

Salary Classifier

The objective of this project was to predict whether given individuals in a dataset make over or under 50,000 dollars.

The dataset used was the 'adult' dataset from the UC Irvine repository. All preprocessing was done within the notebook shown below.

Import Libraries

```
In [122.. from ucimlrepo import fetch_ucirepo
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
```

Fetch dataset

```
In [123.. adult = fetch_ucirepo(id=2)

# data (as pandas dataframes)
X = adult.data.features
y = adult.data.targets
df = X
df.insert(14, '50K', y)
#Replace the target variable from <50K and >50K to 0's and 1's
df.replace(to_replace = '<=50K',value = 0, inplace = True)
df.replace(to_replace = '<=50K.',value = 0, inplace = True)
df.replace(to_replace = '>50K.',value = 1,inplace = True)
df.replace(to_replace = '>50K',value = 1,inplace = True)
```

```
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/3892937393.py:12: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df.replace(to_replace = '>50K',value = 1,inplace = True)
```

```
In [123.. df.columns
```

```
Out[123.. Index(['age', 'workclass', 'fnlwgt', 'education', 'education-num',
        'marital-status', 'occupation', 'relationship', 'race', 'sex',
        'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
        '50K'],
        dtype='object')
```

Find which columns have null values, if any

```
In [123.. df.isnull().sum()
```

```
Out[123.. age                0
workclass            963
fnlwgt               0
education            0
education-num        0
marital-status       0
occupation          966
relationship         0
race                0
sex                 0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country      274
50K                  0
dtype: int64
```

Drop any rows with null values for ease of use.

```
In [123.. df.dropna(inplace = True)
```

Describe the data

```
In [123.. df.describe()
```

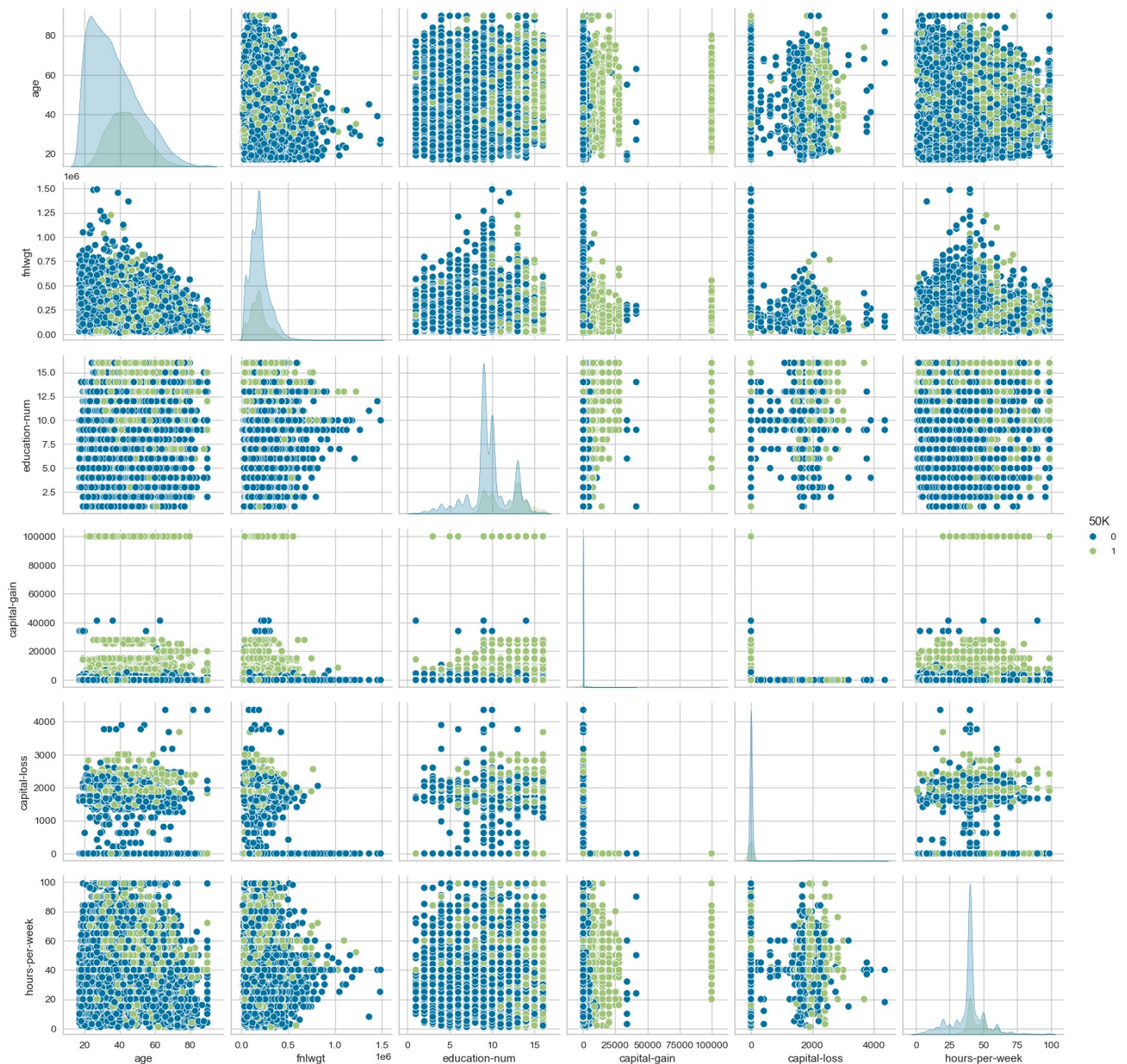
Out[123..

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	50K
count	47621.000000	4.762100e+04	47621.000000	47621.000000	47621.000000	47621.000000	47621.000000
mean	38.640684	1.897271e+05	10.090821	1091.137649	87.853489	40.600050	0.242351
std	13.558961	1.055695e+05	2.568320	7487.228336	404.010612	12.260345	0.428510
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000	0.000000
25%	28.000000	1.175840e+05	9.000000	0.000000	0.000000	40.000000	0.000000
50%	37.000000	1.782820e+05	10.000000	0.000000	0.000000	40.000000	0.000000
75%	48.000000	2.377200e+05	12.000000	0.000000	0.000000	45.000000	0.000000
max	90.000000	1.490400e+06	16.000000	99999.000000	4356.000000	99.000000	1.000000

Pairplot to try and find relationships in the data

In [121.. `sns.pairplot(df, hue = '50K')`

Out[121.. `<seaborn.axisgrid.PairGrid at 0x158fe8110>`



Create our X column

Here I created X_logistic, which includes all of the columns I wished to include in the following models.

In [124.. `X_logistic = df[['age', 'marital-status', 'race', 'sex', 'fnlwgt', 'education-num', 'capital-gain', 'capital-loss', 'hours-per-week', '50K']]`

Marital status, race, and sex were turned into numerical values below in order to be used in the models.

```
#create dummy variables
X_logistic['marital-status'].replace(to_replace = 'Married-civ-spouse', value = 1,inplace = True)
X_logistic['marital-status'].replace(to_replace = 'Married-AF-spouse', value = 1,inplace = True)
X_logistic['marital-status'].replace(to_replace = 'Married-spouse-absent', value = 1,inplace = True)
X_logistic['marital-status'].replace(to_replace = 'Widowed', value = 1,inplace = True)
X_logistic['marital-status'].replace(to_replace = 'Divorced', value = 2,inplace = True)
X_logistic['marital-status'].replace(to_replace = 'Separated', value = 2,inplace = True)
X_logistic['marital-status'].replace(to_replace = 'Never-married', value = 0,inplace = True)

X_logistic['race'].replace(to_replace = 'White', value = 0,inplace = True)
X_logistic['race'].replace(to_replace = 'Black', value = 1,inplace = True)
X_logistic['race'].replace(to_replace = 'Asian-Pac-Islander', value = 2,inplace = True)
X_logistic['race'].replace(to_replace = 'Amer-Indian-Eskimo', value = 3,inplace = True)
X_logistic['race'].replace(to_replace = 'Other', value = 4,inplace = True)

X_logistic['sex'].replace(to_replace = 'Male', value = 1,inplace = True)
X_logistic['sex'].replace(to_replace = 'Female', value = 0,inplace = True)

X_logistic
```

/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['marital-status'].replace(to_replace = 'Married-civ-spouse', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['marital-status'].replace(to_replace = 'Married-civ-spouse', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['marital-status'].replace(to_replace = 'Married-AF-spouse', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['marital-status'].replace(to_replace = 'Married-AF-spouse', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:4: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['marital-status'].replace(to_replace = 'Married-spouse-absent', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['marital-status'].replace(to_replace = 'Married-spouse-absent', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:5: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['marital-status'].replace(to_replace = 'Widowed', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['marital-status'].replace(to_replace = 'Widowed', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:6: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['marital-status'].replace(to_replace = 'Divorced', value = 2,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['marital-status'].replace(to_replace = 'Divorced', value = 2,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:7: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['marital-status'].replace(to_replace = 'Separated', value = 2,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['marital-status'].replace(to_replace = 'Separated', value = 2,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:8: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['marital-status'].replace(to_replace = 'Never-married', value = 0,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:8: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
```

```
X_logistic['marital-status'].replace(to_replace = 'Never-married', value = 0,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['marital-status'].replace(to_replace = 'Never-married', value = 0,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:10: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['race'].replace(to_replace = 'White', value = 0,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['race'].replace(to_replace = 'White', value = 0,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:11: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['race'].replace(to_replace = 'Black', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```


See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['race'].replace(to_replace = 'Black', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:12: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['race'].replace(to_replace = 'Asian-Pac-Islander', value = 2,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['race'].replace(to_replace = 'Asian-Pac-Islander', value = 2,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:13: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['race'].replace(to_replace = 'Amer-Indian-Eskimo', value = 3,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['race'].replace(to_replace = 'Amer-Indian-Eskimo', value = 3,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:14: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['race'].replace(to_replace = 'Other', value = 4,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:14: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
X_logistic['race'].replace(to_replace = 'Other', value = 4,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['race'].replace(to_replace = 'Other', value = 4,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:16: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['sex'].replace(to_replace = 'Male', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

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```
X_logistic['sex'].replace(to_replace = 'Male', value = 1,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:17: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
X_logistic['sex'].replace(to_replace = 'Female', value = 0,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:17: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
```

havior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`

```
X_logistic['sex'].replace(to_replace = 'Female', value = 0,inplace = True)
/var/folders/6p/v9rm9dqj4xq8113by2w3q15m0000gn/T/ipykernel_57349/1078994597.py:17: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X_logistic['sex'].replace(to_replace = 'Female', value = 0,inplace = True)
```

Out[124..

	age	marital-status	race	sex	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week
0	39	0	0	1	77516	13	2174	0	40
1	50	1	0	1	83311	13	0	0	13
2	38	2	0	1	215646	9	0	0	40
3	53	1	1	1	234721	7	0	0	40
4	28	1	1	0	338409	13	0	0	40
...
48836	33	0	0	1	245211	13	0	0	40
48837	39	2	0	0	215419	13	0	0	36
48839	38	1	0	1	374983	13	0	0	50
48840	44	2	2	1	83891	13	5455	0	40
48841	35	1	0	1	182148	13	0	0	60

47621 rows × 9 columns

Logistic Regression

In [124..

```
from sklearn.linear_model import LogisticRegression

X_train, X_test, y_train, y_test = train_test_split(X_logistic, y, test_size=0.33, random_state=42)
lm = LogisticRegression()

lm.fit(X_train, y_train)
pd.DataFrame(lm.coef_, columns = X_logistic.columns)

lr_predictions = lm.predict(X_test)

CR_Logistic = classification_report(y_test, lr_predictions)
CM_Logistic = confusion_matrix(y_test, lr_predictions)

print(CM_Logistic)
print(CR_Logistic)
```

```
[[11486   322]
 [ 3046   861]]

      precision    recall  f1-score   support

     0       0.79      0.97      0.87      11808
     1       0.73      0.22      0.34       3907

 accuracy          0.79      15715
 macro avg       0.76      0.60      0.61      15715
weighted avg       0.77      0.79      0.74      15715
```

/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_logistic.py:469: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
<https://scikit-learn.org/stable/modules/preprocessing.html>
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
n_iter_i = _check_optimize_result(

Decision Tree

In [124..

```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier()
dtree.fit(X_train, y_train)
dt_predictions = dtree.predict(X_test)

CM_DTree = confusion_matrix(y_test, dt_predictions)
```

```
CR_DTree = classification_report(y_test, dt_predictions)
print(CM_DTree)
print(CR_DTree)
```

```
[[10253  1555]
 [ 1590  2317]]
      precision    recall  f1-score   support

      0       0.87       0.87       0.87     11808
      1       0.60       0.59       0.60       3907

 accuracy         0.80         0.80         0.80     15715
 macro avg       0.73       0.73       0.73     15715
weighted avg       0.80       0.80       0.80     15715
```

Random Forest Classifier

```
In [125.. from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators = 250)
rfc.fit(X_train, y_train)
rfcpred = rfc.predict(X_test)
```

```
CM_RF = confusion_matrix(y_test, rfcpred)
CR_RF = classification_report(y_test, rfcpred)
print(CM_RF)
print(CR_RF)
```

```
[[10864   944]
 [ 1648  2259]]
      precision    recall  f1-score   support

      0       0.87       0.92       0.89     11808
      1       0.71       0.58       0.64       3907

 accuracy         0.84         0.84         0.84     15715
 macro avg       0.79       0.75       0.76     15715
weighted avg       0.83       0.84       0.83     15715
```

Support Vector Machines

```
In [125.. from sklearn.svm import SVC
model = SVC()
model.fit(X_train, y_train)
svc_predictions = model.predict(X_test)

CM_SVC = confusion_matrix(y_test, svc_predictions)
CR_SVC = classification_report(y_test, svc_predictions)
print(CM_SVC)
print(CR_SVC)
```

```
[[11782   26]
 [ 3303  604]]
      precision    recall  f1-score   support

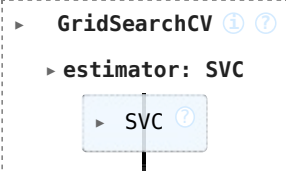
      0       0.78       1.00       0.88     11808
      1       0.96       0.15       0.27       3907

 accuracy         0.79         0.79         0.79     15715
 macro avg       0.87       0.58       0.57     15715
weighted avg       0.83       0.79       0.72     15715
```

```
In [125.. #Search for best parameters with gridsearch
from sklearn.model_selection import GridSearchCV
param_grid = {'C':[0.1, 1, 10], 'gamma':[1, 0.1, 0.01]}
grid = GridSearchCV(SVC(), param_grid, verbose = 3)
grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
[CV 1/5] END .....C=0.1, gamma=1;; score=0.761 total time= 53.0s
[CV 2/5] END .....C=0.1, gamma=1;; score=0.761 total time= 53.7s
[CV 3/5] END .....C=0.1, gamma=1;; score=0.761 total time= 52.4s
[CV 4/5] END .....C=0.1, gamma=1;; score=0.761 total time= 54.1s
[CV 5/5] END .....C=0.1, gamma=1;; score=0.761 total time= 52.4s
[CV 1/5] END .....C=0.1, gamma=0.1;; score=0.761 total time= 53.9s
[CV 2/5] END .....C=0.1, gamma=0.1;; score=0.761 total time= 51.1s
[CV 3/5] END .....C=0.1, gamma=0.1;; score=0.761 total time= 52.3s
[CV 4/5] END .....C=0.1, gamma=0.1;; score=0.761 total time= 56.0s
[CV 5/5] END .....C=0.1, gamma=0.1;; score=0.761 total time= 52.8s
[CV 1/5] END .....C=0.1, gamma=0.01;; score=0.761 total time= 48.2s
[CV 2/5] END .....C=0.1, gamma=0.01;; score=0.761 total time= 46.8s
[CV 3/5] END .....C=0.1, gamma=0.01;; score=0.761 total time= 46.9s
[CV 4/5] END .....C=0.1, gamma=0.01;; score=0.761 total time= 3.3min
[CV 5/5] END .....C=0.1, gamma=0.01;; score=0.761 total time= 48.8s
[CV 1/5] END .....C=1, gamma=1;; score=0.761 total time= 1.1min
[CV 2/5] END .....C=1, gamma=1;; score=0.761 total time= 1.1min
[CV 3/5] END .....C=1, gamma=1;; score=0.761 total time= 1.1min
[CV 4/5] END .....C=1, gamma=1;; score=0.761 total time= 1.1min
[CV 5/5] END .....C=1, gamma=1;; score=0.760 total time= 1.1min
[CV 1/5] END .....C=1, gamma=0.1;; score=0.759 total time= 1.1min
[CV 2/5] END .....C=1, gamma=0.1;; score=0.759 total time= 1.1min
[CV 3/5] END .....C=1, gamma=0.1;; score=0.759 total time= 1.0min
[CV 4/5] END .....C=1, gamma=0.1;; score=0.760 total time= 7.9min
[CV 5/5] END .....C=1, gamma=0.1;; score=0.759 total time= 1.1min
[CV 1/5] END .....C=1, gamma=0.01;; score=0.756 total time= 57.0s
[CV 2/5] END .....C=1, gamma=0.01;; score=0.757 total time= 58.2s
[CV 3/5] END .....C=1, gamma=0.01;; score=0.756 total time= 1.1min
[CV 4/5] END .....C=1, gamma=0.01;; score=0.756 total time= 57.2s
[CV 5/5] END .....C=1, gamma=0.01;; score=0.755 total time= 58.1s
[CV 1/5] END .....C=10, gamma=1;; score=0.759 total time= 1.5min
[CV 2/5] END .....C=10, gamma=1;; score=0.761 total time= 1.4min
[CV 3/5] END .....C=10, gamma=1;; score=0.760 total time= 1.4min
[CV 4/5] END .....C=10, gamma=1;; score=0.760 total time= 1.5min
[CV 5/5] END .....C=10, gamma=1;; score=0.760 total time= 1.5min
[CV 1/5] END .....C=10, gamma=0.1;; score=0.757 total time= 1.2min
[CV 2/5] END .....C=10, gamma=0.1;; score=0.758 total time= 1.2min
[CV 3/5] END .....C=10, gamma=0.1;; score=0.758 total time= 1.2min
[CV 4/5] END .....C=10, gamma=0.1;; score=0.758 total time= 1.2min
[CV 5/5] END .....C=10, gamma=0.1;; score=0.755 total time= 1.2min
[CV 1/5] END .....C=10, gamma=0.01;; score=0.746 total time= 1.2min
[CV 2/5] END .....C=10, gamma=0.01;; score=0.748 total time=13.9min
[CV 3/5] END .....C=10, gamma=0.01;; score=0.746 total time= 1.2min
[CV 4/5] END .....C=10, gamma=0.01;; score=0.748 total time= 1.2min
[CV 5/5] END .....C=10, gamma=0.01;; score=0.740 total time= 1.2min
```

Out[125..



In [125..

```
#Test Support Vector Model with Best Parameters and compare to the original
grid.best_params_
grid.best_estimator_
grid_predict = grid.predict(X_test)
print(confusion_matrix(y_test,grid_predict))
print('\n')
print(classification_report(y_test, grid_predict))
```

```
[[11795   13]
 [ 3890   17]]

              precision    recall  f1-score   support

     0       0.75         1.00         0.86       11808
     1       0.57         0.00         0.01        3907

 accuracy               0.75       15715
 macro avg              0.66         0.50         0.43       15715
 weighted avg           0.71         0.75         0.65       15715
```

The support vector model with best parameters was greatly inferior to the baseline model. Weighted avg accuracy was 0.75 in the best parameters model compared to 0.79 for the original, and precision was also much lower. Baseline model will be used instead.

K-Nearest Neighbors


```
In [126... from sklearn.neighbors import NearestNeighbors
from sklearn.neighbors import KNeighborsClassifier
#Scale the data
from sklearn.preprocessing import StandardScaler
```

For k-Nearest Neighbors, data must be scaled.

```
In [126... scaler = StandardScaler()
scaler.fit(X_logistic)
#Transform the data to center and scale it
scaled_data = scaler.transform(X_logistic)
#Create dataframe of the scaled data
scaled = pd.DataFrame(scaled_data, columns = X_logistic.columns)
scaled
```

```
Out[126...      age  marital-status    race    sex    fnlwgt  education-num  capital-gain  capital-loss  hours-per-week
0  0.026501   -1.227809  -0.349860  0.700779 -1.062924      1.132729    0.144629   -0.217456   -0.048943
1  0.837781    0.230683  -0.349860  0.700779 -1.008031      1.132729   -0.145735   -0.217456   -2.251188
2 -0.047252    1.689176  -0.349860  0.700779  0.245517   -0.424726   -0.145735   -0.217456   -0.048943
3  1.059039    0.230683  1.255062  0.700779  0.426206   -1.203454   -0.145735   -0.217456   -0.048943
4 -0.784780    0.230683  1.255062 -1.426982  1.408394      1.132729   -0.145735   -0.217456   -0.048943
...      ...      ...      ...      ...      ...      ...      ...      ...      ...
47616 -0.416016   -1.227809  -0.349860  0.700779  0.525573      1.132729   -0.145735   -0.217456   -0.048943
47617  0.026501    1.689176  -0.349860 -1.426982  0.243367      1.132729   -0.145735   -0.217456   -0.375201
47618 -0.047252    0.230683  -0.349860  0.700779  1.754843      1.132729   -0.145735   -0.217456    0.766703
47619  0.395264    1.689176  2.859984  0.700779 -1.002537      1.132729    0.582847   -0.217456   -0.048943
47620 -0.268510    0.230683  -0.349860  0.700779 -0.071794      1.132729   -0.145735   -0.217456    1.582350
```

47621 rows × 9 columns

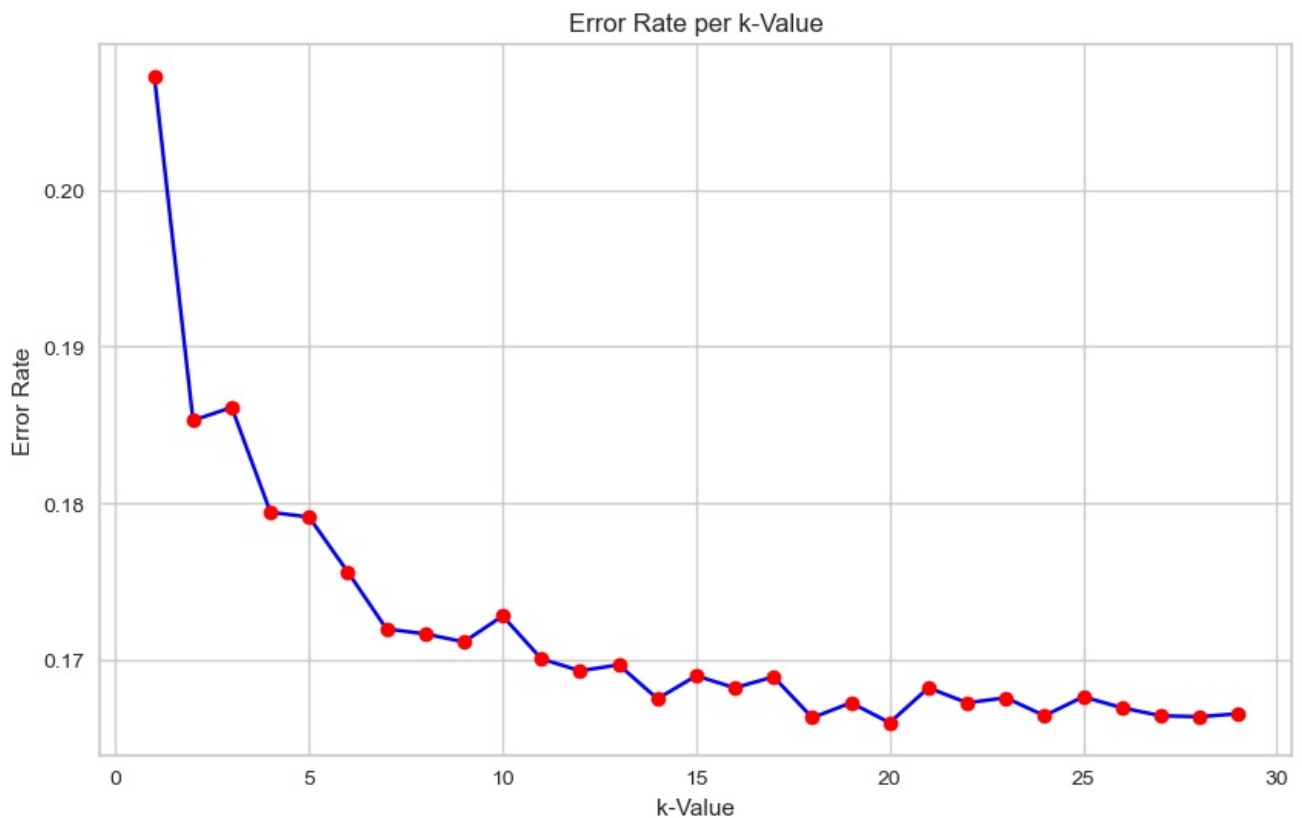
```
In [126... #Split the data
X_train, X_test, y_train, y_test = train_test_split(scaled, y, test_size=0.33, random_state=42)
```

```
In [127... #K Neighbors Classifier
#Elbow Method for Optimal Error Rate
errorRate = []
for i in range(1,30):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train, y_train)
    pred_i = knn.predict(X_test)
    errorRate.append(np.mean(pred_i != y_test))
```

Below is a plot of the error rate to determine the optimal k-value

```
In [127... plt.figure(figsize = (10,6))
plt.plot(range(1,30), errorRate, color = 'blue', marker = 'o', markerfacecolor = 'red')
plt.title('Error Rate per k-Value')
plt.xlabel('k-Value')
plt.ylabel('Error Rate')
```

```
Out[127... Text(0, 0.5, 'Error Rate')
```



The optimal k-Value for this dataset is 18. Now, I will print the confusion matrix and classification report for this dataset.

```
In [127]: knn = KNeighborsClassifier(n_neighbors= 18)
knn.fit(X_train, y_train)
pred18 = knn.predict(X_test)
CM_KNN = confusion_matrix(y_test, pred18)
CR_KNN = classification_report(y_test, pred18)
print(CM_KNN)
print(CR_KNN)
```

```
[[11099  709]
 [ 1905 2002]]
```

	precision	recall	f1-score	support
0	0.85	0.94	0.89	11808
1	0.74	0.51	0.61	3907
accuracy			0.83	15715
macro avg	0.80	0.73	0.75	15715
weighted avg	0.82	0.83	0.82	15715

Assess All Models

Logistic Regression

In [114..

```
print(CM_Logistic)
print(CR_Logistic)
```

[[11486	322]				
[3046	861]]				
		precision	recall	f1-score	support
	0	0.79	0.97	0.87	11808
	1	0.73	0.22	0.34	3907
	accuracy			0.79	15715
	macro avg	0.76	0.60	0.61	15715
	weighted avg	0.77	0.79	0.74	15715

Decision Tree

In [115..

```
print(CM_DTree)
print(CR_DTree)
```

[[10268	1540]				
[1585	2322]]				
		precision	recall	f1-score	support
	0	0.87	0.87	0.87	11808
	1	0.60	0.59	0.60	3907
	accuracy			0.80	15715
	macro avg	0.73	0.73	0.73	15715
	weighted avg	0.80	0.80	0.80	15715

Random Forest

In [115..

```
print(CM_RF)
print(CR_RF)
```

[[10902	906]				
[1632	2275]]				
		precision	recall	f1-score	support
	0	0.87	0.92	0.90	11808
	1	0.72	0.58	0.64	3907
	accuracy			0.84	15715
	macro avg	0.79	0.75	0.77	15715
	weighted avg	0.83	0.84	0.83	15715

Support Vector Machines

In [115..

```
print(CM_SVC)
print(CR_SVC)
```

[[11782	26]				
[3303	604]]				
		precision	recall	f1-score	support
	0	0.78	1.00	0.88	11808
	1	0.96	0.15	0.27	3907
	accuracy			0.79	15715
	macro avg	0.87	0.58	0.57	15715
	weighted avg	0.83	0.79	0.72	15715

k-Nearest Neighbors (n = 16)

In [116..

```
print(CM_KNN)
print(CR_KNN)
```

[[11099	709]				
[1905	2002]]				
		precision	recall	f1-score	support
	0	0.85	0.94	0.89	11808
	1	0.74	0.51	0.61	3907
	accuracy			0.83	15715
	macro avg	0.80	0.73	0.75	15715
	weighted avg	0.82	0.83	0.82	15715

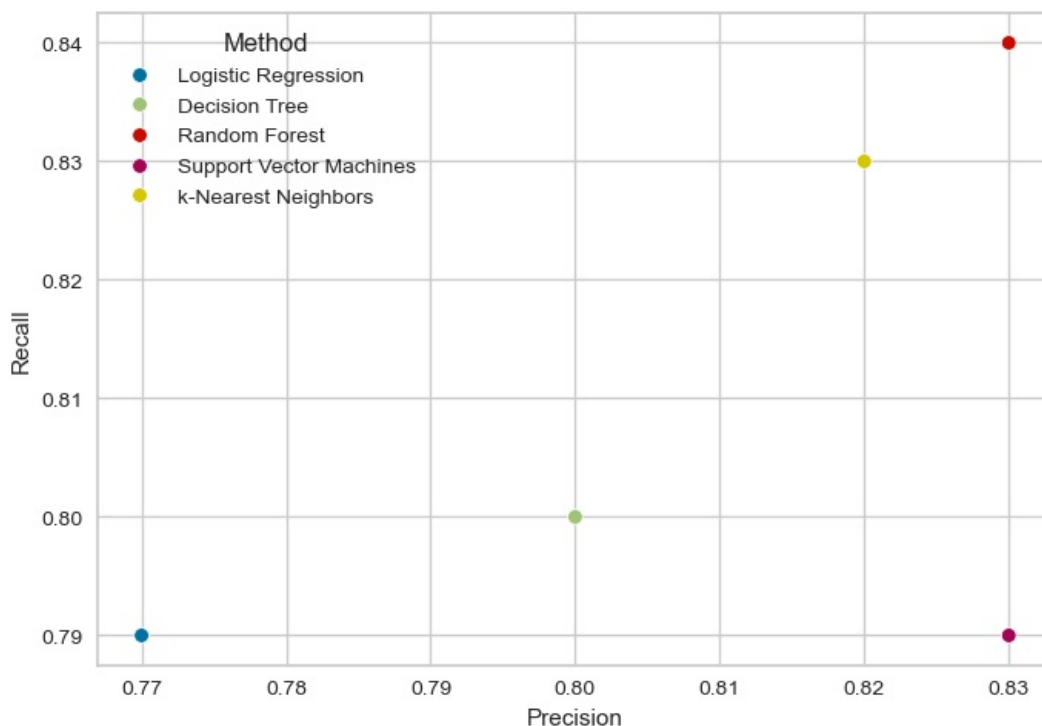
Weighted Avg Precision & Recall

```
In [116.. WtPrecLogistic = float(CR_Logistic[291:295])
WtRecLogistic = float(CR_Logistic[301:305])
F1Logistic = float(CR_Logistic[311:315])
WtPrecDTree = float(CR_DTree[291:295])
WtRecDTree = float(CR_DTree[301:305])
F1DTree = float(CR_DTree[311:315])
WtPrecRF = float(CR_RF[291:295])
WtRecRF = float(CR_RF[301:305])
F1RF = float(CR_RF[311:315])
WtPrecSVC = float(CR_SVC[291:295])
WtRecSVC = float(CR_SVC[301:305])
F1SVC = float(CR_SVC[311:315])
WtPrecKNN = float(CR_KNN[291:295])
WtRecKNN = float(CR_KNN[301:305])
F1KNN = float(CR_KNN[311:315])

MethodPRF1 = pd.DataFrame(['Logistic Regression', WtPrecLogistic, WtRecLogistic, F1Logistic],
                           ['Decision Tree', WtPrecDTree, WtRecDTree, F1DTree],
                           ['Random Forest', WtPrecRF, WtRecRF, F1RF],
                           ['Support Vector Machines', WtPrecSVC, WtRecSVC, F1SVC],
                           ['k-Nearest Neighbors', WtPrecKNN, WtRecKNN, F1KNN]],
                           columns = ['Method', 'Precision', 'Recall', 'F-1 Score'])

sns.scatterplot(data = MethodPRF1, x = 'Precision', y = 'Recall', hue = 'Method')
```

```
Out[116.. <Axes: xlabel='Precision', ylabel='Recall'>
```



After looking at the graph generated above, the random forest model had the highest precision and recall of any of the models. It also had the highest F-1 score of any model, with k-Nearest Neighbors closely trailing behind.

Assessing the Predictions

```
In [ ]: Logistic_TP, Logistic_FN, Logistic_FP, Logistic_TN = CM_Logistic[0][0], CM_Logistic[0][1], CM_Logistic[1][0], CM_Logistic[1][1]
DTree_TP, DTree_FN, DTree_FP, DTree_TN = CM_DTree[0][0], CM_DTree[0][1], CM_DTree[1][0], CM_DTree[1][1]
RF_TP, RF_FN, RF_FP, RF_TN = CM_RF[0][0], CM_RF[0][1], CM_RF[1][0], CM_RF[1][1]
SVC_TP, SVC_FN, SVC_FP, SVC_TN = CM_SVC[0][0], CM_SVC[0][1], CM_SVC[1][0], CM_SVC[1][1]
KNN_TP, KNN_FN, KNN_FP, KNN_TN = CM_KNN[0][0], CM_KNN[0][1], CM_KNN[1][0], CM_KNN[1][1]

MethodPreds = pd.DataFrame(['Logistic Regression', Logistic_TP, Logistic_FN, Logistic_TN, Logistic_FP],
                            ['Decision Tree', DTree_TP, DTree_FN, DTree_TN, DTree_FP],
                            ['Random Forest', RF_TP, RF_FN, RF_TN, RF_FP],
                            ['Support Vector Machines', SVC_TP, SVC_FN, SVC_TN, SVC_FP],
                            ['k-Nearest Neighbors', KNN_TP, KNN_FN, KNN_TN, KNN_FP]],
                            columns = ['Method', 'Pred. <50K (Correct)', 'Pred. >50K (Incorrect)', 'Pred. >50K (Correct)', 'Pred. <50K (Incorrect)'])

In [117.. Results = pd.merge(MethodPRF1, MethodPreds, on = 'Method')
Results
```

Out[117..

	Method	Precision	Recall	F-1 Score	Pred. <50K (Correct)	Pred. >50K (Incorrect)	Pred. >50K (Correct)	Pred. <50K(Incorrect)
0	Logistic Regression	0.77	0.79	0.74	11486	322	861	3046
1	Decision Tree	0.80	0.80	0.80	10268	1540	2322	1585
2	Random Forest	0.83	0.84	0.83	10902	906	2275	1632
3	Support Vector Machines	0.83	0.79	0.72	11782	26	604	3303
4	k-Nearest Neighbors	0.82	0.83	0.82	11099	709	2002	1905

Looking at the predicting, the support vector machine was the best at identifying individuals making < 50K. However, it was very bad at identifying individuals making > 50K.

The random forest model had the best balance of correctly predicting those making < 50K and those making > 50K. Therefore, the random forest model was the best choice for this dataset.

Of the 15,715 individuals in the y_test portion of the dataset, there were 11,808 individuals that earned less than 50K, and 3,907 that earned over 50K. The random forest model correctly labeled 10,902 of the 11,808 earning <50K, and 2,275 of the 3,907 making over 50K.

The random forest model was generated using most of the baseline parameters for ease of use. Next, some fine tuning of the random forest model will be done in order to try and obtain higher accuracy, precision, and recall.

Fine-Tuning The Random Forest Classifier Model

In [129..

```
from sklearn.metrics import accuracy_score, auc, balanced_accuracy_score
from sklearn.model_selection import RandomizedSearchCV

# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(100, 400, 5)]

#Features to consider
max_features = ['auto', 'sqrt']
max_depth = [5, 7, 10]
min_samples_split = [5,10]
min_samples_leaf = [1,5]

#define the grid
grid = {'n_estimators': n_estimators, 'max_features': max_features, 'max_depth':max_depth, 'min_samples_split':

rfc2 = RandomForestClassifier()
rf_random = RandomizedSearchCV(estimator = rfc2, param_distributions = grid, n_iter = 30, cv = 5, verbose = 2,
rf_random.fit(X_train, y_train)
#rfcpred = rfc.predict(X_test)

#CM_RF = confusion_matrix(y_test, rfcpred)
#CR_RF = classification_report(y_test, rfcpred)
#print(CM_RF)
#print(CR_RF)
```

Fitting 5 folds for each of 30 candidates, totalling 150 fits

```
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=400; total time=
0.1s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=400; total time=
0.0s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=400; total time=
0.0s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=400; total time=
0.0s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=10, n_estimators=250; total time=
0.0s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=10, n_estimators=250; total time=
0.0s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=10, n_estimators=250; total time=
0.0s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=10, n_estimators=250; total time=
0.0s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=10, n_estimators=250; total time=
0.0s
[CV] END max_depth=7, max_features=auto, min_samples_leaf=1, min_samples_split=10, n_estimators=250; total time=
0.0s
[CV] END max_depth=5, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=400; total time=
0.0s
[CV] END max_depth=5, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=400; total time=
0.0s
[CV] END max_depth=5, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=400; total time=
```


[illegible]

[illegible]

[illegible]

```
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=400; total time=
5.9s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=400; total time=
5.8s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=400; total time=
5.9s
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=5, min_samples_split=10, n_estimators=175; total time=
2.0s
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=5, min_samples_split=10, n_estimators=175; total time=
2.0s
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=5, min_samples_split=10, n_estimators=175; total time=
2.0s
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=5, min_samples_split=10, n_estimators=175; total time=
2.1s
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=5, min_samples_split=10, n_estimators=175; total time=
2.0s
[CV] END max_depth=10, max_features=auto, min_samples_leaf=5, min_samples_split=10, n_estimators=250; total time
= 0.0s
[CV] END max_depth=10, max_features=auto, min_samples_leaf=5, min_samples_split=10, n_estimators=250; total time
= 0.0s
[CV] END max_depth=10, max_features=auto, min_samples_leaf=5, min_samples_split=10, n_estimators=250; total time
= 0.0s
[CV] END max_depth=10, max_features=auto, min_samples_leaf=5, min_samples_split=10, n_estimators=250; total time
= 0.0s
[CV] END max_depth=10, max_features=auto, min_samples_leaf=5, min_samples_split=10, n_estimators=250; total time
= 0.0s
```

/opt/anaconda3/lib/python3.12/site-packages/sklearn/model_selection/_validation.py:547: FitFailedWarning:
85 fits failed out of a total of 150.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:

85 fits failed with the following error:

Traceback (most recent call last):

File "/opt/anaconda3/lib/python3.12/site-packages/sklearn/model_selection/_validation.py", line 895, in _fit_and_score

estimator.fit(X_train, y_train, **fit_params)

File "/opt/anaconda3/lib/python3.12/site-packages/sklearn/base.py", line 1467, in wrapper

estimator._validate_params()

File "/opt/anaconda3/lib/python3.12/site-packages/sklearn/base.py", line 666, in _validate_params

validate_parameter_constraints()

File "/opt/anaconda3/lib/python3.12/site-packages/sklearn/utils/_param_validation.py", line 95, in validate_parameter_constraints

raise InvalidParameterError(

sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of RandomForestClassifier must be an int in the range [1, inf), a float in the range (0.0, 1.0], a str among {'sqrt', 'log2'} or None. Got 'auto' instead.

warnings.warn(some_fits_failed_message, FitFailedWarning)

/opt/anaconda3/lib/python3.12/site-packages/sklearn/model_selection/_search.py:1051: UserWarning: One or more of the test scores are non-finite: [nan nan nan nan 0.85046711 0.85378929

0.85356991	nan	nan	0.8557325	nan	0.85385199
nan	0.849088	nan	nan	0.85541914	nan
nan	0.85598323	0.85404003	nan	0.84996558	0.85353858
nan	nan	nan	0.85526241	0.85316246	nan

warnings.warn(

Out[129..

```
RandomizedSearchCV
  estimator: RandomForestClassifier
    RandomForestClassifier
```

In [130..

```
#Find the best parameters
rf_random.best_params_
```

Out[130..

```
{'n_estimators': 400,
 'min_samples_split': 5,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 10}
```

In [130..

```
#Fit model using optimal parameters
rf_best = RandomForestClassifier(n_estimators = 400, min_samples_split= 5, min_samples_leaf=1, max_features = 'sqrt', max_depth=10)
rf_best.fit(X_train, y_train)
rfcBestPred = rf_best.predict(X_test)

CM_RF_Best = confusion_matrix(y_test, rfcBestPred)
CR_RF_Best = classification_report(y_test, rfcBestPred)
print(CM_RF_Best)
print(CR_RF_Best)
```

```
[[11330 478]
 [ 1900 2007]]
precision    recall  f1-score   support

0           0.86      0.96      0.91    11808
1           0.81      0.51      0.63     3907

accuracy          0.85    15715
macro avg         0.83      0.74      0.77    15715
weighted avg      0.84      0.85      0.84    15715
```

Comparing The Models

Below is a comparison of the 2 random forest models built, the baseline model and the best parameters model.

```
In [131]: WtPrecRF_Best = float(CR_RF_Best[291:295])
WtRecRF_Best = float(CR_RF_Best[301:305])
F1RF_Best = float(CR_RF_Best[311:315])
MethodPRF1_Best = pd.DataFrame(['Random Forest (Base)', WtPrecRF, WtRecRF, F1RF],
                               ['Random Forest (Best Params)', WtPrecRF_Best, WtRecRF_Best, F1RF_Best]),
                               columns = ['Method', 'Precision', 'Recall', 'F-1 Score'])
MethodPRF1_Best
```

```
Out[131]:
```

	Method	Precision	Recall	F-1 Score
0	Random Forest (Base)	0.83	0.84	0.83
1	Random Forest (Best Params)	0.84	0.85	0.84

```
In [131]: RF_TP, RF_FN, RF_FP, RF_TN = CM_RF[0][0], CM_RF[0][1], CM_RF[1][0], CM_RF[1][1]
RF_Best_TP, RF_Best_FN, RF_Best_FP, RF_Best_TN = CM_RF_Best[0][0], CM_RF_Best[0][1], CM_RF_Best[1][0], CM_RF_Be

MethodPreds_RF = pd.DataFrame(['Random Forest (Base)', RF_TP, RF_FN, RF_TN, RF_FP],
                               ['Random Forest (Best Params)', RF_Best_TP, RF_Best_FN, RF_Best_TN, RF_Best_FP]),
                               columns = ['Method', 'Pred. <50K (Correct)', 'Pred. >50K (Incorrect)', 'Pred. >50K (Correct)', 'Pr

ResultsRF = pd.merge(MethodPRF1_Best, MethodPreds_RF, on = 'Method')
ResultsRF
```

```
Out[131]:
```

	Method	Precision	Recall	F-1 Score	Pred. <50K (Correct)	Pred. >50K (Incorrect)	Pred. >50K (Correct)	Pred. <50K(Incorrect)
0	Random Forest (Base)	0.83	0.84	0.83	10864	944	2259	1648
1	Random Forest (Best Params)	0.84	0.85	0.84	11330	478	2007	1900

Conclusion

After looking at the results, it appears the best parameters random forest model slightly outperforms the baseline model. It was able to correctly predict roughly 500 more individuals that make less than 50K than the baseline model. However, the baseline model was still the best at correctly predicting individuals making more than 50K, and was able to correctly identify 252 more individuals in this group than the best parameters model.

It is inconclusive which model is the best; either model could be chosen as the 'best' model, depending on the use case. If identifying those making over 50K is more beneficial, then the baseline model should be used. If identifying those making less than 50K is more important, or if overall precision and recall is the goal, then the best parameters method than the best parameters model should be used.

```
In [ ]:
```