

# Analysis of Mfeat data set

## Descriptive analysis

### importing libraries

In [8]:

```
#Loading data
import pandas as pd
import pandas as pd
import numpy as np
import seaborn as sns #visualisation
import matplotlib.pyplot as plt #visualisation
from scipy import stats
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

### importing training data

In [9]:

```
data = pd.read_csv("data_train.csv")
```

### Descriptive analysis

In [1357]:

```
description=data.describe()
description.to_csv("description.csv")
```

In [266]:

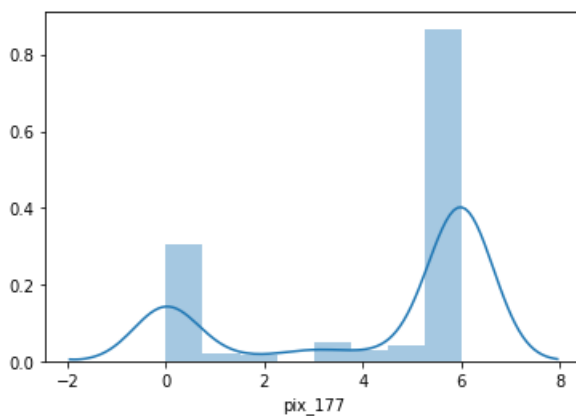
```
data2=data.groupby('class').mean()
data2.to_csv("description2.csv")
```

In [1358]:

```
sns.distplot(data['pix_177'])
```

Out[1358]:

<matplotlib.axes.\_subplots.AxesSubplot at 0xb909b8c8>



## shapiro normality test

In [ ]:

```
from scipy.stats import shapiro
for fea in data.columns:
    print(str(fea)+", "+str(shapiro(data[fea])[1]))
```

## Plotting variables

In [1847]:

```
#defining function for plotting boxplots of variables
def draw_boxplot(df, variables, n_rows, n_cols):
    fig=plt.figure(figsize=(50, 50), dpi= 60, facecolor='w', edgecolor='k')
    for i, var_name in enumerate(variables):
        ax=fig.add_subplot(n_rows,n_cols,i+1)
        df.boxplot(var_name,ax=ax)
        ax.set_title(var_name+" Distribution")
    fig.tight_layout() # Improves appearance a bit.
    fig.savefig("abc.png")
```

In [1849]:

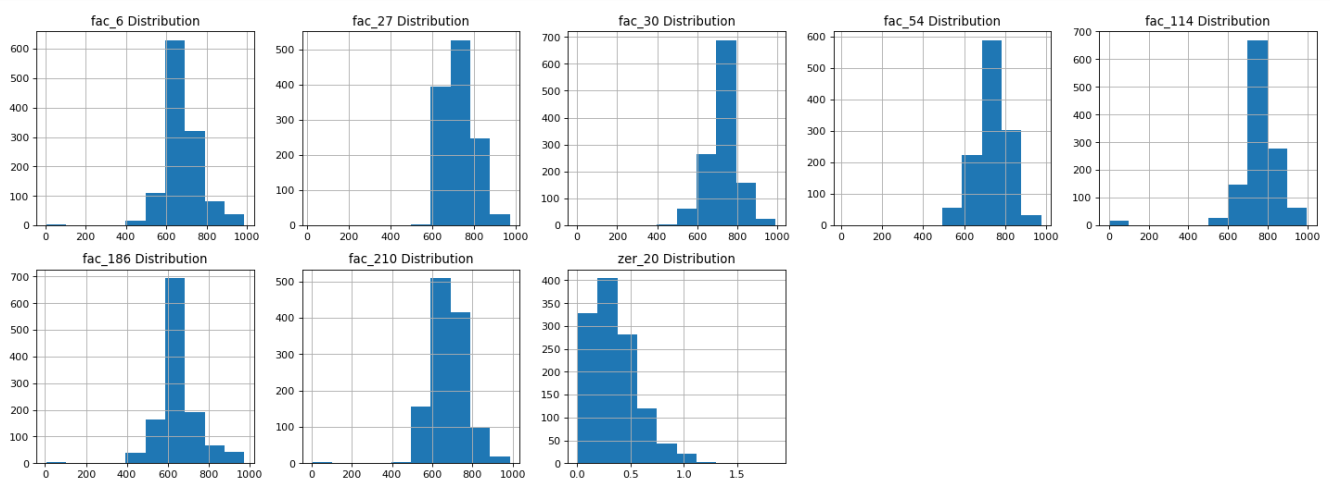
```
#defining function for plotting histograms of variables
def draw_histograms(df, variables, n_rows, n_cols):
    fig=plt.figure(figsize=(18, 16), dpi= 80, facecolor='w', edgecolor='k')
    for i, var_name in enumerate(variables):
        ax=fig.add_subplot(n_rows,n_cols,i+1)
        df[var_name].hist(bins=10,ax=ax)
        ax.set_title(var_name+" Distribution")
    fig.tight_layout() # Improves appearance a bit.
    fig.savefig("abc.png")
```

In [594]:

```
variables=['fac_6','fac_27','fac_30','fac_54','fac_114','fac_186','fac_210','pix_1','pix_15','pix_2',
'pix_23','pix_24','pix_91','pix_105','pix_106','pix_121','pix_136','pix_211','pix_226','pix_240',
'zer_1','zer_2','zer_8','zer_14','zer_20','zer_30','zer_32','zer_39','zer_44']
```

In [1852]:

```
draw_histograms(data,variables,5,5)
```



In [292]:

```
skew=data.skew()
skew.to_csv("skew.csv")
```

```
E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel_launcher.py:2: FutureWarning:
The signature of `Series.to_csv` was aligned to that of `DataFrame.to_csv`, and argument 'header'
will change its default value from False to True: please pass an explicit value to suppress this w
arning.
```

In [295]:

```
median=data.median()
median=median.to_csv("median.csv")
```

```
E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel_launcher.py:2: FutureWarning:
The signature of `Series.to_csv` was aligned to that of `DataFrame.to_csv`, and argument 'header'
will change its default value from False to True: please pass an explicit value to suppress this w
arning.
```

In [296]:

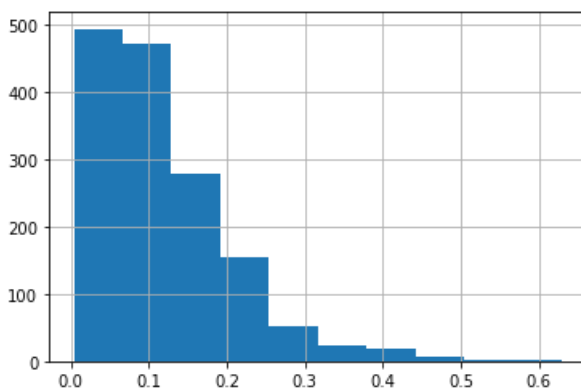
```
mode=data.mode()
mode=mode.to_csv("mode.csv")
```

In [1173]:

```
data['zer_8'].hist()
```

Out[1173]:

<matplotlib.axes.\_subplots.AxesSubplot at 0xb4c677c8>



## Cleaning Data

### Data cleaning (outliers)

In [10]:

```
def outliers_iqr(ys):
    quartile_1, quartile_3 = np.percentile(ys, [25, 75])
    iqr = quartile_3 - quartile_1
    lower_bound = quartile_1 - (iqr * 3)
    upper_bound = quartile_3 + (iqr * 3)
    return np.where((ys > upper_bound) | (ys < lower_bound))
```

In [11]:

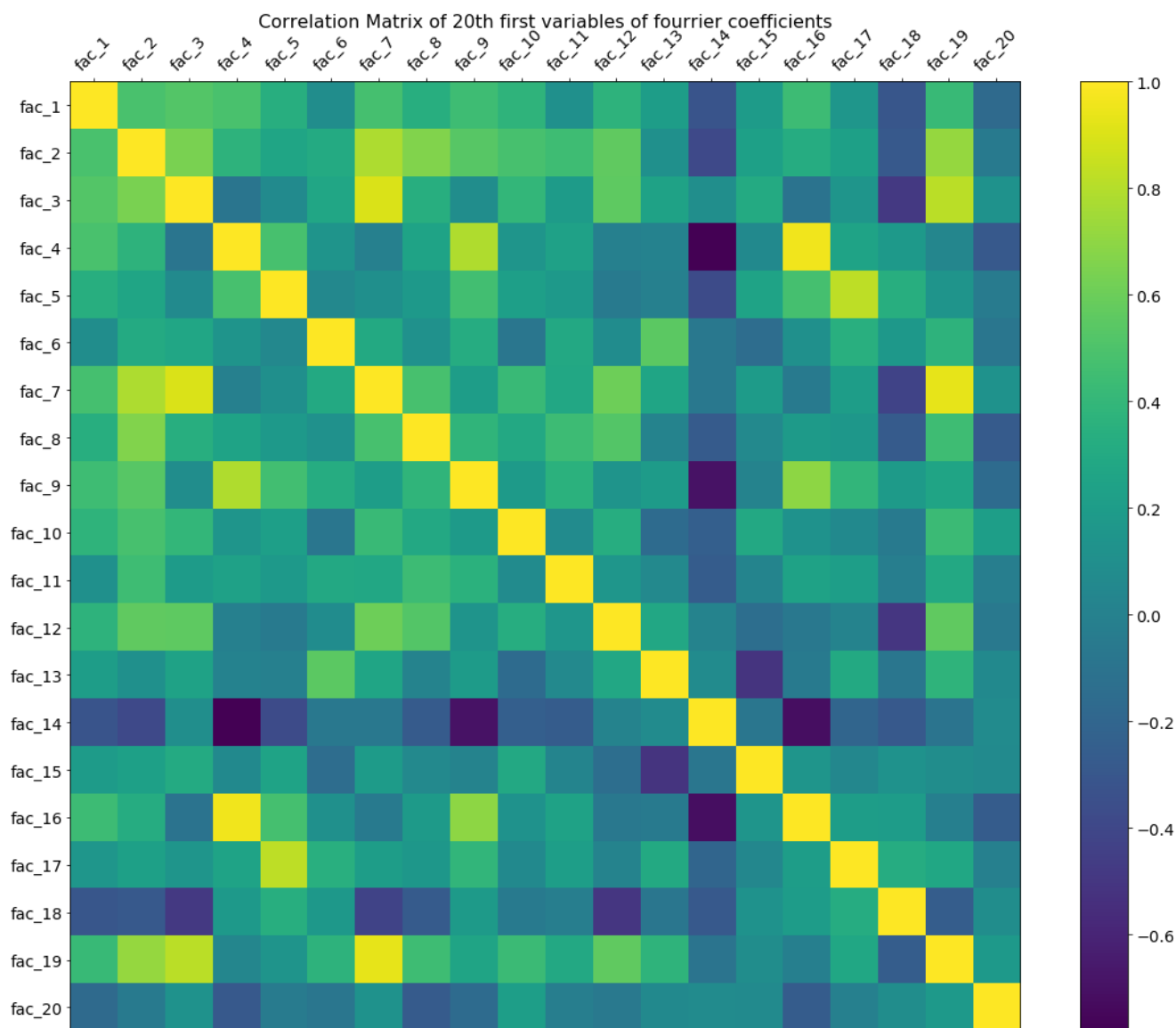
```
variables=['fac_6','fac_27','fac_30','fac_54','fac_114','fac_186','fac_210','zer_20']
index=[]
for var in variables:
    outliers=outliers_iqr(data[var])[0]
    index=np.concatenate((outliers, index), axis=0)
outliers=np.unique(index)
outlier_indexes=outliers.astype(int)
data.drop(outlier_indexes,inplace=True)
```

```
data.drop(columns=indices, inplace=True,
```

## Correlation Matrix

In [628]:

```
df=data.iloc[:,range(0,20)]
f = plt.figure(figsize=(19, 15))
plt.matshow(df.corr(), fignum=f.number)
plt.xticks(range(df.shape[1]), df.columns, fontsize=14, rotation=45)
plt.yticks(range(df.shape[1]), df.columns, fontsize=14)
cb = plt.colorbar()
cb.ax.tick_params(labelsize=14)
plt.title('Correlation Matrix of 20th first variables of fourrier coefficients', fontsize=16);
f.savefig("correlation.png")
```



## Dropping high correlated features

In [12]:

```
df=data
# Create correlation matrix
corr_matrix = df.corr().abs()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))

# Find index of feature columns with correlation greater than 0.95
to_drop = [column for column in upper.columns if any(upper[column] > 0.95)]
```

In [13]:

```
data.drop(data[to_drop], axis=1,inplace=True)
```

### Dropping variables with low variance

In [14]:

```
variables2=['pix_1','pix_15','pix_22','pix_23','pix_24','pix_91','pix_105','pix_106','pix_121','pix_136','pix_211','pix_226','pix_240','zer_1','zer_2','zer_8','zer_32']
```

In [15]:

```
data.drop(data[variables2], axis=1,inplace=True)
```

## Exploratory analysis

### AFM analysis

In [16]:

```
import prince
```

In [17]:

```
X = data.drop(['class'],axis=1)
columns=data.columns.get_values()
index=['classe {}'.format(i+1) for i in range(10)]
```

E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel\_launcher.py:2: FutureWarning: The 'get\_values' method is deprecated and will be removed in a future version. Use '.to\_numpy()' or '.array' instead.

In [18]:

```
#Construct groups of variables
group1=data.columns.get_values()[0:153]
group2=data.columns.get_values()[153:229]
group3=data.columns.get_values()[229:293]
group4=data.columns.get_values()[293:298]
group5=data.columns.get_values()[298:525]
group6=data.columns.get_values()[525:551]
```

E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel\_launcher.py:2: FutureWarning: The 'get\_values' method is deprecated and will be removed in a future version. Use '.to\_numpy()' or '.array' instead.

E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel\_launcher.py:3: FutureWarning: The 'get\_values' method is deprecated and will be removed in a future version. Use '.to\_numpy()' or '.array' instead.

This is separate from the ipykernel package so we can avoid doing imports until

E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel\_launcher.py:4: FutureWarning: The 'get\_values' method is deprecated and will be removed in a future version. Use '.to\_numpy()' or '.array' instead.

after removing the cwd from sys.path.

E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel\_launcher.py:5: FutureWarning: The 'get\_values' method is deprecated and will be removed in a future version. Use '.to\_numpy()' or '.array' instead.

"""

E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel\_launcher.py:6: FutureWarning: The 'get\_values' method is deprecated and will be removed in a future version. Use '.to\_numpy()' or '.array' instead.

E:\CVM\GTU\WPy64-3741\python-3.7.4.amd64\lib\site-packages\ipykernel\_launcher.py:7: FutureWarning:

```
The 'get_values' method is deprecated and will be removed in a future version. Use '.to_numpy()' or '.array' instead.
import sys
```

In [19]:

```
groupes={'groupe1':group1,'groupe2':group2,'groupe3':group3,'groupe4':group4,'groupe5':group5,'groupe6':group6}
```

In [20]:

```
mfa = prince.MFA(
    groups=groupes,
    n_components=552,
    n_iter=3,
    copy=True,
    check_input=True,
    engine='auto',
    random_state=42
)
```

In [21]:

```
mfa = mfa.fit(X)
```

In [22]:

```
mfa.row_coordinates(X)
```

Out[22]:

	0	1	2	3	4	5	6	7	8	9 ...	541	542	
0	3.586230	2.148888	0.058858	0.156174	0.019948	0.550095	1.241363	0.025500	0.759428	0.092222 ...	0.005527	0.003577	0.00
1	3.351882	1.972610	0.510141	0.518834	0.095881	0.890958	1.401210	0.687267	0.058989	0.211366 ...	0.008154	0.001074	0.00
2	2.769339	0.923711	0.556986	0.557096	1.600492	0.892374	2.024398	0.566913	0.943459	2.492594 ...	0.006777	0.009234	0.00
3	2.923882	1.357988	1.010672	0.732647	1.182839	0.786635	0.976628	2.284944	0.544354	0.645414 ...	0.003017	0.000613	0.00
4	3.084450	2.000958	0.706424	0.293951	0.765419	0.505314	1.841370	0.294092	0.658960	0.124180 ...	0.000771	0.002269	0.00
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1495	0.998496	0.201105	1.625644	0.543908	0.375769	1.290984	1.854041	0.875811	0.155084	0.447490 ...	0.002806	0.010712	0.00
1496	0.816900	1.026531	1.730549	0.800533	0.616348	1.434995	0.097577	0.028516	0.072298	0.226435 ...	0.003489	0.014714	0.00
1497	0.994816	1.699053	1.355912	0.075675	2.116691	2.126245	1.295645	0.990727	1.684412	0.486327 ...	0.004448	0.011109	0.00
1498	0.803576	0.838592	1.879528	2.000384	0.419841	1.460013	1.421362	0.290801	0.089692	0.366525 ...	0.008254	0.003061	0.00
1499	1.040357	0.067146	2.150715	1.787893	0.245394	0.935088	0.474119	0.697323	1.302906	0.009137 ...	0.008391	0.013112	0.00

1475 rows × 551 columns

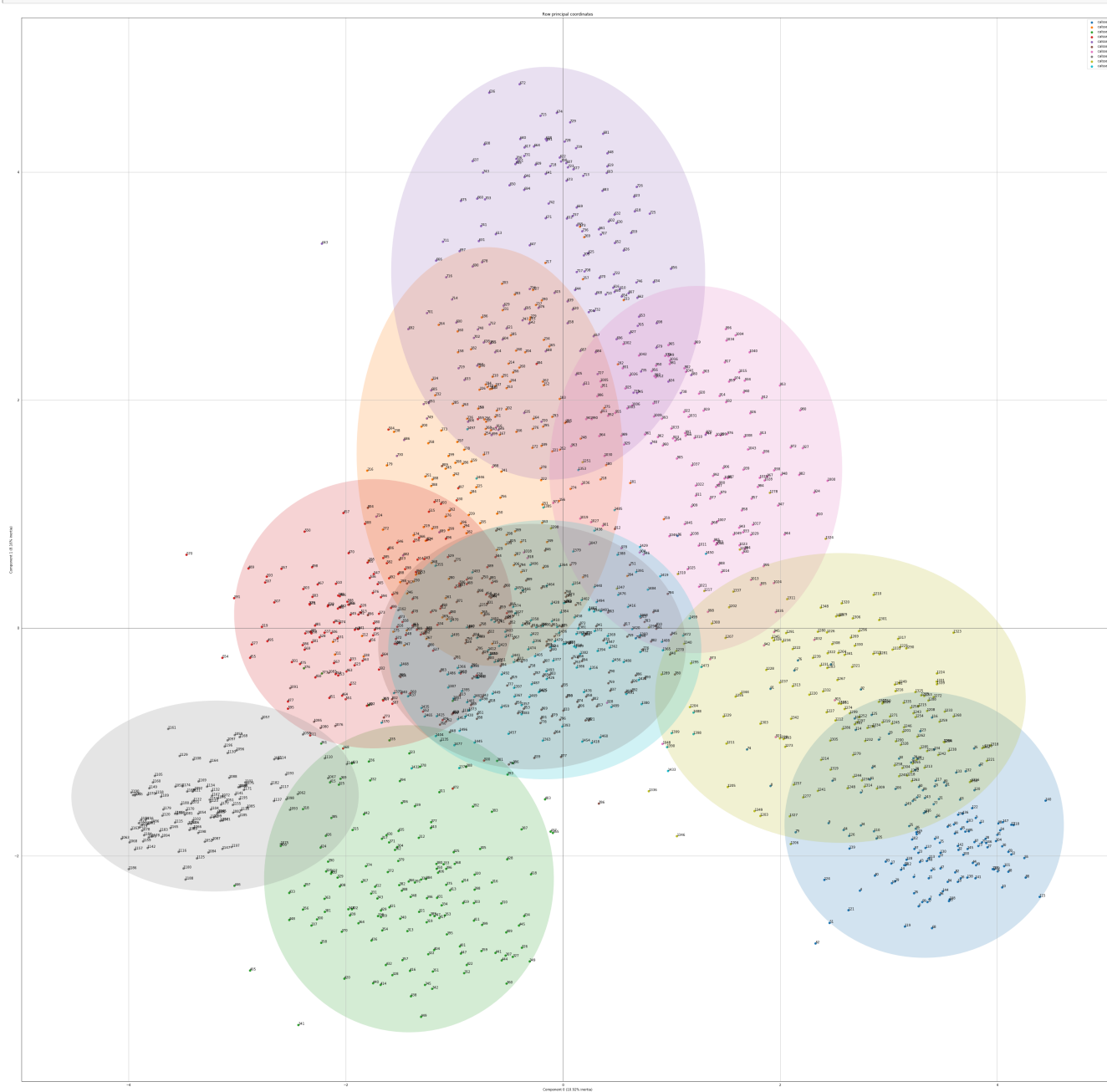
In [1441]:

```
#Plotting individuals in factor plan
ax = mfa.plot_row_coordinates(
    X,
    ax=None,
    figsize=(60, 60),
    x_component=0,
    y_component=1,
    labels=X.index,
```

```

color_labels=['calisse {}'.format(t) for t in data['class']],
ellipse_outline=False,
ellipse_fill=True,
show_points=True
)

```

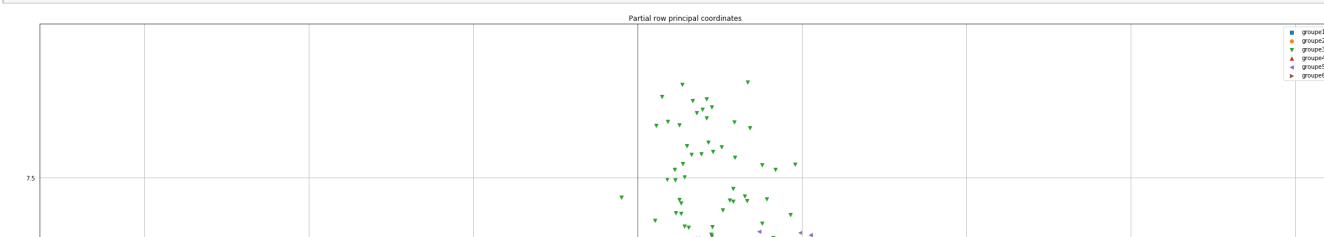


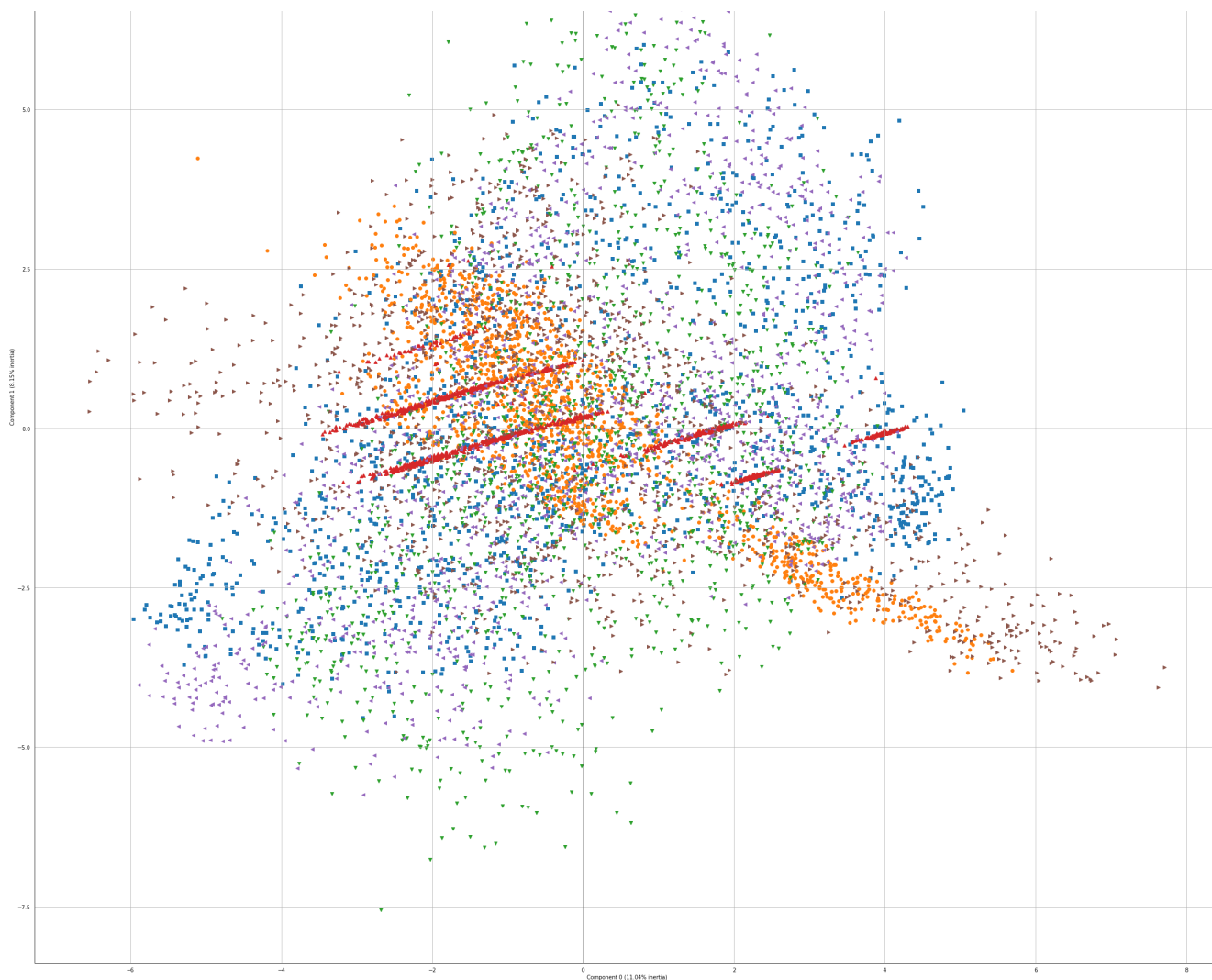
In [1716]:

```

#plotting groups of variables in factor plan
ax = mfa.plot_partial_row_coordinates(
X,
ax=None,
figsize=(40, 40),
x_component=0,
y_component=1,
)
ax.get_figure().savefig('mfa_partial_row_coordinates.svg')

```





In [24]:

```
mfa.explained_inertia_[1:5]
```

Out[24]:

```
[0.08217937708154475,
 0.05961432873508772,
 0.05164220121032245,
 0.04380062719065025]
```

In [25]:

```
mfa.eigenvalues_[1:5]
```

Out[25]:

```
[2.91070069225868, 2.1114721731898367, 1.8291084229501207, 1.5513687303650898]
```

In [815]:

```
for name, fa in sorted(mfa.partial_factor_analysis_.items()): # doctest: +ELLIPSIS
    print('{} eigenvalues: {}'.format(name, fa.eigenvalues_))
```

```
groupe1 eigenvalues: [31.652894448704345, 22.186686645308537, 17.370605332140986,
11.824414087733315, 9.322442930738104]
groupe2 eigenvalues: [11.826189853131451, 5.201117259313143, 4.826680457949398,
2.7460448926675713, 2.5228997397450064]
groupe3 eigenvalues: [5.634611681148499, 5.191973620618263, 3.60443355550322, 3.296018299990814, 2
.6702615969627854]
groupe4 eigenvalues: [3.249032035312228, 1.0867312262405882, 0.6024743026216429,
0.05763218400536026, 0.004130251820181291]
groupe5 eigenvalues: [38.27200100014378, 23.38902551814938, 21.518856530621235,
```



```
15.165299776777033, 13.106170412401877]
groupe6 eigenvalues: [6.946679426942888, 5.035272546562144, 3.128178821658927, 2.4879890692192514,
2.006571668634843]
```

## K-means analysis

In [1918]:

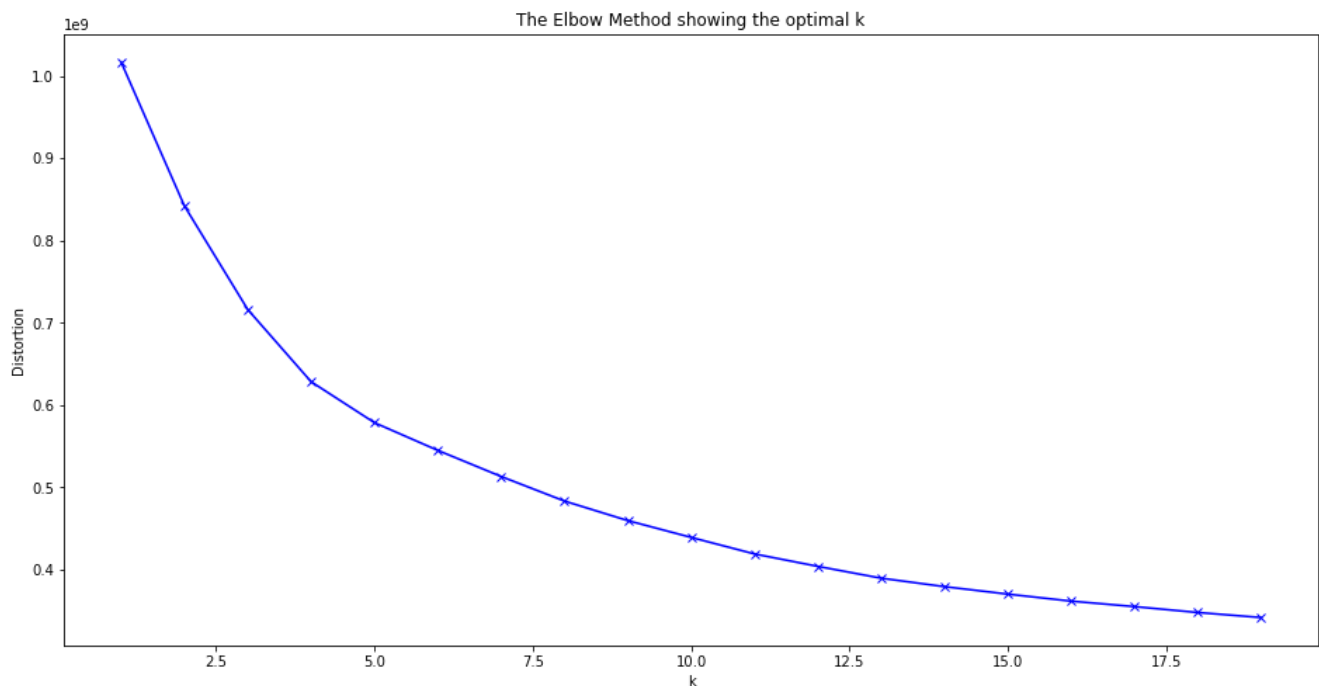
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.cluster import KMeans
from sklearn import datasets
#we took one group or all variables
#df=data.loc[:,group7]
df=data.drop(['class'],axis=1)
```

In [1919]:

```
#Looking for the optimal K
distortions = []
K = range(1,20)
for k in K:
    kmeanModel = KMeans(n_clusters=k)
    kmeanModel.fit(df)
    distortions.append(kmeanModel.inertia_)
```

In [1921]:

```
#Looking for the optimal K
plt.figure(figsize=(16,8))
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```



In [1922]:

```
#train the model with 5 or 10 classes
#kmeanModel = KMeans(n_clusters=5)
kmeanModel = KMeans(n_clusters=10)
kmeanModel.fit(df)
```

Out[1922]:

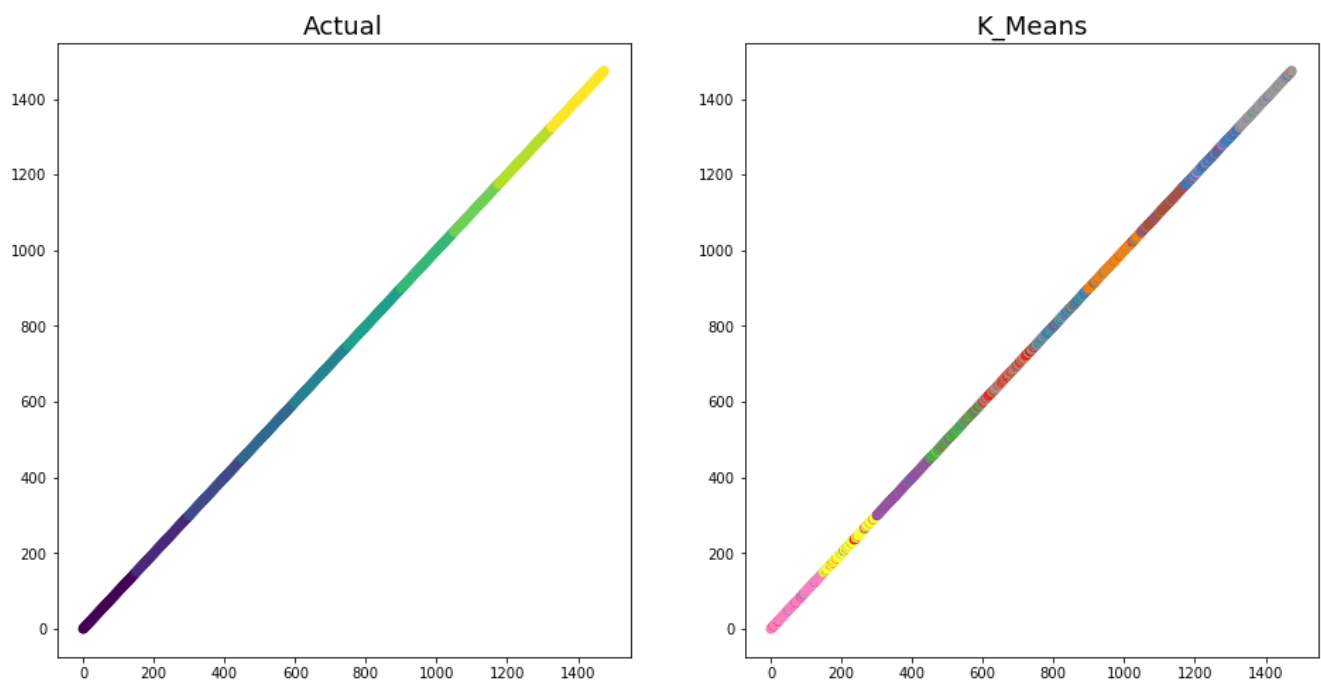
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=10, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

In [1923]:

```
#plot classification of kmean versus real data
df['k_means']=kmeanModel.predict(df)
df['target']=data['class']
fig, axes = plt.subplots(1, 2, figsize=(16,8))
axes[0].scatter(range(len(df)),range(len(df)), c=df['target'])
axes[1].scatter(range(len(df)), range(len(df)), c=df['k_means'], cmap=plt.cm.Set1)
axes[0].set_title('Actual', fontsize=18)
axes[1].set_title('K_Means', fontsize=18)
```

Out[1923]:

Text(0.5, 1.0, 'K\_Means')



## Statistics modelling

### Splitting train set and test set

In [1947]:

```
data = pd.read_csv("data_train.csv")
data, X_test, data_class, y_test = train_test_split(origin.drop(['class'],axis=1), origin['class'],
test_size=0.2, random_state=0)
```

### reset indexes of data

In [1948]:

```
data['class']=data_class
data=data.reset_index(drop=True)
X_test=X_test.reset_index(drop=True)
```

### Solving and transforming data

## Scaling and transforming data

In [1949]:

```
#transform train data and test data
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

dropped_variables=variables2+to_drop
df=data.drop(['class'],axis=1)
df=df.drop(dropped_variables,axis=1)
scaler = StandardScaler()
scaler.fit(df)
df = scaler.transform(df)
X_test=X_test.drop(dropped_variables,axis=1)
scaler.fit(X_test)
X_test=scaler.transform(X_test)
```

## RandoForest Modeling

In [1931]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import cross_val_score

score=[]
for i in [5,10,20,30,40,50,100]:
    regressor = RandomForestRegressor(n_estimators=i, random_state=0)
    model_cv = cross_val_score(regressor,df,data['class'],cv=5)
    score.append(model_cv.mean())
```

In [1950]:

```
score
```

Out[1950]:

```
(1200, 552)
```

In [1951]:

```
#Implement random forest regressor with best parameter
regressor = RandomForestRegressor(n_estimators=50, random_state=0)

regressor.fit(df, data['class'])

y_pred = regressor.predict(X_test)
y_pred=y_pred.astype(int)
```

In [1952]:

```
#Confusion Matrix

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

print(confusion_matrix(y_test,y_pred))
print(classification_report(y_test,y_pred))
print(accuracy_score(y_test, y_pred))
```

```
[[31  0  0  0  0  0  0  0  0  0]
 [ 1 28  2  0  0  0  0  0  0  0]
 [ 0  1 25  4  1  0  0  0  0  0]
 [ 0  0  5 31  0  0  0  0  0  0]
 [ 0  0  0  9 21  0  0  0  0  0]
 [ 0  0  0  1 11  6  0  0  0  0]
 [ 0  0  0  0  0  7 25  0  0  0]
 [ 0  0  1  1  1  4 20  4  0  0]
 [ 0  0  0  0  0  0  0  5 18  0]
 [ 0  0  0  0  1  1  0  1 13 21]]
      precision    recall  f1-score   support

0.00000000  0.00000000  0.00000000  21
0.00000000  0.00000000  0.00000000  28
0.00000000  0.00000000  0.00000000  25
0.00000000  0.00000000  0.00000000  31
0.00000000  0.00000000  0.00000000  9
0.00000000  0.00000000  0.00000000  11
0.00000000  0.00000000  0.00000000  7
0.00000000  0.00000000  0.00000000  4
0.00000000  0.00000000  0.00000000  20
0.00000000  0.00000000  0.00000000  18
0.00000000  0.00000000  0.00000000  13
```

0	0.97	1.00	0.98	31
1	0.97	0.90	0.93	31
2	0.76	0.81	0.78	31
3	0.67	0.86	0.76	36
4	0.60	0.70	0.65	30
5	0.33	0.33	0.33	18
6	0.56	0.78	0.65	32
7	0.40	0.13	0.20	31
8	0.58	0.78	0.67	23
9	1.00	0.57	0.72	37

accuracy			0.70	300
macro avg	0.68	0.69	0.67	300
weighted avg	0.71	0.70	0.68	300

0.7

In [ ]:

```
#### SVM Modeling
```

In [1953]:

```
#Testing poly,rbf and linear kernels
#For rbf kernel, C parameter must be added and vary between 0.1 to 100
#For poly kernel, degree must vary between 2 and 10

score=[]
for i in [1,2,3,5,10] :
    svcclassifier = SVC(kernel='linear')

    model_cv = cross_val_score(svcclassifier,df,data['class'],cv=5)

    score.append(model_cv.mean())
```

In [1954]:

```
max(score)
```

Out[1954]:

0.9858761595111185

In [1957]:

```
#implemnt classifier on train data
svcclassifier = SVC(kernel='linear')
svcclassifier.fit(df, data['class'])
y_pred = svcclassifier.predict(X_test)
```

In [1958]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

print(confusion_matrix(y_test,y_pred))
print(classification_report(y_test,y_pred))
print(accuracy_score(y_test, y_pred))
```

```
[[31  0  0  0  0  0  0  0  0  0]
 [ 0 31  0  0  0  0  0  0  0  0]
 [ 0  0 31  0  0  0  0  0  0  0]
 [ 0  0  0 36  0  0  0  0  0  0]
 [ 0  0  0  0 29  0  1  0  0  0]
 [ 0  0  0  0  0 18  0  0  0  0]
 [ 0  0  0  0  0  0 32  0  0  0]
 [ 0  0  0  0  0  0  0 31  0  0]
 [ 0  0  0  0  0  0  1  0 22  0]
 [ 0  1  0  0  0  0  0  0  0 36]]
      precision    recall  f1-score   support

 0         1.00      1.00      1.00        31
 1         0.97      1.00      0.98        31
```

1	0.97	1.00	0.98	31
2	1.00	1.00	1.00	31
3	1.00	1.00	1.00	36
4	1.00	0.97	0.98	30
5	1.00	1.00	1.00	18
6	0.94	1.00	0.97	32
7	1.00	1.00	1.00	31
8	1.00	0.96	0.98	23
9	1.00	0.97	0.99	37
accuracy			0.99	300
macro avg	0.99	0.99	0.99	300
weighted avg	0.99	0.99	0.99	300

0.99

## Implementing MLP classifier

In [1661]:

```
from sklearn.model_selection import cross_val_score
from sklearn.neural_network import MLPClassifier

score=[]
for i in [5,10,20,30,40,50,100,200]:
    mlp = MLPClassifier(hidden_layer_sizes=(i,i,i), max_iter=1000)
    model_cv = cross_val_score(mlp,df,data['class'],cv=5)
    score.append(model_cv.mean())
```

In [1662]:

score

Out[1662]:

```
[0.8793766302038897,
 0.95496498803918,
 0.970227147774749,
 0.9711510071408801,
 0.9778045539849852,
 0.9771140449006401,
 0.9779396688656433,
 0.9805044232654291]
```

In [1959]:

```
#implemnt classifier on train data
mlp = MLPClassifier(hidden_layer_sizes=(200,200,200), max_iter=1000)
mlp.fit(df, data['class'].values.ravel())
predictions = mlp.predict(X_test)
```

In [1960]:

```
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test,predictions))
print(classification_report(y_test,predictions))
```

```
[[31  0  0  0  0  0  0  0  0  0]
 [ 0 31  0  0  0  0  0  0  0  0]
 [ 0  0 30  0  0  0  0  0  0  1]
 [ 0  0  0 36  0  0  0  0  0  0]
 [ 0  0  0  0 29  0  1  0  0  0]
 [ 0  0  0  0  0 18  0  0  0  0]
 [ 0  0  0  0  0  0 32  0  0  0]
 [ 0  0  0  0  0  0  0 31  0  0]
 [ 0  0  0  0  0  0  1  0 21  1]
 [ 0  1  0  0  0  1  0  0  0 35]]

      precision    recall  f1-score   support

0         1.00        1.00        1.00         31
1         0.97        1.00        0.98         31
2         1.00        0.97        0.98         31
3         1.00        1.00        1.00         36
4         0.97        1.00        0.98         30
5         1.00        1.00        1.00         18
6         0.94        1.00        0.97         32
7         1.00        1.00        1.00         31
8         1.00        0.96        0.98         23
9         1.00        0.97        0.99         37
```

2	1.00	0.97	0.98	31
3	1.00	1.00	1.00	36
4	1.00	0.97	0.98	30
5	0.95	1.00	0.97	18
6	0.94	1.00	0.97	32
7	1.00	1.00	1.00	31
8	1.00	0.91	0.95	23
9	0.95	0.95	0.95	37
accuracy			0.98	300
macro avg	0.98	0.98	0.98	300
weighted avg	0.98	0.98	0.98	300

## Generalization of SVM for all train data

In [1961]:

```
df = pd.read_csv("data_train.csv")
df.drop(outlier_indexes,inplace=True)
df.drop(dropped_variables,axis=1,inplace=True)
Y=df['class']
df.drop(['class'],axis=1,inplace=True)
scaler = StandardScaler()
scaler.fit(df)
df = scaler.transform(df)
```

In [1962]:

```
svclassifier = SVC(kernel='linear')
svclassifier.fit(df, Y)
```

Out[1962]:

```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='linear', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
```

## Produce predictions for test data

In [1966]:

```
df = pd.read_csv("data_test.csv")
df.drop(dropped_variables,axis=1,inplace=True)
scaler = StandardScaler()
scaler.fit(df)
df = scaler.transform(df)
```

In [1967]:

```
y_pred = svclassifier.predict(df)
y_pred
```

Out[1967]:

```
array([1, 9, 1, 9, 6, 8, 0, 8, 4, 5, 6, 3, 2, 4, 1, 2, 7, 8, 3, 7, 0, 3,
       0, 2, 4, 4, 5, 0, 5, 5, 6, 4, 3, 6, 2, 2, 6, 8, 3, 1, 0, 7, 2, 9,
       4, 1, 2, 5, 4, 8, 3, 6, 1, 9, 5, 7, 1, 5, 6, 6, 7, 2, 9, 8, 8, 5,
       2, 2, 1, 8, 5, 5, 0, 4, 6, 4, 3, 7, 2, 2, 8, 9, 3, 9, 6, 3, 1, 0,
       2, 0, 2, 4, 9, 1, 5, 1, 5, 4, 3, 7, 9, 1, 3, 7, 6, 5, 0, 5, 9, 0,
       9, 6, 4, 6, 2, 9, 7, 7, 9, 7, 0, 9, 1, 5, 3, 9, 9, 6, 5, 6, 8, 6,
       1, 3, 2, 9, 2, 1, 4, 6, 8, 4, 7, 3, 5, 0, 8, 2, 4, 6, 8, 8, 1, 2,
       4, 9, 3, 8, 8, 9, 3, 6, 7, 6, 8, 0, 1, 7, 3, 9, 3, 0, 4, 5, 4, 2,
       5, 5, 9, 3, 6, 7, 8, 8, 4, 5, 2, 8, 9, 8, 3, 8, 6, 5, 0, 5, 9, 4,
       3, 0, 1, 5, 7, 0, 2, 0, 1, 2, 4, 2, 8, 1, 8, 7, 7, 8, 8, 8, 2, 4,
       4, 3, 9, 2, 4, 2, 3, 0, 1, 3, 0, 7, 0, 6, 9, 3, 6, 3, 3, 0, 6, 2,
       6, 9, 7, 7, 2, 1, 0, 7, 8, 6, 1, 7, 3, 6, 3, 0, 4, 3, 1, 9, 6, 7,
       5, 9, 6, 3, 4, 1, 8, 7, 0, 5, 5, 4, 2, 2, 3, 9, 0, 0, 4, 6, 1, 7,
       6, 4, 6, 8, 6, 6, 7, 4, 8, 2, 1, 1, 4, 4, 7, 4, 6, 0, 7, 1, 4, 5,
       4, 1, 6, 0, 1, 0, 2, 2, 6, 6, 5, 5, 2, 0, 0, 6, 4, 4, 2, 5, 0, 4])
```

```
4, 1, 0, 9, 1, 0, 2, 2, 0, 0, 3, 3, 3, 0, 0, 0, 4, 4, 3, 3, 9, 4,
1, 0, 7, 4, 7, 4, 3, 7, 4, 1, 6, 1, 7, 1, 0, 7, 7, 1, 9, 7, 9, 6,
1, 6, 8, 5, 0, 0, 1, 1, 9, 5, 7, 7, 3, 1, 2, 2, 8, 3, 9, 0, 5, 4,
9, 9, 5, 5, 9, 1, 0, 7, 6, 6, 0, 0, 8, 6, 2, 5, 8, 9, 8, 1, 7, 5,
2, 6, 1, 4, 1, 2, 2, 3, 5, 0, 0, 5, 1, 7, 8, 6, 0, 3, 7, 3, 3, 2,
8, 1, 3, 8, 9, 3, 0, 7, 0, 5, 5, 4, 1, 3, 8, 6, 5, 8, 4, 3, 1, 2,
9, 0, 9, 2, 1, 8, 5, 7, 7, 0, 4, 5, 9, 9, 4, 3, 9, 9, 8, 3, 8, 0,
2, 2, 4, 1, 2, 3, 5, 3, 8, 4, 0, 2, 8, 1, 0, 5, 0, 5, 1, 4, 8, 1,
7, 9, 9, 7, 4, 9, 4, 7, 0, 3, 6, 2, 2, 8, 8, 9], dtype=int64)
```