Class 7 Predictive Analytics for STP (II): Supervised Learning

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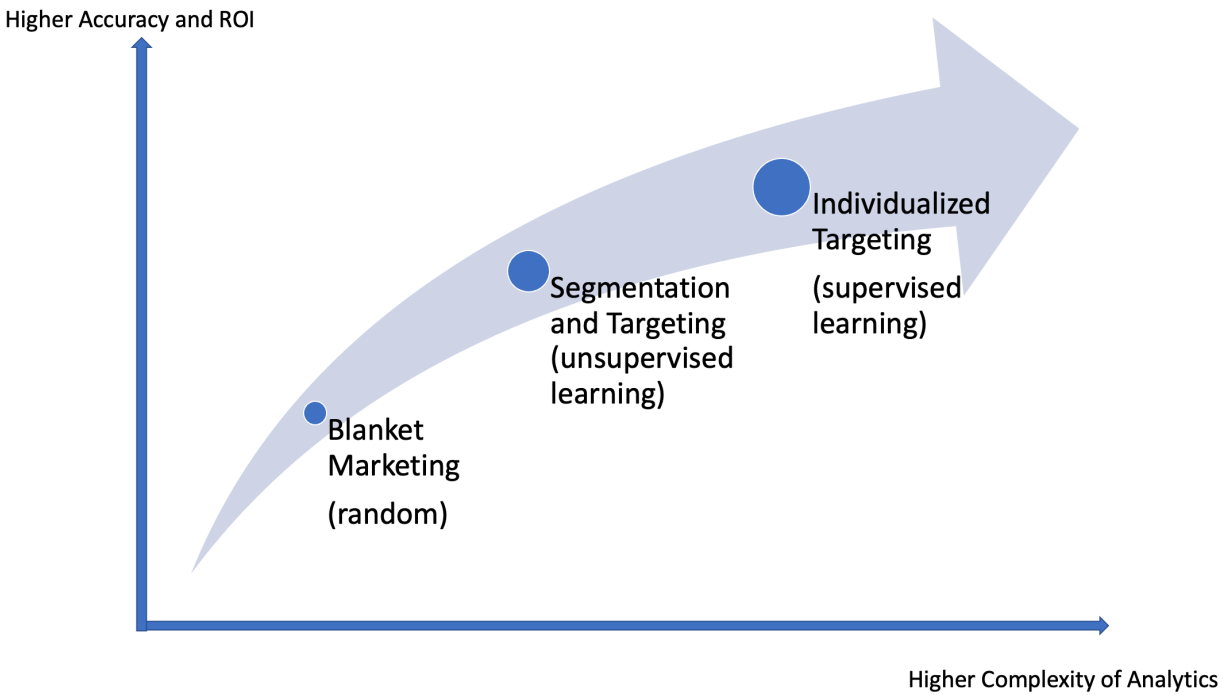
Section 1

Supervised Learning

Motivation: Why Supervised Learning for Business?



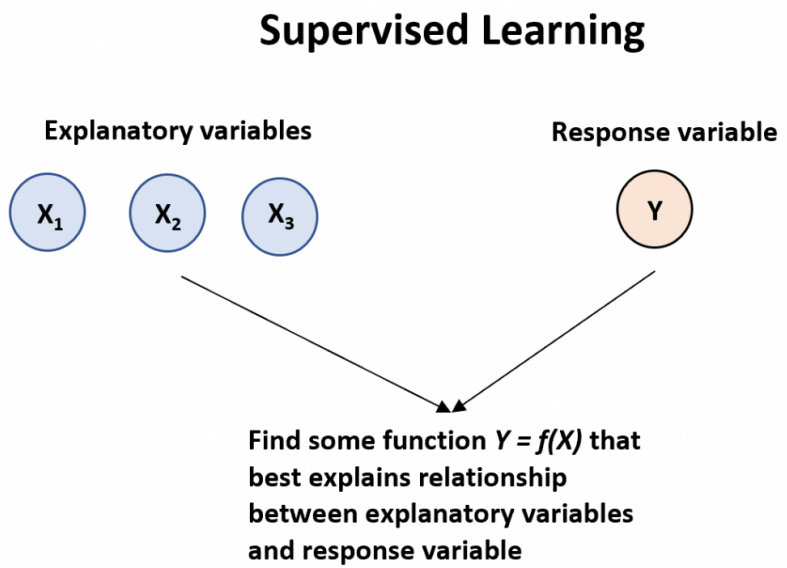
Data Generating Process

$$Y = f(X; \theta) + \epsilon$$

- f is the function that characterizes the true relationship between X and Y
  - f is often called Data Generating Process (DGP), which is NEVER known to us
- Y the **response/outcome/explained** variable to be predicted
  - e.g., whether customer responds to our offer (1/0)
- $X = (X_1, X_2, ..., X_p)$ are a set of **predictors/features/explanatory variables**
  - customers' past purchase history (e.g., spending in each category)
  - demographic variables (e.g., income, age, kids, etc.)
- θ represents the set of **function parameters** of the DGP f
- ϵ is the random **error term**, with mean zero.

Supervised Learning

- A **supervised learning model** is used when we have one or more explanatory variables and a response variable and we would like to find some function that describes the DGP between the explanatory variables and the response variable as accurately as possible.



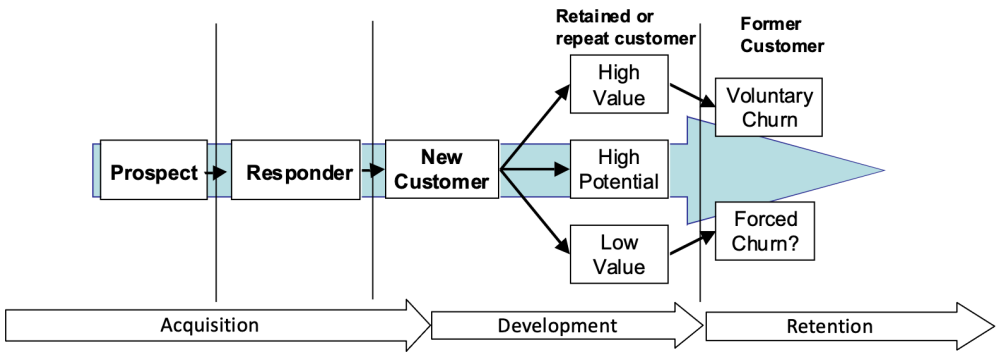
- Since we never know the true DGP: All models are wrong, but some are useful[1]

[1] A famous quote by statistician George Box.

Types of Supervised Learning Tasks for Customer Relationship Management

Depending on the type of the **response variable**, supervised learning tasks can be divided into two major groups

- **Classification tasks**: outcome is a categorical variable
  - Whether a customer responds to marketing offers (acquisition)
  - Whether a customer churns (retention)
- **Regression tasks**: outcome is a continuous variable
  - Probability of customers responding to marketing offers (acquisition)
  - Customer total spending in each period (development)
  - Probability of customer churn (retention)



Difference between Supervised and Unsupervised Learning

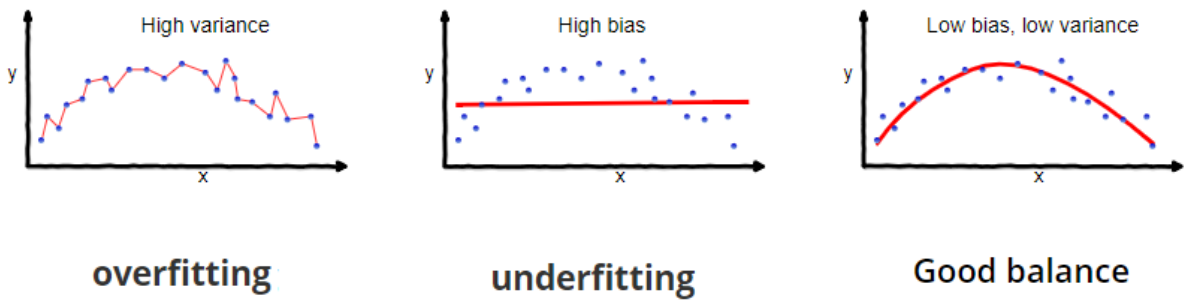
	Supervised Learning	Unsupervised Learning
Description	Involves building a model to estimate or predict an output based on one or more inputs.	Involves finding structure and relationships from inputs. There is no "supervising" output.
Variables	Explanatory and Response variables	Explanatory variables only
End goal	Develop model to **(1)** predict new values or **(2)** understand existing relationship between explanatory and response variables	Develop model to **(1)** place observations from a dataset into a specific cluster or to **(2)** create rules to identify associations between variables.
Types of algorithms	**(1)** Regression and **(2)** Classification	**(1)** Clustering and **(2)** Association

Commonly Used Supervised Learning Models

- Linear regression class models (easy to interpret, low accuracy)
  - OLS, Lasso, Ridge regressions
- **Tree-based Models (good balance between interpretability and accuracy)**
  - Decision tree, random forest
- Neural-network based models (hard to interpret, high accuracy)
  - Deep learning models

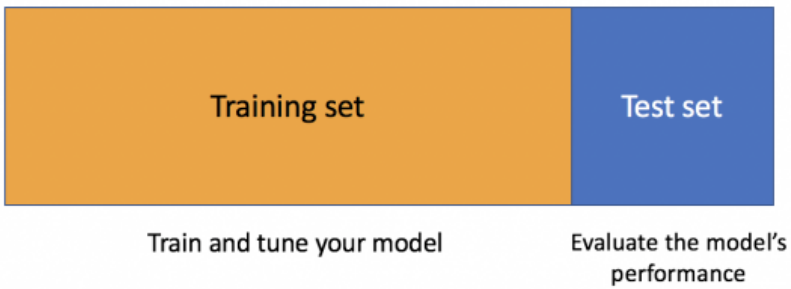
Overfitting and Underfitting

- **Overfitting** means a predictive model corresponds too closely to **historical data**, and therefore fails to predict **new data** reliably.
  - Overfitting leads to high **variance error**, which is the error from being unable to predict for new data points
- **Underfitting** occurs when a predictive model cannot adequately capture the underlying structure of **historical data**.
  - Underfitting leads to high **bias error**, which means high prediction error on the historical data, as the model fails to sufficiently capture the relations between X and Y
  - An underfitting model also tends to have poor predictive performance for future data points.



Mitigate the Underfitting and Overfitting Problems

- To mitigate the underfitting problem, select better models and tune the parameters.
- To mitigate the overfitting problem, when building predictive models, we need to divide the **full labelled historical data** into different sets. The percentage of split depends on the context.
  - **Training set** (70% - 80% of labelled data)**:** train the model parameters
  - **Test set** (20% - 30% of labelled data)**:** evaluate the prediction accuracy



- For more complicated models with hyper-parameters such as deep learning models, we may even need to split our data into 3 sets (training, validation, and test sets). You will learn more details in term 2 from ML specialization modules.

Section 2

Decision Tree and Random Forest

Introduction to Decision Tree

- There are many methodologies for constructing regression trees but one of the oldest and most commonly used is known as the **c**lassification **a**nd **r**egression **t**ree (CART) approach developed by Breiman et al. (1984).

Motivation Example: Predicting mpg from mtcars

- From mtcars, we want to predict the outcome variable mpg based on cyl and hp
  - Predictors X include cyl and hp
  - Outcome variable Y is mpg

```
pacman::p_load(dplyr,modelsummary)
data("mtcars")
# Generate a new data for the task
data_decision_tree <- mtcars %>%
  select(mpg,cyl,hp)
# check first 4 rows
data_decision_tree %>%
  head(n = 4)
```

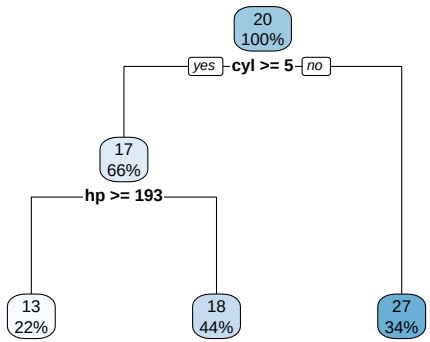
	mpg	cyl	hp
Mazda RX4	21.0	6	110
Mazda RX4 Wag	21.0	6	110
Datsun 710	22.8	4	93
Hornet 4 Drive	21.4	6	110

Implementation of Decision Tree in R

- Package `rpart` provides implementation of decision trees in R
  - `rpart()` is the function in the package to train a decision tree; refer to its help function for more details.
- Package `rpart.plot` provides nice visualizations of decision trees

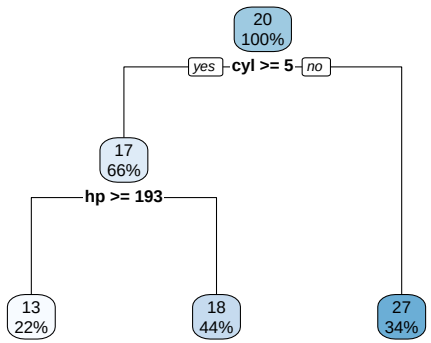
```
# Load the necessary packages
pacman::p_load(rpart,rpart.plot)
# Below example shows how to train a decisin tree
tree1 <- rpart(
  formula = mpg ~ cyl + hp,
  data    = data_decision_tree,
  method  = "anova"
  )
```

Intuition behind Decision Trees



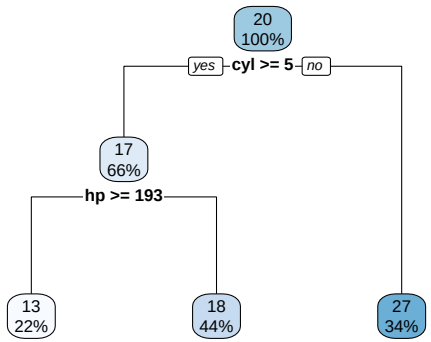
1. First, we find that `cyl` matters more than `hp` in terms of predicting mpg, so we split two branches according to `cyl`. We find that {4} and {6,8} split can best differentiate car models.
   - `cyl` = 4, go to the right branch
   - `cyl` = 6 or 8, go to the left branch

Intuition behind Decision Trees



2. For car models with 4 cylinders, we try all possible splits based on `hp`, and find that 193 can best differentiate car models.
   - `hp` $>=$ 193, use the average `mpg` in that **terminal node,** 13, as the predicted `mpg`
   - `hp` $<$ 193, use the average `mpg` in that **terminal node,** 18, as the predicted `mpg`

Intuition behind Decision Trees



3. For car models with less than 5 cylinders (the right branch), we find that `hp` does not differentiate car models, so we do not further split.
   - Use the average `mpg` in that **terminal node,** 27, as the predicted `mpg`

Pros and Cons of Decision Trees

Advantages of Decision Trees

- They are very interpretable.
- Making predictions is fast.
- It's easy to understand what variables are important in making the prediction. The internal nodes (splits) are those variables that most largely reduce the SSE (criteria for split).

Disadvantages of Decision Trees

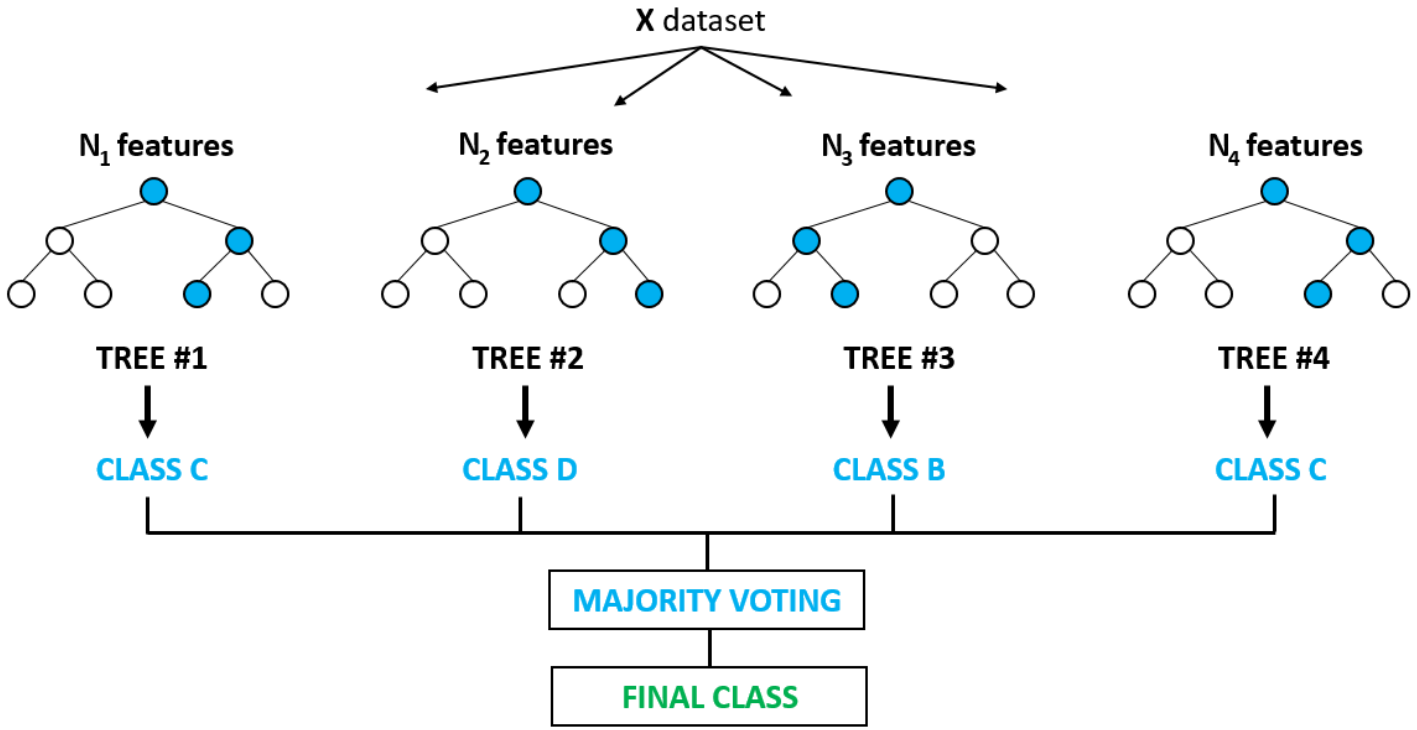
- Single regression trees have high variance (overfitting), resulting in unstable predictions.
- Due to the high variance, single regression trees tend to have poor predictive accuracy.

Random Forest

To overcome the overfitting tendency of a single decision tree, random forest has been developed by (Breiman 2001).

1. **Bootstrap subsampling**
   - Each tree is grown to a bootstrapped subsample
2. **Split-variable randomization**
   - each time a split is to be performed, the search for the split variable is limited to a random subset of *m* out of the *p* variables. For regression trees, typical default values are $m = p/3$.

Visualization of Random Forest



- Each tree gives a prediction
- Random forest takes the majority of voting as the final prediction

Implementation of Random Forest in R

- Package `ranger` provides implementation of random forest in R.
- `ranger()` is the function in the package to train a random forest; refer to its help function for more details.
- The following code shows how to train a random forest consisting of 500 decision trees, where the outcome variable is mpg, and the predictors are 5 car attribute variables.

```
pacman::p_load(ranger)
randomforest1 <- ranger(
    formula   = mpg ~ hp + cyl + disp + wt + gear,
    data      = mtcars, # dataset to train the model
    num.trees = 500, # 500 decision trees
    seed = 888 # make sure of replication
  )
```

Make Predictions from Random Forest

- After we train the predictive model, we can use `predict()` function to make predictions
  - The 1st argument is the trained model object
  - The 2nd argument is the dataset to make predictions on

```
# Make predictions on the mtcars
prediction_rf <- predict(randomforest1,
                         data = mtcars)

# Because prediction_rf is a list object
# Need to use $ to extract the predicted value as a numeric vector
prediction_rf$predictions
```

```
 [1] 20.80814 20.80526 24.13373 20.14718 17.50231 18.98494 14.73153 24.
 [9] 22.84680 18.73638 18.73638 16.26754 16.26130 16.17000 11.96695 11.
[17] 13.35940 29.91299 30.71855 31.04063 22.58045 16.30967 16.48256 14.
[25] 17.42216 29.60584 26.18860 28.29520 15.87313 20.14866 14.97831 22.
```

After-Class Reading

- (optional) Varian, Hal R. "Big data: New tricks for econometrics." Journal of Economic Perspectives 28, no. 2 (2014): 3-28
- (recommended) Decision tree in R
- (recommended) Random forest in R