KUNTUR

ESTUDIOS Y ANÁLISIS

ECONOMÍA Y FINANZAS

CREACIÓN DE UNA CARTERA DE ACCIONES A TRAVÉS DE LA API DE YAHOO FINANCE

Importación de Librerias

In [1]:
```
import numpy as np
import pandas as pd
import pandas_datareader.data as wb
import matplotlib.pyplot as plt
from scipy.stats import norm
```

Recolectar los datos de las acciones que compondran nuestra cartera

In [2]:
```
assets = ['PG','INTC','AA','VIAC']
pf_data = pd.DataFrame()
for a in assets:
    pf_data[a]=wb.DataReader(a,data_source='yahoo', start='2010-1
pf_data
```

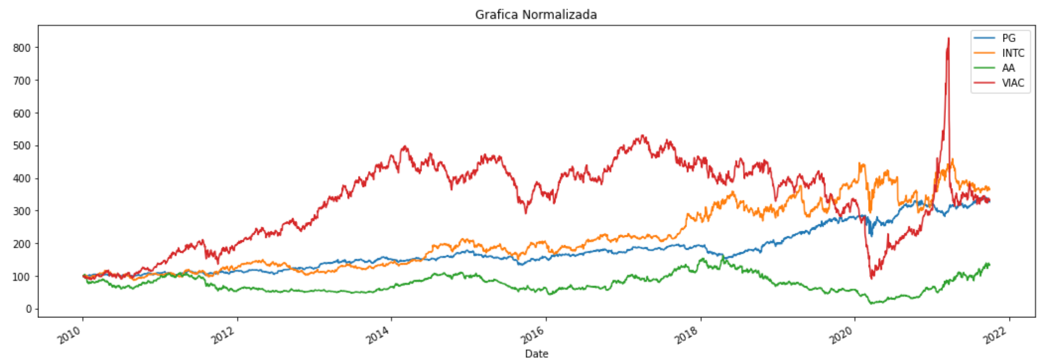
Out[2]:

	PG	INTC	AA	VIAC
Date				
2010-01-04	42.731667	14.678100	37.018944	11.968369
2010-01-05	42.745667	14.671074	35.862804	11.909576
2010-01-06	42.542892	14.621859	37.730427	11.531627
2010-01-07	42.312191	14.481265	36.930016	11.758396
2010-01-08	42.256252	14.642954	37.841587	11.884379
...	...	...	...	...
2021-09-27	141.660004	54.660000	51.560001	40.439999
2021-09-28	140.589996	54.000000	50.980000	40.230000
2021-09-29	142.020004	53.490002	50.580002	40.119999
2021-09-30	139.800003	53.279999	48.939999	39.509998
2021-10-01	139.580002	53.860001	49.770000	39.900002

2958 rows × 4 columns

Evolución del crecimiento porcentual de las acciones

In [3]:
```
plt.show()
```



Calculamos los **rendimientos** logaritmizados diarios de cada acción

In [4]:
```
log_returns=np.log(pf_data/pf_data.shift(1))
log_returns
```

Out[4]:

Date	PG	INTC	AA	VIAC
2010-01-04	NaN	NaN	NaN	NaN
2010-01-05	0.000328	-0.000479	-0.031729	-0.004924
2010-01-06	-0.004755	-0.003360	0.050766	-0.032249
2010-01-07	-0.005438	-0.009662	-0.021442	0.019474
2010-01-08	-0.001323	0.011104	0.024384	0.010657
...	...	...	...	...
2021-09-27	-0.013254	0.008082	0.061389	0.011190
2021-09-28	-0.007582	-0.012148	-0.011313	-0.005206
2021-09-29	0.010120	-0.009489	-0.007877	-0.002738
2021-09-30	-0.015755	-0.003934	-0.032961	-0.015321
2021-10-01	-0.001575	0.010827	0.016817	0.009823

2958 rows × 4 columns

In [5]:
```
log_returns.mean() *250
```

Out[5]:
```
PG      0.100076
INTC    0.109911
```

```
AA      0.025024
VIAC    0.101802
dtype: float64
```

In [6]:
```
print ("Rendimientos")
print()
print(log_returns.mean() *250)
print()
print("Matriz Var-Cov")
print()
print (log_returns.cov() * 250)
print()
print("Matriz Correlaciones")
print()
print (log_returns.corr())

#Hay exactamente 253 días hábiles de negociación en 2020.
```

```
Rendimientos

PG      0.100076
INTC    0.109911
AA      0.025024
VIAC    0.101802
dtype: float64

Matriz Var-Cov

            PG      INTC        AA      VIAC
PG    0.028646  0.018063  0.017456  0.016836
INTC  0.018063  0.081675  0.049936  0.037285
AA    0.017456  0.049936  0.202693  0.069692
VIAC  0.016836  0.037285  0.069692  0.142887

Matriz Correlaciones

            PG      INTC        AA      VIAC
PG    1.000000  0.373440  0.229080  0.263163
INTC  0.373440  1.000000  0.388103  0.345141
AA    0.229080  0.388103  1.000000  0.409512
VIAC  0.263163  0.345141  0.409512  1.000000
```

In [7]:
```
num_assets=len(assets) #Numero de activos que tiene el portafolic
num_assets
```

Out[7]: 4

Generación de Pesos

In [8]:
```
arr = np.random.random(4) #Pesos Aleatorios
print(arr[0])
print(arr[1])
print(arr[2])
print(arr[3])
```

```
print()
arr[0] + arr[1] + arr[2] + arr[3]
```

```
0.5714650474529861
0.7883538364472249
0.13801084619218484
0.45164787684620233
```

Out[8]:
```
1.949477606938598
```

In [9]:
```
weights
```

Out[9]:
```
array([0.14805436, 0.14818514, 0.35597273, 0.34778777])
```

In [10]:
```
weights.sum()
```

Out[10]:
```
1.0
```

Rentabilidad esperada de la cartera

In [11]:
```
np.dot(weights,log_returns.mean() *250)
```

Out[11]:
```
0.07541707058468516
```

In [12]:
```
np.sum(weights*log_returns.mean())*250
```

Out[12]:
```
0.07541707058468518
```

Varianza esperada de la cartera

In [13]:
```
np.dot(weights.T,np.dot(log_returns.cov()*250,weights))
```

Out[13]:
```
0.07612286523387952
```

Volatilidad esperada de la cartera

In [14]:
```
np.sqrt(np.dot(weights.T,np.dot(log_returns.cov()*250,weights)))
```

Out[14]:
```
0.27590372457413387
```

Frontera Eficiente (Proceso Monte Carlo)

En este apartado vamos a encontrar diferentes combinaciones de "pesos" de las acciones en la cartera con la finalidad de elegir la combinación que más se asemeje a nuestros niveles de aversión al riesgo

In [15]:
```
pfolio_w1=[]
pfolio_w2=[]
pfolio_w3=[]
pfolio_w4=[]
for x in range(10000):
    weights = np.random.random(num_assets)
    weights /= np.sum(weights)
    pfolio_w1.append(weights[0])
    pfolio_w2.append(weights[1])
    pfolio_w3.append(weights[2])
    pfolio_w4.append(weights[3])
    pfolio_returns.append(np.sum(weights*log_returns.mean())*250)
    pfolio_volatilities.append(np.sqrt(np.dot(weights.T,np.dot(lo
pfolio_w1=np.array(pfolio_w1)
pfolio_w2=np.array(pfolio_w2)
pfolio_w3=np.array(pfolio_w3)
pfolio_w4=np.array(pfolio_w4)

pfolio_returns = np.array(pfolio_returns)
pfolio_volatilities = np.array(pfolio_volatilities)
#pfolio_returns,pfolio_volatilities
```

In [16]:
```
# Creamos un DataFrame
portafolio = pd.DataFrame({'Return':pfolio_returns,"Volatility":p
portafolio
```

Out[16]:

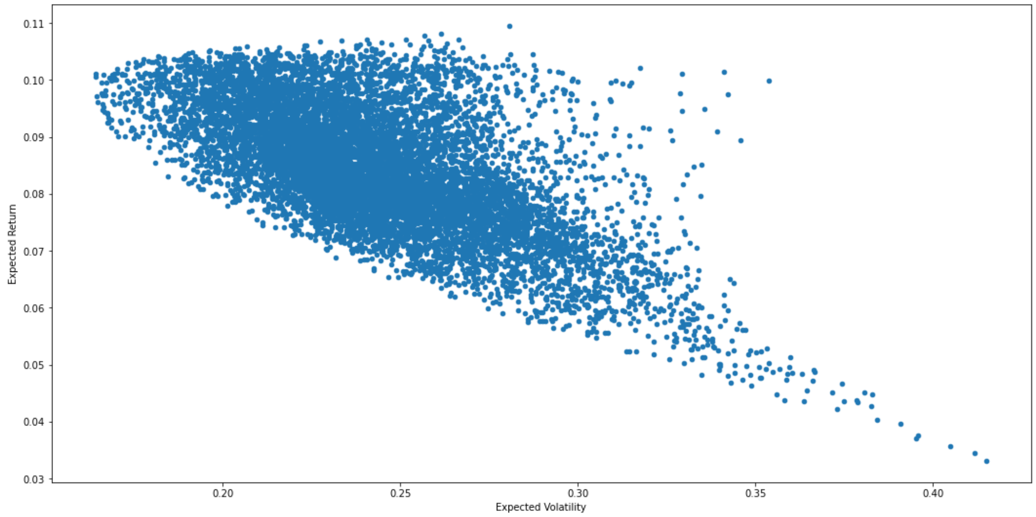
	Return	Volatility	Weight1	Weight2	Weight3	Weight4	Total
0	0.083339	0.221858	0.321560	0.248124	0.259445	0.170871	1.0
1	0.097267	0.243611	0.103391	0.475668	0.106977	0.313963	1.0
2	0.077947	0.225379	0.378371	0.262479	0.329917	0.029233	1.0
3	0.085940	0.248941	0.125872	0.379785	0.243882	0.250462	1.0
4	0.094069	0.224591	0.303019	0.205972	0.115664	0.375345	1.0
...	...	...	...	...	...	...	...
9995	0.068154	0.256105	0.338028	0.135257	0.444934	0.081781	1.0
9996	0.074315	0.251466	0.243019	0.298205	0.384038	0.074738	1.0
9997	0.074024	0.256655	0.212103	0.275623	0.386142	0.126132	1.0
9998	0.083528	0.246409	0.169580	0.311972	0.267152	0.251296	1.0
9999	0.085432	0.226722	0.256656	0.348279	0.244222	0.150844	1.0

10000 rows × 7 columns

In [17]:
```
portafolio.plot(x='Volatility',y='Return', kind='scatter', figsiz
plt.xlabel('Expected Volatility')
```

```
plt.ylabel('Expected Return')
```

Out[17]: Text(0, 0.5, 'Expected Return')



Monte Carlo - Pronóstico de precios de acciones

Movimiento browniano

$$daily\_returns = e^r$$

$$r = drift + stdev \cdot z$$

$$drift = u - \frac{1}{2} \cdot var$$

Pronósticos

$$S_t = S_0 \cdot daily\_return_t$$

$$S_{t+1} = S_t \cdot daily\_return_{t+1}$$

$$\ldots$$

$$S_{t+999} = S_{t+998} \cdot daily\_return_{t+999}$$

In [18]:
```
ticker = 'PG'
```

```
data = pd.DataFrame()
data[ticker] = wb.DataReader(ticker, data_source='yahoo', start='

log_returns = np.log(1 + data.pct_change())
u = log_returns.mean()
var = log_returns.var()
drift = u - (0.5 * var)
stdev = log_returns.std()

#drift.values
#stdev.values



daily_returns = np.exp(drift.values + stdev.values * norm.ppf(np.
```

Cree una variable S0 igual al último precio de cierre ajustado de Microsoft. Método "iloc".

In [19]:
```
S0 = data.iloc[-1]
S0
```

Out[19]:
```
PG     139.580002
Name: 2021-10-01 00:00:00, dtype: float64
```

Cree una lista de precios variable con la misma dimensión que la matriz de devoluciones diarias.

In [20]:
```
price_list = np.zeros_like(daily_returns)
price_list
```

Out[20]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

In [21]:
```
price_list[0]
```

Out[21]:
```
array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0.])
```

Establezca los valores en la primera fila de la matriz de la lista de precios iguales a S0

In [22]:
```
price_list[0] = S0
price_list
```

Out[22]:
```
array([[139.58000183, 139.58000183, 139.58000183, ..., 139.580001
83,
         139.58000183, 139.58000183],
       [  0.        ,   0.        ,   0.        , ...,   0.
```

```
,
            0.          ,   0.          ],
        [   0.          ,   0.          ,   0.          , ...,   0.
,
            0.          ,   0.          ],
        ...,
        [   0.          ,   0.          ,   0.          , ...,   0.
,
            0.          ,   0.          ],
        [   0.          ,   0.          ,   0.          , ...,   0.
,
            0.          ,   0.          ],
        [   0.          ,   0.          ,   0.          , ...,   0.
,
            0.          ,   0.          ]])
```

Cree un bucle en el rango (1, t_intervals) que reasigne al precio en el tiempo t el producto del precio en el día (t-1) con el valor de los rendimientos diarios en t.

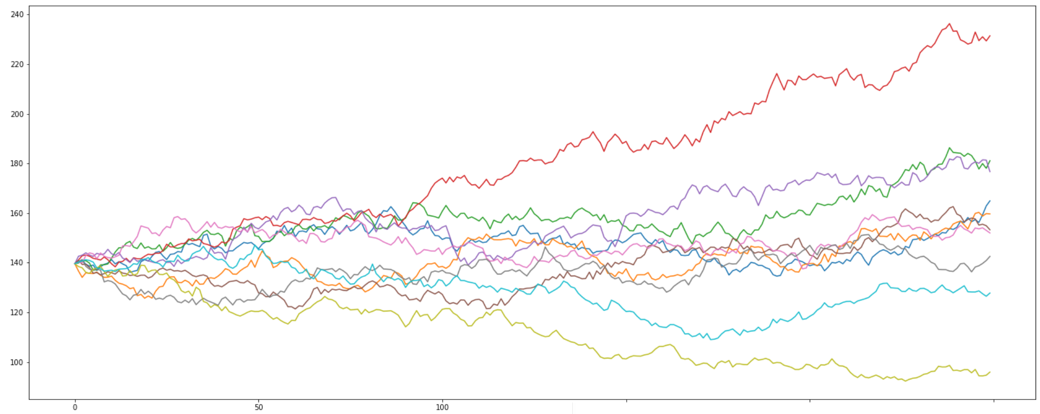
In [23]:
```
for t in range(1, t_intervals):
    price_list[t] = price_list[t - 1] * daily_returns[t]
```

In [24]:
```
price_list
```

Out[24]:
```
array([[139.58000183, 139.58000183, 139.58000183, ..., 139.580001
83,
         139.58000183, 139.58000183],
       [140.3303688 , 136.65868551, 139.83914293, ..., 140.521566
63,
         138.44848936, 140.21824735],
       [140.92906179, 134.07720681, 140.6332626 , ..., 141.271722
04,
         137.95450386, 140.73383203],
       ...,
       [159.29411263, 158.761206  , 179.93249282, ..., 139.685352
03,
          94.40050874, 127.48816862],
       [162.86647958, 159.77766646, 178.01392768, ..., 140.871468
67,
          94.66379365, 126.47058686],
       [164.90628905, 159.66388832, 181.07251979, ..., 142.524607
66,
          95.94426188, 127.78474604]])
```

Finalmente, grafique los datos de la lista de precios obtenidos.

In [25]:
```
plt.figure(figsize=(25,10))
plt.plot(price_list);
```



Wilmer Mateo Heras Vera

Contacto:

https://mateoheras77.github.io/WEB/

https://bit.ly/2XYBOFV