Stock correlation analysis

by Andras Petre

Introducion

- Imagine you are a small investor, who would like to have his/her own portfolio.
- You would like to diversify it as much as you can, so you can protect themselves from the individual volatility of the different financial assets.
- In this analysis we use the 18 historical finance assets from Yahoo Finance to create our personal portfolio.
- But let's say, we can choose only 4 assets from the 18. Which assets are the highly correlated ones? Which assets would you pick up to create the most diverse portfolio?

Querying the assets into a big table to be able to analyze the data

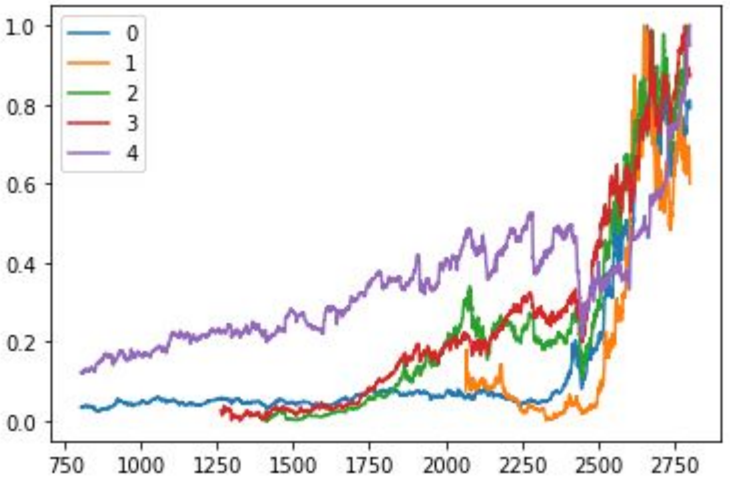
	TSLA	NIO	IQQH.F	BTC-USD	ETH-USD	LTC-USD	AMZN	TWTR	FB	SQ	PYPL	BRK-A
2021-07-27	663.400024	42.439999	10.874	37276.035156	2230.197021	131.232895	3698.500000	68.320000	371.910004	261.279999	305.500000	419810.0
2021-07-28	647.000000	40.910000	10.722	39503.187500	2302.081299	134.767212	3633.780029	68.389999	374.559998	254.029999	300.739990	422250.0
2021-07-29	649.789978	42.250000	11.022	39995.453125	2299.011963	140.299164	3627.750000	69.500000	361.000000	255.509995	285.369995	419635.0
2021-07-30	671.760010	42.230000	10.938	40027.484375	2382.545166	141.471710	3347.949951	69.830002	354.000000	249.279999	280.244995	421770.0
2021-08-02	700.000000	44.650002	11.088	39907.261719	2557.774658	140.542435	3353.100098	70.230003	358.100006	247.929993	276.885010	420985.0
2021-08-03	719.000000	45.230000	10.982	39178.402344	2609.413086	141.468506	3340.719971	69.870003	352.730011	270.429993	272.059998	420576.0
2021-08-04	711.000000	45.470001	11.156	38213.332031	2508.544922	138.486313	3379.350098	68.680000	352.420013	268.000000	274.071014	421988.0
2021-08-05	716.000000	44.750000	11.198	39744.515625	2725.669678	142.627914	3356.219971	68.849998	359.640015	265.600006	277.100006	421358.0
2021-08-06	711.900024	45.549999	11.138	40865.867188	2827.503418	143.548004	3375.000000	69.300003	361.399994	279.510010	280.000000	424426.0
2021-08-09	710.169983	43.700001	11.162	43791.925781	3012.885742	149.818512	3343.610107	67.500000	363.760010	272.989990	280.220001	433056.0
2021-08-10	713.989990	45.470001	11.346	46280.847656	3163.050049	166.467728	3345.010010	67.199997	361.829987	280.010010	278.940002	432690.0
2021-08-11	712.710022	44.709999	11.360	45599.703125	3142.830322	165.408691	3331.449951	65.790001	362.100006	277.760010	277.441986	434655.0
2021-08-12	706.340027	44.349998	11.184	45576.878906	3164.175781	170.879288	3290.000000	64.809998	358.450012	270.450012	274.250000	439121.0
2021-08-13	723.710022	41.900002	11.102	44439.691406	3049.001221	165.511780	3305.669922	64.989998	362.970001	269.950012	276.170013	437935.0
2021-08-16	705.070007	39.459999	NaN	47019.960938	3309.422119	184.776001	3283.000000	64.339996	362.519989	266.350006	273.730011	432443.0

The values of the various assets are sometimes in different dimensions, so they aren't comparable.

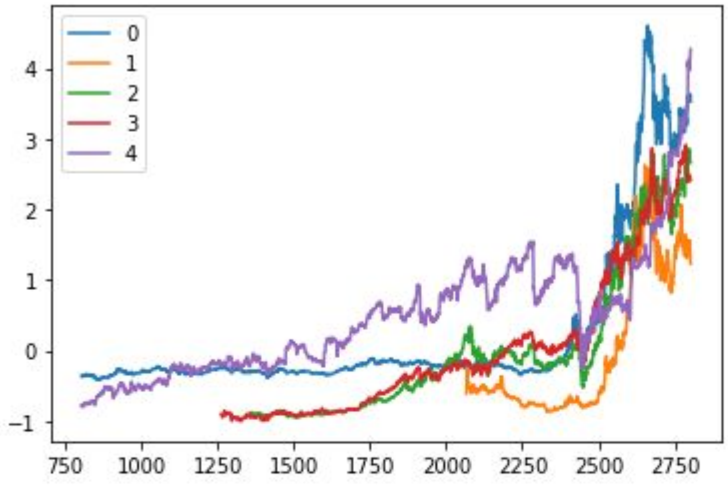
The 'TSLA' asset is about 700, while the 'TWTR' is about 60-70.

The solution for the problem is normalization 1.

1. method



2. method



After the normalization the values are in the same dimension (on both methods above), so they are comparable, doesn't contain outliers or non-standardized values.

The solution for the problem is normalization 2.

	TSLA	NIO	IQQH.F	BTC-USD	ETH-USD	LTC-USD	AMZN	TWTR	FB	SQ	PYPL	BRK-A	^GSPC	GC=F	SI=F
803	0.034325	NaN	0.097923	NaN	NaN	NaN	0.052061	NaN	0.070158	NaN	NaN	0.200573	0.183228	0.319923	0.305166
804	0.033098	NaN	0.097923	NaN	NaN	NaN	0.052580	NaN	0.073721	NaN	NaN	0.199400	0.183057	0.338879	0.327837
805	0.032722	NaN	0.100890	NaN	NaN	NaN	0.053495	NaN	0.073384	NaN	NaN	0.204812	0.188369	0.326477	0.319593
806	0.033839	NaN	0.103116	NaN	NaN	NaN	0.053045	NaN	0.071000	NaN	NaN	0.206730	0.190094	0.314680	0.294037
807	0.033296	NaN	0.103116	NaN	NaN	NaN	0.053177	NaN	0.077003	NaN	NaN	0.207170	0.192471	0.308832	0.303792
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2798	0.800271	0.694479	0.635460	0.727802	0.757658	0.427483	0.890329	0.826735	0.964290	1.000000	0.889829	0.975451	0.991548	0.680480	0.313685
2799	0.798830	0.682560	0.636498	0.717049	0.752814	0.424744	0.886602	0.804844	0.965047	0.991720	0.884457	0.981212	0.993408	0.679169	0.313383
2800	0.791657	0.676913	0.623442	0.716689	0.757928	0.438891	0.875209	0.789629	0.954808	0.964819	0.873010	0.994306	0.994542	0.701754	0.303243
2801	0.811215	0.638488	0.617359	0.698737	0.730336	0.425011	0.879516	0.792423	0.967488	0.962979	0.879895	0.990829	1.000000	0.710426	0.309975
2802	0.790227	0.600220	NaN	0.739469	0.792724	0.474826	0.873284	0.782332	0.966225	0.949731	0.871145	0.974727	0.999072	0.729179	0.321792

After the normalization all values are in the same dimension (between 0 and 1) except the NaN values.

Correlation analysis 1.

	TSLA	NIO	IQQH.F	BTC-USD	ETH-USD	LTC-USD	AMZN	TWTR	FB	SQ	PYPL	BRK-A	^GSPC	GC=
TSLA	1.000000	0.791893	0.335175	0.746569	0.742157	0.653759	0.916686	0.179207	0.880102	0.758126	0.758764	0.907550	0.925877	0.04023
NIO	0.791893	1.000000	0.653509	0.578002	0.690314	0.417618	0.688221	0.642974	0.632683	0.870078	0.664680	0.554085	0.639152	0.56038
IQQH.F	0.335175	0.653509	1.000000	0.378486	0.332793	0.201612	0.337304	0.550939	0.655782	0.656639	0.668145	0.360429	0.376226	0.14614
BTC-USD	0.746569	0.578002	0.378486	1.000000	0.885633	0.912432	0.922647	0.420328	0.951383	0.845818	0.907980	0.886080	0.929843	0.82476
ETH-USD	0.742157	0.690314	0.332793	0.885633	1.000000	0.914235	0.755131	0.646661	0.843244	0.711378	0.743632	0.758923	0.774392	0.63811
LTC-USD	0.653759	0.417618	0.201612	0.912432	0.914235	1.000000	0.803698	0.384815	0.849878	0.691236	0.749353	0.834724	0.824552	0.66676
AMZN	0.916686	0.688221	0.337304	0.922647	0.755131	0.803698	1.000000	0.169340	0.971817	0.958741	0.976761	0.955009	0.981520	0.08467
TWTR	0.179207	0.642974	0.550939	0.420328	0.646661	0.384815	0.169340	1.000000	0.145790	0.877425	0.818642	0.225772	0.228790	0.34851
FB	0.880102	0.632683	0.655782	0.951383	0.843244	0.849878	0.971817	0.145790	1.000000	0.875939	0.939430	0.940839	0.976835	0.31583
SQ	0.758126	0.870078	0.656639	0.845818	0.711378	0.691236	0.958741	0.877425	0.875939	1.000000	0.954994	0.885786	0.948837	0.67036
PYPL	0.758764	0.664680	0.668145	0.907980	0.743632	0.749353	0.976761	0.818642	0.939430	0.954994	1.000000	0.895083	0.974238	0.82297
BRK-A	0.907550	0.554085	0.360429	0.886080	0.758923	0.834724	0.955009	0.225772	0.940839	0.885786	0.895083	1.000000	0.981684	0.01062
^GSPC	0.925877	0.639152	0.376226	0.929843	0.774392	0.824552	0.981520	0.228790	0.976835	0.948837	0.974238	0.981684	1.000000	0.07585
GC=F	0.040236	0.560382	0.146142	0.824764	0.638117	0.666765	0.084673	0.348514	0.315830	0.670366	0.822975	0.010625	0.075854	1.00000
SI=F	-0.459862	0.632119	-0.001630	0.472730	0.448653	0.304029	-0.483553	0.432144	-0.189250	0.333345	0.473477	-0.511406	-0.471846	0.72641
CL=F	-0.580303	0.173214	-0.295289	0.271245	0.532174	0.482322	-0.627545	0.509883	-0.474012	0.381063	0.347429	-0.572380	-0.596067	0.21733
UA	-0.586190	-0.050846	-0.261013	-0.540933	-0.476021	-0.338569	-0.460863	-0.227843	-0.494918	-0.379955	-0.437606	-0.296056	-0.420971	-0.48488
IT	0.898489	0.379286	0.301016	0.847280	0.708788	0.838482	0.965094	0.131158	0.941669	0.851044	0.851638	0.977066	0.977588	-0.00438

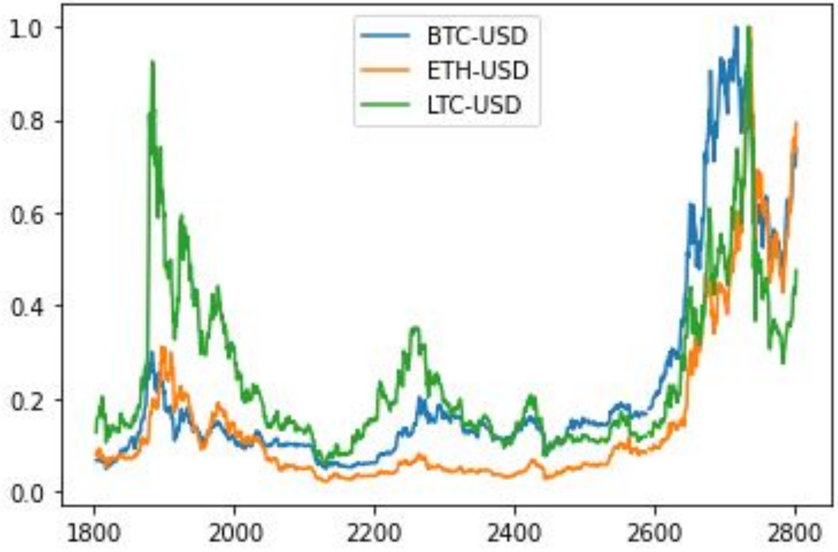
- After running the analysis we can see how the various assets correlate to each other
- If the value is 1.0, then the correlation is 100%
- If the value is lower then 0, then the correlation is negative, the variables change in the opposite direction

Correlation analysis 2.

	TSLA	NIO	IQQH.F	BTC-USD	ETH-USD	LTC-USD	AMZN	TWTR	FB	SQ	PYPL	BRK-A	^GSPC	GC=F	SI=F	CL=F	UA	IT
TSLA	1	0.791893	0.335909	0.746569	0.742157	0.653759	0.916686	0.179207	0.880102	0.758126	0.758764	0.90755	0.925877	0.040247	-0.45986	-0.58031	-0.58619	0.898489
NIO	0.791893	1	0.654846	0.578002	0.690314	0.41762	0.688221	0.642974	0.632683	0.870078	0.66468	0.554085	0.639152	0.560386	0.632117	0.173219	-0.05085	0.379286
IQQH.F	0.335909	0.654846	1	0.379578	0.334108	0.202866	0.33803	0.55161	0.656226	0.657341	0.668782	0.361129	0.376909	0.147047	-0.00119	-0.29507	-0.25959	0.301781
BTC-USD	0.746569	0.578002	0.379578	1	0.885633	0.912432	0.922647	0.420328	0.951383	0.845818	0.90798	0.88608	0.929843	0.824767	0.47273	0.271231	-0.54093	0.84728
ETH-USD	0.742157	0.690314	0.334108	0.885633	1	0.914236	0.755131	0.646661	0.843244	0.711378	0.743632	0.758923	0.774392	0.638126	0.448652	0.532158	-0.47602	0.708788
LTC-USD	0.653759	0.41762	0.202866	0.912432	0.914236	1	0.803698	0.384815	0.849879	0.691238	0.749354	0.834724	0.824552	0.666772	0.304028	0.482313	-0.33856	0.838482
AMZN	0.916686	0.688221	0.33803	0.922647	0.755131	0.803698	1	0.16934	0.971817	0.958741	0.976761	0.955009	0.98152	0.084683	-0.48356	-0.62755	-0.46086	0.965094
TWTR	0.179207	0.642974	0.55161	0.420328	0.646661	0.384815	0.16934	1	0.14579	0.877425	0.818642	0.225772	0.22879	0.348519	0.432144	0.509869	-0.22784	0.131158
FB	0.880102	0.632683	0.656226	0.951383	0.843244	0.849879	0.971817	0.14579	1	0.875939	0.93943	0.940839	0.976835	0.315836	-0.18926	-0.47402	-0.49492	0.941669
SQ	0.758126	0.870078	0.657341	0.845818	0.711378	0.691238	0.958741	0.877425	0.875939	1	0.954994	0.885786	0.948837	0.67037	0.333345	0.381041	-0.37996	0.851044
PYPL	0.758764	0.66468	0.668782	0.90798	0.743632	0.749354	0.976761	0.818642	0.93943	0.954994	1	0.895083	0.974238	0.822977	0.473477	0.347406	-0.43761	0.851638
BRK-A	0.90755	0.554085	0.361129	0.88608	0.758923	0.834724	0.955009	0.225772	0.940839	0.885786	0.895083	1	0.981684	0.010638	-0.51141	-0.57238	-0.29606	0.977066
^GSPC	0.925877	0.639152	0.376909	0.929843	0.774392	0.824552	0.98152	0.22879	0.976835	0.948837	0.974238	0.981684	1	0.075865	-0.47185	-0.59607	-0.42097	0.977588
GC=F	0.040247	0.560386	0.147047	0.824767	0.638126	0.666772	0.084683	0.348519	0.315836	0.67037	0.822977	0.010638	0.075865	1	0.726408	0.217322	-0.48486	-0.00438
SI=F	-0.45986	0.632117	-0.00119	0.47273	0.448652	0.304028	-0.48356	0.432144	-0.18926	0.333345	0.473477	-0.51141	-0.47185	0.726408	1	0.602789	-0.15074	-0.53065
CL=F	-0.58031	0.173219	-0.29507	0.271231	0.532158	0.482313	-0.62755	0.509869	-0.47402	0.381041	0.347406	-0.57238	-0.59607	0.217322	0.602789	1	0.167751	-0.57427
UA	-0.58619	-0.05085	-0.25959	-0.54093	-0.47602	-0.33856	-0.46086	-0.22784	-0.49492	-0.37996	-0.43761	-0.29606	-0.42097	-0.48486	-0.15074	0.167751	1	-0.10613
IT	0.898489	0.379286	0.301781	0.84728	0.708788	0.838482	0.965094	0.131158	0.941669	0.851044	0.851638	0.977066	0.977588	-0.00438	-0.53065	-0.57427	-0.10613	1

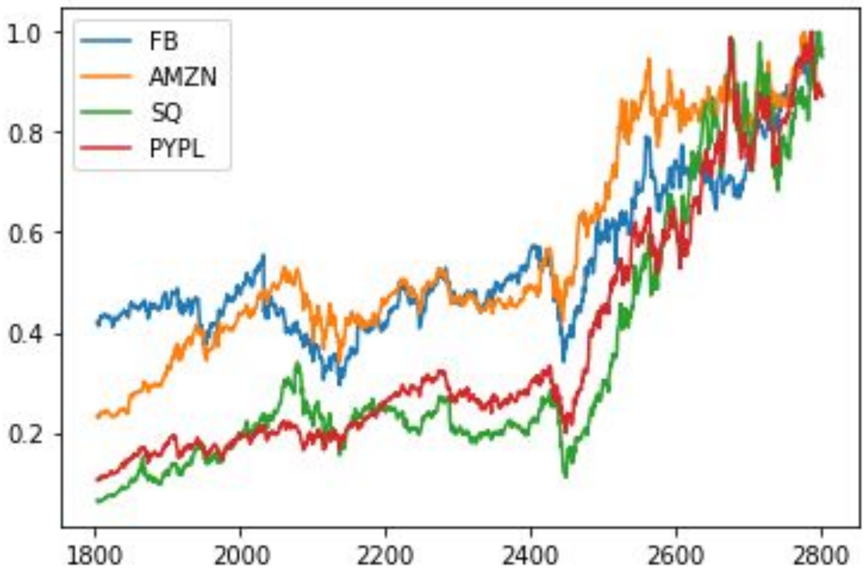
The highly correlated assets are deep green, the most lowest correlated assets are red, so you can distinguish them more easily.

Highly correlated assets 1.



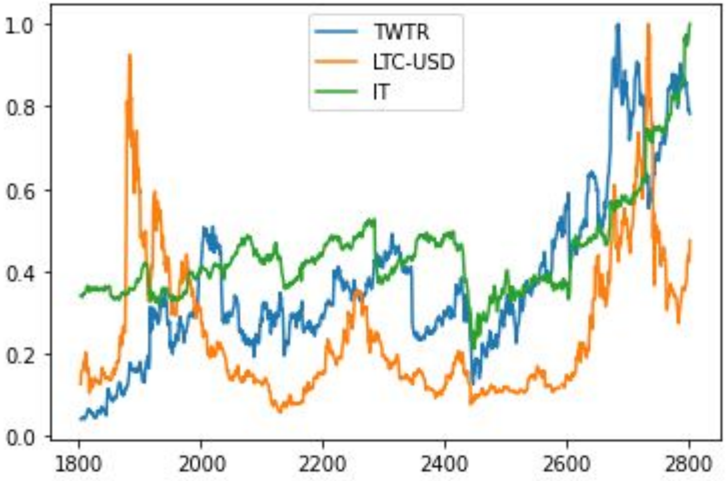
- The three crypto assets are highly correlated, they are moving in the same direction at the same time.
- It’s a good **instance** to have these three assets on your portfolio.

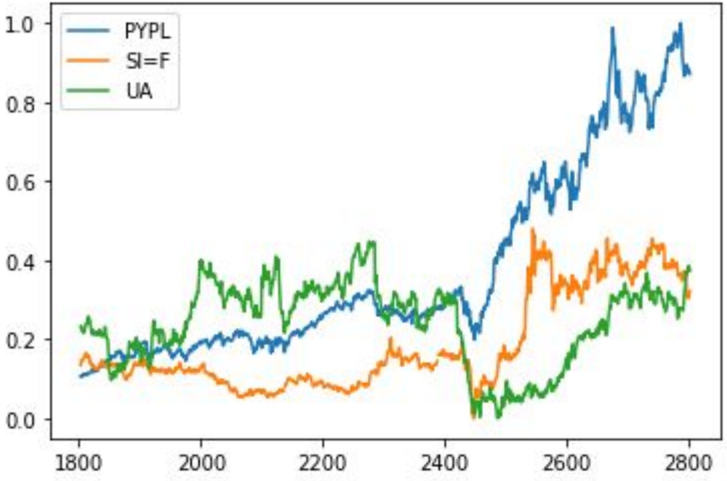
Highly correlated assets 2.



- Facebook (FB), Amazon (AMZN), Square (SQ), and PayPal (PYPL) are also highly correlated assets.
- It could be an alternative **example** to create your own portfolio.

Not correlated assets





These are negative correlated assets examples, which are not recommended to have on your own portfolio.

Conclusion

- If you’d like to have your own portfolio **only in the theory** with multiple assets, it’s recommended to choose assets from the same area e. g. crypto assets, green-trend assets.

- It’s important to have as highly positive correlation between these assets as possible. About 90% (0.9 coefficient value) is a very good number.

- By creating the portfolio you should avoid low and negative correlation. If the coefficient value between two assets is under 0.3, those stocks are quite different, so you shouldn’t use them together.

Thank you.

Contact details: andras.petre@gmail.com