Zach_Yek_Exercise_1

April 8, 2023

1 Import Dependencies

We begin by importing the necessary libraries.

[1]:
```
# System & OS
import os

# Data analysis
import numpy as np
import pandas as pd
pd.options.display.max_columns = None

# ML
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, ConfusionMatrixDisplay

# Data visualization
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
sns.set_style('white')
```

2 Reproducibility

Set the seed to ensure our results are reproducible.

[2]:
```
def set_seed(seed):
    np.random.seed(seed)
    os.environ['PYTHONHASHSEED'] = str(seed)

SEED = 11
set_seed(SEED)
```

3 Preprocessing

Read in the 1994 US Census data. Note, a separate R script was used to export the data into a CSV file.

[3]:
```python
# Read data & drop irrelevant columns
df = pd.read_csv('../data/census_df.csv')
df.drop(columns=['Unnamed: 0'], inplace=True)

# Map income to label
df['label'] = df['income'].map({'<=50K': 0, '>50K': 1})

# Display results
df.head()
```

[3]:
```
   age         workclass  fnlwgt  education  education_1      marital_status  \
0   39         State-gov   77516  Bachelors           13       Never-married
1   50  Self-emp-not-inc   83311  Bachelors           13  Married-civ-spouse
2   38           Private  215646    HS-grad            9            Divorced
3   53           Private  234721       11th            7  Married-civ-spouse
4   28           Private  338409  Bachelors           13  Married-civ-spouse

          occupation   relationship   race     sex  capital_gain  \
0       Adm-clerical  Not-in-family  White    Male          2174
1    Exec-managerial        Husband  White    Male             0
2  Handlers-cleaners  Not-in-family  White    Male             0
3  Handlers-cleaners        Husband  Black    Male             0
4     Prof-specialty           Wife  Black  Female             0

   capital_loss  hours_per_week native_country income  label
0             0              40  United-States  <=50K      0
1             0              13  United-States  <=50K      0
2             0              40  United-States  <=50K      0
3             0              40  United-States  <=50K      0
4             0              40           Cuba  <=50K      0
```

We map the income levels to a binary label according to `0: <=$50K`, and `1: >$50K`.

4 Train-Test Split

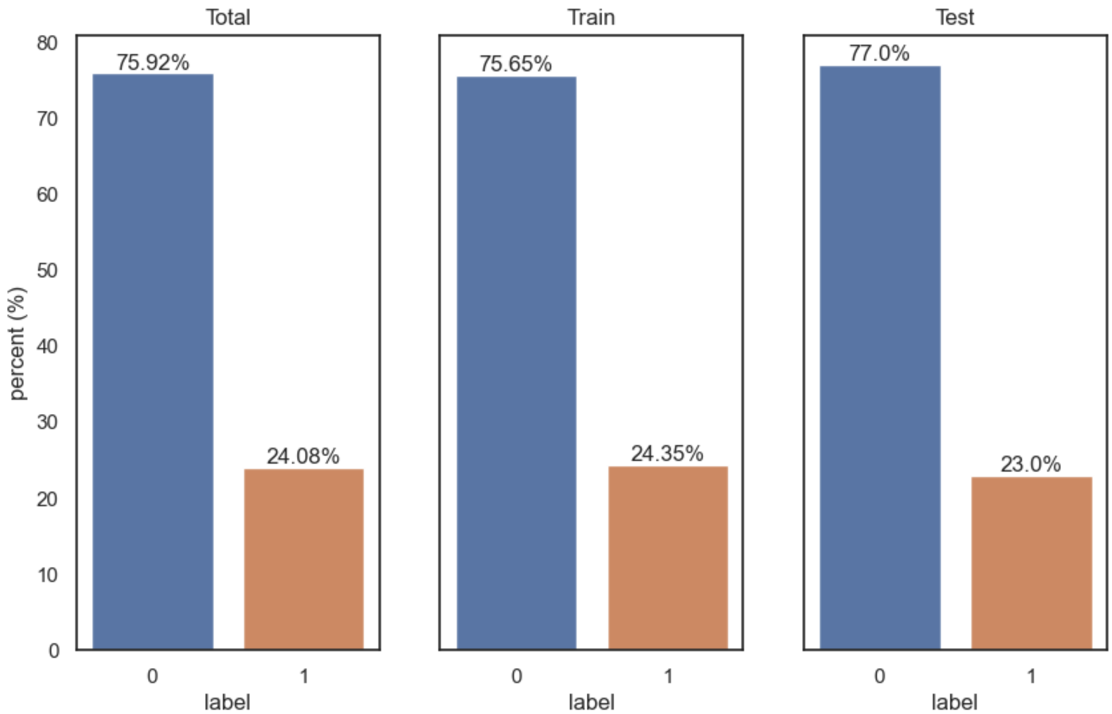
Split the data into `train` and `test` using an 80/20 split.

[4]:
```python
# 80/20 train-test split
train_df, test_df = train_test_split(df, test_size=0.2, random_state=SEED)

# Print results
print(f'Original: {len(df)} entries\nTrain: {len(train_df)} entries\nTest:
 ↪{len(test_df)} entries')
```

```
Original: 32561 entries
Train: 26048 entries
Test: 6513 entries
```

[5]:

```python
# Perform a normalized value count to obtain the percentage of values in each␣
 ↪class
label_counts = df['label'].value_counts(normalize=True).apply(lambda x: x *␣
 ↪100).reset_index()
label_counts.rename(columns={'index': 'label', 'label': 'percent'},␣
 ↪inplace=True)
label_counts.sort_values(by='label', inplace=True)

train_label_counts = train_df['label'].value_counts(normalize=True).
 ↪apply(lambda x: x * 100).reset_index()
train_label_counts.rename(columns={'index': 'label', 'label': 'percent'},␣
 ↪inplace=True)
train_label_counts.sort_values(by='label', inplace=True)

test_label_counts = test_df['label'].value_counts(normalize=True).apply(lambda␣
 ↪x: x * 100).reset_index()
test_label_counts.rename(columns={'index': 'label', 'label': 'percent'},␣
 ↪inplace=True)
test_label_counts.sort_values(by='label', inplace=True)

# Visualize results using a bar graph
fig, ax = plt.subplots(1, 3, figsize=(10, 6), sharey=True)
sns.barplot(x='label', y='percent', data=label_counts, ax=ax[0])
sns.barplot(x='label', y='percent', data=train_label_counts, ax=ax[1])
sns.barplot(x='label', y='percent', data=test_label_counts, ax=ax[2])

ax[0].set_title('Total')
ax[1].set_title('Train')
ax[2].set_title('Test')
ax[0].set_ylabel('percent (%)')
ax[1].set_ylabel('')
ax[2].set_ylabel('')
for index, value in enumerate(label_counts['percent']):
    ax[0].text(index, value+0.5, f'{round(value, 2)}%', ha='center')
for index, value in enumerate(train_label_counts['percent']):
    ax[1].text(index, value+0.5, f'{round(value, 2)}%', ha='center')
for index, value in enumerate(test_label_counts['percent']):
    ax[2].text(index, value+0.5, f'{round(value, 2)}%', ha='center')

plt.show()
```

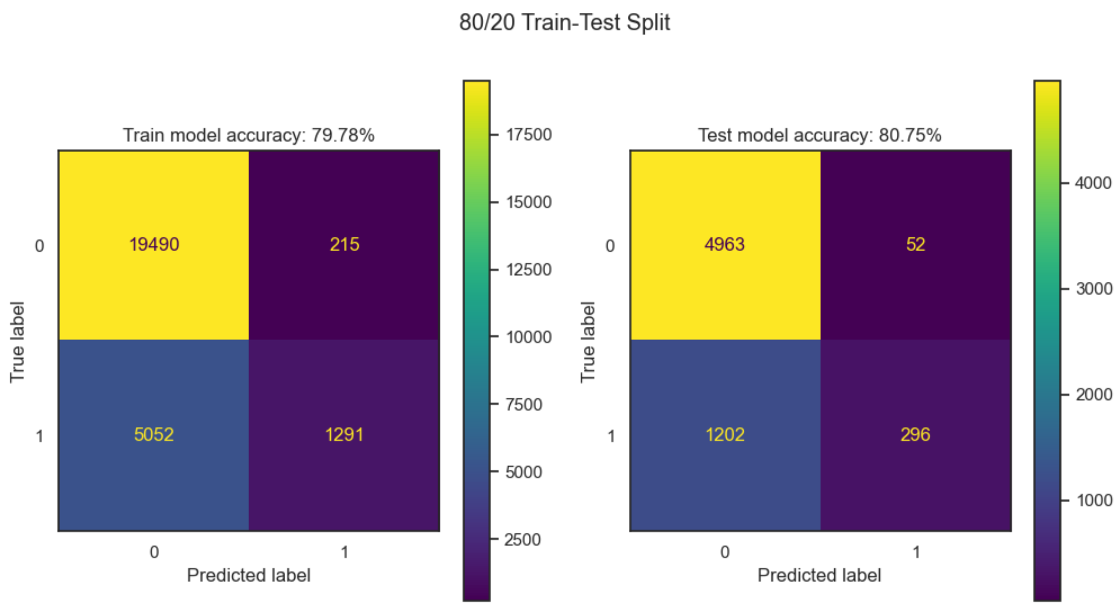


5 Logistic Regression Analysis

Then, we fit a logistic regression model to the data using 1 predictor: `capital_gain`, and compute its confusion matrix and accuracy on `train` and `test`.

[6]:
```
# Split the dataframes into X (features) and y (target)
X_train, y_train, X_test, y_test = train_df['capital_gain'].values.reshape(-1,␣
↪1), train_df['label'].values, test_df['capital_gain'].values.reshape(-1, 1),␣
↪test_df['label'].values

# Create logistic regression object
model_1 = LogisticRegression(random_state=SEED)

# Fit the model to train
model_1.fit(X_train, y_train)

# Generate model predictions on train & test
y_pred_train, y_pred_test = model_1.predict(X_train), model_1.predict(X_test)

# Compute model accuracy
train_accuracy, test_accuracy = accuracy_score(y_train, y_pred_train) * 100,␣
↪accuracy_score(y_test, y_pred_test) * 100
```

```
# Calculate and display the confusion matrix
fig, ax = plt.subplots(1, 2, figsize=(12, 6))
ConfusionMatrixDisplay.from_predictions(y_train, y_pred_train, ax=ax[0])
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test, ax=ax[1])
ax[0].set_title(f'Train model accuracy: {train_accuracy:.2f}%')
ax[1].set_title(f'Test model accuracy: {test_accuracy:.2f}%')
fig.suptitle('80/20 Train-Test Split')
plt.show()
```



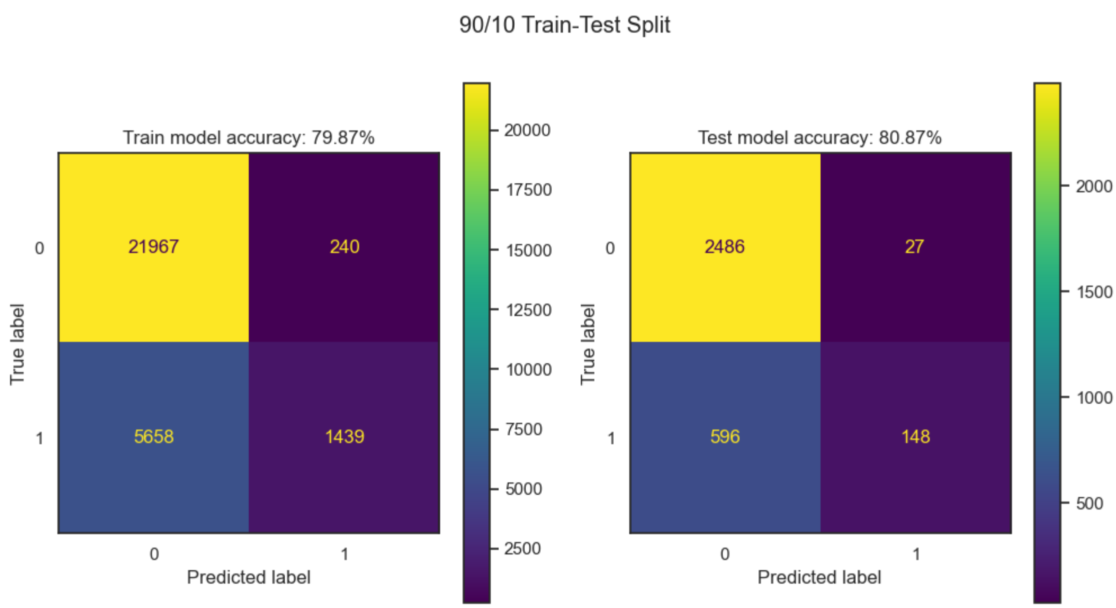
While we notice a marginal improvement w.r.t. the null model, we'll omit discussions regarding the model's interpretation, in favor of testing our hypothesis: "are there any noticeable differences to the model's results if we'd used a different train-test split?"

6 90/10 Split

Repeating the exact same procedure, this time using a 90/10 train-test split.

[7]:
```
# 90/10 train-test split
train_df, test_df = train_test_split(df, test_size=0.1, random_state=SEED)

# Split the dataframes into X (features) and y (target)
X_train, y_train, X_test, y_test = train_df['capital_gain'].values.reshape(-1,␣
 ↪1), train_df['label'].values, test_df['capital_gain'].values.reshape(-1, 1),␣
 ↪test_df['label'].values

# Create logistic regression object
model_1 = LogisticRegression(random_state=SEED)
```

```
# Fit the model to train
model_1.fit(X_train, y_train)

# Generate model predictions on train & test
y_pred_train, y_pred_test = model_1.predict(X_train), model_1.predict(X_test)

# Compute model accuracy
train_accuracy, test_accuracy = accuracy_score(y_train, y_pred_train) * 100,␣
↪accuracy_score(y_test, y_pred_test) * 100

# Calculate and display the confusion matrix
fig, ax = plt.subplots(1, 2, figsize=(12, 6))
ConfusionMatrixDisplay.from_predictions(y_train, y_pred_train, ax=ax[0])
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test, ax=ax[1])
ax[0].set_title(f'Train model accuracy: {train_accuracy:.2f}%')
ax[1].set_title(f'Test model accuracy: {test_accuracy:.2f}%')
fig.suptitle('90/10 Train-Test Split')
plt.show()
```

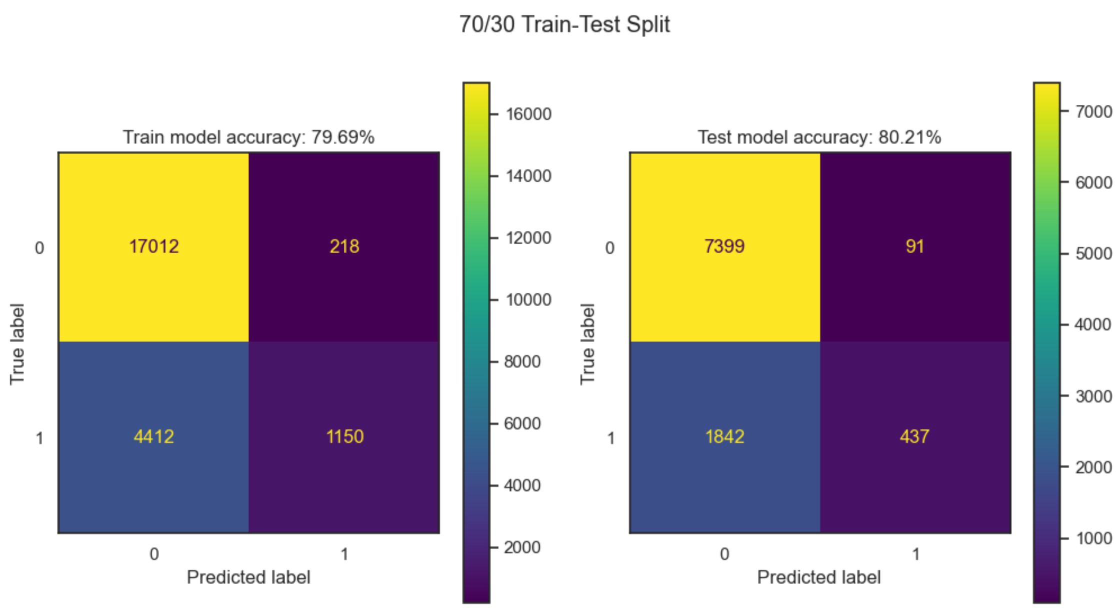


7 70/30 Split

And once more using a 70/30 train-test split.

[8]:
```
# 70/30 train-test split
train_df, test_df = train_test_split(df, test_size=0.3, random_state=SEED)
```

```python
# Split the dataframes into X (features) and y (target)
X_train, y_train, X_test, y_test = train_df['capital_gain'].values.reshape(-1,
    1), train_df['label'].values, test_df['capital_gain'].values.reshape(-1, 1),
    test_df['label'].values

# Create logistic regression object
model_1 = LogisticRegression(random_state=SEED)

# Fit the model to train
model_1.fit(X_train, y_train)

# Generate model predictions on train & test
y_pred_train, y_pred_test = model_1.predict(X_train), model_1.predict(X_test)

# Compute model accuracy
train_accuracy, test_accuracy = accuracy_score(y_train, y_pred_train) * 100,
    accuracy_score(y_test, y_pred_test) * 100

# Calculate and display the confusion matrix
fig, ax = plt.subplots(1, 2, figsize=(12, 6))
ConfusionMatrixDisplay.from_predictions(y_train, y_pred_train, ax=ax[0])
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test, ax=ax[1])
ax[0].set_title(f'Train model accuracy: {train_accuracy:.2f}%')
ax[1].set_title(f'Test model accuracy: {test_accuracy:.2f}%')
fig.suptitle('70/30 Train-Test Split')
plt.show()
```



8 Conclusions

From their accuracies and confusion matrices on both `train` and `test`, we do not notice any significant deviations across all 3 trials, leading us to believe that choosing the correct train-test split is an endeavour with some margin for error.