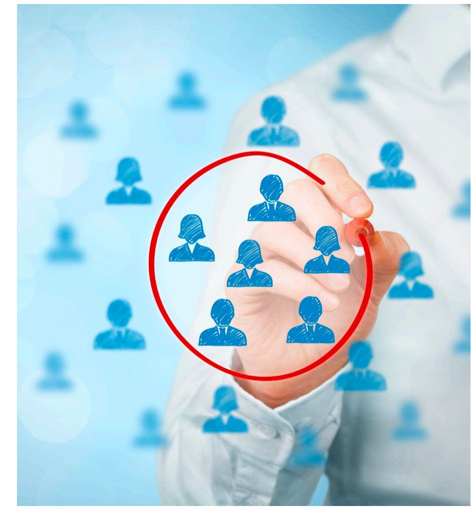
PROBLEM STATEMENT

- 2000 new customers
- Fixed term deposit telemarketing campaign
- Budget for 500 calls

Goal

- Identify which 500 customers to contact to maximise revenue
- Derive recommendations for future campaigns



The bank had just on boarded 2000 new customers and wanted to offer them a term deposit subscription like for existing customers. This was to be achieved through a telemarketing campaign. However due to budget and resourcing constraints, only 500 calls could be made.
The primary goal was to identify which of the 500 customers to contact to maximise revenue. We also wanted to provide recommendations for future campaigns driven by the data.

Image source: https://cmglocalsolutions.com/blog/know-your-target-audience-through-digital-tools

BUSINESS VALUE

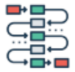
- Successful subscription = revenue
    - $100 per subscription
    - Average uptake: 10-15%
    - Random 500 customers
    - Expected revenue: $5,000-7,500
- Use data science to increase revenue

A successful subscription to a term deposit translates directly into revenue for the bank, as it increases the bank's liquidity and fosters a stronger relationship with the customer. Through speaking with colleagues, we valued each subscription at $100. From past experience, we know uptake for such product through telemarketing campaign is low, at around 10-15%. So contacting the 500 customers randomly would give us expected revenue of between $5,000 and $7,500.

We used data science and predictive modelling to increase revenue.

Image source: https://lucrumconsulting.net/4-ways-to-increase-revenue/

METHODOLOGY

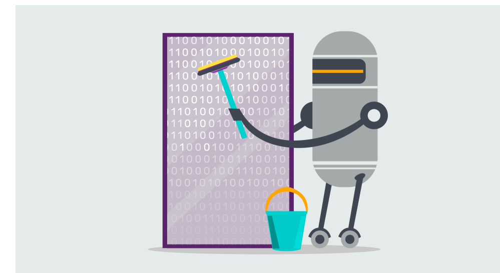
1. Gather and clean data 
2. Explore and visualise data 
3. Train and evaluate models 
4. Final predictions and recommendations 

To solve our problem we performed the following steps. In the next slides, we will go through each step one by one.

Icons source: from OSEMN framework originally by Hilary Mason and Chris Wiggins

1. GATHER AND CLEAN DATA

- Just over 39,000 customer data points
- 20 predictive features including
    - Personal attributes
    - Financial
    - Campaign
    - Economic indicators
- Clean: missing values, syntax

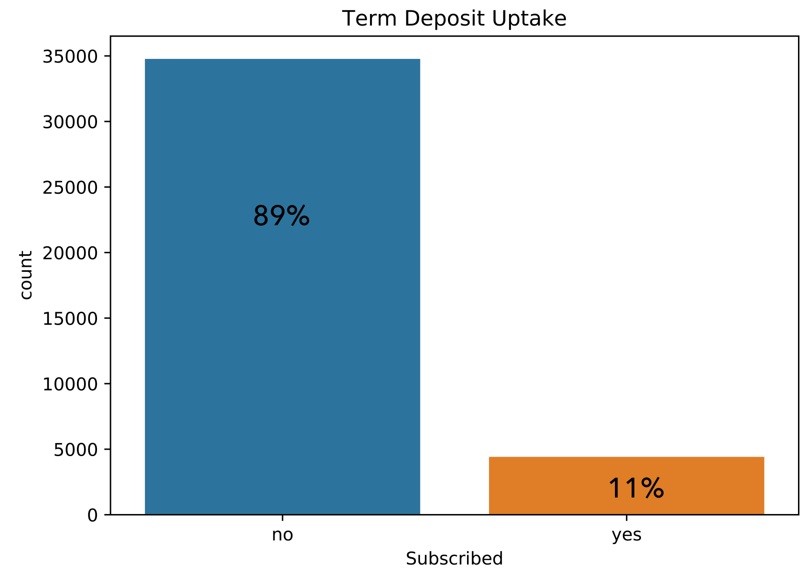


By looking at existing customer data, we had over 39,000 data points. We selected 20 features we thought would be worth investigating and help predict whether a customer would subscribe or not. These include personal attributes (job, age, education), financial (housing loan, personal loan, default credit), campaign (previous campaign results, means of contact, month of contact), economic indicators (consumer price index)

Cleaning involves preparing the data for modelling, such as addressing missing values and removing certain characters from the syntax.

Image source: https://lab.getapp.com/importance-of-data-cleaning-and-governance/

2. EXPLORE AND VISUALISE DATA



In this visualisation, we looked at the number of customers who subscribed to the term deposit in our pool of 39,000 observations. We see that for this campaign uptake was around 11% for our existing client base. This imbalance meant that we had to undertake certain steps to ensure our model was useful and be careful selecting our evaluation metric. I'd be happy to go into further details into the steps taken at the end, time permitting.

3. TRAIN AND EVALUATE MODELS

	Accuracy	F1	Precision	Recall	Profit
Logistic Regression	0.83	0.44	0.36	0.62	38980
KNN	0.60	0.3	0.19	0.75	33860
Decision Tree	0.86	0.47	0.42	0.54	36050
Naive Bayes	0.56	0.28	0.17	0.78	31510
Random Forrest	0.82	0.44	0.35	0.62	38630
Adaboost	0.85	0.46	0.40	0.57	36910
Gradient Boosting	0.85	0.47	0.45	0.59	38760
XGBoost	0.87	0.49	0.38	0.56	**39050**

With our data prepared, we tried various classification models to predict which customers would subscribe. The different algorithms are presented on the left-most column. We then looked at the model's performance across various metrics.
We defined a custom profit metric which took into consideration the expected revenue and cost of a call. I would be happy to go over details in the end and have details in the appendix. For this metric, the higher the value the better the model. As such our final chosen model was an XGBoost classifier. It is essentially a collection of decision trees, think flowcharts where each additional tree is focussed on correcting the errors of the previous one.

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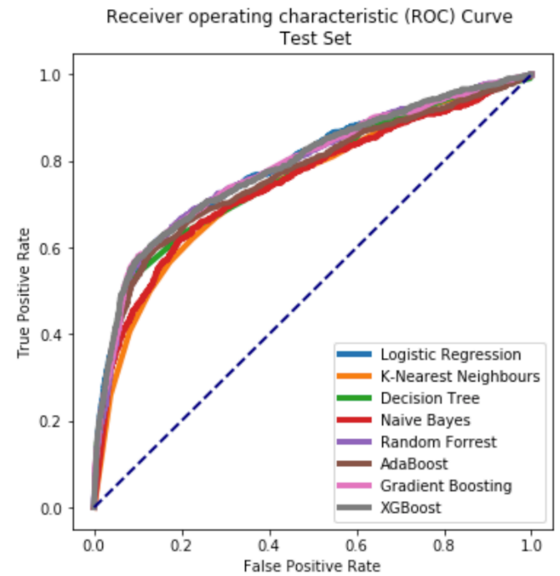

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4. FINAL PREDICTIONS

- 2000 new customers
- 500 calls, subscription value = $100
- Expected revenue: $5,000-7,500

- Used XGBoost classification model to select 500
- 144 customers subscribed
- **$14,400 revenue**

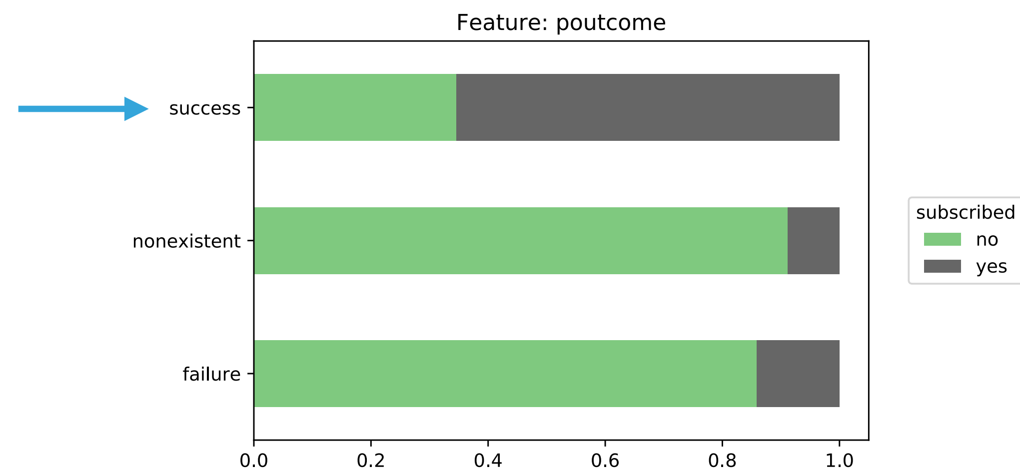
Recall our problem statement. We had 2000 new customers and were making 500 calls. With a subscription valued at $100 and uptake between 10-15%, the expected revenue was between $5,000 and $7,500.

Well we used our XGBoost classification model to select the 500 customers to call. Out of these 144 subscribed, almost 30%. This resulted in revenue of $14,400.

RECOMMENDATION - STUDENT/ RETIRED

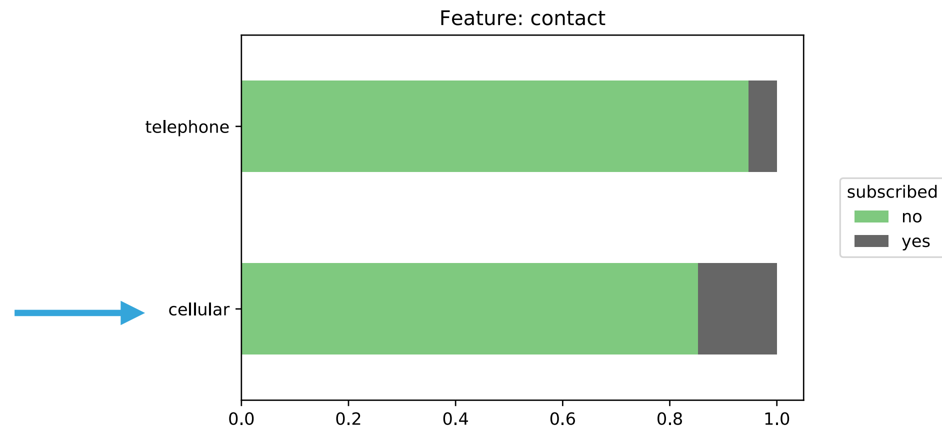
We investigated the rate of subscription amongst various job categories and the results are plotted in the form of a stacked bar chart. We can see that a greater proportion of students and retired customers said yes. As such we would recommend targeted campaigns for these types of customers.

RECOMMENDATION - PREVIOUSLY SUBSCRIBED



We looked at the results of the previous marketing campaign and noted that 65% of subscribers who previously subscribed to a term deposit (value success indicated by the blue arrow) subscribed this time round. As such keeping track of who is interested in the term deposit is useful and these customers should be contacted as a priority.

RECOMMENDATION - CELLULAR CONTACT



We investigated how a customer was contacted and noted a difference between landline and cellular. It appears that cellular calls had a higher chance of resulting in a subscription and thus should be the preferred method of contact.

FUTURE WORK

- Customer segmentation
- Determine optimal number of calls
- Seasonality

Customer segmentation: We would use unsupervised machine learning techniques, namely clustering, to gain a better understanding of the bank's customer base. This would help not only target future similar campaigns but also improve the bank's overall relationship with customers.
Determine optimal number of calls: In this scenario, we were informed that the bank had the budget for 500 calls. But what is the actual optimal number of calls to ensure most potential subscribers are reached, whilst not wasting resources?
Seasonality: We would establish the best month for launching the next campaign, to maximise success.