# Churn prediction fundamentals

MACHINE LEARNING FOR MARKETING IN PYTHON

**Karolis Urbonas**
Head of Analytics & Science, Amazon

# What is churn?

- Churn happens when a customer stops buying / engaging
- The business context could be **contractual** or **non-contractual**
- Sometimes churn can be viewed as either **voluntary** or **involuntary**

# Types of churn

Main churn typology is based on two business model types:

- Contractual (phone subscription, TV streaming subscription)

- Non-contractual (grocery shopping, online shopping)

# Modeling different types of churn

Typically:

- Non-contractual churn is **harder** to define and model, as there's no explicit customer decision
- We will model contractual churn in the telecom business model

# Encoding churn

- Typically 1/0, with 1 = Churn, 0 = No Churn
- Could be a string `Churn` / `No Churn` or `Yes` / `No` - best practice to transform as 1 and 0

```
set(telcom['Churn'])
```

```
{0, 1}
```

# Exploring churn distribution

```
telcom.groupby(['Churn']).size() / telcom.shape[0] * 100
```

```
Churn
0    73.421502
1    26.578498
dtype: float64
```

# Split to training and testing data

```
from sklearn.model_selection import train_test_split
train, test = train_test_split(telcom, test_size = .25)
```

# Separate features and target variables

Separate column names by data types

```
target  = ['Churn']
custid  = ['customerID']
cols    = [col for col in telcom.columns if col not in custid + target]
```

Build training and testing datasets

```
train_X = train[cols]
train_Y = train[target]
test_X  = test[cols]
test_Y  = test[target]
```

# Let's go practice!

# Predict churn with logistic regression

MACHINE LEARNING FOR MARKETING IN PYTHON

**Karolis Urbonas**
Head of Analytics & Science, Amazon

# Introduction to logistic regression

- Statistical classification model for binary responses
- Models log-odds of the probability of the target
- Assumes linear relationship between log-odds target and predictors
- Returns coefficients and prediction probability

$$\log_b \frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

# Modeling steps

1. **Split** data to training and testing
2. **Initialize** the model
3. **Fit** the model on the training data
4. **Predict** values on the testing data
5. **Measure** model performance on testing data

# Fitting the model

Import the Logistic Regression classifier

```
from sklearn.linear_model import LogisticRegression
```

Initialize Logistic Regression instance

```
logreg = LogisticRegression()
```

Fit the model on the training data

```
logreg.fit(train_X, train_Y)
```

# Model performance metrics

Key metrics:

- **Accuracy** - The % of correctly predicted labels (both Churn and non Churn)
- **Precision** - The % of total model's positive class predictions (here - predicted as Churn) that were correctly classified
- **Recall** - The % of total positive class samples (all churned customers) that were correctly classified

# Measuring model accuracy

```python
from sklearn.metrics import accuracy_score
pred_train_Y = logreg.predict(train_X)
pred_test_Y = logreg.predict(test_X)
train_accuracy = accuracy_score(train_Y, pred_train_Y)
test_accuracy = accuracy_score(test_Y, pred_test_Y)
print('Training accuracy:', round(train_accuracy,4))
print('Test accuracy:', round(test_accuracy, 4))
```

```
Training accuracy: 0.8108
Test accuracy: 0.8009
```

# Measuring precision and recall

```
from sklearn.metrics import precision_score, recall_score
train_precision = round(precision_score(train_Y, pred_train_Y), 4)
test_precision = round(precision_score(test_Y, pred_test_Y), 4)
train_recall = round(recall_score(train_Y, pred_train_Y), 4)
test_recall = round(recall_score(test_Y, pred_test_Y), 4)
print('Training precision: {}, Training recall: {}'.format(train_precision, train_recall))
print('Test precision: {}, Test recall: {}'.format(train_recall, test_recall))
```

```
Training precision: 0.6725, Training recall: 0.5736
Test precision: 0.5736, Test recall: 0.4835
```

# Regularization

- Introduces penalty coefficient in the model building phase
- Addresses over-fitting (when patterns are "memorized by the model")
- Some regularization techniques also perform feature selection e.g. L1
- Makes the model more generalizable to unseen samples

# L1 regularization and feature selection

- `LogisticRegression` from `sklearn` performs L2 regularization by default
- L1 regularization or also called LASSO can be called explicitly, and this approach performs feature selection by shrinking some of the model coefficients to zero.

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression(penalty='l1', C=0.1, solver='liblinear')
logreg.fit(train_X, train_Y)
```

- `C` parameter needs to be **tuned** to find the optimal value

# Tuning L1 regularization

```
C = [1, .5, .25, .1, .05, .025, .01, .005, .0025]
l1_metrics = np.zeros((len(C), 5))
l1_metrics[:,0] = C
for index in range(0, len(C)):
    logreg = LogisticRegression(penalty='l1', C=C[index], solver='liblinear')
    logreg.fit(train_X, train_Y)
    pred_test_Y = logreg.predict(test_X)
    l1_metrics[index,1] = np.count_nonzero(logreg.coef_)
    l1_metrics[index,2] = accuracy_score(test_Y, pred_test_Y)
    l1_metrics[index,3] = precision_score(test_Y, pred_test_Y)
    l1_metrics[index,4] = recall_score(test_Y, pred_test_Y)
col_names = ['C','Non-Zero Coeffs','Accuracy','Precision','Recall']
print(pd.DataFrame(l1_metrics, columns=col_names))
```

# Choosing optimal C value

| | C | Non-Zero Coeffs | Accuracy | Precision | Recall |
|---|---|---|---|---|---|
| **0** | 1.000 | 22.000 | 0.800 | 0.656 | 0.481 |
| **1** | 0.500 | 22.000 | 0.799 | 0.652 | 0.481 |
| **2** | 0.250 | 21.000 | 0.802 | 0.660 | 0.486 |
| **3** | 0.100 | 20.000 | 0.803 | 0.665 | 0.479 |
| **4** | 0.050 | 18.000 | 0.802 | 0.663 | 0.479 |
| **5** | 0.025 | 13.000 | 0.797 | 0.658 | 0.448 |
| **6** | 0.010 | 5.000 | 0.790 | 0.662 | 0.387 |
| **7** | 0.005 | 3.000 | 0.783 | 0.685 | 0.301 |
| **8** | 0.003 | 2.000 | 0.746 | 0.833 | 0.022 |

# Choosing optimal C value

| | C | Non-Zero Coeffs | Accuracy | Precision | Recall |
|---|---|---|---|---|---|
| **0** | 1.000 | 22.000 | 0.800 | 0.656 | 0.481 |
| **1** | 0.500 | 22.000 | 0.799 | 0.652 | 0.481 |
| **2** | 0.250 | 21.000 | 0.802 | 0.660 | 0.486 |
| **3** | 0.100 | 20.000 | 0.803 | 0.665 | 0.479 |
| **4** | 0.050 | 18.000 | 0.802 | 0.663 | 0.479 |
| **5** | 0.025 | 13.000 | 0.797 | 0.658 | 0.448 |
| **6** | 0.010 | 5.000 | 0.790 | 0.662 | 0.387 |
| **7** | 0.005 | 3.000 | 0.783 | 0.685 | 0.301 |
| **8** | 0.003 | 2.000 | 0.746 | 0.833 | 0.022 |

# Let's run some logistic regression models!

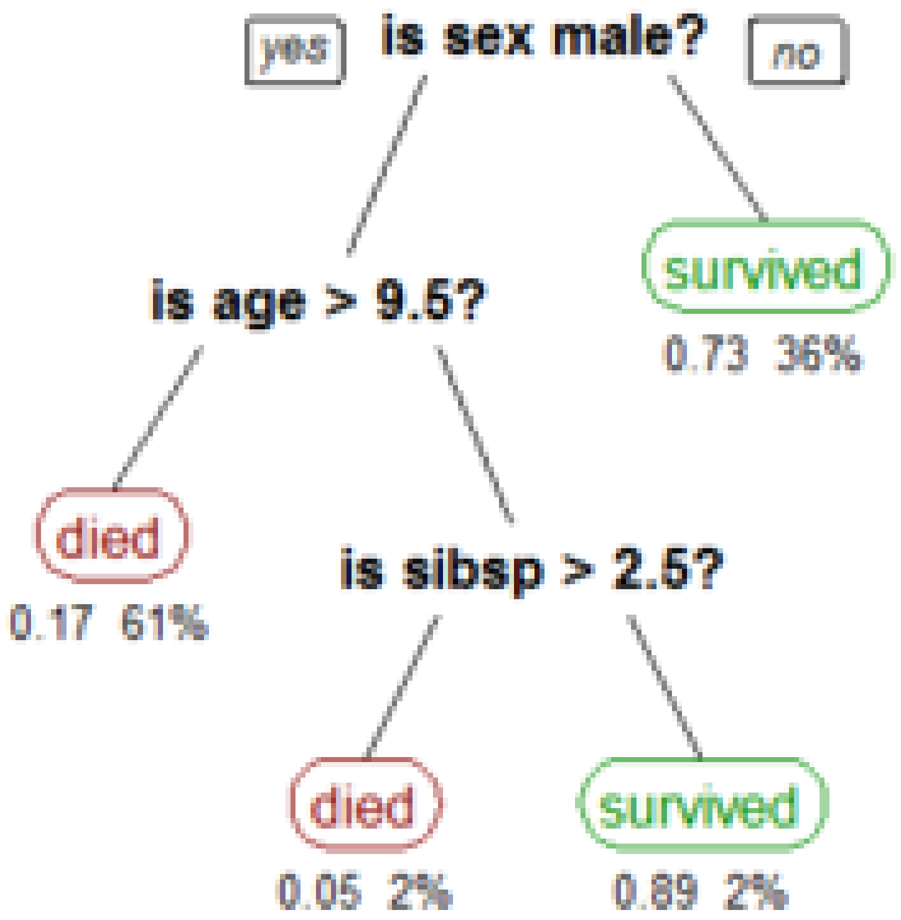
MACHINE LEARNING FOR MARKETING IN PYTHON

# Predict churn with decision trees

MACHINE LEARNING FOR MARKETING IN PYTHON

**Karolis Urbonas**
Head of Analytics & Science, Amazon

# Introduction to decision trees



# Modeling steps

1. **Split** data to training and testing
2. **Initialize** the model
3. **Fit** the model on the training data
4. **Predict** values on the testing data
5. **Measure** model performance on testing data

# Fitting the model

Import the decision tree module

```
from sklearn.tree import DecisionTreeClassifier
```

Initialize the Decision Tree model

```
mytree = DecisionTreeClassifier()
```

Fit the model on the training data

```
treemodel = mytree.fit(train_X, train_Y)
```

# Measuring model accuracy

```python
from sklearn.metrics import accuracy_score
pred_train_Y = mytree.predict(train_X)
pred_test_Y = mytree.predict(test_X)
train_accuracy = accuracy_score(train_Y, pred_train_Y)
test_accuracy = accuracy_score(test_Y, pred_test_Y)
print('Training accuracy:', round(train_accuracy,4))
print('Test accuracy:', round(test_accuracy, 4))
```

```
Training accuracy: 0.9973
Test accuracy: 0.7196
```

# Measuring precision and recall

```
from sklearn.metrics import precision_score, recall_score
train_precision = round(precision_score(train_Y, pred_train_Y), 4)
test_precision = round(precision_score(test_Y, pred_test_Y), 4)
train_recall = round(recall_score(train_Y, pred_train_Y), 4)
test_recall = round(recall_score(test_Y, pred_test_Y), 4)
print('Training precision: {}, Training recall: {}'.format(train_precision, train_recall))
print('Test precision: {}, Test recall: {}'.format(train_recall, test_recall))
```

```
Training precision: 0.9993, Training recall: 0.9906
Test precision: 0.9906, Test recall: 0.4878
```

# Tree depth parameter tuning

```
depth_list = list(range(2,15))
depth_tuning = np.zeros((len(depth_list), 4))
depth_tuning[:,0] = depth_list
for index in range(len(depth_list)):
    mytree = DecisionTreeClassifier(max_depth=depth_list[index])
    mytree.fit(train_X, train_Y)
    pred_test_Y = mytree.predict(test_X)
    depth_tuning[index,1] = accuracy_score(test_Y, pred_test_Y)
    depth_tuning[index,2] = precision_score(test_Y, pred_test_Y)
    depth_tuning[index,3] = recall_score(test_Y, pred_test_Y)
col_names = ['Max_Depth','Accuracy','Precision','Recall']
print(pd.DataFrame(depth_tuning, columns=col_names))
```

# Choosing optimal depth

| | Max_Depth | Accuracy | Precision | Recall |
|---|---|---|---|---|
| 0 | 2.000 | 0.774 | 0.700 | 0.329 |
| 1 | 3.000 | 0.774 | 0.700 | 0.329 |
| 2 | 4.000 | 0.774 | 0.705 | 0.327 |
| 3 | 5.000 | 0.780 | 0.636 | 0.492 |
| 4 | 6.000 | 0.778 | 0.638 | 0.467 |
| 5 | 7.000 | 0.776 | 0.669 | 0.388 |
| 6 | 8.000 | 0.769 | 0.626 | 0.427 |
| 7 | 9.000 | 0.764 | 0.609 | 0.429 |
| 8 | 10.000 | 0.747 | 0.559 | 0.445 |
| 9 | 11.000 | 0.751 | 0.564 | 0.473 |
| 10 | 12.000 | 0.725 | 0.508 | 0.453 |
| 11 | 13.000 | 0.727 | 0.511 | 0.486 |
| 12 | 14.000 | 0.721 | 0.499 | 0.478 |

# Choosing optimal depth

| | Max_Depth | Accuracy | Precision | Recall |
|---|---|---|---|---|
| 0 | 2.000 | 0.774 | 0.700 | 0.329 |
| 1 | 3.000 | 0.774 | 0.700 | 0.329 |
| 2 | 4.000 | 0.774 | 0.705 | 0.327 |
| 3 | 5.000 | 0.780 | 0.636 | 0.492 |
| 4 | 6.000 | 0.778 | 0.638 | 0.467 |
| 5 | 7.000 | 0.776 | 0.669 | 0.388 |
| 6 | 8.000 | 0.769 | 0.626 | 0.427 |
| 7 | 9.000 | 0.764 | 0.609 | 0.429 |
| 8 | 10.000 | 0.747 | 0.559 | 0.445 |
| 9 | 11.000 | 0.751 | 0.564 | 0.473 |
| 10 | 12.000 | 0.725 | 0.508 | 0.453 |
| 11 | 13.000 | 0.727 | 0.511 | 0.486 |
| 12 | 14.000 | 0.721 | 0.499 | 0.478 |

# Let's build a decision tree!

MACHINE LEARNING FOR MARKETING IN PYTHON

# Identify and interpret churn drivers

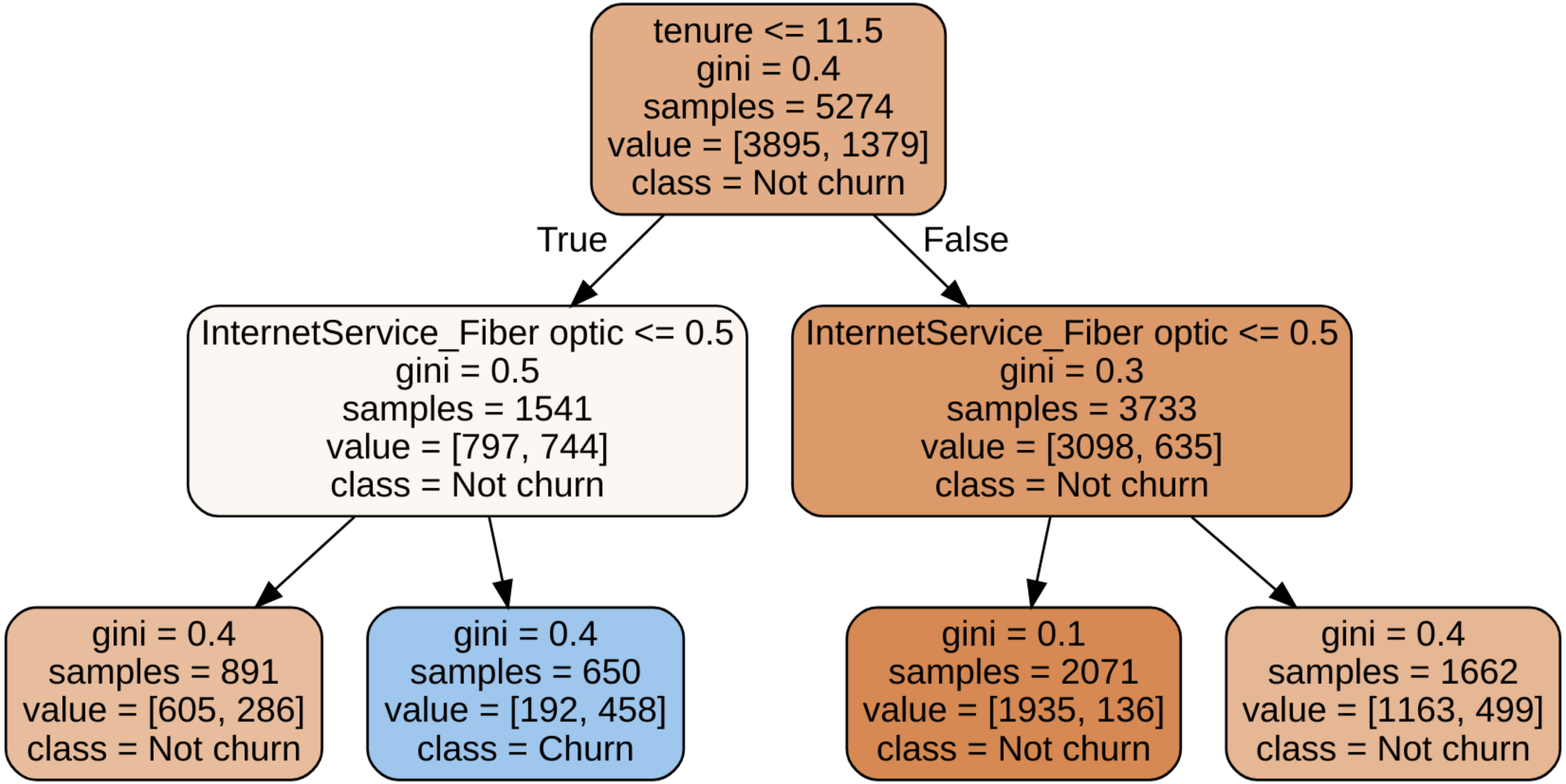
MACHINE LEARNING FOR MARKETING IN PYTHON

**Karolis Urbonas**
Head of Analytics & Science, Amazon

# Plotting decision tree rules

```
from sklearn import tree
import graphviz
exported = tree.export_graphviz(
            decision_tree=mytree,
            out_file=None,
            feature_names=cols,
            precision=1,
            class_names=['Not churn','Churn'],
            filled = True)
graph = graphviz.Source(exported)
display(graph)
```

# Interpreting decision tree chart



# Logistic regression coefficients

- Logistic regression returns beta coefficients
- Can be interpreted as change in **log-odds** of churn associated with 1 unit increase in the feature

$$\log_b \frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

# Extracting logistic regression coefficients

- Coefficients can be extracted using `.coef_` method on fitted Logistic Regression instance

```
logreg.coef_
```

```
array([[ 0.        ,  0.09784772,  0.        , -0.03935476, -0.82068131,
        -0.41231806, -0.14319622, -0.01746504, -0.41830733,  0.        ,
         0.        ,  0.07138468,  0.        ,  0.        ,  0.        ,
         0.        , -0.41424363, -0.59539021,  0.        ,  0.18846525,
         0.        , -0.90766135,  0.90151342,  0.        ]])
```

# Transforming logistic regression coefficients

- **Log-odds** is difficult to interpret
- Solution - calculate **exponent** of the coefficients
- This gives us the change in **odds** associated with 1 unit increase in the feature

```
coefficients = pd.concat([pd.DataFrame(train_X.columns),
                          pd.DataFrame(np.transpose(logit.coef_))],
                          axis = 1)
coefficients.columns = ['Feature', 'Coefficient']
coefficients['Exp_Coefficient'] = np.exp(coefficients['Coefficient'])
coefficients = coefficients[coefficients['Coefficient']!=0]
print(coefficients.sort_values(by=['Coefficient']))
```

# Meaning of transformed coefficients

| | Feature | Coefficient | Exp_Coefficient |
|---|---|---|---|
| **21** | tenure | -0.908 | 0.403 |
| **4** | PhoneService_Yes | -0.821 | 0.440 |
| **17** | Contract_Two year | -0.595 | 0.551 |
| **8** | TechSupport_Yes | -0.418 | 0.658 |
| **16** | Contract_One year | -0.414 | 0.661 |
| **5** | OnlineSecurity_Yes | -0.412 | 0.662 |
| **6** | OnlineBackup_Yes | -0.143 | 0.867 |
| **3** | Dependents_Yes | -0.039 | 0.961 |
| **7** | DeviceProtection_Yes | -0.017 | 0.983 |
| **11** | PaperlessBilling_Yes | 0.071 | 1.074 |
| **1** | SeniorCitizen_Yes | 0.098 | 1.103 |
| **19** | PaymentMethod_Electronic check | 0.188 | 1.207 |
| **22** | MonthlyCharges | 0.902 | 2.463 |

# Let's practice!

MACHINE LEARNING FOR MARKETING IN PYTHON