

Project_IV-Final_Project

Time series exploration 📈 Crypto Price

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Date: September 1st 2022



Hypothesis:

Using Data Analytics can we find potential altcoins that have the condition or potential to generate significant returns by their unique characteristics. can we create a predictive model that can generate a moderate prediction for future investments?

Get Started with Web Scrapping:

For the project ill be extracting the list of all crypto currencies list from the we page listed in the URL = "<https://coinmarketcap.com/>"

We need web page number of page to be added in the url by using the parameter for the url "/?page=3" since the web page only displays 100 coins per page.

By using Selenium we can create a bot that will scroll thought the dynamic page (meaning it loads information while you scroll the page, otherwise it wont give you all the pages information) in order to

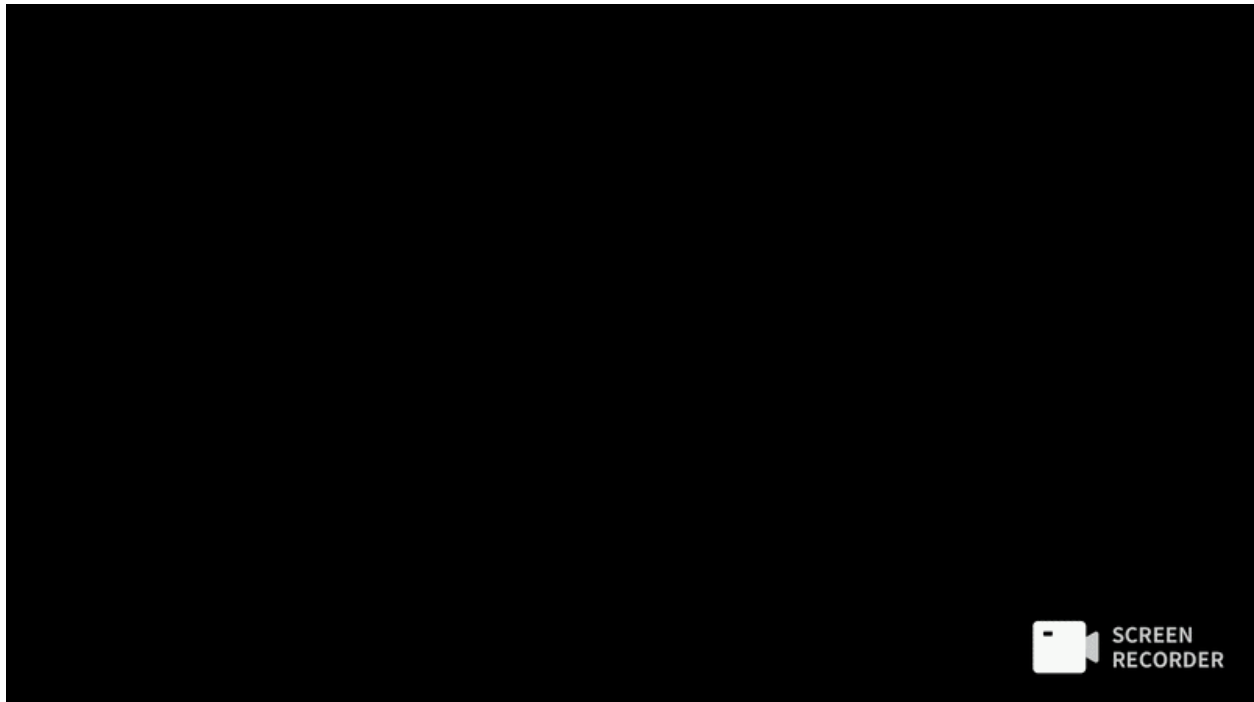
do this we need to make a loop so that we can perform the same task in all the web pages that have information of value. we will only do this for the first 30 pages out of 97. this is because we are only interested in coins that have a market capital (meaning that a significant investment of money is already in capital of said coin).

Code for web scrapping and scrolling selenium:

```
current_scroll_position, new_height= 0, 1
while current_scroll_position <= new_height:
    current_scroll_position += 8
    driver.execute_script("window.scrollTo(0, {});".format(current_scroll_position))
    new_height = driver.execute_script("return document.body.scrollHeight")

html = driver.execute_script("return document.body.outerHTML;")
```

Example of what the bot does:



Following the extraction of the html with selenium, we need to determine what we want to extract, in this case we can start by getting the coins name, ticker, market capital, supply and current price. we do

Example of browser html inspect for info:

Once the information has been extracted and cleaned the text to only have the desired information we temporarily store each column in a list. meaning that we will have to convert them into a data frame using `zip` command for zip list, followed by `pandas.dataframe` to create a table as following:

1	df_crypto.sample(10)				
	name	coin	supply	mcap	price
1595	Golos Blockchain	GLS	307291234	636666	0.00207
16	Wrapped Bitcoin	WBTC	247761	5002514687	20190.88834
873	Phoenix Global (new)	PHB	37136775	6517386	0.17550
1659	Minswap	MIN	25000000	522227	0.02089
564	ZIMBOCASH	ZASH	1590616010	23816732	0.01497
1435	DragonVein	DVC	605026614	1016513	0.00168
1820	Planet Inverse	XIV	33435498	322020	0.00963
2180	Fortuna Sittard Fan Token	FOR	145000	101725	0.70155
548	Cortex	CTXC	199936563	24820749	0.12414
2270	PiplCoin	PIPL	172536809	69663	0.00040

As a result we now have a list of 3000 coins, but how do we determine which ones are the ones we are most interested in and will be using for our analysis?

In order to do this we will need to calculate some field to further filter the coins that are of no use to us.

To get started we need to get familiar with some concepts:

Market Capital = Money invested in one coin

Global Market Capital = Amount of money in all crypto

Circulating supply = Amount of existing coin

Price = Market Capital / Circulating Supply

Knowing this we can use the mathematical rule of three to find out how much a market capital needs to move in order to get a coin to a specific value. In our particular case we want marginal prices that can spike to the amount of \$1. So we create a column to value \$1 and create a column with the new market capital.

Now that we have a new market capital, it would be best to create a column with the variation of price between the initial market capital and the new market capital. As a complement we can add two columns that will tell us the proportion of the new and old market capital represents of the global market capital.

Given this information we can start filtering our 3000 coins and narrowing it down to a more sizable sample to explore and predict.

We want coins who's:

Price < \$1

Market Capital > \$10,000,000.00

Proportion to Global Market Capital <= 1%

Variation between new and old market cap <= 1000

Dataframe once we have created the calculated field and filters:

1	df_altcoin.sample(5)											
	Unnamed: 0	name	coin	supply	mcap	price	set	new-mcap	var	prop-newmcap	prop-mcap	potential
312	312	Origin Protocol	OGN	388570733	66481244	0.17109	1.00000	388570733.00000	584.48000	0.03780	0.00647	5.84482
242	242	MaidSafeCoin	MAID	452552412	117179441	0.25893	1.00000	452552412.00000	386.20000	0.04403	0.01140	3.86205
494	494	smARTOFGIVING	AOG	73780484	29857106	0.40467	1.00000	73780484.00000	247.11000	0.00718	0.00290	2.47112
604	604	Grid+	GRID	39236491	20214435	0.51519	1.00000	39236491.00000	194.10000	0.00382	0.00197	1.94101
158	158	Ellipsis	EPS	723701572	134908234	0.18641	1.00000	723701572.00000	536.44000	0.07041	0.01313	5.36440

After we applied this filters we get as a result a list of 387 coins, we can now use visualization tools to examine any particular tendency and behaviour that can be of our interest so that we can further filter this list to 10 to 20 coins in which we can invest.

Visualization:

To analyze visually even though we can use python, I decided to make a csv file so that I could be imported in Tableau and have a more dynamic analysis. For the coins I want a display of the proportion of the market capital, circulating supply, count of coins, list of those coins, current coin market price, proportion of market capital increase and a calculated field of potential projected increase of value.

The analysis can be seen at the following URL

https://public.tableau.com/app/profile/edgard.cuadra/viz/AltCoins_16617715752970/Alt_coinDash?publish=yes

The filter we want to apply are those coins that have the possibility of 5 folding our initial investment if they happen to reach the value of \$1.00 and we also want coins whose price is under a threshold of \$0.15 per current value.

Visualization before further filter:



Visualizaton after filter:



Now we have found the optimal currencies that we can invest in, now lets see if we can use a predictive model with the time series.

Predictive Model and Sesonality:

The information we extracted with the webscrappe only gives us general characteristics of the coin so we need to find a way to get the time series of said coins.

Using a Yahoo Finances API we can extract the time series of a specific coin and analyze its behaviour over it life cicle an try to undestand.

First we do a query of one coin, in this case ADA - cardano in currency conversion to USD so that we can analyze in a standard conversion. out of this query we get the Adjusted Closing price, the Closing price, High and Low price of the day, the price in which it Open and the Volume of currency that moved that day. the Developer (Free Version) access to the API only allows us to extract daily time series and not hourly so we are limited to the type of analysis that we can conduct. it would be optimal to have a minute movement of the tickers value over time.

Sample of the data we extracted:

Attributes	Adj Close	Close	High	Low	Open	Volume
Symbols	ADA-USD	ADA-USD	ADA-USD	ADA-USD	ADA-USD	ADA-USD
Date						
2017-11-09	0.032053	0.032053	0.035060	0.025006	0.025160	18716200
2017-11-10	0.027119	0.027119	0.033348	0.026451	0.032219	6766780
2017-11-11	0.027437	0.027437	0.029659	0.025684	0.026891	5532220
2017-11-12	0.023977	0.023977	0.027952	0.022591	0.027480	7280250
2017-11-13	0.025808	0.025808	0.026300	0.023495	0.024364	4419440
...
2022-08-24	0.458109	0.458109	0.466601	0.454518	0.465182	494717036
2022-08-25	0.464999	0.464999	0.473415	0.458041	0.458108	525337287
2022-08-26	0.430863	0.430863	0.481639	0.428157	0.464959	1299179883
2022-08-27	0.449703	0.449703	0.450795	0.428077	0.431039	733099946
2022-08-28	0.430049	0.430049	0.453401	0.430049	0.449719	519341943

First lets use the closing price of the coin to evaluate its behaviour over time, inorder to understand the behaviour of this graph we will include:

Moving averagae envelope (MAE) for periods 15

Moving averagae envelope (MAE) for periods 30

Moving averagae envelope (MAE) for periods 45

Tendency line

Sesonality

Residuals

Expanding window

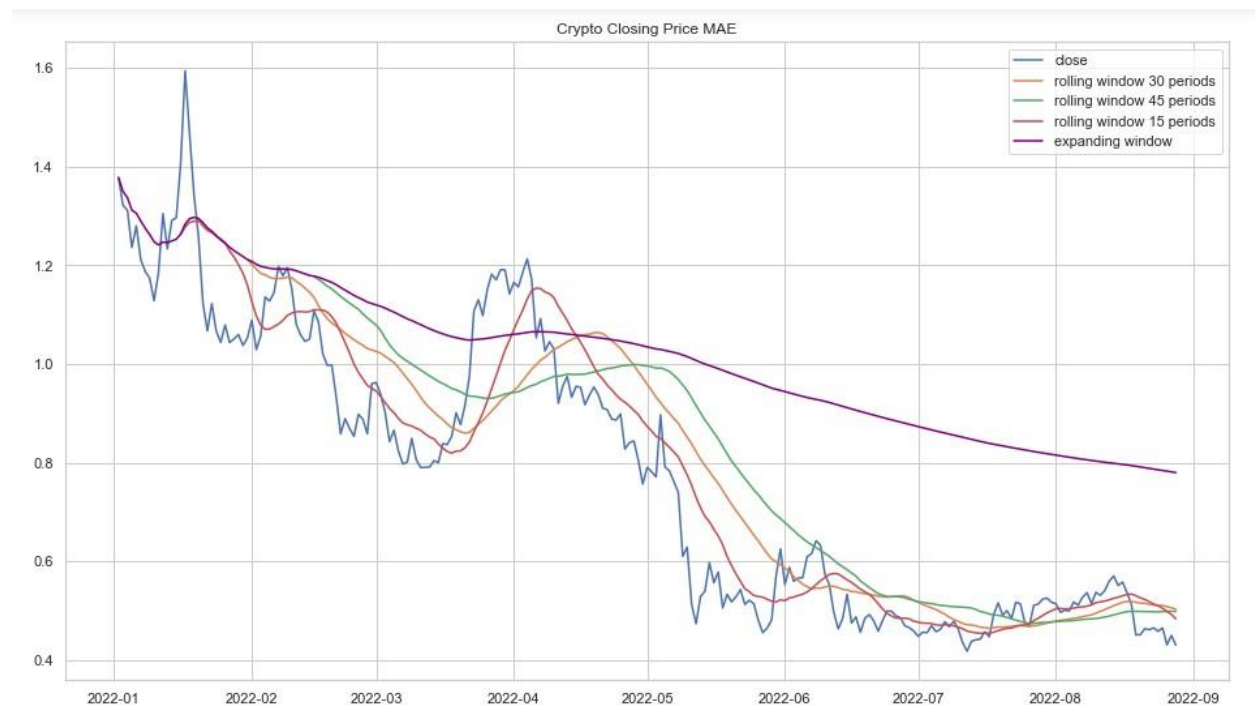
expanding window

Bellow we can see one of the alternate coins that has a moving average and tendancy for 1 year for 2022 as an example. the expanding window give uses a compounded average of the data as the time

series progresses giving us a compounded average which show a general tendency. in this case the tendency is the behaviour of a rolling average of period one.

If the Closing value > than Rolling window the market is ****Bullish****

If the Closing value < than Rolling window the market is ****Bearish****

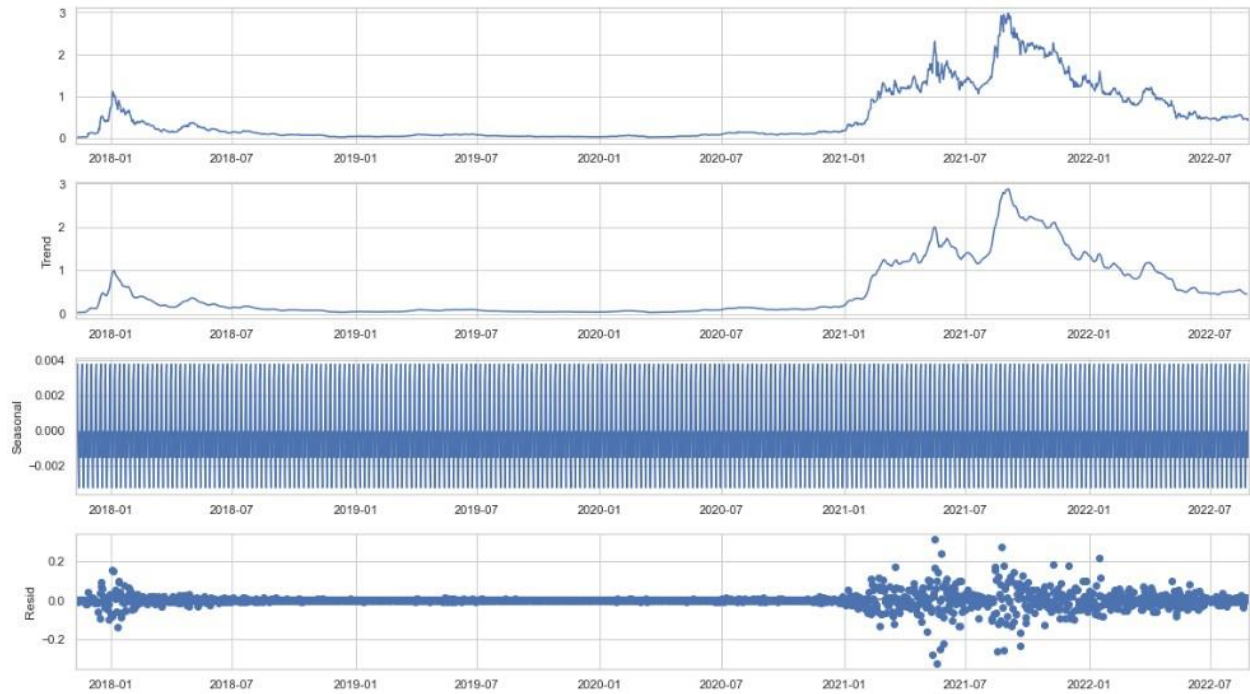


This graph shows us how the market is behaving but won't give us much information of how the market will behave in the future. It's better to have a general understanding on how it's behaving than blindly try to just invest in a coin.

Overall the general trend is a decline over time showing that the market is bearish and has flattened out. It's always recommended to read the latest news of a currency to understand why there has been such negative tendencies to avoid making a decision that might be seen as risky.

For a better understanding of the behaviour we can decompose the time series to see if there are any clear tendencies, seasonality or residuals that might give us a general behaviour of how the time series is behaving and to see if there is a distinct pattern that we can use to make predictions:

Decomposition:



We apply the seasonality to our yearly graphs to see how they are represented in the general yearly graphs. as it can be seen in the following graph there seems to be no general seasonality or behaviour that marks a yearly tendency. this indicates that the market is volatile and unpredictable since there is no repetitive pattern.



Lets see how this affects a predictive model since the seasonality is negligible and it seems that the residuals are low except for the year 2021 where there was a lot of residuals according to the decomposition.

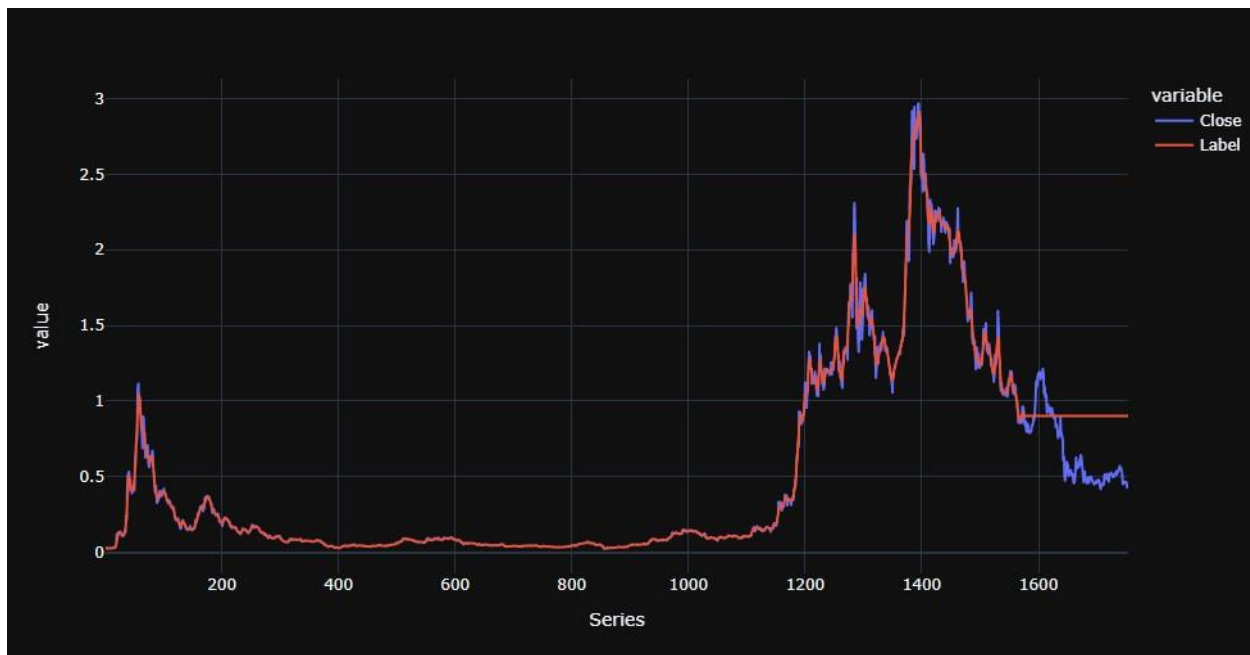
Using the Pycaret machine learning model we set it up so that it uses a time series to make a predictive model. this library allows us to iterate over several predictive models and we select the best one in accordance to our least error measure of our choice (MAE, MSE, RMSE, R2)

```
1 best = compare_models(sort = 'MAE')
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
knn	K Neighbors Regressor	0.4097	0.5165	0.4594	-2.4462	0.2416	0.5360	0.0233
rf	Random Forest Regressor	0.4109	0.5223	0.4611	-2.4061	0.2427	0.5238	0.0833
lightgbm	Light Gradient Boosting Machine	0.4160	0.5346	0.4650	-2.2471	0.2455	0.5028	0.0300
et	Extra Trees Regressor	0.4183	0.5413	0.4678	-2.3853	0.2478	0.5431	0.0633
gbr	Gradient Boosting Regressor	0.4242	0.5539	0.4736	-2.5465	0.2523	0.5341	0.0367
dt	Decision Tree Regressor	0.4262	0.5609	0.4765	-2.5969	0.2542	0.5414	0.0100
ada	AdaBoost Regressor	0.4418	0.5982	0.4889	-2.5332	0.2638	0.5208	0.0467
par	Passive Aggressive Regressor	0.5122	0.7831	0.5540	-3.4622	0.3199	0.6442	0.0133
lasso	Lasso Regression	0.5301	0.8241	0.5709	-3.7139	0.3363	0.6751	0.5933
en	Elastic Net	0.5302	0.8242	0.5710	-3.7277	0.3364	0.6762	0.7500
llar	Lasso Least Angle Regression	0.5391	0.8038	0.5786	-12.4917	0.3419	1.2042	0.7267
dummy	Dummy Regressor	0.5391	0.8038	0.5786	-12.4917	0.3419	1.2042	0.0100
huber	Huber Regressor	0.5406	0.8327	0.5969	-12.9865	0.3577	0.9045	0.0200
ridge	Ridge Regression	0.5495	0.8304	0.6082	-22.3262	0.3662	1.1392	0.5967
br	Bayesian Ridge	0.5506	0.8310	0.6099	-23.6682	0.3673	1.1619	0.0133
lr	Linear Regression	0.5528	0.8318	0.6130	-26.4191	0.3696	1.2083	1.1300
lar	Least Angle Regression	0.5528	0.8318	0.6130	-26.4206	0.3696	1.2083	0.8667
omp	Orthogonal Matching Pursuit	0.5615	0.8293	0.6031	-18.2075	0.3647	1.3554	0.0133

as seen in our comparative models we have a very peculiar R2 being negative which indicates that our model isn't very precise. we are selecting our model in accordance to which ever has the lowest Moving Average Envelope (MAE) in this case being the K Neighbor Regressor.

Once we run our best model and graph it we have the following result:



Conclusion and Recommendations:

The predictive model for time series has no independent variables that affect the dependant so it needs tendency, seasonality and residuals to make an accurate prediction since the seasonality is negligible and it seems that the residuals are low the output of the model is the global average and it outputs a straight line.

this makes sense since it's impossible to make a prediction on a volatile market since it's so unpredictable, otherwise it would be easy to get rich just by learning predictive models.

in this our hypothesis is disproven and we can use the data to understand past behaviours in conjunction with news related to the crypto alternate coin but we can not predict future behaviour using past behaviours since there is no clear tendency.

