

```

In [7]: import pandas as pd
import seaborn as sns1
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
import pylab as pl
import random
from sklearn import preprocessing
from sklearn.decomposition import PCA
import math
import statistics
%matplotlib inline
print("-----dataset 2-----")
df1_1=pd.read_csv('dist1_500_1.txt',sep=" ",header=None);
df1_1.dropna(how="all", inplace=True)
df1_2=pd.read_csv('dist1_500_2.txt',sep=" ",header=None);
df1_2.dropna(how="all", inplace=True)
df1=pd.concat([df1_1,df1_2])
pca = PCA(n_components=3)
pca.fit(df1)
print(pca.components_)
print(pca.explained_variance_)
ratio_arr = pca.explained_variance_ratio_
list=[]
print("-----dataset 2-----")
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
for i in ratio_arr:
    list.append(i*100)
list
df2_1=pd.read_csv('dist2_500_1.txt',sep=" ",header=None);
df2_1.dropna(how="all", inplace=True)
df2_2=pd.read_csv('dist2_500_2.txt',sep=" ",header=None);
df2_2.dropna(how="all", inplace=True)
df2=pd.concat([df2_1,df2_2])
pca = PCA(n_components=3)
pca.fit(df2)
print(pca.components_)
print(pca.explained_variance_)
ratio_arr = pca.explained_variance_ratio_
list=[]

plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
for i in ratio_arr:
    list.append(i*100)
list

```

-----dataset 2-----

```

[[-0.10416282 -0.10385417 -0.10065525 -0.09497416 -0.10889559 -0.0925407
5
-0.09782877 -0.09891933 -0.10123439 -0.10490911 -0.10758328 -0.0944912
9
-0.09475672 -0.09568107 -0.09433805 -0.10092958 -0.09852246 -0.1020829

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3
-0.09072236 -0.09446863 -0.10010197 -0.09716835 -0.09783511 -0.0998539
1
-0.10252807 -0.1006186 -0.09525831 -0.09694633 -0.10942994 -0.1006809
5
-0.10361362 -0.10695543 -0.10015786 -0.10160415 -0.10148048 -0.0915984
9
-0.0964593 -0.10049542 -0.09895829 -0.10000045 -0.09571827 -0.0969179
8
-0.09881569 -0.09905419 -0.10081724 -0.09933673 -0.10384122 -0.0986565
9
-0.10341088 -0.10303236 -0.09777897 -0.10381266 -0.09277577 -0.0991019
9
-0.09721603 -0.10342099 -0.09491655 -0.09851772 -0.10220389 -0.1002370
8
-0.09748887 -0.09554182 -0.09617315 -0.10414511 -0.10042779 -0.0944029
6
-0.09833723 -0.10254708 -0.10567763 -0.10204179 -0.10645483 -0.1092610
9
-0.10207342 -0.09538272 -0.10032654 -0.09601277 -0.10687144 -0.1037770
1
-0.10280366 -0.09525544 -0.10145447 -0.09546948 -0.10055034 -0.1006293
4
-0.10207404 -0.09829762 -0.10030702 -0.10040381 -0.09887769 -0.0979199
6
-0.09747595 -0.09801346 -0.10083288 -0.10169095 -0.1042297 -0.1046497
4
-0.10093911 -0.09934273 -0.10025547 -0.10126546]
[ 0.09054808 0.01861019 0.05971139 0.18128602 0.00604904 0.0152048
3
-0.14362587 -0.10461789 -0.03465931 0.02629723 -0.05762698 0.1138025
3
0.18018496 -0.18585975 -0.15322475 0.02791241 0.04894245 -0.1329730
8
0.06899594 0.06591983 0.04839692 0.04410212 -0.1121235 0.1033278
5
-0.11865324 -0.00671726 0.0953137 -0.04896341 -0.15493518 -0.019518
-0.06085894 -0.01689424 0.02664091 0.24881999 -0.00722471 0.0049113
6
-0.11071621 0.14329884 -0.01809961 0.13199923 0.19196706 -0.0989212
4
0.08418837 -0.02087035 0.04055638 0.15860518 -0.07268528 -0.0968092
9
0.01782804 0.01619907 0.02339142 -0.09413646 0.15667052 -0.1560535
9
0.13669147 0.07496942 0.03809409 -0.00251121 -0.01599632 -0.2430811
4
-0.02758909 -0.2524742 -0.01796575 -0.01321531 -0.19228474 -0.0398782
4
-0.18324346 -0.05744129 0.04973186 0.16551394 -0.03142739 -0.0190068
8
-0.09255106 0.05945107 -0.06880389 0.05554263 -0.09259912 0.0347961
-0.04970389 0.06787659 0.13783529 -0.02827062 0.0383797 0.0213456
9
0.00670288 -0.02634238 -0.06896405 -0.08188155 0.06064285 0.0715070
1
-0.09608421 0.08498539 0.00599124 -0.14777913 0.21067917 0.0529706

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9      0.03991062  0.10556288 -0.02456025 -0.01345482]
[ 0.09843364  0.15259361 -0.01633016 -0.09781642  0.17404741 -0.0590234
6      -0.06324053  0.08551586  0.0003353  0.03620277  0.11473376 -0.0228371
2      0.01323858 -0.21030971 -0.21132323 -0.01237947 -0.16135038 -0.1373156
-0.09835633  0.03211489  0.06274251 -0.00484564  0.01129458 -0.1689734
0.15643266 -0.09642612  0.03681744  0.16632623  0.18375022 -0.0703581
7      -0.04737657 -0.04580845  0.1541632  -0.13588861  0.00345758  0.1820174
6      -0.01349492 -0.00290527 -0.0374535  0.05252719 -0.09322499 -0.1044411
2      -0.0681333  -0.0237704  -0.01524989 -0.08910929  0.03093529 -0.0449184
2      0.10551506  0.04093175 -0.01053461  0.03199764  0.02071162  0.0131625
9      -0.10413665  0.13056628  0.09683734  0.07071657  0.08291163 -0.1056662
6      0.10831625  0.07963907 -0.00308518 -0.04241856 -0.10250783  0.0351588
0.05834943  0.06584422 -0.00219711 -0.0214559  -0.02746326  0.0819634
7      0.00935067 -0.09632349  0.1528906  0.10845223 -0.04423377 -0.0057595
-0.15882931  0.06397666  0.17212361 -0.17335909  0.14220277 -0.0447992
4      0.10893679  0.02538572  0.09114  -0.08371478 -0.00923348 -0.1155410
9      0.16791971 -0.2353445  -0.03093815 -0.14684408  0.1471568  0.0699974
3      -0.13842872 -0.05977211 -0.11996425 -0.08485022]]
[242165.66814866  7119.12908863  6804.72317256]
-----dataset 2-----
[[-9.98177049e-02 -1.03176242e-01 -9.93441289e-02 -1.01774648e-01
-9.55820788e-02 -1.03232146e-01 -1.01978193e-01 -1.04465645e-01
-1.05100279e-01 -9.57022235e-02 -9.54126205e-02 -9.87211636e-02
-1.01001058e-01 -9.76934140e-02 -9.43913613e-02 -9.99668557e-02
-1.04376779e-01 -9.94414194e-02 -9.67351551e-02 -1.02716612e-01
-9.51199259e-02 -9.88147996e-02 -1.01609804e-01 -9.84602302e-02
-1.02488196e-01 -9.86099364e-02 -9.76380690e-02 -1.01862912e-01
-9.89098771e-02 -1.00283985e-01 -9.42556078e-02 -9.99484324e-02
-1.05328054e-01 -9.79220718e-02 -1.01875692e-01 -1.00775361e-01
-9.66226963e-02 -1.05097766e-01 -9.94741600e-02 -9.79730766e-02
-9.35159696e-02 -1.05575123e-01 -1.02840155e-01 -9.53235978e-02
-9.91481336e-02 -1.00015544e-01 -9.37785110e-02 -1.09768798e-01
-1.03041490e-01 -9.74995198e-02 -9.87965458e-02 -1.02586782e-01
-1.00261183e-01 -9.52778152e-02 -9.72672810e-02 -9.79814748e-02
-9.96577614e-02 -9.71385653e-02 -9.64671911e-02 -1.00320560e-01
-1.03512667e-01 -1.00915013e-01 -1.05540260e-01 -1.03142727e-01
-9.94791096e-02 -1.05879154e-01 -9.73840121e-02 -1.01224797e-01
-1.03145811e-01 -9.84994073e-02 -9.77891297e-02 -1.02073055e-01
-9.81738338e-02 -9.79457199e-02 -9.82884765e-02 -1.04898222e-01
-9.87709228e-02 -9.65100520e-02 -9.77529962e-02 -1.00758952e-01
-1.01379679e-01 -9.34374579e-02 -9.85894384e-02 -9.86268030e-02
-1.00405825e-01 -9.70032692e-02 -1.03331185e-01 -9.89896561e-02
-1.01703379e-01 -9.95953345e-02 -1.00895978e-01 -9.75477175e-02
-1.01927857e-01 -9.75490271e-02 -9.94337101e-02 -1.03302748e-01

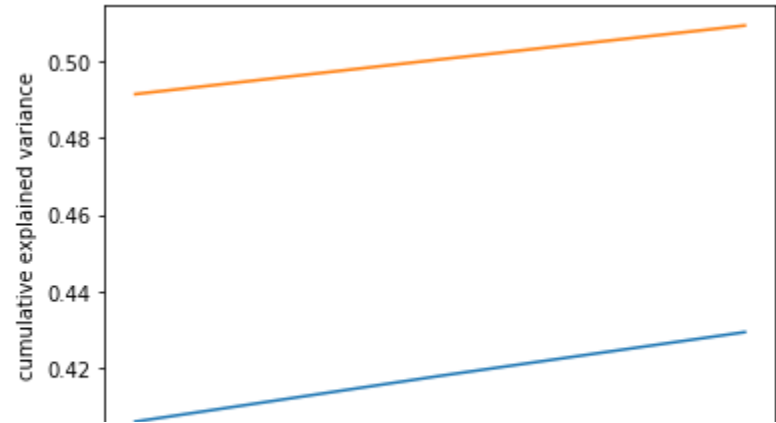
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-1.00853841e-01 -1.06080679e-01 -9.87747318e-02 -1.03856789e-01]
[-6.13859604e-02 -1.29374501e-03 5.67938804e-03 -4.68780635e-02
-9.67608579e-03 9.86014205e-02 -1.43099528e-01 1.50356954e-03
-3.68712172e-02 1.44405038e-01 5.38450504e-02 9.71964035e-02
-5.53406762e-03 -1.29040997e-01 -1.01552092e-01 1.18096864e-01
-1.26999791e-01 -9.67763168e-03 -1.78958744e-03 -1.34475913e-01
1.84404621e-04 8.39892148e-02 8.97771802e-02 -1.49136699e-01
-1.62855176e-01 -1.26603991e-01 -5.99373213e-02 -1.40911101e-01
3.58735982e-02 1.97899013e-01 -2.99801458e-02 1.51091417e-02
-2.89860844e-02 2.38067162e-02 5.89085902e-02 6.31565232e-02
-3.68060485e-02 4.56699749e-02 6.29801296e-02 1.79934976e-01
-3.79391732e-02 -7.06527184e-02 3.37001129e-02 1.74866015e-02
8.18701284e-02 -1.06915646e-01 -2.10375474e-02 -1.86272894e-01
2.00939665e-01 1.34956346e-01 -1.79264886e-01 1.66922439e-01
4.39787714e-02 -5.51925556e-02 2.05180497e-01 -2.06421500e-01
1.78888817e-01 2.12821473e-01 -8.09340346e-02 -2.42017654e-02
5.82455804e-02 1.48711090e-01 3.89854272e-03 9.42697094e-02
4.87875815e-02 -6.66962677e-02 -1.54745246e-02 1.22735967e-01
5.50198923e-02 4.96159638e-04 -1.48417083e-01 -1.18546455e-01
-2.12857997e-02 -6.51502999e-03 -1.85510465e-01 8.00780687e-02
7.43008097e-02 -1.53586155e-02 -1.48421197e-01 -3.80684426e-02
-7.86724364e-02 2.06472782e-02 -1.55092471e-01 -1.28854390e-01
1.24268806e-01 5.68289540e-02 7.39054818e-02 -2.99642513e-02
-6.93918011e-02 -8.37769590e-02 8.70917377e-02 1.32816522e-01
4.67222571e-02 -2.38563465e-02 -8.34410976e-02 1.32163438e-01
-6.34626363e-03 -2.61829577e-02 6.93379755e-03 -5.41393909e-02]
[-1.17346388e-01 -1.51095620e-01 -4.74800852e-02 1.10259788e-01
-8.67778546e-02 -1.07439252e-01 -1.17434430e-01 -6.58631894e-03
-4.15246095e-02 1.30349133e-01 -1.32095806e-01 -6.25604392e-03
1.67224596e-01 2.80422590e-01 -7.14169156e-02 -5.26402719e-02
8.79007911e-02 1.49644384e-01 8.22573369e-03 5.52771434e-02
-3.27925187e-02 7.71760477e-02 2.18813811e-02 -2.10901159e-02
-3.86372188e-02 8.35254138e-02 -1.36536330e-02 -1.67137066e-02
1.24016212e-02 7.30336782e-03 4.44782073e-02 -9.97482952e-02
-5.37372978e-02 1.55219944e-01 4.32374413e-02 -1.40324793e-01
-5.71562229e-02 -1.28854578e-01 -2.47885941e-02 -2.46783808e-01
-1.36181297e-01 -6.18438954e-02 1.16315747e-01 -7.61804134e-02
1.12897170e-01 -7.99790453e-02 3.24214699e-02 8.90780476e-02
1.51204049e-02 3.30643914e-02 9.31926322e-02 -2.58920043e-02
2.48629643e-01 -9.95447780e-03 2.36915743e-01 -4.41946286e-02
1.85736617e-01 -4.97570342e-02 -1.90278344e-01 5.49142571e-02
1.05781855e-01 -1.14534935e-01 -9.14824199e-02 6.75779213e-02
7.45850025e-02 1.13779982e-01 -5.35294544e-03 1.13657351e-01
-5.18601761e-02 -2.05906747e-02 2.21499415e-02 4.24786543e-02
-2.52390484e-01 1.73702725e-02 -5.54305453e-02 -6.51174358e-03
3.24347147e-02 5.26918633e-02 -1.34973500e-01 -3.58995720e-02
-1.07115843e-02 -9.13325762e-02 5.30688473e-02 2.07504763e-01
-1.78773255e-03 -9.15395992e-02 5.75340661e-02 -8.74146825e-03
7.97976254e-02 -7.09218202e-02 9.02243679e-02 -1.01949920e-01
2.17867417e-02 2.25447365e-02 9.31269944e-02 -1.10716607e-01
-7.73798677e-02 -8.35977446e-02 -3.13485022e-02 -6.37582621e-03]]
[240460.62688681 4426.20400544 4324.75657443]

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Out[7]: [49.145245826729, 0.9046257873596385, 0.8838920023744803]



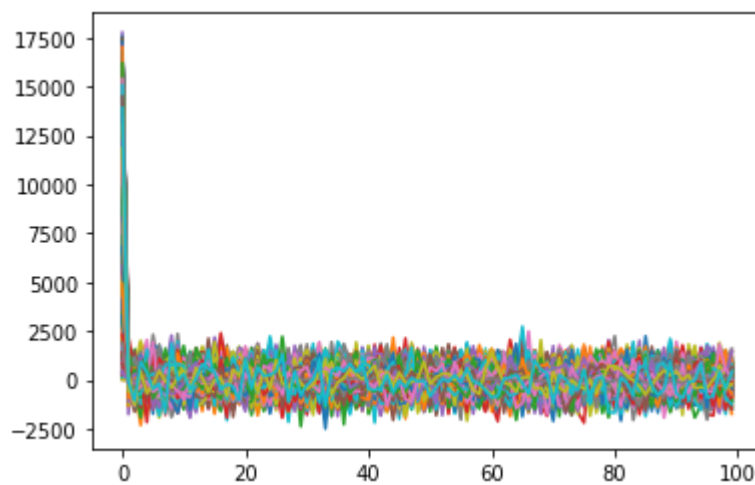
```

In [26]: # df1_1=pd.read_csv('dist1_500_1.txt',sep=" ",header=None);
# df1_1.dropna(how="all", inplace=True)
# df1_2=pd.read_csv('dist1_500_2.txt',sep=" ",header=None);
# df1_2.dropna(how="all", inplace=True)
# df1=pd.concat([df1_1,df1_2])
# print(df1.iloc[0]);

# alpha0=math.sqrt(1/100)
# alpha1=math.sqrt(2/100)
# print(alpha1)
# for x in range(0,100):
#     print(x)
#     cosinetransform=math.cos(((2*x)+1)*x*math.pi/2*100)
#     print(cosinetransform)
#     samation=df1.iloc[x]*cosinetransform
#     print(samation)
# u = []
# for i in range(100):
#     u.append(0)
# for i in range(0,100):
#     if i==0:
#         u[i]=alpha0*samation
#     elif i>0:
#         u[i]=alpha1*samation
#     print(u[0])
def transform(vector):
    result = []
    factor = math.pi / len(vector)
    for i in range(len(vector)):
        sum = 0.0
        for (j, val) in enumerate(vector):
            sum += val * math.cos((j + 0.5) * i * factor)
        result.append(sum)
    return result
dfg1=[]
# list2=[]
for i in range(0,1000):
#     dfg1.append(transform(df1.iloc[i]))
    pl.plot(transform(df1.iloc[i]))
    dfg1.append(transform(df1.iloc[i]))
#     print(statistics.variance(dfg1[i]))

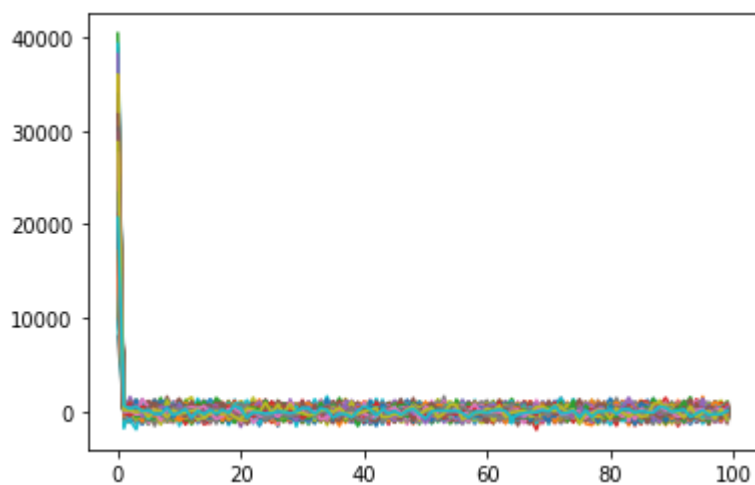
# list2.sort(reverse=True)
# dfg1

```



```
In [27]: ▶ dfg2=[]
for i in range(0,1000):
#     dfg1.append(transform(df1.iloc[i]))
    pl.plot(transform(df2.iloc[i]))
    dfg2.append(transform(df2.iloc[i]))
#     print(statistics.variance(dfg2[i]))
#     list2.append(statistics.variance(dfg1[i]))

# list2.sort(reverse=True)
```



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In [ ]: ▶
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