Classification

Contents

In this chapter, you'll be introduced to classification problems and learn how to solve them using supervised learning techniques. You'll learn how to split data into training and test sets, fit a model, make predictions, and evaluate accuracy. You'll discover the relationship between model complexity and performance, applying what you learn to a churn dataset, where you will classify the churn status of a telecom company's customers.

Machine learning with scikit-learn

Binary classification

In the video, you saw that there are two types of supervised learning — classification and regression. Recall that binary classification is used to predict a target variable that has only two labels, typically represented numerically with a zero or a one.

A dataset, `churn_df`, has been preloaded for you in the console.

Your task is to examine the data and choose which column could be the target variable for binary classification.

```
# edited/added
import pandas as pd
churn_df = pd.read_csv("archive/Supervised-Learning-with-scikit-learn/datasets/telecom_churn_clean.csv", index_col=[0])
churn_df.info()
```

```
## <class 'pandas.core.frame.DataFrame'>
## Int64Index: 3333 entries, 0 to 3332
## Data columns (total 19 columns):
##  #   Column                  Non-Null Count  Dtype  
## ---  ------                  --------------  -----  
##  0   account_length          3333 non-null   int64  
##  1   area_code               3333 non-null   int64  
##  2   international_plan      3333 non-null   int64  
##  3   voice_mail_plan         3333 non-null   int64  
##  4   number_vmail_messages   3333 non-null   int64  
##  5   total_day_minutes       3333 non-null   float64
##  6   total_day_calls         3333 non-null   int64  
##  7   total_day_charge        3333 non-null   float64
##  8   total_eve_minutes       3333 non-null   float64
##  9   total_eve_calls         3333 non-null   int64  
##  10  total_eve_charge        3333 non-null   float64
##  11  total_night_minutes     3333 non-null   float64
##  12  total_night_calls       3333 non-null   int64  
##  13  total_night_charge      3333 non-null   float64
##  14  total_intl_minutes      3333 non-null   float64
##  15  total_intl_calls        3333 non-null   int64  
##  16  total_intl_charge       3333 non-null   float64
##  17  customer_service_calls  3333 non-null   int64  
##  18  churn                   3333 non-null   int64  
## dtypes: float64(8), int64(11)
## memory usage: 520.8 KB
```

- [ ] "`customer_service_calls`"

- [ ] "total_night_charge"
- [x] "churn"
- [ ] "account_length"

Correct! `churn` has values of `0` or `1`, so it can be predicted using a binary classification model.

The supervised learning workflow

Recall that scikit-learn offers a repeatable workflow for using supervised learning models to predict the target variable values when presented with new data.

Reorder the pseudo-code provided so it accurately represents the workflow of building a supervised learning model and making predictions.

- Drag the code blocks into the correct order to represent how a supervised learning workflow would be executed.

```
from sklearn.module import Model
model = Model()
model.fit(X, y)
model.predict(X_new)
```

Great work! You can see how scikit-learn enables predictions to be made in only a few lines of code!

The classification challenge

k-Nearest Neighbors: Fit

In this exercise, you will build your first classification model using the `churn_df` dataset, which has been preloaded for the remainder of the chapter.

The features to use will be `"account_length"` and `"customer_service_calls"`. The target, `"churn"`, needs to be a single column with the same number of observations as the feature data.

You will convert the features and the target variable into NumPy arrays, create an instance of a KNN classifier, and then fit it to the data.

`numpy` has also been preloaded for you as `np`.

- Import `KNeighborsClassifier` from `sklearn.neighbors`.
- Create an array called `X` containing values from the `"account_length"` and `"customer_service_calls"` columns, and an array called `y` for the values of the `"churn"` column.
- Instantiate a `KNeighborsClassifier` called `knn` with `6` neighbors.
- Fit the classifier to the data using the `.fit()` method.

```
# Import KNeighborsClassifier
from sklearn.neighbors import KNeighborsClassifier

# Create arrays for the features and the target variable
y = churn_df["churn"].values
X = churn_df[["account_length", "customer_service_calls"]].values

# Create a KNN classifier with 6 neighbors
knn = KNeighborsClassifier(n_neighbors=6)

# Fit the classifier to the data
knn.fit(X, y)
```

```
## KNeighborsClassifier(n_neighbors=6)
```

Excellent! Now that your KNN classifier has been fit to the data, it can be used to predict the labels of new data points.

k-Nearest Neighbors: Predict

Now you have fit a KNN classifier, you can use it to predict the label of new data points. All available data was used for training, however, fortunately, there are new observations available. These have been preloaded for you as `X_new`.

The model `knn`, which you created and fit the data in the last exercise, has been preloaded for you. You will use your classifier to predict the labels of a set of new data points:

```
X_new = np.array([[30.0, 17.5],
                  [107.0, 24.1],
                  [213.0, 10.9]])
```

- Create `y_pred` by predicting the target values of the unseen features `X_new`.
- Print the predicted labels for the set of predictions.

```
# edited/added
import numpy as np
X_new = np.array([[30.0, 17.5], [107.0, 24.1], [213.0, 10.9]])

# Predict the labels for the X_new
y_pred = knn.predict(X_new)

# Print the predictions for X_new
print("Predictions: {}".format(y_pred))
```

```
## Predictions: [0 1 0]
```

Great work! The model has predicted the first and third customers will not churn in the new array. But how do we know how accurate these predictions are? Let's explore how to measure a model's performance in the next video.

Measuring model performance

Train/test split + computing accuracy

Now that you have learned about the importance of splitting your data into training and test sets, it's time to practice doing this on the `churn_df` dataset!

NumPy arrays have been created for you containing the features as `X` and the target variable as `y`. You will split them into training and test sets, fit a KNN classifier to the training data, and then compute its accuracy on the test data using the `.score()` method.

- Import `train_test_split` from `sklearn.model_selection`.
- Split `X` and `y` into training and test sets, setting `test_size` equal to 20%, `random_state` to `42`, and ensuring the target label proportions reflect that of the original dataset.
- Fit the `knn` model to the training data.
- Compute and print the model's accuracy for the test data.

```
# Import the module
from sklearn.model_selection import train_test_split

X = churn_df.drop("churn", axis=1).values
y = churn_df["churn"].values

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42, stratify=y)
knn = KNeighborsClassifier(n_neighbors=5)

# Fit the classifier to the training data
knn.fit(X_train, y_train)

# Print the accuracy
```

```
## KNeighborsClassifier()
```

```
print(knn.score(X_test, y_test))
```

```
## 0.8740629685157422
```

Excellent! In a few lines of code you split a dataset, fit a KNN model, and found its accuracy to be 87%!

Overfitting and underfitting

Interpreting model complexity is a great way to evaluate performance when utilizing supervised learning. Your aim is to produce a model that can interpret the relationship between features and the target variable, as well as generalize well when exposed to new observations.

You will generate accuracy scores for the training and test sets using a KNN classifier with different `n_neighbor` values, which you will plot in the next exercise.

The training and test sets have been created from the `churn_df` dataset and preloaded as `X_train`, `X_test`, `y_train`, and `y_test`.

In addition, `KNeighborsClassifier` has been imported for you along with `numpy` as `np`.

- Create `neighbors` as a `numpy` array of values from `1` up to and including `12`.
- Instantiate a KNN classifier, with the number of neighbors equal to the `neighbor` iterator.
- Fit the model to the training data.
- Calculate accuracy scores for the training set and test set separately using the `.score()`

method, and assign the results to the index of the `train_accuracies` and `test_accuracies` dictionaries, respectively.

```
# Create neighbors
neighbors = np.arange(1, 13)
train_accuracies = {}
test_accuracies = {}

for neighbor in neighbors:

    # Set up a KNN Classifier
    knn = KNeighborsClassifier(n_neighbors=neighbor)

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

    # Compute accuracy
    train_accuracies[neighbor] = knn.score(X_train, y_train)
    test_accuracies[neighbor] = knn.score(X_test, y_test)
```

```
## KNeighborsClassifier(n_neighbors=1)
## KNeighborsClassifier(n_neighbors=2)
## KNeighborsClassifier(n_neighbors=3)
## KNeighborsClassifier(n_neighbors=4)
## KNeighborsClassifier()
## KNeighborsClassifier(n_neighbors=6)
## KNeighborsClassifier(n_neighbors=7)
## KNeighborsClassifier(n_neighbors=8)
## KNeighborsClassifier(n_neighbors=9)
## KNeighborsClassifier(n_neighbors=10)
## KNeighborsClassifier(n_neighbors=11)
## KNeighborsClassifier(n_neighbors=12)
```

```
print(neighbors, '\n', train_accuracies, '\n', test_accuracies)
```

```
## [ 1  2  3  4  5  6  7  8  9 10 11 12]
##  {1: 1.0, 2: 0.9036009002250562, 3: 0.9114778694673669, 4: 0.8945986496624156, 5:
0.8953488372093024, 6: 0.8893473368342085, 7: 0.8885971492873218, 8:
0.8863465866466617, 9: 0.8870967741935484, 10: 0.8840960240060015, 11:
0.8874718679669917, 12: 0.8837209302325582}
##  {1: 0.7946026986506747, 2: 0.8605697151424287, 3: 0.8500749625187406, 4:
0.8695652173913043, 5: 0.8740629685157422, 6: 0.8650674662668666, 7:
0.8710644677661169, 8: 0.863568215892054, 9: 0.8725637181409296, 10:
0.8665667166416792, 11: 0.8710644677661169, 12: 0.8710644677661169}
```

Notice how training accuracy decreases as the number of neighbors initially gets larger, and vice versa for the testing accuracy? These scores would be much easier to interpret in a line plot, so let's produce a model complexity curve of these results.

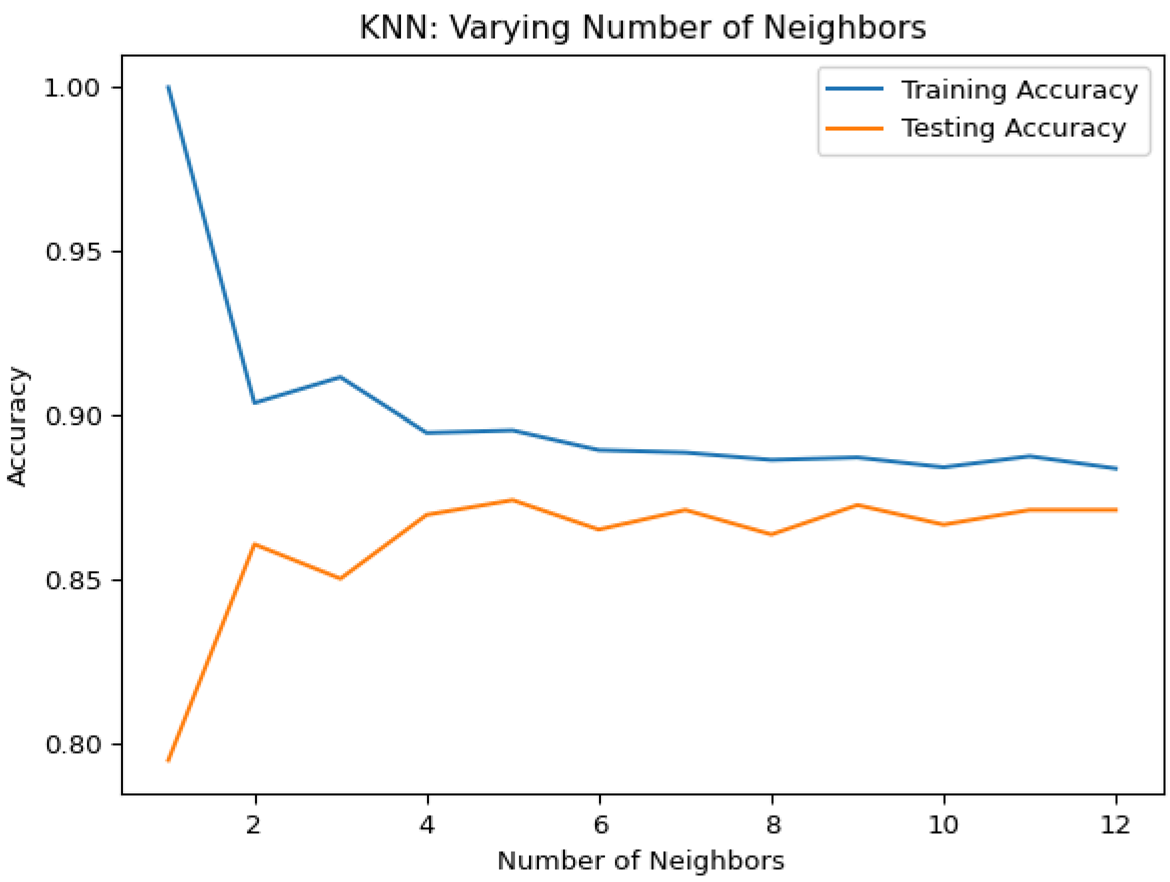
Visualizing model complexity

Now you have calculated the accuracy of the KNN model on the training and test sets using various values of `n_neighbors`, you can create a model complexity curve to visualize how performance changes as the model becomes less complex!

The variables `neighbors`, `train_accuracies`, and `test_accuracies`, which you generated in the previous exercise, have all been preloaded for you. You will plot the results to aid in finding the optimal number of neighbors for your model.

- Add a title `“KNN: Varying Number of Neighbors”`.
- Plot the `.values()` method of `train_accuracies` on the y-axis against `neighbors` on the x-axis, with a label of `“Training Accuracy”`.
- Plot the `.values()` method of `test_accuracies` on the y-axis against `neighbors` on the x-axis, with a label of `“Testing Accuracy”`.
- Display the plot.

```python
# edited/added
import matplotlib.pyplot as plt

# Add a title
plt.title("KNN: Varying Number of Neighbors")

# Plot training accuracies
plt.plot(neighbors, list(train_accuracies.values()), label="Training Accuracy") #
edited/added

# Plot test accuracies
plt.plot(neighbors, list(test_accuracies.values()), label="Testing Accuracy") #
edited/added

plt.legend()
plt.xlabel("Number of Neighbors")
plt.ylabel("Accuracy")

# Display the plot
plt.show()
```



Great work! See how training accuracy decreases and test accuracy increases as the number of neighbors gets larger. For the test set, accuracy peaks with 7 neighbors, suggesting it is the optimal value for our model. Now let’s explore regression models!