hw4

May 15, 2024

1 Support Vector Machine Algorithm

[ ]:
```
# Importing Libraries
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt

from sklearn.svm import SVC
from sklearn.utils import resample
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import GridSearchCV
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪accuracy_score
```

1.1 Loading train and test datasets

Test dataset

[ ]:
```
test_data = pd.read_csv('./data/SalaryData_Test.csv')
print(test_data.head(10))
```

```
   age         workclass     education  educationno        maritalstatus  \
0   25           Private          11th            7        Never-married
1   38           Private       HS-grad            9   Married-civ-spouse
2   28         Local-gov    Assoc-acdm           12   Married-civ-spouse
3   44           Private  Some-college           10   Married-civ-spouse
4   34           Private          10th            6        Never-married
5   63  Self-emp-not-inc   Prof-school           15   Married-civ-spouse
6   24           Private  Some-college           10        Never-married
7   55           Private       7th-8th            4   Married-civ-spouse
8   65           Private       HS-grad            9   Married-civ-spouse
9   36       Federal-gov     Bachelors           13   Married-civ-spouse

          occupation   relationship   race    sex  capitalgain  \
0  Machine-op-inspct      Own-child  Black   Male            0
1    Farming-fishing        Husband  White   Male            0
2    Protective-serv        Husband  White   Male            0
```

```
3  Machine-op-inspct        Husband  Black    Male        7688
4      Other-service  Not-in-family  White    Male           0
5     Prof-specialty        Husband  White    Male        3103
6      Other-service      Unmarried  White  Female           0
7       Craft-repair        Husband  White    Male           0
8  Machine-op-inspct        Husband  White    Male        6418
9       Adm-clerical        Husband  White    Male           0

   capitalloss  hoursperweek          native  Salary
0            0            40   United-States   <=50K
1            0            50   United-States   <=50K
2            0            40   United-States    >50K
3            0            40   United-States    >50K
4            0            30   United-States   <=50K
5            0            32   United-States    >50K
6            0            40   United-States   <=50K
7            0            10   United-States   <=50K
8            0            40   United-States    >50K
9            0            40   United-States   <=50K
```

Train dataset

[ ]:
```
train_data = pd.read_csv('./data/SalaryData_Train.csv')
print(train_data.head(10))
```

```
   age          workclass   education  educationno          maritalstatus  \
0   39          State-gov   Bachelors           13          Never-married
1   50   Self-emp-not-inc   Bachelors           13     Married-civ-spouse
2   38            Private     HS-grad            9               Divorced
3   53            Private        11th            7     Married-civ-spouse
4   28            Private   Bachelors           13     Married-civ-spouse
5   37            Private     Masters           14     Married-civ-spouse
6   49            Private         9th            5  Married-spouse-absent
7   52   Self-emp-not-inc     HS-grad            9     Married-civ-spouse
8   31            Private     Masters           14          Never-married
9   42            Private   Bachelors           13     Married-civ-spouse

          occupation   relationship   race      sex  capitalgain  \
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
5    Exec-managerial           Wife  White   Female            0
6      Other-service  Not-in-family  Black   Female            0
7    Exec-managerial        Husband  White     Male            0
8     Prof-specialty  Not-in-family  White   Female        14084
9    Exec-managerial        Husband  White     Male         5178
```

```
   capitalloss  hoursperweek          native  Salary
0            0            40   United-States   <=50K
1            0            13   United-States   <=50K
2            0            40   United-States   <=50K
3            0            40   United-States   <=50K
4            0            40            Cuba   <=50K
5            0            40   United-States   <=50K
6            0            16         Jamaica   <=50K
7            0            45   United-States    >50K
8            0            50   United-States    >50K
9            0            40   United-States    >50K
```

1.2 Data understanding

1.2.1 Dataset size

[ ]:
```
print(
    f"Test dataset size: {test_data.shape[0]}\n"
    f"Train dataset size: {train_data.shape[0]}"
    )
```

```
Test dataset size: 15060
Train dataset size: 30161
```

[ ]:
```
print(train_data.describe())
print(train_data.info())
```

```
                age   educationno   capitalgain   capitalloss  hoursperweek
count  30161.000000  30161.000000  30161.000000  30161.000000  30161.000000
mean      38.438115     10.121316   1092.044064     88.302311     40.931269
std       13.134830      2.550037   7406.466611    404.121321     11.980182
min       17.000000      1.000000      0.000000      0.000000      1.000000
25%       28.000000      9.000000      0.000000      0.000000     40.000000
50%       37.000000     10.000000      0.000000      0.000000     40.000000
75%       47.000000     13.000000      0.000000      0.000000     45.000000
max       90.000000     16.000000  99999.000000   4356.000000     99.000000
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30161 entries, 0 to 30160
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   age            30161 non-null  int64
 1   workclass      30161 non-null  object
 2   education      30161 non-null  object
 3   educationno    30161 non-null  int64
 4   maritalstatus  30161 non-null  object
 5   occupation     30161 non-null  object
 6   relationship   30161 non-null  object
 7   race           30161 non-null  object
```

```
 8   sex             30161 non-null  object
 9   capitalgain     30161 non-null  int64
 10  capitalloss     30161 non-null  int64
 11  hoursperweek    30161 non-null  int64
 12  native          30161 non-null  object
 13  Salary          30161 non-null  object
dtypes: int64(5), object(9)
memory usage: 3.2+ MB
None
```

1.2.2 Data Description

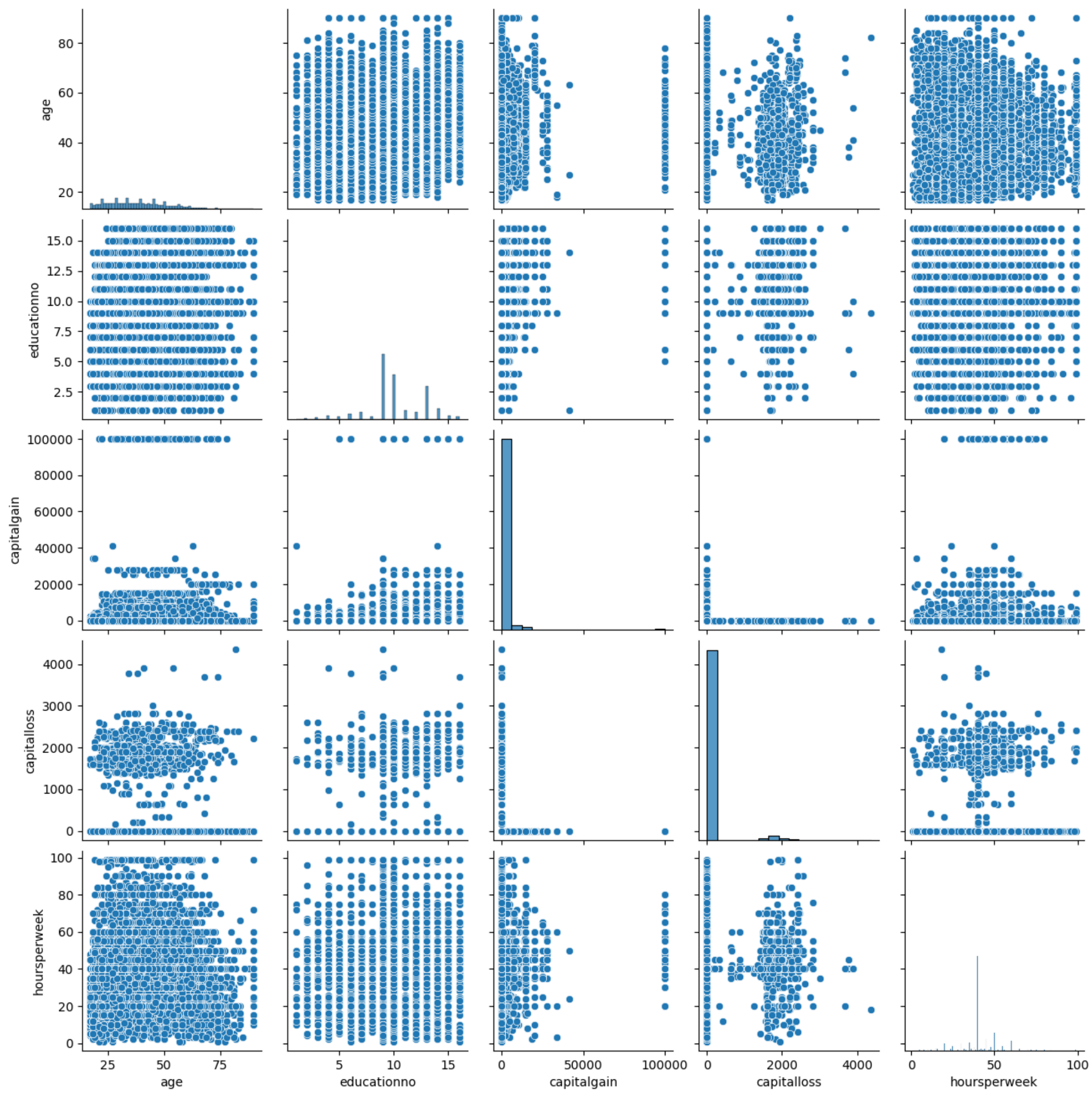
Term	Definition
Education	Highest level of education
workclass	Which business sector a person works for
educationno	Years spent in school?
maritalstatus	Relationship status
occupation	Current occupation
relationship	If they have a spouse or child
race	A social construct to group people
sex	Gender
capitalgain	Profit gained from the sale of property or investment
capitalloss	Value lost from the seller when selling property or investment at a lower cost
hourseperweek	Hours worked per week
native	A person's country of citizenship
Salary	Category on whether a person makes less than or greater than or equal to $50,000

1.3 Data Visualization

1.3.1 Data Scatterplot

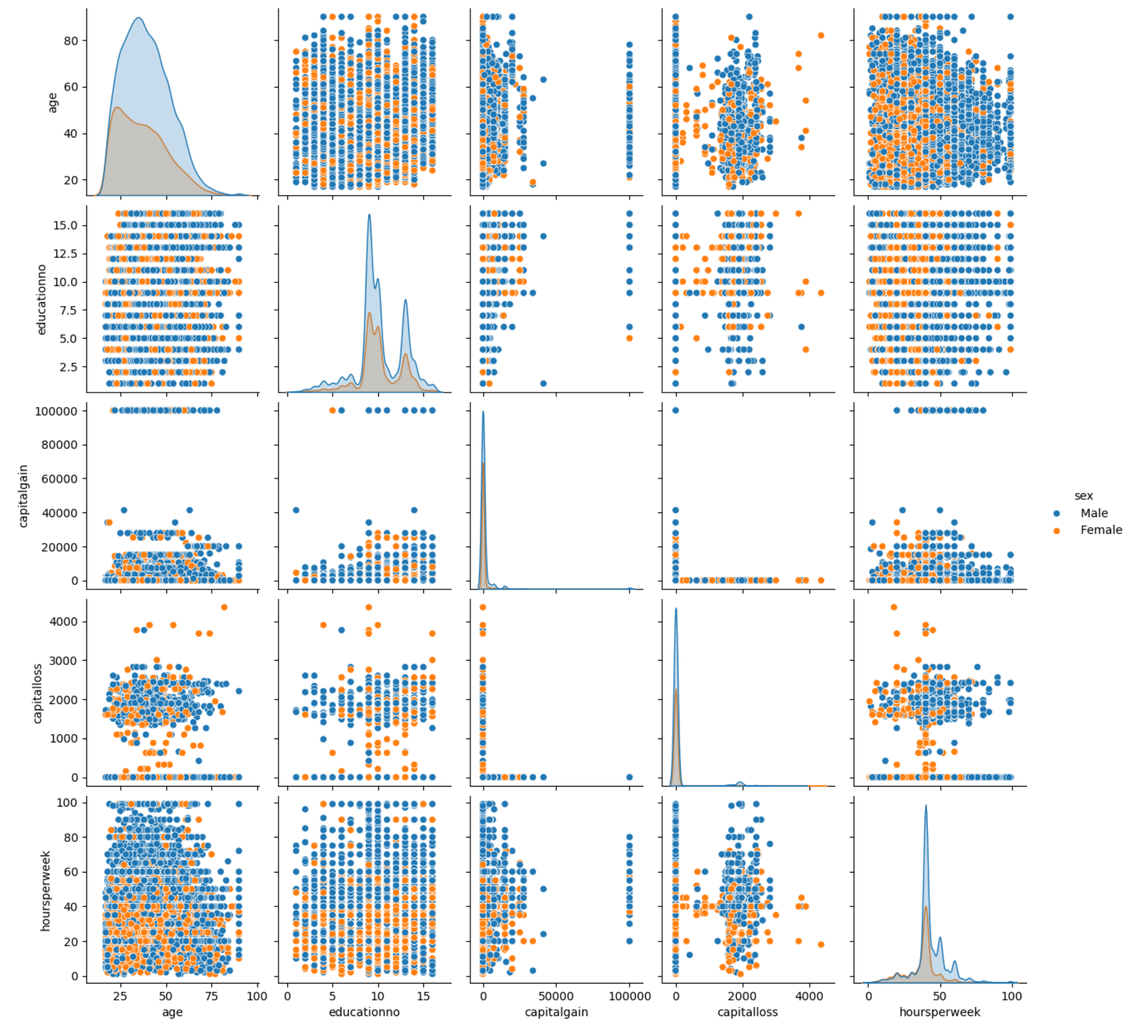
[ ]:
```
sns.pairplot(train_data)
```

[ ]:
```
<seaborn.axisgrid.PairGrid at 0x137ca67b0>
```



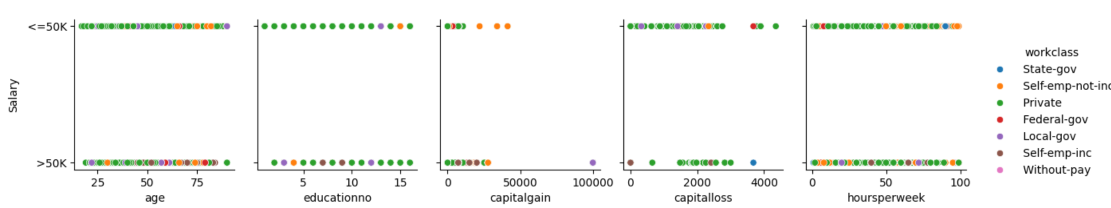
[ ]:
```
sns.pairplot(train_data, hue='sex')
```

[ ]: <seaborn.axisgrid.PairGrid at 0x30960c920>



[ ]:
```
sns.pairplot(train_data, hue='workclass', y_vars=['Salary'])
```

[ ]: <seaborn.axisgrid.PairGrid at 0x30c1d8770>



1.4 Data Processing

1.4.1 Label Encoder

In order for a model to work with the data provided, especially strings, the data must be categorized with discrete values.

Setting `train_data` columns with `object` values into enumerated integers.

[ ]:
```
le = LabelEncoder()
train_data['Salary'] = le.fit_transform(train_data['Salary'])
train_data['workclass'] = le.fit_transform(train_data['workclass'])
train_data['education'] = le.fit_transform(train_data['education'])
train_data['maritalstatus'] = le.fit_transform(train_data['maritalstatus'])
train_data['occupation'] = le.fit_transform(train_data['occupation'])
train_data['relationship'] = le.fit_transform(train_data['relationship'])
train_data['race'] = le.fit_transform(train_data['race'])
train_data['sex'] = le.fit_transform(train_data['sex'])
train_data['native'] = le.fit_transform(train_data['native'])
```

1.5 Model Building

1.5.1 Preparing the train and test values

[ ]:
```
x_train = train_data
y_train = train_data['Salary']
x_test = test_data
y_test = test_data['Salary']

# Perform label encoding
x_test['education'] = le.fit_transform(x_test['education'])
x_test['relationship'] = le.fit_transform(x_test['relationship'])
y_test = le.fit_transform(y_test)

print(f"x_train shape: {x_train.shape}\n"
      f"y_train shape: {y_train.shape}\n"
      f"x_test shape: {x_test.shape}\n"
      f"y_test shape: {y_test.shape}")
```

```
x_train shape: (30161, 14)
y_train shape: (30161,)
x_test shape: (15060, 14)
y_test shape: (15060,)
```

1.5.2 Factors that I believe affect salary the most

I've chosen the following factors that affect salary the most: - Education - A person's level of education gives the access to higher paying opportunities. - Relationship - Dependents may or may not affect a person's ability to work more

```
[ ]: from sklearn import svm
from sklearn.inspection import DecisionBoundaryDisplay

x_train = x_train[['education', 'relationship']].copy()
x_test = x_test[['education', 'relationship']].copy()
```

1.5.3 Training the data

Training with polynomial kernel causes the whole program to freeze

```
[ ]: for kernel in ("linear", "rbf"):
    clf = svm.SVC(kernel=kernel, gamma=2)
    clf.fit(x_train, y_train)

    print(
        f"Accuracy of kernel {kernel}: {accuracy_score(y_test, clf.
 ↪predict(x_test)) * 100:.2f}%"
    )
```

```
Accuracy of kernel linear: 75.43%
Accuracy of kernel rbf: 81.59%
```

1.5.4 Plotting model boundary

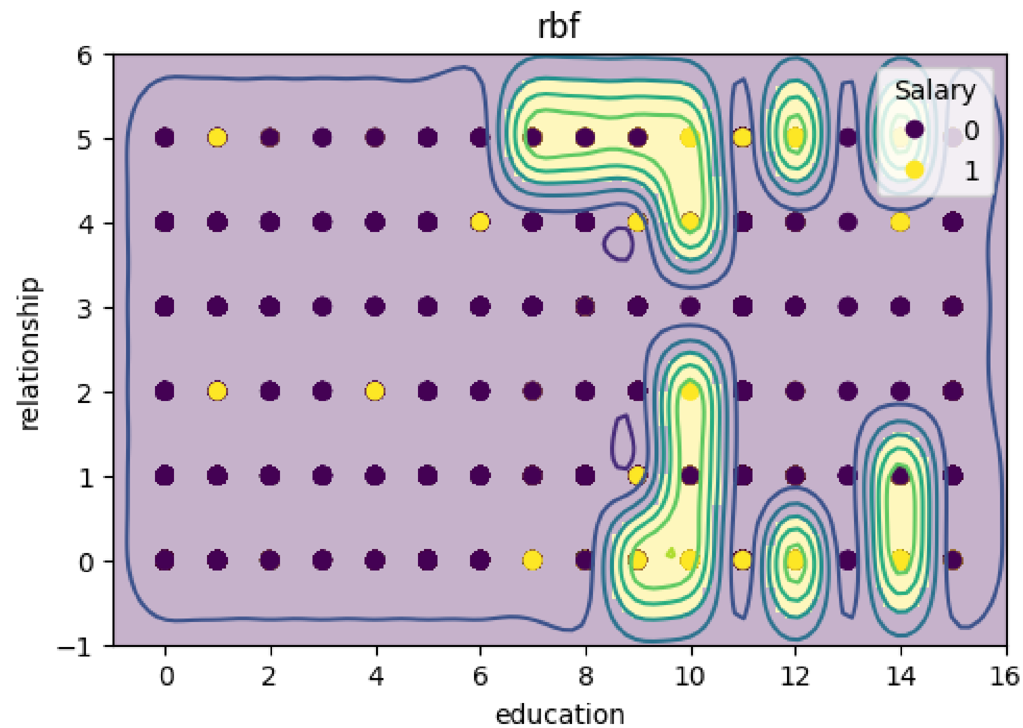
```
[ ]: x_min, x_max = train_data['education'].min() - 1, train_data['education'].max()␣
 ↪+ 1
y_min, y_max = train_data['relationship'].min() - 1, train_data['relationship'].
 ↪max() + 1

fig, ax = plt.subplots(figsize=(6,4))
ax.set(xlim=(x_min, x_max), ylim=(y_min, y_max))

common_params = {
    "estimator": clf,
    "X": x_train,
    "ax": ax
}

DecisionBoundaryDisplay.from_estimator(**common_params,
                                        response_method="predict",
                                        plot_method='pcolormesh',
                                        alpha=0.3)
DecisionBoundaryDisplay.from_estimator(**common_params,
                                        response_method="decision_function",
                                        plot_method="contour",
                                        )
scatter = ax.scatter(
    train_data['education'], train_data['relationship'], c=y_train
```

```
)
ax.legend(*scatter.legend_elements(), loc="upper right", title="Salary")
ax.set_title(kernel)
plt.show()
```



[ ]:

```

```