1 Business Understanding

SyriaTel, a telecommunications company is interested in knowing whether a customer will stop doing business with the company. This will help the business in reducing the on money lost because of customers who do not stick around very long. We will use a classifier model to see whether there are any predicable patterns which in turn will assist Syriatel to have a clear picture of the churn rate.

1.1 Import necessary modules

These modules will be used to prepare the data and model development

In [36]:
```
# Importing packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import OneHotEncoder
from sklearn import tree
```

2 Data Understanding

In [2]:
```
#import the dataset
df = pd.read_csv('bigml_59c28831336c6604c800002a.csv')
df.head()
```

Out[2]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	total eve calls	total eve charge	to ni minu
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	

5 rows × 21 columns

In [3]:
```
df.describe()
```

Out[3]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348	100.114311	17.083540	200.872037	100
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4.310668	50.573847	19
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	23.200000	33
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14.160000	167.000000	87
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17.120000	201.200000	100
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20.000000	235.300000	113
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30.910000	395.000000	175

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   object
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
 3   phone number            3333 non-null   object
 4   international plan      3333 non-null   object
 5   voice mail plan         3333 non-null   object
 6   number vmail messages   3333 non-null   int64
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

From df.info(), the dataset has 21 columns and 3333 rows. We also observe that there are no null values in the dataset

In [5]:
```
df['churn'].value_counts()
```

Out[5]:
```
churn
False    2850
True      483
Name: count, dtype: int64
```

The number of people who churn are less compared to those who do not churn therefore we are dealing with an imbalanced dataset

In [6]:
```
# to analyse which object variable can be used in the model
df.select_dtypes("object").nunique().sort_values()
```

Out[6]:
```
international plan       2
voice mail plan          2
state                   51
phone number          3333
dtype: int64
```

In [63]:
```
nums = df.select_dtypes('number')
nums.head()
```

Out[63]:
```
state_MI                2
state_MO                2
state_MS                2
state_MT                2
state_NC                2
                      ...
total intl minutes      162
account length          212
total night minutes    1591
total eve minutes      1611
total day minutes      1667
Length: 65, dtype: int64
```

3 Data Preparation

3.1 One-Hot Ecoding

From above analysis international plan, voice mail plan, state and area code are categorical features we need to encoode them as numbers

In [9]:
```
df = pd.get_dummies(df, columns=['state', 'area code', 'international plan', 'voice mail plan'], dtype=int, drop_f
df.head()
```

Out[9]:

	account length	phone number	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	...	state_VA	state_VT
0	128	382-4657	25	265.1	110	45.07	197.4	99	16.78	244.7	...	0	0
1	107	371-7191	26	161.6	123	27.47	195.5	103	16.62	254.4	...	0	0
2	137	358-1921	0	243.4	114	41.38	121.2	110	10.30	162.6	...	0	0
3	84	375-9999	0	299.4	71	50.90	61.9	88	5.26	196.9	...	0	0
4	75	330-6626	0	166.7	113	28.34	148.3	122	12.61	186.9	...	0	0

5 rows × 71 columns

3.2 Drop unnecessary columns

In [10]:
```
# the phone number  may not help in predicting churn rate and has 3333 unique values and will make our model more

df = df.drop(columns=['phone number'])
```

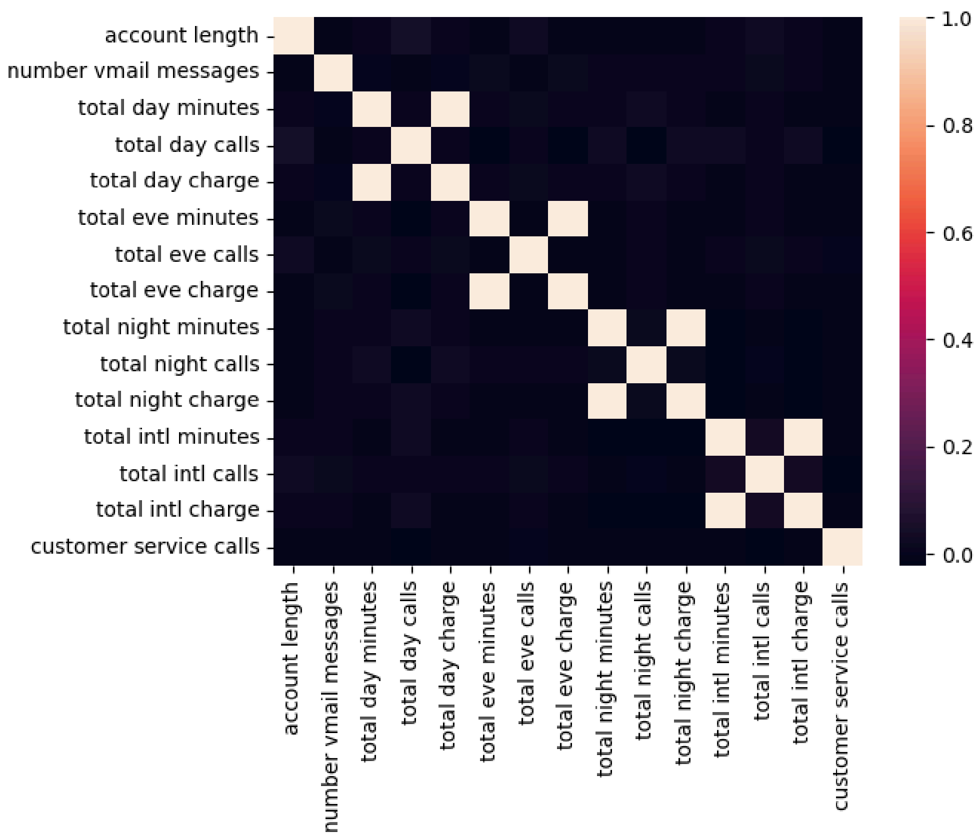
3.3 Check for and removing Multicollinearity

In [12]:
```
#check for numerical variables that are highly correlated. where two variable are highly correlated, we will remov

nums = nums.drop(columns=['area code'])
nums.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 15 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   account length          3333 non-null   int64  
 1   number vmail messages   3333 non-null   int64  
 2   total day minutes       3333 non-null   float64
 3   total day calls         3333 non-null   int64  
 4   total day charge        3333 non-null   float64
 5   total eve minutes       3333 non-null   float64
 6   total eve calls         3333 non-null   int64  
 7   total eve charge        3333 non-null   float64
 8   total night minutes     3333 non-null   float64
 9   total night calls       3333 non-null   int64  
 10  total night charge      3333 non-null   float64
 11  total intl minutes      3333 non-null   float64
 12  total intl calls        3333 non-null   int64  
 13  total intl charge       3333 non-null   float64
 14  customer service calls  3333 non-null   int64  
dtypes: float64(8), int64(7)
memory usage: 390.7 KB
```

In [17]:
```
sns.heatmap(nums.corr())
```

Out[17]: <Axes: >



In [18]:
```
#variables that are highly correlated are total day charge & total day calls, total eve charge & total eve calls,

# we drop the columns with total day, eve, night & intl charges

df = df.drop(columns=['total day charge', 'total eve charge', 'total night charge', 'total intl charge'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 66 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   account length          3333 non-null   int64  
 1   number vmail messages   3333 non-null   int64  
 2   total day minutes       3333 non-null   float64
 3   total day calls         3333 non-null   int64  
 4   total eve minutes       3333 non-null   float64
 5   total eve calls         3333 non-null   int64  
 6   total night minutes     3333 non-null   float64
 7   total night calls       3333 non-null   int64  
 8   total intl minutes      3333 non-null   float64
 9   total intl calls        3333 non-null   int64  
 10  customer service calls  3333 non-null   int64  
 11  churn                   3333 non-null   bool   
 12  state_AL                3333 non-null   int32  
 13  state_AR                3333 non-null   int32  
 14  state_AZ                3333 non-null   int32  
 15  state_CA                3333 non-null   int32  
 16  state_CO                3333 non-null   int32  
 17  state_CT                3333 non-null   int32  
 18  state_DC                3333 non-null   int32  
 19  state_DE                3333 non-null   int32  
 20  state_FL                3333 non-null   int32  
 21  state_GA                3333 non-null   int32  
 22  state_HI                3333 non-null   int32  
 23  state_IA                3333 non-null   int32  
 24  state_ID                3333 non-null   int32  
 25  state_IL                3333 non-null   int32  
 26  state_IN                3333 non-null   int32  
 27  state_KS                3333 non-null   int32  
 28  state_KY                3333 non-null   int32  
 29  state_LA                3333 non-null   int32  
 30  state_MA                3333 non-null   int32  
 31  state_MD                3333 non-null   int32  
 32  state_ME                3333 non-null   int32  
 33  state_MI                3333 non-null   int32  
 34  state_MN                3333 non-null   int32  
 35  state_MO                3333 non-null   int32  
 36  state_MS                3333 non-null   int32  
 37  state_MT                3333 non-null   int32  
 38  state_NC                3333 non-null   int32  
 39  state_ND                3333 non-null   int32  
 40  state_NE                3333 non-null   int32  
 41  state_NH                3333 non-null   int32  
 42  state_NJ                3333 non-null   int32  
 43  state_NM                3333 non-null   int32  
 44  state_NV                3333 non-null   int32  
 45  state_NY                3333 non-null   int32  
 46  state_OH                3333 non-null   int32  
 47  state_OK                3333 non-null   int32  
 48  state_OR                3333 non-null   int32  
 49  state_PA                3333 non-null   int32  
 50  state_RI                3333 non-null   int32  
 51  state_SC                3333 non-null   int32  
 52  state_SD                3333 non-null   int32  
 53  state_TN                3333 non-null   int32  
 54  state_TX                3333 non-null   int32  
 55  state_UT                3333 non-null   int32  
 56  state_VA                3333 non-null   int32  
 57  state_VT                3333 non-null   int32  
 58  state_WA                3333 non-null   int32  
 59  state_WI                3333 non-null   int32  
 60  state_WV                3333 non-null   int32  
 61  state_WY                3333 non-null   int32  
 62  area code_415           3333 non-null   int32  
 63  area code_510           3333 non-null   int32  
 64  international plan_yes  3333 non-null   int32  
 65  voice mail plan_yes     3333 non-null   int32  
dtypes: bool(1), float64(4), int32(54), int64(7)
memory usage: 992.9 KB
```

3.4 Train - Test Split the dataset

In [19]:
```
#split the dataset into train and test sets

X = df.drop('churn', axis=1)
y = df['churn']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

3.5 Normalize the numeric data

In [20]:
```
#scale the features

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(X_train)

X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

4 Modelling

4.1 Build a vanilla logistic regression model

In [29]:
```
#Build a classifier

#Instantiate the model
model = LogisticRegression()

# Fit the model
model.fit(X_train, y_train)

# Generate predictions for the test set
y_test_pred = model.predict(X_test)
```

4.1.1 Calculate and evaluate the metrics using Classification report

In [68]:
```
# Calculate and evaluate the metrics using Classification report

from sklearn.metrics import classification_report

report = classification_report(y_true=y_test, y_pred=y_test_pred)
print(report)
```

```
              precision    recall  f1-score   support

       False       0.87      0.97      0.92       566
        True       0.58      0.21      0.31       101

    accuracy                           0.86       667
   macro avg       0.73      0.59      0.61       667
weighted avg       0.83      0.86      0.83       667
```

4.2 Build a logistic regression model with SMOTE

In [24]:
```
# We had noted earlier that this is an imbalanced dataset therefore we need to SMOTE to address the class imbalanc

from imblearn.over_sampling import SMOTE
```

In [25]:
```
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)

y_train_smote.value_counts()
```

Out[25]:
```
churn
False    2284
True     2284
Name: count, dtype: int64
```

In [31]:
```
#Instantiate the model
model2 = LogisticRegression()

# Fit the model
model2.fit(X_train_smote, y_train_smote)

# Generate predictions for the test set
y_pred_smote = model2.predict(X_test)
```

In [32]:
```
# Calculate and evaluate the metrics using Classification report
report2 = classification_report(y_true=y_test, y_pred=y_pred_smote)
print(report2)
```

```
              precision    recall  f1-score   support

       False       0.94      0.80      0.86       566
        True       0.39      0.73      0.51       101

    accuracy                           0.79       667
   macro avg       0.67      0.76      0.69       667
weighted avg       0.86      0.79      0.81       667
```

In [33]:
```
# AUC & ROC Curve

#AUC without smote

from sklearn.metrics import roc_curve, auc

fpr1,tpr1,_ = roc_curve(y_true=y_test, y_score=model.decision_function(X_test))
area = auc(fpr1,tpr1)
area
```

Out[33]:
```
0.8165168106916699
```

In [34]:
```
# AUC & ROC Curve

#With smote
fpr2,tpr2,_ = roc_curve(y_true=y_test, y_score=model2.decision_function(X_test))
area2 = auc(fpr2,tpr2)
area2
```

Out[34]:
```
0.8218346569639298
```

4.3 Decision Tree

In [45]:
```
# Decision trees

#Create the classifier, fit it on the training data and make predictions on the test set

clf = DecisionTreeClassifier(random_state=10, criterion='entropy')
clf.fit(X_train, y_train)
```

Out[45]:
```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=10)
```

In [47]:
```
#Evaluate the predictive performance

y_pred_clf = clf.predict(X_test)
print('Accuracy: ', accuracy_score(y_test, y_pred_clf))
```

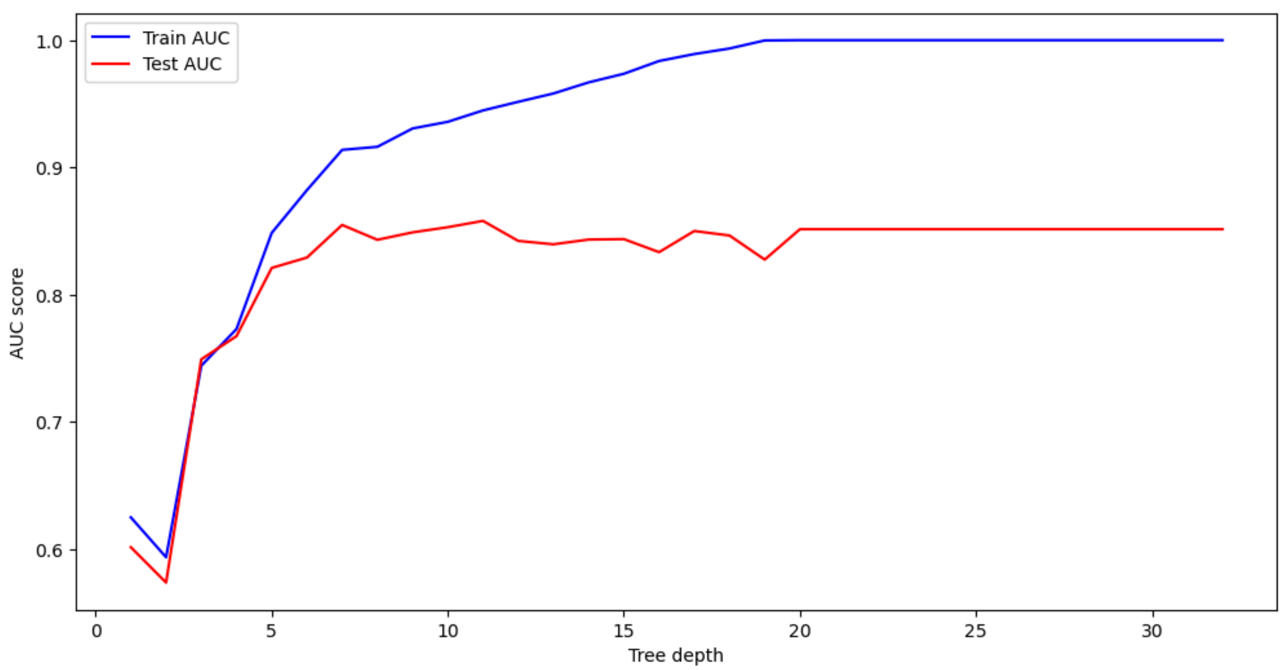
```
Accuracy:  0.9205397301349325
```

In [53]:
```
# Check the AUC of predictions
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred_clf)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

Out[53]:
```
0.8515026414302208
```

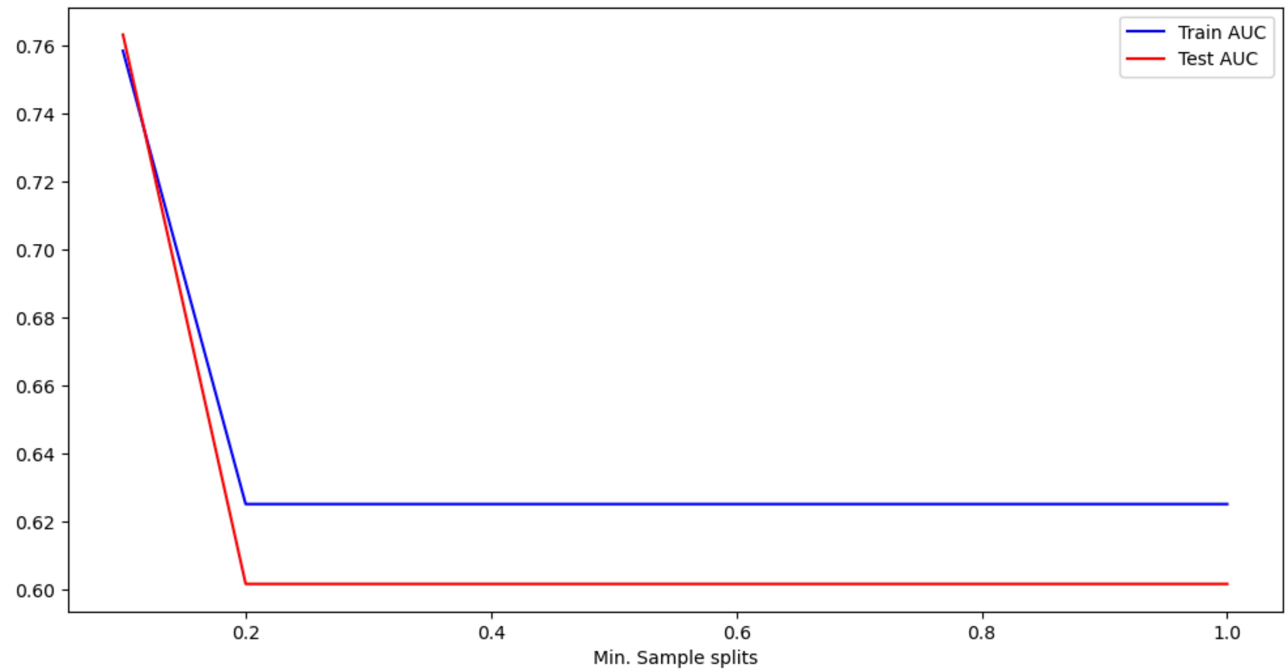
4.4 Hyperparameter Tuning and Pruning the Decision tree

In [54]:
```
#Hyperparameter tuning using max_depth
# Identify the optimal tree depth for given data
max_depths = list(range(1, 33))
train_results = []
test_results = []
for max_depth in max_depths:
    clf = DecisionTreeClassifier(criterion='entropy', max_depth=max_depth, random_state=10)
    clf.fit(X_train, y_train)
    train_pred = clf.predict(X_train)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train, train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    # Add auc score to previous train results
    train_results.append(roc_auc)
    y_pred = clf.predict(X_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    # Add auc score to previous test results
    test_results.append(roc_auc)

plt.figure(figsize=(12,6))
plt.plot(max_depths, train_results, 'b', label='Train AUC')
plt.plot(max_depths, test_results, 'r', label='Test AUC')
plt.ylabel('AUC score')
plt.xlabel('Tree depth')
plt.legend()
plt.show()
```



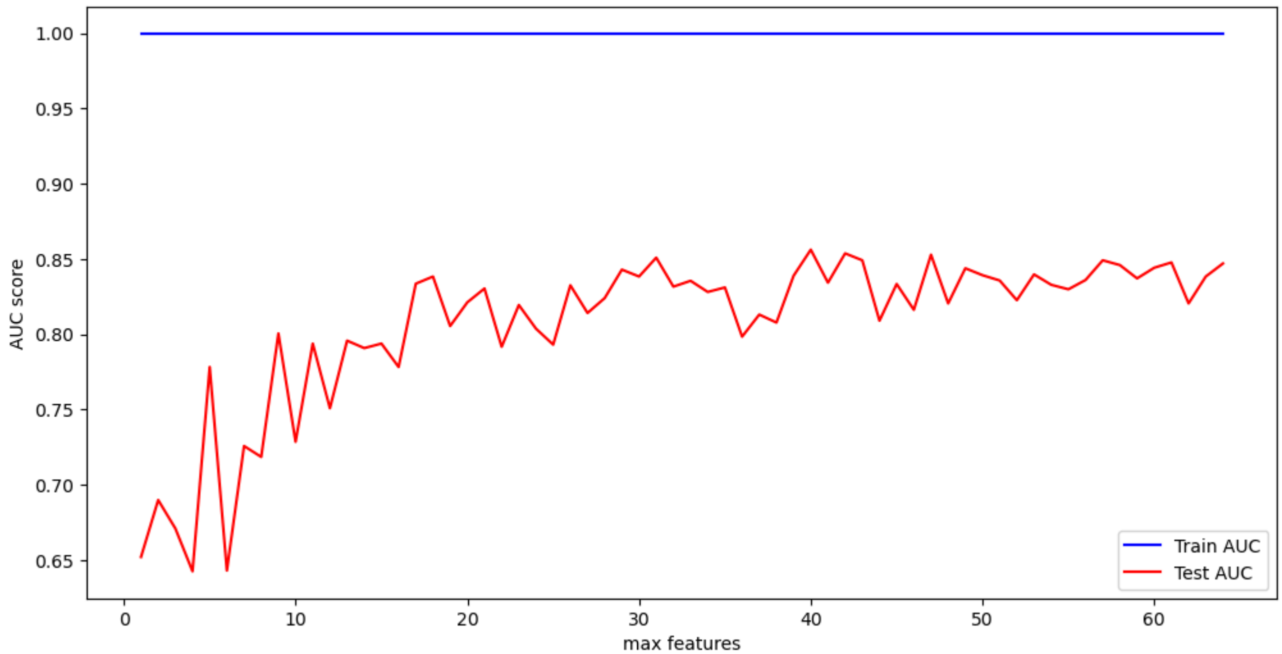
Training and test errors rise rapidly between the depths of 2 and 3. We choose our Max_depth as 3

In [55]:
```
# Hyperparameter tuning using min_samples_split
# Identify the optimal min-samples-split for given data
min_samples_splits = np.linspace(0.1, 1.0, 10, endpoint=True)
train_results = []
test_results = []
for min_samples_split in min_samples_splits:
    clf = DecisionTreeClassifier(criterion='entropy', min_samples_split=min_samples_split, random_state=10)
    clf.fit(X_train, y_train)
    train_pred = clf.predict(X_train)
    false_positive_rate, true_positive_rate, thresholds =    roc_curve(y_train, train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = clf.predict(X_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)

plt.figure(figsize=(12,6))
plt.plot(min_samples_splits, train_results, 'b', label='Train AUC')
plt.plot(min_samples_splits, test_results, 'r', label='Test AUC')
plt.xlabel('Min. Sample splits')
plt.legend()
plt.show()
```



AUC for both test and train data stabilizes at 0.2 therefore the min_samples_split will be 0.2

In [58]:
```
# Hyperparameter tuning using max_features
# Find the best value for optimal maximum feature size
max_features = list(range(1, X_train.shape[1]))
train_results = []
test_results = []
for max_feature in max_features:
    clf = DecisionTreeClassifier(criterion='entropy', max_features=max_feature, random_state=10)
    clf.fit(X_train, y_train)
    train_pred = clf.predict(X_train)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train, train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = clf.predict(X_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)

plt.figure(figsize=(12,6))
plt.plot(max_features, train_results, 'b', label='Train AUC')
plt.plot(max_features, test_results, 'r', label='Test AUC')
plt.ylabel('AUC score')
plt.xlabel('max features')
plt.legend()
plt.show()
```




```
The highest AUC value is seen at 40 therefore we will choose max_features = 40
```

In [65]:
```
# Train a classifier with optimal values identified above
dt = DecisionTreeClassifier(criterion='entropy',
                            max_features=40,
                            max_depth=3,
                            min_samples_split=0.2,
                            random_state=10)

dt.fit(X_train, y_train)
y_pred = dt.predict(X_test)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

Out[65]: 0.7256236224329147

5 Evaulating

Logistic regression

We evaluated the the logistic regression models using the classification report (where we were interested in the accuracy score) and we also added the AUC for comparison but this being an imbalance dataset, the AUC will be more suitable as measure.

Vanilla Logistic regression(without SMOTE)

    AUC - 0.81

Logistic regression with SMOTE

    AUC - 0.82

Based on the AUC results above we can see there was a slight increase which means the model performance improved with SMOTE

Decision tree

We have the decision tree using AUC both for the vanilla decison tree and decision tree with hyperparemeter tuning and pruning.

Vanilla Decision tree

    AUC - 0.85

Decision tree with hyperparemeter tuning and pruning

    AUC - 0.72

Based on the AUC results above, there was a reduction in AUC which means the decision tree did not perform better with hyperparemeter tuning and pruning

6 Deployement/Conclusion

Overall the Logistic regression with SMOTE performance tells us that the model can be used as good predictor of the churn rate for SyriaTel telecommunications company

In [ ]: