In [10]:

```
# Estimation of Change in Price of Rice Commodity in India


# Importing all libraries used
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import pyplot
from datetime import datetime
from pandas import Series
from pandas import DataFrame
from pandas import concat
import seaborn as sns
from sklearn import metrics
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import Normalizer
from pandas import read_csv
from numpy import set_printoptions
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from tabulate import tabulate
%matplotlib inline

pd.set_option('display.max_rows', None)
```

In [11]:

```
# Load food-prices dataset
df = pd.read_csv("wfp_market_food_prices.csv", encoding="latin-1")

# Drop unnecessary features
df.drop(['mp_commoditysource','cm_id','mkt_id','mkt_name','cur_id','pt_id','pt
_name', 'um_id','um_name','adm0_id','adm1_id','adm1_name','cur_name'],inplace=
True,axis=1)

# Consider only Rice commodity in India
df = df[df.adm0_name == "India"]
df = df[df.cm_name =='Rice']
```

In [12]:

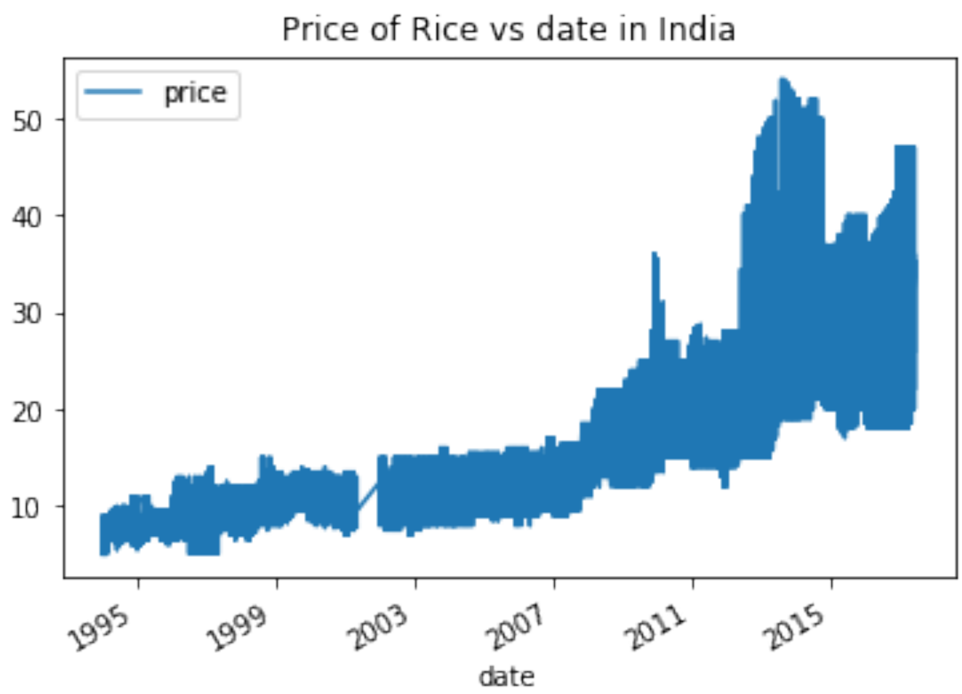
```
# Preprocessing of data

df['date'] = df.apply(lambda x: datetime(x['mp_year'],x["mp_month"],1),axis=1)
df = df.rename(columns={'mp_month':'month','mp_year':'year','mp_price':'price'
})
df.drop(['adm0_name', 'cm_name'],inplace=True,axis=1)
df.index = np.arange(1, len(df) + 1)
```

In [15]:

```
# Feature Engineering

# Read carbon dioxide data
df_co2 = pd.read_csv("carbon_india.csv", sep=';')
# Merge co2 values into main dataframe
df = df.merge(df_co2.set_index('year'), on='year', how='left')

# Read temperature data
df_temp = pd.read_excel("temperature.xls")
df_temp = df_temp.rename(columns={' Month': 'month','\tYear':'year','tas':'tem
perature'})
df_temp['date'] = df_temp.apply(lambda x: datetime(int(x['year']),int(x['month
']),1),axis=1)
df_temp.drop([' Country', 'month', 'year'],axis=1,inplace=True)
df = df.merge(df_temp.set_index('date'), on='date', how='left')

# Read inflation rate data
df_inf = pd.read_excel("inflation_rate_india.xls")
df = df.merge(df_inf.set_index('year'), on='year', how='left')

# Read consumer price index data
df_cpi = pd.read_excel("consumer_price_index_india.xls")
df = df.merge(df_cpi.set_index('year'), on='year', how='left')

# Read rainfall data
df_rain = pd.read_excel("rainfall.xls")
df_rain = df_rain.rename(columns={' Month': 'month','\tYear':'year','pr':'rain
fall'})
df_rain['date'] = df_rain.apply(lambda x: datetime(int(x['year']),int(x['month
']),1),axis=1)
df_rain.drop([' Country', 'month', 'year'],axis=1,inplace=True)
df = df.merge(df_rain.set_index('date'), on='date', how='left')
```

In [16]:

```
# Plot price versus date
dfp = pd.DataFrame(pd.Series(data=df.loc[:,'price'].values).values,columns=['p
rice'],index=df['date'])
dfp.plot()
plt.title("Price of Rice vs date in India")
plt.show()
```



In [17]:

```
# Calculate 3 month mean of price
width = 3
lag1 = dfp.shift(1)
lag3 = dfp.shift(width - 1)
window = lag1.rolling(window=width)
df3 = concat([window.mean()], axis=1)
df3.columns = ['3 month mean price']
df['3 month mean'] = df3.values

# Calculate 6 month mean of price
width = 6
lag1 = dfp.shift(1)
lag3 = dfp.shift(width - 1)
window = lag1.rolling(window = width)
df6 = concat([window.mean()], axis=1)
df6.columns = ['6 month mean price']
df['6 month mean'] = df6.values

# Calculate 9 month mean of price
width = 9
lag1 = dfp.shift(1)
lag3 = dfp.shift(width - 1)
window = lag1.rolling(window=width)
df9 = concat([window.mean()], axis=1)
df9.columns = ['9 month mean price']
df['9 month mean'] = df9.values

# Calculate 12 month mean of price
width = 12
lag1 = dfp.shift(1)
lag3 = dfp.shift(width - 1)
window = lag1.rolling(window=width)
df12 = concat([window.mean()], axis=1)
df12.columns = ['12 month mean price']
df['12 month mean'] = df12.values

df.dropna(axis=0,inplace=True)
```

In [9]:

```
# Description of dataset

actual_df = df
print('Shape:',df.shape)
print('\nColumns:',df.columns)
print('\nDatatypes:',df.dtypes)
display(df.describe(include="all").T)
```

```
Shape: (7369, 13)

Columns: Index(['month', 'year', 'price', 'date', 'co2', 'temperat
ure', 'inflation',
       'consumer_price_index', 'rainfall', '3 month mean', '6 mont
h mean',
       '9 month mean', '12 month mean'],
      dtype='object')

Datatypes: month                            int64
year                            int64
price                         float64
date                   datetime64[ns]
co2                           float64
temperature                   float64
inflation                     float64
consumer_price_index          float64
rainfall                      float64
3 month mean                  float64
6 month mean                  float64
9 month mean                  float64
12 month mean                 float64
dtype: object
```

	count	unique	top	freq	first	last	mean	
month	7369	NaN	NaN	NaN	NaN	NaN	6.34957	3.
year	7369	NaN	NaN	NaN	NaN	NaN	2008.87	6.
price	7369	NaN	NaN	NaN	NaN	NaN	19.6229	8.
date	7369	275	2017-01-01 00:00:00	59	1994-01-01 00:00:00	2017-06-01 00:00:00	NaN	N
co2	7369	NaN	NaN	NaN	NaN	NaN	1744.13	55
temperature	7369	NaN	NaN	NaN	NaN	NaN	25.4841	4.
inflation	7369	NaN	NaN	NaN	NaN	NaN	7.15222	2.
consumer_price_index	7369	NaN	NaN	NaN	NaN	NaN	104.009	40
rainfall	7369	NaN	NaN	NaN	NaN	NaN	85.1589	89
3 month mean	7369	NaN	NaN	NaN	NaN	NaN	19.6173	8.
6 month mean	7369	NaN	NaN	NaN	NaN	NaN	19.6133	8.
9 month mean	7369	NaN	NaN	NaN	NaN	NaN	19.6094	8.
12 month mean	7369	NaN	NaN	NaN	NaN	NaN	19.6056	8.

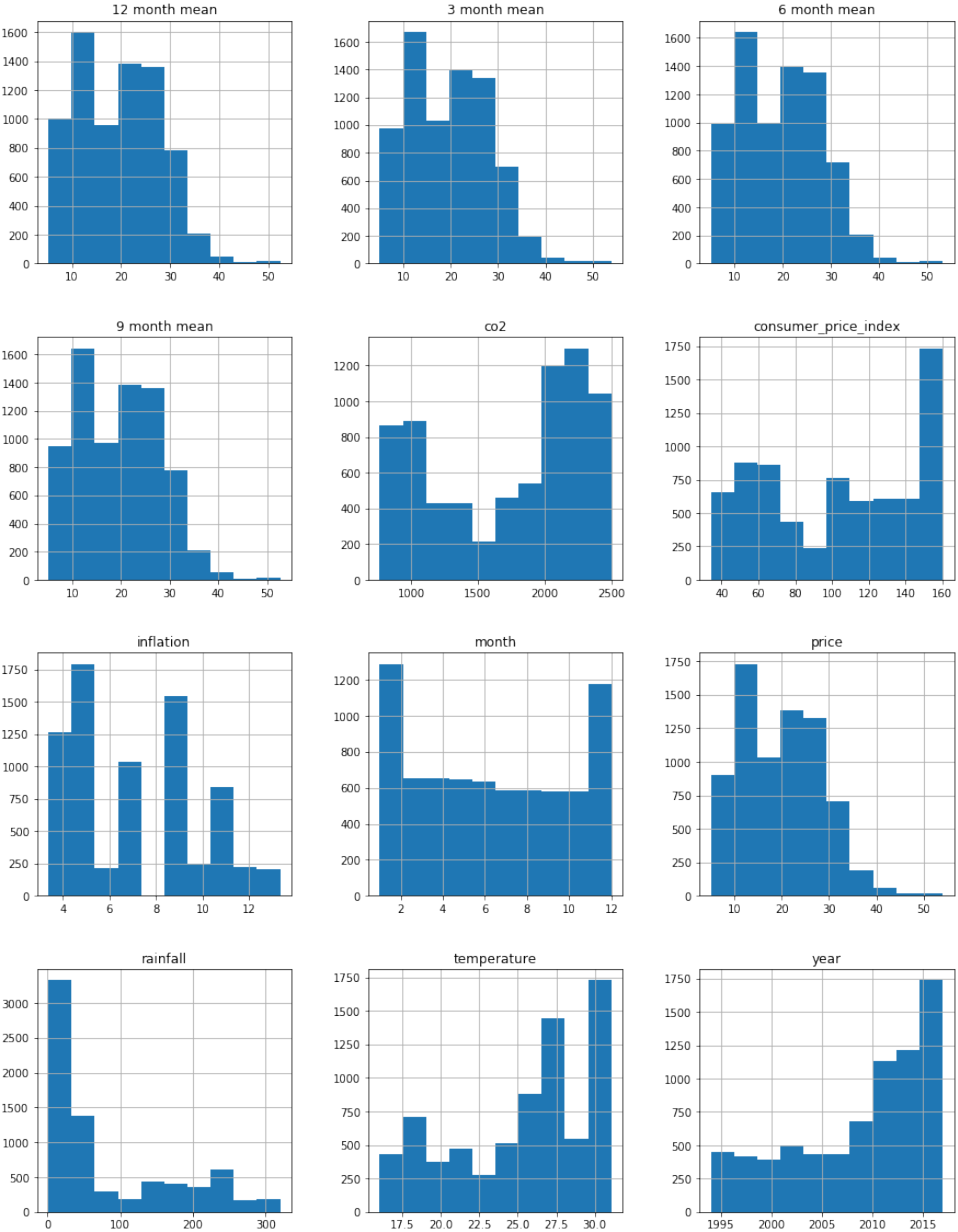
In [11]:

```
# Plot histogram of dataset

fig = plt.figure(figsize = (15,20))
ax = fig.gca()
df.hist(ax=ax)
```

```
D:\Anaconda\lib\site-packages\IPython\core\interactiveshell.py:296
1: UserWarning: To output multiple subplots, the figure containing
the passed axes is being cleared
  exec(code_obj, self.user_global_ns, self.user_ns)
```

Out[11]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC0A35BA8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC1080FD0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC10B06A0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC10D6D30>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC110A400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC110A438>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC132C940>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC1353FD0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC13846A0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC13ADD30>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC13DD400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012
DC1405A90>]],
      dtype=object)
```


12 month mean
3 month mean
6 month mean
9 month mean
co2
consumer_price_index
inflation
month
price
rainfall
temperature
year

In [6]:

```
# Calculate qcut which will be a label to indicate the percentage change in pr
ice

qcut = pd.qcut((df.price.sort_values(ascending=True).values), 10,labels=[1,2,3
,4,5,6,7,8,9,10])
print(qcut)
df.sort_values(by=['price'], inplace=True)
df['label'] = qcut
df.sort_index(inplace=True)
df.dropna(axis=0,inplace=True)
```

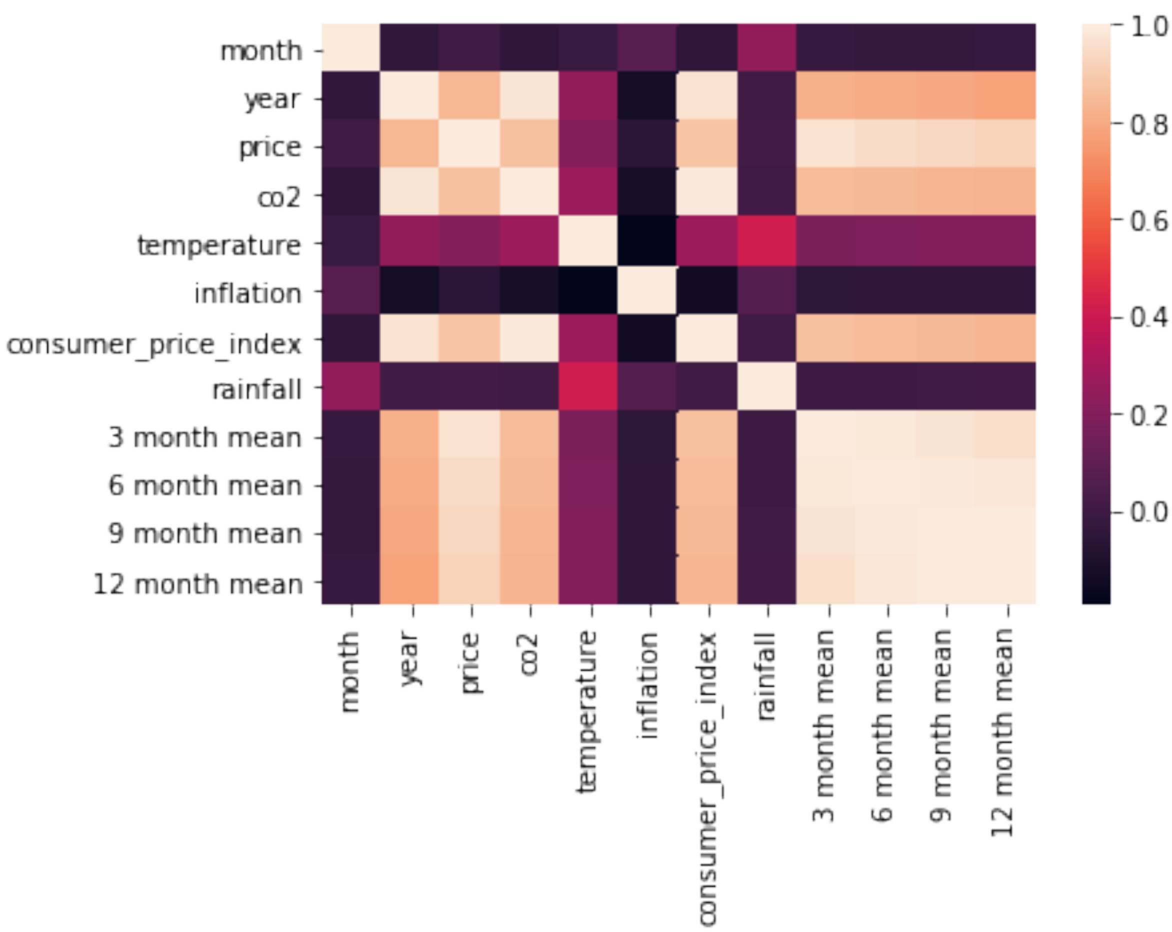
```
[1, 1, 1, 1, 1, ..., 10, 10, 10, 10, 10]
Length: 7381
Categories (10, int64): [1 < 2 < 3 < 4 ... 7 < 8 < 9 < 10]
```

In [13]:

```
# Plot correlation matrix plot

correlations = df.corr()
sns.heatmap(correlations, xticklabels=correlations.columns.values, yticklabels
=correlations.columns.values)
```

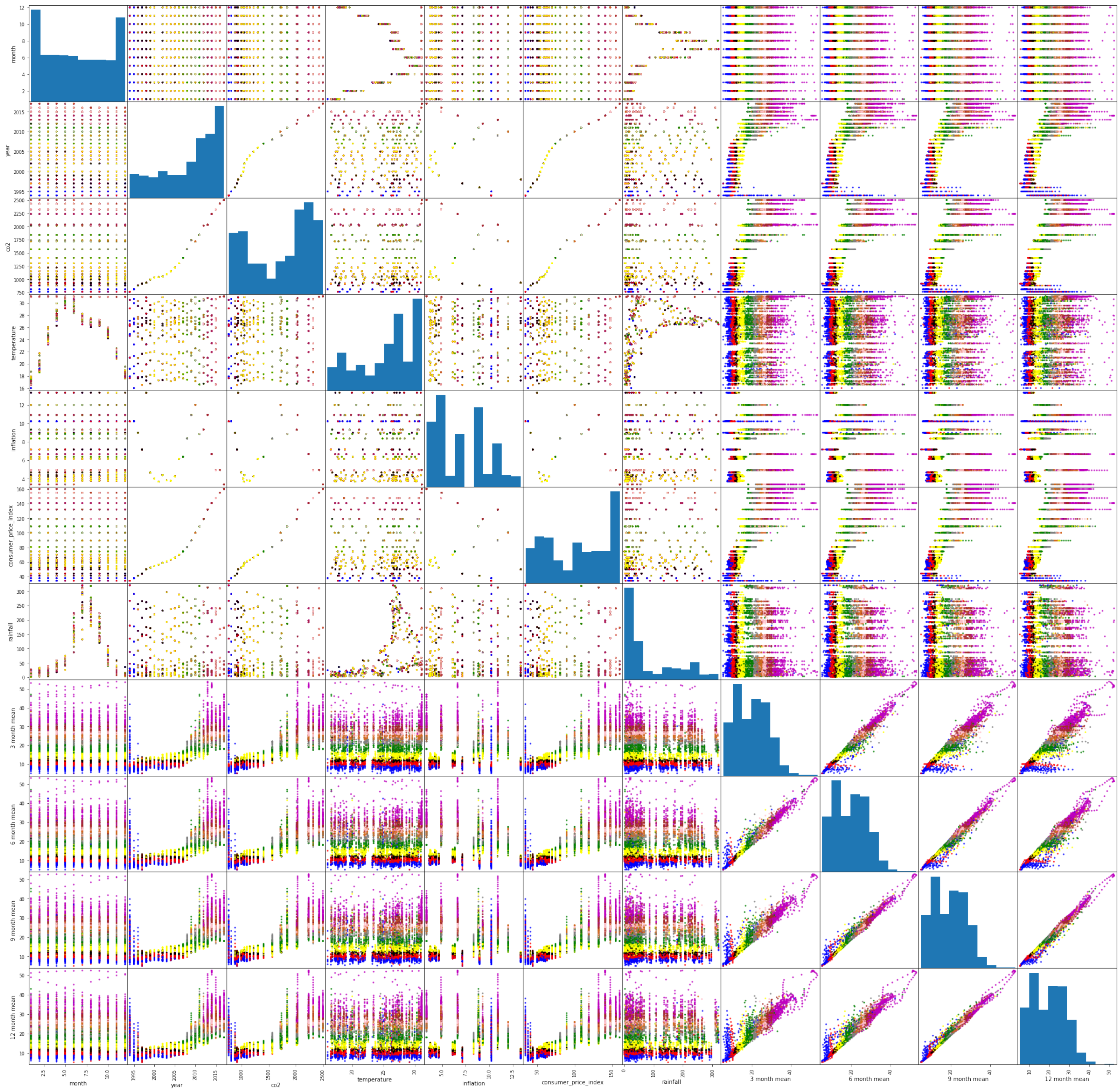
Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x12dc16650b8>
```



In [14]:

```
# Plot scatter matrix of the dataset

df.drop(columns=['date','price'],inplace=True)
palette = {1 : 'blue', 2 : 'red',3:'black',4:'yellow',5:'green',6:'gray',7:'ch
ocolate',8:'pink',9:'brown',10:'m'}
labels=df['label']
labels_c = list(map(lambda x: palette[int(x)], labels))
grr = pd.plotting.scatter_matrix(df,figsize=(35,35), alpha=0.8, c=labels_c)
```



In [16]:

```
#Standardizing data for Gaussian distribution

array = df.values
# separate array into input and output components
cols = 11
X = array[:,:cols]
Y = array[:,cols]
scaler = StandardScaler().fit(X)
X = scaler.transform(X)

# summarize transformed data
np.set_printoptions(precision=3)
print(X[0:5,:])

# split train and test data
test_size = 0.33
seed = 7
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=test_size,
random_state=seed)
Y_train = Y_train.astype('int')
Y_test = Y_test.astype('int')
actual = Y_test
```

```
[[-1.26  -1.786 -1.48  -1.483  0.004 -1.471 -0.906 -1.344 -1.317 -
1.326
  -1.345]
 [-0.97  -1.786 -1.48  -0.337  0.004 -1.471 -0.772 -1.364 -1.327 -
1.329
  -1.34 ]
 [-0.681 -1.786 -1.48   0.169  0.004 -1.471 -0.523 -1.344 -1.337 -
1.329
  -1.34 ]
 [-0.391 -1.786 -1.48   0.803  0.004 -1.471 -0.491 -1.304 -1.337 -
1.329
  -1.338]
 [-0.101 -1.786 -1.48   0.799  0.004 -1.471  0.715 -1.285 -1.337 -
1.329
  -1.335]]

D:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: Dat
aConversionWarning: Data with input dtype object was converted to
float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
D:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: Dat
aConversionWarning: Data with input dtype object was converted to
float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

In [17]:

```
# Gaussian NB model

Y = Y.astype('int')
kfold = KFold(n_splits=10, random_state=7)
model = GaussianNB()
model.fit(X_train,Y_train)
results = cross_val_score(model, X, Y, cv=kfold, scoring='accuracy')
print('Gaussian NB model Accuracy:\nMean=',round(results.mean()*100,3), '%\tSt
d deviation=',round(results.std()*100,3), '%')

prediction = model.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
Gaussian NB model Accuracy:
Mean= 62.952 %  Std deviation= 5.199 %

   precision    recall    fscore    support
-----------  --------  --------  ---------
   0.849057  0.54      0.660147        250
   0.674129  0.818731  0.739427        331
   0.528926  0.825806  0.644836        155
   0.746914  0.461832  0.570755        262
   0.625731  0.730375  0.674016        293
   0.559585  0.404494  0.469565        267
   0.484429  0.608696  0.539499        230
   0.450292  0.442529  0.446377        174
   0.633758  0.802419  0.708185        248
   0.873418  0.621622  0.726316        222
```

In [18]:

```
# Decision Tree Classifier model

clf = DecisionTreeClassifier()
clf.fit(X_train, Y_train)
kfold = KFold(n_splits=10, random_state=7)
model = DecisionTreeClassifier()
model.fit(X_train,Y_train)
results = cross_val_score(model, X, Y, cv=kfold, scoring='accuracy')
print('Decision Tree Classifier Accuracy:\nMean=',round(results.mean()*100,3),
'%\tStd deviation= ',round(results.std()*100,3), '%')

prediction = model.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
Decision Tree Classifier Accuracy:
Mean= 68.354 %  Std deviation=  3.637 %

   precision    recall    fscore    support
-----------  --------  --------  ---------
   0.818584  0.74      0.777311        250
   0.727794  0.767372  0.747059        331
   0.616438  0.580645  0.598007        155
   0.758865  0.816794  0.786765        262
   0.785714  0.788396  0.787053        293
   0.707317  0.651685  0.678363        267
   0.620087  0.617391  0.618736        230
   0.613402  0.683908  0.646739        174
   0.726908  0.729839  0.72837         248
   0.820276  0.801802  0.810934        222
```

In [19]:

```
# SVC model

alphas = np.array([1,0.1,0.01,0.001,0.0001,0])
param_grid = [
  {'C': [1, 10, 100, 1000], 'kernel': ['linear']},
  {'C': [1, 10, 100, 1000], 'gamma': [0.001, 0.0001], 'kernel': ['rbf']},
 ]
model = SVC()
grid = GridSearchCV(estimator=model, param_grid=param_grid)
grid.fit(X_train, Y_train)
print(grid.best_params_)
print('SVC model Accuracy:',grid.best_score_*100)

prediction = grid.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
{'C': 1000, 'gamma': 0.001, 'kernel': 'rbf'}
SVC model Accuracy: 76.88879886570791

   precision    recall    fscore    support
-----------  --------  --------  ---------
   0.88835   0.732     0.802632        250
   0.76781   0.879154  0.819718        331
   0.769737  0.754839  0.762215        155
   0.821561  0.843511  0.832392        262
   0.812057  0.78157   0.796522        293
   0.735178  0.696629  0.715385        267
   0.649402  0.708696  0.677755        230
   0.678788  0.643678  0.660767        174
   0.733096  0.830645  0.778828        248
   0.907216  0.792793  0.846154        222
```

In [20]:

```
# Logistic Regression model

kfold = KFold(n_splits=10, random_state=7)
model = LogisticRegression()
model.fit(X_train,Y_train)
results = cross_val_score(model, X, Y, cv=kfold)
print('Logistic Regression model Accuracy:\nMean=',round(results.mean()*100,3)
, '%\tStd deviation= ',round(results.std()*100,3), '%')

prediction = model.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
Logistic Regression model Accuracy:
Mean= 45.922 %  Std deviation=  6.39 %

   precision    recall    fscore    support
-----------  --------  --------  ---------
   0.644737  0.588     0.615063        250
   0.485944  0.731118  0.583836        331
   0         0         0               155
   0.362264  0.366412  0.364326        262
   0.434615  0.771331  0.555966        293
   0.490909  0.202247  0.286472        267
   0.342857  0.156522  0.214925        230
   0         0         0               174
   0.405896  0.721774  0.519594        248
   0.770751  0.878378  0.821053        222
```

In [21]:

```
# Linear Discrimination model

num_folds = 10
kfold = KFold(n_splits=10, random_state=7)
model = LinearDiscriminantAnalysis()
model.fit(X_train,Y_train)
results = cross_val_score(model,X, Y, cv=kfold)
print('Linear Discrimination model Accuracy:\nMean=',round(results.mean()*100,
3), '%\tStd deviation= ',round(results.std()*100,3), '%')

prediction = model.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
Linear Discrimination model Accuracy:
Mean= 51.744 %  Std deviation=  4.474 %

   precision     recall    fscore    support
-----------  ---------  --------  ---------
   0.560137  0.652      0.602588        250
   0.51      0.616314   0.55814         331
   0.230769  0.0967742  0.136364        155
   0.505208  0.370229   0.427313        262
   0.555838  0.74744    0.637555        293
   0.369792  0.265918   0.309368        267
   0.456835  0.552174   0.5             230
   0.525773  0.293103   0.376384        174
   0.600559  0.866935   0.709571        248
   0.921212  0.684685   0.78553         222

D:\Anaconda\lib\site-packages\sklearn\discriminant_analysis.py:442
: UserWarning: The priors do not sum to 1. Renormalizing
  UserWarning)
D:\Anaconda\lib\site-packages\sklearn\discriminant_analysis.py:442
: UserWarning: The priors do not sum to 1. Renormalizing
  UserWarning)
D:\Anaconda\lib\site-packages\sklearn\discriminant_analysis.py:442
: UserWarning: The priors do not sum to 1. Renormalizing
  UserWarning)
```

In [22]:

```
# KNeighborsClassifier model

num_folds = 10
kfold = KFold(n_splits=10, random_state=7)
model = KNeighborsClassifier(n_neighbors=15)
model.fit(X_train,Y_train)
results = cross_val_score(model, X, Y, cv=kfold)
print('KNeighborsClassifier model Accuracy:\nMean=',round(results.mean()*100,3
), '%\tStd deviation= ',round(results.std()*100,3), '%')

prediction = model.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
KNeighborsClassifier model Accuracy:
Mean= 63.129 %  Std deviation=  3.599 %

  precision    recall    fscore    support
-----------  --------  --------  ---------
   0.743961  0.616     0.673961        250
   0.582589  0.78852   0.67009         331
   0.5       0.303226  0.37751         155
   0.694561  0.633588  0.662675        262
   0.629179  0.706485  0.665595        293
   0.556017  0.501873  0.527559        267
   0.454225  0.56087   0.501946        230
   0.5       0.33908   0.40411         174
   0.623333  0.754032  0.682482        248
   0.860465  0.666667  0.751269        222
```

In [23]:

```
# Bagging Classifier model

seed = 7
kfold = KFold(n_splits=10, random_state=seed)
cart = DecisionTreeClassifier()
num_trees = 130
model = BaggingClassifier(base_estimator=cart, n_estimators=num_trees,max_feat
ures = 5, random_state=seed)
model.fit(X_train,Y_train)
results = cross_val_score(model, X, Y, cv=kfold)
print('Bagging Classifier Accuracy:\nMean=',round(results.mean()*100,3), '%\tS
td deviation= ',round(results.std()*100,3), '%')

prediction = model.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
Bagging Classifier Accuracy:
Mean= 75.424 %  Std deviation=  2.271 %

   precision    recall    fscore    support
-----------  --------  --------  ---------
   0.868644  0.82      0.843621        250
   0.792507  0.830816  0.811209        331
   0.742857  0.670968  0.705085        155
   0.8125    0.89313   0.850909        262
   0.8157    0.8157    0.8157          293
   0.746888  0.674157  0.708661        267
   0.663934  0.704348  0.683544        230
   0.692308  0.672414  0.682216        174
   0.745455  0.826613  0.783939        248
   0.894472  0.801802  0.845606        222
```

In [24]:

```
# Random forest classifier model

num_trees = 150
max_features = 6
kfold = KFold(n_splits=10, random_state=7)
model = RandomForestClassifier(n_estimators=num_trees, max_features=max_featur
es)
model.fit(X_train, Y_train)
results = cross_val_score(model, X, Y, cv=kfold)
print('Random forest classifier Accuracy:\nMean=',round(results.mean()*100,3),
'%\tStd deviation= ',round(results.std()*100,3), '%')

prediction = model.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
Random forest classifier Accuracy:
Mean= 77.731 %  Std deviation=  2.442 %

   precision    recall    fscore    support
-----------  --------  --------  ---------
   0.869748  0.828     0.848361        250
   0.8       0.833837  0.816568        331
   0.730496  0.664516  0.695946        155
   0.826241  0.889313  0.856618        262
   0.844595  0.853242  0.848896        293
   0.800885  0.677903  0.73428         267
   0.674419  0.756522  0.713115        230
   0.691011  0.706897  0.698864        174
   0.762846  0.778226  0.770459        248
   0.874419  0.846847  0.860412        222
```

In [25]:

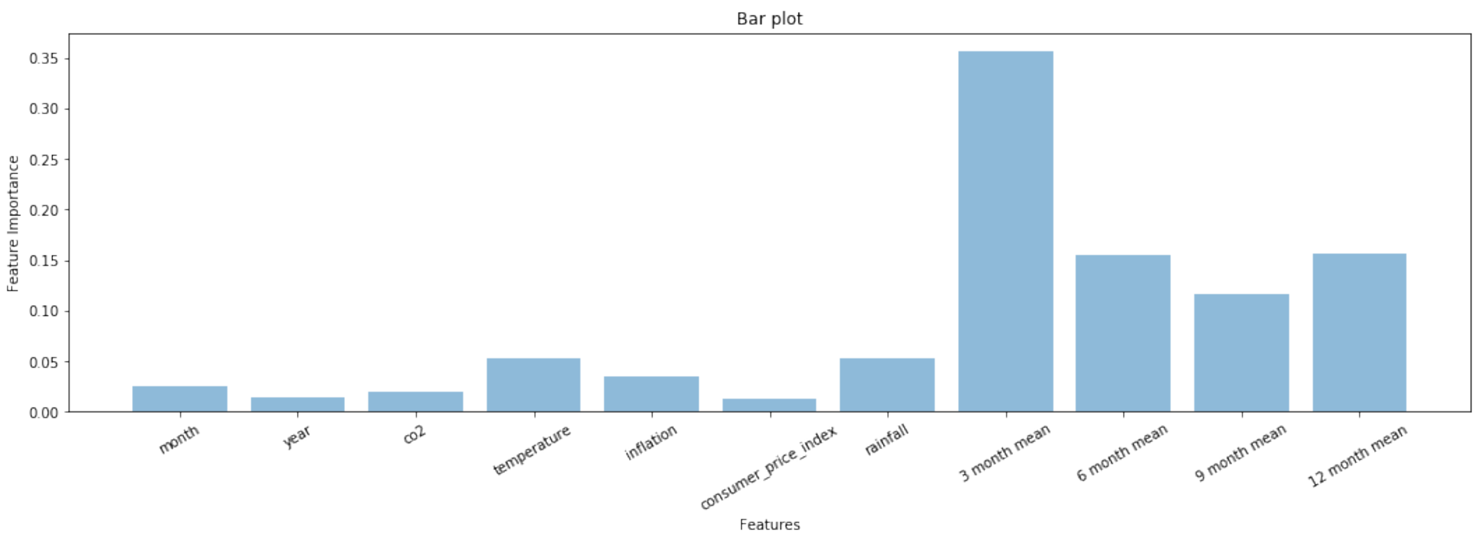
```
# Gradient Boosting Classifier model

seed = 7
num_trees = 100
kfold = KFold(n_splits=10, random_state=seed)
model = GradientBoostingClassifier(n_estimators=num_trees, random_state=seed)
model.fit(X_train,Y_train)
results = cross_val_score(model, X, Y, cv=kfold)
print('Gradient Boosting Classifier Accuracy:\nMean=',round(results.mean()*100
,3), '%\tStd deviation= ',round(results.std()*100,3), '%')

prediction = model.predict(X_test)
precision,recall,fscore,support = metrics.precision_recall_fscore_support(actu
al,prediction,average=None)
results = {"precision":precision,"recall":recall,"fscore":fscore,"support" : s
upport}
print("\n",tabulate(results,headers="keys"))
```

```
Gradient Boosting Classifier Accuracy:
Mean= 78.423 %  Std deviation=  2.679 %

   precision    recall    fscore    support
-----------  --------  --------  ---------
   0.882096  0.808     0.843424        250
   0.788301  0.854985  0.82029         331
   0.774436  0.664516  0.715278        155
   0.816901  0.885496  0.849817        262
   0.857143  0.83959   0.848276        293
   0.784483  0.681648  0.729459        267
   0.660079  0.726087  0.691511        230
   0.674033  0.701149  0.687324        174
   0.742424  0.790323  0.765625        248
   0.857143  0.810811  0.833333        222
```

In [26]:

```
# Feature importances for Gradient Boosting Classifier model

print('\nFeature importances:',model.feature_importances_)
y_pos = np.arange(cols)
x = model.feature_importances_
f, ax = plt.subplots(figsize=(18,5))
plt.bar(y_pos, x, width=0.8,align='center', alpha=0.5)
plt.title('Bar plot')
plt.xticks(y_pos, df.columns,fontsize=10,rotation=30)
plt.ylabel('Feature Importance')
plt.xlabel('Features')
plt.show()
```

```
Feature importances: [0.026 0.014 0.02  0.054 0.034 0.014 0.053 0.
357 0.155 0.117 0.157]
```



In [ ]: