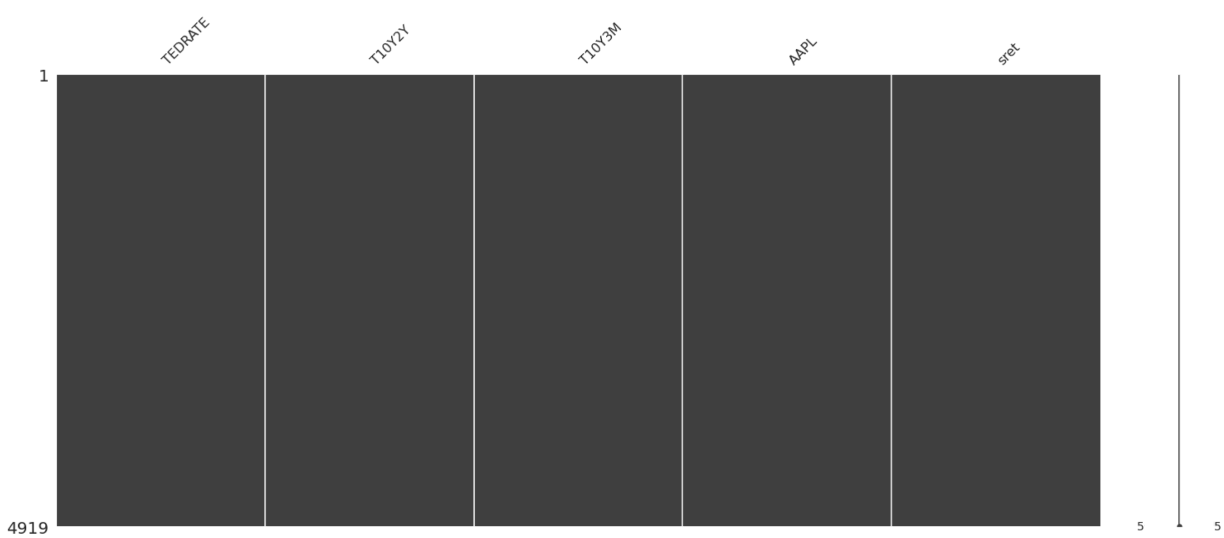
In [ ]:
```
##Regime Detection of Apple
```

In [2]:
```
import pandas as pd
import pandas_datareader.data as web
import sklearn.mixture as mix

import numpy as np
import scipy.stats as scs

import matplotlib as mpl
from matplotlib import cm
import matplotlib.pyplot as plt
from matplotlib.dates import YearLocator, MonthLocator
%matplotlib inline

import seaborn as sns
import missingno as msno
from tqdm import tqdm
p=print
import datetime
```

In [29]:
```
# get fed data

f1 = 'TEDRATE' # ted spread
f2 = 'T10Y2Y' # constant maturity ten yer - 2 year
f3 = 'T10Y3M' # constant maturity 10yr - 3m

start = pd.to_datetime('2002-01-01')
end = pd.datetime.today()

mkt = 'AAPL'
MKT = (web.DataReader([mkt], 'yahoo', start, end)['Adj Close']
       .rename(columns={mkt:mkt})
       .assign(sret=lambda x: np.log(x[mkt]/x[mkt].shift(1)))
       .dropna())

data = (web.DataReader([f1, f2, f3], 'fred', start, end)
        .join(MKT, how='inner')
        .dropna()
       )

p(data.head())

# gives us a quick visual inspection of the data
msno.matrix(data)
```

```
C:\Users\HP\AppData\Local\Temp/ipykernel_11804/1187959211.py:8: FutureWarning:
The pandas.datetime class is deprecated and will be removed from pandas in a fu
ture version. Import from datetime module instead.
  end = pd.datetime.today()

            TEDRATE  T10Y2Y  T10Y3M      AAPL      sret
2002-01-03     0.18    1.97    3.43  0.360552  0.011946
2002-01-04     0.18    1.99    3.46  0.362235  0.004656
2002-01-07     0.21    2.01    3.41  0.350155 -0.033916
2002-01-08     0.19    2.03    3.42  0.345721 -0.012746
2002-01-09     0.19    2.07    3.42  0.331042 -0.043387
```

Out[29]: <AxesSubplot:>



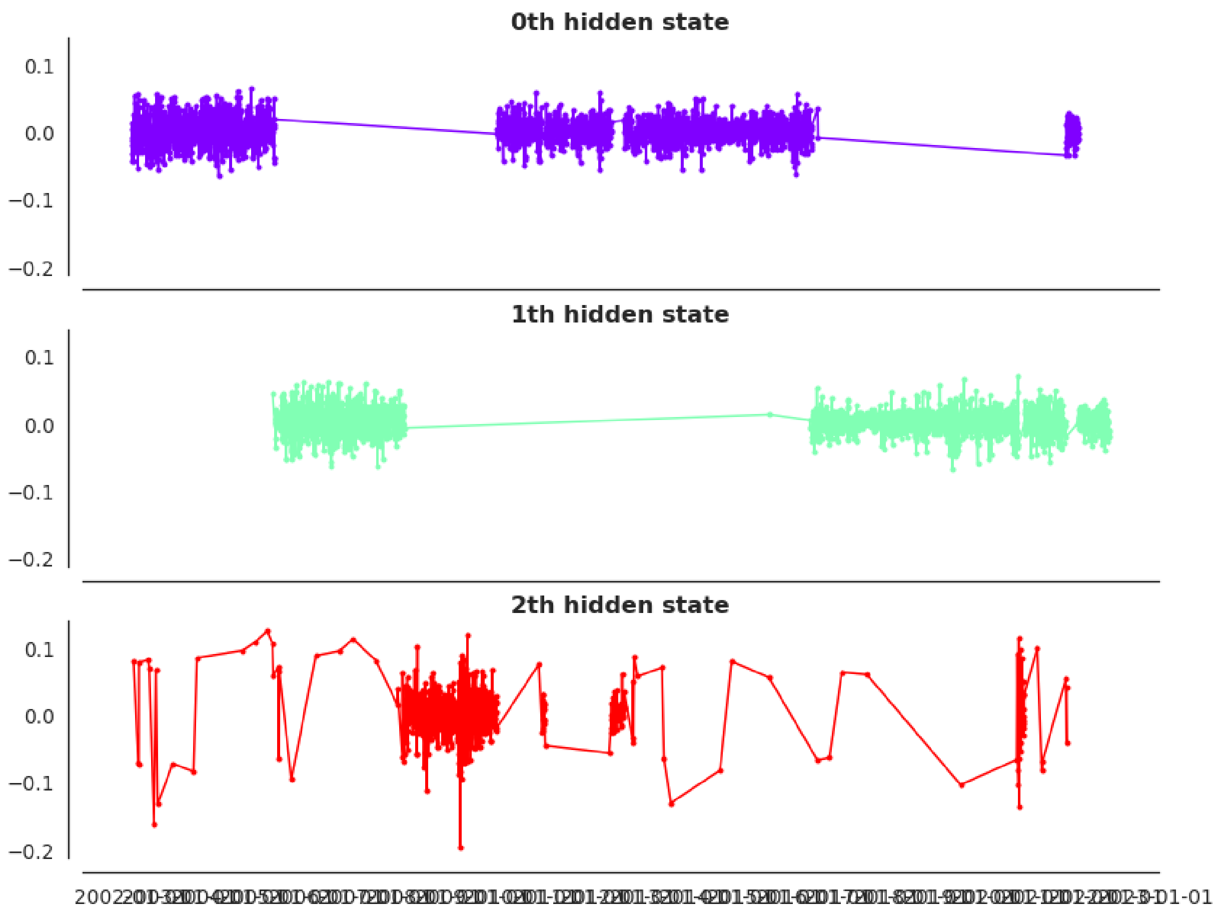
Next we will use the sklearn's GaussianMixture to fit a model that estimates these regimes. We will explore mixture models in more depth in part 2 of this series. The important takeaway is that mixture models implement a closely related unsupervised form of density estimation. It makes use of the expectation-maximization algorithm to estimate the means and covariances of the hidden states (regimes). For now, it is ok to think of it as a magic button for guessing the transition and emission probabilities, and most likely path.

We have to specify the number of components for the mixture model to fit to the time series. In this example the components can be thought of as regimes. We will arbitrarily classify the regimes as High, Neutral and Low Volatility and set the number of components to three.

```
In [11]: # code adapted from http://hmmlearn.readthedocs.io
         # for sklearn 18.1

         col = 'sret'
         select = data.loc[:].dropna()

         ft_cols = [f1, f2, f3, 'sret']
         X = select[ft_cols].values

         model = mix.GaussianMixture(n_components=3,
                                     covariance_type="full",
                                     n_init=100,
                                     random_state=7).fit(X)

         # Predict the optimal sequence of internal hidden state
         hidden_states = model.predict(X)

         print("Means and vars of each hidden state")
         for i in range(model.n_components):
             print("{0}th hidden state".format(i))
             print("mean = ", model.means_[i])
             print("var = ", np.diag(model.covariances_[i]))
             print()

         sns.set(font_scale=1.25)
         style_kwds = {'xtick.major.size': 1, 'ytick.major.size': 1,
                       'font.family':u'courier prime code', 'legend.frameon': True}
         sns.set_style('white', style_kwds)

         fig, axs = plt.subplots(model.n_components, sharex=True, sharey=True, figsize=(12
         colors = cm.rainbow(np.linspace(0, 1, model.n_components))

         for i, (ax, color) in enumerate(zip(axs, colors)):
             # Use fancy indexing to plot data in each state.
             mask = hidden_states == i
             ax.plot_date(select.index.values[mask],
                          select[col].values[mask],
                          ".-", c=color)
             ax.set_title("{0}th hidden state".format(i), fontsize=16, fontweight='demi')

             # Format the ticks.
             ax.xaxis.set_major_locator(YearLocator())
             ax.xaxis.set_minor_locator(MonthLocator())
             sns.despine(offset=10)
         plt.tight_layout()
         fig.savefig('Hidden Markov (Mixture) Model_Regime Subplots.png')
```

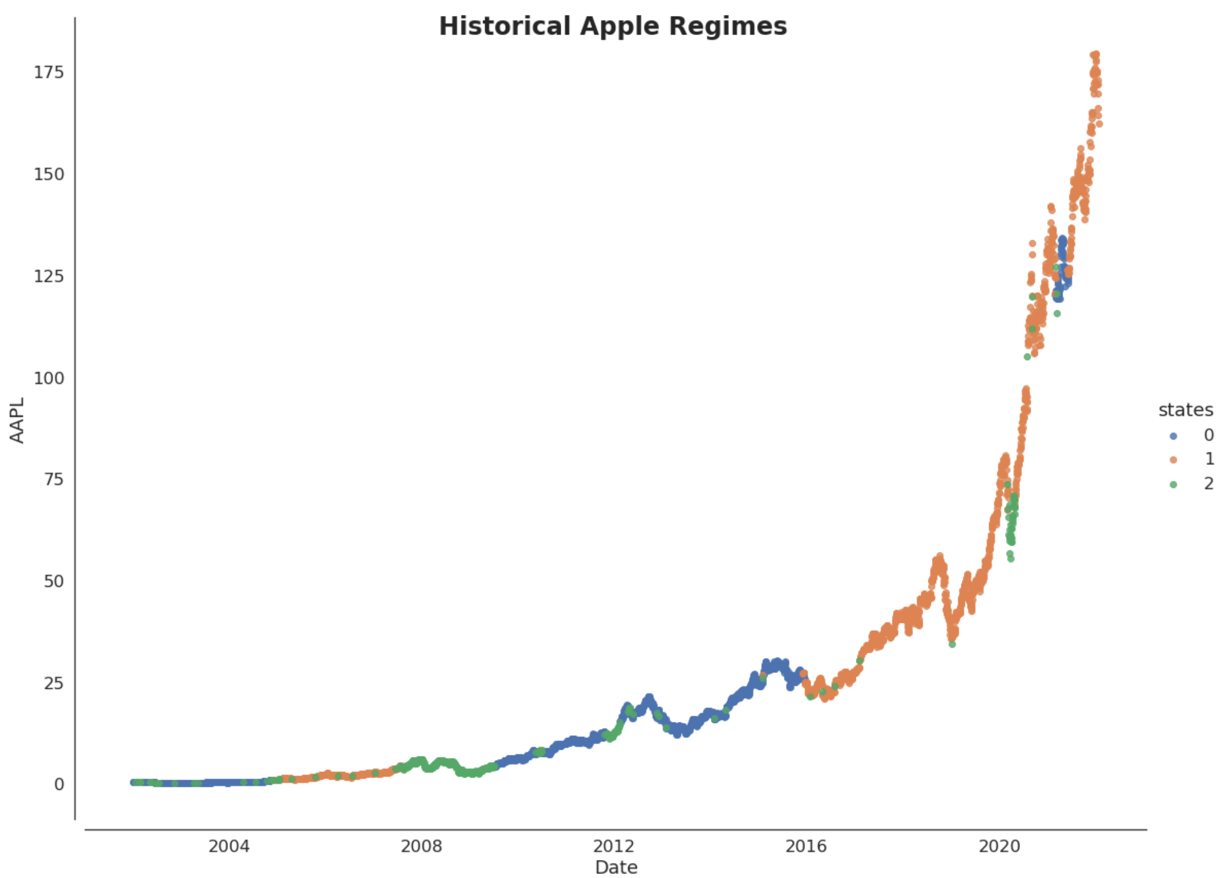
```
Means and vars of each hidden state
0th hidden state
mean =  [2.27723730e-01 2.04021876e+00 2.61233184e+00 7.91014566e-04]
var =  [4.30395204e-03 2.23040090e-01 4.07274702e-01 3.23204848e-04]

1th hidden state
mean =  [0.33897944 0.5236647  0.784171   0.00148548]
var =  [2.29812766e-02 1.99146324e-01 5.02041373e-01 3.08223754e-04]
```

```
2th hidden state
mean =  [1.06616393e+00 1.48817728e+00 1.95472199e+00 9.05984448e-04]
var =  [0.51434304 0.39514382 0.88054745 0.00138042]
```



In [12]:
```
sns.set(font_scale=1.5)
states = (pd.DataFrame(hidden_states, columns=['states'], index=select.index)
          .join(select, how='inner')
          .assign(mkt_cret=select.sret.cumsum())
          .reset_index(drop=False)
          .rename(columns={'index':'Date'}))
p(states.head())

sns.set_style('white', style_kwds)
order = [0, 1, 2]
fg = sns.FacetGrid(data=states, hue='states', hue_order=order, aspect=1.31, size=
fg.map(plt.scatter, 'Date', mkt, alpha=0.8).add_legend()
sns.despine(offset=10)
fg.fig.suptitle('Historical Apple Regimes', fontsize=24, fontweight='demi')
fg.savefig('Hidden Markov (Mixture) Model_AAPL Regimes.png')
```

```
        Date  states  TEDRATE  T10Y2Y  T10Y3M      AAPL      sret  mkt_cret
0 2002-01-03       0     0.18    1.97    3.43  0.360552  0.011946  0.011946
1 2002-01-04       0     0.18    1.99    3.46  0.362235  0.004656  0.016601
2 2002-01-07       0     0.21    2.01    3.41  0.350155 -0.033916 -0.017315
3 2002-01-08       0     0.19    2.03    3.42  0.345721 -0.012746 -0.030060
4 2002-01-09       0     0.19    2.07    3.42  0.331042 -0.043387 -0.073448

C:\Users\HP\anaconda3\lib\site-packages\seaborn\axisgrid.py:337: UserWarning: T
he `size` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



Finding Equillibrium Matrix

In [3]:
```
start = pd.to_datetime('2002-01-01')
end = pd.datetime.today()

df = web.DataReader("AAPL", 'yahoo', start, end)
df
```

```
C:\Users\HP\AppData\Local\Temp/ipykernel_13232/3560409931.py:2: FutureWarning:
The pandas.datetime class is deprecated and will be removed from pandas in a fu
ture version. Import from datetime module instead.
  end = pd.datetime.today()
```

Out[3]:

	High	Low	Open	Close	Volume	Adj Close
Date						
2002-01-02	0.416071	0.392143	0.393750	0.416071	529496800.0	0.356271
2002-01-03	0.424107	0.406607	0.410714	0.421071	612007200.0	0.360552
2002-01-04	0.427679	0.410536	0.416786	0.423036	409976000.0	0.362235
2002-01-07	0.428571	0.406250	0.423571	0.408929	444584000.0	0.350155
2002-01-08	0.411607	0.401071	0.406250	0.403750	450038400.0	0.345721
...	...	...	...	...	...	...
2022-04-25	163.169998	158.460007	161.119995	162.880005	96046400.0	162.880005
2022-04-26	162.339996	156.720001	162.250000	156.800003	95623200.0	156.800003
2022-04-27	159.789993	155.380005	155.910004	156.570007	88063200.0	156.570007
2022-04-28	164.520004	158.929993	159.250000	163.639999	130216800.0	163.639999
2022-04-29	166.199997	157.250000	161.839996	157.649994	131587100.0	157.649994

5118 rows × 6 columns

In [4]:
```
df["state"]=df["Close"].astype(float).pct_change()
df['state']=df['state'].apply(lambda x: 'Upside' if (x > 0.001) else ('Downside'
df
```

Out[4]:

	High	Low	Open	Close	Volume	Adj Close	state
Date							
2002-01-02	0.416071	0.392143	0.393750	0.416071	529496800.0	0.356271	Consolidation
2002-01-03	0.424107	0.406607	0.410714	0.421071	612007200.0	0.360552	Upside
2002-01-04	0.427679	0.410536	0.416786	0.423036	409976000.0	0.362235	Upside
2002-01-07	0.428571	0.406250	0.423571	0.408929	444584000.0	0.350155	Downside
2002-01-08	0.411607	0.401071	0.406250	0.403750	450038400.0	0.345721	Downside
...	...	...	...	...	...	...	...
2022-04-25	163.169998	158.460007	161.119995	162.880005	96046400.0	162.880005	Upside
2022-04-26	162.339996	156.720001	162.250000	156.800003	95623200.0	156.800003	Downside
2022-04-27	159.789993	155.380005	155.910004	156.570007	88063200.0	156.570007	Downside
2022-04-28	164.520004	158.929993	159.250000	163.639999	130216800.0	163.639999	Upside
2022-04-29	166.199997	157.250000	161.839996	157.649994	131587100.0	157.649994	Downside

5118 rows × 7 columns

In [5]:
```python
df['priorstate']=df['state'].shift(1)
df.tail()
```

Out[5]:

Date	High	Low	Open	Close	Volume	Adj Close	state	priorsta
2022-04-25	163.169998	158.460007	161.119995	162.880005	96046400.0	162.880005	Upside	Downsi
2022-04-26	162.339996	156.720001	162.250000	156.800003	95623200.0	156.800003	Downside	Upsi
2022-04-27	159.789993	155.380005	155.910004	156.570007	88063200.0	156.570007	Downside	Downsi
2022-04-28	164.520004	158.929993	159.250000	163.639999	130216800.0	163.639999	Upside	Downsi
2022-04-29	166.199997	157.250000	161.839996	157.649994	131587100.0	157.649994	Downside	Upsi

Transition Matrix for Markov Chain Model

In [6]:
```python
df["state"]=df["Close"].astype(float).pct_change()
df['state']=df['state'].apply(lambda x: 'Upside' if (x > 0.001) else ('Downside'

df['priorstate']=df['state'].shift(1)

states = df [['priorstate','state']].dropna()
states_matrix = states.groupby(['priorstate','state']).size().unstack().fillna(0)

transition_matrix= states_matrix.apply(lambda x: x/float(x.sum()),axis=1)
print(transition_matrix)
```

```
state          Downside    Upside
priorstate
Consolidation  0.000000  1.000000
Downside       0.495127  0.504873
Upside         0.508036  0.491964
```

In [7]:
```
df["state"]=df["Close"].astype(float).pct_change()
df['state']=df['state'].apply(lambda x: 'Upside' if (x > 0) else 'Downside' )

df['priorstate']=df['state'].shift(1)

states = df [['priorstate','state']].dropna()
states_matrix = states.groupby(['priorstate','state']).size().unstack().fillna(0)

transition_matrix= states_matrix.apply(lambda x: x/float(x.sum()),axis=1)
print(transition_matrix)
```

```
state       Downside    Upside
priorstate
Downside    0.469959  0.530041
Upside      0.479345  0.520655
```

In [8]:
```
t_0 = transition_matrix.copy()
t_1 =t_0.dot(t_0)
t_1
```

Out[8]:

state priorstate	Downside	Upside
Downside	0.474934	0.525066
Upside	0.474846	0.525154

In [9]:
```
t_0 = transition_matrix.copy()
t_1 =t_0.dot(t_0)
t_1
```

Out[9]:

state priorstate	Downside	Upside
Downside	0.474934	0.525066
Upside	0.474846	0.525154

In [ ]:
```
t_0 = transition_matrix.copy()
t_1 =t_0.dot(t_0)
t_365
```

In [ ]:
```
## Equilibrium Matrix using Python
```

In [10]:

```
## Equilibrium Matrix using Python

t_0 = transition_matrix.copy()

t_m = t_0.copy()
t_n = t_0.dot(t_0)

i = 1
while(not(t_m.equals(t_n))):
    i += 1
    t_m = t_n.copy()
    t_n = t_n.dot(t_0)

print("Equilibrium Matrix Number: " + str(i))
print(t_n)
```

```
Equilibrium Matrix Number: 9
state       Downside    Upside
priorstate
Downside    0.474888  0.525112
Upside      0.474888  0.525112
```

The equilibrium Matrix is a stationary state. So, As per the theory of the Markov Chain, This figure will stay the same for foreseeable data points

In [11]:
```
##Random Walk

symbol = "AAPL"
days = 10000
end_date = datetime.datetime.now().strftime("%d-%b-%Y")
end_date = str(end_date)

start_date = (datetime.datetime.now()- datetime.timedelta(days=days)).strftime("%
start_date = str(start_date)

#df=index_history("SPY",start_date,end_date)
df = web.DataReader("AAPL", 'yahoo', start_date, end_date)

df["state"]=df["Close"].astype(float).pct_change()
df['state']=df['state'].apply(lambda x: 'Upside' if (x > 0) else 'Downside' )

df['priorstate']=df['state'].shift(1)

states = df [['priorstate','state']].dropna()
states_matrix = states.groupby(['priorstate','state']).size().unstack().fillna(0)

transition_matrix= states_matrix.apply(lambda x: x/float(x.sum()),axis=1)
t_0 = transition_matrix.copy()

t_m = t_0.copy()
t_n = t_0.dot(t_0)

i = 1
while(not(t_m.equals(t_n))):
    i += 1
    t_m = t_n.copy()
    t_n = t_n.dot(t_0)

print("Equilibrium Matrix Number: " + str(i))
print(t_n)
```

```
Equilibrium Matrix Number: 9
state        Downside    Upside
priorstate
Downside     0.487522  0.512478
Upside       0.487522  0.512478
```

Type *Markdown* and LaTeX: α^2

In [ ]: