



Memecoins Analysis

Web Scrapping Project

coinmarketcap.com

Agenda

01. The project introduction

02. Summary of the project's methodology

03. Visualization of analysis

04. Summary & Conclusions

About Project's aim



- Examine the rapidly growing memecoin market.
- Assess the stability and reliability of memecoins.
- Explore insights and confirm the opinion that investing in memecoins can be similar to gambling.
- Compare memecoins with major cryptocurrencies (Bitcoin, Ethereum, Solana) to identify differences, correlations and trends.

Data Collection

coinmarketcap.com/views/memes

Data collection was made 1st of August

Code

Markdown

Run All

Restart

Clear All Outputs

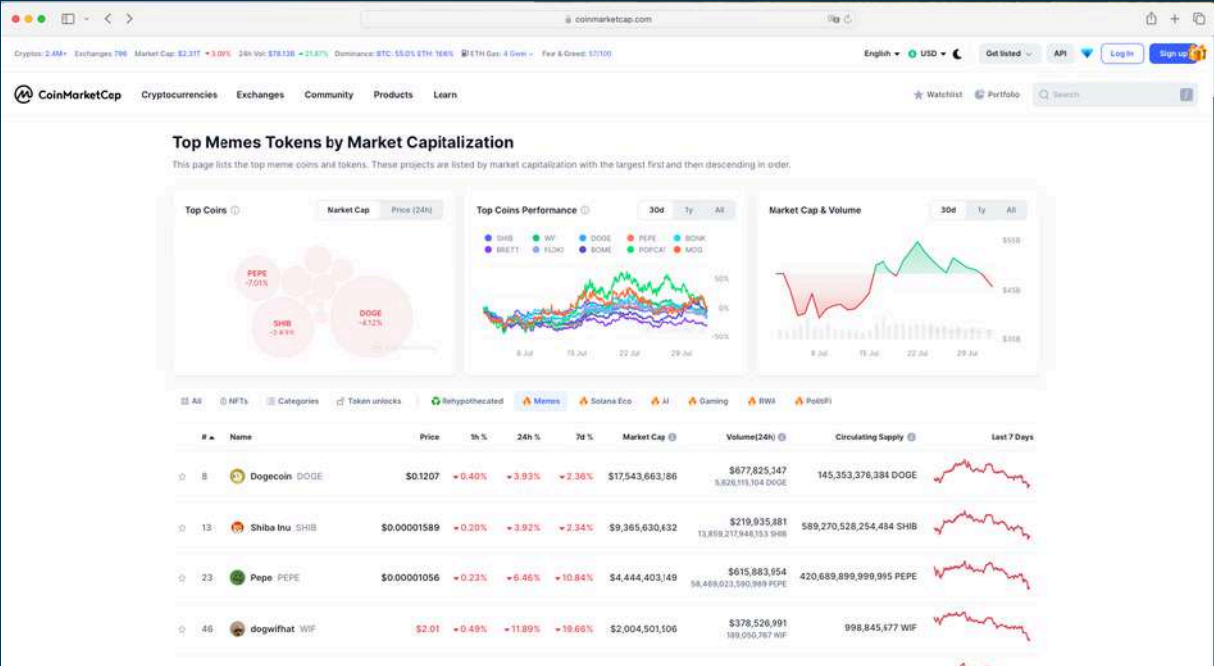
Variables

Outline

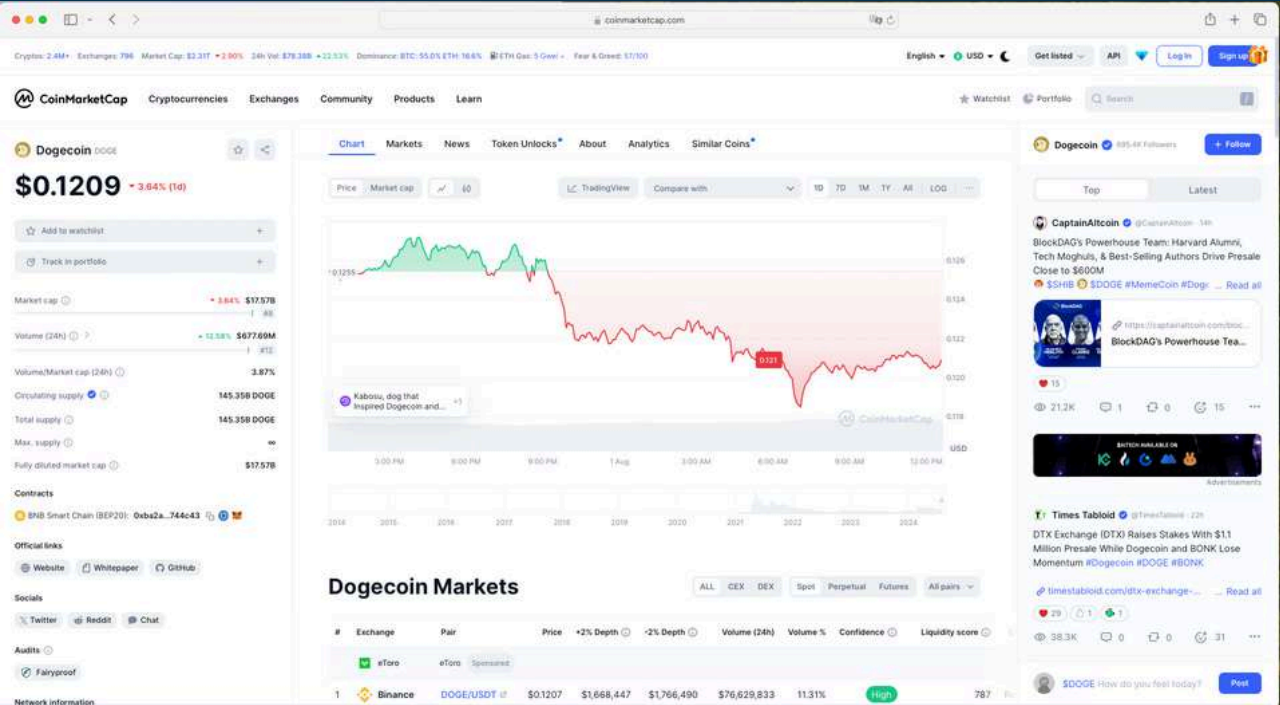
```
def get_data(soup):  
    """  
    This function parses the data based on BeautifulSoup object and extracts the required data from the meme coin page  
    Args:  
        object of the BeautifulSoup class  
    Returns:  
        List of the extracted data  
    """  
    data = []  
    # Checking if the required data is present on the page  
    if not soup.find('div', {'class': 'sc-65e7f566-0 DDohe flexStart alignBaseline'}):  
        print("Required data not found, ending the function.")  
        return None  
    # Extracting the data using functions: format_replace() and extract_and_format_price()  
    try:  
        other_values = soup.find('div', {'class': 'sc-65e7f566-0 eQBACE coin-metrics-table'})  
        name = soup.find('span', {'data-role': 'coin-name'})['title']  
  
        price = extract_and_format_price(soup.find('div', {'class': 'sc-65e7f566-0 DDohe flexStart alignBaseline'}))  
        market_cap = format_replace(other_values.find_all('dd')[0].text.split('%').pop(1))  
        volume_24h = format_replace(other_values.find_all('dd')[1].text.split('%').pop(1))  
        circulating_supply = format_replace(other_values.find_all('dd')[3].text.split('%').pop(1))  
  
        try:  
            supply_verified = other_values.find('span', {'class': 'sc-71024e3e-0 IERaG BasePopover_base_T5y0f'}).find('use')['href'].replace('#', '')  
        except AttributeError:  
            supply_verified = 'not verified'  
  
        total_supply = format_replace(other_values.find_all('dd')[4].text.split('%').pop(1))  
        max_supply = format_replace(other_values.find_all('dd')[5].text.split('%').pop(1))  
        fully_diluted_market_cap = format_replace(other_values.find_all('dd')[6].text)  
        low_price_24h = extract_and_format_price(soup.select_one('div.sc-65e7f566-0.eQBACE :has(div.label:-soup-contains("Low"))'))  
        high_price_24h = extract_and_format_price(soup.select_one('div.sc-65e7f566-0.eQBACE.tl:has(div.label:-soup-contains("High"))'))  
        try:  
            all_time_high = extract_and_format_price(soup.find_all('div', {'class': 'sc-65e7f566-0 bWZaRS'})[0])  
        except (IndexError, AttributeError):  
            all_time_high = None  
        try:  
            all_time_low = extract_and_format_price(soup.find_all('div', {'class': 'sc-65e7f566-0 bWZaRS'})[1])  
        except (IndexError, AttributeError):  
            all_time_low = None  
  
        ucid = int(soup.find('div', {'data-role': 'chip-content-item'}).text.strip())  
        popularity_watchlists = format_replace(soup.find('span', {'class': 'sc-65e7f566-0 loopdw base-text'}).text.split('x').pop(0))  
  
        data.append([name, price, market_cap, volume_24h, circulating_supply, supply_verified, total_supply, max_supply, fully_diluted_market_cap, low_pri
```

Se & BeautifulSoup

API



Detailed memcoin's page



Project Structure

01

INTERACTING WITH SELENIUM

Navigating through multiple pages

02

PARSING AND COLLECTING DATA

Using BeautifulSoup to parse and collect data for each page and memecoin.

03

DATA FORMATTING

Preparing data during the collection process with custom functions.

04

DATA FRAME CREATION

Creating and saving data frame for further analysis

05

ANALYSIS & VISUALIZATION

Analyzing selected variables and visualize the result.

06

SELECTION TOP 6 MEMECOINS

using rank for examined and select the best memecoins for further analysis

07

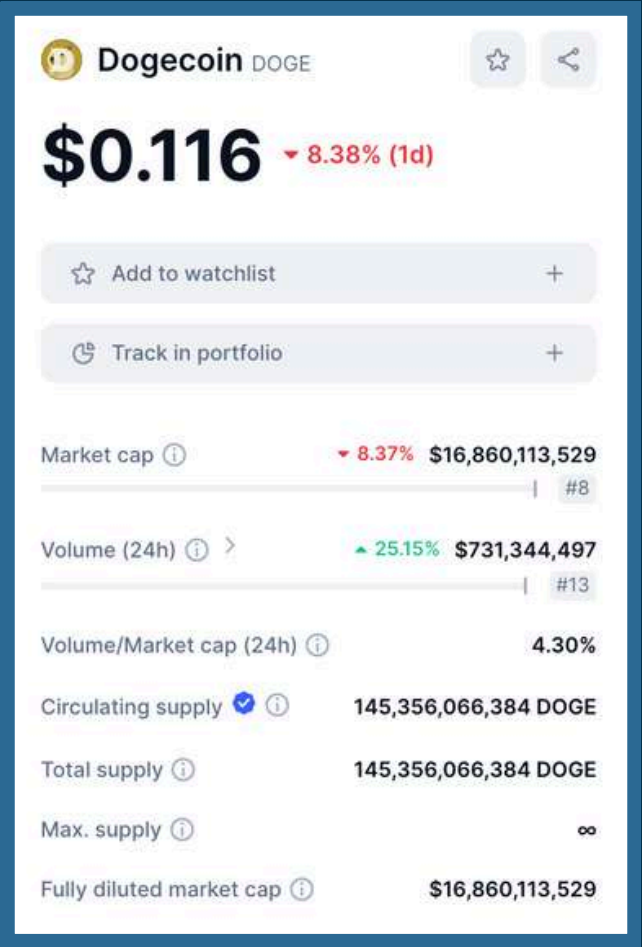
HISTORICAL DATA COLLECTION

using API endpoints to collect data (1-year period) for selected memecoins and major cryptocurrencies: Bitcoin, Ethereum, Solana. Checking trends and visualize them

DATASETS

I Memecoins dataset:

- 1552 rows
- 15 variables scraped from the page
- Mainly current values
- Scraped with BS and Selenium



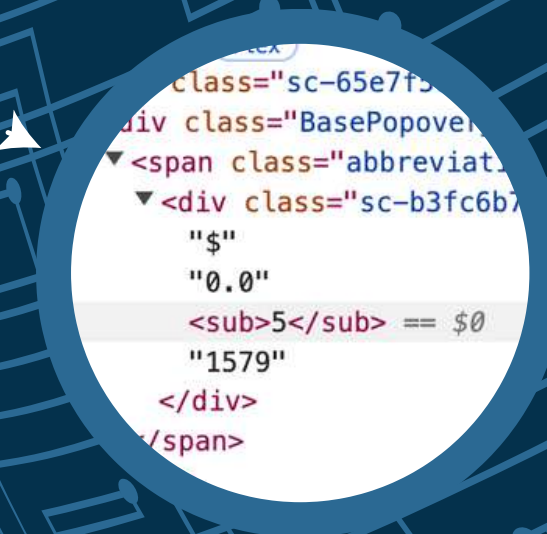
	name	current_price	market_cap	volume_day	circulating_supply	supply_verified	total_supply	max_supply	fully_diluted_market_cap	low_price_day	high_price_day	all_time_high	all_time_low	ucid	popularity_watchlists
222	SMILEY	3.596000e-12	NaN	5.518148e+06	NaN	not verified	NaN	NaN	NaN	3.579000e-12	3.776000e-12	5.515000e-11	2.010000e-13	26994	3557.0
243	Arbi Pepe	1.060000e-05	NaN	1.860798e+06	NaN	not verified	1.000000e+11	NaN	1060088.0	1.440000e-14	1.161000e-05	2.719000e-02	1.440000e-14	24549	1902.0
259	DogeSwap	3.143000e-03	NaN	1.031007e+06	NaN	not verified	NaN	1.000000e+09	3142704.0	2.870000e-03	3.508000e-03	1.706000e-02	5.089000e-04	12078	1524.0
269	TON FISH MEMECOIN	4.053000e-08	NaN	8.895040e+05	NaN	not verified	4.206900e+14	NaN	17048698.0	3.984000e-08	4.293000e-08	1.163000e-07	1.726000e-08	30117	5046.0
342	APED	3.154000e-01	NaN	2.544720e+05	NaN	not verified	1.000000e+06	1.000000e+06	315409.0	3.113000e-01	3.305000e-01	1.322000e+01	2.076000e-01	24533	1372.0
436	Feisty Doge NFT	1.296000e-04	NaN	1.092750e+05	NaN	not verified	1.000000e+11	NaN	12958865.0	4.001000e-06	1.537000e-04	1.614000e-03	4.001000e-06	11368	1954.0
537	Pig Finance	2.057000e-08	NaN	2.868500e+04	NaN	not verified	1.000000e+15	1.000000e+15	20572135.0	2.057000e-08	2.139000e-08	5.509000e-06	NaN	8829	56683.0
540	GM Wagmi	1.947000e-06	NaN	2.811000e+04	NaN	not verified	1.000000e+12	NaN	1947868.0	1.894000e-06	1.966000e-06	9.851000e-04	1.658000e-06	14271	12933.0
570	Alux Jownes	6.555000e-04	NaN	2.321900e+04	NaN	not verified	NaN	NaN	NaN	6.510000e-04	8.003000e-04	1.024000e-02	3.988000e-04	31043	383.0
636	Fronk	1.035000e-08	NaN	8.150000e+03	NaN	not verified	5.098326e+13	NaN	527904.0	1.035000e-08	1.202000e-08	1.952000e-07	5.199000e-10	23179	5675.0
651	Toad Killer	7.483000e-09	NaN	8.255000e+03	NaN	not verified	4.206900e+14	4.206900e+14	3147898.0	7.483000e-09	7.753000e-09	4.113000e-08	2.902000e-09	25177	704.0
685	YES Money	4.140000e+00	NaN	6.658000e+03	NaN	not verified	6.449348e+07	NaN	266951878.0	4.060000e+00	4.150000e+00	7.070000e+00	3.160000e+00	29620	1020.0
695	UpSideDownCat	4.436000e-05	NaN	5.316000e+03	NaN	not verified	8.000000e+09	NaN	354852.0	4.356000e-05	5.535000e-05	3.813000e-03	2.820000e-05	29625	662.0
702	Pepe AI	2.401000e-13	NaN	5.341000e+03	1.000000e+09	not verified	1.000000e+09	1.000000e+09	NaN	2.119000e-13	3.200000e-13	2.199000e-04	1.031000e-13	29747	773.0
717	Ryoshis Vision	7.050000e-09	NaN	1.466000e+03	NaN	not verified	4.783559e+14	9.783559e+14	6897155.0	7.050000e-09	7.685000e-09	5.647000e-06	2.219000e-09	11283	16680.0
787	Arbidoge	1.427000e-07	NaN	2.208000e+03	NaN	not verified	1.000000e+13	1.000000e+13	1427112.0	1.427000e-07	1.544000e-07	1.510000e-03	5.071000e-09	11878	1039.0
848	Cramer Coin	5.610000e-04	NaN	1.359000e+03	NaN	not verified	1.000000e+09	NaN	560987.0	5.481000e-04	5.855000e-04	1.428000e-02	NaN	21946	816.0
888	Potato	7.380000e-08	NaN	1.019000e+03	NaN	not verified	NaN	NaN	NaN	4.765000e-08	8.373000e-08	1.749000e-06	2.611000e-09	11814	5568.0
909	Akita Inu	3.435000e-05	NaN	3.730000e+02	NaN	not verified	1.000000e+00	NaN	NaN	3.262000e-05	3.480000e-05	1.255000e-04	2.742000e-05	30120	109.0
917	Wagmi Coin	6.531000e-10	NaN	8.110000e+02	4.562041e+08	not verified	4.206900e+14	NaN	274753.0	6.531000e-10	6.885000e-10	4.823000e-08	2.231000e-10	25385	1745.0
951	Kitty Coin Solana	4.977000e-04	NaN	6.260000e+02	NaN	not verified	5.400000e+08	NaN	268738.0	4.452000e-04	4.977000e-04	2.770610e+03	1.323000e-05	15892	3543.0
962	CHILI	4.081000e-11	NaN	5.670000e+02	NaN	not verified	3.134793e+13	NaN	1279.0	3.999000e-11	4.671000e-11	5.427000e-07	2.080000e-13	23172	2493.0
968	Dino	3.341000e-04	NaN	4.540000e+02	NaN	not verified	5.000000e+08	NaN	167068.0	3.306000e-04	3.546000e-04	4.027000e-02	NaN	12513	1541.0

	price	volume	market_cap	name	date
0	29161.811946	1.278036e+10	5.671181e+11	Bitcoin	2023-08-03
1	29174.381837	1.203664e+10	5.673854e+11	Bitcoin	2023-08-04
2	29075.388956	6.598366e+09	5.654874e+11	Bitcoin	2023-08-05
3	29043.701980	7.269807e+09	5.649005e+11	Bitcoin	2023-08-06
4	29038.512846	1.361816e+10	5.648257e+11	Bitcoin	2023-08-07
5	29180.018862	1.757056e+10	5.676019e+11	Bitcoin	2023-08-08
6	29766.695596	1.837952e+10	5.790439e+11	Bitcoin	2023-08-09
7	29563.971837	1.186534e+10	5.751236e+11	Bitcoin	2023-08-10
8	29424.902575	1.019517e+10	5.724460e+11	Bitcoin	2023-08-11
9	29399.786655	6.194358e+09	5.719875e+11	Bitcoin	2023-08-12
10	29416.593599	7.329897e+09	5.723390e+11	Bitcoin	2023-08-13
11	29283.262943	1.401370e+10	5.697765e+11	Bitcoin	2023-08-14
12	29408.048590	1.264020e+10	5.722360e+11	Bitcoin	2023-08-15
13	29169.074020	1.494927e+10	5.676158e+11	Bitcoin	2023-08-16
14	28699.802840	3.112085e+10	5.585113e+11	Bitcoin	2023-08-17
15	26636.078402	2.402624e+10	5.183722e+11	Bitcoin	2023-08-18
16	26047.832979	1.063144e+10	5.069483e+11	Bitcoin	2023-08-19
17	26096.861226	9.036580e+09	5.079292e+11	Bitcoin	2023-08-20
18	26188.690651	1.337156e+10	5.097435e+11	Bitcoin	2023-08-21
19	26130.748016	1.450382e+10	5.086381e+11	Bitcoin	2023-08-22
20	26040.473652	1.698527e+10	5.069053e+11	Bitcoin	2023-08-23
21	26431.519892	1.287153e+10	5.145411e+11	Bitcoin	2023-08-24
22	26163.680054	1.240605e+10	5.093486e+11	Bitcoin	2023-08-25
23	26047.235240	6.034817e+09	5.071037e+11	Bitcoin	2023-08-26
24	26008.241801	6.913769e+09	5.063637e+11	Bitcoin	2023-08-27
25	26089.614923	1.100281e+10	5.079666e+11	Bitcoin	2023-08-28
26	26102.485832	2.936839e+10	5.082438e+11	Bitcoin	2023-08-29
27	27726.084034	1.634366e+10	5.398788e+11	Bitcoin	2023-08-30
28	27301.929317	2.018100e+10	5.316441e+11	Bitcoin	2023-08-31

II Selected cryptocurrencies:

- 3621 rows
- 5 variables
- Fetched from API endpoint
- Period - 1 year (data updated in real time)

Technical considerations and assumptions



In few variables for some memecoins the price was reflected like this, where 5 means how many 0 is after dots.

I was possible to collect information from the graphic sign if supply is verified or not

BASE CAT	BASECAT	\$0.013601	0.00%	0.00%	9.78%	\$3,601	1,000,000,000,000 BASECAT
Pepenator	NATOR	\$0.006012	0.00%	0.00%	7.74%	\$6,012	1,000,000 NATOR
Sol Killer	DAMN	\$0.00001196	0.00%	1.08%	2.50%	\$825,467	69,000,000,000 DAMN
Wojak The Wanker	WANK	\$0.00009357	0.00%	0.00%	61.25%	\$93,568	1,000,000,000 WANK
Wrapped Dogecoin	WDOGE	\$0.1197	0.46%	4.18%	3.43%	\$8,627	\$304,201 2,540,186 WDOGE 72,050 WDOGE
Einsteinium	EMC2	--	--	--	--	--	--
Pepe Cash	PEPECASH	--	--	--	--	--	--
Jesus Coin	JC	--	--	--	--	--	--

Only around 1,6k memecoins have data, when there is no data available scraping is finished.

Created Functions

URLS GATHERING

FORMATTING AND ADJUSTING

DATA GATHERING

VISUALIZATION

API DATA

GET_LIST_LINKS()

ALL_URLS()

FORMAT_REPLACE()

EXTRACT_FORMAT_PRICE()

GET_DATA()

GET_PAGE()

PLOT_ANNOTATE()

FETCH_API_DATA()

Using BeautifulSoup it parses all urls from a single page and returns the list.

Using Selenium it navigates through all pages and using `get_list_link()` it creates the final list with urls for all memecoins.

It replaces some symbols with NaN, deletes useless symbols and convert all for floats.

Using regular expressions it extracts elements of prices with number reflecting appearances of 0 after dot. Returns float.

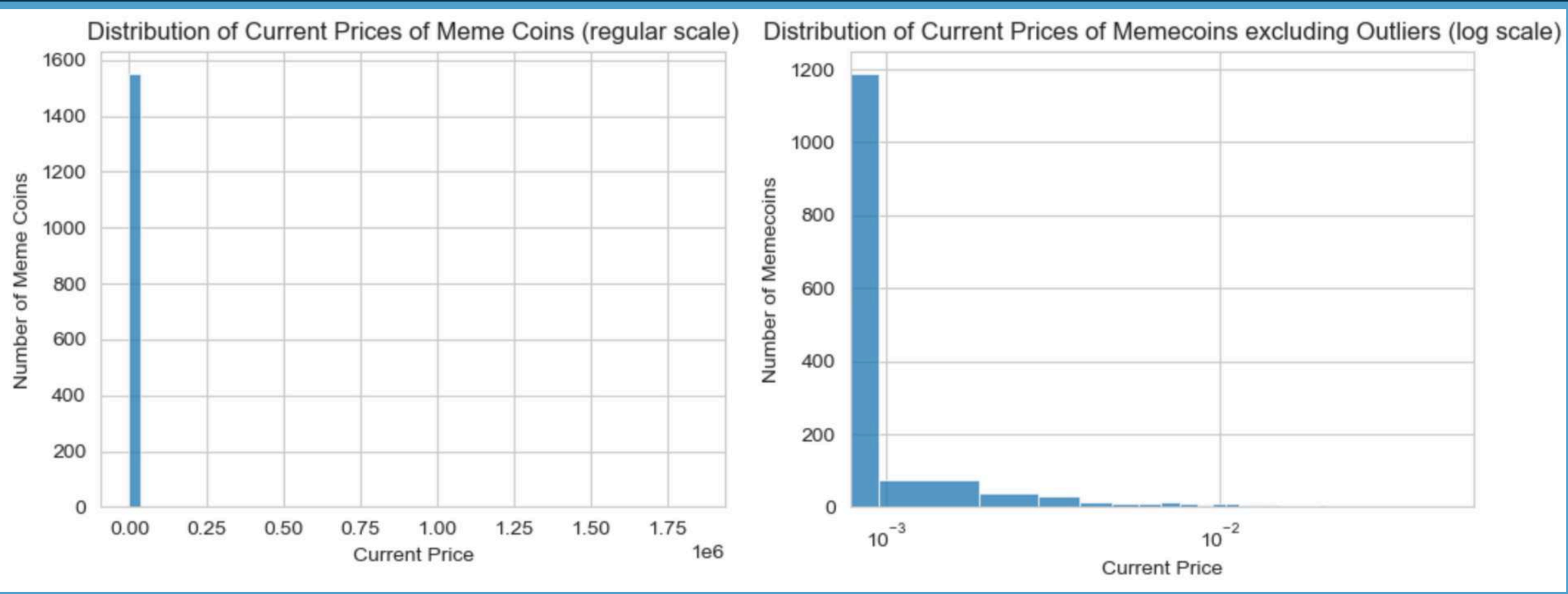
Using BeautifulSoup and formatting functions it extracts all detailed variables.

It iterates through all urls and gather data by `get_data()` function.

It plotting two stacked bar graphs with annotations about share for each patch.

It gathers data from API endpoint and extracts from json variables. Returns data frame.

Distribution of Current Price



	count	mean	std	min	25%	50%	75%	max
Current price	1552.0	1209.942706	46877.503234	3.130000e-22	2.052750e-08	0.000022	0.000823	1846533.47

Memecoins with Verified and Unverified supply

**Market Cap
vs.
Volume(24h)**

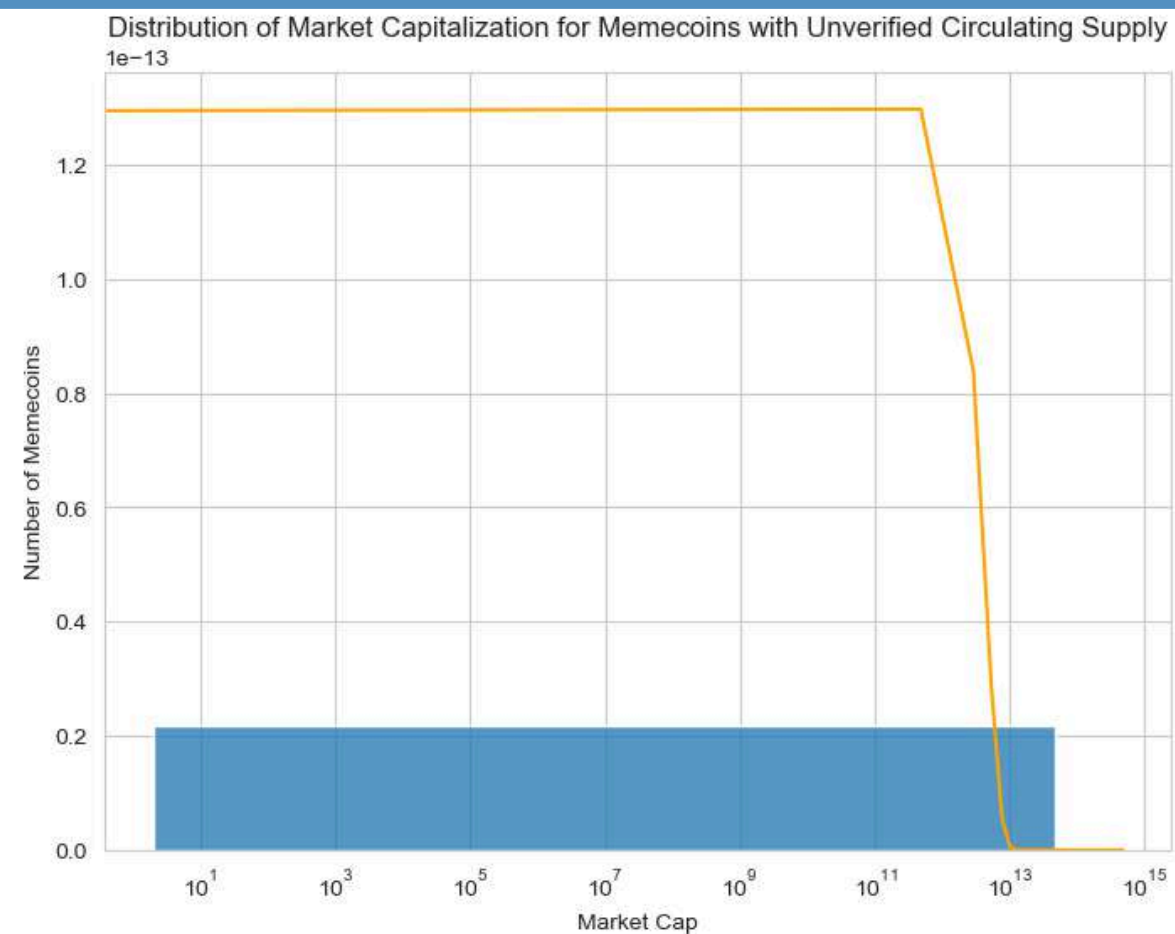
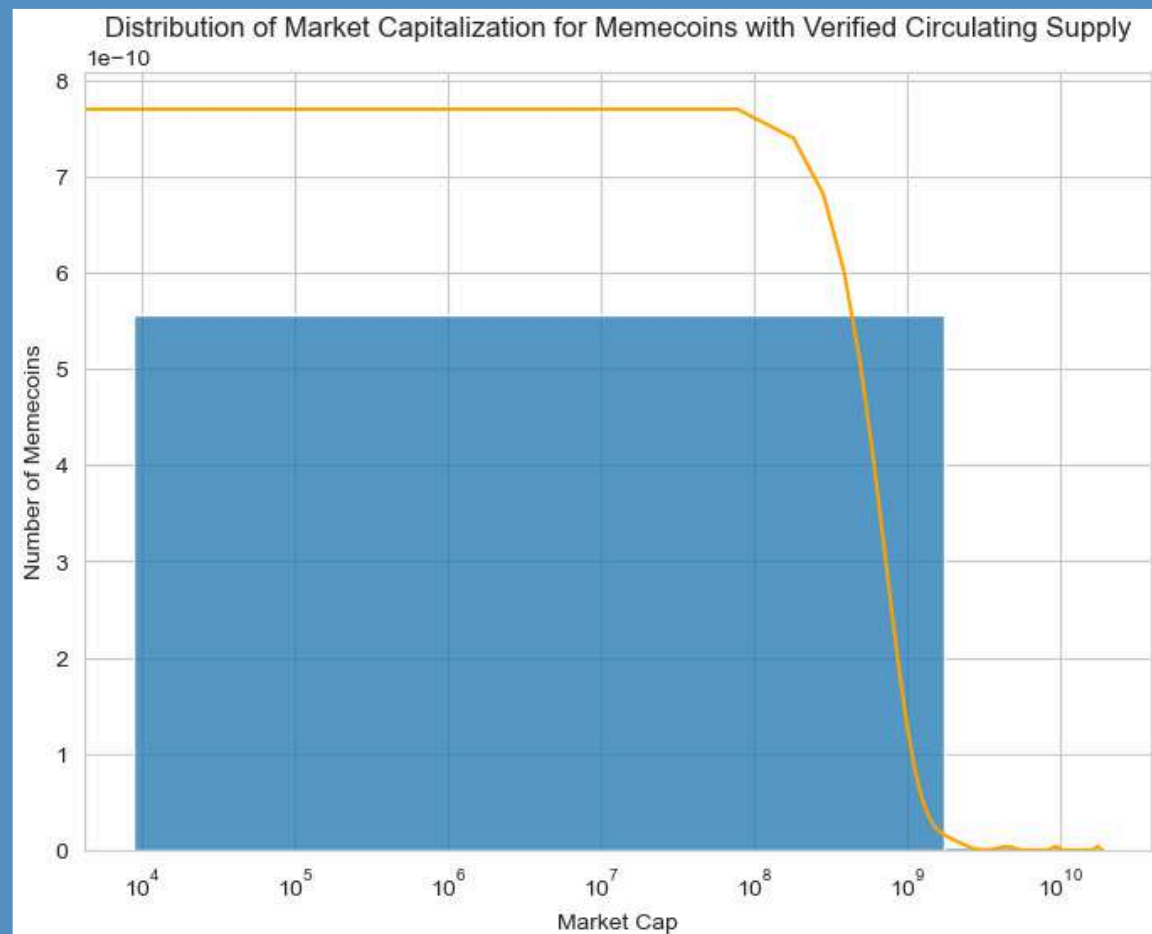
Verified

Unverified

Correlation

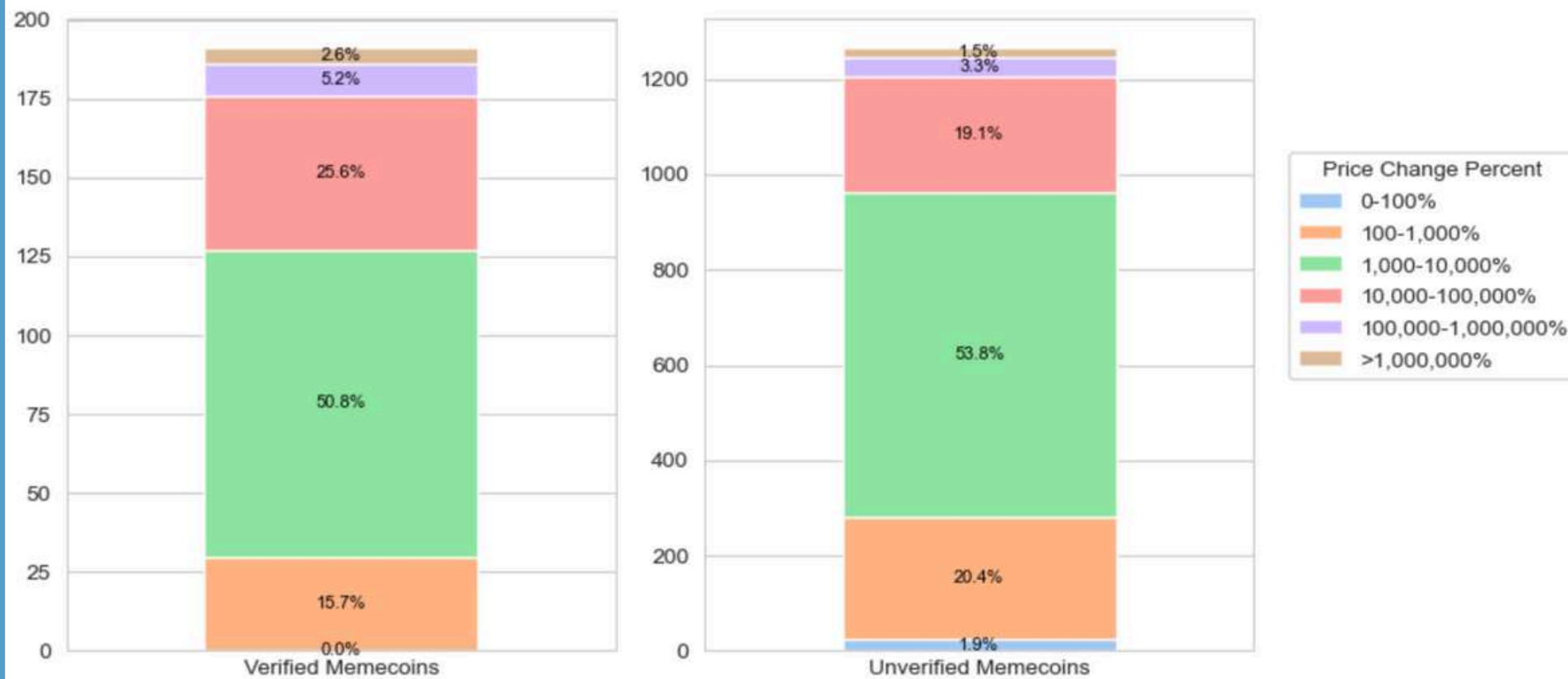
0.811

-0.005

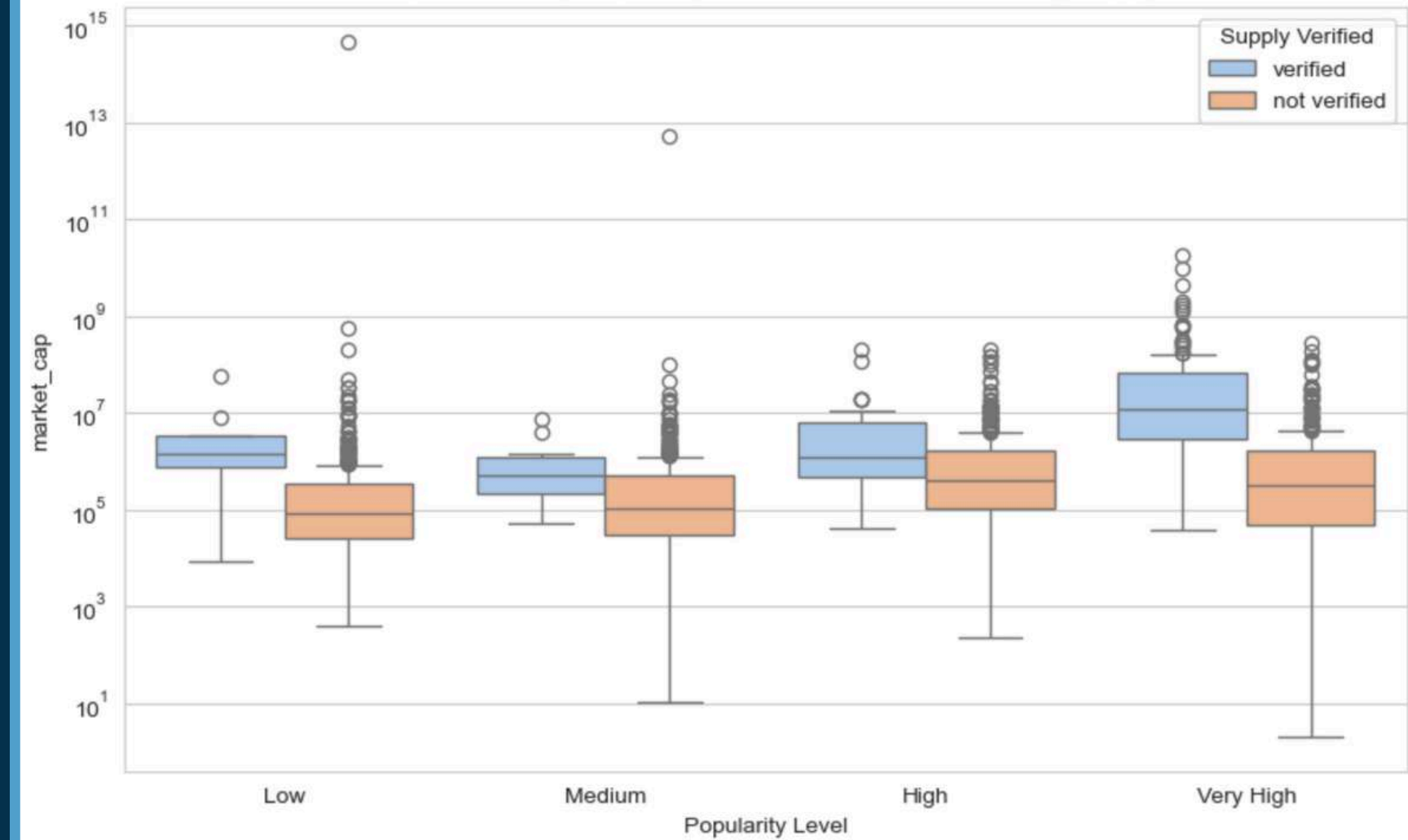


Memecoins with Verified and Unverified supply

Percentage Difference between ATH and ATL for Memecoins



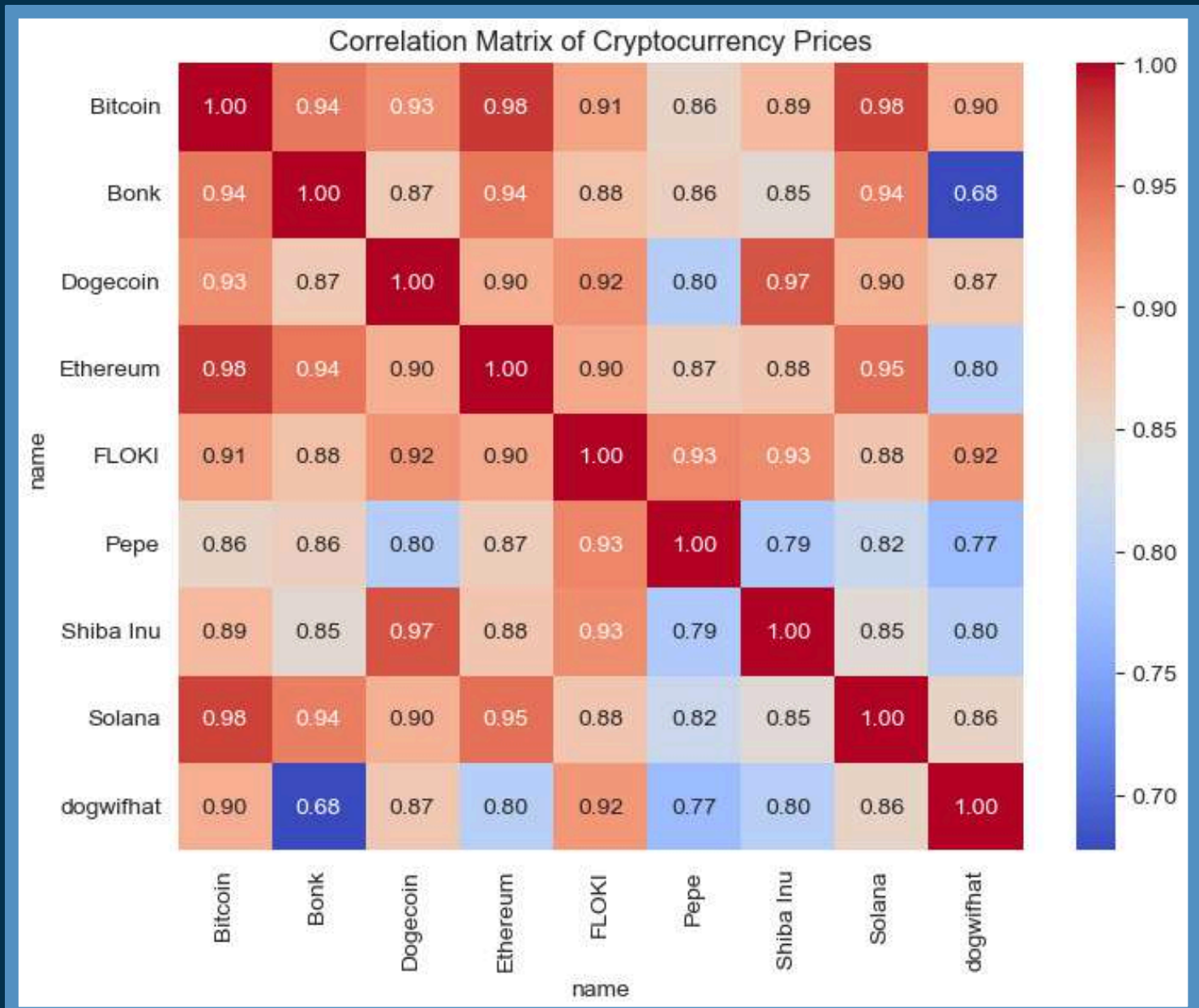
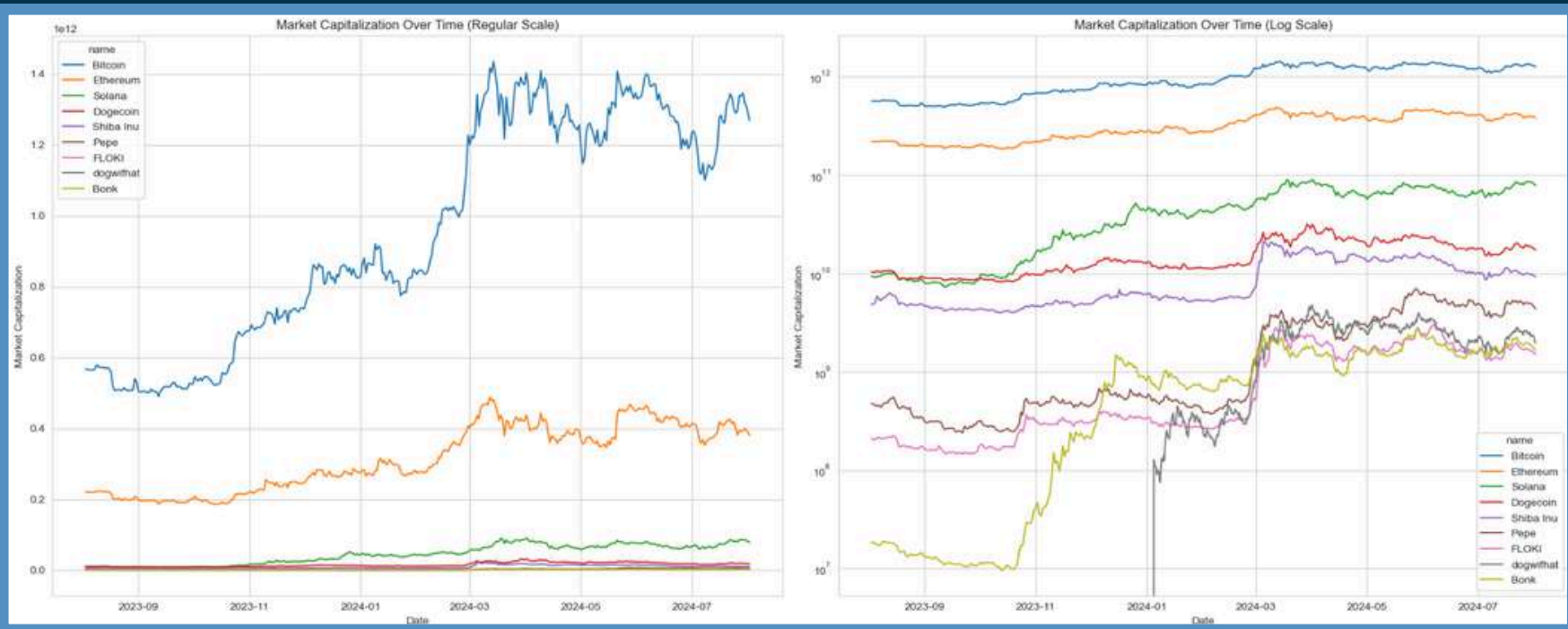
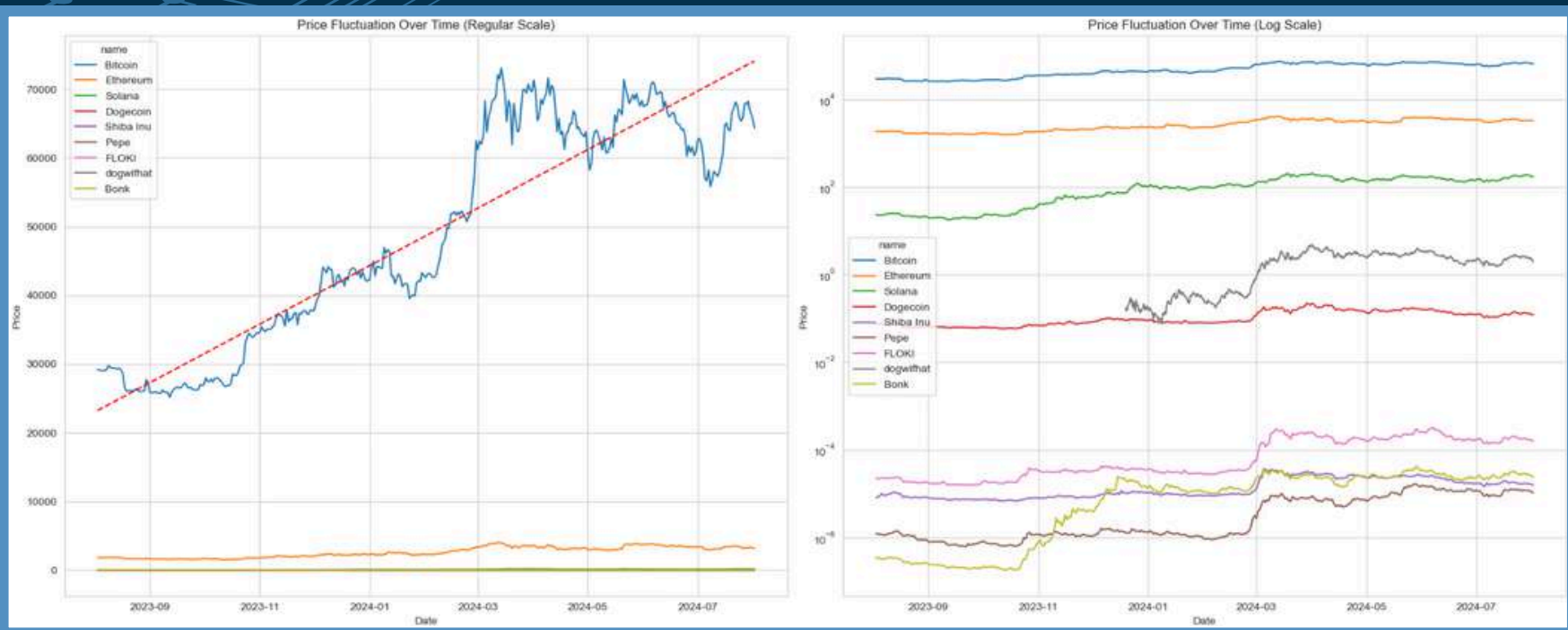
Market Capitalization by Popularity on Watchlists and Circulating Supply Status



Selected Memecoins for further Analysis

	name	market_cap	volume_day	popularity_watchlists	rank_market_cap	rank_volume	rank_popularity	total_rank
0	Dogecoin	1.760678e+10	675443576.0	1931564.0	1.0	1.0	3.0	5.0
1	Shiba Inu	9.394850e+09	229218347.0	2074704.0	2.0	5.0	2.0	9.0
2	Pepe	4.461763e+09	610203547.0	437401.0	3.0	2.0	6.0	11.0
5	FLOKI	1.508927e+09	185934507.0	423008.0	6.0	6.0	7.0	19.0
3	dogwifhat	1.997920e+09	371202832.0	155667.0	4.0	3.0	13.0	20.0
4	Bonk	1.656968e+09	183254549.0	266408.0	5.0	7.0	8.0	20.0

Comparison of Top Memecoins with Bitcoin, Ethereum, Solana



Summary & Conclusions

Difficulties

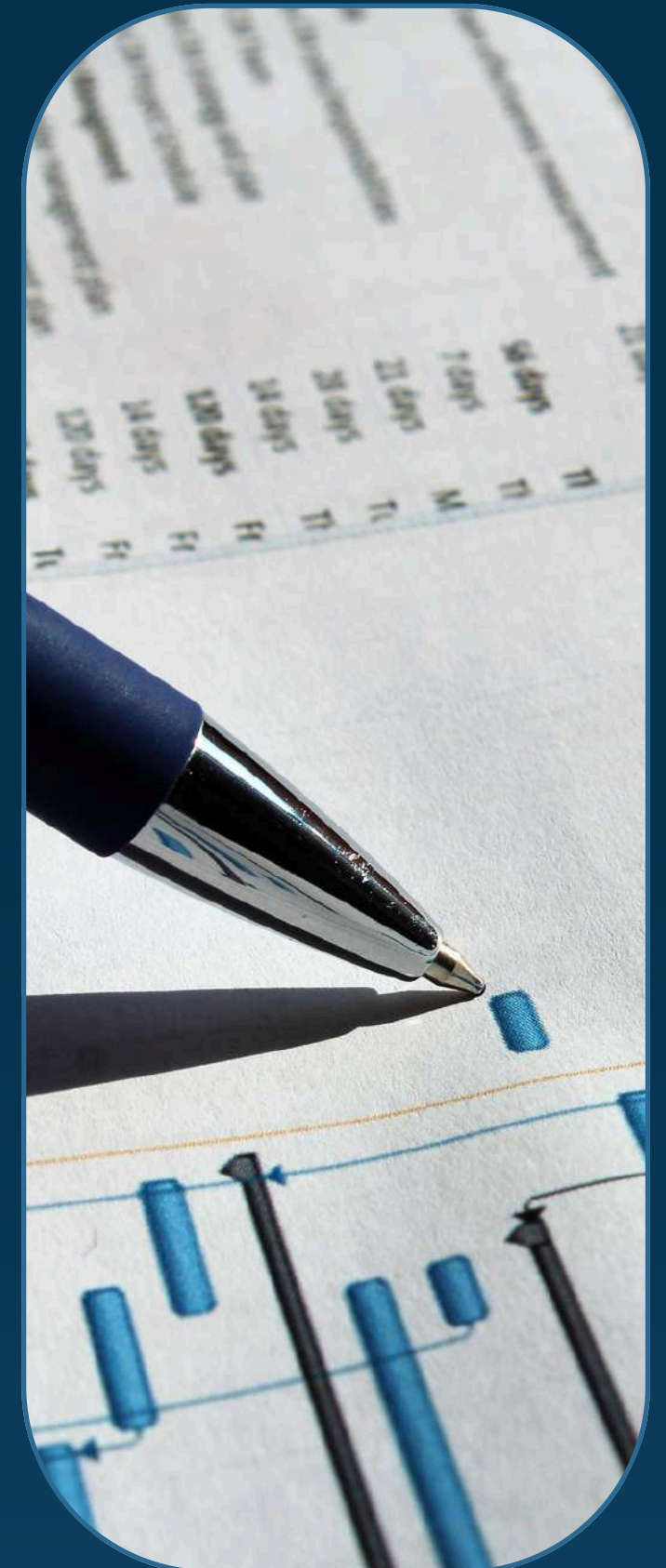
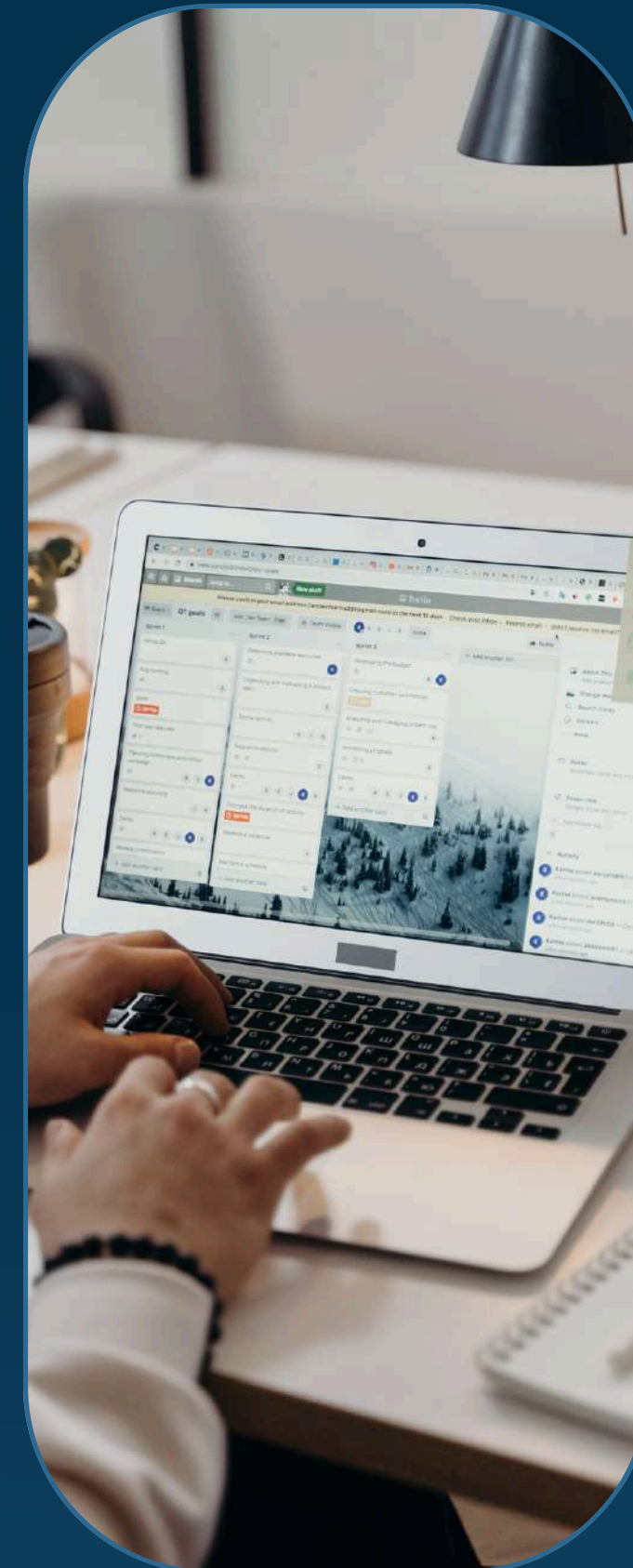
- Frequent website changes.
- Changing HTML code.
- Hidden elements.
- Changes in displaying elements.

Conclusions

- Memecoins are connected with high risk.
- Verified vs unverified memecoins - useful analysis.
- Higher stability of major cryptocurrencies.
- High correlation between major cryptocurrencies.

Next Steps

- Using API.
- Expanding analysis.
- Analysis of sentiment.



Thank You

Karina Oborska-Balkowiec

