

# **Customer Churn Data**

### **Features**

customerID, gender, SeniorCitizen, Partner, Dependents, tenure, PhoneService, MultipleLines, InternetService, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies, Contract, PaperlessBilling, PaymentMethod, MonthlyCharges, TotalCharges,

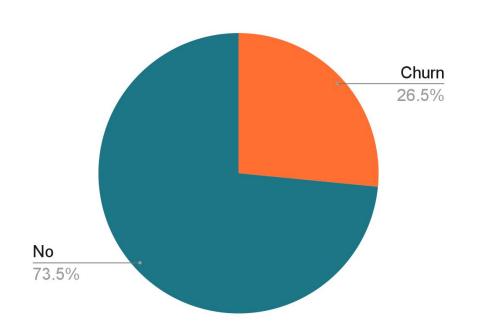
## **Target Label**

Churn



### =

# **Customer Churn Statistics**



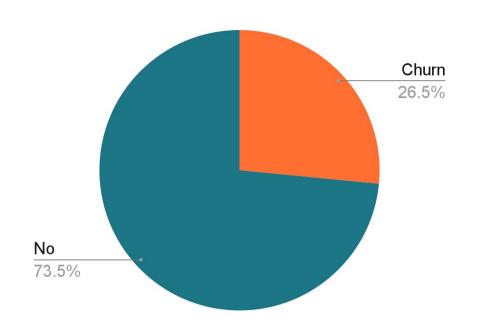
73.5%

No Churn

26.5%

Churn

# **Imbalance Data Problem**



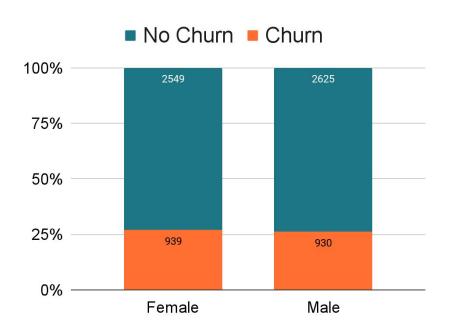
The target class has an **uneven distribution** of observations:

- Churn class label has a very low number of observations
- No Churn class label has a very high number of observations.



# Analyzing Churn Likelihood

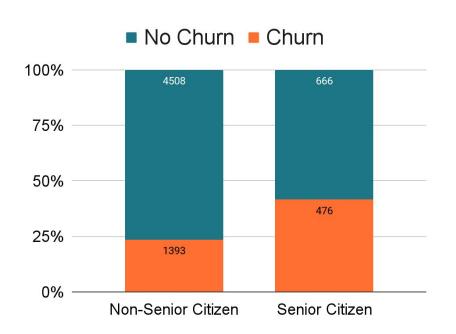
# Churn Likelihood - Gender



Both male and female have a **similar proportion** of "Churn vs No Churn", i.e. around 25% of them churn.

Thus, customer gender does not significantly affect the prediction whether a customer will churn or not.

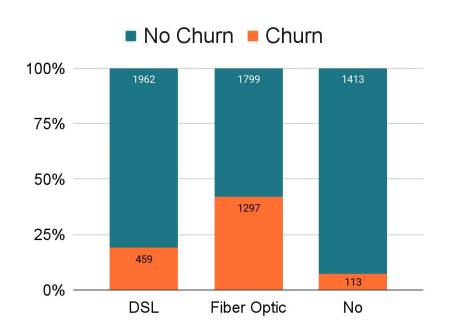




Almost half of Senior Citizen churn, while only a quarter of Non-Senior Citizen churn.

Thus, Senior Citizen is more likely to churn compared to Non-Senior Citizen

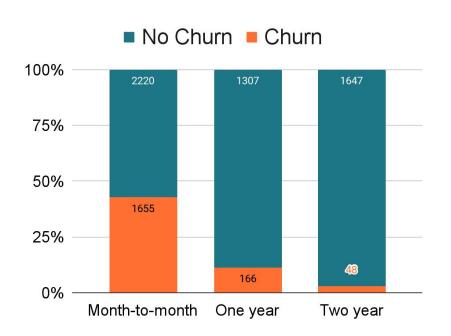
# **Churn Likelihood - Internet Service**



Less than 25% of customers who use DSL and No internet service churn, while almost half of Fiber Optic customer churn.

Thus, Fiber Optic customers are more likely to churn compared to DSL and No Internet Service customers

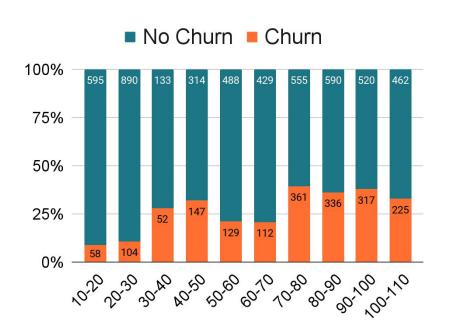
# Churn Likelihood - Contract



The customers with month-to-month contract have the highest churn proportion. The customers with two year contract have the lowest churn proportion.

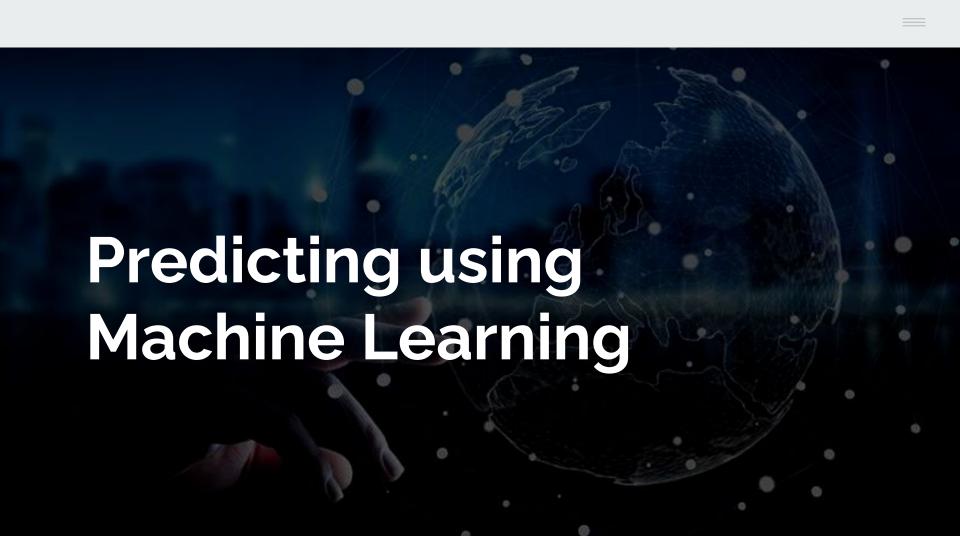
The longer customer contract will make the customer less likely to churn

# **Churn Likelihood - Monthly Charges**



The monthly charges are binned into 10 bins with interval size 10. There is an uptrend pattern on the churn proportion when the monthly charges increases.

The customers who have a higher monthly charges are more likely to churn



# Predicting using Machine Learning

# Converting Categorical Feature into Numerical Feature

Categorical data are variables that contain label values rather than numeric values. For example, there are 3 different internet service categories, i.e. fiber optic, DSL, and no service

ML algorithms require all input variables and output variables to be numeric.

## **Ordinal Encoding**

Citizen Seniority	Citizen
Senior Citizen	1
Non-Senior Citizen	0
Foreigner	2
Senior Citizen	1

## **One Hot Encoding**

Inet Service	IS_FO	IS_DSL	IS_No
Fiber Optic	1	0	0
DSL	0	1	0
No	0	0	1
DSL	0	1	0

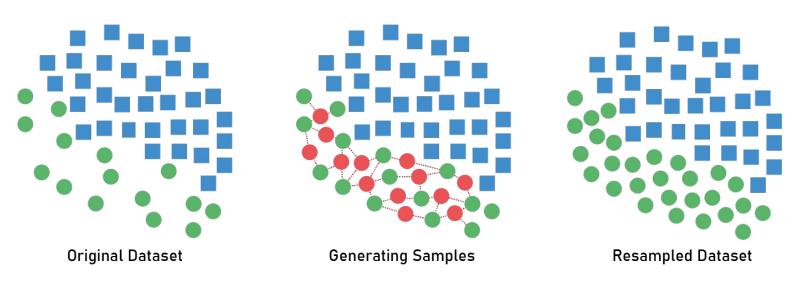
# Handling Imbalance Data? Oversampling



Generate examples from the minority class, i.e. creating more churn data

# **SMOTE: Synthetic Minority Oversampling Technique**

It generates new instances with the help of interpolation between the positive instances that lie together.



Hence, SMOTE helps to overcome the overfitting problem posed by random oversampling.

# Appropriate Evaluation Metric for Imbalance Data

### **Accuracy Paradox**

When one class of labels is underrepresented, it might get ignored while still keeping high accuracy of the model

### F1 score

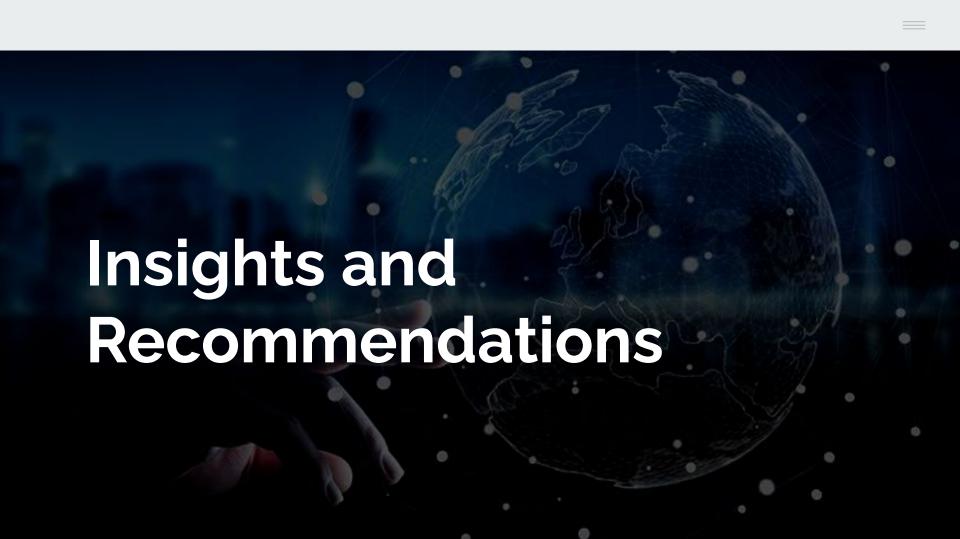
F1 score is very useful when dealing with imbalanced classes problems

$$F1 \ score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

# **Evaluating Machine Learning Models**

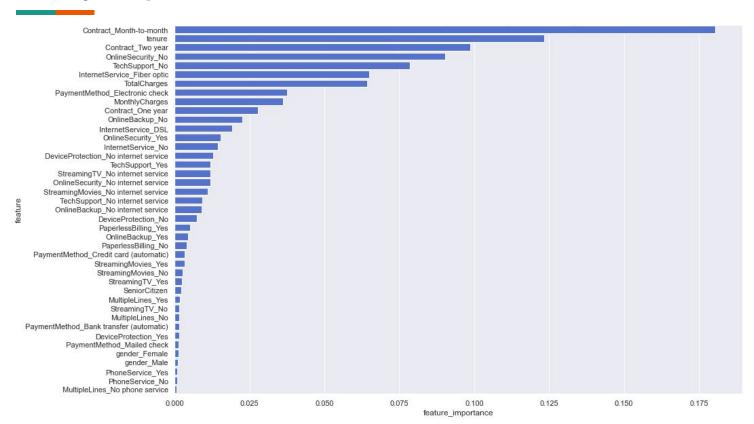
ML Model	Acc Train	Acc Test	F1 Train	F1 Test
Gaussian	0.77	0.77	0.78	0.78
kNN	0.83	0.76	0.83	0.78
MLP	0.75	0.75	0.73	0.73
RandomForest	0.85	0.84	0.85	0.85

RandomForest model achieves the best F1 score on both train and test data



# Insights and Recommendations

# **Analyzing Importance Features**



# **Top 6 Importance Features**



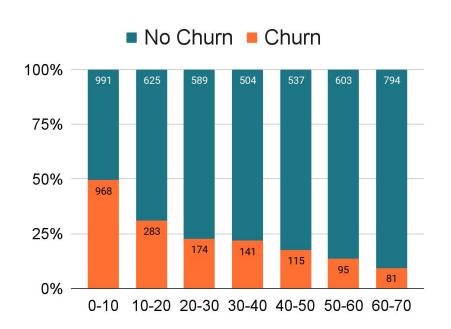
- O1 | Contract\_Month-to-month
- 02 | tenure
- 03 | Contract\_Two year
- 04 | OnlineSecurity\_No
- 05 | TechSupport\_No
- 06 | InternetService\_Fiber Optic

# **Business Strategy**

- 01 | Contract\_Month-to-month
- 03 | Contract\_Two year
- >> | Upsell customers who subscribe month-to-month contract into a longer contract, e.g. two year contract
- 02 | tenure
- Add more discount in the first year or revise pricing strategy with marketing budget.
  The goal is to prolong the user until they belong to a tenure bin where the churn rate is low (check next slide)
- 04 | OnlineSecurity No
- 05 | TechSupport\_No
- >> | Offer bundled/discounted "tech support and online security" for those potentially upselling customers
- 06 | InternetService Fiber Optic
- >> | Consider widening the fibre optic outreach.

  How to prioritize the outreach area? Reverse code from the customerID

# **Churn Likelihood - Tenure**



The tenure are binned into 7 bins with interval size 10. There is a downtrend pattern on the churn proportion when the tenure increases.

The customer who has a higher tenure is less likely to churn.

# About me!

My Personal Website: <u>mhilmiasyrofi.qithub.io</u>

Source Code: <a href="mailto:github.com/mhilmiasyrofi/CustomerChurnAnalytics">github.com/mhilmiasyrofi/CustomerChurnAnalytics</a>