13-3

```
# Import required dependencies
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

Preprocess data:

df = df.drop(columns='whatever column you want to drop')
df.dtypes – to check data types
df.info()
print(df.columns)
df.reset_index(drop=True, inplace=True) # resets index
IFF the target column has an alphanumeric (not a discrete value); see below.

```
# Drop rows with null values
df_clean = df.dropna().copy()

# Convert y to numeric
df_clean['y'] = pd.get_dummies(df_clean['y'], drop_first = True, dtype=int)

# Drop all non-numeric columns
df_clean = df_clean.select_dtypes(include='number')

# Verify changes with the info method
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5897 entries, 0 to 33904
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       5897 non-null   int64
 1   balance   5897 non-null   int64
 2   day       5897 non-null   int64
 3   duration  5897 non-null   int64
 4   campaign  5897 non-null   int64
 5   pdays     5897 non-null   float64
 6   previous  5897 non-null   int64
 7   y         5897 non-null   uint8
dtypes: float64(1), int64(6), uint8(1)
memory usage: 374.3 KB
```

train_test_split(X,y):

X=df.copy()
X=X.drop(columns='target')
y=df['target']

df['target'].value_counts()
X_train, X_test, y_train, y_test = train_test_split(X,y)

IFF the target is not a discrete value, encode:

```
# Since the target column is an object, we need to convert the data to numerical classes
# Encode the y data
# Create an instance of the label encoder
le = LabelEncoder()

# Fit and transform the y training and testing data using the label encoder
y_train_encoded = le.fit_transform(y_train)
y_test_encoded = le.transform(y_test)
y_train_encoded
```

```
array([2, 2, 0, ..., 0, 2, 0])
```

OneHotEncoder for non-oriented data – colors, favorities

```
# Remember that all of the columns in the DataFrame are objects
# Use a OneHotEncoder to convert the training data to numerical values
ohe = OneHotEncoder(handle_unknown='ignore', sparse_output=False, dtype='int')
X_train_encoded = pd.DataFrame(data=ohe.fit_transform(X_train), columns=ohe.get_feature_names_out())
X_train_encoded
```

```
# Encode the test data
X_test_encoded = pd.DataFrame(data=ohe.transform(X_test), columns=ohe.get_feature_names_out())
X_test_encoded
```

OrdinalEncoder for things like grades, days of week

```
# Create an encoder for the grade column – there is a numerical equivalent
grade_ord_enc = OrdinalEncoder(categories = [['F', 'D', 'C', 'B', 'A']], encoded_missing_value=-1,
handle_unknown='use_encoded_value', unknown_value=-1)

# Train the encoder
grade_ord_enc.fit(X_train['grade'].values.reshape(-1,1))
```

```
OrdinalEncoder(categories=[['F', 'D', 'C', 'B', 'A']], encoded_missing_value=-1,
               handle_unknown='use_encoded_value', unknown_value=-1)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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xpand output; double click to hide output

Scale if necessary – use when values are different by orders of magnitude:

scaler = StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)

Note about the X_train and y_train variable.

Some of the X_train and y_train variables are X_train_encode and y_train_encode.
I use X_train_scaled and y_train_scaled.
Same for the X_test/y_test; I use X_test_scaled/y_test_scaled.

Model and Fit to a Support Vector Machine

```
# Create the support vector machine classifier model with a 'poly' kernel
svm_model = SVC(kernel='poly')

# Fit the model to the training data
svm_model.fit(X_train_encoded, y_train_encoded)
```

```
SVC(kernel='poly')
```

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```
# Validate the model by checking the model accuracy with model.score
print('Train Accuracy: %.3f' % svm_model.score(X_train_encoded, y_train_encoded))
print('Test Accuracy: %.3f' % svm_model.score(X_test_encoded, y_test_encoded))
```

```
Train Accuracy: 0.998
Test Accuracy: 0.977
```

Model and Fit to a Logistic Regression Classifier

```
# Create the logistic regression classifier model with a random_state of 1
lr_model = LogisticRegression(random_state=1)

# Fit the model to the training data
lr_model.fit(X_train_encoded, y_train_encoded)
```

```
LogisticRegression(random_state=1)
```

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```
# Validate the model by checking the model accuracy with model.score
print('Train Accuracy: %.3f' % lr_model.score(X_train_encoded, y_train_encoded))
print('Test Accuracy: %.3f' % lr_model.score(X_test_encoded, y_test_encoded))
```

```
Train Accuracy: 0.925
Test Accuracy: 0.917
```

Model and Fit to a Decision Tree Classifier

```
# Create the decision tree classifier model
dt_model = DecisionTreeClassifier()

# Fit the model to the training data
dt_model.fit(X_train_encoded, y_train_encoded)
```

```
DecisionTreeClassifier()
```

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```
# Validate the model by checking the model accuracy with model.score
print('Train Accuracy: %.3f' % dt_model.score(X_train_encoded, y_train_encoded))
print('Test Accuracy: %.3f' % dt_model.score(X_test_encoded, y_test_encoded))
```

```
Train Accuracy: 1.000
Test Accuracy: 0.968
```

Model and Fit to a Random Forest Classifier

```
# Create the random forest classifier model
# with n_estimators=128 and random_state=1
rf_model = RandomForestClassifier(n_estimators=128, random_state=1)

# Fit the model to the training data
rf_model.fit(X_train_encoded, y_train_encoded)
```

```
RandomForestClassifier(n_estimators=128, random_state=1)
```

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```
# Validate the model by checking the model accuracy with model.score
print('Train Accuracy: %.3f' % rf_model.score(X_train_encoded, y_train_encoded))
print('Test Accuracy: %.3f' % rf_model.score(X_test_encoded, y_test_encoded))
```

```
Train Accuracy: 1.000
Test Accuracy: 0.961
```

See next page to optimize the max_depth of the RFC model

Optimize the hyperparameter "max_depth" for the Random Forest Classifier

```
# Try the following values for max_depth

max_depths = range(1, 10)
models = {'train_score': [], 'test_score': [], 'max_depth': []}

# Loop through each value in max_depths
for depth in max_depths:
    clf = RandomForestClassifier(max_depth = depth)
    clf.fit(X_train, y_train)

    train_pred = clf.predict(X_train)
    test_pred = clf.predict(X_test)

    train_score = balanced_accuracy_score(y_train, train_pred)
    test_score = balanced_accuracy_score(y_test, test_pred)

    models['train_score'].append(train_score)
    models['test_score'].append(test_score)
    models['max_depth'].append(depth)

# Create a dataframe from the models dictionary with max_depth as the index
models_df = pd.DataFrame(models).set_index('max_depth')
```

```
# Plot the results
models_df.plot()
```

```
clf = RandomForestClassifier(max_depth=5)
clf.fit(X_train, y_train)

train_pred = clf.predict(X_train)
test_pred = clf.predict(X_test)

print(balanced_accuracy_score(y_train, train_pred))
print(balanced_accuracy_score(y_test, test_pred))
```

```
0.6322281365725427
0.5937545762574925
```

```
# Check the model's balanced accuracy on the test set

y_pred = model.predict(X_test)
print(balanced_accuracy_score(y_test, y_pred))
```

```
0.5790651053107311
```

```
# Check the model's balanced accuracy on the training set

y_train_pred = model.predict(X_train)
print(balanced_accuracy_score(y_train, y_train_pred))
```

```
0.6257478761408065
```

KNN without optimization

```
# Create the KNN model with 9 neighbors
knn_model = KNeighborsClassifier(n_neighbors=9)

# Fit the model to the training data
knn_model.fit(X_train_encoded, y_train_encoded)
```

```
KNeighborsClassifier(n_neighbors=9)
```

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```
# Validate the model by checking the model accuracy with model.score
print('Train Accuracy: %.3f' % knn_model.score(X_train_encoded, y_train_encoded))
print('Test Accuracy: %.3f' % knn_model.score(X_test_encoded, y_test_encoded))
```

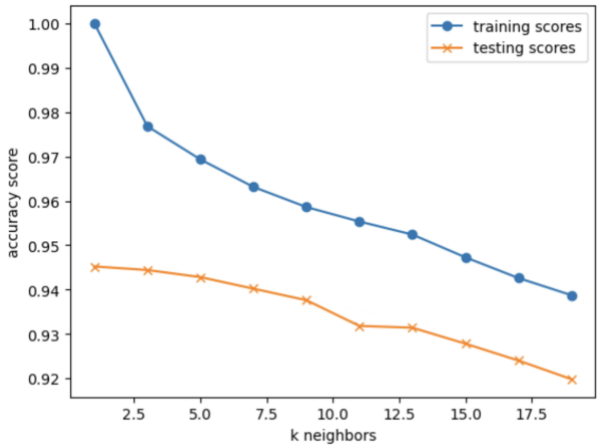
```
Train Accuracy: 0.960
Test Accuracy: 0.919
```

Model and Fit to a KNN Model

```
import matplotlib.pyplot as plt
# Loop through different k values to find which has the highest accuracy.
# Note: We use only odd numbers because we don't want any ties.
train_scores = []
test_scores = []
for k in range(1, 20, 2):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train_encoded)
    train_score = knn.score(X_train_scaled, y_train_encoded)
    test_score = knn.score(X_test_scaled, y_test_encoded)
    train_scores.append(train_score)
    test_scores.append(test_score)
    print(f"k: {k}, Train/Test Score: {train_score:.3f}/{test_score:.3f}")

# Plot the results
plt.plot(range(1, 20, 2), train_scores, marker='o', label="training scores")
plt.plot(range(1, 20, 2), test_scores, marker="x", label="testing scores")
plt.xlabel("k neighbors")
plt.ylabel("accuracy score")
plt.legend()
plt.show()
```

```
k: 1, Train/Test Score: 1.000/0.945
k: 3, Train/Test Score: 0.977/0.944
k: 5, Train/Test Score: 0.969/0.943
k: 7, Train/Test Score: 0.963/0.940
k: 9, Train/Test Score: 0.959/0.938
k: 11, Train/Test Score: 0.955/0.932
k: 13, Train/Test Score: 0.952/0.931
k: 15, Train/Test Score: 0.947/0.928
k: 17, Train/Test Score: 0.943/0.924
k: 19, Train/Test Score: 0.939/0.920
```




```
# Create the KNN model with 3 neighbors
knn_model = KNeighborsClassifier(n_neighbors=3)

# Fit the model to the training data
knn_model.fit(X_train_scaled, y_train_encoded)
```

```
KNeighborsClassifier(n_neighbors=3)
```

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```
# Validate the model by checking the model accuracy with model.score
print(f"Training Data Score: {knn_model.score(X_train_scaled, y_train_encoded)}")
print(f"Testing Data Score: {knn_model.score(X_test_scaled, y_test_encoded)}")
```

```
Training Data Score: 0.9768
Testing Data Score: 0.9444
```

Model and Fit to a Gradient Boosting Classifier

```
# Train the Gradient Boosting classifier
clf = GradientBoostingClassifier(random_state=1).fit(X_train_scaled, y_train_encoded)

# Evaluate the model
print(f'Training Score: {clf.score(X_train_scaled, y_train_encoded)}')
print(f'Testing Score: {clf.score(X_test_scaled, y_test_encoded)}')
```

```
Training Score: 0.9622666666666667
Testing Score: 0.9152
```

Model and Fit to an Adaptive Boosting Classifier

```
# Train the AdaBoostClassifier
clf = AdaBoostClassifier(random_state=1).fit(X_train_scaled, y_train_encoded)

# Evaluate the model
print(f'Training Score: {clf.score(X_train_scaled, y_train_encoded)}')
print(f'Testing Score: {clf.score(X_test_scaled, y_test_encoded)}')
```

```
Training Score: 0.274
Testing Score: 0.2776
```

13-3-4: Familiar Regressors:

```
%matplotlib inline
from matplotlib import pyplot as plt
from sklearn.datasets import make_regression, make_swiss_roll
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
def test_model(model, data):
    X_train_scaled, X_test_scaled, y_train, y_test = data
    reg = model.fit(X_train_scaled, y_train)
    print(f'Model: {type(reg).__name__}')
    print(f'Train score: {reg.score(X_train_scaled, y_train)}')
    print(f'Test Score: {reg.score(X_test_scaled, y_test)}\n')
    plt.show()
```

```
# Create data
X, y = make_regression(random_state=1)
X = pd.DataFrame(X)
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
scaler = StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
data = [X_train_scaled, X_test_scaled, y_train, y_test]
```

```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor, ExtraTreesRegressor, AdaBoostRegressor
from sklearn.svm import SVR
```

```
test_model(LinearRegression(), data)

test_model(KNeighborsRegressor(), data)
test_model(RandomForestRegressor(), data)
test_model(ExtraTreesRegressor(), data)
test_model(AdaBoostRegressor(), data)
test_model(SVR(C=1.0, epsilon=0.2), data)
```

```
Model: LinearRegression
Train score: 1.0
Test Score: 0.8288596458298328

Model: KNeighborsRegressor
Train score: 0.5300655721367826
Test Score: 0.07078594554559592

Model: RandomForestRegressor
Train score: 0.9081964906139426
Test Score: 0.28468630340953627

Model: ExtraTreesRegressor
Train score: 1.0
Test Score: 0.46765205432533674

Model: AdaBoostRegressor
Train score: 0.9321517489091534
Test Score: 0.3563551886522288

Model: SVR
Train score: 0.006215310460808365
Test Score: -0.010118247516417211
```

```python
# Plot the result
ax = plt.figure().add_subplot(projection='3d')
ax.view_init(7, -80)
ax.scatter(X[0], X[1], X[2],
           color=plt.cm.jet(y/y.max()),
           s=20, edgecolor='k')
plt.savefig("swiss_roll.png")
plt.show()
```