In [2]:	<pre>import numpy as np import pandas as pd</pre>
In [3]: In [5]:	<pre>df = pd:Tead_csv(bacaset Final Exam:csv , sep= , , neader=None)</pre> <pre>df head()</pre>
Out[5]:	0 1 2 3 4 5 6 7 8 9 10 11 0 121 22 74 223 54 254 132 17 77 232 50 249 1 108 30 80 175 40 300 123 32 79 192 64 315 2 122 49 87 266 41 223 129 31 96 250 55 319
In [7]:	3 77 37 66 178 80 209 131 23 67 291 48 310 4 140 35 71 175 38 261 110 24 96 239 42 268 df_array = df.values
In [11]:	1. Compute the eigen values and corresponding eigenvectors of covariance matrix of the data Calculate the covariance matrix cov_matrix = np.cov(df_array)
In [12]:	Compute the eigen values and corresponding eigenvetcors of covariance matrix
In [13]: Out[13]:	<pre>array([1.61144702e+05+0.0000000e+00j, 3.02150989e+03+0.0000000e+00j,</pre>
	1.70301341e+03+0.0000000e+00j, 1.24683741e+03+0.0000000e+00j, 6.05961223e+02+0.0000000e+00j, 5.13606549e+02+0.0000000e+00j, 4.33538836e+02+0.0000000e+00j, 2.79820250e+02+0.0000000e+00j, 9.99169851e+01+0.0000000e+00j, 6.46542242e+01+0.0000000e+00j, 4.72197353e+01+0.0000000e+00j, 7.05342510e-12+0.0000000e+00j, -3.87211306e-12+0.0000000e+00j, -2.56017107e-12+4.4252166e-13j, -2.56017107e-12-4.4252166e-13j, 2.66140327e-12+0.0000000e+00j,
In [15]:	1.75829854e-12+0.0000000e+00j, 8.66221612e-13+0.0000000e+00j, -3.97552641e-13+8.9093833e-14j, -3.97552641e-13-8.9093833e-14j]) the eigenvectors are v:
Out[15]:	0.02897941+0.j , 0.01785256+0.j , 0.14341725+0.j , 0.23928671+0.j , -0.29034263+0.j , -0.32665894+0.j , 0.11154024+0.j , -0.03818529+0.j , 0.07299793+0.j , 0.58479252+0.j ,
	0.06914614+0.j , 0.06562965+0.1794376j , 0.06562965-0.1794376j , 0.07294149+0.j , 0.04674205+0.j , -0.09394113+0.j , -0.20001793-0.06927581j, -0.20001793+0.06927581j], [-0.2375551 +0.j , 0.03676923+0.j , -0.50511715+0.j , -0.10069305+0.j , -0.29072141+0.j , 0.14892796+0.j ,
	0.36782412+0.j , -0.273773 +0.j , -0.2399054 +0.j , 0.18522274+0.j , -0.01664072+0.j , -0.21057783+0.j , 0.13630588+0.j , 0.02988464+0.12937947j, 0.02988464-0.12937947j, 0.04147694+0.j , -0.11957747+0.j , -0.17608583+0.j , -0.23811405-0.09635452j, -0.23811405+0.09635452j],
	[-0.24074403+0.j , -0.14505034+0.j , 0.18805723+0.j , -0.51311768+0.j , 0.45997858+0.j , -0.00309595+0.j , 0.10443368+0.j , 0.13381827+0.j , -0.1922277 +0.j , 0.05934263+0.j , -0.07855447+0.j , -0.22598327+0.j , 0.14096269+0.j , 0.10555996+0.09177507j, 0.10555996-0.09177507j, 0.23884943+0.j ,
	0.19581873+0.j , 0.26810166+0.j , 0.22285071+0.07913985j, 0.22285071-0.07913985j], [-0.23513568+0.j , 0.24870562+0.j , 0.50028877+0.j , -0.20216978+0.j , -0.23740992+0.j , 0.40409945+0.j , 0.22308116+0.j , -0.06828526+0.j , 0.17644174+0.j , -0.0208232 +0.j ,
	-0.16933988+0.j , 0.0797985 +0.j , -0.18475975+0.j , -0.09965848-0.07728204j, -0.09965848+0.07728204j, 0.11177164+0.j , -0.23022086+0.j , -0.11373889+0.j , -0.0096744 +0.01658992j, -0.0096744 -0.01658992j], [-0.22525712+0.j , -0.04807457+0.j , -0.0388007 +0.j , 0.21389391+0.j ,
	-0.0518221 +0.j , -0.31200064+0.j , 0.14944391+0.j , -0.07667185+0.j , -0.13611852+0.j , -0.10834483+0.j , 0.14264432+0.j , 0.25078092+0.j , -0.19644096+0.j , 0.5195753 +0.j , 0.5195753 -0.j , 0.26267487+0.j , -0.01964951+0.j , 0.116842 +0.j ,
	-0.01949124-0.05276126j, -0.01949124+0.05276126j], [-0.20869806+0.j , -0.54645275+0.j , 0.23956697+0.j , -0.03871384+0.j , -0.29163671+0.j , -0.04596679+0.j , 0.14331209+0.j , 0.08377293+0.j , 0.01917624+0.j , 0.08841875+0.j , -0.14569303+0.j , 0.1379338 +0.j ,
	0.18588715+0.j
	0.22303625+0.j , -0.43011331+0.j , 0.39601049+0.j , 0.00715969+0.j , 0.20794094+0.j , -0.08515635+0.05363623j, -0.08515635-0.05363623j, -0.03109924+0.j , 0.01497451+0.j , 0.06546839+0.j , -0.14719211-0.14464789j, -0.14719211+0.14464789j], [-0.21821454+0.j , 0.02662209+0.j ,
	0.04745986+0.j , -0.18324273+0.j , -0.19891062+0.j , -0.03408796+0.j , -0.17071882+0.j , -0.13838422+0.j , -0.55322722+0.j , -0.28022853+0.j , 0.22681792+0.j , -0.06391512+0.j , -0.23126718+0.j , -0.07451254-0.12392564j, -0.07451254+0.12392564j, -0.00429446+0.j ,
	0.18551371+0.j , -0.00618431+0.j , 0.05483229+0.16639751j, 0.05483229-0.16639751j], [-0.22493075+0.j , -0.09712674+0.j , -0.01086398+0.j , 0.24960573+0.j , 0.06507747+0.j , -0.15928497+0.j , 0.11977803+0.j , -0.19779652+0.j , -0.11515304+0.j , -0.3822026 +0.j ,
	-0.33791127+0.j , 0.07554234+0.j , 0.43728503+0.j , -0.4532368 -0.12398867j, -0.4532368 +0.12398867j, 0.16990495+0.j , 0.13704872+0.j , 0.14074627+0.j , 0.35798605+0.08185784j, 0.35798605-0.08185784j], [-0.24240293+0.j , 0.24217039+0.j , 0.24217039+0.j , 0.04877833+0.j , 0.04878345+0.j , 0.048788345+0.j , 0.04878345+0.j , 0.048788345+0.j , 0.0
	-0.11109116+0.j , -0.08799234+0.j , 0.09028438+0.j , 0.26944387+0.j , 0.2136273 +0.j , 0.3511583 +0.j , 0.3819922+0.j , 0.27399684+0.j , 0.39640653+0.j , -0.09760668-0.07838063j, -0.09760668+0.07838063j, 0.07932584+0.j , 0.20304901+0.j , 0.22375083+0.j , 0.10657685+0.20750648j, 0.10657685-0.20750648j],
	[-0.2231001 +0.j
	-0.1268194 -0.05205708j, -0.56351886+0.j , -0.54587489+0.j , 0.06933604+0.j , 0.03568305-0.01164776j, 0.03568305+0.01164776j], [-0.22238945+0.j , 0.04255912+0.j , -0.07624655+0.j , -0.28418979+0.j , 0.19259532+0.j , -0.26947791+0.j , -0.26293062+0.j , 0.10578673+0.j ,
	-0.15032239+0.j , 0.40712331+0.j , -0.15553634+0.j , 0.17824276+0.j , -0.08874527+0.j , -0.10217923-0.1118537j , -0.10217923+0.1118537j , 0.00354229+0.j , -0.11145567+0.j , -0.31261837+0.j , -0.14413041-0.12166388j, -0.14413041+0.12166388j], [-0.21246133+0.j , -0.40204153+0.j ,
	-0.32607725+0.j , -0.07612021+0.j , 0.06173788+0.j , 0.16406661+0.j , 0.18151422+0.j , -0.03905083+0.j , 0.35486806+0.j , 0.08206663+0.j , 0.25378588+0.j , -0.10052913+0.j , -0.39912937+0.j , -0.20694131-0.16710106j, -0.20694131+0.16710106j, 0.1394013 +0.j ,
	0.20237432+0.j , 0.1886881 +0.j , 0.35217406+0.0959033j , 0.35217406-0.0959033j], [-0.19855991+0.j , 0.08953525+0.j , -0.01679749+0.j , 0.29363384+0.j , 0.2461571 +0.j , 0.07183505+0.j , -0.08637812+0.j , 0.18707022+0.j , 0.01014215+0.j , -0.05175944+0.j , 0.033156786+0.j , -0.05175944+0.j , 0.033156786+0.j , 0.033156786+0.j , 0.013213231+0.j , 0.033156786+0.j , 0.013213231+0.j , 0.033156786+0.j , 0.013213231+0.j , 0.01321323141+0.j , 0.0132141+0.j , 0.0132141+0.j , 0.0132141+0.j
	0.33156786+0.j , -0.11331321+0.j , 0.04405722+0.j , 0.07668238+0.08350062j, 0.07668238-0.08350062j, -0.01371466+0.j , -0.37377934+0.j , -0.63307498+0.j , 0.17672185+0.0799223j , 0.17672185-0.0799223j], [-0.21019657+0.j , 0.23640311+0.j , 0.1857049 +0.j , 0.17391113+0.j , -0.25775689+0.j , 0.18190264+0.j ,
	-0.32290426+0.j , -0.18563975+0.j , -0.06406031+0.j , 0.33102973+0.j , 0.11876119+0.j , -0.21487283+0.j , 0.10233005+0.j , 0.08806148+0.00027843j, 0.08806148-0.00027843j, 0.13059066+0.j , 0.35499276+0.j , 0.24316595+0.j , 0.36935314+0.j , 0.36935314-0.j],
	[-0.23572075+0.j , 0.09678348+0.j , 0.20759731+0.j , 0.10061708+0.j , 0.36742988+0.j , -0.10424664+0.j , 0.15090711+0.j , -0.39150611+0.j , 0.29127743+0.j , -0.03537984+0.j , 0.18566305+0.j , -0.3027663 +0.j , 0.10135356+0.j , 0.08194975-0.05878449j,
	0.08194975+0.05878449j, -0.12998844+0.j , 0.11259598+0.j , -0.00507008+0.j , -0.33774521-0.0568601j , -0.33774521+0.0568601j], [-0.23720374+0.j , 0.25374981+0.j , 0.01444574+0.j , 0.12297294+0.j , -0.03825101+0.j , -0.27906567+0.j , 0.21357162+0.j , 0.16756334+0.j ,
	0.15171473+0.j , -0.10264319+0.j , -0.38525035+0.j , -0.07269736+0.j , -0.41846505+0.j , 0.16359153+0.1150344j , 0.16359153-0.1150344j , 0.09505162+0.j , 0.26301805+0.j , -0.13334922+0.j , 0.01746735-0.01125317j, 0.01746735+0.01125317j], [-0.21319548+0.j , -0.36000346+0.j , 0.15744169+0.j , 0.29289024+0.j ,
	-0.18683328+0.j , -0.18688669+0.j , , , , , , , , , , , , , , , , , , ,
	-0.18482894+0.01152633j, -0.18482894-0.01152633j], [-0.20815042+0.j , 0.05636968+0.j , 0.08790932+0.j , 0.36358754+0.j , 0.24441433+0.j , 0.27374537+0.j , 0.25382303+0.j , 0.34302462+0.j , -0.38475879+0.j , 0.09598762+0.j , 0.12537585+0.j , 0.15043851+0.j ,
	-0.09051312+0.j , -0.17865328-0.00371411j, -0.17865328+0.00371411j, -0.30835922+0.j , -0.11073022+0.j , 0.1992339 +0.j , -0.19355774-0.12139977j, -0.19355774+0.12139977j], [-0.20992135+0.j , 0.02315776+0.j , -0.35106461+0.j , 0.03261913+0.j , 0.10479045+0.j , 0.45290972+0.j , -0.34389905+0.j , 0.19019633+0.j ,
	0.0730208 +0.j , -0.28123025+0.j , -0.41195968+0.j , -0.12943298+0.j , -0.01713095+0.j , 0.26350384-0.04204039j, 0.26350384+0.04204039j, -0.0642151 +0.j , 0.00999399+0.j , 0.0282345 +0.j , -0.11244688-0.01367986j, -0.11244688+0.01367986j]])
In [34]:	2. Find the proportion of the total variance explained by the componets def show_proportion_of_total_variance(data): from sklearn.decomposition import PCA from sklearn.preprocessing import StandardScaler import matplotlib.pyplot as plt
	<pre>sc = StandardScaler() sc.fit(data) X_train_std = sc.transform(data) # # Instantiate PCA #</pre>
	<pre>pca = PCA() # # Determine transformed features # X_train_pca = pca.fit_transform(X_train_std) # # Determine explained variance using explained_variance_ration_ attribute</pre>
	<pre>exp_var_pca = pca.explained_variance_ratio_ # # Cumulative sum of eigenvalues; This will be used to create step plot # for visualizing the variance explained by each principal component. # cum_sum_eigenvalues = np.cumsum(exp_var_pca)</pre>
	<pre># # Create the visualization plot # plt.bar(range(0,len(exp_var_pca)), exp_var_pca, alpha=0.5, align='center', label='Individual explained variance') plt.step(range(0,len(cum_sum_eigenvalues)), cum_sum_eigenvalues, where='mid',label='Cumulative explained variance') plt.ylabel('Explained variance ratio') plt.xlabel('Principal component index')</pre>
	<pre>plt.legend(loc='best') plt.tight_layout() plt.show() print(cum_sum_eigenvalues)</pre> Class One
In [35]:	show_proportion_of_total_variance(df_array[:,:6]) 10 - Cumulative explained variance Individual explained variance
	0.6 - 0.0 - 0.4 -
In [36]:	Principal component index [0.28065052 0.50001345 0.67389854 0.83315606 0.92739607 1.] Class Two show_proportion_of_total_variance(df_array[:,6:12])
	1.0 - Cumulative explained variance Individual explained variance
	0.6 - Paging 0.4 - O.2 - O.2 - O.2 - O.3 -
	0.0 1 2 3 4 5 Principal component index [0.3025184 0.5471895 0.73429941 0.86907317 0.94932685 1.]
	3. How much of the total variance account of first two principal components From the graph above: For group one the total cumulative variance of the first two principal components is 0.50001345, and for group two, it is 0.5471895
	4. Plot eigenvalues to visualize the proportion of variance explained by each subsequential eigenvalueSee the plot above5. Use PCA to transforms the data into a new set of variables (PCs).
In [42]: In [45]:	Trom skiedin.decomposition import FCA
In [51]: Out[51]: In [62]:	(20, 6)
	# Show the first ten transformed dataset PCs1[:10] array([[2.95855406e+01,
	[7.33590225e+01, 1.80561182e+01, 2.26865371e+00, 2.55280398e+01, -1.18482170e+01, -2.79241192e+00], [-1.73078743e+01, 6.36302576e+01, -2.36981746e+01, -5.71272977e+00, -1.19577840e+00, -5.91896560e+00], [-1.63538209e+01, -2.15793445e+01, 3.80172637e+00, 7.73820269e+00, 1.03899916e+01, 5.99788322e+00], [4.79477477e+01, 1.61066481e+01, -1.65991050e+01,
	-8.16642089e+00, 1.11677116e+01, -1.23526371e+00], [1.45888192e+00, 1.65109788e+01, 1.52143518e+00, -1.28063812e+01, 2.24243943e+01, -7.06842434e+00], [5.57689169e+00, 1.80258311e+01, 2.15045621e+01, -1.89776666e+01, -1.15200007e+01, -1.95812627e+00], [6.33592677e+00, -3.47624299e+01, 1.68524134e+01, -2.07153944e+00, -1.02093509e+01, -1.47505438e+01],
In [63]:	[-3.00515242e+01, -1.95890840e+01, -3.79466049e+00, -3.06080860e+00, 5.50127482e+00, -3.41556633e-01]]) pca = PCA() PCs2 = pca.fit_transform(df_array[:,6:12])
In [64]: Out[64]: In [65]:	(20, 6)
Out[65]:	PCs2[:10] array([[2.57987568e+01, -4.44996417e-01, -1.36587030e+01,
	[-3.57185310e+01, -7.59731771e+00, 1.99682674e+01, 3.89541223e+00, -1.12608034e+01, 9.26376967e-01], [-3.80795840e+01, -4.68440883e+01, 1.44431891e+01, 7.47341690e-01, 2.24085124e+01, 6.88124030e-01], [2.01706192e+01, -7.22063755e+00, 1.12826372e+01, -1.62821365e+00, -5.32677627e+00, 6.93451440e+00], [9.42216922e+01, -1.15579932e+01, 4.24446586e+01,
	-5.40734636e+00, 8.31219725e+00, -8.33845688e-02], [-3.27328458e+01, 1.59619735e+01, 2.06471902e+01, -2.06716231e+01, -2.60369028e+00, 6.76587287e+00], [-1.60668186e+01, 4.25459049e+00, 1.19255363e+01, 1.03632796e+01, -1.64871753e+01, 3.27343404e+00], [5.31503747e+00, -2.24090026e+01, -2.13695812e+00, 1.54438195e+01, -1.40463416e+01, 2.68544536e+00], [-4.47924520e+01, 6.28367625e+00, -5.64217643e-01,
	-2.07886207e+01, 8.90666627e-02, -7.74991201e+00]]) 6. Find and plot top first 2 PCs Group One
In [69]:	<pre>import matplotlib.pyplot as plt plt.scatter(PCs1[:, 0], PCs1[:, 1], edgecolor='none') plt.xlabel('component 1') plt.ylabel('component 2') plt.colorbar();</pre>
	60 0.8
	The state of the s
	-40 -20 0 20 40 60 component 1 Group Two
In [68]:	<pre>import matplotlib.pyplot as plt plt.scatter(PCs2[:, 0], PCs2[:, 1],edgecolor='none') plt.xlabel('component 1') plt.ylabel('component 2') plt.colorbar();</pre>
	40 - 0.8
	-0.6 -0.4 -0.2
	7. Calculate the correlation between the original data and the component. Interpreted based which variable they are most correlated in either a
In [77]:	positive or negative direction
In [78]:	<pre>for i in range(0,6): print(pearsonr(df_array[:,i],PCs1[:,i])) (0.06443976579649642, 0.7872312944499033) (-0.23561348797700016, 0.3173008531423038)</pre>
Tr	(0.48627097053316576, 0.029705481882213156) (-0.0199265233478159, 0.9335462703764398) (-0.029205019669966647, 0.9027212706909494) (-0.023247303429626366, 0.9225012869007734) Group Two, the first column is the correlation, while the second column is the p-value of it
In [80]:	print(pearsonr(df_array[:,6+i],PCs2[:,i])) (-0.6967817622764083, 0.0006410022205784092) (0.3171408130009202, 0.1730547124932433) (-0.04261720113097531, 0.8584101937933257) (-0.008883966504801565, 0.9703473814209748)
	(-0.05857956480843332, 0.8062106147959324) (0.009756211602223001, 0.9674374413498783)