Choice 2: Classification on the Telco-Churn Dataset The dataset and its description is available at Kaggle. The goal of this task is to analyze the behavior of telecom customers and understand what factors are important to retain customers.

1. Visualize the univariate distribution of each input variable and the target variable “churn”.
2. Split data into training and test sets. Convert each categorical variable into numerical variables using one-hot-encoding. Example of one-hot encoding: Gender: Male -> (1, 0), Female -> (0, 1) Ethnicity: 1. Caucasian, 2. African American, 3. Hispanic, 4. Asian, 5 Native American, 6 Pacific Islander One-hot encoded labels: 1 → (1, 0, 0, 0, 0, 0)

```
2 → (0, 1, 0, 0, 0, 0)
6 → (0, 0, 0, 0, 0, 1)
```

3. Evaluate the following classification models: a. Logistic Regression b. Support Vector Machine c. K Nearest Neighbors d. Decision Trees e. Random Forests Note that you need to decide the choice of hyper-parameters for the models, such as the value of k for k nearest neighbor method and the maximum depth for the random forest method.
4. Choose the best model by analyzing the accuracy, precision, recall, and F-1 score.
5. Which types of customers are less likely to end the service?

```
import string
import numpy as np
import pandas as pd
from pandas import *
import matplotlib.pyplot as plt
%matplotlib inline
```

```
raw_data = pd.read_csv("/content/WA_Fn-UseC_-Telco-Customer-Churn.csv", sep=',')
raw_data
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecuri
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	N
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Ye
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Ye
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Ye
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	N
...	...	...	...	...	...	...	...	...	...	
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	Ye
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	N
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	Ye
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	Fiber optic	Ye

```
raw_data.shape
```

```
(7043, 21)
```

```
raw_data.dtypes
```

```
customerID          object
gender              object
SeniorCitizen        int64
Partner             object
Dependents          object
tenure               int64
PhoneService        object
MultipleLines       object
InternetService     object
OnlineSecurity      object
OnlineBackup        object
DeviceProtection    object
TechSupport         object
StreamingTV         object
```

```
    StreamingMovies      object
    Contract             object
    PaperlessBilling     object
    PaymentMethod        object
    MonthlyCharges      float64
    TotalCharges         object
    Churn                object
    dtype: object
```

```
# Are there any missing values?
raw_data.isnull().sum()
```

```
    customerID          0
    gender              0
    SeniorCitizen       0
    Partner             0
    Dependents          0
    tenure              0
    PhoneService        0
    MultipleLines       0
    InternetService     0
    OnlineSecurity      0
    OnlineBackup        0
    DeviceProtection    0
    TechSupport         0
    StreamingTV         0
    StreamingMovies     0
    Contract            0
    PaperlessBilling    0
    PaymentMethod       0
    MonthlyCharges      0
    TotalCharges        0
    Churn               0
    dtype: int64
```

```
raw_data.columns
```

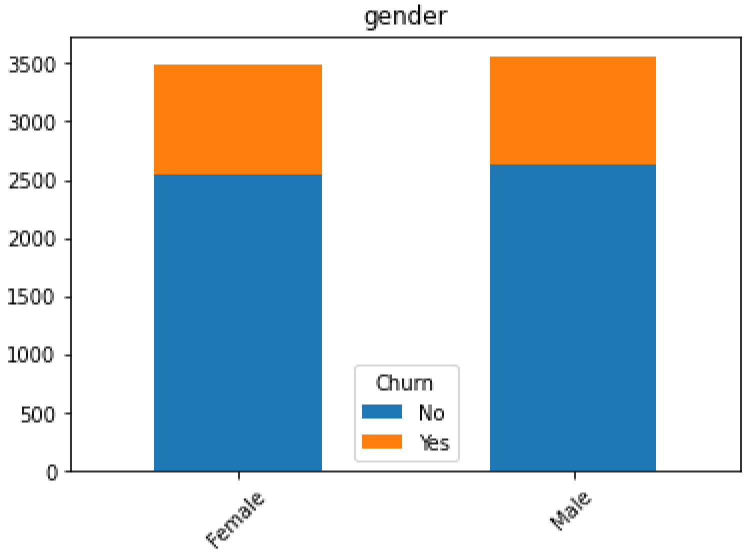
```
    Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
           'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
           'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
           'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
           'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
          dtype='object')
```

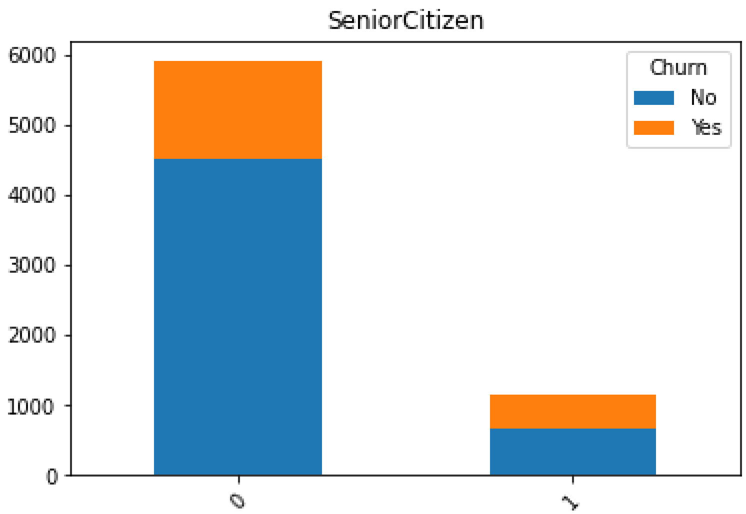
```
raw_data['Churn'].value_counts().sort_index()
```

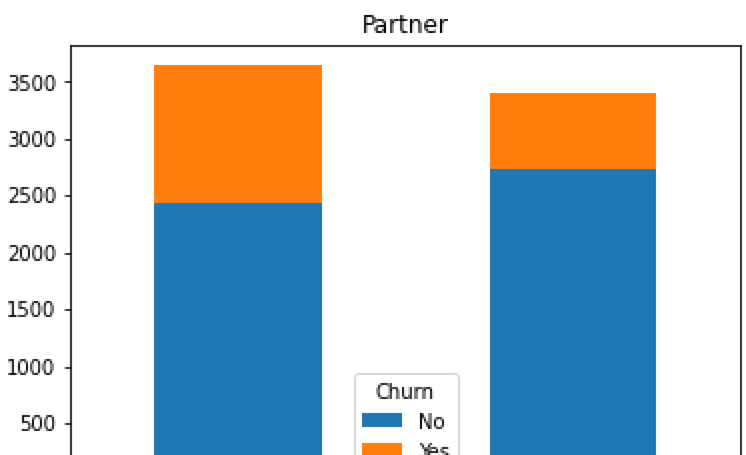
```
No     5174
Yes    1869
Name: Churn, dtype: int64
```

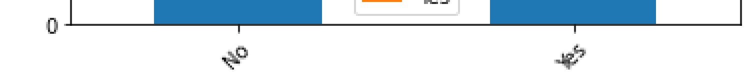
1. Visualize the univariate distribution of each input variable and the target variable “churn”.

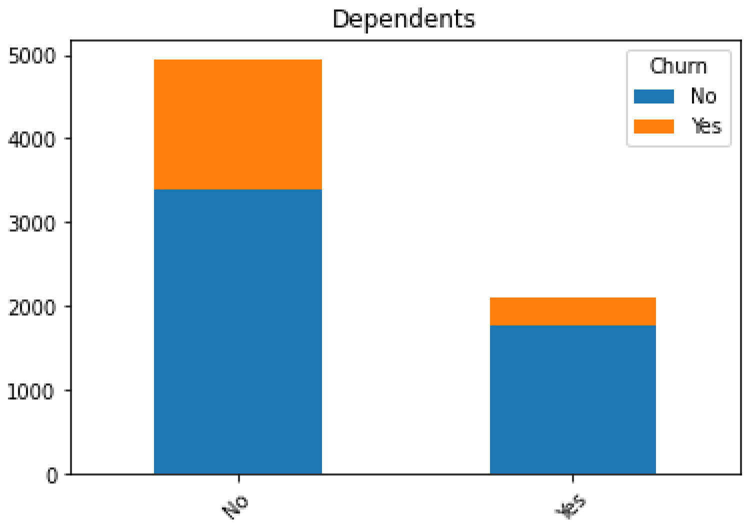
```
#Drop Customer ID
data = raw_data.drop(['customerID'], axis=1)

special_col = ['TotalCharges','tenure','MonthlyCharges']

b_names = data.columns.to_list()

#remove columns from column name list
for i in special_col:
  b_names.remove(i)


for i in b_names:
  chart = pd.crosstab(data[i], data['Churn']).plot(kind='bar', stacked=True)
  chart.set(title=i)
  chart.set_xticklabels(chart.get_xticklabels(),rotation = 45)
  chart.set(xlabel =" ")
  chart
```

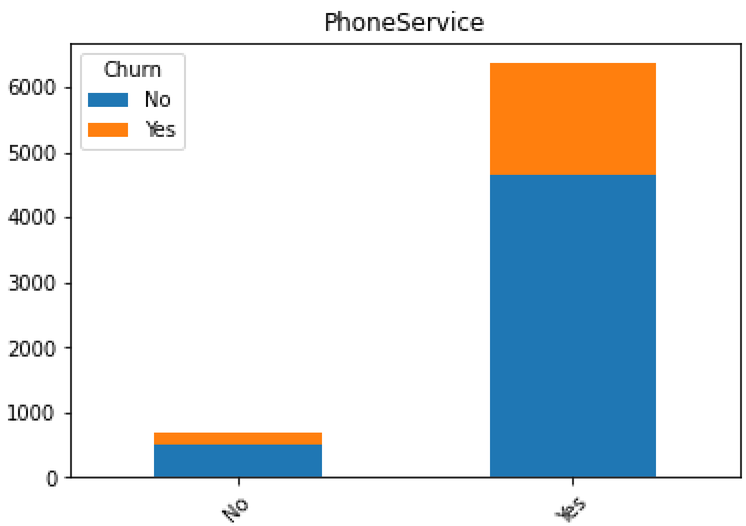

gender
3500
3000
2500
2000
1500
1000
500
0
Churn
No
Yes
Female
Male

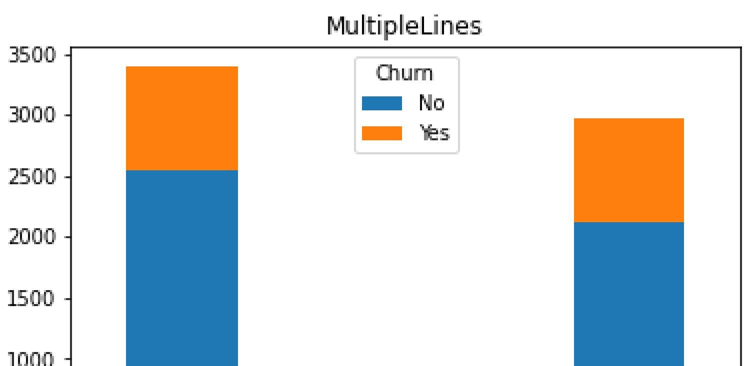

SeniorCitizen
6000
5000
4000
3000
2000
1000
0
Churn
No
Yes
0
1

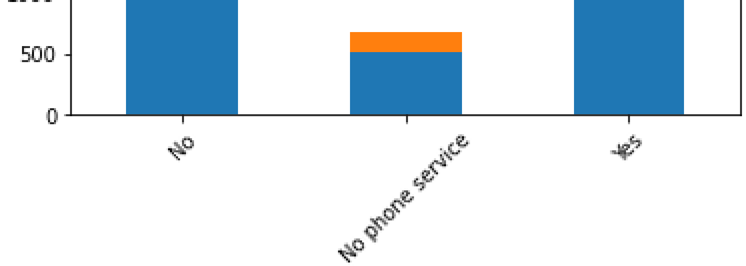

Partner
3500
3000
2500
2000
1500
1000
500
Churn
No
Yes


0
No
Yes

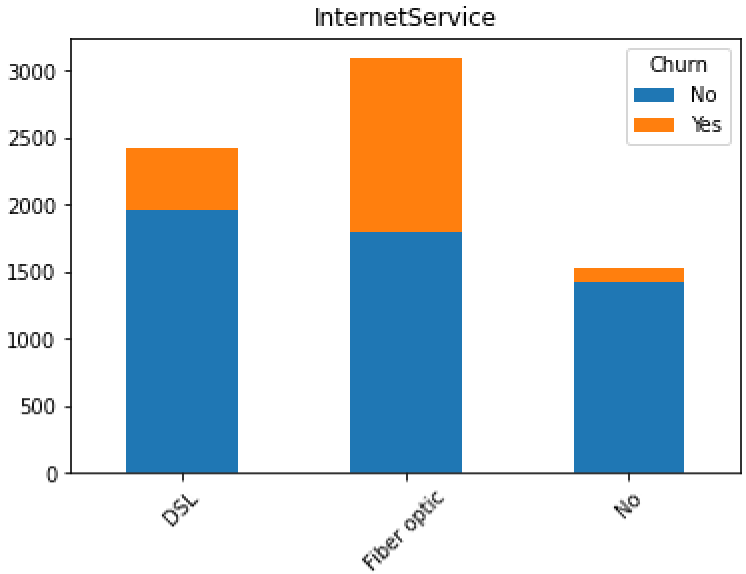

Dependents
Churn
No
Yes
5000
4000
3000
2000
1000
0
No
Yes


PhoneService
Churn
No
Yes
6000
5000
4000
3000
2000
1000
0
No
Yes

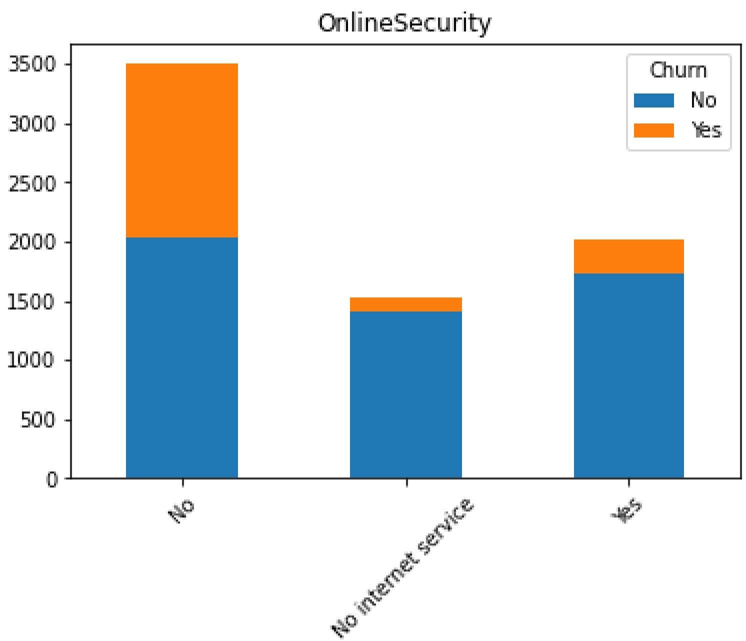

MultipleLines
Churn
No
Yes
3500
3000
2500
2000
1500
1000



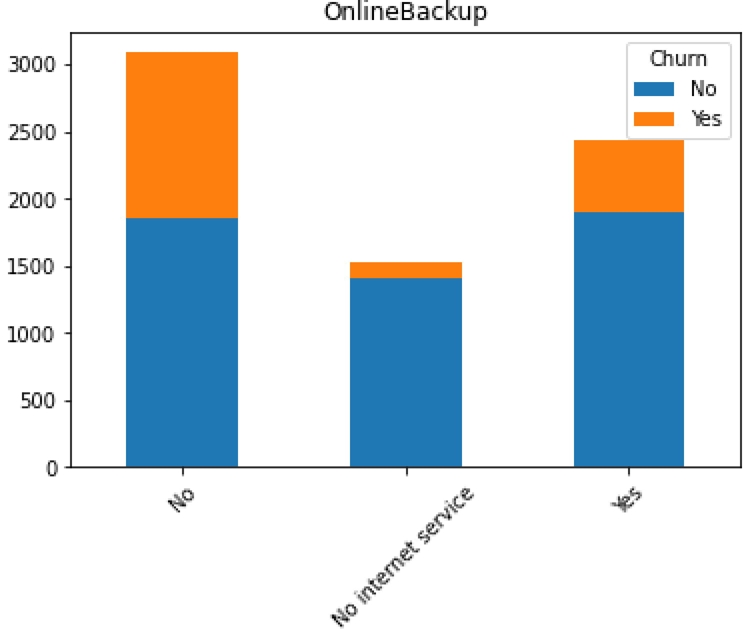
500
0
No
No phone service
Yes

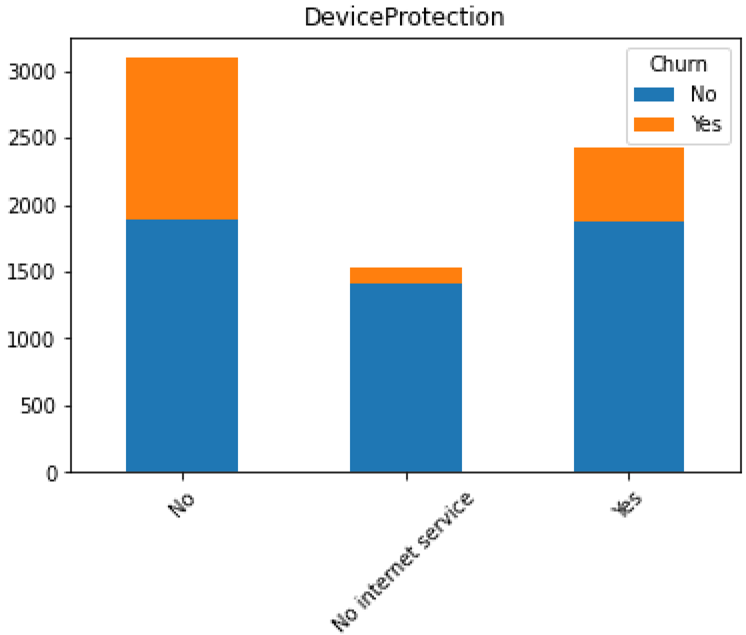


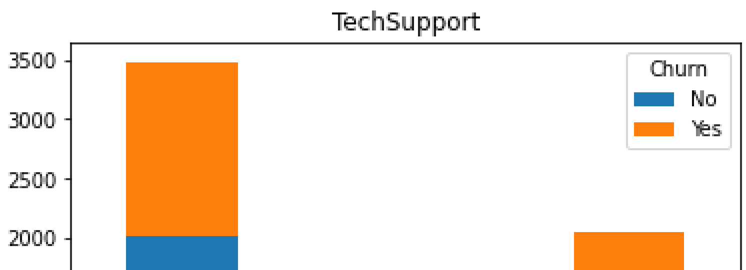
InternetService
Churn
No
Yes
3000
2500
2000
1500
1000
500
0
DSL
Fiber optic
No

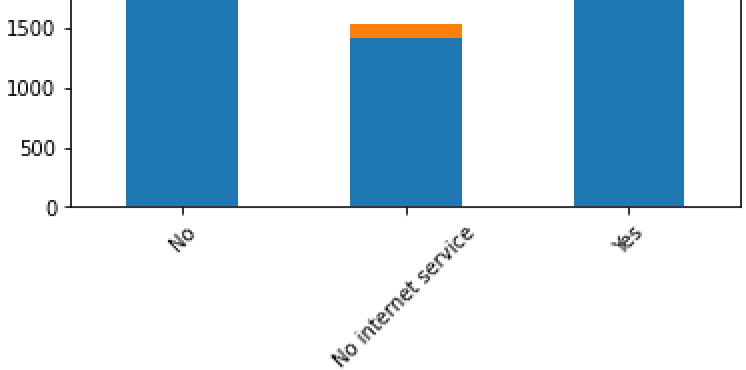


OnlineSecurity
Churn
No
Yes
3500
3000
2500
2000
1500
1000
500
0
No
No internet service
Yes

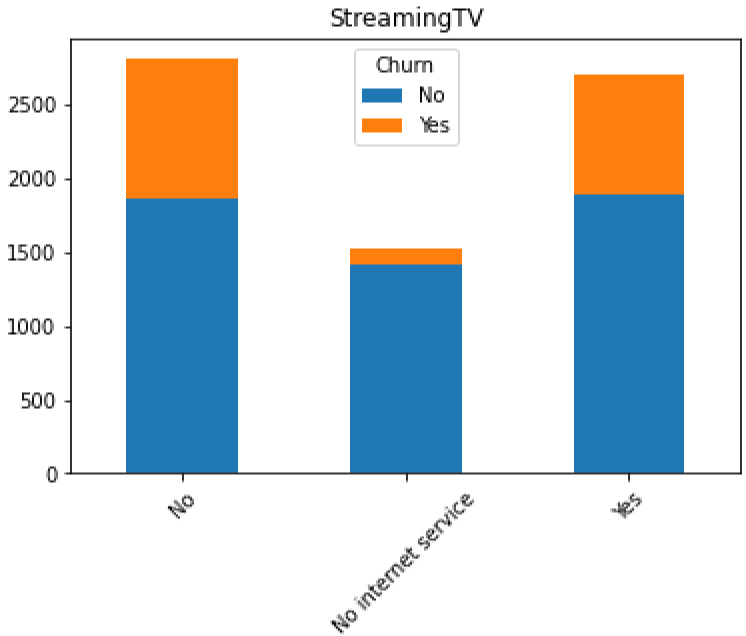

OnlineBackup
Churn
No
Yes
3000
2500
2000
1500
1000
500
0
No
No internet service
Yes


DeviceProtection
Churn
No
Yes
3000
2500
2000
1500
1000
500
0
No
No internet service
Yes

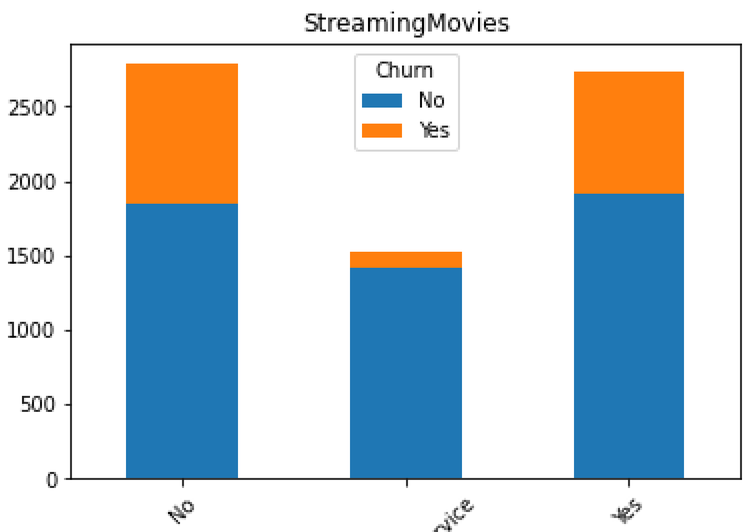

TechSupport
Churn
No
Yes
3500
3000
2500
2000



1500
1000
500
0
No
No internet service
Yes

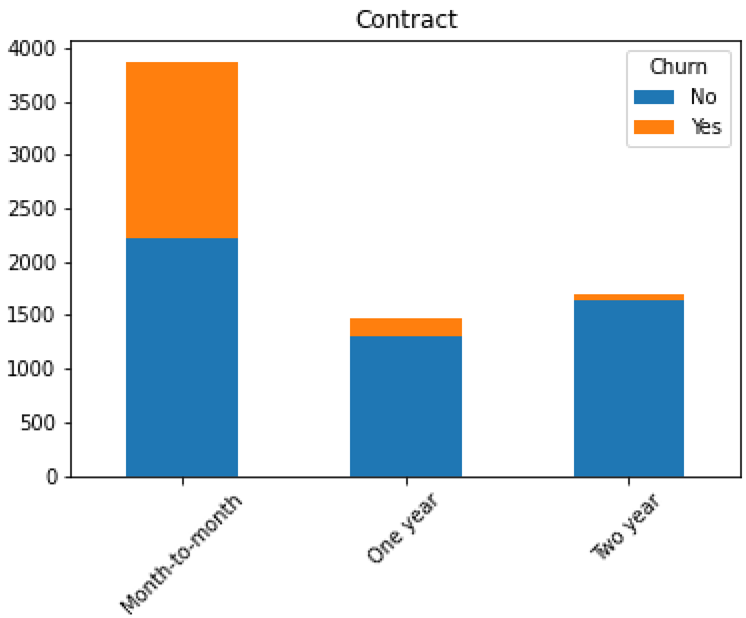


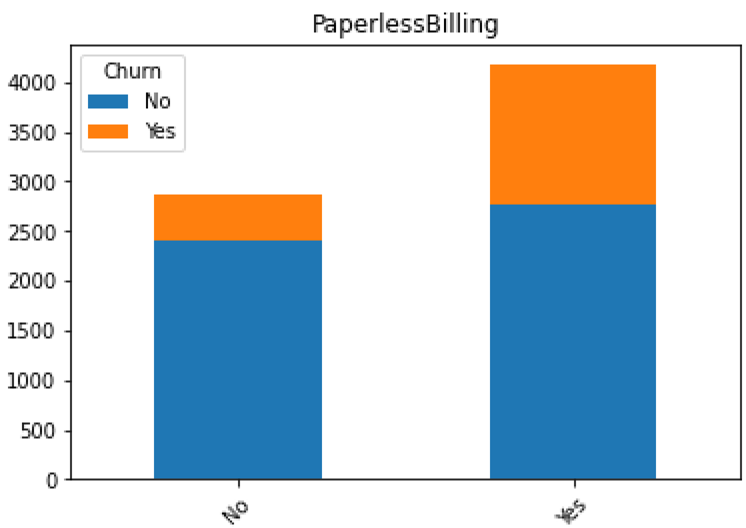
StreamingTV
Churn
No
Yes
2500
2000
1500
1000
500
0
No
No internet service
Yes

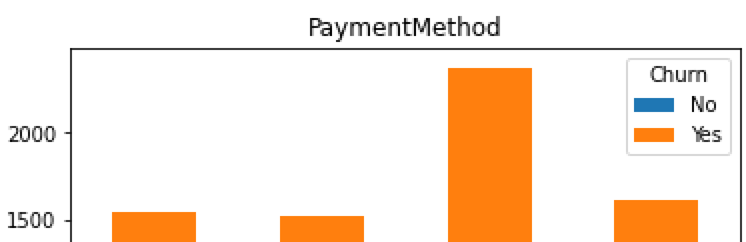


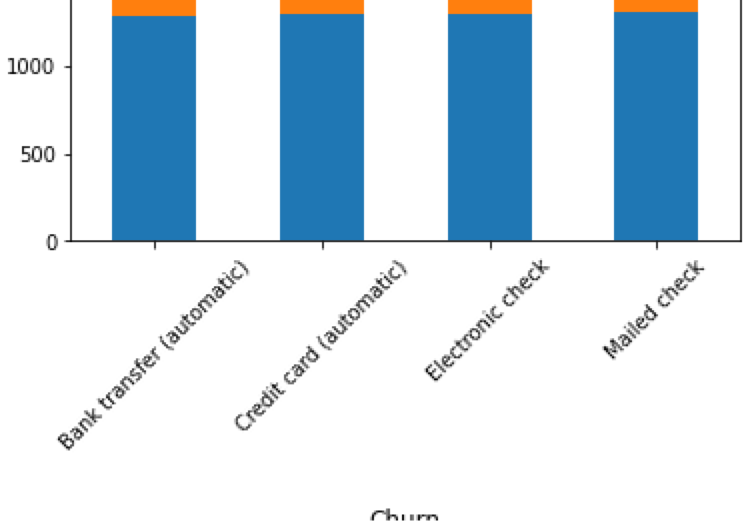
StreamingMovies
Churn
No
Yes
2500
2000
1500
1000
500
0
No
Yes


No internet ser


Contract
Churn
No
Yes
0
500
1000
1500
2000
2500
3000
3500
4000
Month-to-month
One year
Two year


PaperlessBilling
Churn
No
Yes
0
500
1000
1500
2000
2500
3000
3500
4000
No
Yes


PaymentMethod
Churn
No
Yes
1500
2000



2. Split data into training and test sets. Convert each categorical variable into numerical variables using one-hot-encoding.

```
# print(data.loc[[1340]])
# data['TotalCharges'].repalce({" ": 0.0}, inplace = True)
# data['TotalCharges'] = data.TotalCharges.astype(float)
# data.dtypes
```

```
data.dtypes
```

```
gender              object
SeniorCitizen        int64
Partner             object
Dependents          object
tenure               int64
PhoneService        object
MultipleLines       object
InternetService     object
OnlineSecurity      object
OnlineBackup        object
DeviceProtection    object
TechSupport         object
StreamingTV         object
StreamingMovies     object
Contract            object
PaperlessBilling    object
PaymentMethod       object
```

```
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

```
df2 = raw_data.drop(['customerID','tenure','MonthlyCharges','TotalCharges'], axis=1)
one_hot_encoding = pd.get_dummies(df2, sparse=True)
one_hot_encoding
```

	SeniorCitizen	gender_Female	gender_Male	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes	PhoneService_No	PhoneS
0	0	1	0	0	1	1	0	1	
1	0	0	1	1	0	1	0	0	
2	0	0	1	1	0	1	0	0	
3	0	0	1	1	0	1	0	1	
4	0	1	0	1	0	1	0	0	
...	...	...	...	...	...	...	...	...	
7038	0	0	1	0	1	0	1	0	
7039	0	1	0	0	1	0	1	0	
7040	0	1	0	0	1	0	1	1	
7041	1	0	1	0	1	1	0	0	
7042	0	0	1	1	0	1	0	0	

7043 rows × 44 columns

```
one_hot_encoding.shape
```

```
(7043, 44)
```

```
one_hot_encoding.columns
```

```
Index(['SeniorCitizen', 'gender_Female', 'gender_Male', 'Partner_No',
       'Partner_Yes', 'Dependents_No', 'Dependents_Yes', 'PhoneService_No',
```

```
 'PhoneService_Yes', 'MultipleLines_No',
 'MultipleLines_No phone service', 'MultipleLines_Yes',
 'InternetService_DSL', 'InternetService_Fiber optic',
 'InternetService_No', 'OnlineSecurity_No',
 'OnlineSecurity_No internet service', 'OnlineSecurity_Yes',
 'OnlineBackup_No', 'OnlineBackup_No internet service',
 'OnlineBackup_Yes', 'DeviceProtection_No',
 'DeviceProtection_No internet service', 'DeviceProtection_Yes',
 'TechSupport_No', 'TechSupport_No internet service', 'TechSupport_Yes',
 'StreamingTV_No', 'StreamingTV_No internet service', 'StreamingTV_Yes',
 'StreamingMovies_No', 'StreamingMovies_No internet service',
 'StreamingMovies_Yes', 'Contract_Month-to-month', 'Contract_One year',
 'Contract_Two year', 'PaperlessBilling_No', 'PaperlessBilling_Yes',
 'PaymentMethod_Bank transfer (automatic)',
 'PaymentMethod_Credit card (automatic)',
 'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check',
 'Churn_No', 'Churn_Yes'],
dtype='object')
```

```
# Split the data set into training set (80%) and test set (20%),
from sklearn.model_selection import train_test_split
training_data, test_data = train_test_split(one_hot_encoding, test_size=0.2)
```

```
# Display the shape of training set
training_data.shape
```

```
(5634, 44)
```

```
# Display the shape of test set
test_data.shape
```

```
(1409, 44)
```

```
names = training_data.columns.to_list()
names.remove('Churn_Yes')
names.remove('Churn_No')
names
```

```
['SeniorCitizen',
 'gender_Female',
 'gender_Male',
 'Partner_No',
 'Partner_Yes',
```

```
 'Dependents_No',
 'Dependents_Yes',
 'PhoneService_No',
 'PhoneService_Yes',
 'MultipleLines_No',
 'MultipleLines_No phone service',
 'MultipleLines_Yes',
 'InternetService_DSL',
 'InternetService_Fiber optic',
 'InternetService_No',
 'OnlineSecurity_No',
 'OnlineSecurity_No internet service',
 'OnlineSecurity_Yes',
 'OnlineBackup_No',
 'OnlineBackup_No internet service',
 'OnlineBackup_Yes',
 'DeviceProtection_No',
 'DeviceProtection_No internet service',
 'DeviceProtection_Yes',
 'TechSupport_No',
 'TechSupport_No internet service',
 'TechSupport_Yes',
 'StreamingTV_No',
 'StreamingTV_No internet service',
 'StreamingTV_Yes',
 'StreamingMovies_No',
 'StreamingMovies_No internet service',
 'StreamingMovies_Yes',
 'Contract_Month-to-month',
 'Contract_One year',
 'Contract_Two year',
 'PaperlessBilling_No',
 'PaperlessBilling_Yes',
 'PaymentMethod_Bank transfer (automatic)',
 'PaymentMethod_Credit card (automatic)',
 'PaymentMethod_Electronic check',
 'PaymentMethod_Mailed check']
```

3. Evaluate the following classification models:

Logistic Regression

```
import numpy as np
```

```
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
```

```
# Build the logistic regression model
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit(training_data[names], training_data['Churn_Yes'])
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
test_predictions = model.predict(test_data[names])
print(test_predictions)
```

```
[1 0 1 ... 0 0 0]
```

```
# 1. Find the prediction accuracy on test set
from sklearn.metrics import accuracy_score
accuracy_score(test_data['Churn_Yes'], test_predictions)
```

```
0.7977288857345636
```

```
from sklearn.metrics import precision_score, recall_score, f1_score
precision = precision_score(test_data['Churn_Yes'], test_predictions)
recall = recall_score(test_data['Churn_Yes'], test_predictions)
f1 = f1_score(test_data['Churn_Yes'], test_predictions)

print("Precision Score is: ", precision)
print("Recall Score is: ", recall)
print("F1 Score is: ", f1)
```

```
Precision Score is:  0.6222222222222222
Recall Score is:  0.5414364640883977
F1 Score is:  0.5790251107828656
```

SVM

```
from sklearn.svm import LinearSVC
model_svm = LinearSVC()
model_svm.fit(training_data[names], training_data['Churn_Yes'])
```

```
LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,
          intercept_scaling=1, loss='squared_hinge', max_iter=1000,
          multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
          verbose=0)
```

```
predictions = model_svm.predict(test_data[names])
print(predictions)
```

```
[1 0 1 ... 0 0 0]
```

```
accuracy_score(test_data['Churn_Yes'], predictions)
```

```
0.801277501774308
```

```
precision = precision_score(test_data['Churn_Yes'], predictions)
recall = recall_score(test_data['Churn_Yes'], predictions)
f1 = f1_score(test_data['Churn_Yes'], predictions)

print("Precision Score is: ", precision)
print("Recall Score is: ", recall)
print("F1 Score is: ", f1)
```

```
Precision Score is:  0.6375838926174496
Recall Score is:  0.5248618784530387
F1 Score is:  0.5757575757575757
```

K - Nearest Neighbor

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(training_data[names], training_data['Churn_Yes'])
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
```

```
                     metric_params=None, n_jobs=None, n_neighbors=3, p=2,
                     weights='uniform')
```

```
knn_predictions = knn.predict(test_data[names])
print(knn_predictions)
```

```
[1 0 1 ... 0 0 0]
```

```
accuracy_score(test_data['Churn_Yes'], knn_predictions)
```

```
0.7430801987224982
```

```
precision = precision_score(test_data['Churn_Yes'], knn_predictions)
recall = recall_score(test_data['Churn_Yes'], knn_predictions)
f1 = f1_score(test_data['Churn_Yes'], knn_predictions)

print("Precision Score is: ", precision)
print("Recall Score is: ", recall)
print("F1 Score is: ", f1)
```

```
Precision Score is:  0.5
Recall Score is:  0.5220994475138122
F1 Score is:  0.5108108108108109
```

Decision Tree's

```
# 2. Build decision trees
from sklearn.tree import DecisionTreeClassifier

x = training_data[names]
y = training_data['Churn_Yes']

x_test = test_data[names]
y_test = test_data['Churn_Yes']

tree_clf = DecisionTreeClassifier(max_depth=3, random_state = 43)

tree_clf.fit(x,y)
```

```
    DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                           max_depth=3, max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, presort='deprecated',
                           random_state=43, splitter='best')
```

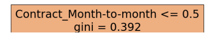
```
pred_test = tree_clf.predict(x_test)
print(accuracy_score(y_test,pred_test))
```

```
    0.7920511000709723
```

```
precision = precision_score(test_data['Churn_Yes'], pred_test)
recall = recall_score(test_data['Churn_Yes'], pred_test)
f1 = f1_score(test_data['Churn_Yes'], pred_test)

print("Precision Score is: ", precision)
print("Recall Score is: ", recall)
print("F1 Score is: ", f1)
```

```
    Precision Score is:  0.5945205479452055
    Recall Score is:  0.5994475138121547
    F1 Score is:  0.5969738651994498
```

```
from sklearn.tree import plot_tree
plt.figure(figsize = (80,10))
plot_tree(tree_clf, feature_names = x.columns, filled = True)
plt.show()
```



Random Forests


```
from sklearn.ensemble import RandomForestClassifier

rf_class = RandomForestClassifier(n_estimators = 500, max_depth = 2, n_jobs = -1)
rf_class.fit(x,y)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=2, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=-1, oob_score=False, random_state=None, verbose=0,
                       warm_start=False)
```

```
y_pred_test = rf_class.predict(x_test)
print(accuracy_score(y_test, y_pred_test))
```

```
0.7430801987224982
```

```
precision = precision_score(test_data['Churn_Yes'], y_pred_test)
recall = recall_score(test_data['Churn_Yes'], y_pred_test)
f1 = f1_score(test_data['Churn_Yes'], y_pred_test)

print("Precision Score is: ", precision)
print("Recall Score is: ", recall)
print("F1 Score is: ", f1)
```

```
Precision Score is:  0.0
Recall Score is:  0.0
F1 Score is:  0.0
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision is ill-defined
  _warn_prf(average, modifier, msg_start, len(result))
```

```
print("The Accuracy Score for Logistic Regression is: ", accuracy_score(test_data['Churn_Yes'], test_predictions))
print("The Accuracy Score for SVM is:                 ", accuracy_score(test_data['Churn_Yes'], predictions))
print("The Accuracy Score for K Nearest Neighbor is:  ", accuracy_score(y_test,pred_test))
print("The Accuracy Score for Random Forest is:       ", accuracy_score(y_test, y_pred_test))
```

```
print("The Accuracy Score for Random Forrest is:      ", accuracy_score(y_test, y_pred_test))
```

```
The Accuracy Score for Logistic Regression is:  0.7977288857345636
The Accuracy Score for SVM is:                  0.801277501774308
The Accuracy Score for K Nearest Neighbor is:   0.7906316536550745
The Accuracy Score for Random Forrest is:       0.7430801987224982
```

4. In Conclussion, Logistric Regression and SVM are the best models to use since they have the highest Accuracy scores and the best Precision, Recall, and F1 scores overall. However SVM has slightly highesr scores so it is the best.

5. Based off of our Decision Tree we can see that most customers left because of:

1. Customers with a "Month to Month" style of contract are more likely to leave than customers with a different contract.
2. Customers with a Fiber Optic conection were also more likely to leave than other customers.
3. Customers who had no internet security were also more likely to leave.

We can also see in our Decision Tree that customers were more likely to stay if:

1. They did not have a Fiber Optic Connection
2. Along with having Internet Security