Regime detection and prediction in Financial Markets Lesson 2: Application of Gaussian Mixture Model

4 min read · Jul 3, 2022

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Hello guys. Welcome back to the 2nd lesson of Market regime classification/detection in Financial Markets series, presented by T-ballz Finance. Last time I briefly covered K-means clustering method and its application for regime classification in financial markets. This weekend, I am going to walk through an alternative but slightly more conplex method. It's called Gaussian Mixture Model.

When people from academic Finance studied the stock market in the old days, they assumed that the stock market returns follow the Normal distribution. Later on they realized that's certainly not necessarily true. Instead, one can possibly divide the stock returns into different subgroups/regimes but each of them can be normally distributed instead. Gaussian Mixture Model is therefore a useful method for classifying market regimes. Gaussian Mixture model, similar to the family of Markov switching models or finite mixture models, is estimated by maximum likelihood method using the Expectation-Maximization (EM) algorithm. I am not going to cover EM algorithm here as it's not meaningful to go through the math. As a quant trader/investor, most of us are practitioners, we only want to apply these tools to help build our trading strategies so It's enough to just know what these tools are used for and how to apply them, we can skip the underlying theories. (But if you are really interested, you should find some more material and learn the math behind it. There's lots of free material for stats and machine learning online)

For example, for the difference between k-means and GMM, you can check this stackexchange post: clustering — In cluster analysis, how does Gaussian mixture model differ from K Means when we know the clusters are spherical? — Cross Validated (stackexchange.com)

Alright, enough talk, let's get our hands dirty. I'll use the same dataset as last time. Using the yfinance package to download the S&P 500 and VIX data from Yahoo Finance, I calculate the corresponding ATR-Price ratio, relative volume and daily return of S&P 500:

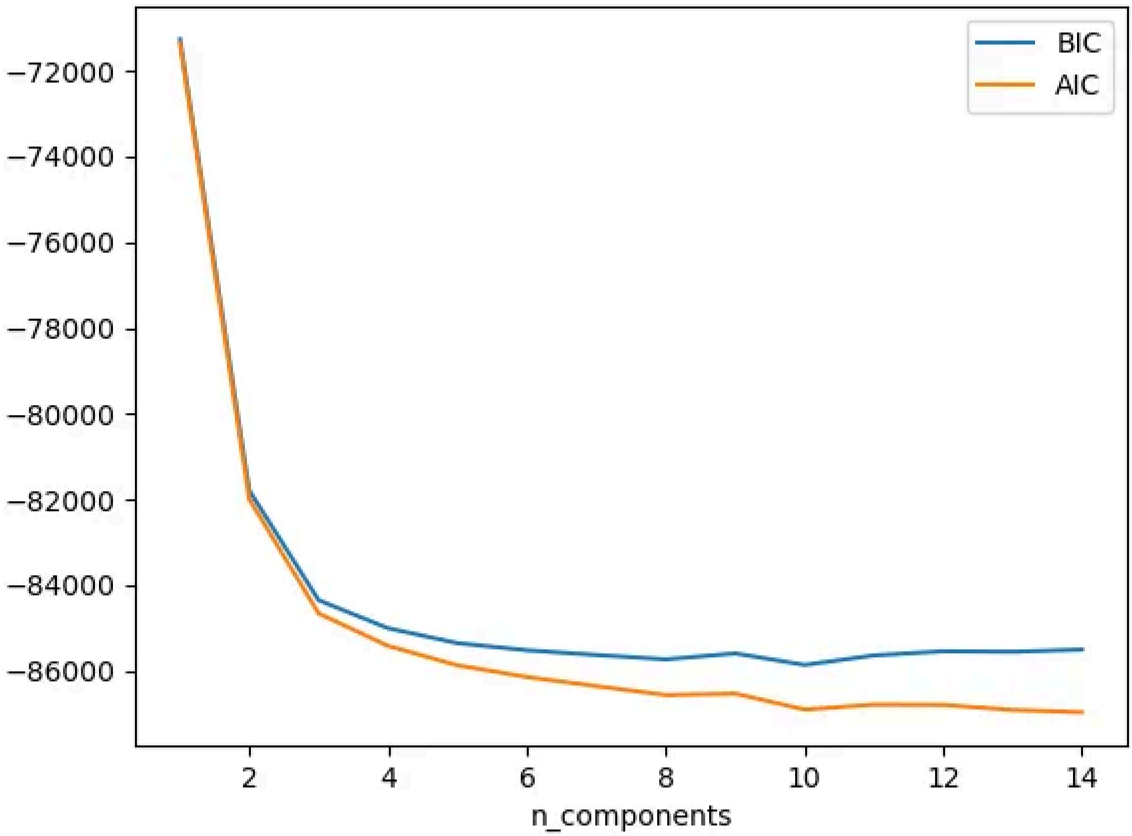
```
import yfinance as yf
import datetime
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import Stock_quant.ATR
import Stock_quant.wwma
from sklearn.mixture import GaussianMixture

pd.set_option('display.max_columns', None)

#Get the data ready
end_time = datetime.date.today()
start_time = end_time - datetime.timedelta(days = 11850)
df = yf.download('^GSPC',start = start_time, end = end_time)
df_replace = yf.download('^GSPC',start = start_time, end = end_time)


VIX = yf.download('^VIX',start = start_time, end = end_time)
df['daily return'] = df['Close']/ df['Close'].shift(1) -1
df['ATR_price'] = Stock_quant.ATR.ATR(df['Low'], df['High'],df['Close'], 14)/df['Close']
df['relative_Volume'] = df['Volume'] / df['Volume'].rolling(40).mean()
df['VIX'] = VIX['Close']
df = df[['daily return',  'ATR_price', 'VIX', 'relative_Volume']]
df = df[40:]
df_replace = df_replace[40:]
```

Just like the previous lesson, fire up python ,import the necessary packages and load the data

First step we need to do is determine the optimal number of 'components' for the GMM model. For simplicity, think of components just as the clusters/regimes. To determine the optimal number, we use the AIC and BIC information criteria. For those who took statistics and econometrics courses in college, you should be familiar with them. For those who have no idea what they are, all you need to know is we pick the number that minimize both the AIC and BIC:

```
#Check how many regimes we should have optimally
n_components = np.arange(1, 15)
models = [GaussianMixture(n, covariance_type='full', random_state=0).fit(df) for n in n_components]
plt.plot(n_components, [m.bic(df) for m in models], label='BIC')
plt.plot(n_components, [m.aic(df) for m in models], label='AIC')
plt.legend(loc='best')
plt.xlabel('n_components')
plt.show()
```

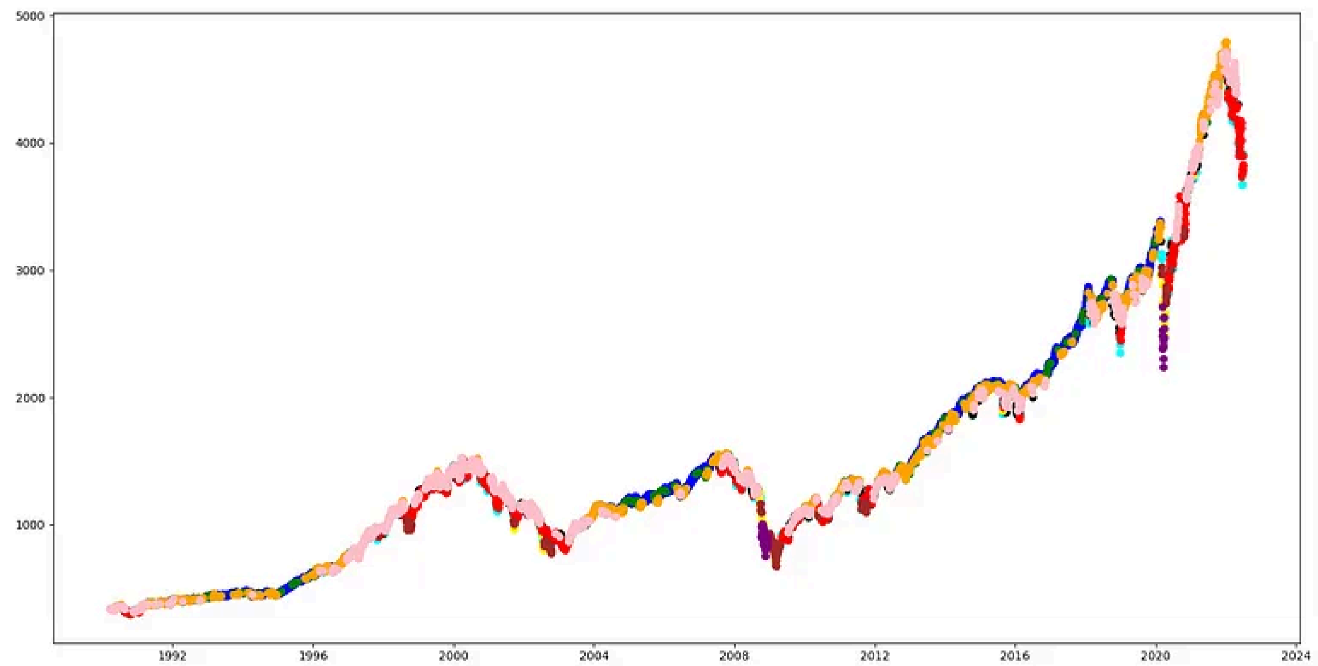
Determining the optimal number of components/regimes



Seems 10 regimes are the optimal…… so let's go ahead with 10 regimes

```
gmm = GaussianMixture(n_components=10)
gmm.fit(df)

#predictions from gmm
labels = gmm.predict(df)
frame = pd.DataFrame(df)
df_replace['regime'] = labels


color=['blue','green','cyan', 'black', 'yellow', 'red','brown','orange','purple','pink']
#color=['blue','green','cyan', 'black']
for k in range(0,10):
    data = df_replace[df_replace["regime"]==k]
    plt.scatter(data.index,data['Close'],c=color[k])

plt.show()
```

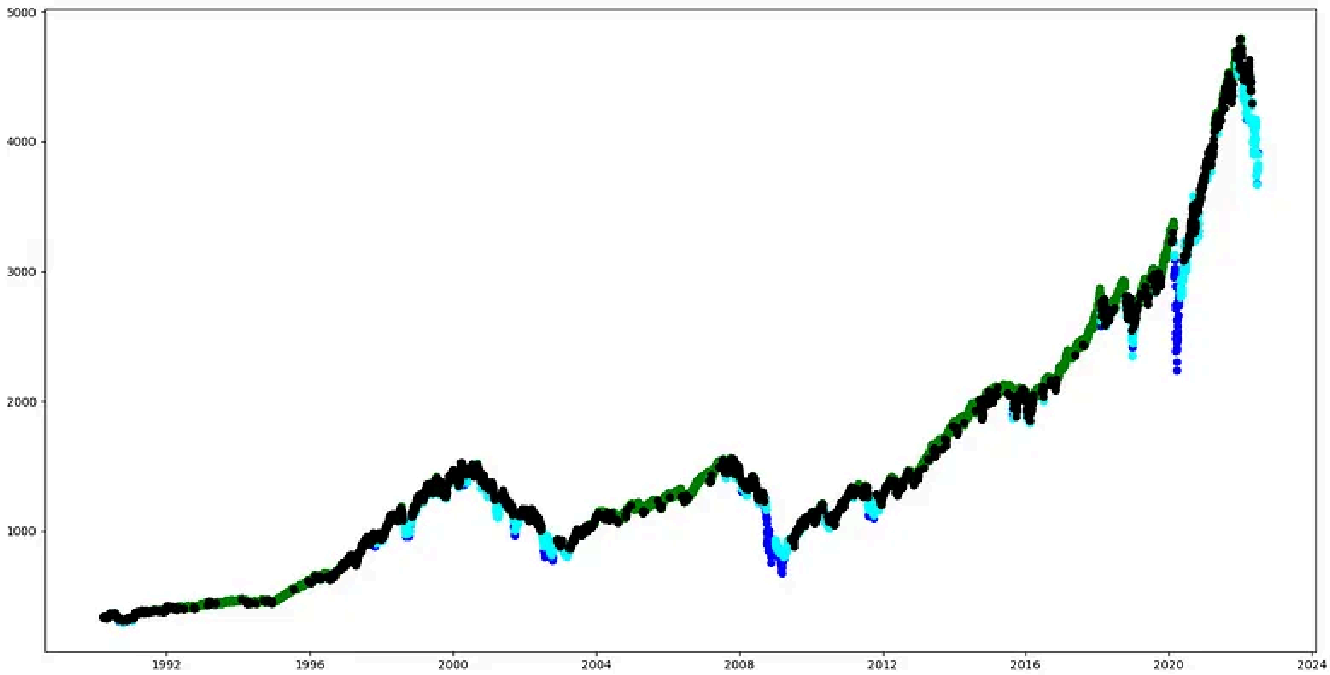
Estimate the model with 10 components and result visualization using Matplotlib



Ok, we can see that whenever the market is in the 'purple' regime, it's close to bottoming. But 10 regimes seem too much even though the model suggest it's the best. What if we just go with 4 regimes, just like K-means suggest? Let's run the code again but specify n_components = 4 only this time:

```
gmm = GaussianMixture(n_components=4)
gmm.fit(df)

#predictions from gmm
labels = gmm.predict(df)
frame = pd.DataFrame(df)
df_replace['regime'] = labels


#color=['blue','green','cyan', 'black', 'yellow', 'red','brown','orange','purple','pink']
color=['blue','green','cyan', 'black']
for k in range(0,4):
    data = df_replace[df_replace["regime"]==k]
    plt.scatter(data.index,data['Close'],c=color[k])

plt.show()
```

Run the code again but n_components = 4 this time



The visualized results look more or less the same as the k-means results from the previous lesson. It seems both the 'buy and hold' and 'buy the dip' are both good strategies to be used in the 'Green regime' . In the cyan regime, you probably should sell and maybe consider shorting the market too to hedge your portfolio. Compared to K-means, the GMM doesn't seem to be better at finding the bottoming regime (blue regime here or brown regime in the previous lesson), market seems always close to bottom if there's consecutive blue dots clustering together.

I plan to make 1 or 2 more lessons about market regime classification (one for trend filtering algorithm, the other one for model based classification such as regime switching/ finite mixture models) depending how many people really like my educational contents or I could move to other areas of quant trading/finance. I hope you enjoy my medium articles and follow me on medium or follow me on twitter:

T-Ballz🔺 (@Clark_SM7) / Twitter

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Written by T-Ballz Finance

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I am a PhD dropout who trades stocks, crypto, shitcoins, options, futures, NFTs.

Responses (2)

Wangchuyin

What are your thoughts?

Demid Fedorov
Jul 4, 2022

Awesome article, would love to see part 3!

1 Reply

arbitech
Jul 5, 2022

No predictability powerness. By nature mixtures, and hidden Markova chains are backward calculating.

1 reply Reply

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```
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
import ATR
import RSI
from sklearn.cluster import KMeans
sns.set()

pd.set_option('display.max_columns', None)
end_time = datetime.date.today()
start_time = end_time - datetime.timedelta(days = 11850)
df = yf.download('^GSPC',start = start_time, end = end_time)
df_replace =  yf.download('^GSPC',start = start_time, end = end_time)
```

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```
for i in range(0,len(df_replace)):
    if df_replace['regime'].iloc[i] == 0:
        col.append('blue')
    elif df_replace['regime'].iloc[i] == 1:
        col.append('red')
    elif df_replace['regime'].iloc[i] ==2:
        col.append('orange')
    else:
        col.append('brown')

print(df.groupby(by=df['regime']).mean())

print(df[df['regime']==2])

plt.scatter(df_replace.index, df_replace['Close'], c= col)
plt.show()


df.to_csv(r'C:\Users\clark\PycharmProjects\Stock_quant\Data\df_regime.csv')
df_replace.to_csv(r'C:\Users\clark\PycharmProjects\Stock_quant\Data\df_regime_replace.csv')
```

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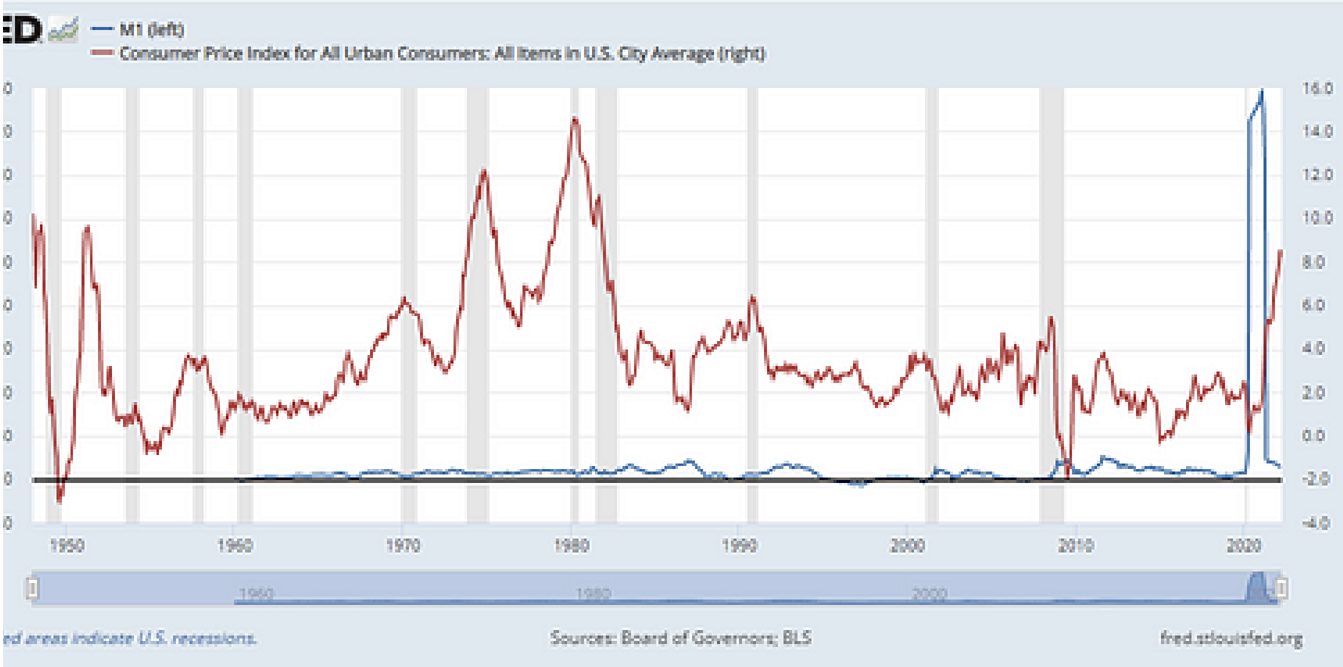

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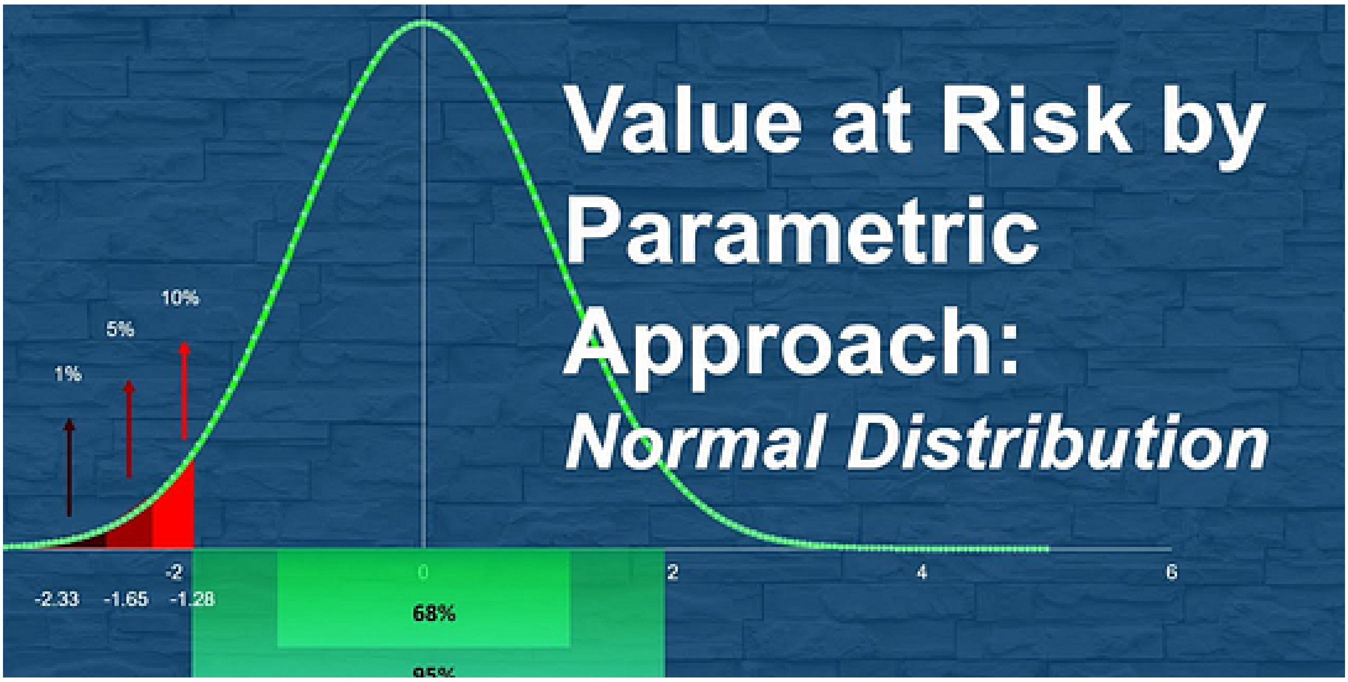

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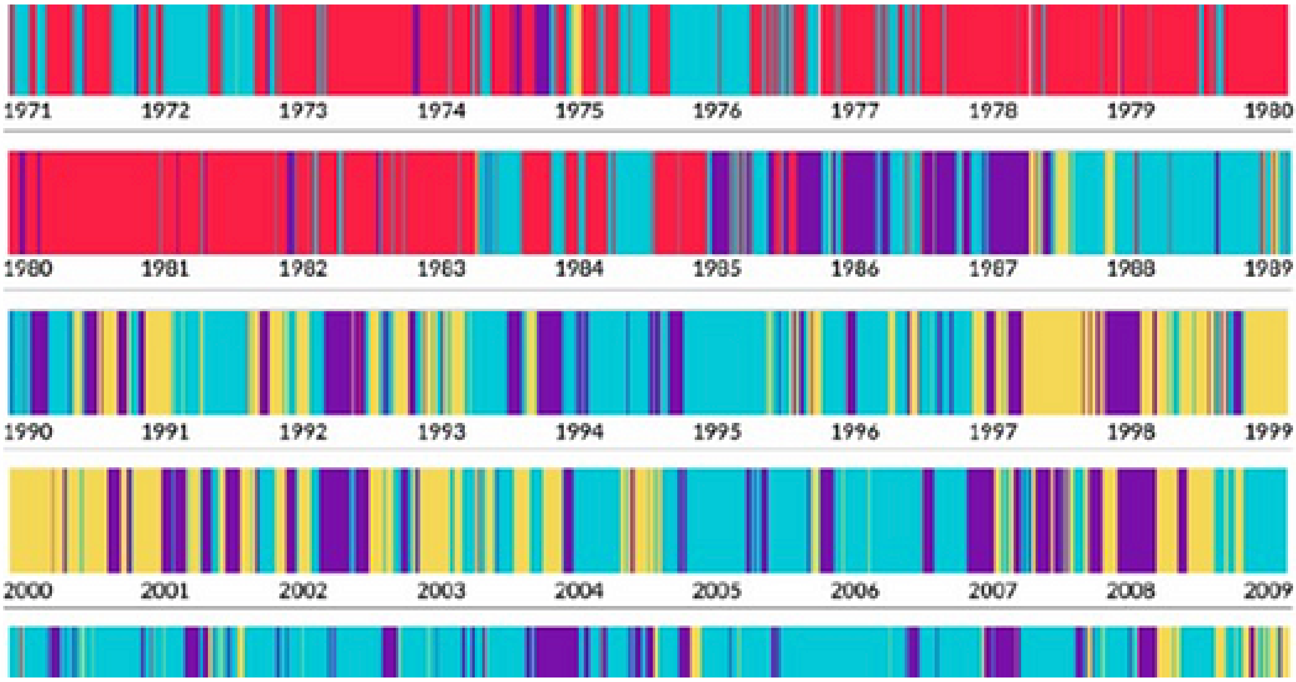

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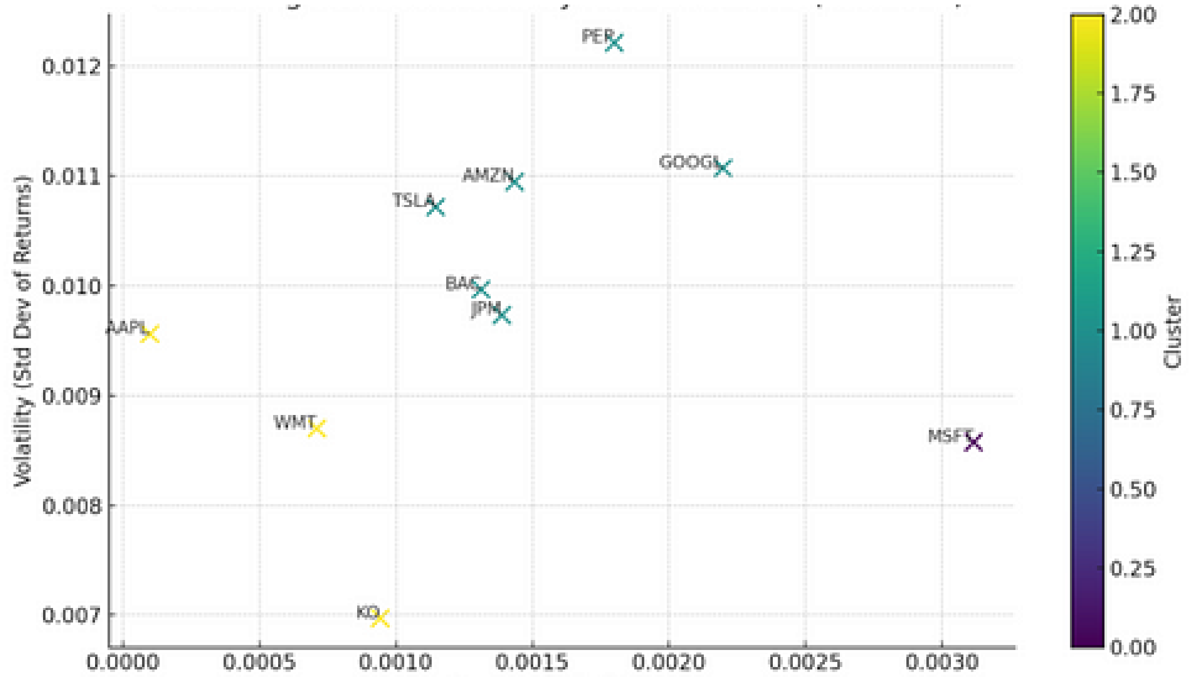

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