Week 7 Lab (Naive Bayes)

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About The Data

We'll be using the Adult Dataset from kaggle for this lab, but feel free to follow along with your own dataset. The dataset contains the following attributes:

- age
- workclass
- fnlwgt
- education
- education_num
- marital_status
- occupation
- relationship
- race
- sex
- capital_gain
- capital_loss
- hours_per_week
- native_country
- income

Our goal is to predict whether income exceeds $50k/yr based on census data

Exploratory Data Analysis

Let's begin by importing some necessary libraries that we'll be using to explore the data.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
from matplotlib import rcParams
rcParams['figure.figsize'] = 15, 5
sns.set_style('darkgrid')
```

Our first step is to load the data into a pandas DataFrame. For some reason, this dataset did not come with a header/column names, so we will specify that when loading the data and manually add the column names ourselves.

In [3]:
```
adult_df = pd.read_csv('adult.csv', header=None)
adult_df.columns = ['age', 'workclass', 'fnlwgt', 'education', 'education_num', 'marital_status', 'occupatio
                    'relationship','race', 'sex', 'capital_gain', 'capital_loss', 'hours_per_week', 'native_
                    'income']
adult_df.head()
```

Out[3]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capita
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	

Calling ***.info()*** we can see that there are no missing values in our dataset since there are 32561 entries in total, and 32561 non-null entries in every column.

In [4]:
```
adult_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64
 3   education       32561 non-null  object
 4   education_num   32561 non-null  int64
 5   marital_status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital_gain    32561 non-null  int64
 11  capital_loss    32561 non-null  int64
 12  hours_per_week  32561 non-null  int64
 13  native_country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

When working with a lot of variables, it's usually a good idea to keep track of your categorical and numerical columns in a separate array so that way we can easilly index our dataframe by that array if for some reason we only want to work with the numerical columns. For example, when calculating correlations we only want to work with the numerical columns else we will get an error.

In [5]:
```
categoricals = ['workclass', 'education', 'marital_status', 'occupation', 'relationship', 'race', 'sex',
                'native_country', 'income']
numericals = ['age', 'fnlwgt', 'education_num', 'capital_gain', 'capital_loss', 'hours_per_week']
```

Now we can easily explore just categorical or numericals at a time. 😊 Let's begin exploring the categorical variables first.

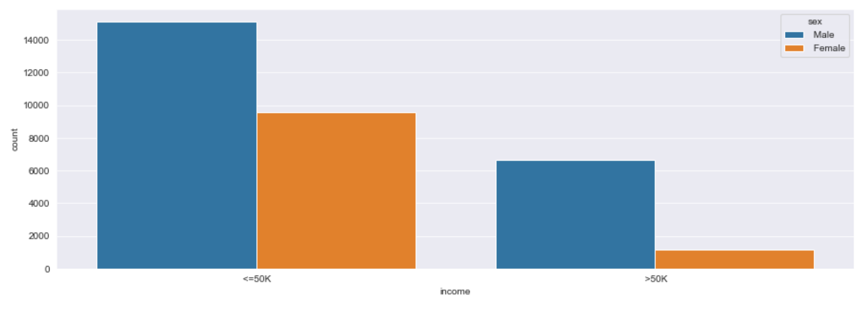
In [6]:
```
adult_df[categoricals].head()
```

Out[6]:

	workclass	education	marital_status	occupation	relationship	race	sex	native_country	income
0	State-gov	Bachelors	Never-married	Adm-clerical	Not-in-family	White	Male	United-States	<=50K
1	Self-emp-not-inc	Bachelors	Married-civ-spouse	Exec-managerial	Husband	White	Male	United-States	<=50K
2	Private	HS-grad	Divorced	Handlers-cleaners	Not-in-family	White	Male	United-States	<=50K
3	Private	11th	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	United-States	<=50K
4	Private	Bachelors	Married-civ-spouse	Prof-specialty	Wife	Black	Female	Cuba	<=50K

Does one sex tend to earn more than the other in this dataset?

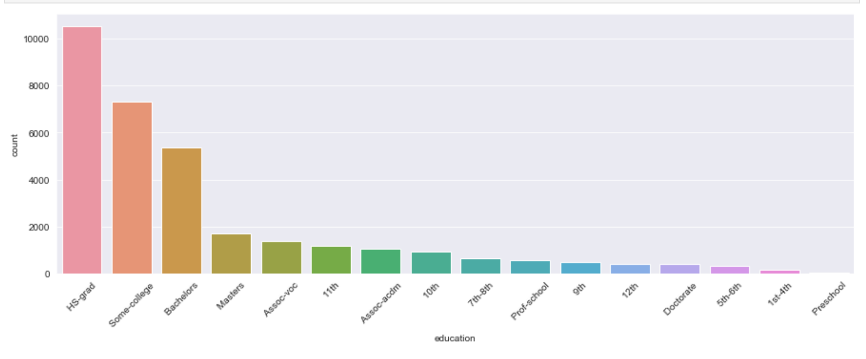
In [7]:
```
sns.countplot(x=adult_df['income'], hue='sex', data=adult_df)
plt.show()
```



Interpretation: majority of our dataset consist of people earning <=50k, but we can see that in both categories (<=50k and >50k), majority of the men earn more.

What's the most common education people in our dataset have?

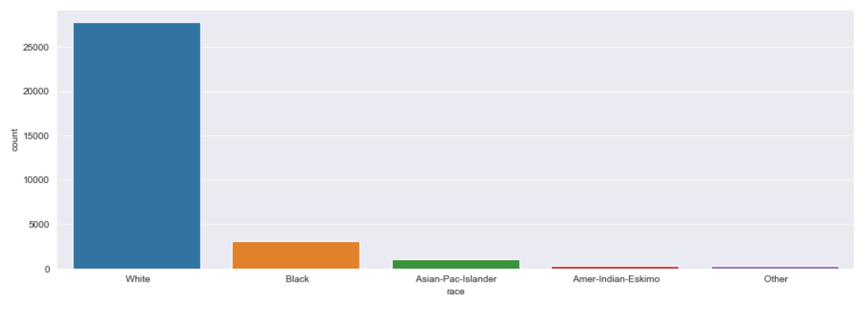
In [8]:
```
# order= is an optional parameter, which is just sorting the bars in this case.
sns.countplot(x=adult_df['education'], order=adult_df['education'].value_counts().index)
plt.xticks(rotation=45)
plt.show()
```



Interpretation: high school, some college, and bachelors degrees seem to be most common in our dataset.

Let's see how many counts of each race we have in this dataset

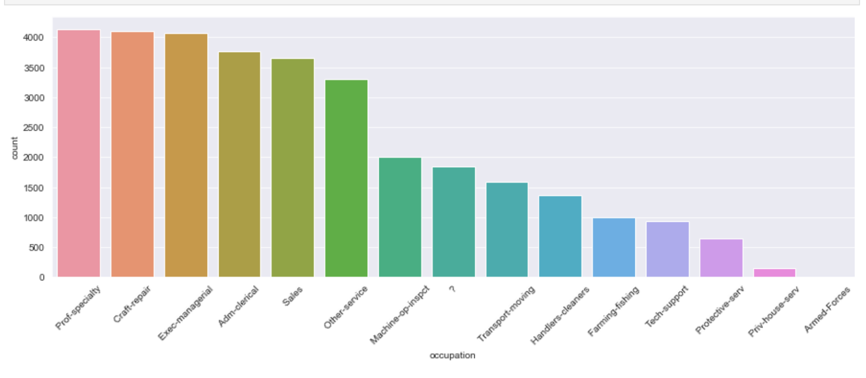
In [9]:
```
sns.countplot(x=adult_df['race'], data=adult_df)
plt.show()
```



Interpretation: our dataset mostly consists of people from the white race category. Thus, inferences based on race from this dataset could be biased since we do not have enough data from other race categories.

What sort of occupations do we have in our dataset, and which are most common?

In [10]:
```
sns.countplot(x=adult_df['occupation'], data=adult_df, order=adult_df['occupation'].value_counts().index)
plt.xticks(rotation=45)
plt.show()
```



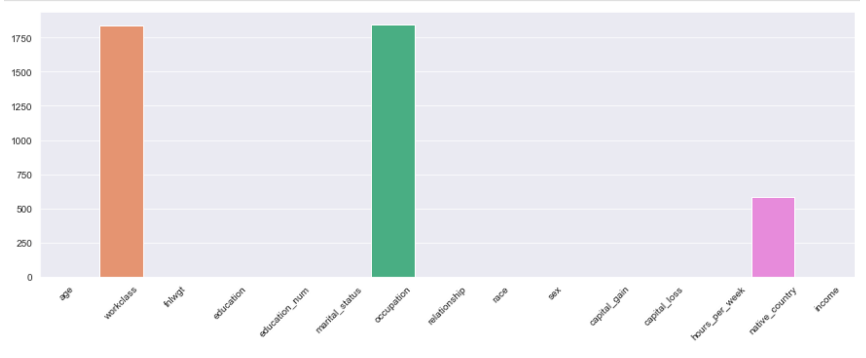
Interpretation: Prof-specialty, craft-repair, and Exec-managerial are the top 3 occupations in our dataset. Also, there's a '?' signifying unknown. We'll have to make sure to replace those question marks with null/nan values since these should really be missing values. If you take a look, you'll see that workclass and native_country also have '?' values, so we'll replace those with NaN as follows:

In [11]:
```
adult_df['workclass'] = adult_df['workclass'].replace(' ?', np.NaN)
adult_df['occupation'] = adult_df['occupation'].replace(' ?', np.NaN)
adult_df['native_country'] = adult_df['native_country'].replace(' ?', np.NaN)
```

Note: There was a small space infront of the question mark, so make sure to include that if you're using the same dataset.

After running the cell above, we can see that we have the following missing values, which we'll have to take care of.

In [12]:
```
sns.barplot(x=adult_df.columns, y=adult_df.isnull().sum().values)
plt.xticks(rotation=45)
plt.show()
```



Let's now briefly explore the numerical variables

In [13]:
```
adult_df[numericals].head()
```

Out[13]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
0	39	77516	13	2174	0	40
1	50	83311	13	0	0	13
2	38	215646	9	0	0	40
3	53	234721	7	0	0	40
4	28	338409	13	0	0	40

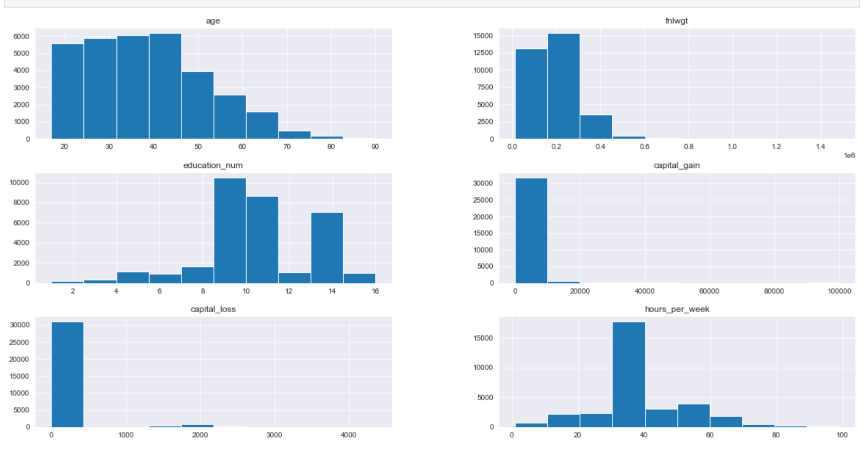
Let's check if there are any '?' missing values in any of the numerical columns like we had in the categoricals. We can do this by looping through every variable in the numericals list and printing a note if that column contains a ' ?'.

In [14]:
```
for variable in numericals:
    if not adult_df[adult_df[variable] == ' ?'].empty:
        print(f'{variable} contains missing values ( ?)')
```

Great, there are no missing vlaues to take care of here, we'll just have to take care of the categorical missing values in later.

What do the distributions of our numerical variables look like?

In [15]:
```
adult_df[numericals].hist(figsize=(20, 10))
plt.show()
```



I encourage you to go ahead and explore the dataset some more to see if you can find some more interesting points, but I'll jump to the pre-processing now since you should be comfortable exploring datasets by now, and the main goal of this lab is to learn how to create and evaluate a Naive Bayes model in sklearn.

Pre-Processing

We'll first take care of the missing categorical values. One option is to replace the missing values with the most frequent/mode, which we'll do below. However, options for dealing with missing ***categorical*** variables include:

- Remove observations with missing values if we are dealing with a large dataset and the number of records containing missing values are few.
- Remove the variable/column if it is not significant.
- Develop a model to predict missing values. KNN for example.
- Replace missing values with the most frequent in that column.

In [16]:
```
adult_df['workclass'].fillna(adult_df['workclass'].mode()[0], inplace=True)
adult_df['occupation'].fillna(adult_df['occupation'].mode()[0], inplace=True)
adult_df['native_country'].fillna(adult_df['native_country'].mode()[0], inplace=True)
```

Our next step is to encode these categories. Since our categories don't really have any type of order to preserve, we'll use one hot encoding / get dummies. Refer back to lab 5 if you're having trouble using dummy variables, but we'll encode as follows:

In [17]:
```
adult_df = pd.get_dummies(data=adult_df, columns=categoricals, drop_first=True)
```

In [18]:
```
adult_df.head()
```

Out[18]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week	workclass_ Local-gov	workclass_ Never-worked	workclass_ Private	workclass_ Self-emp-inc	...
0	39	77516	13	2174	0	40	0	0	0	0	...
1	50	83311	13	0	0	13	0	0	0	0	...
2	38	215646	9	0	0	40	0	0	1	0	...
3	53	234721	7	0	0	40	0	0	1	0	...
4	28	338409	13	0	0	40	0	0	1	0	...

5 rows × 98 columns

Let's now map all of our variables onto the same scale. We'll follow the same steps as the KNN lab. The only difference from KNN lab is that here we're using RobustScaler, which just scales features using statistics that are robust to outliers.

In [26]:
```
from sklearn.preprocessing import RobustScaler

# all columns except our target column for X
X = adult_df.drop('income_ >50K', axis=1)
y = adult_df['income_ >50K']

# create our scaler object
scaler = RobustScaler()
# use our scaler object to transform/scale our data and save it into X_scaled. Only need to
# transform numerical data.
X_scaled = scaler.fit_transform(X[numericals])
# reassign X[numericals] to the transformed numerical data.
X[numericals] = X_scaled
```

In [27]:
```
X.head()
```

Out[27]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week	workclass_ Local-gov	workclass_ Never-worked	workclass_ Private	workclass_ Self-emp-inc
0	0.10	-0.845803	1.000000	2174.0	0.0	0.0	0	0	0	0
1	0.65	-0.797197	1.000000	0.0	0.0	-5.4	0	0	0	0
2	0.05	0.312773	-0.333333	0.0	0.0	0.0	0	0	1	0
3	0.80	0.472766	-1.000000	0.0	0.0	0.0	0	0	1	0
4	-0.45	1.342456	1.000000	0.0	0.0	0.0	0	0	1	0

5 rows × 97 columns

Creating our Model

We're now ready to begin creating and training our model. We first need to split our data into training and testing sets. This can be done using sklearn's ***train_test_split(X, y, test_size)*** function. This function takes in your features (X), the target variable (y), and the test_size you'd like (Generally a test size of around 0.3 is good enough). It will then return a tuple of X_train, X_test, y_train, y_test sets for us. We will train our model on the training set and then use the test set to evaluate the model.

In [28]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

In [29]:
```
from sklearn.naive_bayes import GaussianNB

# instantiate the model to train a Gaussian Naive Bayes classifier
gnb = GaussianNB()

# fit the model
gnb.fit(X_train, y_train)
```

Out[29]: GaussianNB()

Model Evaluation

Now that we've finished training, we can make predictions off of the test data and evaluate our model's performance using the corresponding test data labels (y_test).

In [30]:
```
y_pred = gnb.predict(X_test)
```

Check accuracy score:

In [31]:
```
from sklearn.metrics import accuracy_score

print('Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy score: 0.8228
```

Compare the train set and test set accuracy:

In [32]:
```
y_pred_train = gnb.predict(X_train)

print('Training set score: {:.4f}'.format(gnb.score(X_train, y_train)))
print('Test set score: {:.4f}'.format(gnb.score(X_test, y_test)))
```

```
Training set score: 0.8241
Test set score: 0.8228
```

The training set accuracy score is 0.8241 while the test set accuracy is 0.8228. These two values are quite comparable, so there is no sign of overfitting.

Confussion matrix results:

In [33]:
```
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred)

print('Confusion matrix\n\n', cm)
print('\nTrue Positives(TP) = ', cm[0,0])
print('\nTrue Negatives(TN) = ', cm[1,1])
print('\nFalse Positives(FP) = ', cm[0,1])
print('\nFalse Negatives(FN) = ', cm[1,0])
```

```
Confusion matrix

 [[6299 1090]
 [ 641 1739]]

True Positives(TP) =  6299

True Negatives(TN) =  1739

False Positives(FP) =  1090

False Negatives(FN) =  641
```

Classification report is another way to evaluate the classification model performance. It displays the precision, recall, f1 and support scores for the model. Let's print these as well.

In [34]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.85      0.88      7389
           1       0.61      0.73      0.67      2380

    accuracy                           0.82      9769
   macro avg       0.76      0.79      0.77      9769
weighted avg       0.84      0.82      0.83      9769
```

Let's also perform k-Fold Cross Validation (10-fold below). We can do this using ***cross_val_score(model, X_train, y_train, k, scoring)***

In [37]:
```
from sklearn.model_selection import cross_val_score

# Applying 10-Fold Cross Validation
scores = cross_val_score(gnb, X_train, y_train, cv = 10, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))

# compute Average cross-validation score
print('\nAverage cross-validation score: {:.4f}'.format(scores.mean()))
```

```
Cross-validation scores:[0.82587719 0.82763158 0.82272927 0.81263712 0.83501536 0.82053532
 0.82404563 0.83457657 0.81000439 0.82316806]

Average cross-validation score: 0.8236
```

interpretation:

- Using the mean cross-validation, we can conclude that we expect the model to be around 0.8236% accurate on average.
- If we look at all the 10 scores produced by the 10-fold cross-validation, we can also conclude that there is a relatively small variance in the accuracy between folds, so we can conclude that the model is independent of the particular folds used for training.

Great job! You now know how to use a Naive Bayes model in sklearn. 😊 Try using this on your own dataset and refer back to this