PCA_Mini_Project_Solution

January 28, 2026

0.0.1 PCA Mini Project - Solution

In the lesson, you saw how you could use PCA to substantially reduce the dimensionality of the handwritten digits. In this mini-project, you will be using the **cars.csv** file.

To begin, run the cell below to read in the necessary libraries and the dataset. I also read in the helper functions that you used throughout the lesson in case you might find them helpful in completing this project. Otherwise, you can always create functions of your own!

[1]:
```
import pandas as pd
import numpy as np
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from helper_functions import do_pca, scree_plot, plot_components, pca_results
from IPython import display
import test_code2 as t

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

df = pd.read_csv('./data/cars.csv')
```

1. Now your data is stored in **df**. Use the below cells to take a look your dataset. At the end of your exploration, use your findings to match the appropriate variable to each key in the dictionary below.

[2]:
```
df.head()
```

[2]:
```
                          Sports  SUV  Wagon  Minivan  Pickup  AWD  RWD  \
Acura 3.5 RL                   0    0      0        0       0    0    0
Acura 3.5 RL Navigation        0    0      0        0       0    0    0
Acura MDX                      0    1      0        0       0    1    0
Acura NSX S                    1    0      0        0       0    0    1
Acura RSX                      0    0      0        0       0    0    0
```

```
                          Retail  Dealer  Engine  Cylinders  Horsepower  \
Acura 3.5 RL               43755   39014     3.5          6         225
Acura 3.5 RL Navigation    46100   41100     3.5          6         225
Acura MDX                  36945   33337     3.5          6         265
Acura NSX S                89765   79978     3.2          6         290
Acura RSX                  23820   21761     2.0          4         200

                          CityMPG  HighwayMPG  Weight  Wheelbase  Length  Width
Acura 3.5 RL                   18          24    3880        115     197     72
Acura 3.5 RL Navigation        18          24    3893        115     197     72
Acura MDX                      17          23    4451        106     189     77
Acura NSX S                    17          24    3153        100     174     71
Acura RSX                      24          31    2778        101     172     68
```

[3]:
```
df.describe()
```

[3]:
```
           Sports         SUV       Wagon     Minivan  Pickup         AWD  \
count  387.000000  387.000000  387.000000  387.000000   387.0  387.000000
mean     0.116279    0.152455    0.072351    0.054264     0.0    0.201550
std      0.320974    0.359926    0.259404    0.226830     0.0    0.401677
min      0.000000    0.000000    0.000000    0.000000     0.0    0.000000
25%      0.000000    0.000000    0.000000    0.000000     0.0    0.000000
50%      0.000000    0.000000    0.000000    0.000000     0.0    0.000000
75%      0.000000    0.000000    0.000000    0.000000     0.0    0.000000
max      1.000000    1.000000    1.000000    1.000000     0.0    1.000000

              RWD         Retail         Dealer      Engine   Cylinders  \
count  387.000000     387.000000     387.000000  387.000000  387.000000
mean     0.242894   33231.180879   30440.653747    3.127390    5.757106
std      0.429387   19724.634576   17901.179282    1.014314    1.490182
min      0.000000   10280.000000    9875.000000    1.400000    3.000000
25%      0.000000   20997.000000   19575.000000    2.300000    4.000000
50%      0.000000   28495.000000   26155.000000    3.000000    6.000000
75%      0.000000   39552.500000   36124.000000    3.800000    6.000000
max      1.000000  192465.000000  173560.000000    6.000000   12.000000

       Horsepower     CityMPG  HighwayMPG       Weight   Wheelbase  \
count  387.000000  387.000000  387.000000   387.000000  387.000000
mean   214.444444   20.312661   27.263566  3532.457364  107.211886
std     70.262822    5.262333    5.636005   706.003622    7.086553
min     73.000000   10.000000   12.000000  1850.000000   89.000000
25%    165.000000   18.000000   24.000000  3107.000000  103.000000
50%    210.000000   19.000000   27.000000  3469.000000  107.000000
75%    250.000000   21.500000   30.000000  3922.000000  112.000000
max    493.000000   60.000000   66.000000  6400.000000  130.000000
```

```
           Length       Width
count  387.000000  387.000000
mean   184.961240   71.276486
std     13.237999    3.368329
min    143.000000   64.000000
25%    177.000000   69.000000
50%    186.000000   71.000000
75%    193.000000   73.000000
max    221.000000   81.000000
```

[4]:
```
df.shape
```

[4]:
```
(387, 18)
```

[5]:
```
a = 7
b = 66
c = 387
d = 18
e = 0.23
f = 0.05


solution_1_dict = {
    'The number of cars in the dataset': c,
    'The number of car features in the dataset': d,
    'The number of dummy variables in the dataset': a,
    'The proportion of minivans in the dataset': f,
    'The max highway mpg for any car': b
}
```

[6]:
```
# Check your solution against ours by running this cell
display.HTML(t.check_question_one(solution_1_dict))
```

```
Nice job!  Looks like your dataset matches what we found!
```

[6]:
```
<IPython.core.display.HTML object>
```

2. There are some particularly nice properties about PCA to keep in mind. Use the dictionary below to match the correct variable as the key to each statement. When you are ready, check your solution against ours by running the following cell.

[7]:
```
a = True
b = False

solution_2_dict = {
    'The components span the directions of maximum variability.': a,
    'The components are always orthogonal to one another.': a,
    'Eigenvalues tell us the amount of information a component holds': a
}
```

[8]:
```
# Check your solution against ours by running this cell
t.check_question_two(solution_2_dict)
```

```
That's right these are all true.  Principal components are orthogonal, span the
directions of maximum variability, and the corresponding eigenvalues tell us how
much of the original variability is explained by each component.
```

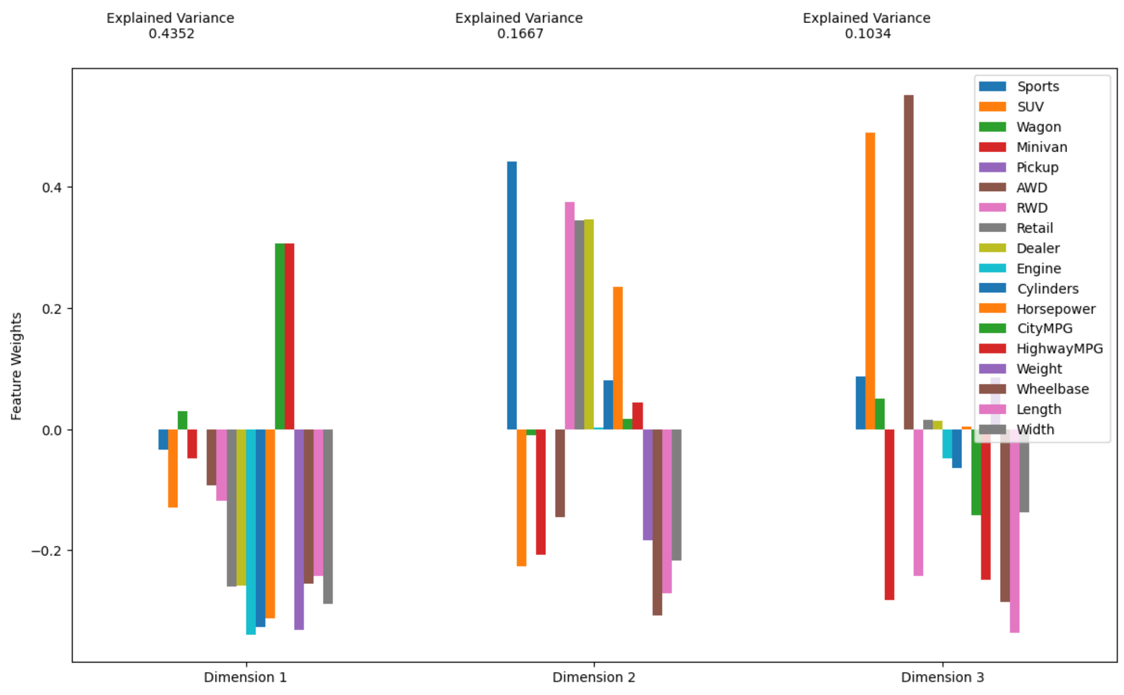
`3.` Fit PCA to reduce the current dimensionality of the datset to 3 dimensions. You can use the helper functions, or perform the steps on your own. If you fit on your own, be sure to standardize your data. At the end of this process, you will want an X matrix with the reduced dimensionality to only 3 features. Additionally, you will want your **pca** object back that has been used to fit and transform your dataset.

[9]:
```
pca, X_pca = do_pca(3, df)
```

`4.` Once you have your pca object, you can take a closer look at what comprises each of the principal components. Use the **pca_results** function from the **helper_functions** module assist with taking a closer look at the results of your analysis. The function takes two arguments: the full dataset and the pca object you created.

[10]:
```
pca_results(df, pca)
```

[10]:
```
             Explained Variance  Sports     SUV   Wagon  Minivan  Pickup  \
Dimension 1              0.4352 -0.0343 -0.1298  0.0289  -0.0481    -0.0
Dimension 2              0.1667  0.4420 -0.2261 -0.0106  -0.2074     0.0
Dimension 3              0.1034  0.0875  0.4898  0.0496  -0.2818     0.0

                AWD     RWD  Retail  Dealer  Engine  Cylinders  Horsepower  \
Dimension 1 -0.0928 -0.1175 -0.2592 -0.2576 -0.3396    -0.3263     -0.3118
Dimension 2 -0.1447  0.3751  0.3447  0.3453  0.0022     0.0799      0.2342
Dimension 3  0.5506 -0.2416  0.0154  0.0132 -0.0489    -0.0648      0.0040

             CityMPG  HighwayMPG  Weight  Wheelbase  Length   Width
Dimension 1   0.3063      0.3061 -0.3317    -0.2546 -0.2414 -0.2886
Dimension 2   0.0169      0.0433 -0.1832    -0.3066 -0.2701 -0.2163
Dimension 3  -0.1421     -0.2486  0.0851    -0.2846 -0.3361 -0.1369
```



5. Use the results, to match each of the variables as the value to the most appropriate key in the dictionary below. When you are ready to check your answers, run the following cell to see if your solution matches ours!

[11]:
```
a = 'car weight'
b = 'sports cars'
c = 'gas mileage'
d = 0.4352
e = 0.3061
f = 0.1667
g = 0.7053

solution_5_dict = {
    'The first component positively weights items related to': c,
    'The amount of variability explained by the first component is': d,
    'The largest weight of the second component is related to': b,
    'The total amount of variability explained by the first three components': g
}
```

[12]:
```
# Run this cell to check if your solution matches ours.
t.check_question_five(solution_5_dict)
```

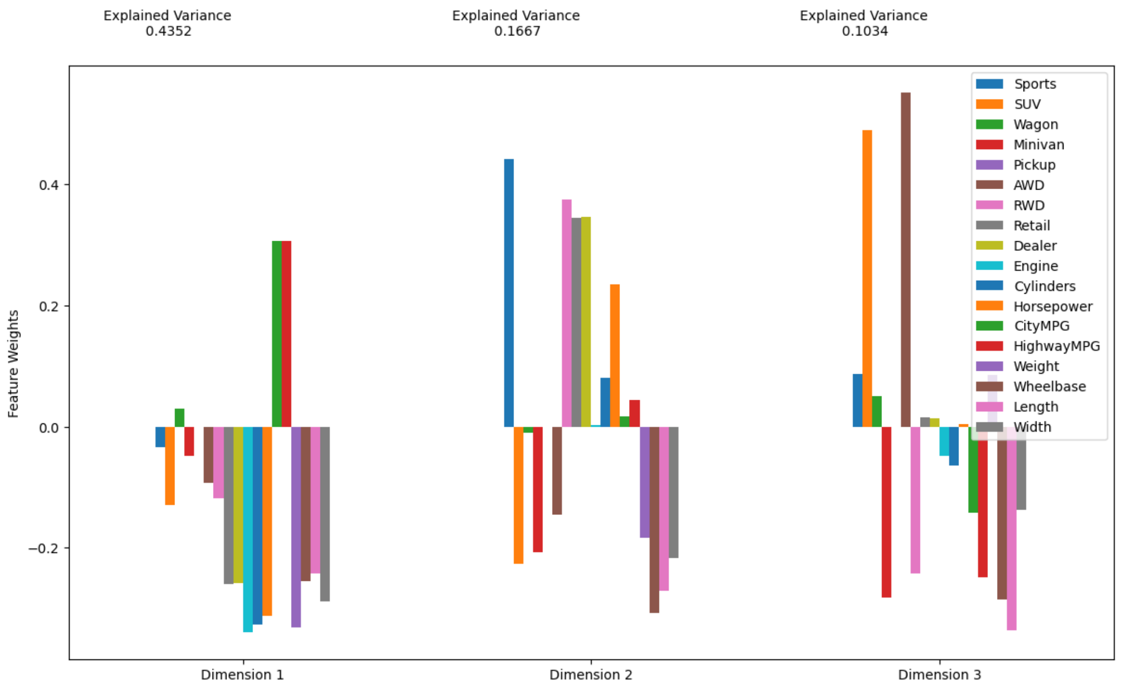
```
That's right!  Looks like you know a lot about PCA!
```

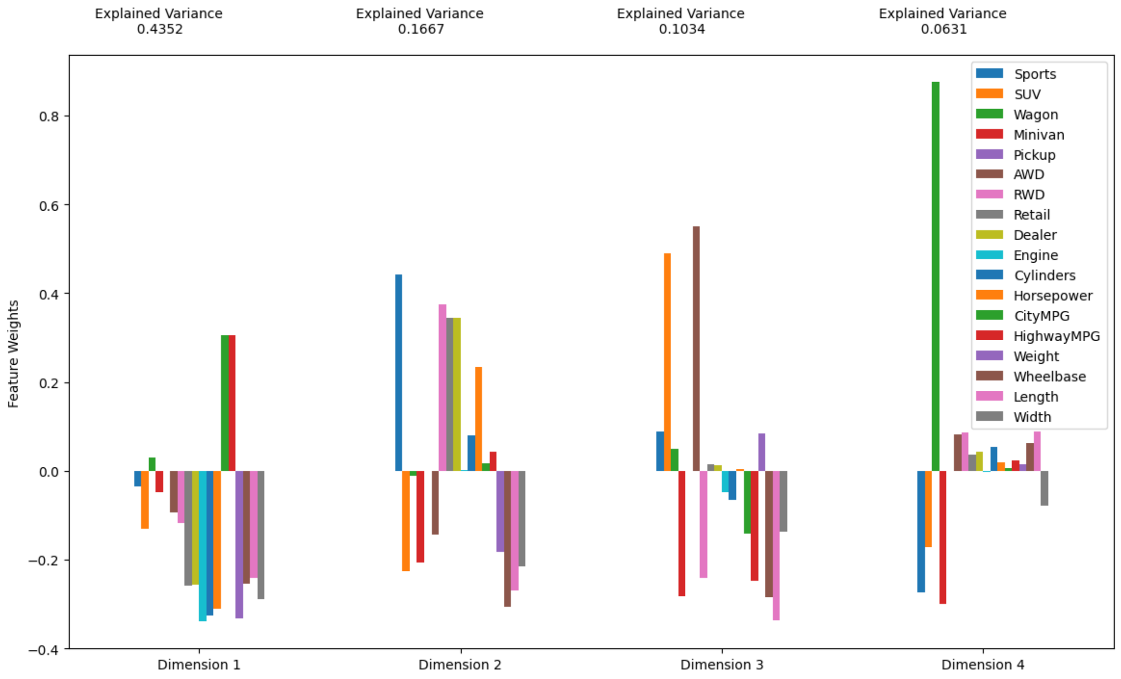
6. How many components need to be kept to explain at least 85% of the variability in the original dataset? When you think you have the answer, store it in the variable `num_comps`. Then run the

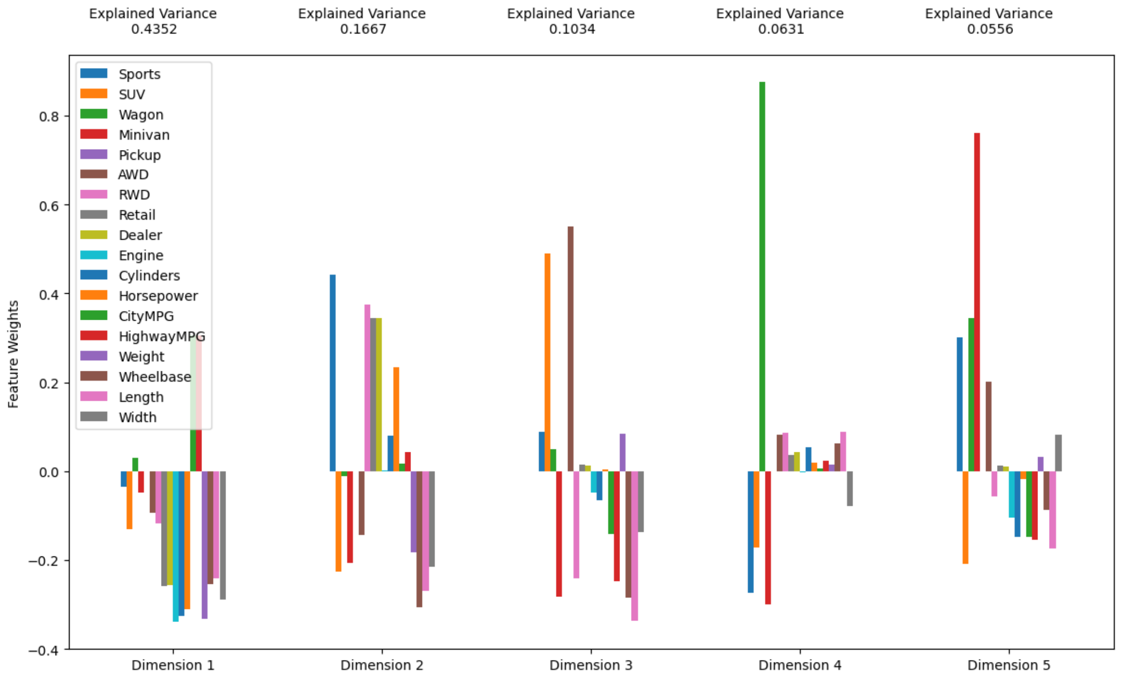
following cell to see if your solution matches ours!

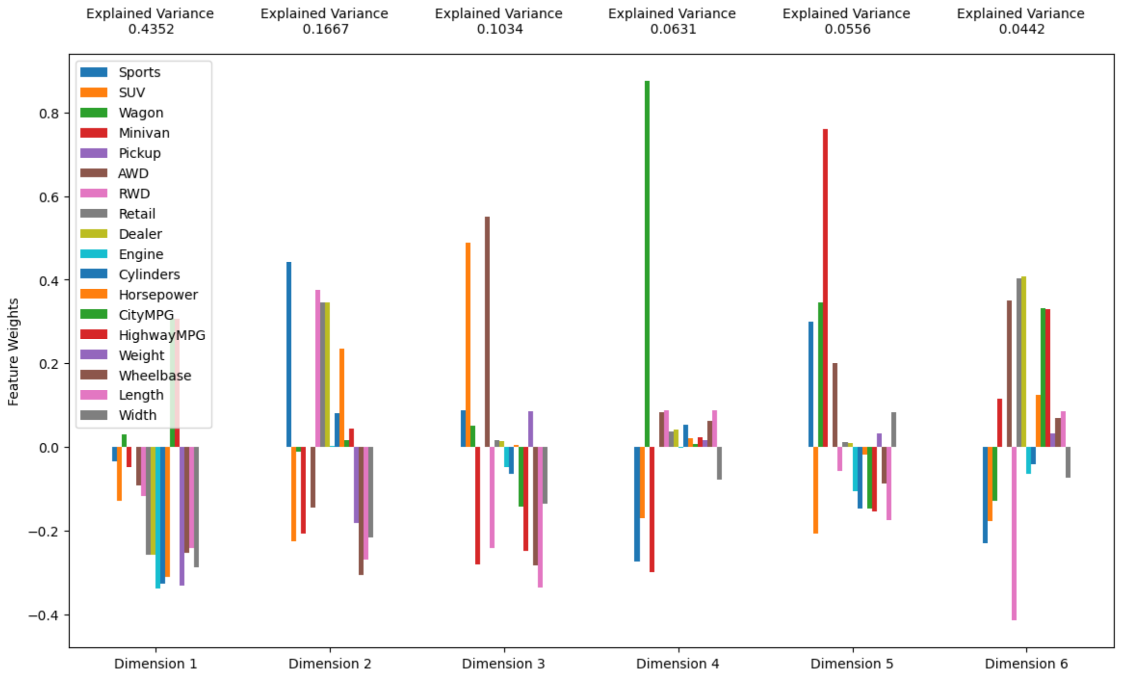
[13]:
```python
for comp in range(3, df.shape[1]):
    pca, X_pca = do_pca(comp, df)
    comp_check = pca_results(df, pca)
    if comp_check['Explained Variance'].sum() > 0.85:
        break


num_comps = comp_check.shape[0]
print("Using {} components, we can explain {}% of the variability in the␣
 ↪original data.".format(comp_check.shape[0],comp_check['Explained Variance'].
 ↪sum()))
```

```
Using 6 components, we can explain 0.8682000000000001% of the variability in the
original data.
```




Explained Variance 0.4352
Explained Variance 0.1667
Explained Variance 0.1034
Explained Variance 0.0631
Feature Weights
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
Dimension 1
Dimension 2
Dimension 3
Dimension 4
Sports
SUV
Wagon
Minivan
Pickup
AWD
RWD
Retail
Dealer
Engine
Cylinders
Horsepower
CityMPG
HighwayMPG
Weight
Wheelbase
Length
Width


Explained Variance 0.4352
Explained Variance 0.1667
Explained Variance 0.1034
Explained Variance 0.0631
Explained Variance 0.0556
Feature Weights
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
Dimension 1
Dimension 2
Dimension 3
Dimension 4
Dimension 5
Sports
SUV
Wagon
Minivan
Pickup
AWD
RWD
Retail
Dealer
Engine
Cylinders
Horsepower
CityMPG
HighwayMPG
Weight
Wheelbase
Length
Width



[14]:
```
# How check your answer here to complete this mini project
display.HTML(t.question_check_six(num_comps))
```

```
Nice job!  That's right!  With 6 components, you can explain more than 85% of
the variability in the original dataset.
```

[14]:
```
<IPython.core.display.HTML object>
```

[ ]:
```
```