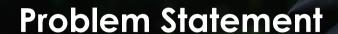


## **Contents**

- Problem Statement
- Goal & Questions
- Dataset Review
- Approach & Challenges





"Churn is important for Singapore's Telco because the market is no longer growing and so to acquire new customers they must persuade users to leave their existing operator."

Opensignal, 09/02/2021

"With an increase in the number of Telco, the level of competition is quite high. To sustain in this competition, Telco often try to retain their customers than acquiring new ones as it proved to be much costlier. Hence predicting churn is very important. Hence, to reduce customer churn, Telco need to predict which customer are at high risk or churn."

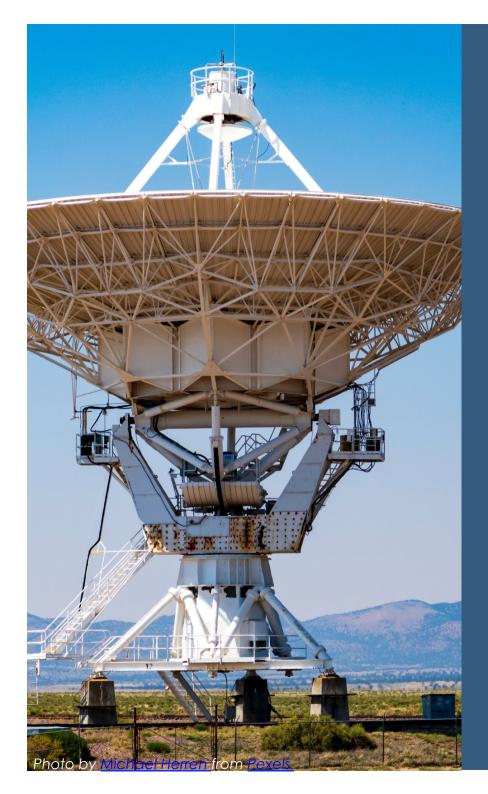
Medium.com, 22/08/2020

### Goal

To find out the most striking behaviour of customers through EDA and train the most predictive machine learning (ML) model to determine the customers who are most likely to churn.

### Questions

- What's the % of churn and customers that still in active services?
- Can we see different patterns in churn customers based on the type of service provided?
- Any difference pattern of churn between demographics?
- Any difference between customers that pay monthly and by year?
- Any other questions will be raise through EDA...
- What's the best classification ML model for prediction?
- What's the best hyper-parameters for selected ML model?



## **Dataset**

File:

Dataset\_(Jia Yang).csv

From:

www.kaggle.com

### **Description:**

Each row represents a customer, each column contains customer's attributes such as Churn/No-Churn, Signed-up Services, Account Info and Demographic Info

21 Columns & 7043 Rows

### **Dataset**

#### Total: 21 Columns & 7043 Rows



Churn/No-Churn

Target
D.Type: Character
Var.Type: Categorical
Column: 1

Churn



Services

Predictor
D.Type: Character
Var.Type: Categorical
Column: 9

Phone Service
Multiple Lines
Internet Service
Online Security
Online Backup
Device Protection
Tech Support
Streaming TV
Streaming Movies



Account Info

Predictor
D.Type: Num./Char.
Var.Type: Cont./Cat.
Column: 7

Customer ID
Tenure
Monthly Charges
Total Charges
Contract
Paperless
Payment Method



Demographics

Predictor
D.Type: Character
Var.Type: Categorical
Column: 4

Gender Partners Dependents Senior Citizen

# Dataset

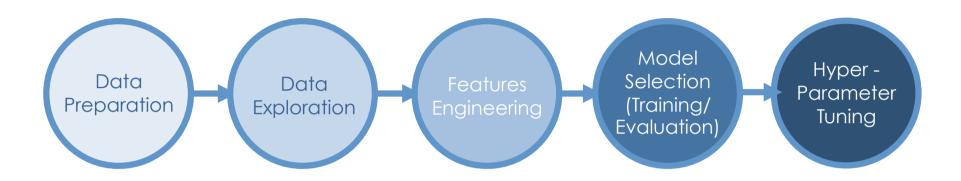
## Snapshot

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	 DeviceProtection
0	7590- VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	 No
1	5575- GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	 Yes
2	3668- QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	 No
3	7795- CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	 Yes
4	9237- HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	 No

5 rows x 21 columns

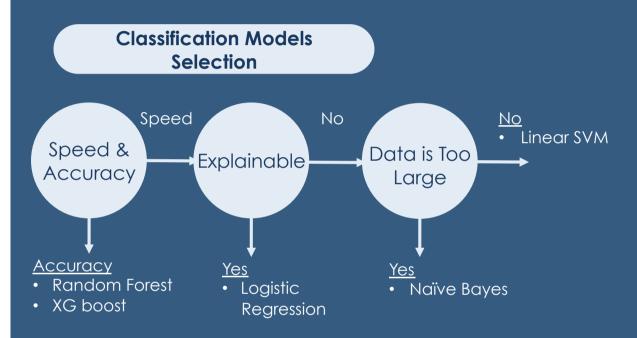
DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
No	No	No	No	Month- to-month	Yes	Electronic check	29.85	29.85	No
Yes	No	No	No	One year	No	Mailed check	56.95	1889.5	No
No	No	No	No	Month- to-month	Yes	Mailed check	53.85	108.15	Yes
Yes	Yes	No	No	One year	No	Bank transfer (automatic)	42.30	1840.75	No
No	No	No	No	Month- to-month	Yes	Electronic check	70.70	151.65	Yes

## **Approach & Challenges**



- Null values treatment
- Duplicate records
- Joining of datasets
- Relationship between variables
- Answer most of the identified questions
- Create new meaningful features
- Reduce unused features
- Data unbalance.
- Encode categorical features
- Scale overall dataset
- Choose the best
   Classification ML model
   based on different
   evaluation method
- Choose the best hyper parameter

# **Approach & Challenges**



#### **Evaluation Methods**

- Confusion Matrix
  - Accuracy
  - F1-Score
  - ROC / AUC

