

Image source: <https://appsamurai.com/mobile-audience-targeting-how-to-hit-the-bulls-eye/>

## PROBLEM STATEMENT

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

### Goal

- ▶ Identify which 500 customers to contact to maximise revenue
- ▶ Data-driven recommendations for future campaigns



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



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



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

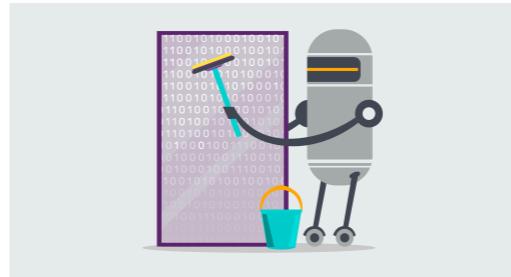
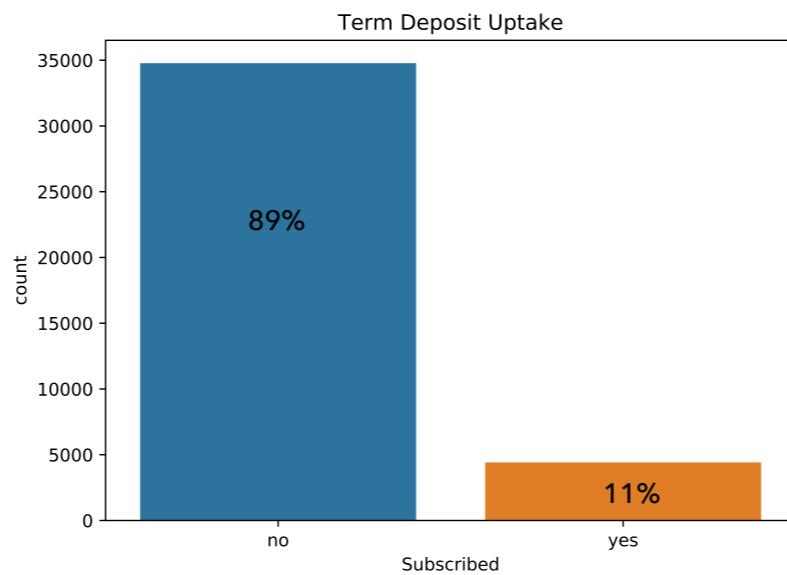


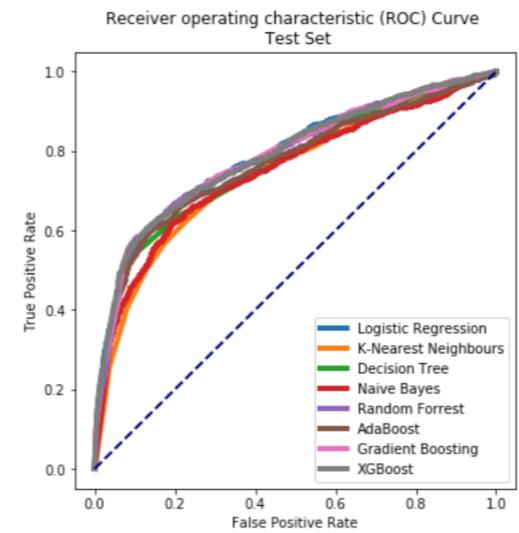
Image source: <https://lab.getapp.com/importance-of-data-cleaning-and-governance/>

## 2. EXPLORE AND VISUALISE DATA



### 3. TRAIN AND EVALUATE MODELS

	Accuracy	F1	Recall	Profit
Logistic Regression	0.83	0.44	0.62	38980
KNN	0.60	0.3	0.75	33860
Decision Tree	0.86	0.47	0.54	36050
Naive Bayes	0.56	0.28	0.78	31510
Random Forrest	0.82	0.44	0.62	38630
Adaboost	0.85	0.46	0.57	36910
Gradient Boosting	0.85	0.47	0.59	38760
XGBoost	0.87	0.49	0.56	<b>39050</b>

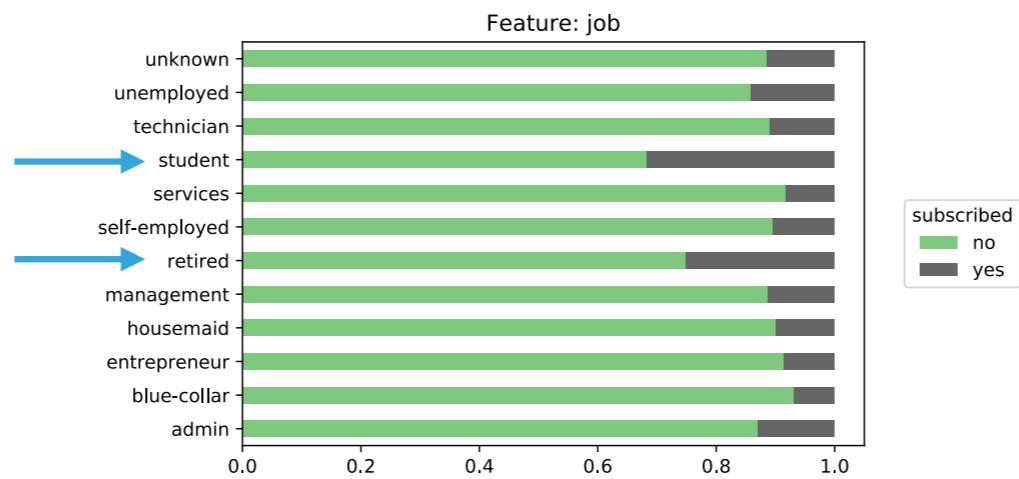


## 4. FINAL PREDICTIONS

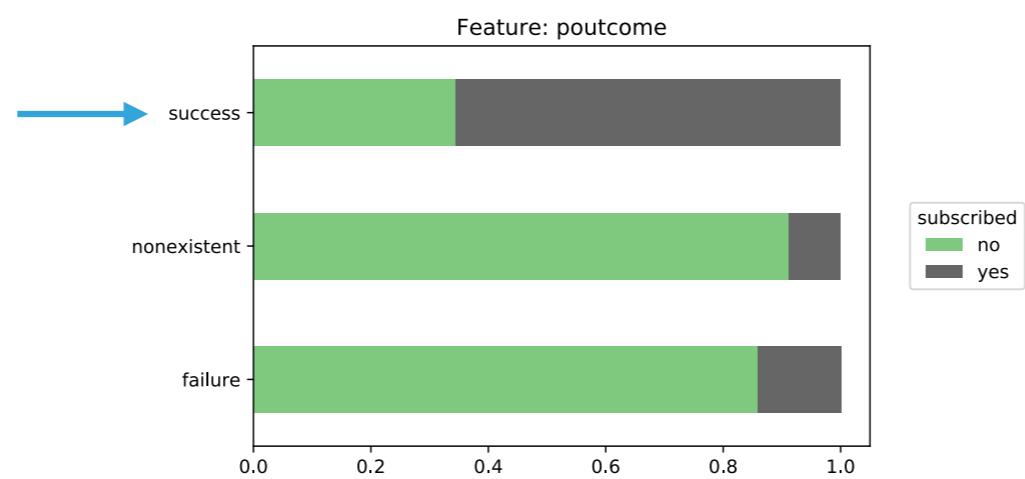
- ▶ 2000 new customers
- ▶ 500 calls, subscription value = \$100
- ▶ Expected revenue: \$5,000-7,500
  
- ▶ Used XGBoost classification model to select 500
- ▶ 145 customers subscribed
- ▶ **\$14,500 revenue**



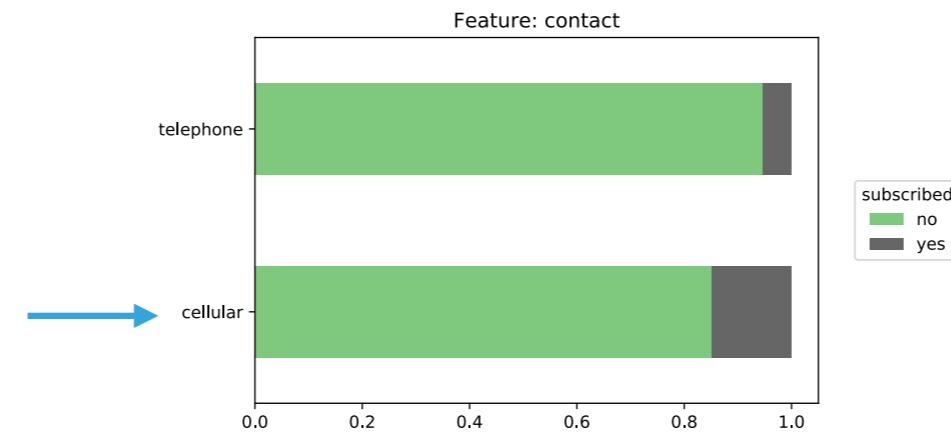
## RECOMMENDATION - STUDENT/ RETIRED



## RECOMMENDATION - PREVIOUSLY SUBSCRIBED



## RECOMMENDATION - CELLULAR CONTACT



## FUTURE WORK

- ▶ Customer segmentation
- ▶ Determine optimal number of calls
- ▶ Explore alternative marketing models
- ▶ Seasonality
- ▶ Deep learning

# THANK YOU

NADINE AMERSI-BELTON

 nzamersi@gmail.com

 datascimum

 nadinezab

## PROFIT METRIC 1/2

	Predict No	Predict Yes
Actual No	0	 False Positive FP
Actual Yes	0	 True Positive TP

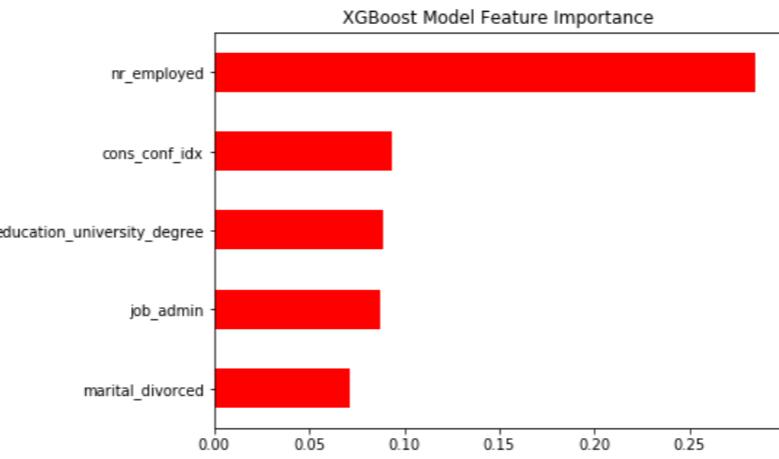
$$\text{Profit} = \text{TP} * (R-C) + \text{FP} * (-C)$$

## PROFIT METRIC 2/2

	Predict No	Predict Yes
Actual No	0	-10 <small>False Positive FP</small>
Actual Yes	0	100 - 10 <small>True Positive TP</small>

$$\text{Profit} = 90\text{TP} - 10\text{FP}$$

# FEATURE IMPORTANCE



# LOGISTIC REGRESSION

- ▶ Uses logistic function
- ▶ Best parameters:
  - ▶ C = 0.1
  - ▶ Solver = Liblinear
- ▶ Accuracy: 0.83
- ▶ F1: 0.44
- ▶ Recall: 0.63
- ▶ Profit: 38980

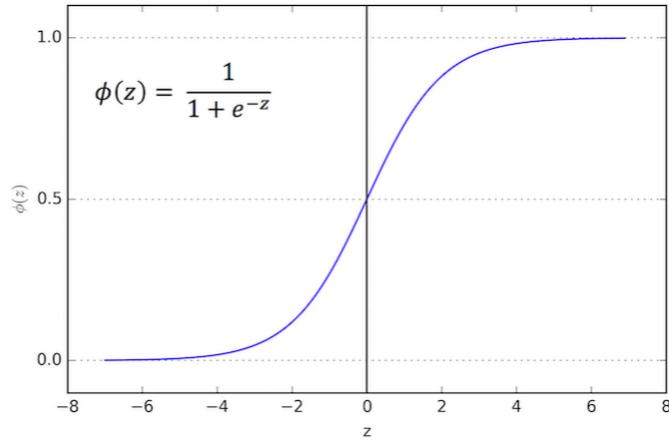


Image: <https://www.analyticsvidhya.com/blog/2020/04/machine-learning-using-c-linear-logistic-regression/logistic-4/>

## K-NEAREST NEIGHBOURS

- ▶ Distance-based classifier
- ▶ Best parameters:
  - ▶ Number of neighbours = 15
  - ▶ Weights = uniform
  - ▶ P = 5 (Minkowski power)
- ▶ Accuracy: 0.60
- ▶ F1: 0.30
- ▶ Recall: 0.75
- ▶ Profit: 33860

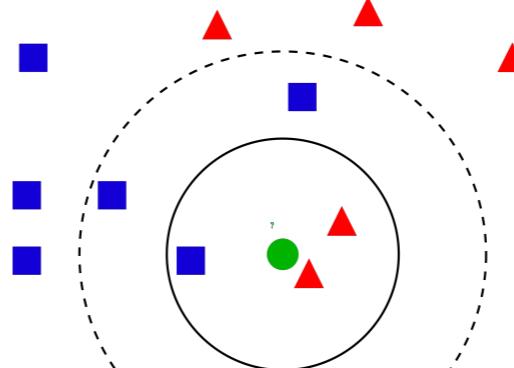
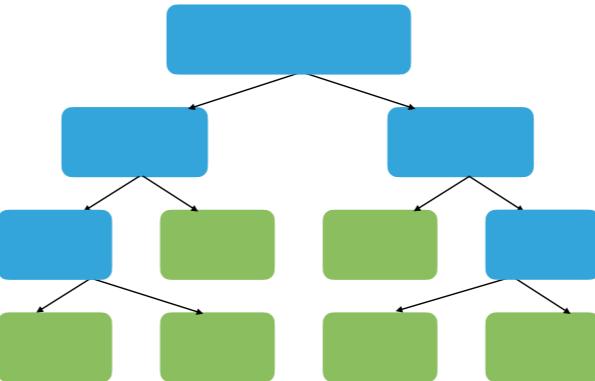


Image source: <https://www.analyticsvidhya.com/blog/2018/03/introduction-k-neighbours-algorithm-clustering/>

# DECISION TREE

- ▶ Directed acyclic graph, greedy algorithm
- ▶ Best parameters:
  - ▶ Criterion = Gini
  - ▶ Max Depth = 5
  - ▶ Min Samples Split = 3
- ▶ Accuracy: 0.84
- ▶ F1: 0.31
- ▶ Recall: 0.32
- ▶ Profit: 20280



## NAIVE BAYES

- ▶ Based on Bayes' Theorem
- ▶ Naive assumption of independence between features
- ▶ Accuracy: 0.56
- ▶ F1: 0.28
- ▶ Recall: 0.78
- ▶ Profit: 31510



Image source: [https://en.wikipedia.org/wiki/Thomas\\_Bayes](https://en.wikipedia.org/wiki/Thomas_Bayes)

# RANDOM FOREST

- ▶ Ensemble method, multiple decision trees
- ▶ Best parameters:
  - ▶ Criterion = Gini
  - ▶ Number of estimators = 100
  - ▶ Max depth = 4
  - ▶ Min samples split = 10
- ▶ Accuracy: 0.82
- ▶ F1: 0.44
- ▶ Recall: 0.62
- ▶ Profit: 38630

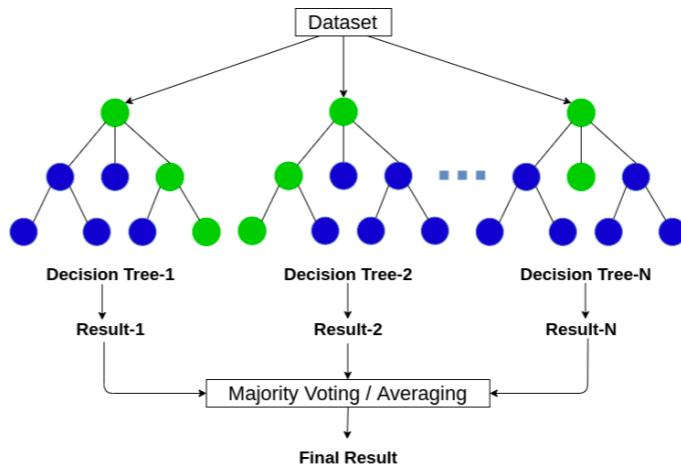


Image source: <https://www.analyticsvidhya.com/blog/2020/05/decision-tree-vs-random-forest-algorithm/>

# ADABOOST

- ▶ Ensemble method
- ▶ Adjusts weights to focus on difficult cases
- ▶ Best parameters:
  - ▶ Number of estimators = 100
  - ▶ Learning rate = 1
- ▶ Accuracy: 0.85
- ▶ F1: 0.46
- ▶ Recall: 0.57
- ▶ Profit: 36910

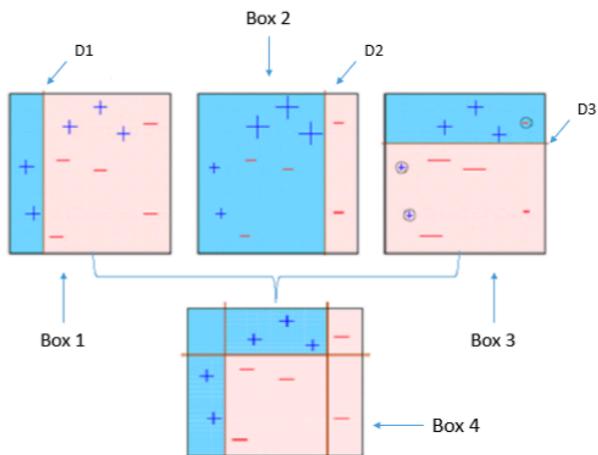


Image source: <https://towardsdatascience.com/understanding-adaboost-2f94f22d5bfe>

# GRADIENT BOOSTING

- ▶ Ensemble of weak learners, decision trees
- ▶ Optimizes differentiable loss function
- ▶ Best parameters:
  - ▶ Number of estimators = 20
  - ▶ Max depth = 3
  - ▶ Min samples split = 3
- ▶ Accuracy: 0.85
- ▶ F1: 0.47
- ▶ Recall: 0.59
- ▶ Profit: 38760

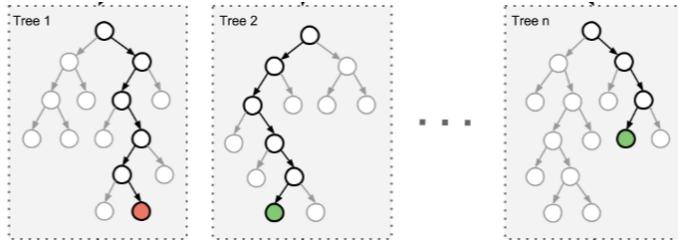


Image source: <https://blog.statsbot.co/ensemble-learning-d1dcd548e936>

# XGBOOST

- ▶ Ensemble method, multiple decision trees
- ▶ Best parameters:
  - ▶ Number of estimators = 20
  - ▶ Max depth = 3
  - ▶ Min child weight = 3
- ▶ Accuracy: 0.87
- ▶ F1: 0.49
- ▶ Recall: 0.56
- ▶ Profit: 39050

