Principal Component Analysis (PCA) Exercício 01 Implemente o PCA em C / C++ / Java / Python. PCA com 2 componentes. Teste o funcionamento usando: "Alps Water"; "US Census Dataset". Definição das funções In [1]: #Definição da biblioteca pandas para importar o dataset import pandas as pd #Definição da biblioteca numpy para calculo dos auto-valores import numpy as np Dataset - Subtração da média In [2]: #Subtraindo a média para definição do novo Dataset: #Cálculo da média: def calculo mean(x): """Retorna a média da entrada.""" soma=[] soma i = 0for i in range(len(x)): soma i = soma i + x[i]media = (soma i)/len(x)return media **def** subtract mean (x, y, z=0): new X = [i - calculo_mean(x) for i in x] new_Y = [i - calculo_mean(y) for i in y] **if** z==0: #Defining dataset after subtract mean: dataset2=[[i,j] for i, j in zip(new_X, new_Y)] return dataset2 $new_Z = [i - calculo_mean(z) for i in z]$ dataset3=[[i,j,z] for i, j, z in zip(new_X, new_Y,new_Z)] return dataset3 Cálculo da matriz de covariância In [3]: #Cálculo da matriz de covariância def cov matrix(dataset): """Retorna a matriz de covariância da entrada.""" **if** len(dataset[0]) == 2: soma=0 for i in range(len(dataset)): soma = soma + dataset[i][0]*dataset[i][1] diag_cov_element = soma/(len(dataset)-1) diag_cov_element soma=0for i in range(len(dataset)): soma = soma + dataset[i][0]*dataset[i][0] first_cov_element = soma/(len(dataset)-1) first_cov_element soma=0 for i in range(len(dataset)): soma = soma + dataset[i][1]*dataset[i][1] last cov element = soma/(len(dataset)-1) last cov element covariance_matrix = [[first_cov_element,diag_cov_element],[diag_cov_element,last_cov_element]] return covariance_matrix **if** len(dataset[0]) == 3: #cov(x,x)soma=0 for i in range(len(dataset)): soma = soma + dataset[i][0]*dataset[i][0] $cov_x_x = soma/(len(dataset)-1)$ #cov(y,y)soma=0 for i in range(len(dataset)): soma = soma + dataset[i][1]*dataset[i][1] $cov_y_y = soma/(len(dataset)-1)$ #cov(z,z)soma=0 for i in range(len(dataset)): soma = soma + dataset[i][2]*dataset[i][2] $cov_z_z = soma/(len(dataset)-1)$ #cov(x,y) = cov(y,x)for i in range(len(dataset)): soma = soma + dataset[i][0]*dataset[i][1] $cov_x_y = soma/(len(dataset)-1)$ #cov(x,z) = cov(z,x)for i in range(len(dataset)): soma = soma + dataset[i][0]*dataset[i][2] $cov_x_z = soma/(len(dataset)-1)$ #cov(y,z) = cov(z,y)soma=0for i in range(len(dataset)): soma = soma + dataset[i][1]*dataset[i][2] cov y z = soma/(len(dataset)-1)covariance_matrix = [[cov_x_x,cov_x_y,cov_x_z], [cov x y,cov y y,cov y z], [cov_x_z,cov_y_z,cov_z_z]] return covariance matrix Cálculo da matriz transposta In [4]: | #Função para calcular a matriz transposta: def transposta(X): """Retorna a transposta da matriz de entrada""" return [[X[j][i] for j in range(len(X))] for i in range(len(X[0]))] Multiplicação de duas matrizes #Multiplicação de duas matrizes: In [5]: def multiply_matrix_matrix(mult1, mult2): """Retorna o produto escalar de duas matrizes""" for i in range(0,len(mult1)): y=[] for j in range(0,len(mult2[0])): total = 0for k in range(0,len(mult1[0])): total = total + mult1[i][k]*mult2[k][j] y.append(total) x.append(y)return x Alps Water In [6]: #1° Passo - Pegar os dados / Importar o dataset alps water = pd.read csv('DataSets/alpswater1.txt', sep='\t', header=None) alps_water.columns= ['Row','Pressure','Boiling'] alps water.drop(columns='Row', inplace=True) alps_water.head() # 1° Passo - Transformando as entradas em listas x alps = [i for i in alps water['Boiling']] y_alps = [i for i in alps_water['Pressure']] #Defining dataset to apply PCA dataset_alps=[[i,j] for i, j in zip(x_alps, y_alps)] #2° Passo - Subtraindo a média new dataset alps = subtract mean(x alps, y alps) #3° Passo - Cálculo da matriz de covariância covariance_matrix_alps = cov_matrix(new_dataset_alps) #4° Passo - Encontrar os autovalores, checar se estão na ordem autovalores_alps = np.linalg.eig(covariance_matrix_alps)[0] #4° Passo - Encontrar os autovetores autovetores alps = np.linalg.eig(covariance matrix alps)[1] #5° Passo - Escolher os componentes FeatureVector = autovetores alps #6° Passo - Derive the new #Multiplicar os autovetores pela matriz após subtração da média: pca alps = multiply matrix matrix(transposta(FeatureVector), transposta(new dataset alps)) pca_alps #Organizando a resposta pca_alps_answer = [[pca_alps[0][i],pca_alps[1][i]] for i in range(len(pca_alps[0]))] pca_alps_answer Out[6]: [[-9.46867735263238, 0.13862918119196577], [-9.64586459136409, 0.23139060868544403],[-5.709764802870609, -0.011957814406917233],[-5.141568778925107, -0.004658610852802614],[-4.033005159282153, -0.043216375364096615],[-3.4972756349593705, -0.0979327053660839],[-2.3608835870683698, -0.0833342982578602],[-2.1373156345899202, -0.08750210638548084],[-1.8576205623683082, -0.2000661618159525],[-1.9508522531088361, -0.16254481000579746],[0.6109030576440994, -0.22819332734663744],[2.1600834578811017, 0.5748882921177365], [7.3916805107456645, 0.003230810351890767], [6.2557587261017105, -0.22607618729820267],[8.709897868743049, -0.0660728480967765],[10.162619296606008, 0.1215449896155345], [10.511885439447706, 0.1418713632338635]] In [7]: #Checando a resposta from sklearn.decomposition import PCA pca = PCA(n components = 2)pca.fit(dataset_alps) pca.explained_variance_ratio_ pca.singular_values_ Transformed_X = pca.transform(dataset_alps) Transformed X Out[7]: array([[-9.46867735e+00, 1.38629181e-01], [-9.64586459e+00, 2.31390609e-01], [-5.70976480e+00, -1.19578144e-02],[-5.14156878e+00, -4.65861085e-03], [-4.03300516e+00, -4.32163754e-02],[-3.49727563e+00, -9.79327054e-02],[-2.36088359e+00, -8.33342983e-02],[-2.13731563e+00, -8.75021064e-02],[-1.85762056e+00, -2.00066162e-01], [-1.95085225e+00, -1.62544810e-01],[6.10903058e-01, -2.28193327e-01], [2.16008346e+00, 5.74888292e-01], [7.39168051e+00, 3.23081035e-03], [6.25575873e+00, -2.26076187e-01], [8.70989787e+00, -6.60728481e-02], [1.01626193e+01, 1.21544990e-01], [1.05118854e+01, 1.41871363e-01]]) **US Census Dataset** In [8]: #1° Passo - Pegar os dados / Importar o dataset us census = pd.read csv('DataSets/US-Census.txt', sep='\t', header=None) us_census.columns = ['x', 'y'] #atribuição de nomes às colunas # 1° Passo - Transformando as entradas em listas x us = [i for i in us census['x']] y us = [i for i in us_census['y']] dataset_us = [[i,j] for i,j in zip(y_us,x_us)] #2° Passo - Subtraindo a média new_dataset_us = subtract_mean(y_us,x_us) new_dataset_us #3° Passo - Cálculo da matriz de covariância covariance_matrix_us = cov_matrix(new_dataset_us) covariance_matrix_us #4° Passo - Encontrar os autovalores autovalores_us = np.linalg.eig(covariance_matrix_us)[0] autovalores_us #4° Passo - Encontrar os autovetores autovetores_us = np.linalg.eig(covariance_matrix_us)[1] autovetores_us #5° Passo - Escolher os componentes FeatureVector_us = autovetores_us #6° Passo - Derive the new dataset pca_us = multiply_matrix_matrix(transposta(FeatureVector_us),transposta(new_dataset_us)) pca_us #Organizando a resposta pca_us_answer = [[pca_us[0][i],pca_us[1][i]] for i in range(len(pca_us[0]))] pca_us_answer Out[8]: [[-102.26303932718267, -5.880648264018603], [-83.52185636156509, -3.8725172799329215],[-66.79343152132931, -0.8858932050646011],[-46.68972462365029, 0.45985304598454846],[-34.70360255157288, 5.751925765936422],[-13.218485251487028, 6.426105713392109],[16.898648352180082, 2.903870698679783], [42.75553385936203, 1.4527356710262147], [68.07640335102677, 0.2621823601315576], [93.24887914712045, -0.8562300392442808], [126.21067492709801, -5.761384466890277]] In [9]: #Checando a resposta import numpy as np from sklearn.decomposition import PCA pca = PCA(n components = 2)pca.fit(dataset us) pca.explained_variance_ratio_ pca.singular values Transformed X = pca.transform(dataset us) Transformed X Out[9]: array([[-102.26303933, -5.88064826], [-83.52185636, -3.87251728], [-66.79343152, -0.88589321],[-46.68972462, 0.45985305],[-34.70360255, 5.75192577],[-13.21848525, 6.42610571],[16.89864835, 2.9038707], [42.75553386, 1.45273567], 0.26218236], [68.07640335, 93.24887915, -0.85623004], [126.21067493, -5.76138447]]) Exercício 02 Implemente o PCA em C / C++ / Java Python. PCA com 3 componentes Pode usar um solucionador para os autovalores: numpy.linalg.eig Teste o funcionamento usando: "Books x Grades" **Books x Grades** #1° Passo - Pegar os dados / Importar o dataset In [10]: books attend grade = pd.read csv('DataSets/Books attend grade.txt', sep='\t', header=None) books_attend_grade.columns=['Books', 'Attend', 'Grade'] #1° Passo - Transformando as features em linhas books = [i for i in books attend grade['Books']] attend = [i for i in books_attend_grade['Attend']] grade = [i for i in books_attend_grade['Grade']] dataset books=[[i,j,k] for i, j, k in zip(books,attend,grade)] #2° Passo - Subtraindo a média new dataset books = subtract mean(x=books, y=attend, z=grade) #3° Passo - Cálculo da matriz de covariância covariance_matrix_books = cov_matrix(new_dataset_books) #4° Passo - Encontrar os autovalores autovalores_books = np.linalg.eig(covariance_matrix_books)[0] #Ordenando os autovalores autovalores books order=[autovalores books[0],autovalores books[2],autovalores books[1]] autovalores_books_order #4° Passo - Encontrar os autovetores autovetores books = np.linalg.eig(covariance matrix books)[1] #Ordenando (para seguir a ordem dos autovalores) autovetores_books_order=[[autovetores_books[0][0],autovetores_books[0][2],autovetores_books[0][1]], [autovetores books[1][0], autovetores books[1][2], autovetores books[1][1]], [autovetores_books[2][0],autovetores_books[2][2],autovetores_books[2][1]]] #5° Passo - Escolher os componentes Feature = autovetores books order #6° Passo - Derive the new dataset pca_books = multiply_matrix_matrix(transposta(Feature),transposta(new_dataset_books)) pca_books_answer = [[pca_books[0][i],pca_books[1][i],pca_books[2][i]] for i in range(len(pca_books[0]]))] pca books answer Out[10]: [[-19.120804656379264, 2.764724624002969, -0.929315364134587], [-6.415968932866218, -1.6608246798150847, -0.8885403960499472],[-18.991919282209103, 1.7780490661827764, -1.028612413059671],[-12.18896168749004, -3.5365507956094957, 0.18579949131701012],[0.993327687092036, 4.048313636919347, 2.353073905169412], [25.06930570477028, -2.772788839906002, 0.6738349427458701], [-19.81118936814235, 0.5644214506876208, -0.10346132420851861],[24.078561171032163, -2.905208539965853, 0.703672702449031],[25.373034294022887, 2.387541006869924, 0.14587204959505362], [-4.477068939024697, -1.3014529220802702, -1.9428262935293443],[1.641123325220414, 6.343149167849807, 0.5326094871702681], [1.2522165886983854, 1.371884036304108, -0.9286483758250665],[-6.892290123189728, -5.03686812618085, 1.8272373510971882],[-16.967841141098166, 1.9483561086873658, -0.09367755439291742],[1.5559451779509954, 6.532213883080033, -1.4566112689758828],[-22.912308343526856, 1.1538379083282595, 0.08534900382604826],[-7.192649945164756, -2.9689846529253527, 1.0312210708742808],[-26.78899017794387, -0.2679840921162242, -0.8892073843594677],[-17.78936184104296, -7.1965633118140655, -0.9276754753123517],[-5.684113300734452, 1.1480246208600056, 2.3633441252413707], [-16.71118854602388, 0.6780834780218363, 2.790856530901225],[0.9921952263465159, -4.5860566530617835, -2.4892032877454855],[33.2564014902931, 3.541430964963844, -1.0874404061033094], [-8.31227985307303, -2.1147287951650116, 1.160355879502526],[-11.716009264444114, -7.388720669275152, -1.2059990824564015],[-3.6555482390798986, 7.8434664984211615, -1.1088283726099102],[5.5581436192605835, -0.2608529943270972, 0.7426272436582726],[15.981130453322372, -2.883358225009356, 0.04706145092632702], [7.3681582389319455, 1.0851943212279096, -0.21236160489604078],[-1.6774279388812507, 0.8800925785094424, 0.15547528135749178],[23.649315974886974, 0.1493504911098369, 0.006953471151207591], [-8.701186589595059, -7.085993926710712, -0.3009019834928088],[-20.75934482824576, 0.3374693930126571, 0.9209868135677178],[28.98969476608803, -2.148577682051485, -0.4401264741398493],[20.115583036079702, -3.434887340205257, 0.8230237412616748],[31.01377290719897, -1.9782706395468956, 0.49480838452690434], [-4.131869429403409, 4.467423052055397, 1.6069493745372252],[-8.308911085795447, 5.11348452486641, -0.16362329387119795],[24.468586060820225, 1.3629781066049929, -0.9181976176999449], [-2.149262208661147, 4.029183967200244, -1.5358543280134072]]In [11]: #Checando a resposta import numpy as np from sklearn.decomposition import PCA pca = PCA(n_components = 3) pca.fit(dataset_books) pca.explained variance ratio pca.singular values Transformed X = pca.transform(dataset books) Transformed X Out[11]: array([[-1.91208047e+01, 2.76472462e+00, -9.29315364e-01], [-6.41596893e+00, -1.66082468e+00, -8.88540396e-01],[-1.89919193e+01, 1.77804907e+00, -1.02861241e+00],[-1.21889617e+01, -3.53655080e+00, 1.85799491e-01], [9.93327687e-01, 4.04831364e+00, 2.35307391e+00], [2.50693057e+01, -2.77278884e+00, 6.73834943e-01], [-1.98111894e+01, 5.64421451e-01, -1.03461324e-01], [2.40785612e+01, -2.90520854e+00, 7.03672702e-01], [2.53730343e+01, 2.38754101e+00, 1.45872050e-01], [-4.47706894e+00, -1.30145292e+00, -1.94282629e+00],[1.64112333e+00, 6.34314917e+00, 5.32609487e-01], [1.25221659e+00, 1.37188404e+00, -9.28648376e-01], [-6.89229012e+00, -5.03686813e+00, 1.82723735e+00], [-1.69678411e+01, 1.94835611e+00, -9.36775544e-02],[1.55594518e+00, 6.53221388e+00, -1.45661127e+00], [-2.29123083e+01, 1.15383791e+00, 8.53490038e-02], [-7.19264995e+00, -2.96898465e+00, 1.03122107e+00], [-2.67889902e+01, -2.67984092e-01, -8.89207384e-01],[-1.77893618e+01, -7.19656331e+00, -9.27675475e-01],[-5.68411330e+00, 1.14802462e+00, 2.36334413e+00], [-1.67111885e+01, 6.78083478e-01, 2.79085653e+00], [9.92195226e-01, -4.58605665e+00, -2.48920329e+00], [3.32564015e+01, 3.54143096e+00, -1.08744041e+00], [-8.31227985e+00, -2.11472880e+00, 1.16035588e+00], [-1.17160093e+01, -7.38872067e+00, -1.20599908e+00],[-3.65554824e+00, 7.84346650e+00, -1.10882837e+00],[5.55814362e+00, -2.60852994e-01, 7.42627244e-01], [1.59811305e+01, -2.88335823e+00, 4.70614509e-02],[7.36815824e+00, 1.08519432e+00, -2.12361605e-01], [-1.67742794e+00, 8.80092579e-01, 1.55475281e-01], [2.36493160e+01, 1.49350491e-01, 6.95347115e-03], [-8.70118659e+00, -7.08599393e+00, -3.00901983e-01],[-2.07593448e+01, 3.37469393e-01, 9.20986814e-01],[2.89896948e+01, -2.14857768e+00, -4.40126474e-01], [2.01155830e+01, -3.43488734e+00, 8.23023741e-01], [3.10137729e+01, -1.97827064e+00, 4.94808385e-01],[-4.13186943e+00, 4.46742305e+00, 1.60694937e+00], [-8.30891109e+00, 5.11348452e+00, -1.63623294e-01],[2.44685861e+01, 1.36297811e+00, -9.18197618e-01], [-2.14926221e+00, 4.02918397e+00, -1.53585433e+00]]) Exercício 03 Compare PCA com o método dos mínimos quadrados. Compare a reta gerada pelos mínimos quadrados e a gerada pelo PCA. To solve this exercise I'll use Alps Water Dataset Obs: All the resolution was solved without libraries (except linalg.eig - autorized by teacher). Now, I will use libraries just to plot and compare the results of last exercise (Least Squares) with these (PCA) in a faster way. Import Libraries In [12]: import matplotlib.pyplot as plt from sklearn.linear model import LinearRegression #for plot the result of least squares import pandas as pd **Original Data** In [49]: # Plot Original Data plt.scatter(y_alps, x_alps, alpha=0.2) plt.legend(['Original data']); 212.5 Original data 210.0 207.5 205.0 202.5 200.0 197.5 195.0 22 26 **PCA x Original Data** In [50]: #Using library just to compare the plots pca = PCA(n_components=1) X= alps water pca.fit(X) X_pca = pca.transform(X) X_new = pca.inverse_transform(X_pca) plt.scatter(X.iloc[:, 0], X.iloc[:, 1], alpha=0.2) plt.scatter(X_new[:, 0], X_new[:, 1], alpha=0.8, s=8, c='k') model = LinearRegression() X=alps_water[['Boiling']] y=alps_water['Pressure'] plt.legend(['Original data','PCA']); 212.5 Original data 210.0 207.5 205.0 202.5 200.0 197.5 195.0 30 22 24 26 Least Square x Original Data In [51]: #Using library just to compare the plots plt.scatter(alps_water.iloc[:, 0], alps_water.iloc[:, 1], alpha=0.2) model.fit(X,y)model.predict(X) model = LinearRegression() X=alps water[['Pressure']] y= alps water['Boiling'] model.fit(X,y)model.predict(X) plt.scatter(X, model.predict(X), label='predicted', alpha=0.5, s=8, c='k') plt.legend(['Original data','Least Square']); 212.5 Original data Least Square 210.0 207.5 205.0 202.5 200.0 197.5 195.0 22 24 26 28 30 Original Dat x PCA x Least Square In [52]: #Using library just to compare the plots #Original plt.scatter(alps water.iloc[:, 0], alps water.iloc[:, 1], alpha=0.2) plt.scatter(X new[:, 0], X new[:, 1], alpha=0.8, s=8, c='k') model = LinearRegression() X=alps water[['Boiling']] y=alps water['Pressure'] #Square model.fit(X,y)model.predict(X) model = LinearRegression() X=alps water[['Pressure']] y= alps water['Boiling'] model.fit(X, y)model.predict(X) plt.scatter(X, model.predict(X), label='predicted', alpha=0.5, s=8, c='k') plt.legend(['Original data','PCA','Least Square']); 212.5 Original data 210.0 Least Square 207.5 205.0 202.5 200.0 197.5 195.0 26 30