

Optimizing Targeted Telemarketing Strategies

Institute of Data Capstone Project
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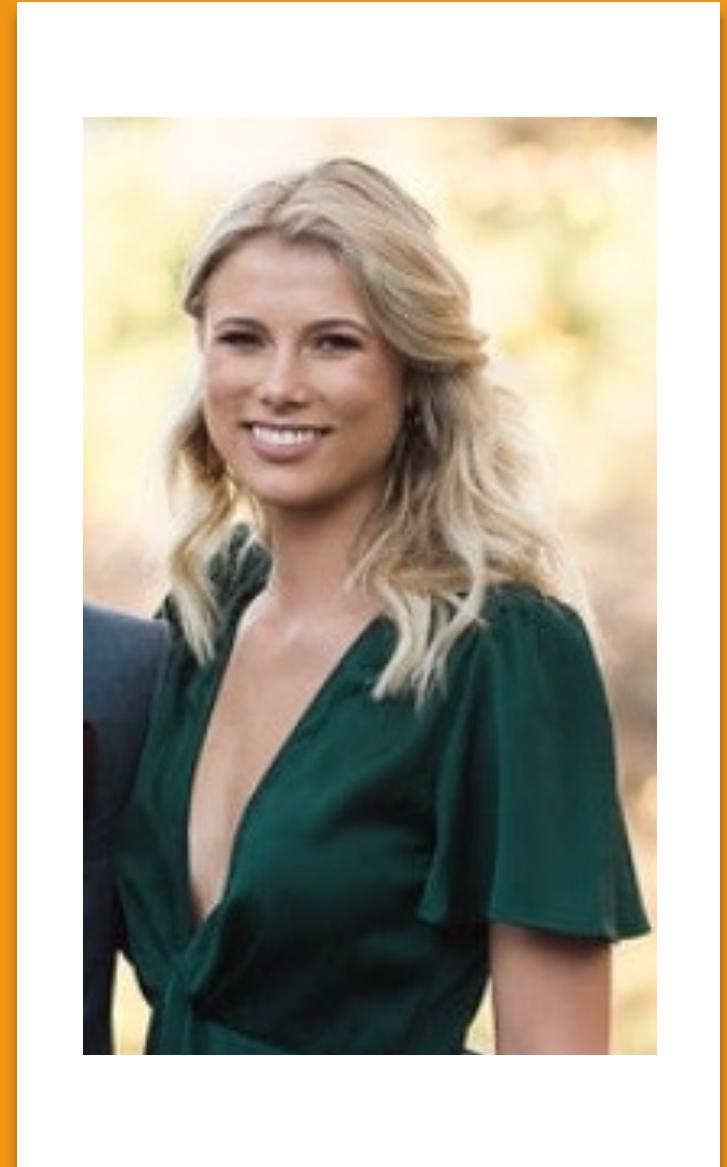


Today's Agenda

1. Who am I and what can I do for YOU?
2. Case Context
3. Defining the Problem
4. Exploring the Data
 - Process Flow
 - Initial Findings
5. Delivering the Solution
 - Feature Engineering
 - Machine Learning Models
6. Overall Findings
 - Supervised ML
 - Unsupervised ML
7. Next Steps

Anna-Maria Schreiner

- **Academic Background:**
 - Bachelor of International Business Management at University of Queensland (Australia) and Universität St Gallen (Switzerland)
 - RMIT / Udacity Business Analytics Nanodegree
 - Institute of Data Graduate Certificate of Data Science and Artificial Intelligence (in completion)



Case Context: Declining Revenue in Retail Banking



- Retail bank problem area:
 - Problem → Declining revenue
 - Strategized Solution → deploying direct telemarketing campaigns to promote long-term deposits
- How can I help?
 - Modeling the success of the marketing campaigns will be indispensable knowledge gained and add significant value:
 - ✓ Success rate of the campaign (present and future)
 - ✓ Which clients are most financially viable to target
 - ✓ Optimize marketing strategies and improve effectiveness

Time to Solve Some Problems!

- *Can customers be targeted more effectively to increase the ratio of successful telemarketing phone calls?*

Business
Question

Data
Question

- *Can a Machine Learning model predict which clients are most likely to successfully respond to telemarketing calls?*

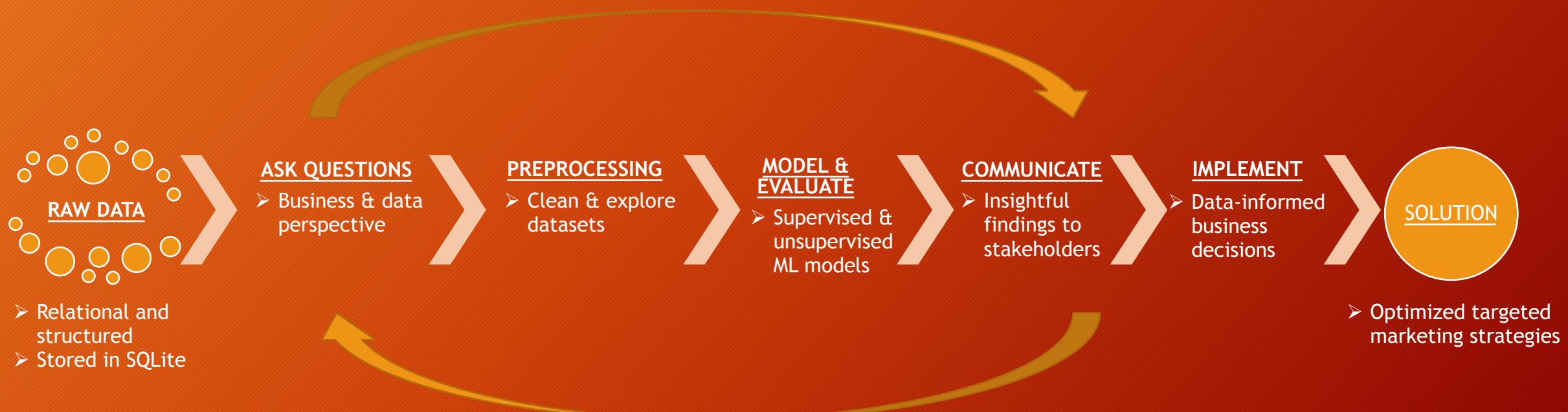
- *Provide granular customer insights to stakeholders with the aim to optimize telemarketing strategies and improve effectiveness.*

Desired
Output

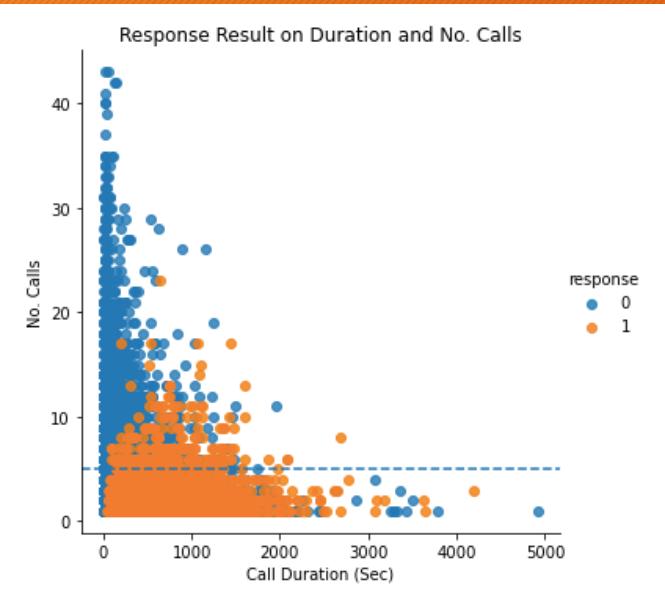


Exploring the Data: Data Science Process Flow

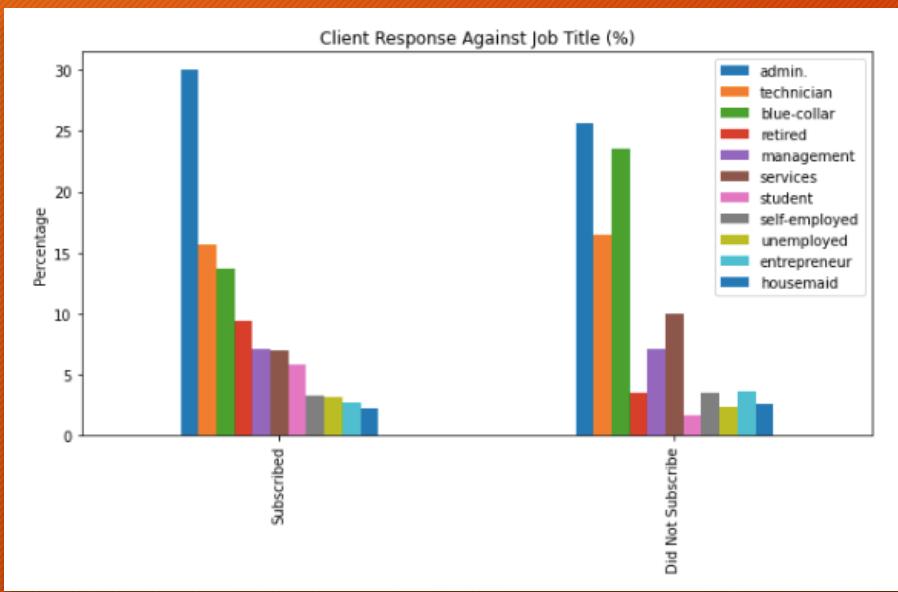
To be iterated in line with the business and
data questions, via stakeholders



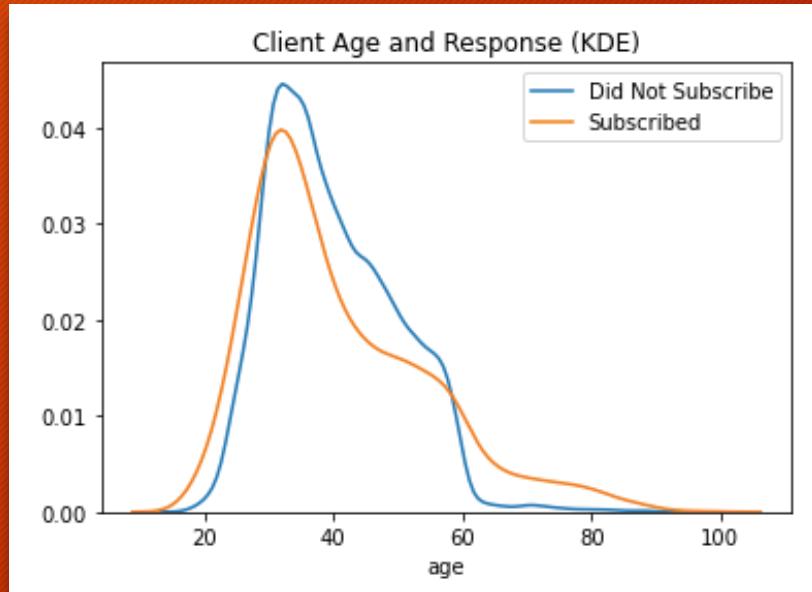
1.



2.



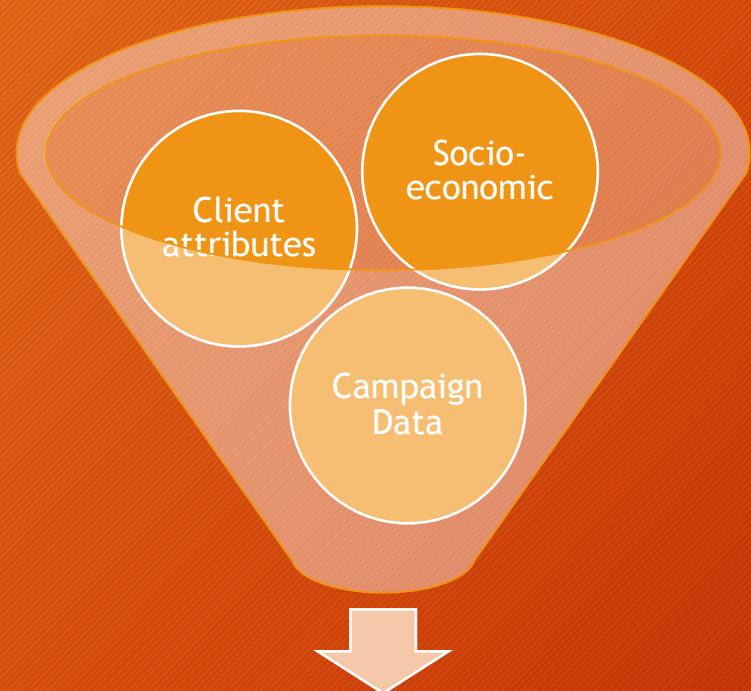
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Exploring the Data: Initial Findings

Delivering the Solution: Feature Engineering

Inputs: Predictor Variables



Preparing the Feature Vector:

1. To maintain a strong model, most features were used - only those that deemed inaccurate or incomplete were removed.
2. Categorical attributes had to be converted numerical by mapping binary variables or one-hot encoding nominal variables
3. Normalized scaler to standardize dummy variables with original numerical data
4. SMOTE: Synthetic resampling technique for class imbalance

Delivering the Solution: ML Models

Binary Classification Modelling (Supervised):

1. Logistic regression (With and without synthetic resampling)
 - Adapts so that binary target variable remains discrete
 - Logit function: $\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X$
 - Calculate predicted y: $\hat{y} = \beta_0 + \beta_1 X$
 - Calculate p (probability of True, where $0 < p > 1$):

$$p = \frac{e^{\hat{y}}}{e^{\hat{y}} + 1} = \frac{1}{1 + e^{-\hat{y}}}$$

2. Support Vector Machine

- Concept based upon the mapping of an optimal hyper-plane for linearly separable classifiers
- Function in Lagrangian form:

$$\text{Minimize: } J(w, b, a) = \frac{1}{2} w^T w - \sum_{i=1}^N a_i d_i (w^T x_i + b) + \sum_{i=1}^N a_i$$

Clustering Challenge! (Unsupervised):

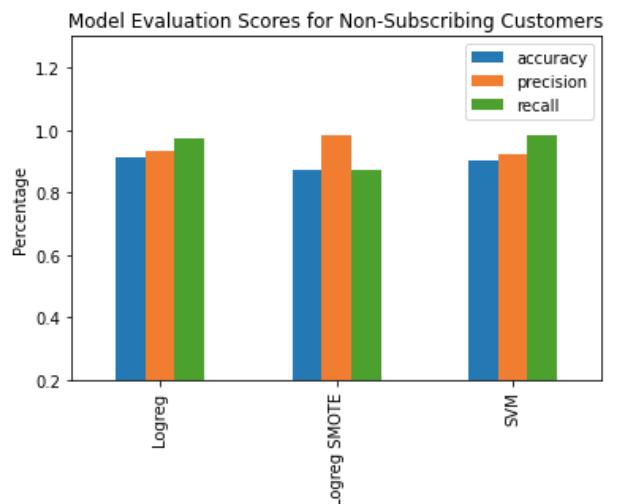
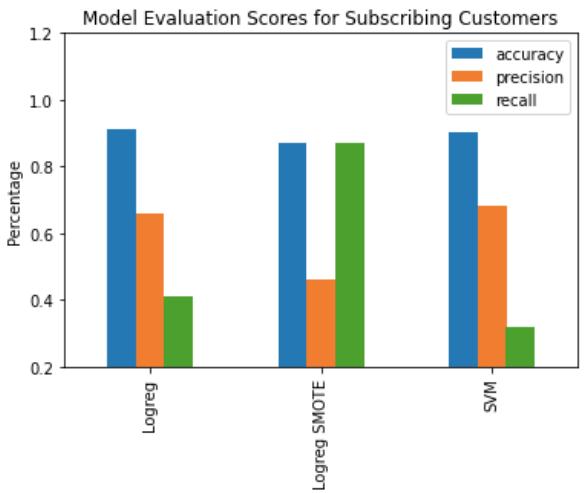
1. K-means

- An iterative algorithm that attempts to partition the data into distinct subgroups
- Objective function: $J = \sum_{i=1}^m \sum_{k=1}^K w_{ik} \|x^i - \mu_k\|^2$
- Will one cluster of client attributes be likely to respond more positively to the telemarketing campaign than another?

(1) Findings: Supervised ML

- Model Evaluation
 - Accuracy Score maintained consistency but deemed potentially unreliable on an unbalanced classifier dataset. However, accuracy of below 90% implies less risk of overfitting the data.
 - Logistic regression was comparatively insensitive in its detection of classes UNTIL the data was synthetically resampled (SMOTE) (From 41% recall to 87%!)
 - SVM had stronger precision but significantly low recall in detecting positive responses (subscribing clients)
- Conclusion:
 - With 87% accuracy (room for generalizability) and 87% recall (sensitivity in detecting positive instances) the model to most effectively predict the response of customers would be logistic regression on a synthetically resampled dataset.

	accuracy	precision	recall
Logreg	0.91	0.66	0.41
Logreg SMOTE	0.87	0.46	0.87
SVM	0.90	0.68	0.32



(2) Findings: Unsupervised ML

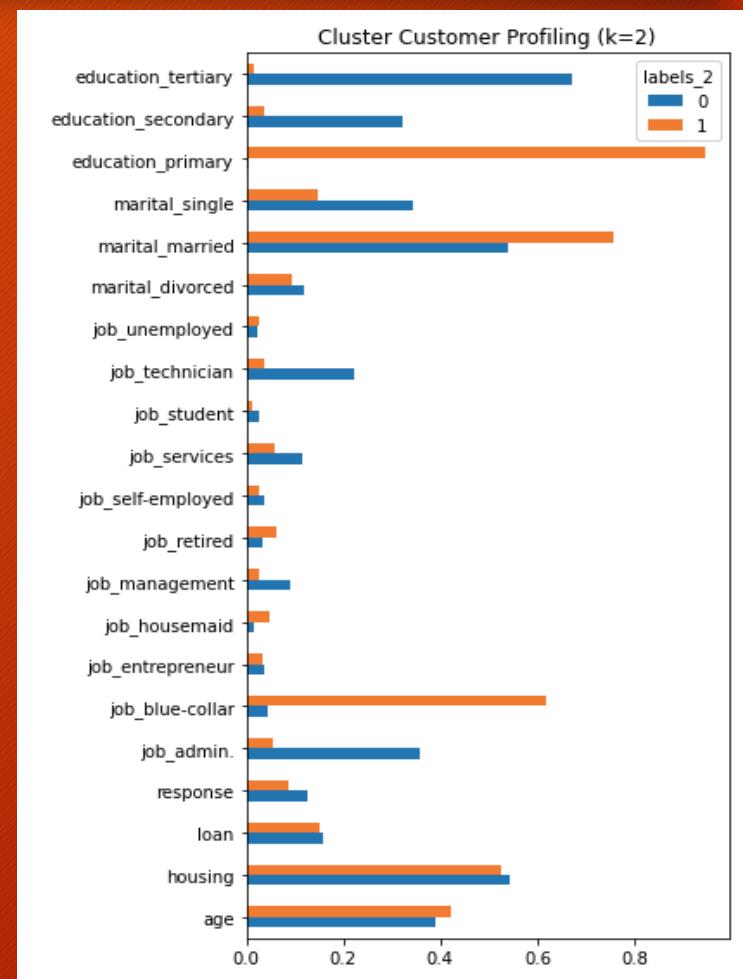
K-Means Customer Profiling (when optimal k=2)

CLUSTER 0

- More likely to subscribe
- Age: Less than 40
- Education: Tertiary
- Marital: Highest representation of singles
- Job: administration and technician roles

CLUSTER 1

- Less likely to subscribe
- Age: 40+
- Education: Base-level education
- Marital: Married
- Job: Blue-collar roles



Next Steps

Implementation of insights:

- Targeted campaigns to ensure optimized success rate based of:
 - Proficient predictive modelling
 - Clustered client attributes with increased successful response potential
 - Refined methods of contact (e.g. no more than 5 calls per client)
- Stakeholder value:
 - Optimized marketing strategies = more efficient targeted approach
 - Understanding customer needs = more effective campaigns, smarter product design and greater customer satisfaction

Future adaptations:

- Exploration of client attributes to business engagement
- Modelling monetary cost-benefit analysis across multiple models of interest
- Adjusting for limitations caused by a significantly imbalanced classifier, incompleteness of data and handling of multiple categorical variables

Any Questions?

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