In [134]:

```python
import numpy as np
import pandas as pd
from pandas_datareader import data as wb
import matplotlib.pyplot as plt
import datetime
import seaborn as sns
from plotly import __version__
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot

print(__version__) # requires version >= 1.9.0
import cufflinks as cf
# For Notebooks
init_notebook_mode(connected=True)
# For offline use
cf.go_offline()
```

3.9.0

In [113]:

```python
tickers = ['BTC-USD','ETH-USD', 'LTC-USD','DOGE-USD','XRP-USD','XMR-USD','XVG
mydata = pd.DataFrame()
for t in tickers:
    mydata[t]= wb.DataReader(t, data_source = 'yahoo', start = '2018-1-1')['A
```

In [114]:

```python
mydata.head()
```

Out[114]:

Date	BTC-USD	ETH-USD	LTC-USD	DOGE-USD	XRP-USD	XMR-USD	XVG-USD	XLM-USD	VT U
2018-01-01	13850.490234	741.090027	226.520004	0.008739	1.98	331.829987	0.2110	0.3540	6.4
2018-01-02	13444.879883	756.169983	224.339996	0.009590	2.05	338.079987	0.1722	0.4848	7.3
2018-01-03	14754.089844	861.969971	251.809998	0.009246	2.19	364.429993	0.1479	0.5570	7.5
2018-01-04	15156.490234	941.000000	244.630005	0.009260	2.73	385.820007	0.1456	0.8860	7.1
2018-01-05	15180.080078	944.830017	238.300003	0.010680	2.73	372.269989	0.1785	0.6948	7.7

In [146]:

```
mydata.tail()
```

Out[146]:

Date	BTC-USD	ETH-USD	LTC-USD	DOGE-USD	XRP-USD	XMR-USD	XVG-USD	XLM-USD
2019-07-01	10844.129883	291.609985	118.680000	0.003145	0.3984	86.660004	0.007699	0.10300
2019-07-02	11981.610352	302.170013	121.970001	0.003235	0.4056	90.040001	0.007788	0.10590
2019-07-03	11156.519531	283.100006	119.669998	0.003235	0.3874	87.970001	0.007252	0.09932
2019-07-04	10993.250000	287.899994	118.529999	0.003848	0.3795	89.419998	0.007365	0.10000
2019-07-06	11585.799805	295.010010	120.110001	0.003592	0.4003	96.620003	0.007647	0.10480

In [147]:

```
mydata.iloc[0]
```

Out[147]:

```
BTC-USD      13444.879883
ETH-USD        756.200012
LTC-USD        224.339996
DOGE-USD         0.008739
XRP-USD          2.050000
XMR-USD        338.170013
XVG-USD          0.157300
XLM-USD          0.484000
VTC-USD          6.712000
ETC-USD         29.230000
USDT-USD         1.010000
ZEC-USD        518.489990
BCH-USD       2319.120117
Name: 2018-01-01 00:00:00, dtype: float64
```

In [ ]:

```


```

In [148]:

```
mydata.loc['2019-01-03']
```

Out[148]:

```
BTC-USD      3835.860107
ETH-USD       149.440002
LTC-USD        32.029999
DOGE-USD        0.002340
XRP-USD         0.360700
XMR-USD        50.459999
XVG-USD         0.006981
XLM-USD         0.113200
VTC-USD         0.291500
ETC-USD         5.130000
USDT-USD        1.010000
ZEC-USD        59.490002
BCH-USD       160.990005
Name: 2019-01-03 00:00:00, dtype: float64
```

In [149]:

```
returns=(mydata / mydata.shift(1))-1
returns.tail()
```

Out[149]:

Date	BTC-USD	ETH-USD	LTC-USD	DOGE-USD	XRP-USD	XMR-USD	XVG-USD	XLM-USD
2019-07-01	0.023816	-0.008703	-0.032526	-0.042035	-0.017994	-0.026511	-0.043602	-0.024621
2019-07-02	0.104894	0.036213	0.027722	0.028617	0.018072	0.039003	0.011560	0.028155
2019-07-03	-0.068863	-0.063110	-0.018857	0.000000	-0.044872	-0.022990	-0.068824	-0.062134
2019-07-04	-0.014634	0.016955	-0.009526	0.189490	-0.020392	0.016483	0.015582	0.006847
2019-07-06	0.053901	0.024696	0.013330	-0.066633	0.054809	0.080519	0.038239	0.048000

In [150]:

```
(returns / returns.iloc[1] * 100).plot(figsize=(15,6))
plt.show()
```

In [151]:

```
annual_returns = returns.mean()*250
```

In [152]:

```
annual_returns
```

Out[152]:

```
BTC-USD      0.152002
ETH-USD     -0.060328
LTC-USD      0.114086
DOGE-USD     0.133485
XRP-USD     -0.284334
XMR-USD     -0.160228
XVG-USD     -0.649943
XLM-USD     -0.169427
VTC-USD     -0.541177
ETC-USD     -0.124101
USDT-USD     0.006461
ZEC-USD     -0.323971
BCH-USD     -0.155663
dtype: float64
```

In [153]:

```
returns.std()*365**0.5
```

Out[153]:

```
BTC-USD     0.661617
ETH-USD     0.854149
LTC-USD     0.903038
DOGE-USD    1.052954
XRP-USD     0.964262
XMR-USD     0.899342
XVG-USD     1.212605
XLM-USD     1.042367
VTC-USD     1.193996
ETC-USD     0.957055
USDT-USD    0.136689
ZEC-USD     0.899609
BCH-USD     1.141810
dtype: float64
```

In [154]:

```
sec_returns = np.log(mydata / mydata.shift(1))
```

In [155]:

```
sec_returns
```

Out[155]:

	BTC-USD	ETH-USD	LTC-USD	DOGE-USD	XRP-USD	XMR-USD	XVG-USD	XLM-USD
Date								
2018-01-01	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-02	0.092925	0.130915	0.115512	0.029429	0.066062	0.074813	-0.088342	0.138683
2018-01-03	0.026914	0.087829	-0.028928	0.026967	0.220400	0.057009	0.008299	0.464593
2018-01-04	0.001547	0.003956	-0.026216	0.033710	0.000000	-0.035859	0.097062	-0.241450
2018-01-05	0.110566	0.023328	0.025726	0.271819	-0.084019	-0.040936	0.114444	-0.082444
2018-01-06	0.012748	0.039812	0.131669	0.151301	0.054277	0.095641	-0.027120	0.071012
2018-01-07	-0.056550	0.104928	-0.026705	0.145108	0.047891	0.017373	0.037655	0.025718
2018-01-08	-0.080288	0.016292	-0.065902	-0.129477	-0.142824	0.003269	-0.022874	-0.138203
2018-								

01-09	-0.034486	0.126443	-0.032824	-0.118711	-0.156921	0.022980	0.085411	-0.089561
2018-01-10	0.030695	-0.031718	0.012360	-0.026155	-0.054877	-0.017613	-0.145295	-0.004284
2018-01-11	-0.114299	-0.091904	-0.094977	-0.149356	-0.010309	-0.133900	-0.152454	-0.004123
2018-01-12	0.039279	0.101497	0.038196	0.131266	0.045578	0.098281	0.098287	0.188232
2018-01-13	0.028625	0.093786	0.091653	-0.028171	-0.009950	0.066775	-0.014655	-0.021053
2018-01-14	-0.043368	-0.018612	-0.085258	-0.066663	-0.088831	-0.053864	-0.126405	-0.060131
2018-01-15	-0.000488	-0.061266	-0.021206	-0.154951	-0.097498	0.045494	-0.172032	-0.035651
2018-01-16	-0.189167	-0.196798	-0.232089	-0.388243	-0.367056	-0.276457	-0.330814	-0.329406
2018-01-17	-0.010674	-0.024648	0.023384	0.131294	0.130265	0.019169	0.099854	0.090840
2018-01-18	0.001148	-0.011503	0.014872	0.015685	0.181049	-0.034132	0.197535	0.043621
2018-01-19	0.030512	0.023792	0.006470	0.015953	-0.019293	0.163389	-0.042015	0.016129
2018-01-20	0.103952	0.103518	0.091440	0.058859	0.019293	0.053367	0.020315	0.050693
2018-01-21	-0.101510	-0.092274	-0.099482	-0.165142	-0.136265	-0.101592	-0.038197	-0.153169
2018-01-22	-0.065790	-0.048283	-0.061129	-0.049465	-0.022141	-0.096472	-0.110332	0.057478
2018-01-23	0.004034	-0.015292	-0.008395	-0.012154	0.000000	-0.023143	-0.008627	0.012061
2018-01-24	0.051232	0.075599	0.014895	0.083382	0.014815	0.039084	0.016969	0.161681
2018-01-25	-0.022399	-0.014620	-0.009011	0.054067	-0.045120	-0.009692	-0.056682	0.066822
2018-01-26	-0.006434	0.002110	-0.018725	-0.051570	-0.071744	0.019694	-0.021373	0.030931
2018-01-27	0.031514	0.056094	0.028400	0.031502	0.008230	0.003065	0.080681	-0.013809
2018-01-28	0.026525	0.104767	0.066988	0.010948	0.108634	0.031640	-0.026464	0.008853
2018-01-29	-0.046421	-0.051328	-0.068427	-0.078130	-0.068468	-0.058772	-0.086571	-0.074157
2018-01-30	-0.105687	-0.095169	-0.087208	-0.155324	-0.134657	-0.134625	-0.209873	-0.184256
...	...	...	...	...	...	...	...	...
2019-	0.024703	0.000441	0.049640	0.024653	0.001427	0.006867	0.024647	0.019771

06-06								
2019-06-07	-0.008641	-0.020813	0.012140	-0.008689	-0.029183	-0.006637	-0.025973	-0.026986
2019-06-08	-0.037282	-0.054529	-0.031196	-0.063031	-0.057418	-0.041013	-0.064030	-0.045257
2019-06-09	0.048215	0.068990	0.122425	0.048052	0.040386	0.039175	0.083627	0.038800
2019-06-10	-0.013010	-0.011356	0.047017	-0.012878	-0.020879	-0.002649	-0.021699	-0.004057
2019-06-11	0.031923	0.070433	0.000588	0.004973	0.023861	0.042117	0.031946	0.035932
2019-06-12	0.007487	-0.030728	-0.039703	0.007577	-0.008224	-0.014591	-0.028297	-0.024614
2019-06-13	0.054166	0.033423	0.014038	0.026876	0.010951	0.018894	-0.021309	0.008804
2019-06-14	0.018191	0.020489	0.041620	-0.009954	0.017665	0.046570	0.037623	0.013455
2019-06-15	0.014089	-0.002566	-0.010171	0.014098	0.040511	0.010038	0.004443	0.021004
2019-06-16	0.038970	0.019874	-0.020359	0.009815	0.046095	0.027298	0.009363	0.007669
2019-06-17	-0.027616	-0.034957	0.006981	-0.027469	-0.048902	-0.022420	-0.037654	-0.055766
2019-06-18	0.021657	0.016869	0.012502	0.021465	0.019481	0.043952	0.031745	0.004835
2019-06-19	0.027243	0.011825	-0.007703	-0.033191	-0.011550	0.043051	-0.045407	-0.026060
2019-06-20	0.069073	0.083887	0.023942	0.068993	0.034033	0.045454	-0.009175	0.019608
2019-06-21	0.045030	0.044206	0.019229	0.013366	0.065619	0.043304	0.045055	0.044311
2019-06-22	0.015451	-0.006615	-0.035467	-0.017349	-0.014191	0.003208	0.038413	-0.014030
2019-06-23	0.016422	0.012448	-0.010506	0.016444	0.008708	0.019290	-0.030072	0.003917
2019-06-24	0.061892	0.016918	0.000812	-0.007275	-0.015342	-0.052469	0.025560	-0.032581
2019-06-25	0.095225	0.053004	-0.037519	0.021072	-0.009276	-0.077949	-0.094553	-0.016287
2019-06-26	-0.146450	-0.126604	-0.133225	-0.003282	-0.130625	-0.086440	-0.102642	-0.121175
2019-06-27	0.102259	0.050720	0.044680	-0.002993	0.046565	0.071332	0.058453	0.031922
2019-06-28	-0.038864	0.025373	0.110670	-0.002401	0.002590	-0.020339	0.019144	0.029193
2019-	-0.098525	-0.089513	-0.088320	-0.029580	-0.077968	-0.125417	-0.084537	-0.095049

06-29								
2019-06-30	-0.016590	0.013760	0.004166	0.015966	0.030787	0.011411	0.037463	0.012387
2019-07-01	0.023537	-0.008741	-0.033067	-0.042944	-0.018157	-0.026869	-0.044582	-0.024929
2019-07-02	0.099749	0.035573	0.027344	0.028215	0.017911	0.038262	0.011494	0.027766
2019-07-03	-0.071349	-0.065190	-0.019037	0.000000	-0.045910	-0.023258	-0.071307	-0.064148
2019-07-04	-0.014743	0.016813	-0.009572	0.173525	-0.020603	0.016348	0.015462	0.006823
2019-07-06	0.052499	0.024396	0.013242	-0.068956	0.053360	0.077441	0.037526	0.046884

552 rows × 13 columns

In [156]:

```
sec_returns.mean()*365
```

Out[156]:

```
BTC-USD     -0.067522
ETH-USD     -0.427086
LTC-USD     -0.283464
DOGE-USD    -0.403448
XRP-USD     -0.741098
XMR-USD     -0.568404
XVG-USD     -1.372001
XLM-USD     -0.694206
VTC-USD     -1.215180
ETC-USD     -0.583957
USDT-USD    -0.002703
ZEC-USD     -0.726739
BCH-USD     -0.780460
dtype: float64
```

In [157]:

```
sec_returns.std()*365**0.5
```

Out[157]:

```
BTC-USD     0.664494
ETH-USD     0.859294
LTC-USD     0.888527
DOGE-USD    1.032507
XRP-USD     0.953970
XMR-USD     0.907288
XVG-USD     1.198213
XLM-USD     1.019656
VTC-USD     1.149921
ETC-USD     0.962671
USDT-USD    0.134978
ZEC-USD     0.897434
BCH-USD     1.110357
dtype: float64
```

In [158]:

```
(sec_returns / sec_returns.iloc[1] * 100).plot(figsize=(15,6))
plt.show()
```

In [ ]:

```

```

In [159]:

```
#Covariance and Correlation
```

In [160]:

```
var = sec_returns.var()
var
```

Out[160]:

```
BTC-USD     0.001766
ETH-USD     0.002954
LTC-USD     0.003158
DOGE-USD    0.004264
XRP-USD     0.003640
XMR-USD     0.003293
XVG-USD     0.005743
XLM-USD     0.004159
VTC-USD     0.005289
ETC-USD     0.003707
USDT-USD    0.000073
ZEC-USD     0.003222
BCH-USD     0.004932
dtype: float64
```

In [178]:

```
var = sec_returns.var()*250
var
```

Out[178]:

```
BTC-USD     0.441552
ETH-USD     0.738386
LTC-USD     0.789480
DOGE-USD    1.066071
XRP-USD     0.910059
XMR-USD     0.823171
XVG-USD     1.435713
XLM-USD     1.039698
VTC-USD     1.322318
ETC-USD     0.926736
USDT-USD    0.018219
ZEC-USD     0.805387
BCH-USD     1.232894
dtype: float64
```

In [179]:

```
var.iplot()

```

(https://plot.ly/)

In [24]:

```python
cov_matrix = sec_returns.cov()
cov_matrix
```

Out[24]:

	BTC-USD	ETH-USD	LTC-USD	DOGE-USD	XRP-USD	XMR-USD	XVG-USD	XLM-USD	
BTC-USD	1.759599e-03	0.001875	0.001917	0.001739	0.001800	0.001987	0.002156	0.001890	
ETH-USD	1.874693e-03	0.002957	0.002543	0.002097	0.002542	0.002542	0.002922	0.002559	
LTC-USD	1.916776e-03	0.002543	0.003168	0.002317	0.002472	0.002570	0.002803	0.002476	
DOGE-USD	1.738971e-03	0.002097	0.002317	0.004219	0.002344	0.002253	0.002741	0.002491	
XRP-USD	1.800277e-03	0.002542	0.002472	0.002344	0.003645	0.002525	0.003033	0.003069	
XMR-USD	1.987460e-03	0.002542	0.002570	0.002253	0.002525	0.003292	0.002898	0.002664	
XVG-USD	2.156100e-03	0.002922	0.002803	0.002741	0.003033	0.002898	0.005755	0.002934	
XLM-USD	1.890106e-03	0.002559	0.002476	0.002491	0.003069	0.002664	0.002934	0.004165	
VTC-USD	2.002094e-03	0.002519	0.002498	0.002645	0.002491	0.002697	0.003174	0.002835	
ETC-USD	1.845697e-03	0.002619	0.002470	0.002305	0.002573	0.002535	0.002852	0.002649	
USDT-USD	-7.030871e-07	0.000013	0.000023	-0.000012	0.000024	0.000008	0.000026	0.000020	-
ZEC-USD	1.803170e-03	0.002434	0.002340	0.002173	0.002382	0.002552	0.002680	0.002556	
BCH-USD	2.328620e-03	0.002974	0.003096	0.002494	0.002827	0.003047	0.003312	0.002929	

In [112]:

```
cov_matrix_a = sec_returns.cov() *250
cov_matrix_a
```

Out[112]:

	BTC-USD	ETH-USD	LTC-USD	DOGE-USD	XRP-USD	XMR-USD	XVG-USD	XLM-USD	VT
BTC-USD	0.441639	0.469214	0.478649	0.431702	0.451031	0.497835	0.539245	0.473548	0.
ETH-USD	0.469214	0.738459	0.634255	0.523797	0.634596	0.635120	0.729773	0.639623	0.
LTC-USD	0.478649	0.634255	0.789555	0.576031	0.616726	0.640913	0.699048	0.617732	0.
DOGE-USD	0.431702	0.523797	0.576031	1.064528	0.582103	0.561164	0.684770	0.621031	0.
XRP-USD	0.451031	0.634596	0.616726	0.582103	0.910243	0.631549	0.756949	0.766594	0.
XMR-USD	0.497835	0.635120	0.640913	0.561164	0.631549	0.823557	0.724090	0.666420	0.
XVG-USD	0.539245	0.729773	0.699048	0.684770	0.756949	0.724090	1.435273	0.732744	0.
XLM-USD	0.473548	0.639623	0.617732	0.621031	0.766594	0.666420	0.732744	1.039785	0.
VTC-USD	0.499703	0.628187	0.622550	0.658141	0.621540	0.672723	0.791500	0.707224	1.
ETC-USD	0.460478	0.653089	0.615121	0.574719	0.641669	0.631800	0.711471	0.660641	0.
USDT-USD	-0.000100	0.003361	0.005867	-0.002862	0.006164	0.001976	0.006631	0.005055	-0.
ZEC-USD	0.451647	0.607956	0.583744	0.540431	0.595420	0.638266	0.669108	0.638799	0.
BCH-USD	0.582415	0.742567	0.772027	0.621043	0.705918	0.761211	0.826800	0.731813	0.

In [113]:

```
corr_matrix = sec_returns.corr()
corr_matrix
```

Out[113]:

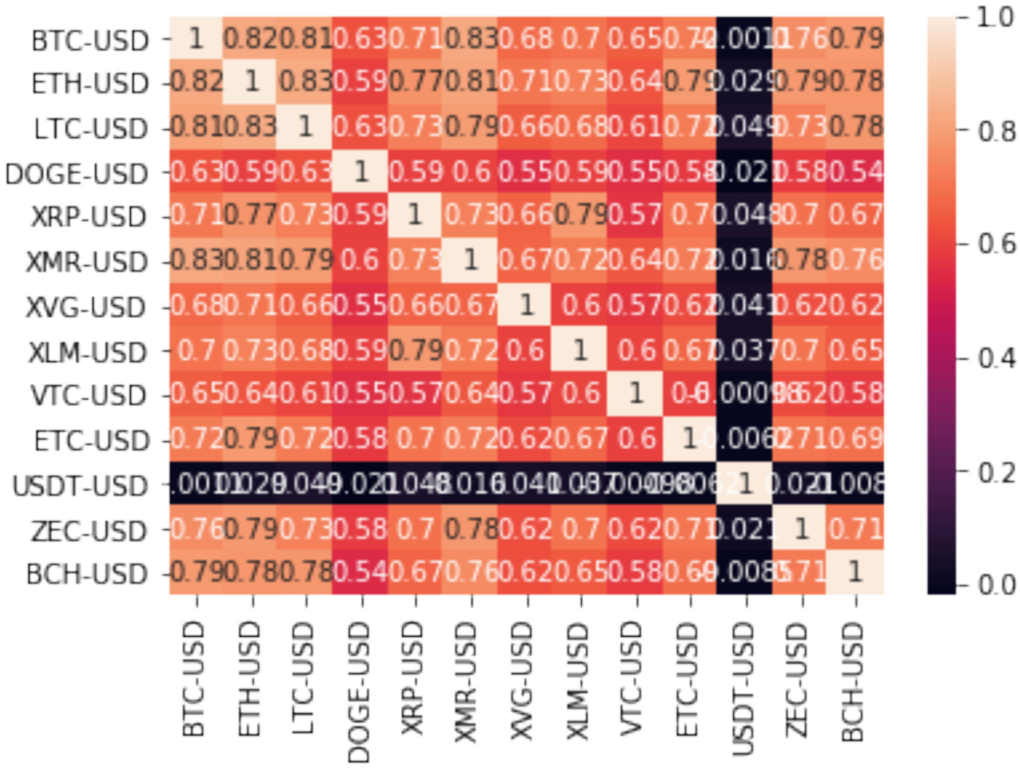
	BTC-USD	ETH-USD	LTC-USD	DOGE-USD	XRP-USD	XMR-USD	XVG-USD	XLM-USD	VT
BTC-USD	1.000000	0.821625	0.810573	0.629610	0.711368	0.825477	0.677306	0.698809	0.
ETH-USD	0.821625	1.000000	0.830634	0.590774	0.774026	0.814414	0.708855	0.729943	0.
LTC-USD	0.810573	0.830634	1.000000	0.628313	0.727481	0.794806	0.656671	0.681769	0.
DOGE-USD	0.629610	0.590774	0.628313	1.000000	0.591347	0.599328	0.553986	0.590286	0.
XRP-USD	0.711368	0.774026	0.727481	0.591347	1.000000	0.729426	0.662247	0.787980	0.
XMR-USD	0.825477	0.814414	0.794806	0.599328	0.729426	1.000000	0.666006	0.720161	0.
XVG-USD	0.677306	0.708855	0.656671	0.553986	0.662247	0.666006	1.000000	0.599809	0.
XLM-USD	0.698809	0.729943	0.681769	0.590286	0.787980	0.720161	0.599809	1.000000	0.
VTC-USD	0.653900	0.635710	0.609279	0.554720	0.566531	0.644648	0.574535	0.603141	1.
ETC-USD	0.719785	0.789472	0.719113	0.578635	0.698650	0.723202	0.616904	0.673009	0.
USDT-USD	-0.001115	0.028973	0.048917	-0.020554	0.047864	0.016133	0.041003	0.036726	-0.
ZEC-USD	0.757159	0.788190	0.731903	0.583558	0.695291	0.783568	0.622230	0.697934	0.
BCH-USD	0.789291	0.778235	0.782491	0.542103	0.666367	0.755433	0.621543	0.646348	0.

In [114]:

```
sns.heatmap(corr_matrix, annot=True)
```

Out[114]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a227a36a0>
```



In [ ]:

```
#-------------------------------
```

In [136]:

```
tickers = ['BTC-USD', 'ETH-USD']
sec_data = pd.DataFrame()
for t in tickers:
    sec_data[t] = wb.DataReader(t, data_source = 'yahoo', start = '2018-1-1')
```

In [137]:

```
sec_data.tail()
```

Out[137]:

	BTC-USD	ETH-USD
Date		
2019-07-22	9854.150391	212.210007
2019-07-23	9772.139648	216.660004
2019-07-24	9882.429688	219.410004
2019-07-25	9847.450195	219.229996
2019-07-27	9435.040039	207.910004

In [138]:

```
(sec_data / sec_data.iloc[0] * 100).plot(figsize=(15,6))
plt.show()
```

In [139]:

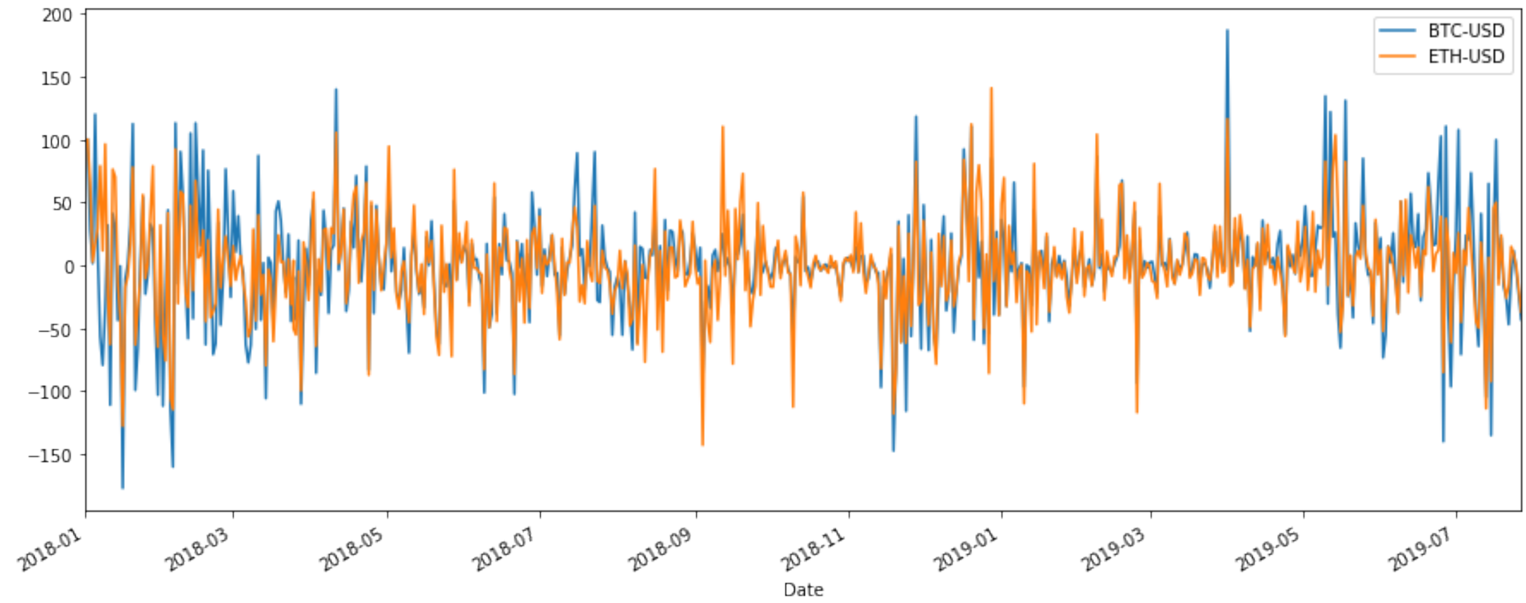
```
returns=(sec_data / sec_data.shift(1))-1
returns.tail()
```

Out[139]:

	BTC-USD	ETH-USD
Date		
2019-07-22	-0.045683	-0.023064
2019-07-23	-0.008322	0.020970
2019-07-24	0.011286	0.012693
2019-07-25	-0.003540	-0.000820
2019-07-27	-0.041880	-0.051635

In [140]:

```
(returns / returns.iloc[1] * 100).plot(figsize=(15,6))
plt.show()
```



In [ ]:

```

```

In [141]:

```
sec_returns = np.log(sec_data / sec_data.shift(1))
```

In [133]:

```
sec_returns
```

Out[133]:

	BTC-USD	ETH-USD
Date		
2018-01-01	NaN	NaN
2018-01-02	0.092925	0.130915
2018-01-03	0.026914	0.087829
2018-01-04	0.001547	0.003956
2018-01-05	0.110566	0.023328
2018-01-06	0.012748	0.039812
2018-01-07	-0.056550	0.104928
2018-01-08	-0.080288	0.016292
2018-01-09	-0.034486	0.126443
2018-01-10	0.030695	-0.031718
2018-01-11	-0.114299	-0.091904
2018-01-12	0.039279	0.101497
2018-01-13	0.028625	0.093786

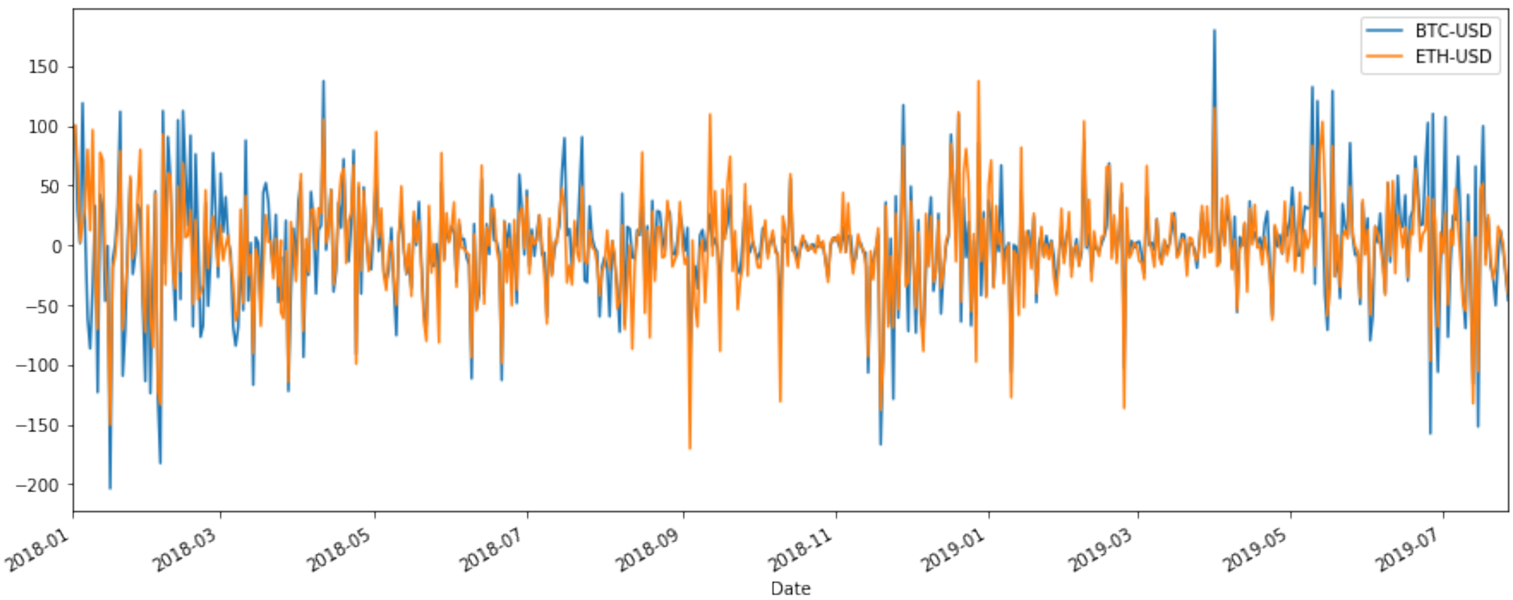
2018-01-13	0.028625	0.093786
2018-01-14	-0.043368	-0.018612
2018-01-15	-0.000488	-0.061266
2018-01-16	-0.189167	-0.196798
2018-01-17	-0.010674	-0.024648
2018-01-18	0.001148	-0.011503
2018-01-19	0.030512	0.023792
2018-01-20	0.103952	0.103518
2018-01-21	-0.101510	-0.092274
2018-01-22	-0.065790	-0.048283
2018-01-23	0.004034	-0.015292
2018-01-24	0.051232	0.075599
2018-01-25	-0.022399	-0.014620
2018-01-26	-0.006434	0.002110
2018-01-27	0.031514	0.056094
2018-01-28	0.026525	0.104767
2018-01-29	-0.046421	-0.051328
2018-01-30	-0.105687	-0.095169
...	...	...
2019-06-26	-0.146450	-0.126604
2019-06-27	0.102259	0.050720
2019-06-28	-0.038864	0.025373
2019-06-29	-0.098525	-0.089513
2019-06-30	-0.016590	0.013760
2019-07-01	0.023537	-0.008741
2019-07-02	0.099749	0.035573
2019-07-03	-0.071349	-0.065190
2019-07-04	-0.014743	0.016813
2019-07-05	0.022992	0.000278
2019-07-06	0.019834	0.062098
2019-07-07	0.069179	0.022300
2019-07-08	0.021789	-0.017546
2019-07-09	-0.037943	-0.064562
2019-07-10	-0.064521	-0.072106
2019-07-11	0.039265	0.025187
2019-07-12	-0.037429	-0.023773

2019-07-13	-0.107628	-0.173246
2019-07-14	0.061369	0.008717
2019-07-15	-0.140989	-0.138113
2019-07-16	0.028529	0.061385
2019-07-17	0.092736	0.067702
2019-07-18	-0.009958	-0.021504
2019-07-19	0.021274	0.033026
2019-07-20	-0.016182	-0.014578
2019-07-21	-0.024947	-0.036966
2019-07-22	-0.046760	-0.023334
2019-07-23	-0.008357	0.020753
2019-07-24	0.012346	0.014207
2019-07-26	-0.016230	-0.020597

572 rows × 2 columns

In [142]:

```
(sec_returns / sec_returns.iloc[1] * 100).plot(figsize=(15,6))
plt.show()
```



In [ ]:

```

```

In [ ]:

```

```

In [124]:

```
#Bitcoin 的风险
```

In [143]:

```
sec_returns['BTC-USD'].mean()
```

Out[143]:

-0.0006191747084414376

In [144]:

```
sec_returns['BTC-USD'].mean()*365
```

Out[144]:

-0.22599876858112472

In [145]:

```
sec_returns['BTC-USD'].std()
```

Out[145]:

0.04254407610198515

In [146]:

```
sec_returns['BTC-USD'].std()*365**0.5
```

Out[146]:

0.8128034326641337

In [147]:

```
#ETC的风险
```

In [148]:

```
sec_returns['ETH-USD'].mean()
```

Out[148]:

-0.0022573436997031745

In [149]:

```
sec_returns['ETH-USD'].mean()*365
```

Out[149]:

-0.8239304503916587

In [150]:

```
sec_returns['ETH-USD'].std()
```

Out[150]:

```
0.05460205534021087
```

In [151]:

```
sec_returns['ETH-USD'].std()*365**0.5
```

Out[151]:

```
1.04317080254963
```

In [152]:

```
#Covariance and Correlation
```

In [153]:

```
BTC_var = sec_returns['BTC-USD'].var()
BTC_var
```

Out[153]:

```
0.0018099984113715036
```

In [154]:

```
ETH_var = sec_returns['ETH-USD'].var()
ETH_var
```

Out[154]:

```
0.0029813844473754506
```

In [155]:

```
BTC_var = sec_returns['BTC-USD'].var()*365
BTC_var

```

Out[155]:

```
0.6606494201505988
```

In [156]:

```
ETH_var = sec_returns['ETH-USD'].var()*365
ETH_var
```

Out[156]:

```
1.0882053232920395
```

In [157]:

```
cov_matrix = sec_returns.cov()
cov_matrix
```

Out[157]:

	BTC-USD	ETH-USD
BTC-USD	0.001810	0.001915
ETH-USD	0.001915	0.002981

In [158]:

```
cov_matrix_a = sec_returns.cov() *365
cov_matrix_a
```

Out[158]:

	BTC-USD	ETH-USD
BTC-USD	0.660649	0.699129
ETH-USD	0.699129	1.088205

In [159]:

```
corr_matrix = sec_returns.corr()
corr_matrix
```

Out[159]:

	BTC-USD	ETH-USD
BTC-USD	1.000000	0.824549
ETH-USD	0.824549	1.000000

In [160]:

```
sns.heatmap(cov_matrix_a)
```

Out[160]:

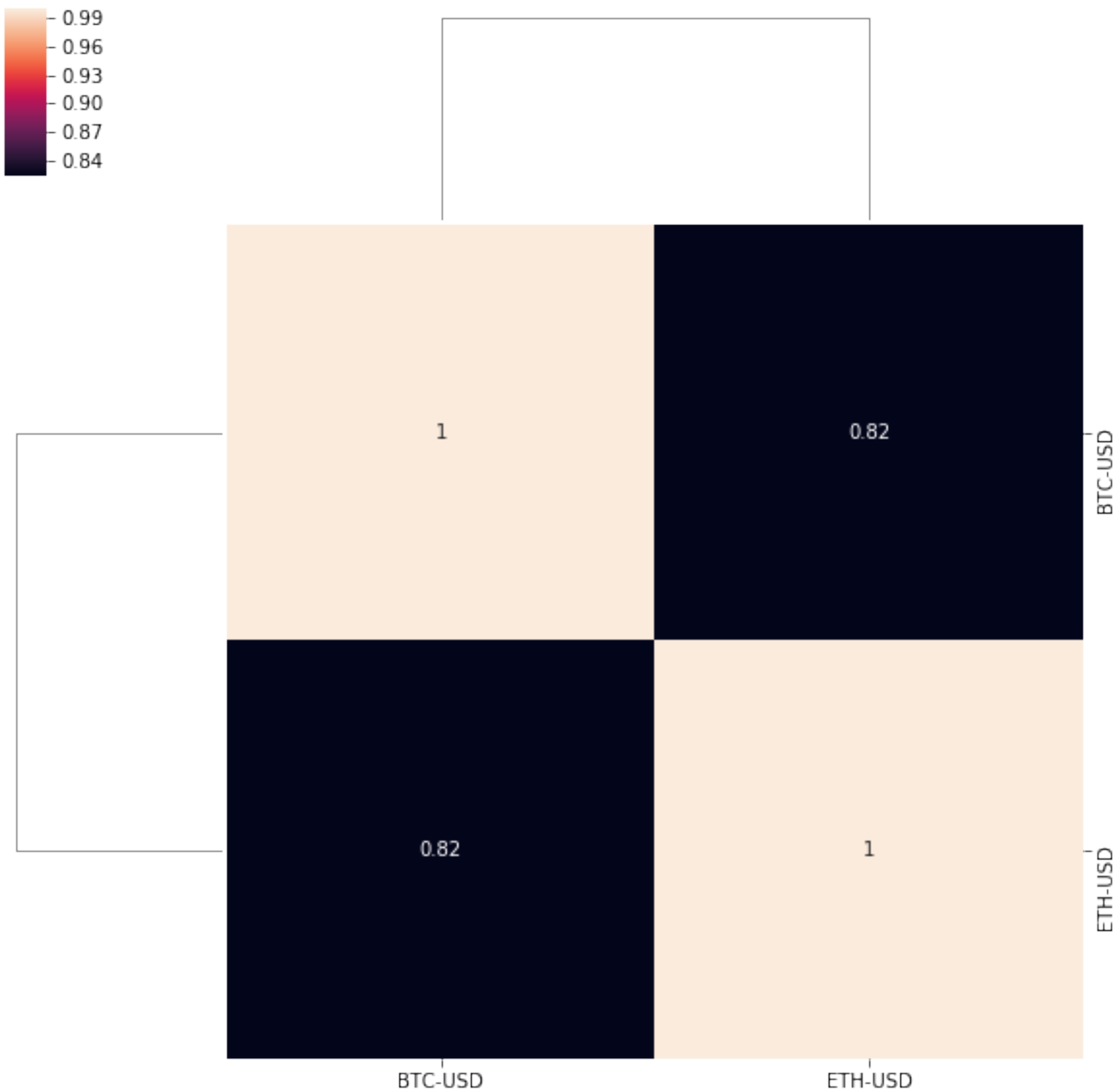
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c1eead048>
```

In [161]:

```
sns.clustermap(corr_matrix, annot=True )
```

Out[161]:

```
&lt;seaborn.matrix.ClusterGrid at 0x1c1f44fe80&gt;
```



In [162]:

```
#Calculating Portfoilo Risk
```

In [181]:

```
weights = np.array([0.5,0.5])
```

In [182]:

```
pfolio_var = np.dot(weights.T, np.dot(sec_returns.cov()*365,weights))
pfolio_var
```

Out[182]:

```
0.7867780858018025
```

In [183]:

```
pfolio_vol = (np.dot(weights.T, np.dot(sec_returns.cov()*365, weights)))**0.5
pfolio_vol
```

Out[183]:

```
0.8870051216322274
```

In [184]:

```
print(str(round(pfolio_vol, 5)*100) + '%')
```

```
88.701%
```

In [185]:

```
#Calculating Diversifiable and non-diversifiable Risk of a portfolio
```

In [186]:

```
weights = np.array([0.5,0.5])
```

In [187]:

```
weights[0]
```

Out[187]:

```
0.5
```

In [188]:

```
weights[1]
```

Out[188]:

```
0.5
```

In [189]:

```
BTC_var_a =  sec_returns[['BTC-USD']].var()*365
BTC_var_a
```

Out[189]:

```
BTC-USD    0.660649
dtype: float64
```

In [190]:

```
ETH_var_a =  sec_returns[['ETH-USD']].var()*365
ETH_var_a
```

Out[190]:

```
ETH-USD    1.088205
dtype: float64
```

In [191]:

```
dr = pfolio_var - (weights[0] ** 2 * BTC_var_a) - (weights[1] ** 2 * ETH_var_
dr
```

Out[191]:

```
BTC-USD   NaN
ETH-USD   NaN
dtype: float64
```

In [192]:

```
float(BTC_var_a)
```

Out[192]:

```
0.6606494201505988
```

In [193]:

```
BTC_var_a =  sec_returns['BTC-USD'].var()*365
BTC_var_a
```

Out[193]:

```
0.6606494201505988
```

In [196]:

```
ETH_var_a =  sec_returns['ETH-USD'].var()*365
ETH_var_a
```

Out[196]:

```
1.0882053232920395
```

In [195]:

```
#diversifiable risk
dr = pfolio_var - (weights[0] ** 2 * BTC_var_a) - (weights[1] **2*ETH_var_a)
dr
```

Out[195]:

```
ETH-USD    0.349564
dtype: float64
```

In [69]:

```
#non-diversifiable risk
#method 1
n_dr_1 = pfolio_var - dr
n_dr_1
```

Out[69]:

```
0.29476967575196655
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```
#----------------
```

In [ ]:

```
#Obtaining the efficient frontier in Python
```

In [119]:

```
assets = ['BTC-USD', 'ETH-USD']
pf_data = pd.DataFrame()
for t in assets:
    pf_data[t] = wb.DataReader(t, data_source = 'yahoo', start = '2018-1-1',
```

In [120]:

```
pf_data.tail()
```

Out[120]:

	BTC-USD	ETH-USD
Date		
2019-07-14	10850.259766	228.139999
2019-07-15	9423.440430	198.710007
2019-07-16	9696.150391	211.289993
2019-07-17	10638.349609	226.089996
2019-07-18	10532.940430	221.279999

In [121]:

```
(pf_data / pf_data.iloc[1] *100).plot(figsize = (10,5))
```

Out[121]:

<matplotlib.axes._subplots.AxesSubplot at 0x1c1f32c668>

In [122]:

```
log_returns = np.log(pf_data / pf_data.shift(1))
```

In [123]:

```
log_returns.mean()*365
```

Out[123]:

```
BTC-USD   -0.157967
ETH-USD   -0.795284
dtype: float64
```

In [124]:

```
#运动方向是否一样
log_returns.cov()*365
```

Out[124]:

	BTC-USD	ETH-USD
BTC-USD	0.666505	0.705871
ETH-USD	0.705871	1.099533

In [125]:

```
log_returns.corr()
```

Out[125]:

	BTC-USD	ETH-USD
BTC-USD	1.000000	0.824555
ETH-USD	0.824555	1.000000

In [34]:

```

num_assets = len(assets)
```

In [35]:

```
num_assets
```

Out[35]:

2

In [36]:

```
arr = np.random.random(2)
```

In [37]:

```
arr
```

Out[37]:

```
array([0.89269844, 0.15286453])
```

In [38]:

```

arr[0] +arr[1]
```

Out[38]:

```
1.0455629691354043
```

In [39]:

```
weights = np.random.random(num_assets)
```

In [40]:

```
#w = w / sum(w)
weights /= np.sum(weights)
```

In [41]:

```
weights
```

Out[41]:

```
array([0.35314849, 0.64685151])
```

In [42]:

```
weights[0] + weights[1]
```

Out[42]:

```
1.0
```

In [43]:

```
#Expected portfolio return:
np.sum(weights * log_returns.mean()) *365
```

Out[43]:

```
0.16153317177480772
```

In [44]:

```
pfolio_returns = []
pfolio_volatilities = []

for x in range(1000):
    weights = np.random.random(num_assets)
    weights /= np.sum(weights)
    pfolio_returns.append(np.sum(weights * log_returns.mean()) *250)
    pfolio_volatilities.append(np.sqrt(np.dot(weights.T, np.dot(log_returns.c

pfolio_returns, pfolio_volatilities
```

Out[44]:

```
([0.20553545628814068,
  0.021251263451447414,
  0.20878156849870458,
  0.09561963237341516,
  0.0969250348948364,
  -0.05028874037750978,
  0.1740123664472133,
  0.16612600401516503,
  0.18261840340655436,
  0.09954362392327731,
  -0.06370370911995592,
  0.004812590149562973,
  0.16609913134424556,
  0.10154344034400317,
  0.1612321649522507,
  0.06970385236808237,
  0.09833239492845436,
  0.06982174293814153,
```

In [45]:

```
#将列表转化为数组
pfolio_returns = []
pfolio_volatilities = []

for x in range(1000):
    weights = np.random.random(num_assets)
    weights /= np.sum(weights)
    pfolio_returns.append(np.sum(weights * log_returns.mean()) *250)
    pfolio_volatilities.append(np.sqrt(np.dot(weights.T, np.dot(log_returns.c

pfolio_returns = np.array(pfolio_returns)
pfolio_volatilities = np.array(pfolio_volatilities)

pfolio_returns, pfolio_volatilities
```

Out[45]:

```
(array([ 4.72432890e-02,  1.61980244e-02,  7.93999160e-02,  2.499324
26e-01,
         2.18741424e-01,  2.84681654e-01,  1.62634106e-01,  1.086921
39e-01,
        -6.04599824e-02,  2.55046615e-01,  2.87445872e-01, -1.507732
59e-02,
         2.05578962e-01,  2.03707522e-01,  1.33444615e-01,  2.301248
89e-01,
         6.37838564e-02,  1.11536376e-01,  1.97386848e-01,  1.538873
84e-01,
         2.62343854e-01,  2.07473244e-01,  7.96358244e-02,  1.686577
53e-01,
         1.57651943e-01, -7.14675750e-02,  9.49604761e-02, -8.469117
90e-02,
        -5.90159990e-02,  2.31631911e-01,  2.02928490e-01,  7.547568
73e-02,
         1.22651602e-01, -9.25062848e-02, -3.33543321e-02,  7.435203
28e-02,
```

In [46]:

```

portfolios = pd.DataFrame({'Return': pfolio_returns, 'Volatility': pfolio_vol
```

In [47]:

```
portfolios.head()
```

Out[47]:

	Return	Volatility
0	0.047243	0.428678
1	0.016198	0.476077
2	0.079400	0.381372
3	0.249932	0.214379
4	0.218741	0.226079

In [50]:

```
portfolios.tail()
```

Out[50]:

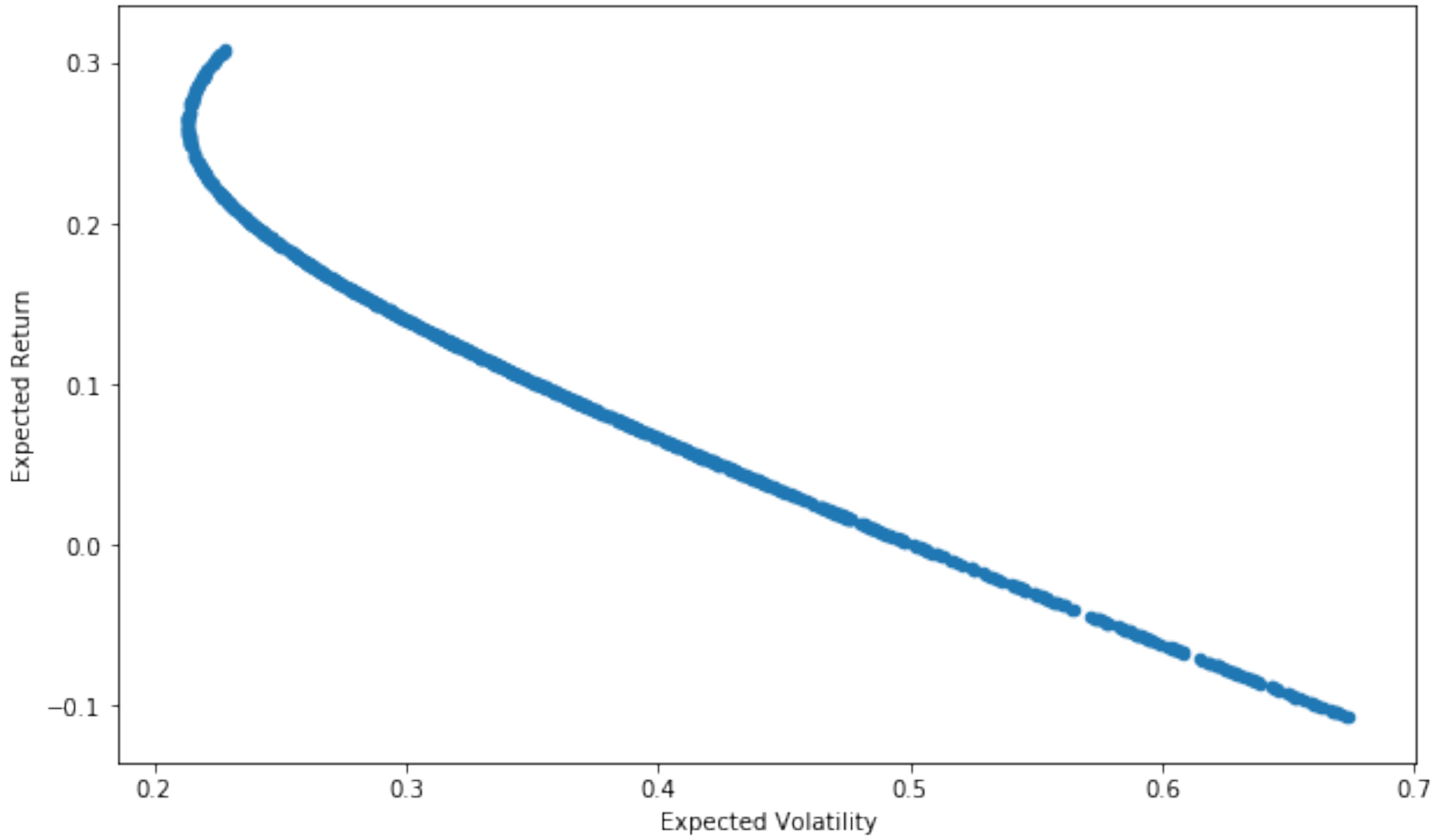
	Return	Volatility
995	0.125317	0.318568
996	0.175362	0.260742
997	0.095414	0.358714
998	0.158016	0.279096
999	0.129353	0.313411

In [51]:

```
portfolios.plot(x = 'Volatility', y= 'Return', kind = 'scatter', figsize =(10
plt.xlabel('Expected Volatility')
plt.ylabel('Expected Return')
```

Out[51]:

```
Text(0, 0.5, 'Expected Return')
```



In [394]:

```
df = pd.read_csv('/Users/zhangjingyi/Desktop/companylist.csv')
```

In [395]:

```
df.head()
```

Out[395]:

	Symbol	Name	LastSale	MarketCap	ADR TSO	IPOyear	Sector	
0	YI	111, Inc.	4.65	6.001846e+07	12907195.0	2018.0	Health Care	Medica
1	PIH	1347 Property Insurance Holdings, Inc.	5.10	3.066510e+07	NaN	2014.0	Finance	Casualty
2	PIHPP	1347 Property Insurance Holdings, Inc.	25.20	1.764000e+07	NaN	NaN	Finance	Casualty
3	TURN	180 Degree Capital Corp.	1.96	6.099826e+07	NaN	NaN	Finance	Finance/
4	FLWS	1-800 FLOWERS.COM, Inc.	19.75	1.270278e+09	NaN	1999.0	Consumer Services	Other

In [170]:

```
df.iloc[:,0]
```

Out[170]:

```
0          YI
1         PIH
2       PIHPP
3        TURN
4        FLWS
5        BCOW
6        FCCY
7        SRCE
8        VNET
9        TWOU
10       QFIN
11       JOBS
12        JFK
13      JFKKR
14      JFKKU
15      JFKKW
16       EGHT
17       AAON
18       ABEO
19      ABEOW
20       ABIL
21       ABMD
22       AXAS
23       ACIU
24       ACIA
25       ACTG
26       ACHC
```

```
27        ACAD
28        ACAM
29       ACAMU
         ...
3502       YIN
3503      YMAB
3504      YOGA
3505      YGYI
3506      YRCW
3507        YJ
3508        YY
3509      ZFGN
3510      ZAGG
3511      ZLAB
3512      ZEAL
3513      ZBRA
3514         Z
3515        ZG
3516        ZN
3517     ZNWAA
3518      ZION
3519     ZIONW
3520      ZIOP
3521      ZIXI
3522      ZKIN
3523      ZGNX
3524        ZM
3525      ZSAN
3526       ZVO
3527        ZS
3528      ZUMZ
3529      ZYNE
3530      ZYXI
3531      ZNGA
Name: Symbol, Length: 3532, dtype: object
```

In [183]:

```
for symbol in df[df.columns[0]]:
    try:
        df_data[symbol] = wb.DataReader(symbol, data_source = 'yahoo', start
    except Exception:pass
```

In [186]:

```
df_data.tail()
```

Out[186]:

Date	BTC-USD	TSLA	YI	PIH	PIHPP	TURN	FLWS	BCOW	FCCY
2019-07-14	10850.259766	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-07-15	9423.440430	253.500000	4.99	4.95	25.125000	1.95	19.160000	9.2100	18.330000
2019-07-16	9696.150391	252.380005	4.85	5.28	25.362000	1.95	19.680000	9.1000	18.290001
2019-07-17	10701.549805	254.860001	4.75	5.00	25.000000	1.97	19.549999	9.0500	18.170000
2019-07-19	10486.370117	258.179993	4.55	4.65	25.190001	1.95	19.129999	9.3344	18.200001

5 rows × 3439 columns

In [401]:

```
pf_returns = np.log(pf_data / pf_data.shift(1))
```

In [402]:

```
pf_returns
```

Out[402]:

Date	BTC-USD	WTRH
2018-01-01	NaN	NaN
2018-01-02	0.092925	NaN
2018-01-03	0.026914	0.000000
2018-01-04	0.001547	0.003014
2018-01-05	0.110566	0.000000
2018-01-06	0.012748	NaN
2018-01-07	-0.056550	NaN
2018-01-08	-0.080288	NaN
2018-01-09	-0.034486	0.000000
2018-01-10	0.030695	-0.000901
2018-01-11	-0.114299	0.000901
2018-01-12	0.039279	0.000000

2018-01-13	0.028625	NaN
2018-01-14	-0.043368	NaN
2018-01-15	-0.000488	NaN
2018-01-16	-0.189167	NaN
2018-01-17	-0.010674	0.001001
2018-01-18	0.001148	0.000000
2018-01-19	0.030512	0.000000
2018-01-20	0.103952	NaN
2018-01-21	-0.101510	NaN
2018-01-22	-0.065790	NaN
2018-01-23	0.004034	-0.003004
2018-01-24	0.051232	0.000000
2018-01-25	-0.022399	0.000000
2018-01-26	-0.006434	0.000000
2018-01-27	0.031514	NaN
2018-01-28	0.026525	NaN
2018-01-29	-0.046421	NaN
2018-01-30	-0.105687	-0.001004
...	...	...
2019-06-19	0.027243	-0.022691
2019-06-20	0.069073	-0.019868
2019-06-21	0.045030	-0.080043
2019-06-22	0.015451	NaN
2019-06-23	0.016422	NaN
2019-06-24	0.061892	NaN
2019-06-25	0.095225	0.028597
2019-06-26	-0.146450	0.043803
2019-06-27	0.102259	-0.052129
2019-06-28	-0.038864	0.050540
2019-06-29	-0.098525	NaN
2019-06-30	-0.016590	NaN
2019-07-01	0.023537	NaN
2019-07-02	0.099749	0.007843
2019-07-03	-0.071349	-0.015748
2019-07-04	-0.014743	NaN
2019-07-05	0.022992	NaN

2019-07-05	0.022992	NaN
2019-07-06	0.019834	NaN
2019-07-07	0.069179	NaN
2019-07-08	0.021789	NaN
2019-07-09	-0.037943	0.046597
2019-07-10	-0.064521	0.028848
2019-07-11	0.039265	-0.003165
2019-07-12	-0.037429	-0.048711
2019-07-13	-0.107628	NaN
2019-07-14	0.061369	NaN
2019-07-15	-0.140989	NaN
2019-07-16	0.028529	-0.057264
2019-07-17	0.092736	-0.023078
2019-07-18	-0.011787	-0.027615

565 rows × 2 columns

In [232]:

```
correlation = pf_data.corr()
correlation
```

Out[232]:

	BTC-USD	TSLA	YI	PIH	PIHPP	TURN	FLWS	BCOW
BTC-USD	1.000000	-0.138058	-0.176649	0.507214	0.523351	0.087181	-0.126816	-0.65165
TSLA	-0.138058	1.000000	0.274283	0.231750	-0.425634	0.213932	-0.658606	0.49960
YI	-0.176649	0.274283	1.000000	0.561079	0.017724	0.755686	-0.542288	0.42042
PIH	0.507214	0.231750	0.561079	1.000000	0.349758	0.556785	-0.466407	-0.05244
PIHPP	0.523351	-0.425634	0.017724	0.349758	1.000000	0.339086	0.405701	-0.47807
TURN	0.087181	0.213932	0.755686	0.556785	0.339086	1.000000	-0.275218	-0.19831
FLWS	-0.126816	-0.658606	-0.542288	-0.466407	0.405701	-0.275218	1.000000	-0.36627
BCOW	-0.651652	0.499608	0.420421	-0.052445	-0.478079	-0.198316	-0.366272	1.00000
FCCY	-0.018565	0.330639	0.713066	0.612109	-0.013907	0.618631	-0.474127	0.14748
SRCE	0.290856	0.274250	0.740996	0.848888	0.354451	0.747422	-0.388376	-0.10252
VNET	-0.332825	0.396771	0.609382	-0.092837	-0.074681	0.381775	-0.249181	0.27624
TWOU	0.060056	0.455258	0.559815	0.760033	-0.033359	0.448847	-0.534820	0.60180
QFIN	-0.224028	-0.166532	0.281510	0.193921	0.252888	-0.187470	0.288648	0.29083
JOBS	0.087571	-0.055663	-0.180660	0.484302	0.258034	0.329776	0.098170	0.10558

JFK	0.267798	0.391714	-0.441048	-0.186477	-0.143151	0.257068	0.421906	-0.02208
JFKKR	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
JFKKU	0.829827	-0.174965	-0.805656	-0.175430	0.512416	0.337021	0.114547	-0.73321
JFKKW	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
EGHT	0.020439	-0.646438	-0.228769	-0.142110	0.603809	0.164468	0.644340	-0.49579
AAON	0.035191	-0.621967	-0.389677	-0.452694	0.484341	-0.250006	0.854497	-0.39834
ABEO	0.381410	0.410033	0.868714	0.850343	0.015983	0.438282	-0.646217	0.67765
ABEOW	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
ABIL	-0.308063	0.221933	0.767862	0.279653	0.015308	0.606135	-0.270464	0.61928
ABMD	-0.419407	0.279550	0.745965	0.287803	-0.064888	0.681483	-0.314568	0.30093
AXAS	0.368602	0.434043	0.814398	0.856191	0.070699	0.546698	-0.689765	0.71114
ACIU	0.326933	0.632058	0.302810	0.505986	-0.284617	0.233806	-0.799659	0.33376
ACIA	-0.212126	-0.450260	-0.425177	-0.582969	0.284545	-0.394455	0.781911	0.05087
ACTG	0.335440	0.440075	0.585927	0.838559	0.139227	0.593715	-0.455663	0.53186
ACHC	0.405686	0.192714	0.395959	0.813897	0.376149	0.592771	-0.420690	-0.44901
ACAD	0.353453	-0.281974	-0.434805	-0.183719	0.254284	-0.556649	0.378597	-0.14991
...	...	...	...	...	...	...	...	.
YTEN	0.370933	0.451668	0.642891	0.764225	0.012572	0.221620	-0.636312	0.65692
YIN	0.251753	0.566646	0.220876	0.648647	-0.265230	0.101003	-0.607152	0.55355
YMAB	0.034831	0.174454	0.357915	0.386906	0.396647	0.402782	0.001621	0.37322
YOGA	0.601508	0.375374	0.537944	0.801418	0.073917	0.143296	-0.537231	0.34465
YGYI	-0.346943	-0.131715	0.224343	-0.540356	-0.090727	-0.187177	0.140215	0.06954
YRCW	0.424118	0.426734	0.684428	0.766874	0.176280	0.442285	-0.521828	0.53914
YJ	-0.575495	0.347352	0.328615	-0.317751	-0.175126	0.043795	0.419155	0.61429
YY	0.574204	0.346959	-0.019938	0.710116	0.128877	0.096239	-0.367042	0.53104
ZFGN	-0.007219	0.554455	0.782158	0.571878	-0.074215	0.554116	-0.769148	0.47194
ZAGG	0.251830	0.622275	0.762007	0.749713	-0.059070	0.587104	-0.709698	0.41832
ZLAB	0.060168	-0.490615	-0.661514	-0.395295	0.228630	-0.304872	0.819712	-0.50471
ZEAL	0.349854	-0.778932	-0.287821	-0.158034	0.557226	-0.193778	0.717126	-0.49371
ZBRA	-0.444951	-0.504709	-0.333531	-0.596564	0.326987	-0.161191	0.801735	0.13053
Z	0.451438	0.084370	-0.001028	0.809423	0.326791	0.495109	-0.234865	-0.60336
ZG	0.447417	0.100781	0.016396	0.812128	0.314637	0.498426	-0.249580	-0.61485
ZN	0.412565	0.340635	0.640900	0.792349	-0.006141	0.218931	-0.512459	0.62303
ZION	0.320443	0.322077	0.592329	0.824969	0.257443	0.486350	-0.382346	0.17464
ZIONW	0.316590	0.391249	0.677056	0.838408	0.191780	0.490703	-0.471997	0.23200
ZIOP	0.632457	-0.466944	-0.435547	0.203366	0.544228	-0.183189	0.408355	-0.47607

ZIXI	-0.163414	-0.647799	-0.493828	-0.613899	0.387901	-0.220265	0.868923	-0.70453
ZKIN	0.653467	0.393376	0.752691	0.747988	-0.012215	0.148149	-0.596306	0.53406
ZGNX	-0.259357	0.097523	0.081276	0.094715	0.133766	0.335213	0.178676	0.21515
ZM	0.670129	-0.164725	-0.648893	0.294551	0.441482	0.583511	0.143854	-0.63634
ZSAN	0.435648	0.252286	0.201449	0.435108	0.078481	-0.023088	-0.276670	0.38705
ZVO	-0.876213	0.527696	0.651313	-0.410615	-0.606534	-0.424703	0.210474	0.75253
ZS	0.136873	-0.666032	-0.559555	-0.502267	0.408013	-0.354569	0.895034	-0.44845
ZUMZ	-0.067069	-0.197000	0.250209	0.237575	0.357626	0.507630	0.218547	0.11928
ZYNE	0.764396	-0.435640	-0.214752	0.392433	0.638689	0.036627	0.236899	-0.59360
ZYXI	0.302761	-0.712606	-0.507191	-0.336449	0.470265	-0.349472	0.772223	-0.64438
ZNGA	-0.007628	-0.785048	-0.506982	-0.426590	0.455366	-0.193651	0.913283	-0.53443

3439 rows × 3439 columns

In [233]:

```
d = correlation[0:1]
```

In [272]:

```
d
```

Out[272]:

	BTC-USD	TSLA	YI	PIH	PIHPP	TURN	FLWS	BCOW	FC
BTC-USD	1.0	-0.138058	-0.176649	0.507214	0.523351	0.087181	-0.126816	-0.651652	-0.018

1 rows × 3439 columns

In [405]:

```
a = d.sort_values("BTC-USD", axis=1).iloc[:,0:15]
```

In [406]:

```
a
```

Out[406]:

	EMMA	MREO	CVET	XAIR	GNLN	APLT	HOOK	ZVO	
BTC-USD	-1.0	-0.909515	-0.903967	-0.901592	-0.894123	-0.890201	-0.880063	-0.876213	-0.

In [ ]:

```
#-------------
```

In [60]:

```
import numpy as np
import pandas as pd
from pandas_datareader import data as wb

tickers = ['BTC-USD', '^GSPC']
data = pd.DataFrame()
for t in tickers:
    data[t] = wb.DataReader(t, data_source = 'yahoo', start = '2018-1-1')['Ad
```

In [72]:

```
sec_return = np.log(data / data.shift(1))
sec_return
```

Out[72]:

	BTC-USD	^GSPC
Date		
2018-01-01	NaN	NaN
2018-01-02	0.092925	NaN
2018-01-03	0.026914	0.006378
2018-01-04	0.001547	0.004021
2018-01-05	0.110566	0.007009
2018-01-06	0.012748	NaN
2018-01-07	-0.056550	NaN
2018-01-08	-0.080288	NaN
2018-01-09	-0.034486	0.001302
2018-01-10	0.030695	-0.001113
2018-01-11	-0.114299	0.007009
2018-01-12	0.039279	0.006727
2018-01-13	0.028625	NaN
2018-01-14	-0.043368	NaN
2018-01-15	-0.000488	NaN
2018-01-16	-0.189167	NaN
2018-01-17	-0.010674	0.009371
2018-01-18	0.001148	-0.001618
2018-01-19	0.030512	0.004376

2018-01-20	0.103952	NaN
2018-01-21	-0.101510	NaN
2018-01-22	-0.065790	NaN
2018-01-23	0.004034	0.002172
2018-01-24	0.051232	-0.000560
2018-01-25	-0.022399	0.000602
2018-01-26	-0.006434	0.011772
2018-01-27	0.031514	NaN
2018-01-28	0.026525	NaN
2018-01-29	-0.046421	NaN
2018-01-30	-0.105687	-0.010959
...	...	...
2019-06-22	0.015451	NaN
2019-06-23	0.016422	NaN
2019-06-24	0.061892	NaN
2019-06-25	0.095225	-0.009542
2019-06-26	-0.146450	-0.001235
2019-06-27	0.102259	0.003816
2019-06-28	-0.038864	0.005741
2019-06-29	-0.098525	NaN
2019-06-30	-0.016590	NaN
2019-07-01	0.023537	NaN
2019-07-02	0.099749	0.002924
2019-07-03	-0.071349	0.007643
2019-07-04	-0.014743	NaN
2019-07-05	0.022992	NaN
2019-07-06	0.019834	NaN
2019-07-07	0.069179	NaN
2019-07-08	0.021789	NaN
2019-07-09	-0.037943	0.001236
2019-07-10	-0.064521	0.004501
2019-07-11	0.039265	0.002283
2019-07-12	-0.037429	0.004610
2019-07-13	-0.107628	NaN
2019-07-14	0.061369	NaN
2019-07-15	-0.140989	NaN

2019-07-16	0.028529	-0.003410
2019-07-17	0.092736	-0.006553
2019-07-18	-0.009958	0.003576
2019-07-19	0.021274	-0.006196
2019-07-20	-0.014115	NaN
2019-07-22	0.000903	NaN

568 rows × 2 columns

In [98]:

```
cov =sec_return.cov()
cov
```

Out[98]:

	BTC-USD	^GSPC
BTC-USD	0.001818	0.000020
^GSPC	0.000020	0.000086

In [99]:

```
cov.iloc[0,0] *365
```

Out[99]:

```
0.6633976912848524
```

In [101]:

```
cov.iloc[0,1]*250
```

Out[101]:

```
0.004966519640959774
```

In [103]:

```
cov_with_market = cov.iloc[0,1]*250
cov_with_market
```

Out[103]:

```
0.004966519640959774
```

In [104]:

```
market_value = sec_return['^GSPC'].var()*250
market_value
```

Out[104]:

0.02153234583598596

In [105]:

```
Bitcoin_beta = cov_with_market / market_value
Bitcoin_beta
```

Out[105]:

0.23065390453925702

In [106]:

```
Bitcoin_er = 0.025 + Bitcoin_beta * 0.05
```

In [107]:

```
Bitcoin_er
```

Out[107]:

0.036532695226962855

In [108]:

```
sharp = (Bitcoin_er - 0.025) / (sec_return['BTC-USD'].std() * 365 ** 0.5)
sharp
```

Out[108]:

0.014159366959600326

In [115]:

```

```