

The image displays two sequential screenshots of a Jupyter Notebook environment, likely JupyterLab, showing the process of reading data from CSV files into pandas DataFrames.

Top Screenshot:

- Title Bar:** solution.ipynb X
- Breadcrumbs:** E > University > Semester 4 > Pattern Recognition > Assignments > Assignment_1 > assignment_solution > solution.ipynb > ...
- Toolbar:** + Code + Markdown | ▶ Run All ⏻ Restart 🗑 Clear All Outputs | 📄 Variables 📖 Outline ...
- Language:** base (Python 3.11.7)
- Section Header:** Import important libraries
- Code Cell [1]:**

```
import pandas as pd
import numpy as np
```

Execution time: 8.4s

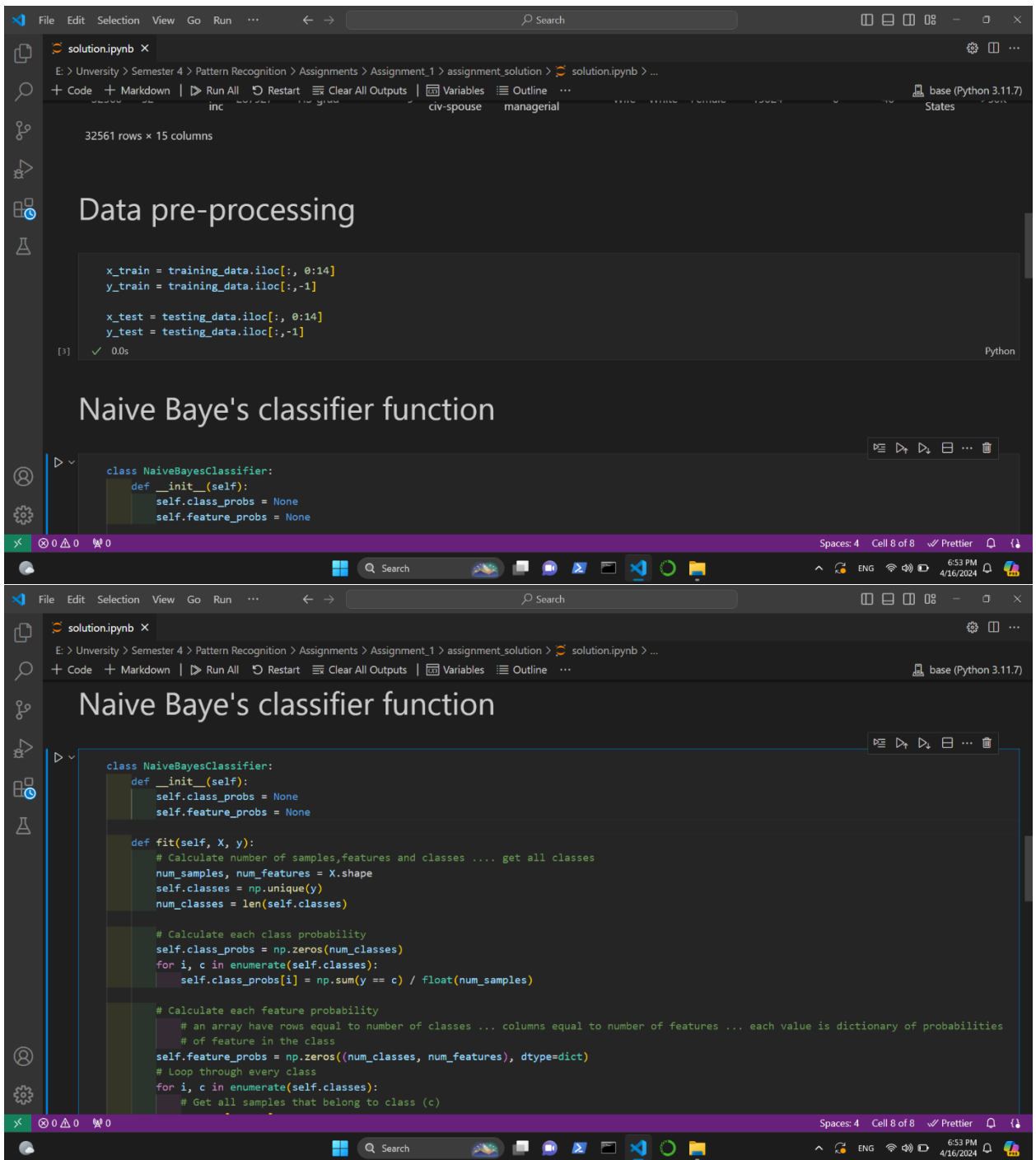
Bottom Screenshot:

- Title Bar:** solution.ipynb X
- Breadcrumbs:** E > University > Semester 4 > Pattern Recognition > Assignments > Assignment_1 > assignment_solution > solution.ipynb > ...
- Toolbar:** + Code + Markdown | ▶ Run All ⏻ Restart 🗑 Clear All Outputs | 📄 Variables 📖 Outline ...
- Language:** base (Python 3.11.7)
- Section Header:** Read data from csv
- Code Cell [2]:**

```
training_data = pd.read_csv("training.csv")
testing_data = pd.read_csv("testing.csv")
training_data
```

Execution time: 0.4s
- Data Output:** A pandas DataFrame is displayed with the following columns: age, workclass, fnlwtg, education, education-num, marital-status, occupation, relationship, race, sex, capital-gain, capital-loss, hours-per-week, native-country, income. The first five rows of data are visible:

	age	workclass	fnlwtg	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	income
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K



```
File Edit Selection View Go Run ... Search
solution.ipynb X
E: > University > Semester 4 > Pattern Recognition > Assignments > Assignment_1 > assignment_solution > solution.ipynb > ...
+ Code + Markdown | Run All Restart Clear All Outputs Variables Outline ... base (Python 3.11.7)

def fit(self, X, y):
    # Calculate number of samples, features and classes .... get all classes
    num_samples, num_features = X.shape
    self.classes = np.unique(y)
    num_classes = len(self.classes)

    # Calculate each class probability
    self.class_probs = np.zeros(num_classes)
    for i, c in enumerate(self.classes):
        self.class_probs[i] = np.sum(y == c) / float(num_samples)

    # Calculate each feature probability
    # an array have rows equal to number of classes ... columns equal to number of features ... each value is dictionary of probabilities
    # of feature in the class
    self.feature_probs = np.zeros((num_classes, num_features), dtype=dict)
    # Loop through every class
    for i, c in enumerate(self.classes):
        # Get all samples that belong to class (c)
        X_c = X[y == c]
        # Loop through every feature
        for j in range(num_features):
            # Get every unique value in feature j and its count
            values, counts = np.unique(X_c[:, j], return_counts=True)
            # For this class ... save probability of each unique value for this feature ( contained in dictionary )
            self.feature_probs[i][j] = dict(zip(values, counts / len(X_c)))

def predict(self, X):
    num_samples, num_features = X.shape
    predictions = []
    # Loop through each sample
    for sample in X:
        class_probs = []
        # Loop through each class
        for i, c in enumerate(self.classes):
            class_prob = self.class_probs[i]
            # Loop through each feature
            for j in range(num_features):
                # Check if new feature value exists in trained model
                if sample[j] in self.feature_probs[i][j]:
                    class_prob *= self.feature_probs[i][j][sample[j]]
                else:
                    # Handle unseen feature values
                    class_prob = float('-inf') # Assign zero probability
                    break # No need to continue with this class
            # Append current class probability
            class_probs.append(class_prob)
        # Append class with maximum probability for this sample to predictions
        predictions.append(self.classes[np.argmax(class_probs)])
    return predictions

# Example
nb_classifier = NaiveBayesClassifier()
```

The image shows a Jupyter Notebook interface with two cells. The top cell contains Python code for a Naive Bayes classifier. The bottom cell shows the output of the code, which includes the number of correct predictions, sensitivity, specificity, and the posterior probability of making over 50K a year.

```
# Example
nb_classifier = NaiveBayesClassifier()
nb_classifier.fit(np.array(x_train), np.array(y_train))
predictions = nb_classifier.predict(np.array(x_test))

# Calculate sensitivity/specificity/posterior probability
actual_values = np.array(y_test)
tp = 0
tn = 0
fp = 0
fn = 0
for actual, predicted in zip(actual_values, predictions):
    if ">" in actual and ">" in predicted:
        tp += 1
    elif "<" in actual and "<" in predicted:
        tn += 1
    elif ">" in actual and "<" in predicted:
        fp += 1
    else:
        fn += 1
sensitivity = (tp / (tp+fn))
specificity = (tn / (tn+fp))
posterior_prob = (tp / (tp+tn))
print(f"Correct predictions: {tp+tn}")
print(f"Sensitivity: {sensitivity}")
print(f"Specificity: {specificity}")
print(f"Posterior probability of making over 50K a year: {posterior_prob}")
```

Correct predictions: 12647
Sensitivity: 0.5413416536661466
Specificity: 0.8208062987533717
Posterior probability of making over 50K a year: 0.10974934767138451