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***Title: Exploring the Relationship
Between Google Trends and
Cryptocurrency Prices***

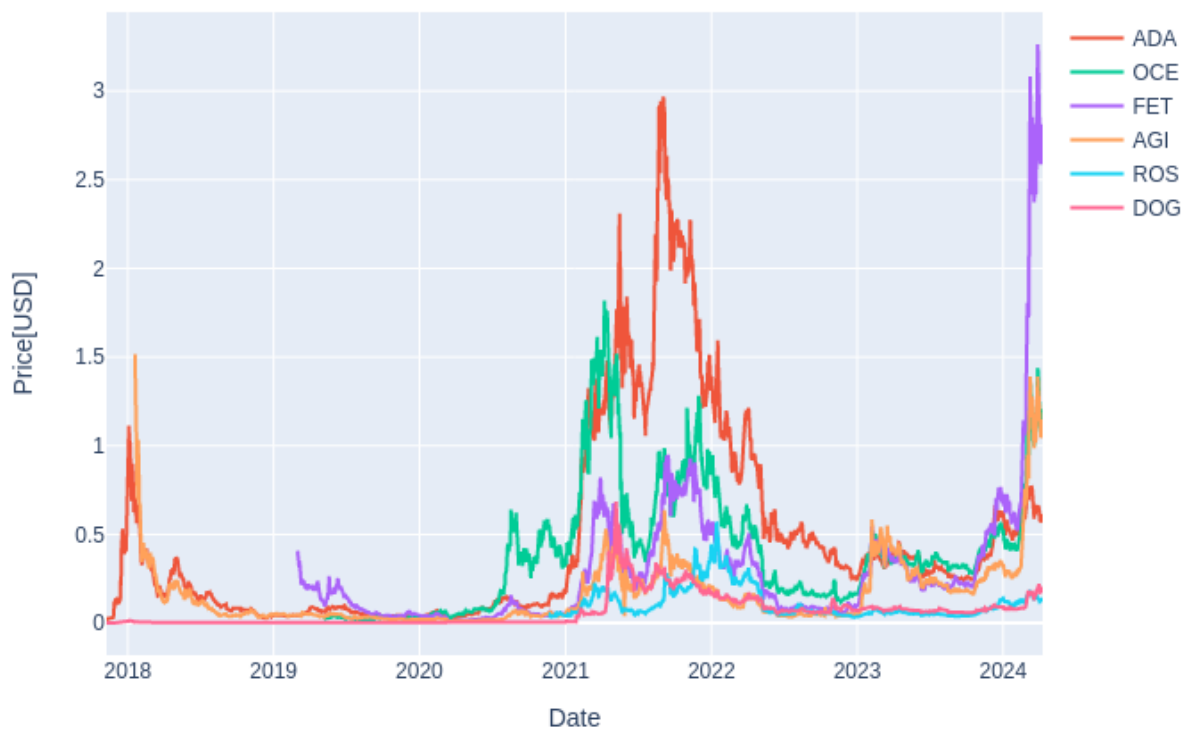
Introduction

This report presents the findings of our research analyzing the link between Google search interest in cryptocurrencies and their corresponding market values. Leveraging techniques from data science, the goal was to develop a deeper understanding of factors influencing cryptocurrency price movements over time. We began by conducting exploratory data analysis on Google Trends data and cryptocurrency price data from several top coins. This allowed us to uncover basic trends and correlations between search volume and price changes. Advanced machine learning models were developed and applied to forecast future price trends based on historical Google Trends patterns. This provided insights into how search interest predicts upcoming price swings within familiar cyclical patterns. The results summarized here add to our body of knowledge around predicting cryptocurrency market behaviors. Key findings are discussed regarding correlation strengths, predictive model performance, and periodic patterns observed. We believe this research furthers the scientific exploration of linkage between public interest and digital asset valuation.

Exploratory Data Analysis

We began our exploration of the relationships between Google Trends and market data by generating visualizations of key metrics over time. As shown by the charts that follow

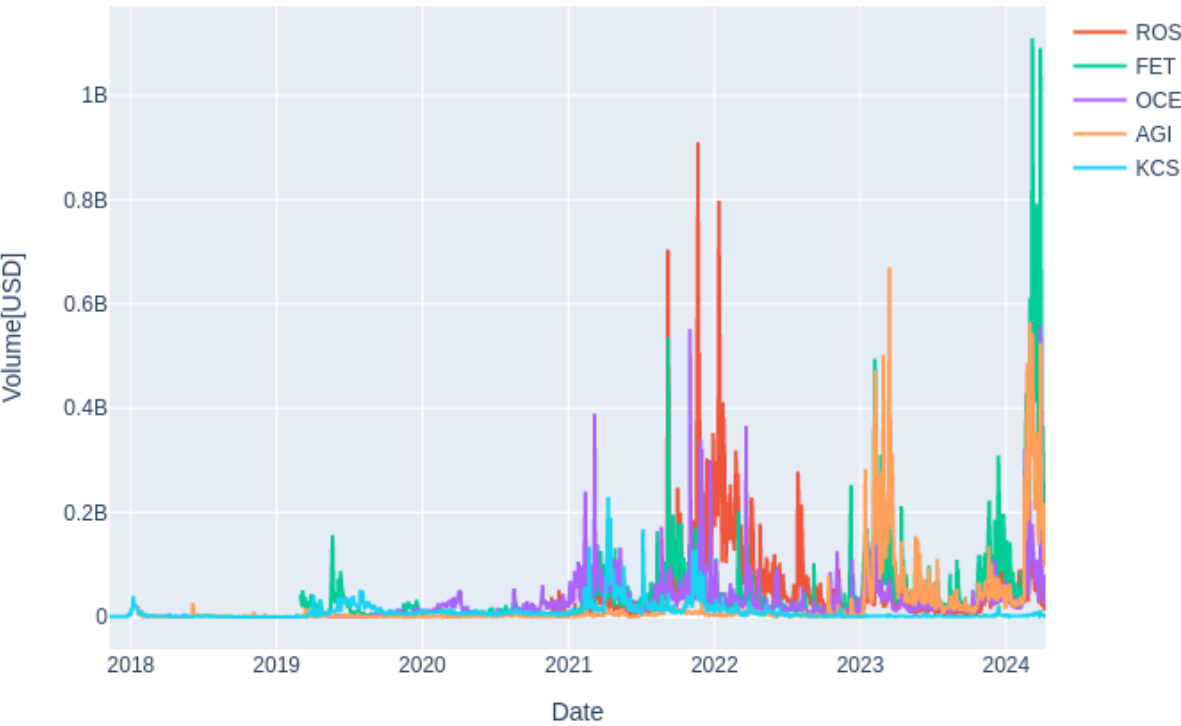
Trend comparison of Daily Price(Bottom 6 coins)



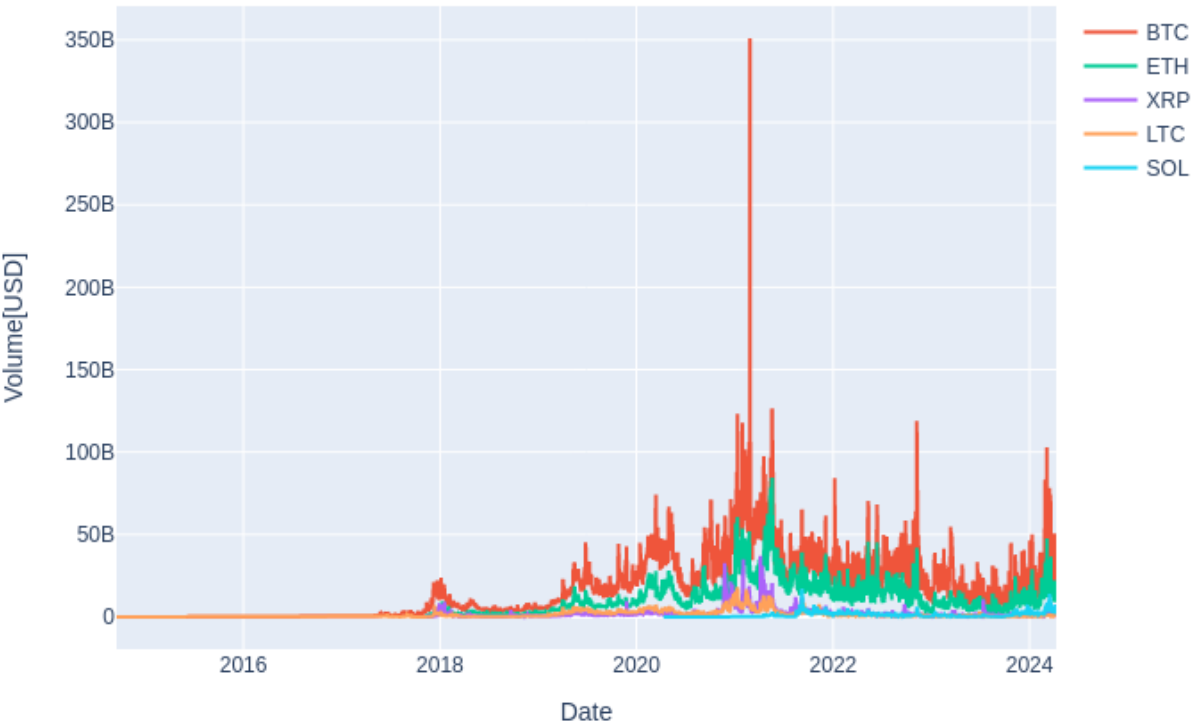
Trend comparison of Daily Price(Top 5 coins)



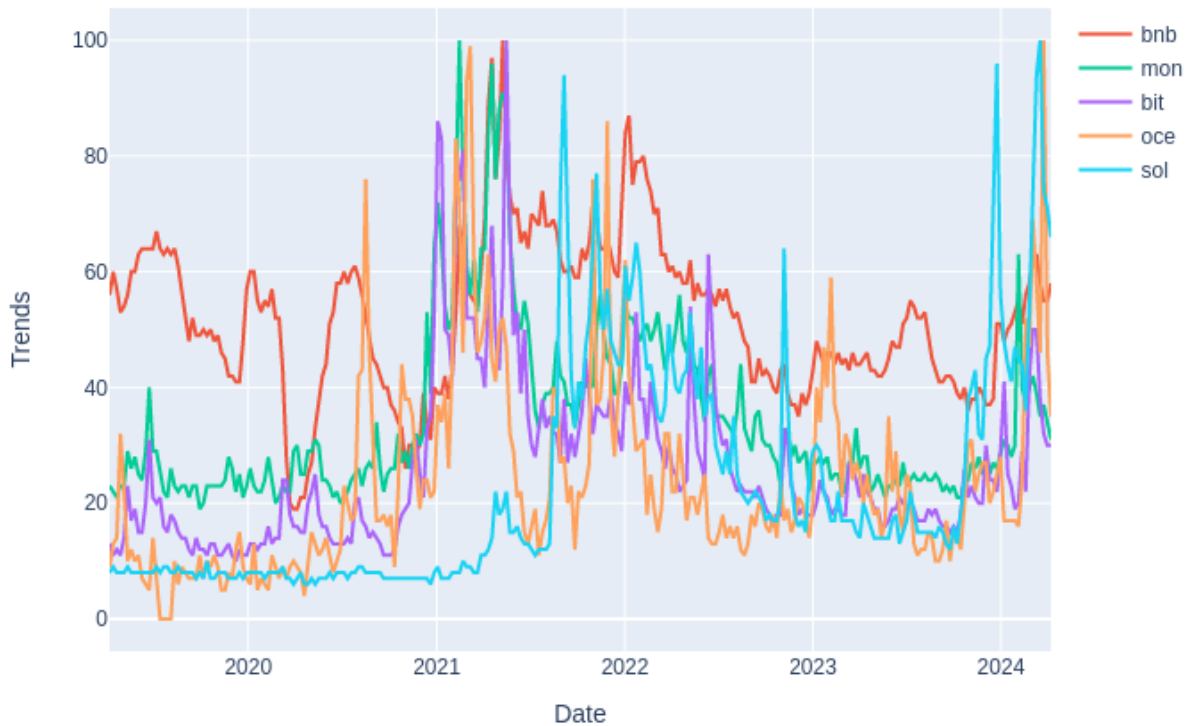
Trend comparison of Volume(Bottom 5 coins)



Trend comparison of Volume(Top 5 coins)



Trend comparison of Weekly Trends(Top 5 coins)



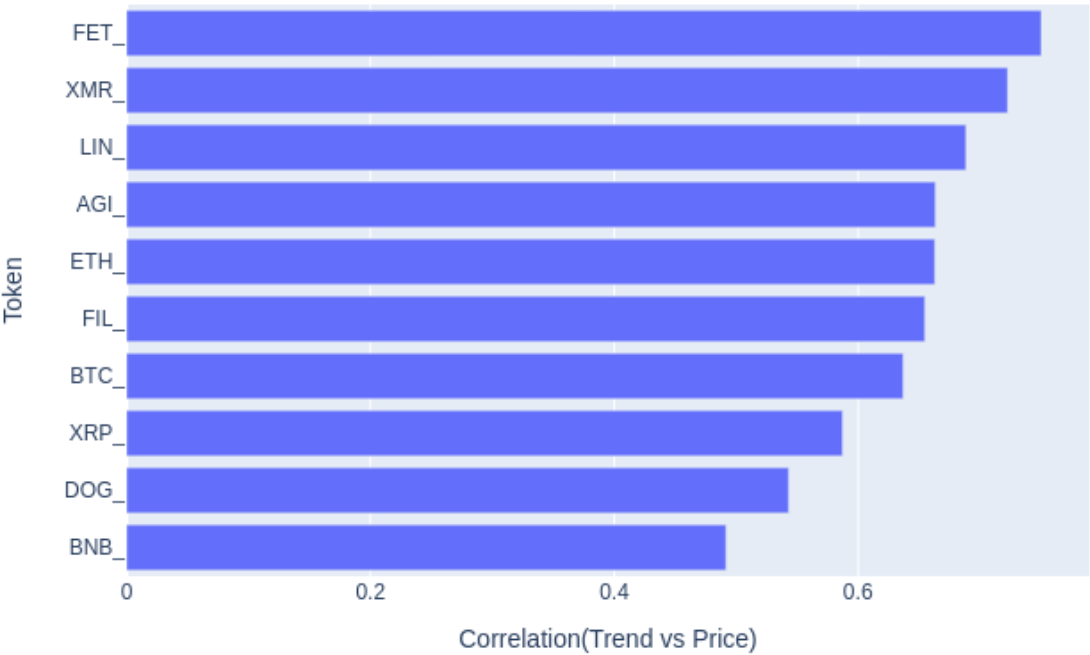
Correlation between Token prices and their respective Google trends was calculated.

Correlation(Trends vs Prices)

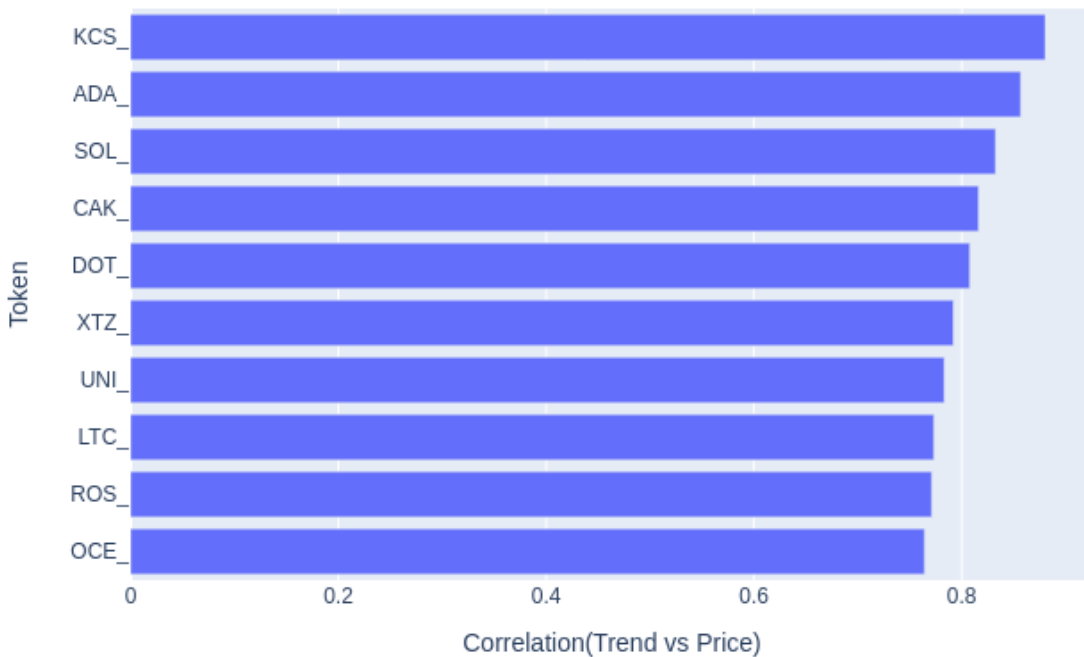
Most coins show moderate to strong positive correlations, in the 0.4-0.8 range. This indicates trends and prices generally move together as expected. Coins like SOL, CAR, PAN, KUC with correlations above 0.8 have very strong relationships where trends strongly predict price behavior. Weaker correlations below 0.5 for coins like DOG, BNB indicate trends are less reliable for predicting their price movements. Other factors may influence prices more. The range of values shows correlations are coin-specific and not uniform. Not all trend-price dynamics can be modeled the same way. Coins with very high or very low correlations may warrant further investigation.

The outcomes are as shown in the following plots

Correlation(Bottom 10): Google Trend vs Price(USD)

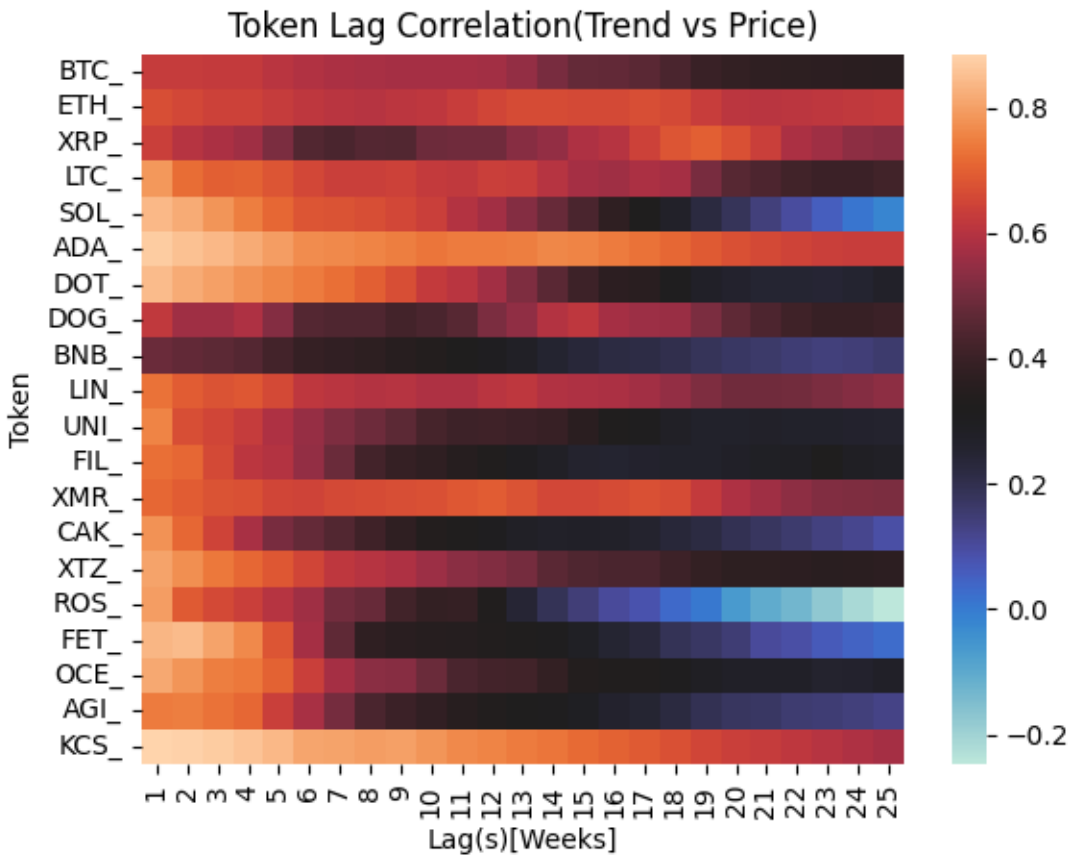


Correlation(Top 10): Google Trend vs Price(USD)



Correlation (Time lag)

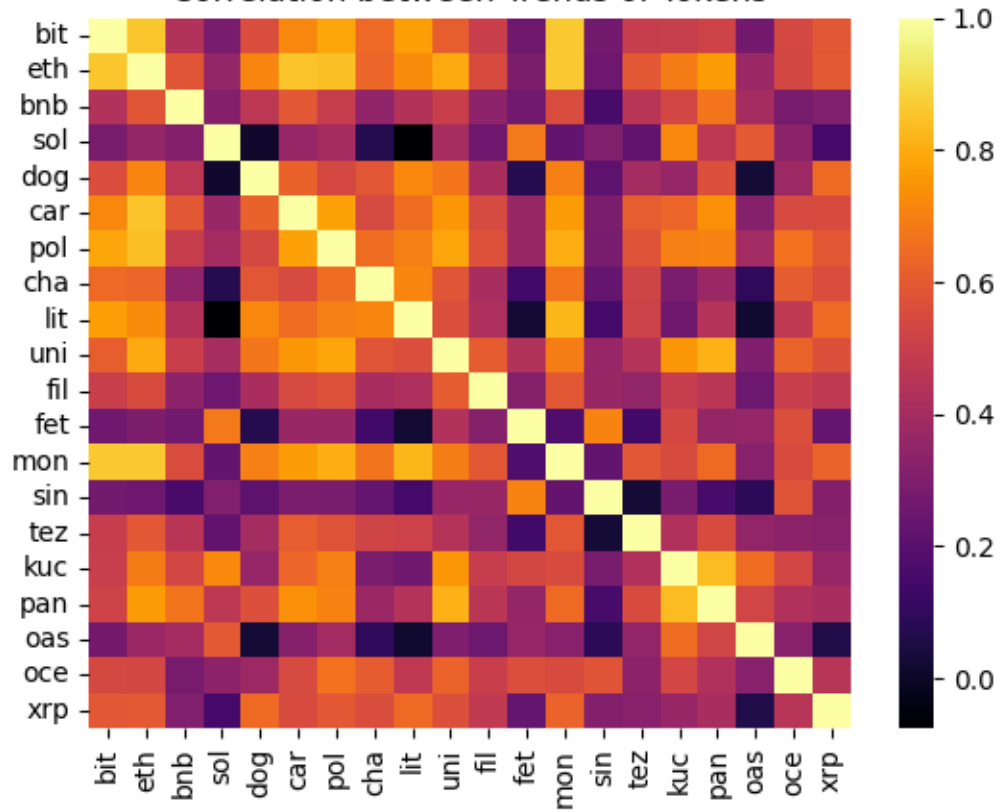
To gain further insights, we calculated the correlation between Google Trends data and cryptocurrency prices using a range of time lags. Results proved that correlations tended to be maximized with lags ranging from 3 to 8 weeks. These findings suggest that public interest in cryptocurrencies, as captured by Google searches, helps predict price movements with a time lag of approximately 25 weeks (or 5-6 months). This lag period aligns with the typical crypto market cycle timeframes that have been observed historically. Incorporating time delays uncovered ideal correlation windows and provided valuable insight that search interest predicts mid-term price cycles instead of short-term fluctuations. These relationships can guide effective predictive modeling strategies leveraging historical patterns.



Correlation (Token Patterns)

Having understood the individual relationships between each cryptocurrency's price data and Google Trends, we further examined the correlation patterns between different coins/tokens. This revealed analogous behaviors across assets.

Correlation between Trends of Tokens



Model

We decided to build an autoregressive model to predict the google trends for Ocean Protocol token. The data was split into training(90 percent) and testing(10 percent). Mean Absolute Error(MAE) was to be used as an accuracy metric. First a baseline model was built and had MAE of 12.27. Then the model was trained and was able to predict with an MAE of 6.29. We unsuccessfully tried to better the model using walk forward validation which we believe would have improved the model's MAE.