritized or ignored.
- The model can be used to target or avoid many different marketing segments which can have a hugely significant impact on overall market share.
- In the overall grand scheme of marketing share, both avoiding and targeting certain markets is more critical here compared to some of the other business metrics discussed.

Job Segmentation

- Segmenting customers based on their job can be a critical strategy.
- The job segments with a higher ratio of positives cases to all cases can be prioritized.
- Our models auc_roc metric on the test data proves our model’s ability to correctly classify job segments that are less valuable to invest in.

Cross Selling

- Cross-Sell Ratio: Average number of additional products that a term deposit customer holds with the bank.
- Our model metrics indicate that the model has moderate ability to discern buyers.
- When the focus of marketing is on likely buyers rather than the population, there is more opportunity for cross selling because a buyer of the term deposit product is more likely to buy other products.

Model Deployment with Flask API

Start Flask API

```
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://localhost:5000
Press CTRL+C to quit
```

Make a request with csv file of input features. The model makes the corresponding predictions and the API sends them back.

```
D:\repos\Week_13>curl -X POST -F "file=@test_data_X.csv" http://localhost:5000/predict
{"predictions":[true,false,true,false,false,false,false,false,false,false,false,true,false,false,false,false,true,false,false,false]}
```

Post request under predict route has been logged.

```
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://localhost:5000
Press CTRL+C to quit
127.0.0.1 - - [29/Jul/2024 13:44:38] "POST /predict HTTP/1.1" 200 -
```

Testing has been done: A post request has been sent with part of the original data used to test the model to see if the pickled and loaded model works the same as the original model. They output the same classes for the same feature inputs which indicates success.

Thank You