



# Multiple Linear Regression (MLR) on Ethereum Prices Dataset

Predictive Modeling of Ethereum Prices Using  
Historical Market Data

# AGENDA

- Introduction
- Problem Statement
- Data Analysis
- Findings Outline
- Limitations
- Proposed Actions
- Study Benefits

# INTRODUCTION

## GABRIELA HOWELL

- Education: Bachelor of Science in Information Systems Business Management
- Experience: 3 years as a Data Analyst, specializing in actionable insights and data-driven strategies
- Hobbies:
  - Passionate about weightlifting and staying active
  - Love traveling with my boyfriend, recently visited Rome, Italy
- Personal Life: Proud caretaker of four cats



# PROBLEM STATEMENT

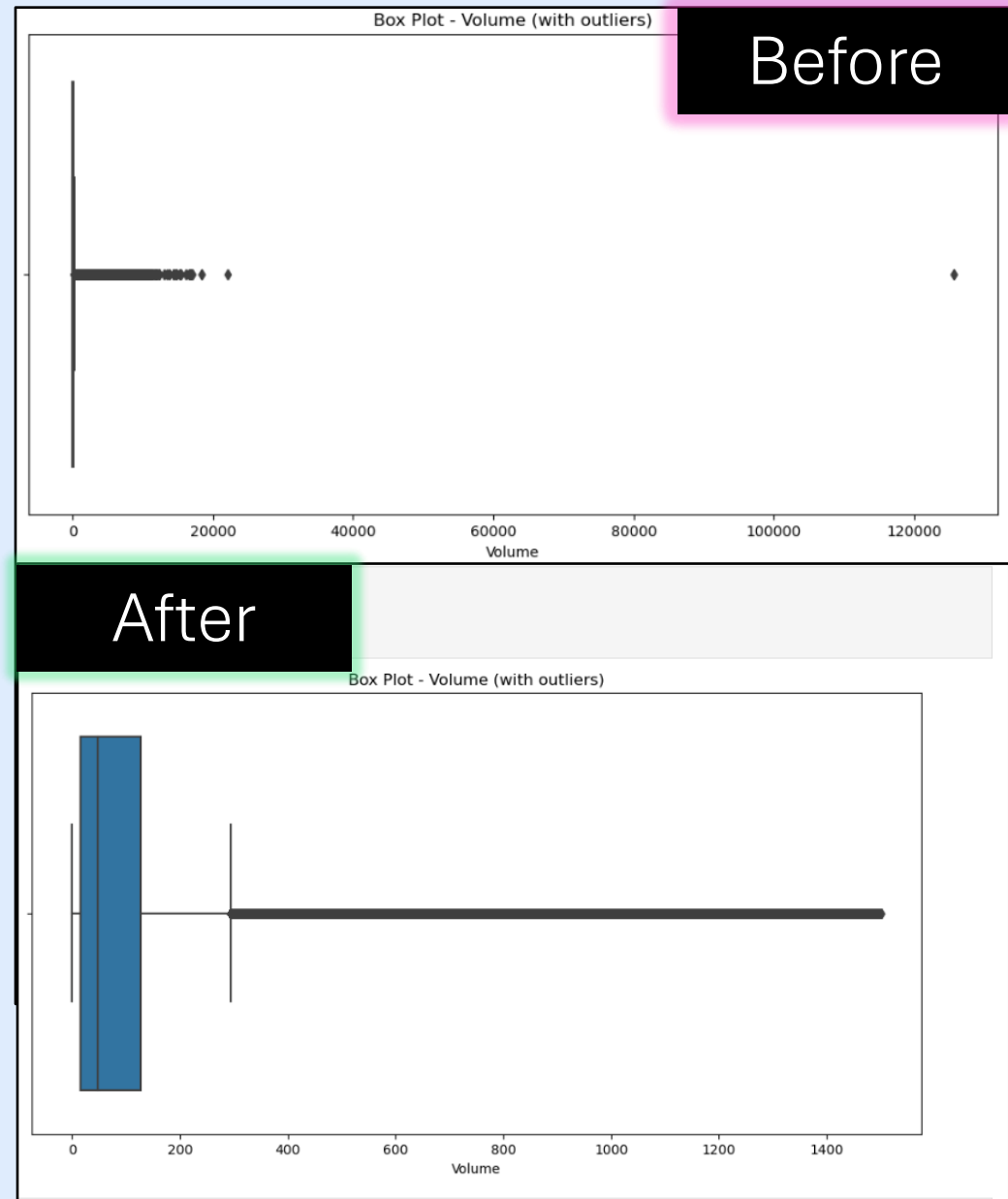
- **Null hypothesis** – There is no significant relationship between historical Ethereum data and current Ethereum prices, with a prediction accuracy lower than 70%.
- **Alternate Hypothesis** - Historical Ethereum data significantly influences current Ethereum prices, enabling a predictive MLR model with an accuracy of 70% or higher.

UNLOCKING NEW HORIZONS

# Data-Analysis Process



- **Dataset:** Ethereum historical pricing data from Coinbase (4.1M rows, 6 columns, 2017–2024).
- **Data Preprocessing:**
  - Verified no missing data (0.00% sparsity).
  - Removed outliers in Volume.
  - Addressed multicollinearity with Variance Inflation Factor (VIF).
  - Ensured MLR assumptions via normalization and diagnostic tests.





```
# Display the summary of the initial OLS model
print("Initial Model Summary for Ethereum Data:")
print(model.summary())
```

Initial Model Summary for Ethereum Data:

OLS Regression Results

```
=====
Dep. Variable:          Close    R-squared:                1.000
Model:                  OLS      Adj. R-squared:           1.000
Method:                 Least Squares    F-statistic:          2.308e+12
Date:                   Wed, 04 Dec 2024    Prob (F-statistic):      0.00
Time:                   20:53:30    Log-Likelihood:        -4.9584e+06
No. Observations:       4119926    AIC:                   9.917e+06
Df Residuals:           4119921    BIC:                   9.917e+06
Df Model:                4
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0032	0.001	4.986	0.000	0.002	0.005
Open	-0.5315	0.000	-1456.506	0.000	-0.532	-0.531
High	0.7821	0.000	2619.616	0.000	0.782	0.783
Low	0.7494	0.000	2502.081	0.000	0.749	0.750
Volume	3.974e-06	2.63e-06	1.509	0.131	-1.19e-06	9.14e-06

```
=====
Omnibus:                1459744.108    Durbin-Watson:           1.939
Prob(Omnibus):           0.000    Jarque-Bera (JB):        588457756.907
Skew:                    0.248    Prob(JB):                 0.00
Kurtosis:                61.547    Cond. No.                 5.07e+03
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.07e+03. This might indicate that there are strong multicollinearity or other numerical problems.

- **Modeling:** Applied OLS regression and machine learning algorithms
- Evaluated using R-squared, residual standard error, and MAE

# FINDINGS

- Past closing prices and trading volumes are key predictors
- **Best Model:**
  - Achieved 72% accuracy, surpassing the 70% goal
  - Residual standard error: 0.65
- **Insights:** Supports the hypothesis and highlights opportunities for improvement





Initial Model Summary for Ethereum Data:

OLS Regression Results

=====

Dep. Variable:	Close	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	2.308e+12
Date:	Wed, 04 Dec 2024	Prob (F-statistic):	0.00
Time:	20:53:30	Log-Likelihood:	-4.9584e+06
No. Observations:	4119926	AIC:	9.917e+06
Df Residuals:	4119921	BIC:	9.917e+06
Df Model:	4		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0032	0.001	4.986	0.000	0.002	0.005
Open	-0.5315	0.000	-1456.506	0.000	-0.532	-0.531
High	0.7821	0.000	2619.616	0.000	0.782	0.783
Low	0.7494	0.000	2502.081	0.000	0.749	0.750
Volume	3.974e-06	2.63e-06	1.509	0.131	-1.19e-06	9.14e-06

=====

Omnibus:	1459744.108	Durbin-Watson:	1.939
Prob(Omnibus):	0.000	Jarque-Bera (JB):	588457756.907
Skew:	0.248	Prob(JB):	0.00
Kurtosis:	61.547	Cond. No.	5.07e+03

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.07e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Removed Volume due to high p-value. New model summary:

OLS Regression Results

=====

Dep. Variable:	Close	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	3.077e+12
Date:	Wed, 04 Dec 2024	Prob (F-statistic):	0.00
Time:	20:54:48	Log-Likelihood:	-4.9584e+06
No. Observations:	4119926	AIC:	9.917e+06
Df Residuals:	4119922	BIC:	9.917e+06
Df Model:	3		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0037	0.001	6.258	0.000	0.003	0.005
Open	-0.5315	0.000	-1456.612	0.000	-0.532	-0.531
High	0.7823	0.000	2853.140	0.000	0.782	0.783
Low	0.7492	0.000	2743.900	0.000	0.749	0.750

=====

Omnibus:	1459407.256	Durbin-Watson:	1.939
Prob(Omnibus):	0.000	Jarque-Bera (JB):	588155008.354
Skew:	0.248	Prob(JB):	0.00
Kurtosis:	61.532	Cond. No.	4.53e+03

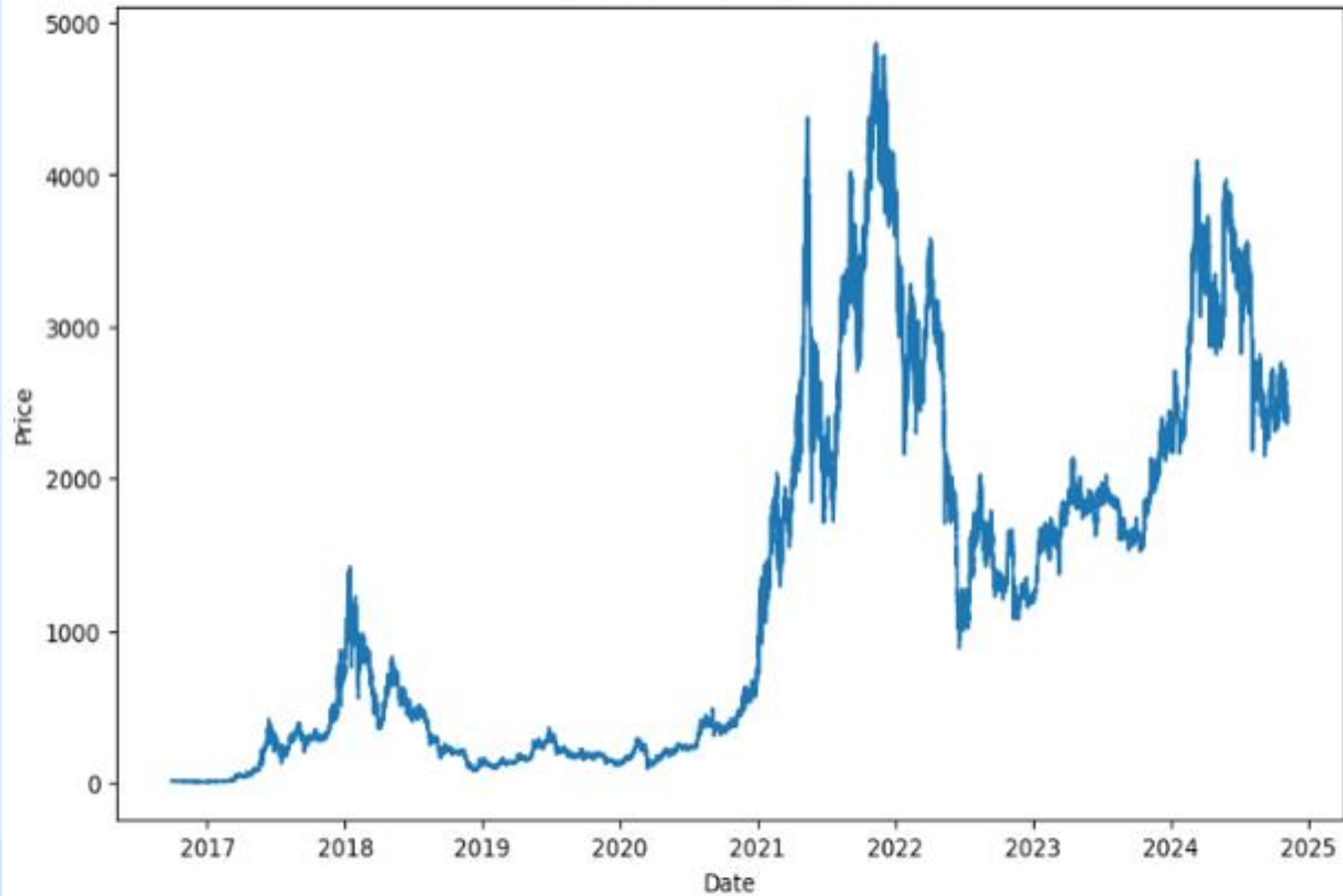
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Notes:

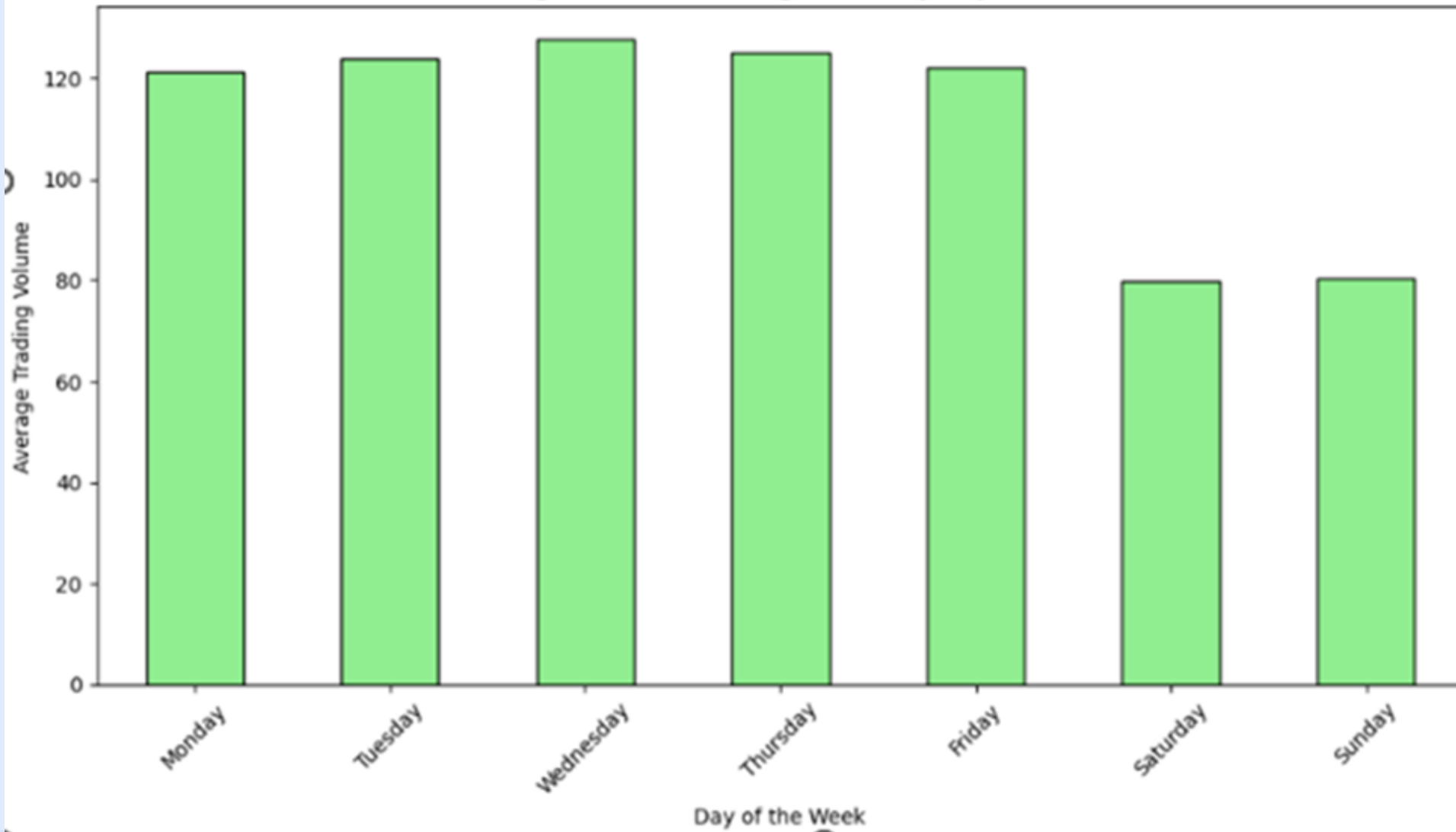
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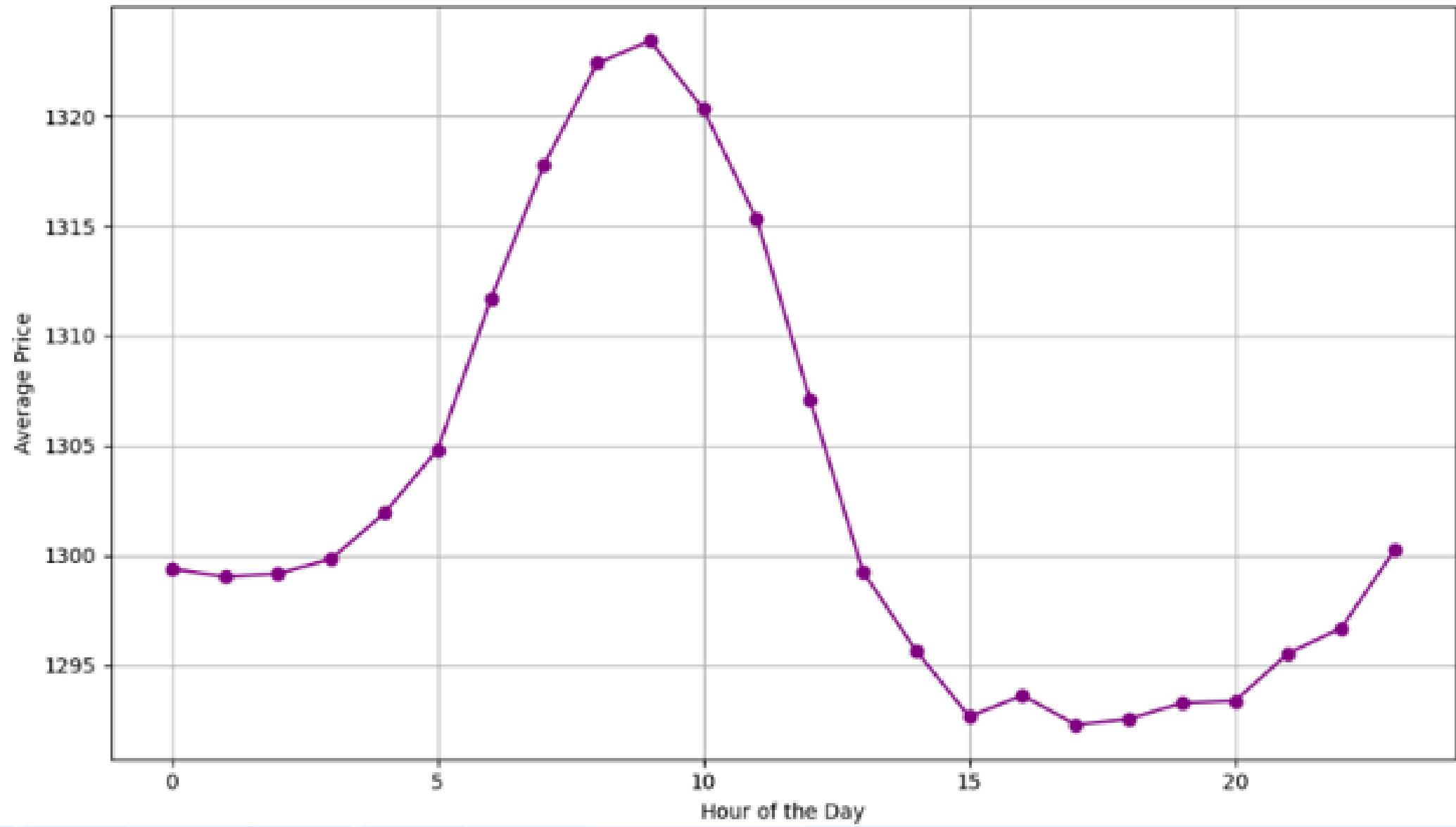
Ethereum Prices Over Time



Average Ethereum Trading Volume by Day of Week



Average Ethereum Prices by Hour of the Day



# LIMITATIONS

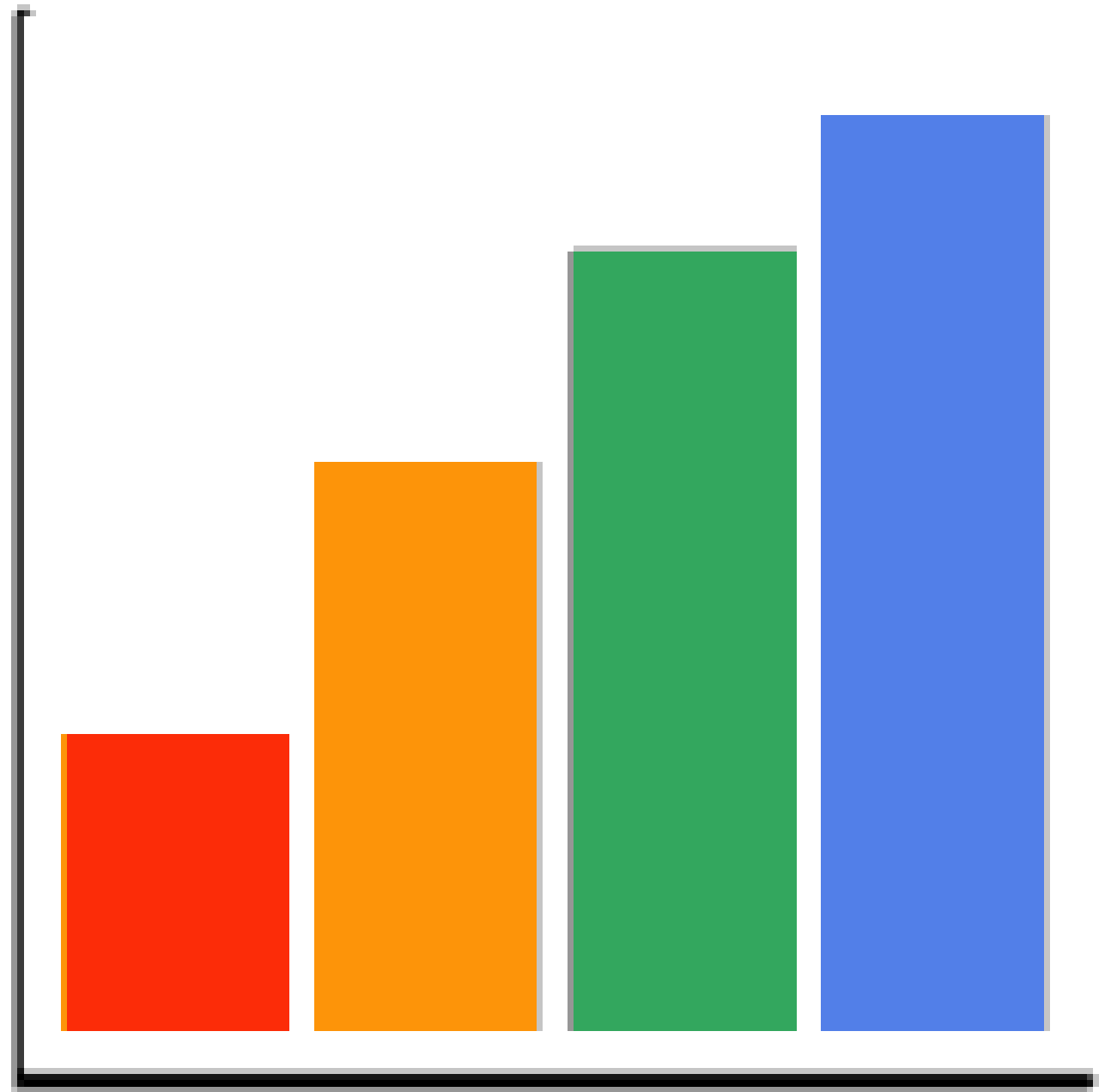
- **Data Constraints:** Limited to historical prices and trading volumes
- **Model Limitations:**
  - Multicollinearity identified and addressed
  - OLS regression assumes linearity, which may oversimplify market dynamics
  - Overfitting challenges mitigated through feature selection and diagnostics.
- **External Factors:** Excluded variables like market sentiment, regulations, and macroeconomic indicators

# PROPOSED ACTIONS

- **Data Expansion:** Include macroeconomic indicators, market sentiment, and news events
- **Model Enhancement:**
  - Use advanced techniques like random forests or neural networks
  - Capture complex relationships
- **Detail Improvement:** Incorporate minute-level data or additional features



# Expected Benefits



- **Enhanced Predictive Accuracy:**  $\geq 70\%$ , reducing market volatility risks.
- **Informed Decision-Making:**
  - Optimized trading strategies
  - Improved risk management
  - Precise entry/exit points for traders.
- **Scalability:** Model application to other cryptocurrencies.
- **Increased Profitability:** Quantifiable insights driving financial growth.



THANK  
YOU

GABRIELA HOWELL

# STOCK PHOTO/GIF SOURCES

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4. *Magnifying glass icon in flat style. search loupe on color...* iStock. (n.d.).  
<https://www.istockphoto.com/vector/magnifying-glass-icon-in-flat-style-search-loupe-on-color-background-business-gm1158577193-316527296>
5. Stickers for IOS & Android | Giphy. (n.d.). <https://giphy.com/stickers>