```
In [62]: import pandas as pd
import statsmodels.api as sm
           import matplotlib.pyplot as plt
 In [18]: data = pd.read csv("EE627A HW1 Data.csv")
           df = pd.DataFrame(data, columns = ['Mkt-RF','SMB','HML','Mom'])
           df.corr()
 Out[18]:
                    Mkt-RF
                              SMB
                                      HML
                                                Mom
           Mkt-RF 1.000000 0.326863 0.216145 -0.338343
             SMB 0.326863 1.000000 0.094113 -0.164023
            HML 0.216145 0.094113 1.000000 -0.400635
             Mom -0.338343 -0.164023 -0.400635 1.000000
In [22]: df1 = pd.DataFrame(data)
         pd.DataFrame(corr, columns=['Mkt-RF','SMB','HML','Mom'])
Out[22]:
           Date -0.015422 -0.016286 0.011771 0.019824
           Mkt-RF 1.000000 0.326863 0.216145 -0.338343
          SMB 0.326863 1.000000 0.094113 -0.164023
            HML 0.216145 0.094113 1.000000 -0.400635
           RF -0.068723 -0.059640 0.012115 0.039130
            Mom -0.338343 -0.164023 -0.400635 1.000000
          Food 0.835924 0.201698 0.215132 -0.280289
            Beer 0.707673 0.351039 0.214982 -0.200077
           Smoke 0.584268 0.103154 0.171809 -0.219165
           Games 0.830211 0.412089 0.250387 -0.358992
           Books 0.830092 0.408145 0.250608 -0.306399
           Hehld 0.816234 0.261883 0.107373 -0.199683
           Ciths 0.780630 0.460134 0.246719 -0.360482
             Hith 0.804022 0.208896 0.084393 -0.225778
           Cheme 0.883889 0.208012 0.192392 -0.301203
            Txtis 0.823438 0.495356 0.347476 -0.371137
            Cnetr 0.913608 0.401464 0.247212 -0.323221
            Steel 0.867909 0.363120 0.343723 -0.394459
           FabPr 0.925046 0.406788 0.260264 -0.372352
           EICEQ 0.904103 0.257442 0.202407 -0.324623
           Autos 0.843297 0.285971 0.302826 -0.389308
            Carry 0.832370 0.362621 0.337407 -0.343814
           Mines 0.706160 0.343889 0.245741 -0.271214
            Coal 0.490542 0.267311 0.172241 -0.137088
          Oli 0.772597 0.137730 0.302340 -0.249883
             Util 0.761767 0.175149 0.354729 -0.331665
           Telcm 0.755235 0.160554 0.099079 -0.293874
            Serva 0.495806 0.285080 -0.084935 -0.092488
           BusEq 0.842644 0.329809 -0.066278 -0.228394
           Paper 0.869099 0.275653 0.197336 -0.300174
           Trans 0.858688 0.348099 0.430456 -0.423153
            Whisi 0.796012 0.459826 0.209154 -0.260379
           Rtall 0.858747 0.302931 0.114997 -0.309388
            Media 0.753859 0.368637 0.163557 -0.250813
           Fin 0.915884 0.282586 0.324566 -0.420421
            Other 0.842008 0.423908 0.165099 -0.290321
```

From the above correlation matrix, I infer that market risk free factor correlates highly with every industry. Momentum correlates most negatively with every industry. While RF (risk free rate) correlates negatively for most of the industries

```
In [89]: lagged_data_mkt_RF = pd.Series(sm.tsa.acf(data['Mkt-RF'],nlags = 10))
           lagged_data_SMB = pd.Series(sm.tsa.acf(data['SMB'],nlags = 10))
lagged_data_HML = pd.Series(sm.tsa.acf(data['HML'],nlags = 10))
            lagged_data_momentum = pd.Series(sm.tsa.acf(data['Mom'],nlags = 10))
           print("Mkt-RF",'\n',lagged_data_mkt_RF[1:],'\n')
print("SMB",'\n',lagged_data_SMB[1:],'\n')
print("HML",'\n',lagged_data_HML[1:],'\n')
print("Momentum",'\n',lagged_data_momentum[1:],'\n')
           Mkt-RF
                   0.107165
            1
                  -0.016334
                  -0.108150
                   0.005641
                   0.070126
                  -0.020113
                   0.012570
                   0.036685
                   0.081705
            10
                   0.018962
            dtype: float64
            SMB
                    0.075347
                   0.059214
           3
                  -0.054104
           4
                  -0.031584
                  -0.053806
                   0.009881
                   0.022554
                   0.026380
           8
                   0.083590
            10
                   0.024877
           dtype: float64
           HML
                    0.178028
            1
                  -0.013279
                  -0.031619
           4
                  -0.080457
                  -0.061377
                   0.007784
                   0.064510
                  -0.002250
                   0.114856
            10
                  0.026137
           dtype: float64
           Momentum
                   0.057801
            1
                  -0.077419
                  -0.049174
                  -0.038990
                  0.051111
                  -0.036235
                  -0.015936
                   0.012242
            10
                 -0.044102
           dtype: float64
```

Referring the above Autocorrelation vs lag for each factor. I conclude Momentum factor to be AR (1) model. Also, I observed that higher the correlation, higher will be the order of ACF. That is, we can consider more observations from the past to predict present of the highly correlated features.

```
In [77]: #Visualization
    flag = True
    if flag:
        plt.plot(lagged_data_mkt_RF,label = 'Mkt_RF')
        plt.plot(lagged_data_SMB, label = 'SMB')
        plt.plot(lagged_data_HML, label = 'HML')
        plt.plot(lagged_data_momentum, label = 'Momentum')
    plt.ylabel('values')
    plt.xlabel('lags')
    plt.legend(loc = 'upper right')
```

## Out[77]: cmatplotlib.legend.Legend at 0x1e92625e9e8>

