exercise1_q3

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1 Advanced Course in Machine Learning

1.1 Exercise Session 1

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1.2 3. Eigen-value decomposition (programming exercise)

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

```
Exercise 3.a
```

```
[8]: data_X = pd.read_csv("ex_1_data.csv", header=None)
data_X
```

```
[8]: 0 1 2 3 4
0 -0.235 -0.671 -1.056 -0.960 -0.429
1 -0.080 0.202 0.554 0.124 -0.280
2 -0.134 -0.217 -0.164 0.160 0.338
3 0.156 0.048 0.291 0.237 0.245
4 -0.022 0.092 0.075 -0.083 -0.198
.. ... ... ...
195 -0.513 -0.216 -0.477 -0.077 0.012
196 1.779 1.243 2.056 1.055 0.428
197 0.141 -0.133 -0.318 0.118 0.044
198 -0.173 -0.484 -0.561 -0.439 -0.047
199 0.057 0.286 0.457 0.057 -0.312
```

[200 rows x 5 columns]

For data set X -> N = 200 and D = 5

```
Exercise 3.b
```

```
[9]: # Covariance Matrix
    cov_mat_X = data_X.cov()
    print('\nThe covariance matrix equals: \n')
    print(cov_mat_X)

# Compute eigenvalues and eigenvectorors
    eigVal, eigVec = np.linalg.eig(cov_mat_X)
    eigVals_ = pd.DataFrame(eigVal, columns=['eigVals'])
    eigVecs_ = pd.DataFrame(eigVec)

# Print eigenvalues in descending order
    eigVals_ = eigVals_.sort_values('eigVals', ascending=False)
    print('\n eigenvalues in descendig order are: \n')
    print(eigVals_)
```

The covariance matrix equals:

```
0 1 2 3 4
0 0.408549 0.236535 0.502366 0.304702 0.174483
1 0.236535 0.252841 0.465531 0.306768 0.108594
2 0.502366 0.465531 0.926864 0.635711 0.272427
3 0.304702 0.306768 0.635711 0.571994 0.301852
4 0.174483 0.108594 0.272427 0.301852 0.237854
```

eigenvalues in descendig order are:

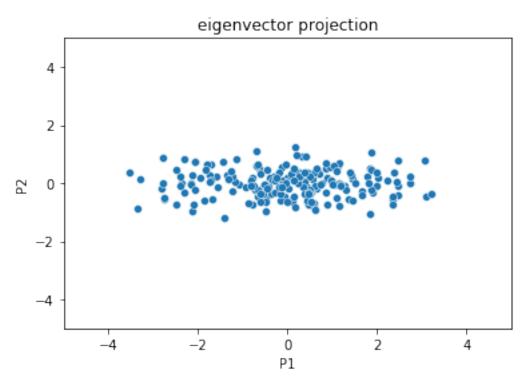
eigVals
0 2.012650
1 0.222862
2 0.142902
3 0.010429
4 0.009259

Exercise 3.c

```
for i in range(len(project)):
    project[i] = project[i].transpose()

# Plot two max projections
sns.scatterplot(x = project[4].iloc[:,0], y = project[4].iloc[:,1]).plot()
plt.title('eigenvector projection')
plt.xlabel('P1')
plt.ylabel('P2')

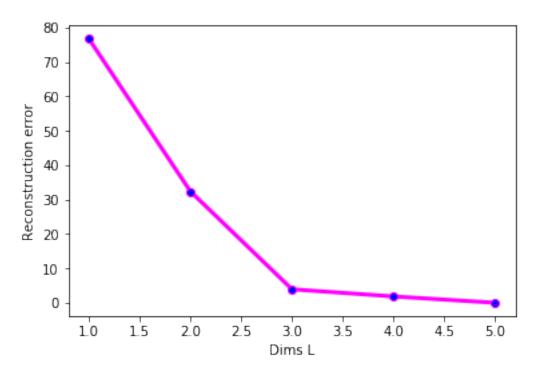
# Its better to have equal scaling for the axes
plt.xlim(-5,5);
plt.ylim(-5,5)
plt.show()
```



Exercise 3.d [11]: #reconstruction error as a function of reduced dimentionality for i in range(len(project)): project[i] = pd.DataFrame(project[i], columns=None)

```
\#D = 5 in this data set
#reconstructing the error from L=1 to L=5
reconst_error = list()
for i in range(len(eigVec)):
reconst_error.append(np.dot(eigVecs_.iloc[0:(i+1),:].transpose(), project[i].
 →transpose()).transpose())
# Then we can calculate error in the matrix
data_0 = data_X.copy()
loss = list()
for r in reconst_error:
 loss_Mat = data_0.sub(r)
loss_Mat = loss_Mat**2
loss.append(loss_Mat.values.sum())
# Plot the error as a function of reduced dimensionality L
plt.plot( range(1,6), loss, marker='o', markerfacecolor='blue', markersize=6,__
print(loss)
plt.xlabel('Dims L')
plt.ylabel('Reconstruction error')
plt.show()
```

[76.70497237116592, 32.355438425310766, 3.9179041657145457, 1.8425906022674972, 6.556759099102598e-27]



About relation to the eigenvalues computed in step (b), I assume if we devide the reconstruction error by N, the results would be close to summing up the eigenvalues corresponding to the Lth eigenvectors that we are not including (in each step). Here is a simple calculation to demonstrate it better:

```
[12]: #N=200 compute average of loss
N = 200
loss_ave = [x / N for x in loss]
print(loss_ave)
```

[0.3835248618558296, 0.16177719212655384, 0.019589520828572727, 0.009212953011337486, 3.2783795495512993e-29]

[]: