```
In [1]:
```

```
import numpy as np
import pandas as pd
import sklearn
from matplotlib import pyplot as plt
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
```

## In [2]:

```
X_train = pd.read_csv('./Data/orange_small_train.data', sep='\t')
X_test = pd.read_csv('./Data/orange_small_test.data', sep='\t')
y_train_churn = pd.read_csv('./Data/orange_small_train_churn.labels.txt',header=None)
y_train_apt = pd.read_csv('./Data/orange_small_train_appetency.labels',header=None)
y_train_upsell = pd.read_csv('./Data/orange_small_train_upselling.labels',header=None)
```

#### In [3]:

```
y_train_apt.value_counts(normalize=True), y_train_churn.value_counts(normalize=True), y_tra
normalize=True)
```

## Out[3]:

```
(-1 0.9822
1 0.0178
dtype: float64,
-1 0.92656
1 0.07344
dtype: float64,
-1 0.92636
1 0.07364
dtype: float64)
```

#### In [4]:

```
# dropping any column with missing value

# collect minimum no of records to be present value for data
# using data with high percentage of missing records makes bad training set and will induce
missing_perc = 20
min_count = int(((100 - missing_perc) / 100) * X_train.shape[0] + 1)
min_count
```

#### Out[4]:

40001

# Feature engineering

#### In [5]:

```
#drop all missing and only continous variable
prefered_uniques = 10
# create a list of numeric values and less than prefered uniques categorical columns
fe unique columns = list(X train.select dtypes(include='number').columns) + list(
    (X_train.select_dtypes(include='object').nunique() < prefered_uniques).index[
        X_train.select_dtypes(include='object').nunique() < prefered_uniques])</pre>
# collect only numeric features
X train all missing drop continous = X train.dropna( axis=1,thresh=min count).dropna(axis=0
numeric_col_after_drop = X_train_all_missing_drop_continous.columns
# create X train with categorical variables with less than 10 uniques
X train all missing dropped prefered unique cat = X train[fe unique columns].dropna( axis=1
feature_prefered_columns = list(X_train_all_missing_dropped_prefered_unique_cat.columns)
# creating dummy variables for the data with categorical variables
X_train_encoded = pd.get_dummies(X_train_all_missing_dropped_prefered_unique_cat,drop_first
X_train_numeric = X_train_all_missing_drop_continous
del X_train_all_missing_drop_continous
# selecting X test with the appropriate predictors for numeric predictors and selected uniq
X test numeric = X test[numeric col after drop]
X test encoded = pd.get dummies(X test[feature prefered columns],drop first=True)[X train e
```

## In [6]:

```
X_train_encoded.columns
```

#### Out[6]:

#### In [7]:

```
features=np.array(X_train_encoded.columns[:38])
```

## In [8]:

```
type(features)
```

## Out[8]:

numpy.ndarray

```
In [9]:
extra_features=['Var196','Var203','Var205','Var208','Var210','Var211','Var218','Var221','Va
In [10]:
#features.append(extra_features)
for i in range(len(extra_features)):
         features=np.append(features,extra features[i])
In [11]:
features
Out[11]:
array(['Var6', 'Var7', 'Var13', 'Var21', 'Var22', 'Var24', 'Var25',
                'Var28', 'Var35', 'Var38', 'Var44', 'Var57', 'Var65',
                'Var74', 'Var76', 'Var78', 'Var81', 'Var83', 'Var85', 'Var109',
                'Var112', 'Var113', 'Var119', 'Var123', 'Var125', 'Var132',
                'Var133', 'Var134', 'Var140', 'Var143', 'Var144', 'Var149',
                'Var153', 'Var160', 'Var163', 'Var173', 'Var181', 'Var196',
                'Var203', 'Var205', 'Var208', 'Var210', 'Var211', 'Var218',
                'Var221', 'Var223', 'Var227'], dtype=object)
In [12]:
X_train = pd.read_csv('./Data/orange_small_train.data', sep='\t')
X_test = pd.read_csv('./Data/orange_small_test.data', sep='\t')
y_train_churn = pd.read_csv('./Data/orange_small_train_churn.labels.txt',header=None)
y_train_apt = pd.read_csv('./Data/orange_small_train_appetency.labels',header=None)
y_train_upsell = pd.read_csv('./Data/orange_small_train_upselling.labels',header=None)
In [13]:
X_train=X_train[features]
X_test=X_test[features]
In [14]:
X train.columns
Out[14]:
Index(['Var6', 'Var7', 'Var13', 'Var21', 'Var22', 'Var24', 'Var25', 'Var28',
                 'Var35', 'Var38', 'Var44', 'Var57', 'Var65', 'Var73', 'Var74', 'Var7
6',
                'Var78', 'Var81', 'Var83', 'Var85', 'Var109', 'Var112', 'Var113',
                'Var119', 'Var123', 'Var125', 'Var132', 'Var133', 'Var134', 'Var140'
                'Var143', 'Var144', 'Var149', 'Var153', 'Var160', 'Var163', 'Var173', 'Var181', 'Var196', 'Var203', 'Var205', 'Var208', 'Var210', 'Var211', 'Var21', 'Var21',
                'Var218', 'Var221', 'Var223', 'Var227'],
             dtype='object')
In [15]:
X train=pd.get dummies(X train,columns=extra features)
```

## localhost:8888/notebooks/Desktop/tree/P1-sumanth\_dev/first\_cut.ipynb

X\_test=pd.get\_dummies(X\_test,columns=extra\_features)

```
In [16]:
```

```
X_train['churn']=y_train_churn
X_train['apt']=y_train_apt
X_train['upsell']=y_train_upsell
```

## In [17]:

```
X_train.columns
```

```
Out[17]:
```

```
Index(['Var6', 'Var7', 'Var13', 'Var21', 'Var22', 'Var24', 'Var25', 'Var28',
        'Var35', 'Var38', 'Var44', 'Var57', 'Var65', 'Var73', 'Var74', 'Var7
6',
        'Var78', 'Var81', 'Var83', 'Var85', 'Var109', 'Var112', 'Var113',
        'Var119', 'Var123', 'Var125', 'Var132', 'Var133', 'Var134', 'Var140', 'Var143', 'Var144', 'Var149', 'Var153', 'Var160', 'Var163', 'Var173',
        'Var181', 'Var196_1K8T', 'Var196_JA1C', 'Var196_mKeq', 'Var196_z3mO',
        'Var203_9_Y1', 'Var203_F3hy', 'Var203_HLqf', 'Var203_dgxZ',
        'Var203_pybr', 'Var205_09_Q', 'Var205_vpaQ , var203_332.13
'Var208_kIsH', 'Var208_sBgB', 'Var210_3av_', 'Var210_7A3j', 'Var210_tbar210_ot7d', 'Var210_uKAI',
                                                             'Var205_sJzTlal',
        'Var210_DM_V', 'Var210_g5HH', 'Var210_oT7d', 'Var210_uKAI',
        'Var211_L84s', 'Var211_Mtgm', 'Var218_UYBR', 'Var218_cJvF',
        'Var221_Al6ZaUT', 'Var221_JIiEFBU', 'Var221_QKW8DRm', 'Var221_d0EEeJ
i',
        'Var221_oslk', 'Var221_z4pH', 'Var221_zCkv', 'Var223_LM81689q0p',
        'Var223_M_8D', 'Var223_bCPvVye', 'Var223_jySVZN10Jy', 'Var227_02N6s8
f',
        'Var227_6fzt', 'Var227_RAYp', 'Var227_ZI9m', 'Var227_nIGXDli',
        'Var227_nIGjgSB', 'Var227_vJ_w8kB', 'churn', 'apt', 'upsell'],
       dtype='object')
```

#### In [18]:

```
X_train.dropna(inplace=True)
X_test.dropna(inplace=True)
```

#### In [19]:

X\_train.shape

#### Out[19]:

(42153, 83)

#### In [20]:

```
X_train.head()
```

## Out[20]:

	Var6	Var7	Var13	Var21	Var22	Var24	Var25	Var28	Var35	Var38	 Var227_02I
0	1526.0	7.0	184.0	464.0	580.0	14.0	128.0	166.56	0.0	3570.0	 
1	525.0	0.0	0.0	168.0	210.0	2.0	24.0	353.52	0.0	4764966.0	
2	5236.0	7.0	904.0	1212.0	1515.0	26.0	816.0	220.08	0.0	5883894.0	
4	1029.0	7.0	3216.0	64.0	80.0	4.0	64.0	200.00	0.0	0.0	
5	658.0	7.0	3156.0	224.0	280.0	2.0	72.0	200.00	5.0	0.0	

5 rows × 83 columns

```
→
```

#### In [21]:

```
xc_train,xc_test=train_test_split(X_train,train_size=0.9)
```

#### In [22]:

```
xc_train.columns
```

#### Out[22]:

```
Index(['Var6', 'Var7', 'Var13', 'Var21', 'Var22', 'Var24', 'Var25', 'Var28',
        'Var35', 'Var38', 'Var44', 'Var57', 'Var65', 'Var73', 'Var74', 'Var7
6',
       'Var78', 'Var81', 'Var83', 'Var85', 'Var109', 'Var112', 'Var113',
       'Var119', 'Var123', 'Var125', 'Var132', 'Var133', 'Var134', 'Var140',
       'Var143', 'Var144', 'Var149', 'Var153', 'Var160', 'Var163', 'Var173',
       'Var181', 'Var196_1K8T', 'Var196_JA1C', 'Var196_mKeq', 'Var196_z3mO',
       'Var203_9_Y1', 'Var203_F3hy', 'Var203_HLqf', 'Var203_dgxZ',
       'Var203_pybr', 'Var205_09_Q', 'Var205_VpdQ', 'Var205_sJzTlal',
       'Var208_kIsH', 'Var208_sBgB', 'Var210_3av_', 'Var210_7A3j',
       'Var210_DM_V', 'Var210_g5HH', 'Var210_oT7d', 'Var210_uKAI', 'Var211_L84s', 'Var211_Mtgm', 'Var218_UYBR', 'Var218_cJvF',
       'Var221 Al6ZaUT', 'Var221 JIiEFBU', 'Var221 QKW8DRm', 'Var221 d0EEeJ
i',
       'Var221 oslk', 'Var221 z4pH', 'Var221 zCkv', 'Var223 LM81689qOp',
       'Var223 M 8D', 'Var223 bCPvVye', 'Var223 jySVZNlOJy', 'Var227 02N6s8
f',
       'Var227 6fzt', 'Var227 RAYp', 'Var227 ZI9m', 'Var227 nIGXDli',
       'Var227_nIGjgSB', 'Var227_vJ_w8kB', 'churn', 'apt', 'upsell'],
      dtype='object')
```

```
In [23]:
```

```
xc_test.head()
```

## Out[23]:

/ar35	Var38	 Var227_02N6s8f	Var227_6fzt	Var227_RAYp	Var227_ZI9m	Var227_nIGXDli	Va
0.0	210516.0	 0	1	0	0	0	
0.0	240900.0	 0	0	0	1	0	
0.0	4954734.0	 0	0	1	0	0	
0.0	3114666.0	 0	0	0	0	1	
0.0	587202.0	 0	0	1	0	0	

**←** 

## In [24]:

```
max_depths=[5,10,15,20,25,30]
```

## In [26]:

```
yc_train,yc_test=xc_train['churn'],xc_test['churn']
yu_train,yu_test=xc_train['upsell'],xc_test['upsell']
ya_train,ya_test=xc_train['apt'],xc_test['apt']
```

## In [27]:

```
xc_train,xc_test=xc_train.drop(columns=['apt','churn','upsell']),xc_test.drop(columns=['apt
```

## In [32]:

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

## In [33]:

```
accuracy_churn=[]
```

# In [35]:

```
#for churn

for i in range(len(max_depths)):
    modelchurn=DecisionTreeClassifier(max_depth=max_depths[i])

modelchurn.fit(xc_train,yc_train)

preds=modelchurn.predict(xc_test)

accuracy=accuracy_score(yc_test,preds)

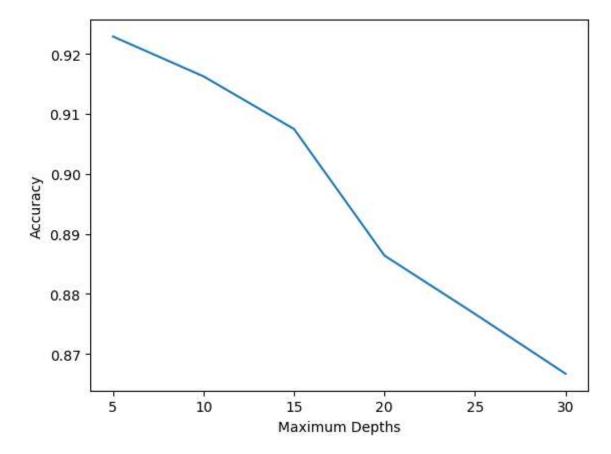
accuracy_churn.append(accuracy)
```

## In [37]:

```
plt.plot(max_depths,accuracy_churn)
plt.xlabel('Maximum Depths')
plt.ylabel('Accuracy')
plt.plot()
```

## Out[37]:

[]



## In [38]:

```
accuracy_upsell=[]
```

## In [40]:

```
#for upsell

for i in range(len(max_depths)):
    modelchurn=DecisionTreeClassifier(max_depth=max_depths[i])

modelchurn.fit(xc_train,yu_train)

preds=modelchurn.predict(xc_test)

accuracy=accuracy_score(yu_test,preds)

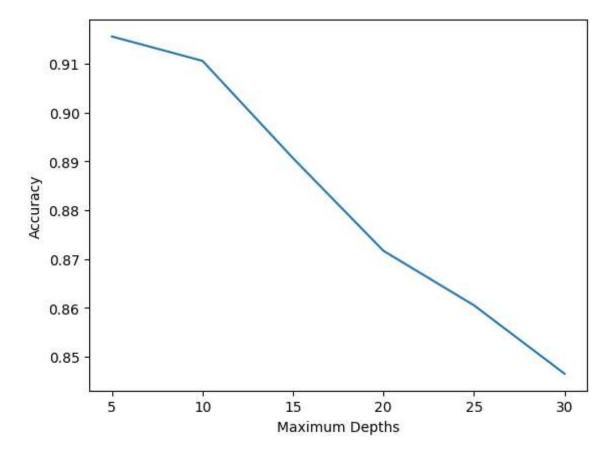
accuracy_upsell.append(accuracy)
```

## In [41]:

```
plt.plot(max_depths,accuracy_upsell)
plt.xlabel('Maximum Depths')
plt.ylabel('Accuracy')
plt.plot()
```

# Out[41]:

[]



## In [42]:

```
accuracy_apt=[]
```

## In [44]:

```
#for apt

for i in range(len(max_depths)):
    modelchurn=DecisionTreeClassifier(max_depth=max_depths[i])

modelchurn.fit(xc_train,ya_train)

preds=modelchurn.predict(xc_test)

accuracy=accuracy_score(ya_test,preds)

accuracy_apt.append(accuracy)
```

## In [46]:

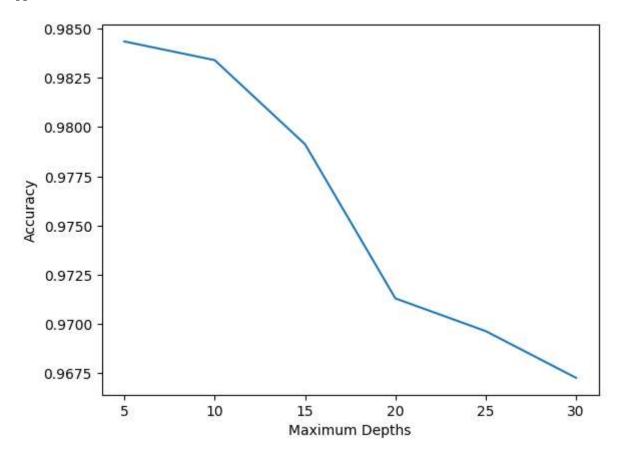
```
plt.plot(max_depths,accuracy_apt)

plt.xlabel('Maximum Depths')
plt.ylabel('Accuracy')

plt.plot()
```

#### Out[46]:

[]



## In [47]:

```
#Therefore max_depth=5 seems suitable
```

#### In [48]:

```
model_churn=DecisionTreeClassifier(max_depth=5)
model_apt=DecisionTreeClassifier(max_depth=5)
model_upsell=DecisionTreeClassifier(max_depth=5)

model_churn.fit(xc_train,yc_train)
model_apt.fit(xc_train,ya_train)
model_upsell.fit(xc_train,yu_train)
```

#### Out[48]:

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5)
```

#### In [49]:

```
model_churn.feature_importances_
```

## Out[49]:

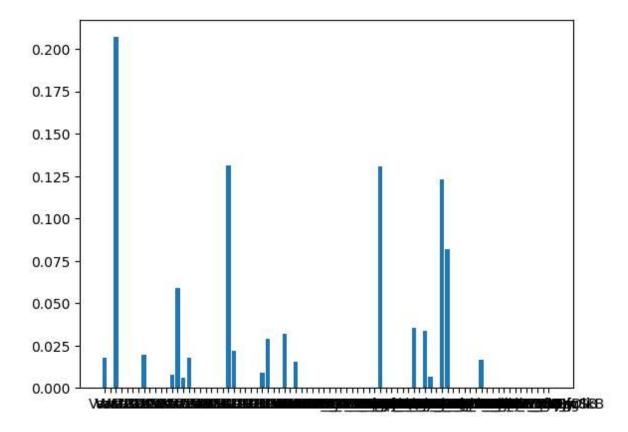
```
array([0.01765469, 0.
                          , 0.20698696, 0.
                                                , 0.
             , 0.
                          , 0.01941337, 0.
                                            , 0.
      0.
                          , 0.00749139, 0.05907929, 0.00625282,
               , 0.
      0.
                          , 0.
      0.01759149, 0.
                                , 0. , 0.
               , 0.
                         , 0.13141547, 0.02196302, 0.
      0.
               , 0.
      0.
                          , 0. , 0.00873278, 0.02864451,
      0.
               , 0.
                          , 0.03154154, 0.
                                             , 0.01559011,
                         , 0.
               , 0.
                                               , 0.
      0.
                                , 0.
               , 0.
                          , 0.
                                    , 0.
                                               , 0.
      0.
               , 0.
                          , 0.
                                     , 0.
      0.
                                                , 0.13064787,
              , 0.
                         , 0.
                                    , 0.
                                                , 0.
      0.
                          , 0.03373739, 0.00643362, 0.
      0.03510297, 0.
      0.12297843, 0.08204916, 0.
                               , 0.
               , 0.
                     , 0.01669313, 0.
                                                , 0.
               , 0.
                         , 0.
                                                , 0.
      0.
                               , 0.
      0.
               , 0.
                                     , 0.
                          , 0.
                                                , 0.
                                                           ])
```

# In [50]:

```
plt.bar(xc_train.columns,model_churn.feature_importances_)
plt.plot()
```

# Out[50]:

[]



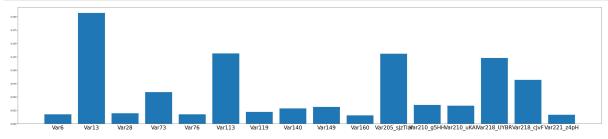
## In [64]:

```
importances=model_churn.feature_importances_
indicesc=[]

for i in range(len(importances)):
    if(importances[i]>0.01):
        indicesc.append(i)
```

# In [73]:

```
plt.figure(figsize=(50,10))
plt.bar(xc_train.columns[indicesc],importances[indicesc])
plt.xticks(fontsize=25)
plt.show()
```



## In [74]:

predictions=model\_churn.predict(xc\_test)

#### In [79]:

```
from sklearn.metrics import plot_roc_curve

plot_roc_curve(model_churn,xc_test,yc_test)

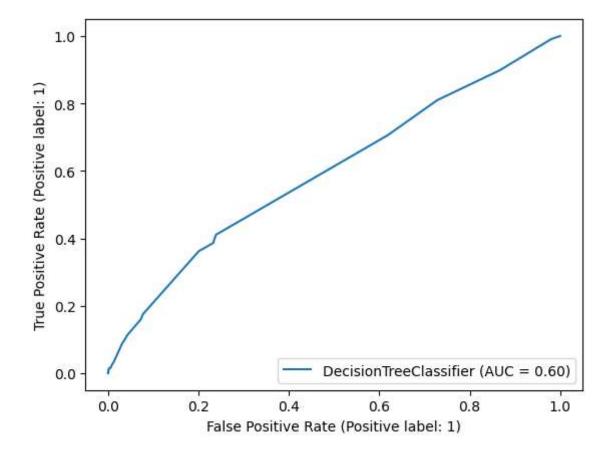
plt.plot()
```

C:\Users\chinm\AppData\Local\Programs\Python\Python310\lib\site-packages\skl earn\utils\deprecation.py:87: FutureWarning: Function plot\_roc\_curve is deprecated; Function :func:`plot\_roc\_curve` is deprecated in 1.0 and will be rem oved in 1.2. Use one of the class methods: :meth:`sklearn.metrics.RocCurveDisplay.from\_predictions` or :meth:`sklearn.metrics.RocCurveDisplay.from\_estim ator`.

warnings.warn(msg, category=FutureWarning)

## Out[79]:

[]

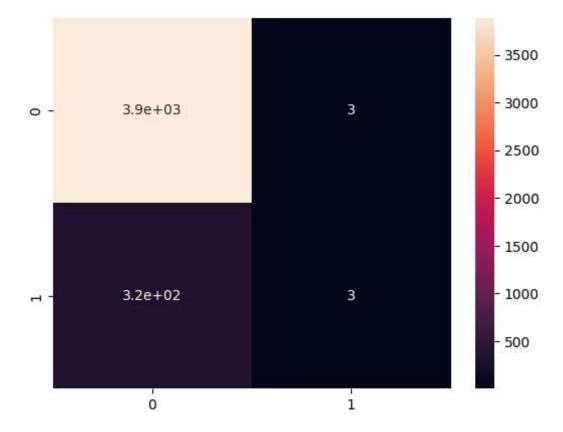


# In [81]:

```
from sklearn.metrics import confusion_matrix
confusionmatrix=confusion_matrix(yc_test,predictions)
import seaborn as sns
sns.heatmap(confusionmatrix,annot=True)
```

## Out[81]:

# <AxesSubplot: >



# In [85]:

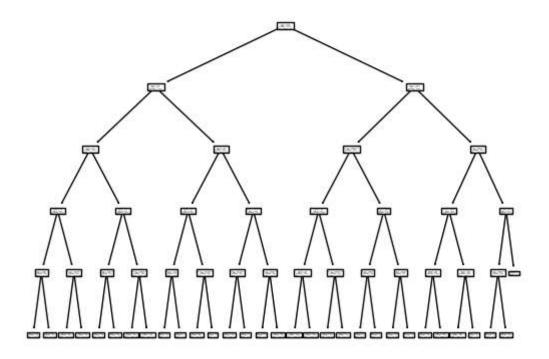
```
from sklearn.tree import plot_tree

plot_tree(model_churn)

plt.plot()
```

# Out[85]:

[]

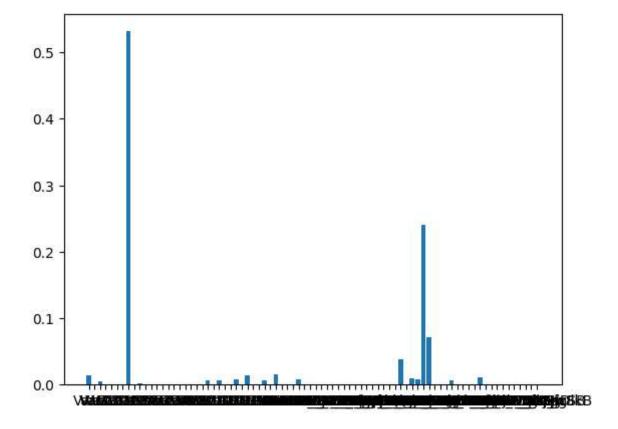


# In [51]:

```
plt.bar(xc_train.columns,model_upsell.feature_importances_)
plt.plot()
```

# Out[51]:

[]

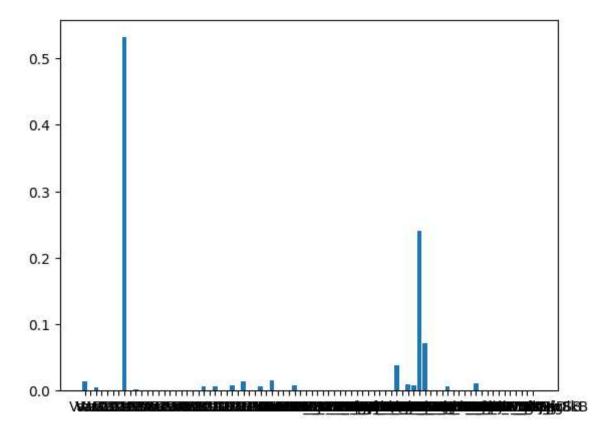


```
In [52]:
```

```
plt.bar(xc_train.columns,model_upsell.feature_importances_)
plt.plot()
```

# Out[52]:

[]



# In [53]:

```
X_test = pd.read_csv('./Data/orange_small_test.data', sep='\t')
```

# In [54]:

```
X_test=X_test[features]
```

```
In [55]:
```

```
X_test.dropna(inplace=True)
```

In [56]:

X\_test=pd.get\_dummies(X\_test,columns=extra\_features)

In [57]:

X\_test.head()

Out[57]:

	Var6	Var7	Var13	Var21	Var22	Var24	Var25	Var28	Var35	Var38	 Var223_M_
0	1225.0	7.0	100.0	156.0	195.0	0.0	72.0	166.56	0.0	4259232.0	 
1	259.0	0.0	0.0	192.0	240.0	0.0	40.0	300.32	5.0	4859550.0	
2	861.0	14.0	236.0	32.0	40.0	0.0	8.0	186.64	0.0	10038840.0	
3	1568.0	7.0	1232.0	448.0	560.0	4.0	88.0	166.56	0.0	116760.0	
4	1197.0	7.0	204.0	100.0	125.0	8.0	40.0	133.12	0.0	257772.0	

5 rows × 79 columns

 $local host: 8888/notebooks/Desktop/tree/P1-sumanth\_dev/first\_cut.ipynb$ 

```
In [58]:
```

PREDICTIONS CHURN=model churn.predict(X test)

```
PREDICTIONS_UPSELL=model_upsell.predict(X_test)
PREDICTIONS_APT=model_apt.predict(X_test)
C:\Users\chinm\AppData\Local\Programs\Python\Python310\lib\site-packages\skl
earn\base.py:493: FutureWarning: The feature names should match those that w
ere passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- Var210_eyPI
Feature names seen at fit time, yet now missing:
- Var203 pybr
- Var210_oT7d
  warnings.warn(message, FutureWarning)
ValueError
                                          Traceback (most recent call last)
Cell In [58], line 1
---> 1 PREDICTIONS CHURN=model churn.predict(X test)
      2 PREDICTIONS_UPSELL=model_upsell.predict(X_test)
      3 PREDICTIONS APT=model apt.predict(X test)
File ~\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\tre
e\ classes.py:505, in BaseDecisionTree.predict(self, X, check input)
    482 """Predict class or regression value for X.
    484 For a classification model, the predicted class for each sample in X
is
   (\ldots)
    502
            The predicted classes, or the predict values.
    503 """
    504 check_is_fitted(self)
--> 505 X = self._validate_X_predict(X, check_input)
    506 proba = self.tree_.predict(X)
    507 n samples = X.shape[0]
File ~\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\tre
e\_classes.py:471, in BaseDecisionTree._validate_X_predict(self, X, check_in
put)
    469 """Validate the training data on predict (probabilities)."""
    470 if check input:
            X = self. validate data(X, dtype=DTYPE, accept sparse="csr", res
--> 471
et=False)
    472
            if issparse(X) and (
    473
                X.indices.dtype != np.intc or X.indptr.dtype != np.intc
    474
            ):
    475
                raise ValueError("No support for np.int64 index based sparse
matrices")
File ~\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\bas
e.py:600, in BaseEstimator._validate_data(self, X, y, reset, validate_separa
tely, **check_params)
    597
            out = X, y
    599 if not no_val_X and check_params.get("ensure_2d", True):
--> 600
            self._check_n_features(X, reset=reset)
    602 return out
File ~\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\bas
e.py:400, in BaseEstimator. check n features(self, X, reset)
```

**ValueError**: X has 79 features, but DecisionTreeClassifier is expecting 80 fe atures as input.

# In [59]:

```
csdv=np.zeros(shape=len(X_test))
```

## In [60]:

```
X_test['Var203_pybr']=csdv
X_test['Var210_oT7d']=csdv
```

## In [61]:

```
X_test=X_test.drop(columns=['Var210_eyPI'])
```

#### In [62]:

```
X_test.head()
```

# Out[62]:

	Var6	Var7	Var13	Var21	Var22	Var24	Var25	Var28	Var35	Var38	 Var223_jyS
0	1225.0	7.0	100.0	156.0	195.0	0.0	72.0	166.56	0.0	4259232.0	 
1	259.0	0.0	0.0	192.0	240.0	0.0	40.0	300.32	5.0	4859550.0	
2	861.0	14.0	236.0	32.0	40.0	0.0	8.0	186.64	0.0	10038840.0	
3	1568.0	7.0	1232.0	448.0	560.0	4.0	88.0	166.56	0.0	116760.0	
4	1197.0	7.0	204.0	100.0	125.0	8.0	40.0	133.12	0.0	257772.0	

5 rows × 80 columns

1

## In [63]:

```
PREDICTIONS_CHURN=model_churn.predict(X_test)
PREDICTIONS_UPSELL=model_upsell.predict(X_test)
PREDICTIONS_APT=model_apt.predict(X_test)
```

C:\Users\chinm\AppData\Local\Programs\Python\Python310\lib\site-packages\skl earn\base.py:493: FutureWarning: The feature names should match those that w ere passed during fit. Starting version 1.2, an error will be raised. Feature names must be in the same order as they were in fit.

warnings.warn(message, FutureWarning)

C:\Users\chinm\AppData\Local\Programs\Python\Python310\lib\site-packages\skl earn\base.py:493: FutureWarning: The feature names should match those that w ere passed during fit. Starting version 1.2, an error will be raised. Feature names must be in the same order as they were in fit.

warnings.warn(message, FutureWarning)

C:\Users\chinm\AppData\Local\Programs\Python\Python310\lib\site-packages\skl earn\base.py:493: FutureWarning: The feature names should match those that w ere passed during fit. Starting version 1.2, an error will be raised. Feature names must be in the same order as they were in fit.

warnings.warn(message, FutureWarning)