HW#6

May 11, 2020

1 Part 1

In class, we talked about the loss functions (also called the objective functions) for LASSO and Ridge regression. Write a function penalty that takes in a list of coefficients (coefs) and calculates the penalty term for LASSO when the argument lasso = True, and for Ridge when lasso = False.

The penalty terms for LASSO and Ridge are listed below (K is the number of coefficients):

LASSO: $\alpha \sum_j^K |\beta_j|$

Ridge: $\alpha \sum_j^K \beta_j^2$

Note: for computational reasons, computer programs often use slightly different objective/loss functions. But the simple ones we're using here still effectively communicate the ideas behind Ridge and Lasso

[1]:
```python
def penalty(alpha = 0.01,coefs = [1,1,1], lasso = True):
    coefs_list = []
    if lasso == False:
        for i in coefs:
            newCoef = i*i
            coefs_list.append(newCoef)
        final_coefs = sum(coefs_list)
        answer = alpha * final_coefs
    if lasso == True:
        for i in coefs:
            newCoef = abs(i)
            coefs_list.append(newCoef)
        final_coefs = sum(coefs_list)
        answer = alpha * final_coefs
    return answer
    pass
```

[2]:
```python
penalty(alpha = 1, coefs = [1,2,3,4,5,6], lasso = False)
```

[2]:
```
91
```

[3]:
```python
penalty(alpha = 1, coefs = [1,2,3,4,5,6], lasso = True)
```

[3]:
```
21
```

2 Part 2

Below are two simulated data sets, related and unrelated. related has relationships/correlations between the variables. unrelated does not. Use PCA on these two simple data sets (variables are ALREADY standardized), make a scree plot for each data set and compare the amount of variance accounted for by the first Principal Components. In words, explain why you think they're different.

[3]:
```
import pandas as pd
from plotnine import *
from sklearn.decomposition import PCA
```

[4]:
```
unrelated = pd.read_csv("https://raw.githubusercontent.com/cmparlettpelleriti/
↪CPSC392ParlettPelleriti/master/Data/unrelated.csv")
related = pd.read_csv("https://raw.githubusercontent.com/cmparlettpelleriti/
↪CPSC392ParlettPelleriti/master/Data/related.csv")
```

[5]:
```
unrelated.head()
```

[5]:
```
         V1        V2        V3        V4        V5        V6        V7  \
0 -1.648512 -0.311947  0.709889 -0.450921  0.078148  1.647467  1.261174
1  2.322691  0.166211  1.979451 -0.389167 -0.361379 -0.897038 -0.887620
2 -0.136621 -1.255330  0.896551 -0.777137  0.229754  1.190060  0.160624
3 -0.392706  0.572386 -0.309853 -0.582313  0.352875 -0.656241 -0.613229
4 -0.380287  1.629653  0.935198  0.327958 -1.474270  0.813000  1.493190

         V8        V9       V10
0  0.409624 -1.088260 -0.522964
1  0.821673 -0.035624  0.720553
2 -0.440312  1.016557  0.788108
3  0.581652 -0.907961 -0.885951
4  0.691941  1.016842  0.319527
```

[7]:
```
features = unrelated.columns[1:10]
pca = PCA()
pca.fit(unrelated[features])
```

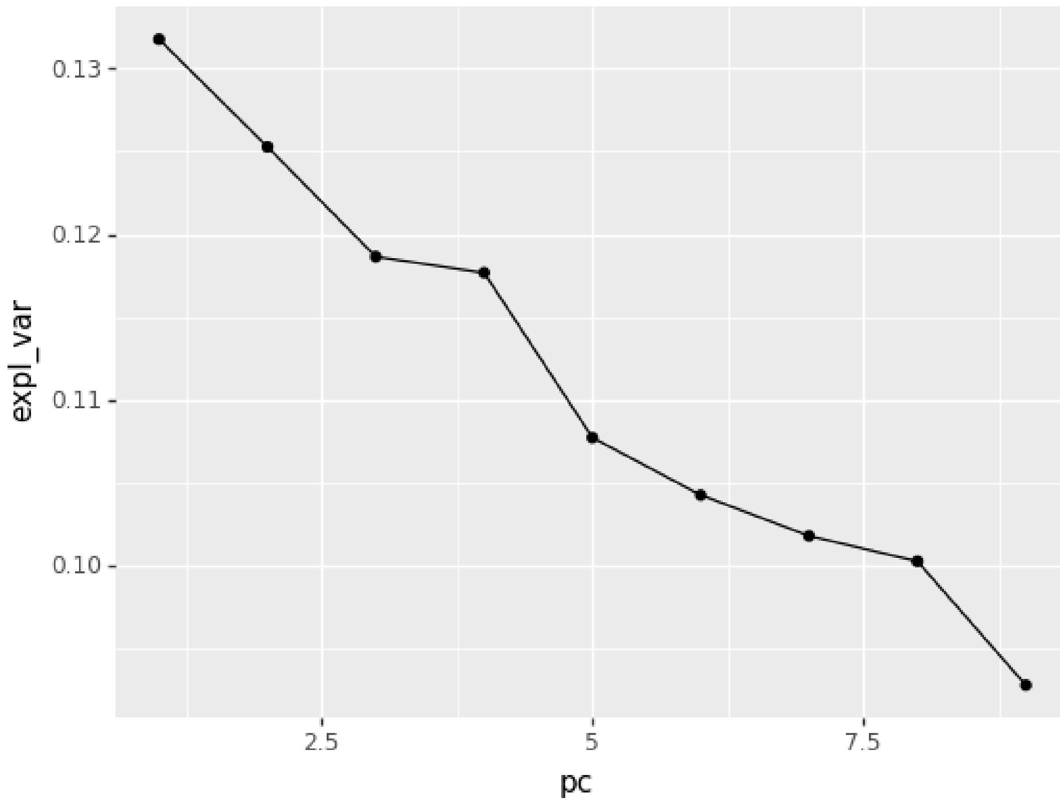
[7]:
```
PCA(copy=True, iterated_power='auto', n_components=None, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

[9]:
```
pcaDF = pd.DataFrame({"expl_var" : pca.explained_variance_ratio_, "pc":␣
↪range(1,10), "cum_var": pca.explained_variance_ratio_.cumsum()})
pcaDF.head()
```

[9]:
```
   expl_var  pc   cum_var
0  0.131769   1  0.131769
1  0.125279   2  0.257048
2  0.118632   3  0.375680
3  0.117665   4  0.493345
```

```
4  0.107701   5  0.601045
```

[10]:
```
(ggplot(pcaDF, aes(x = "pc", y = "expl_var")) + geom_line() + geom_point())
```



[10]: <ggplot: (316997601)>

[12]:
```
related.head()
```

[12]:
```
         V1        V2        V3        V4        V5        V6        V7  \
0 -0.162819 -1.571162 -1.151371 -0.315459 -1.391184 -1.003480 -1.115696
1 -0.096220  0.657607  0.548894 -0.166629  0.815083  1.103737  0.464634
2  0.667393 -0.210511 -0.371827 -0.738546 -0.335431 -0.836773 -0.814206
3  1.810516  1.450446  1.944058  1.178601  1.337714  2.193921  0.857411
4 -0.109431 -0.581918 -1.065343 -0.402842 -1.540439 -1.179681 -1.086468

         V8        V9       V10
0 -1.066398 -1.403418 -1.887823
1  0.523476  1.351986  0.393608
2 -1.380620  0.095171  0.223744
3  0.366791  1.491955  2.181504
4 -0.150108 -0.994551 -1.437609
```

[13]:
```
features2 = related.columns[1:10]
pca2 = PCA()
pca2.fit(related[features2])
```

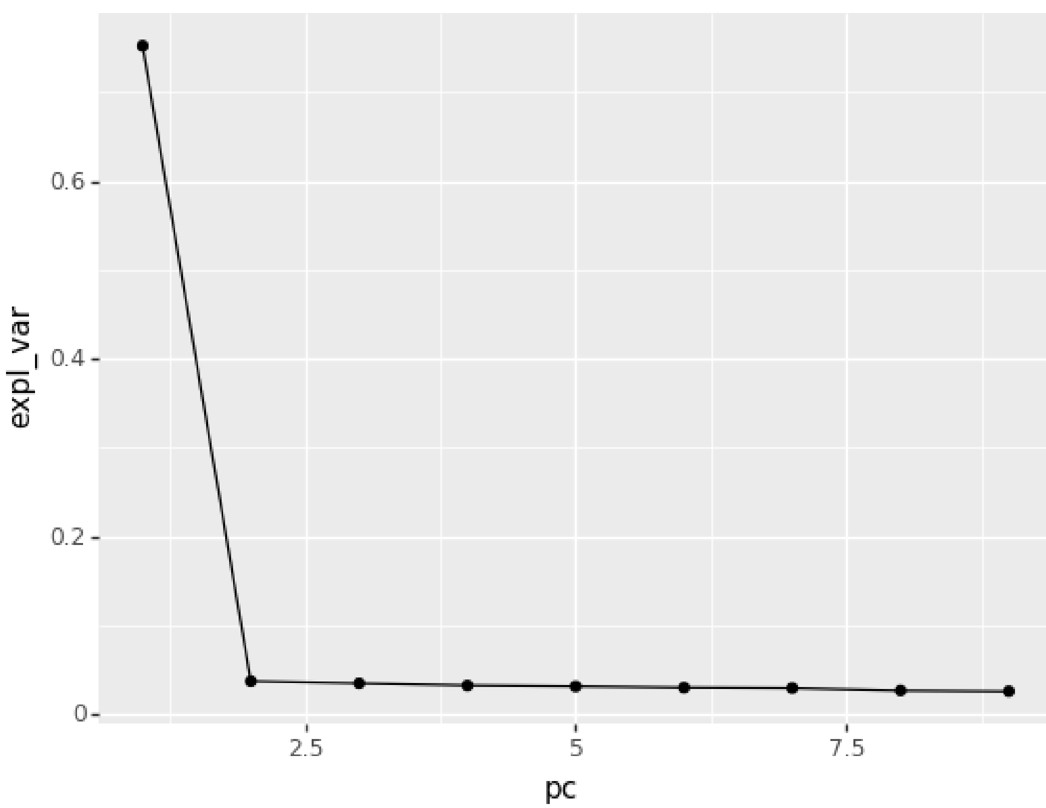
[13]:
```
PCA(copy=True, iterated_power='auto', n_components=None, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

[14]:
```
pcaDF2 = pd.DataFrame({"expl_var" : pca2.explained_variance_ratio_, "pc":␣
 ↪range(1,10), "cum_var": pca.explained_variance_ratio_.cumsum()})
pcaDF2.head()
```

[14]:

	expl_var	pc	cum_var
0	0.752052	1	0.131769
1	0.037199	2	0.257048
2	0.034878	3	0.375680
3	0.032425	4	0.493345
4	0.031428	5	0.601045

[17]:
```
(ggplot(pcaDF2, aes(x = "pc", y = "expl_var")) + geom_line() + geom_point())
```



[17]: <ggplot: (285788377)>

The Scree plots for the unrelated and related datasets are different to the how similar or not similar the variables are in each dataset. The Unrelated datasets scree plot takes on a more linear shape because of the multiple different components in the dataset. This is a result of the vast difference between values. Compared to the related dataset, the shape of the scree plot is more log looking which means most of the values in the datasets are similar to each other and can fit in one component.