



SPE-224146-MS

Leveraging Language Models for Carbon Market Insights: News Sentiment and Price Dynamics

Ge Zhang¹, David Yin², Tae Wook Kim¹, Anthony R. Kovscek¹

¹Department of Energy Science and Engineering, Stanford University, Stanford, CA, US

²Department of Computer Science, Stanford University, Stanford, CA, US

gmzhang@stanford.edu; kovscek@stanford.edu

Content

Carbon Credit Price and Prediction

Approach, Results, and Discussion

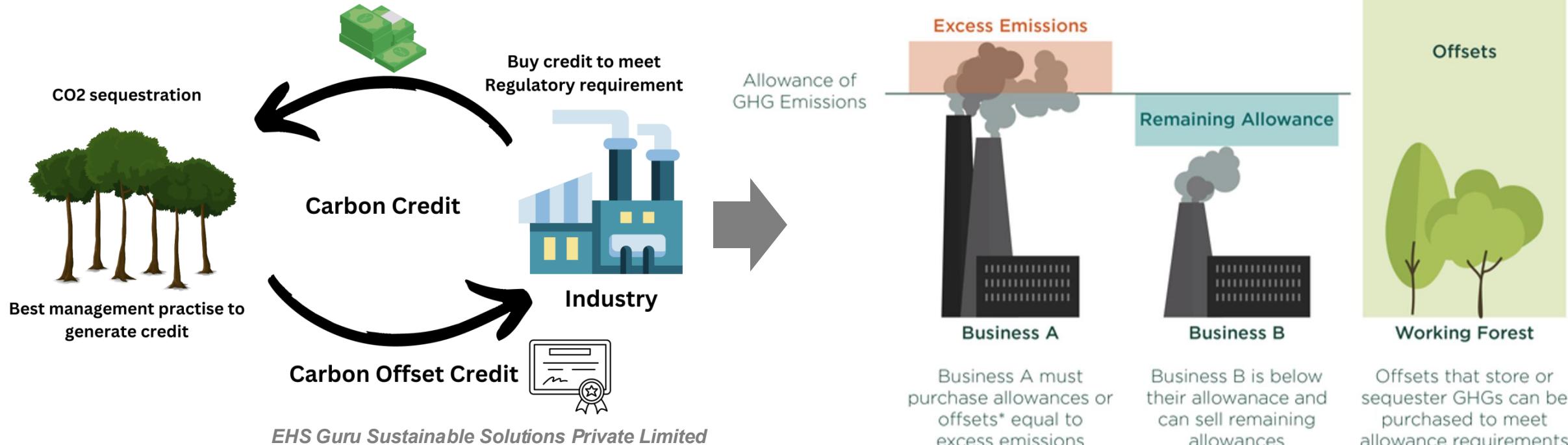
- I. Market Forecast with Price & Volume
- II. Uncovering Market Sentiment
- III. Enhancing Forecasts with Sentiment
- IV. Capturing Long-Term Price Dynamics

Conclusion and Future Work

Key References and Appendix

Stanford | Doerr
School of Sustainability

Carbon Credit System



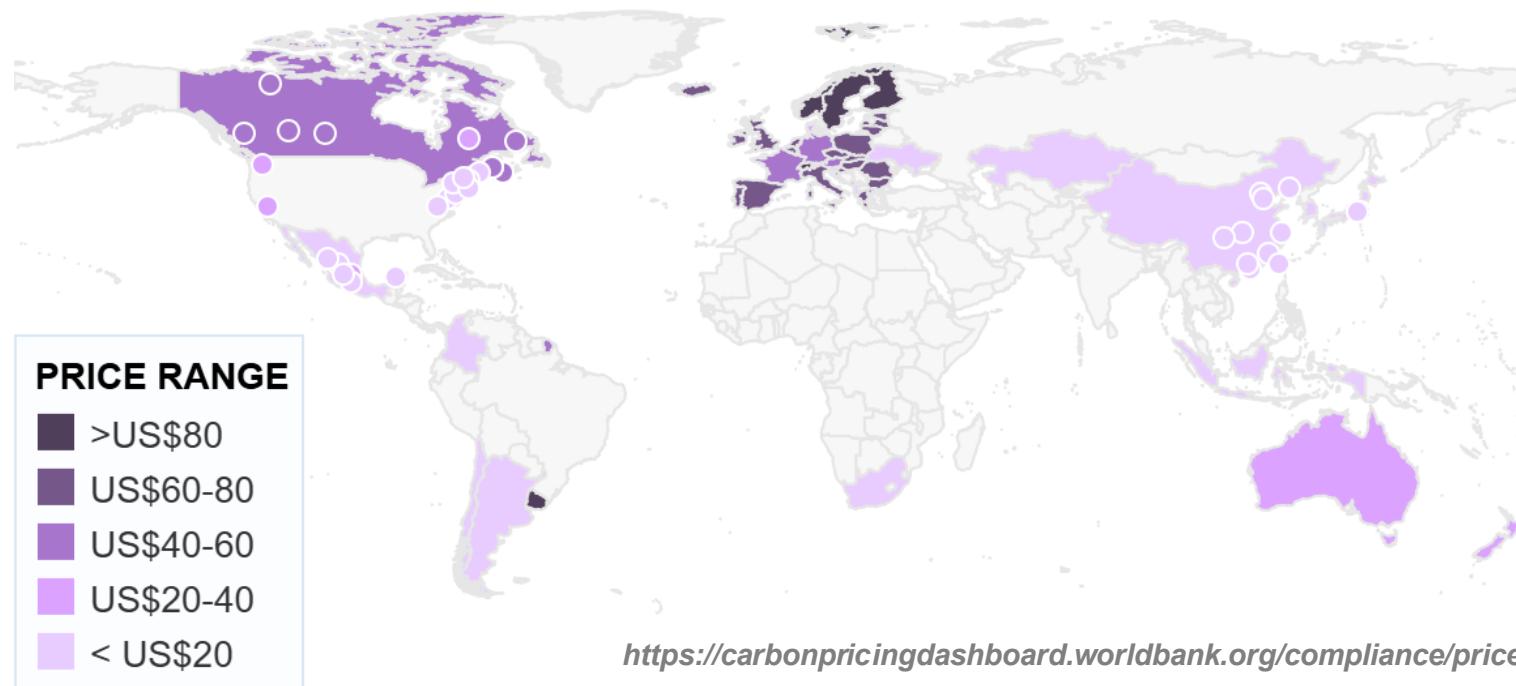
*Purchase of offsets to meet emissions allowances is often limited to a percentage of overall emissions reductions

Reproduced from *Forest Carbon and Climate Program, Department of Forestry, Michigan State University*

Buying & Selling: Is the Carbon Price Predictable?

Price of carbon around the world, 2024

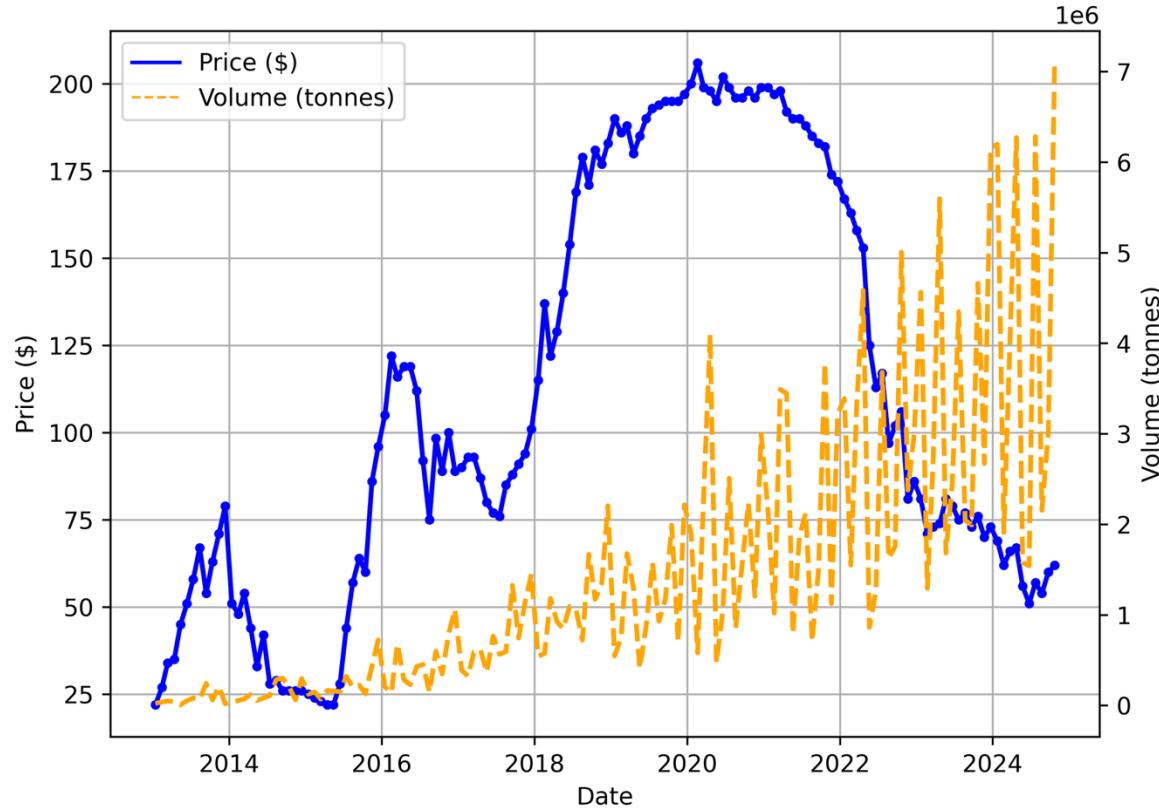
Heat map shows the level of the main price set by emissions trading systems or Carbon taxes in each jurisdiction (US\$/tCO₂e), subject to any filters applied. The year can be adjusted using the slider below the map.



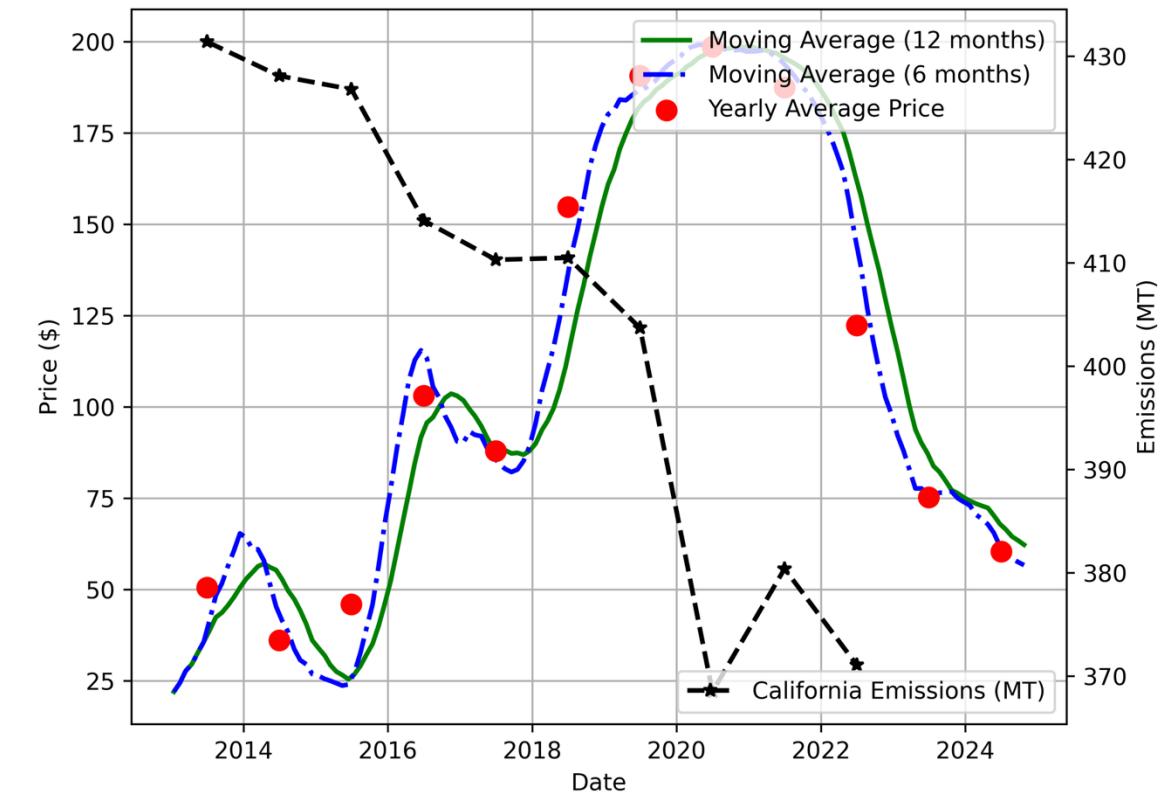
- Accurate predictions enable more effective strategies
- Businesses and individuals remain competitive in the decarbonization landscape

California's Low Carbon Fuel Standard (LCFS) Carbon Credit

- Selected data from January 2013 to research date (October 2024) of month scale



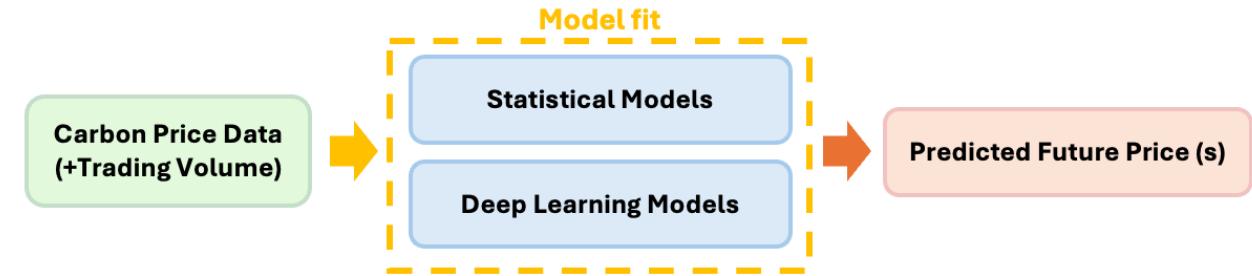
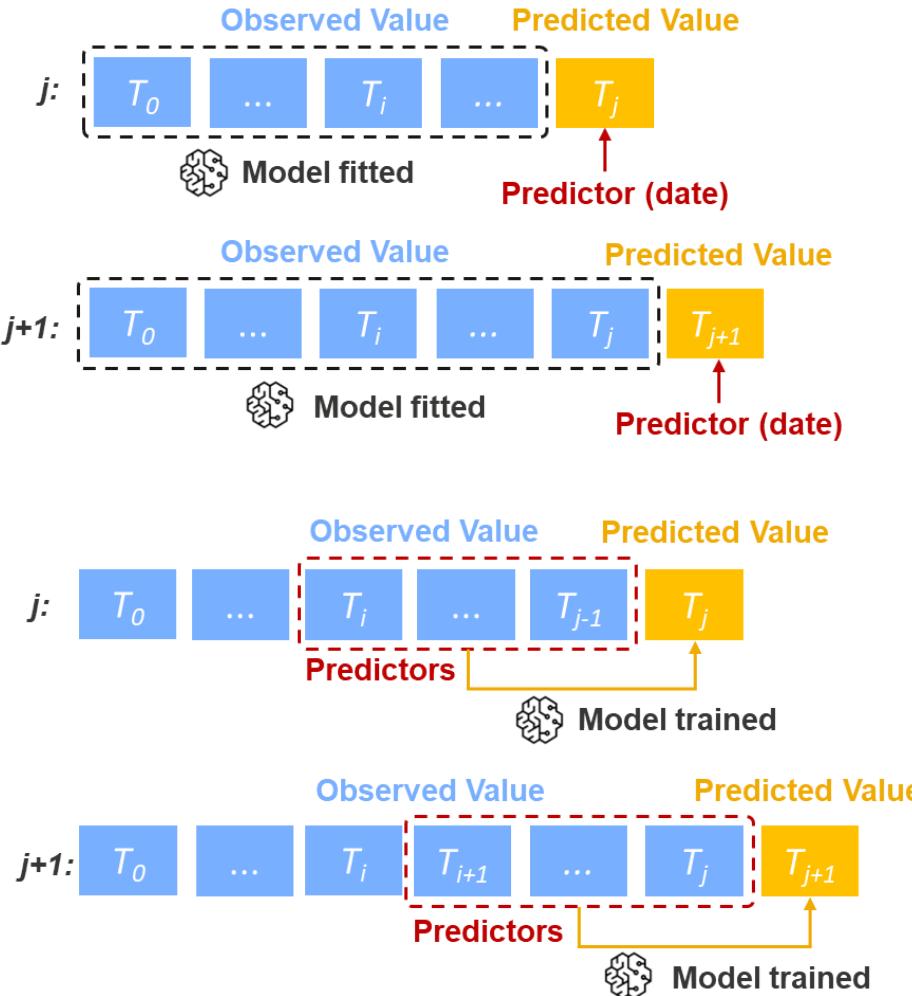
Historical LCFS carbon credit prices and trading volume from January 2013 to October 2024



Moving average trends with step size 6 and 12 months, yearly average price, and California's annual CO₂ emissions

Technical Analysis: Market Forecast with Price & Volume

Rolling Prediction



Methods used for time series analysis (see appendix):

- 1) Kalman Filter (KF)
- 2) ARIMA (Autoregressive Integrated Moving Average)
- 3) XGBoost (eXtreme Gradient Boosting)
- 4) Prophet (<https://facebook.github.io/prophet/>)
- 5) LSTM (Long Short-Term Memory)
- 6) TFT (Temporal fusion transformer)

Evaluation Metrics

- **Price Accuracy:** mean squared error (MSE) and mean prediction accuracy (MPA)
- **Directional Accuracy:** F1 score and moving direction accuracy (MDA)

$$(1) \quad \text{MSE} = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2$$

where \hat{y}_i indicates the predicted price for i -th observed price y_i .

$$(2) \quad \text{MPA (\%)} = \frac{1}{N} \sum_{i=1}^N \left(1 - \frac{|y_i - \hat{y}_i|}{y_i} \right) \times 100$$

$$(3) \quad \text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

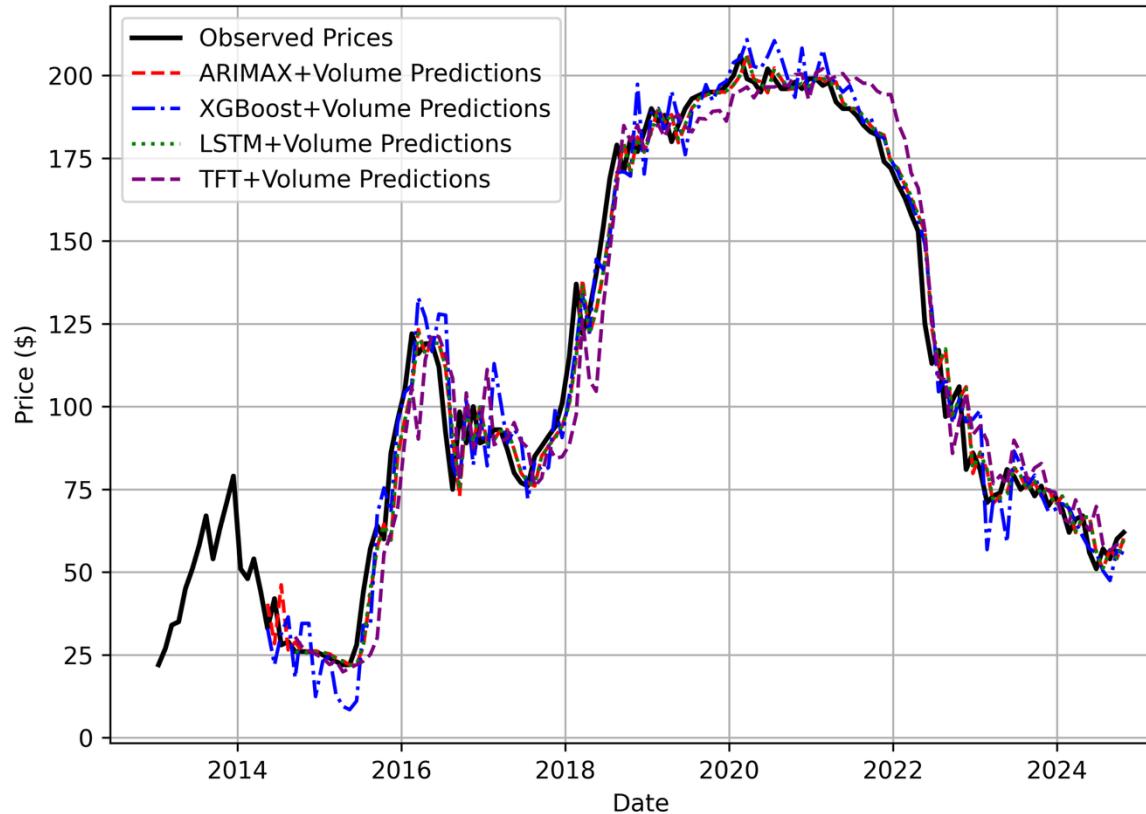
where we assume price increase as positive

where the Precision = $\frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$ and the Recall = $\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$

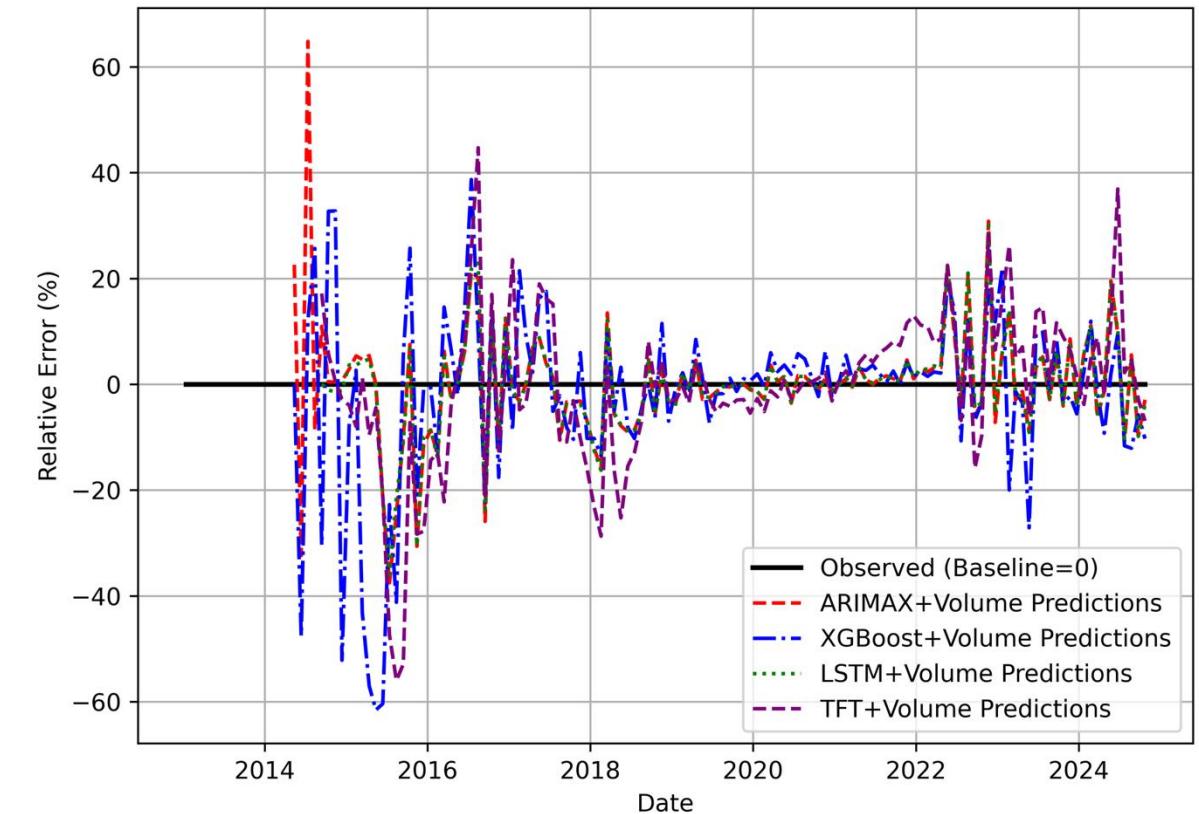
$$(4) \quad \text{MDA (\%)} = \frac{1}{N-1} \sum_{i=1}^{N-1} 1 \{ \text{sign}(y_{i+1} - y_i) = \text{sign}(\hat{y}_{i+1} - \hat{y}_i) \} \times 100$$

where i to $i + 1$ represents a one-month window for short-term price predictions or a one-year window for long-term forecasts.

I. Market Forecast with Price & Volume – Price



Rolling prediction results of LCFS carbon prices over time



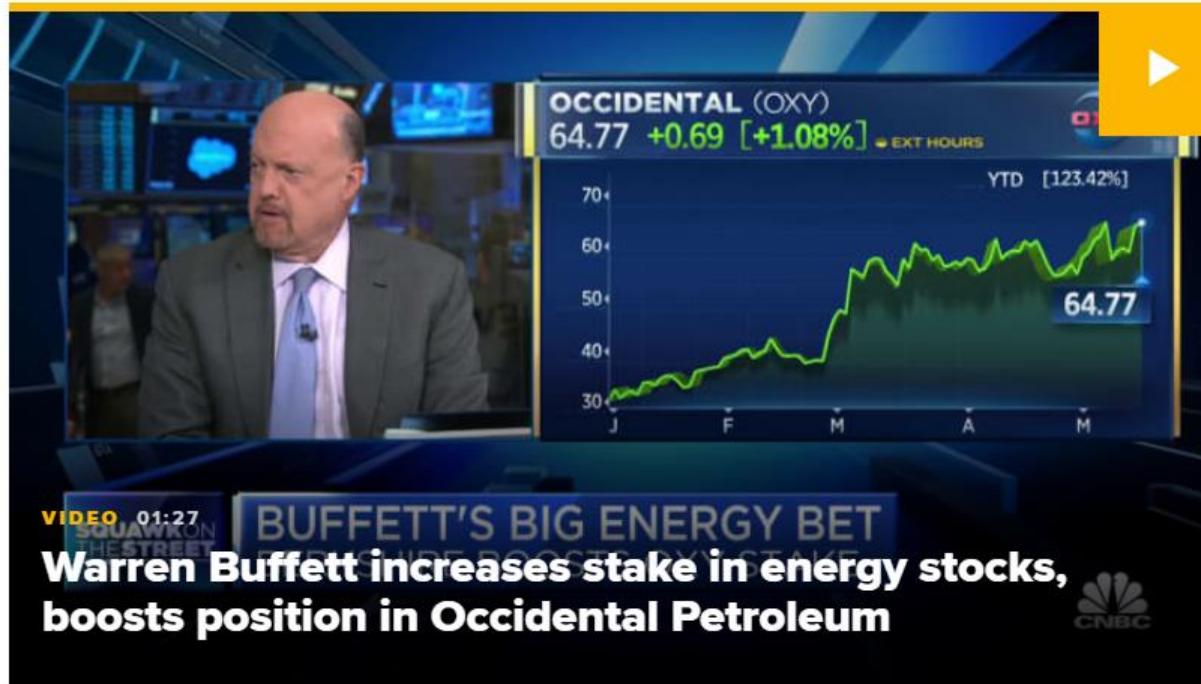
Relative percentage error between predicted prices and actual prices (baseline = 0)

I. Market Forecast with Price & Volume – Metrics

Methods	MSE	MPA (%)	F1 Score	MDA (%)
Kalman Filtering	76.2509	91.69	0.3433	49.65
ARIMA	73.3472	92.89	0.3515	50.40
ARIMAX (+volume)	74.5750	92.76	0.3403	48.80
XGBoost	107.4929	90.24	0.3517	50.41
XGBoost (+volume)	108.2244	89.32	0.3401	48.80
Prophet	104.7966	91.06	0.3124	44.80
LSTM	71.0222	93.74	0.3521	50.41
LSTM (+volume)	<u>70.3150</u>	<u>93.78</u>	0.3521	50.41
TFT	211.2333	89.50	<u>0.3747</u>	<u>53.72</u>
TFT (+volume)	179.8393	89.70	0.3288	47.11

Market Driven also by External Forces

- Example: Sentiment impact on OXY stock price (2022)



<https://cnb.cx/3QxuYxw>

GZ

Assume you are an expert in hedge fund strategy and market behavior. If Warren Buffett announces an intention to purchase shares of a specific company, how would you expect the stock price to respond, both immediately and in the short to medium term? Please explain the potential market dynamics and investor reactions involved.

The Buffett Effect: Market Summary

When Warren Buffett announces a company investment:



Immediate: 4-7% price jump, high trading volume, "Buffett Bounce"

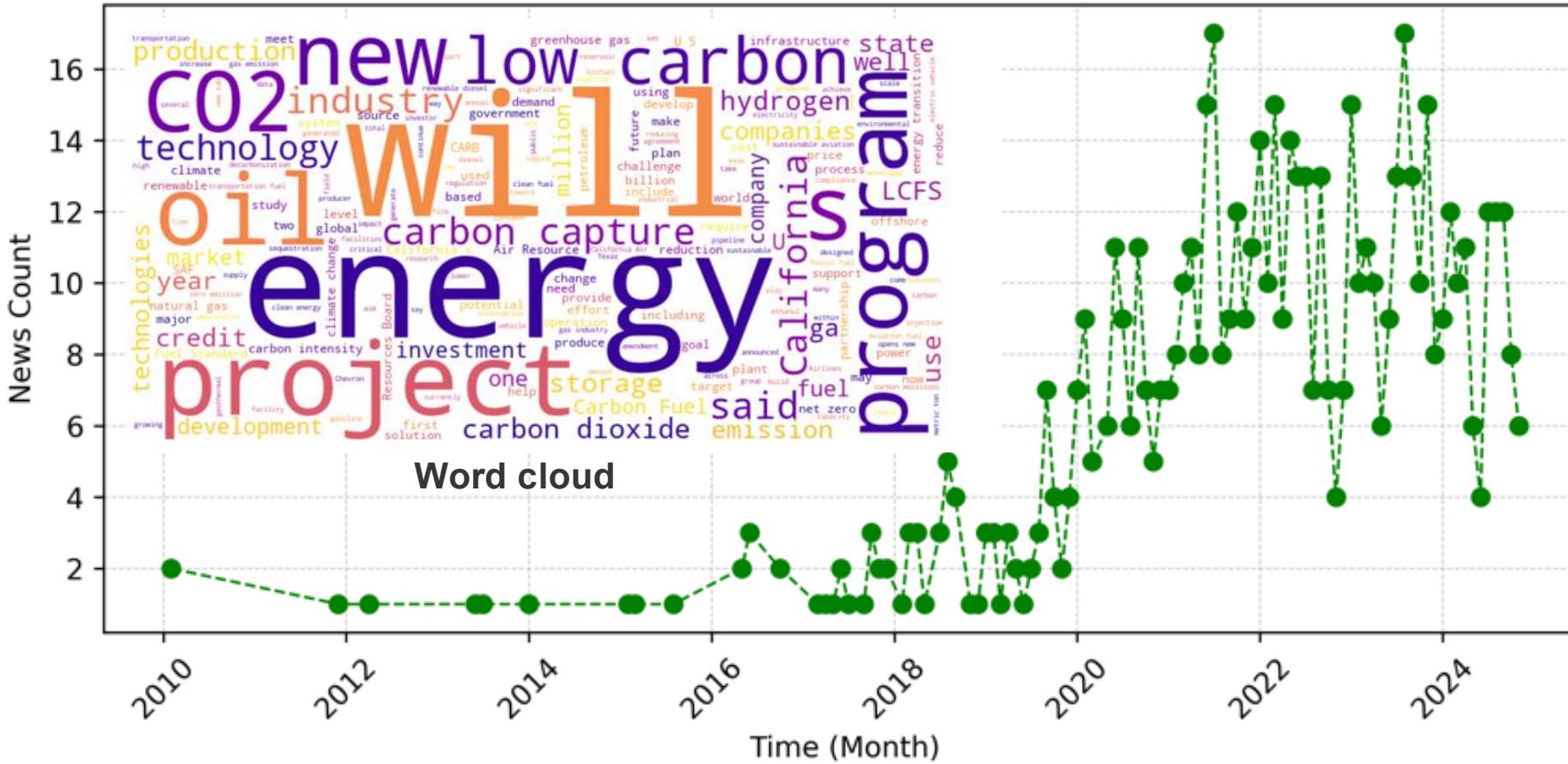
Short-term: Analyst upgrades, multiple expansion, institutional followers

Medium-term: Industry-wide effects, management alignment, stabilization at 10-15% above pre-announcement levels

The effect stems from Buffett's reputation for identifying undervalued companies, his long-term investment horizon, and the credibility his involvement brings to management teams.

II. Uncover Carbon Market Sentiment

News related to LCFS and carbon emissions distributed in monthly scale

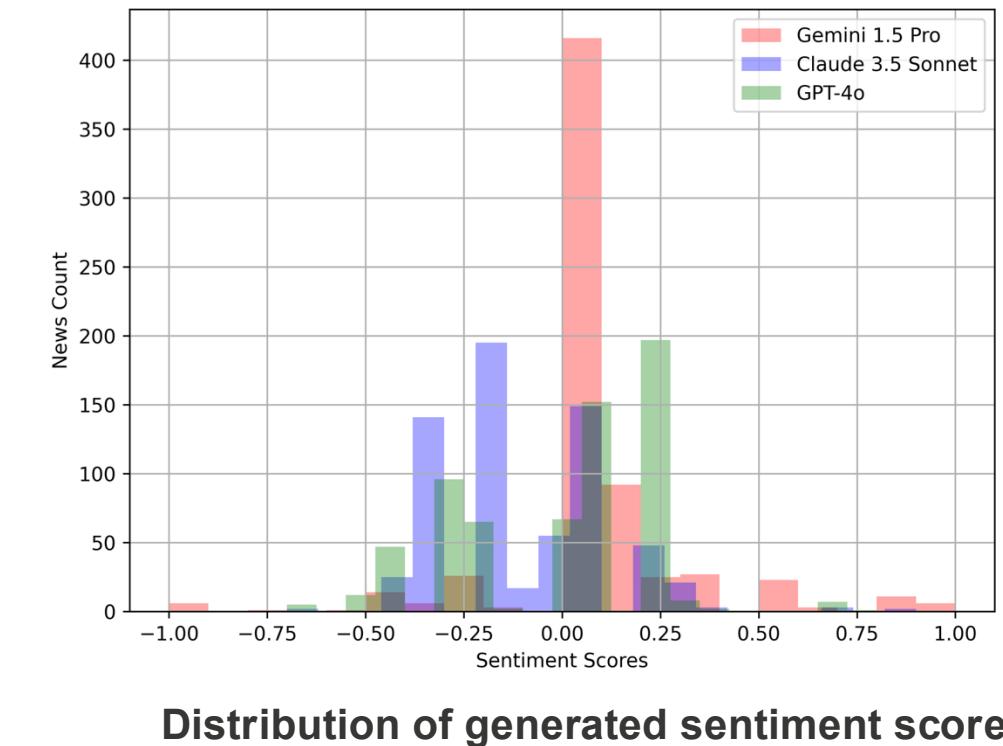
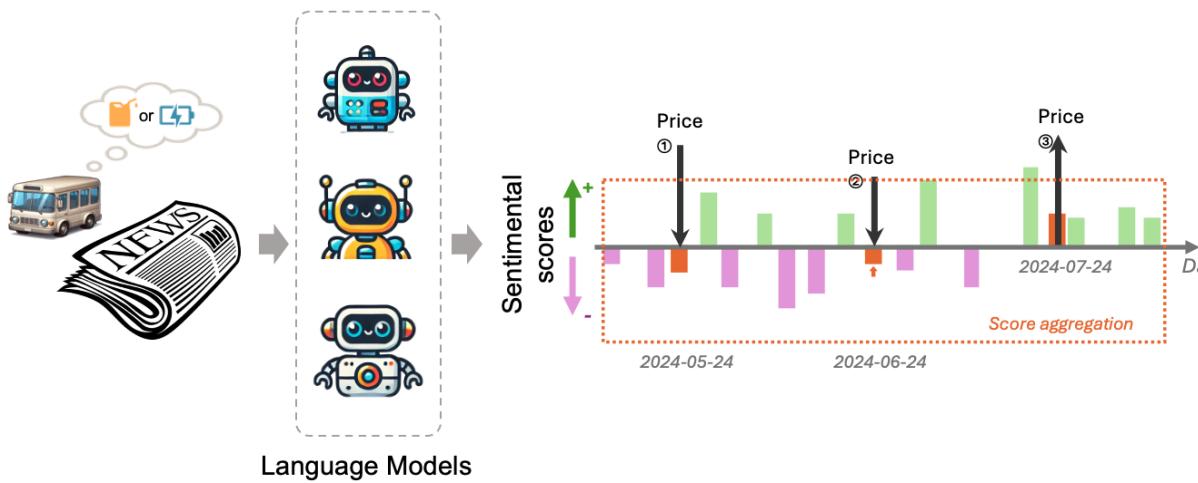


658 news articles (February 2010 to October 2024):

- 22 from the California Air Resources
 - 16 from Thomson Reuters
 - 620 pieces from SPE
 - 3 from other online sources

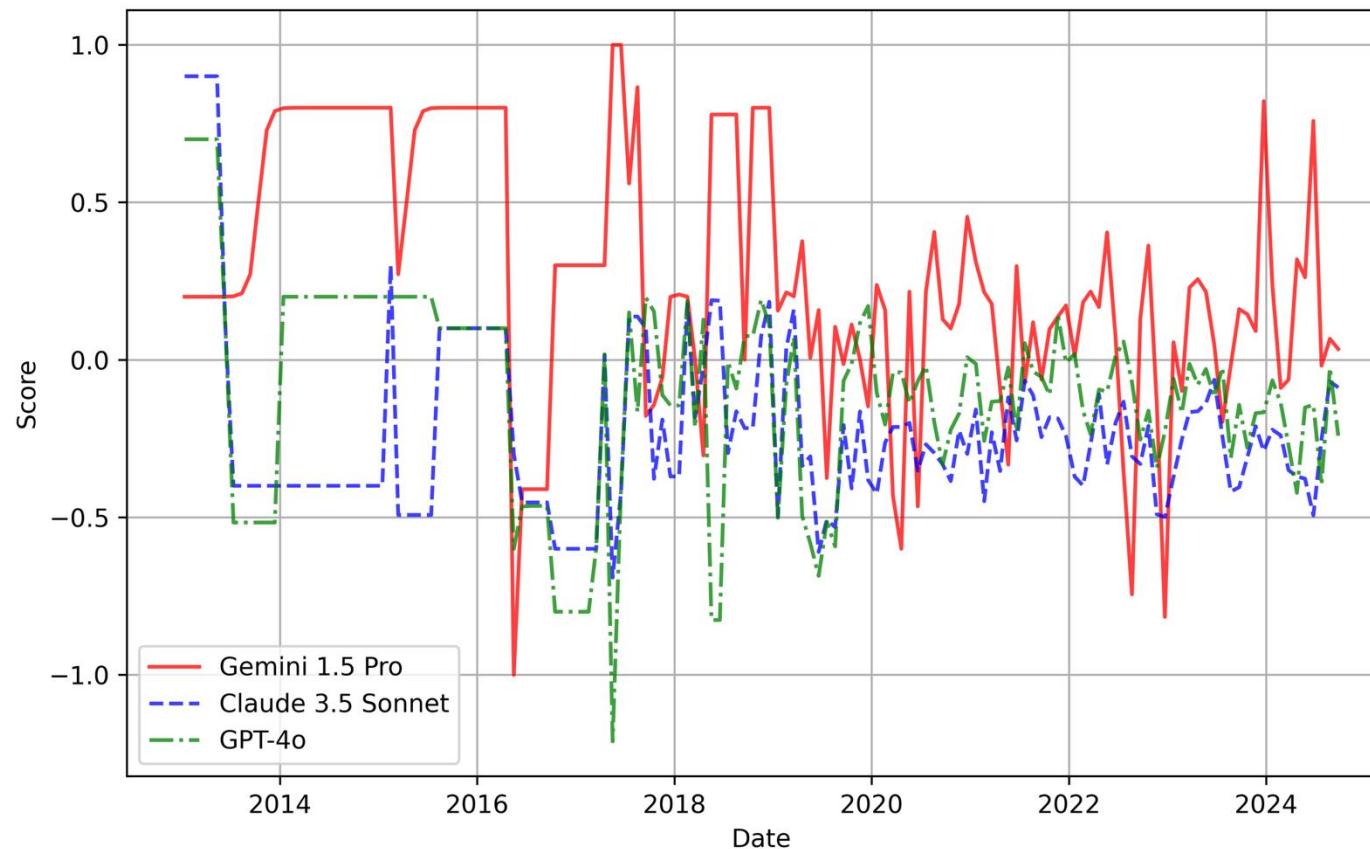
Turn News into Sentiments

- LLMs: Gemini 1.5 Pro, Claude 3.5 Sonnet, and GPT-4o (prompt in the appendix)
- Gemini tends to assign more positive scores while Claude more cautious
- Sentiments: Positive → Price Decrease; Negative → Price Increase



Sentiments – Date Alignment

Aggregated Sentiment Scores vs. Time



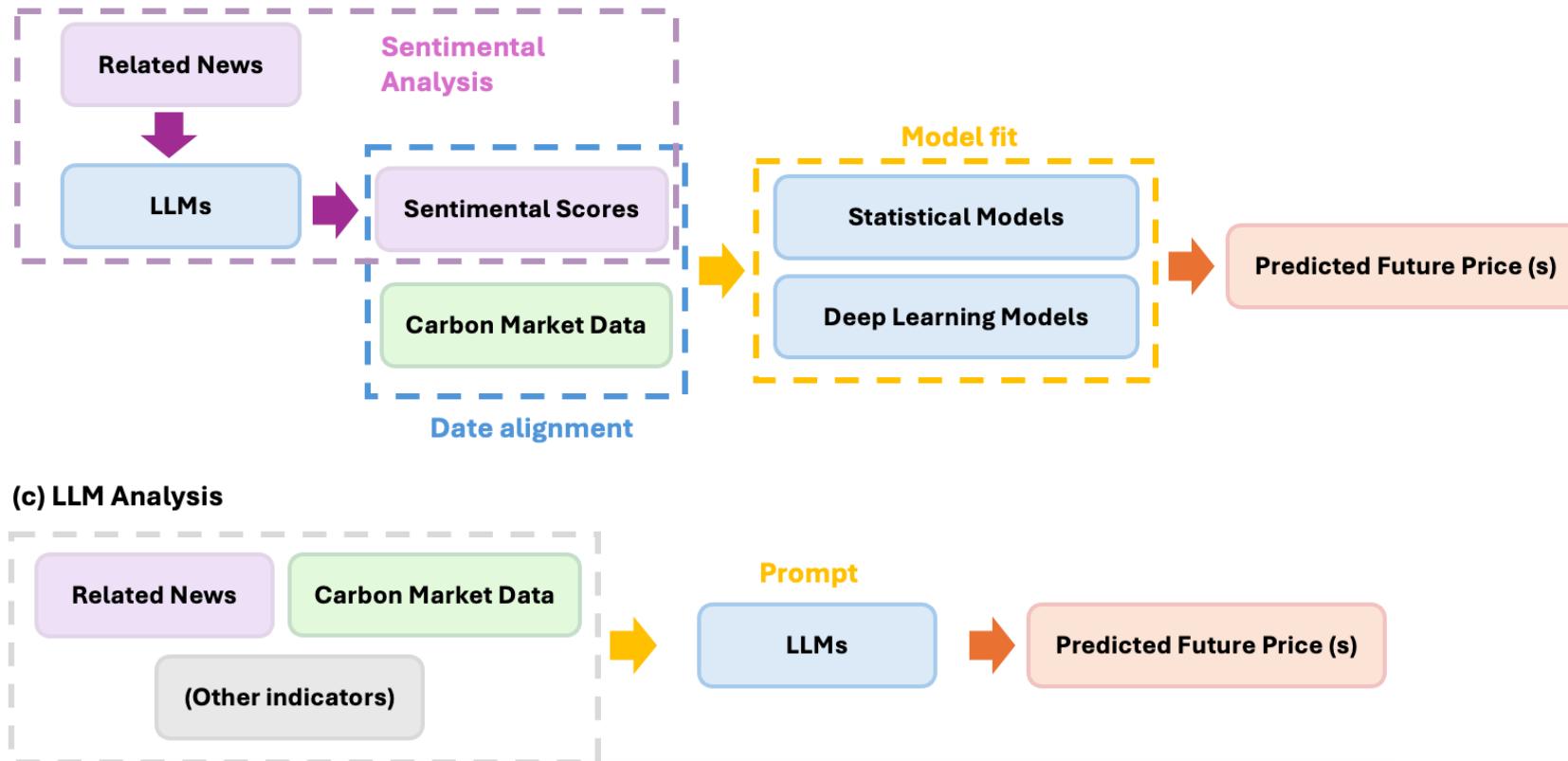
Exponential decay with tuned
time length of impact

$$p_{ij} = s_i \exp\left(\frac{C_i}{\Delta t_{ij}}\right) \quad P_j = \sum_{\forall i \leq j} p_{ij}$$

All alignment percentages above 50%

- Gemini 51.06%
- Claude 60.28%
- GPT-4o 53.19%

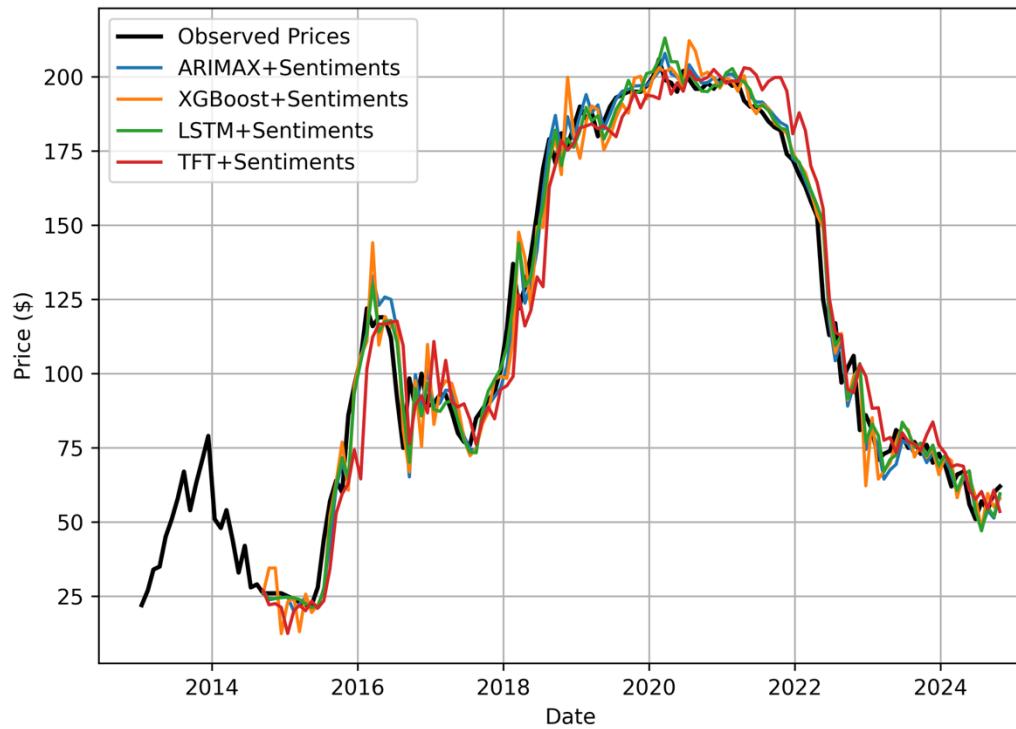
III. Enhance Forecasts with Sentiment



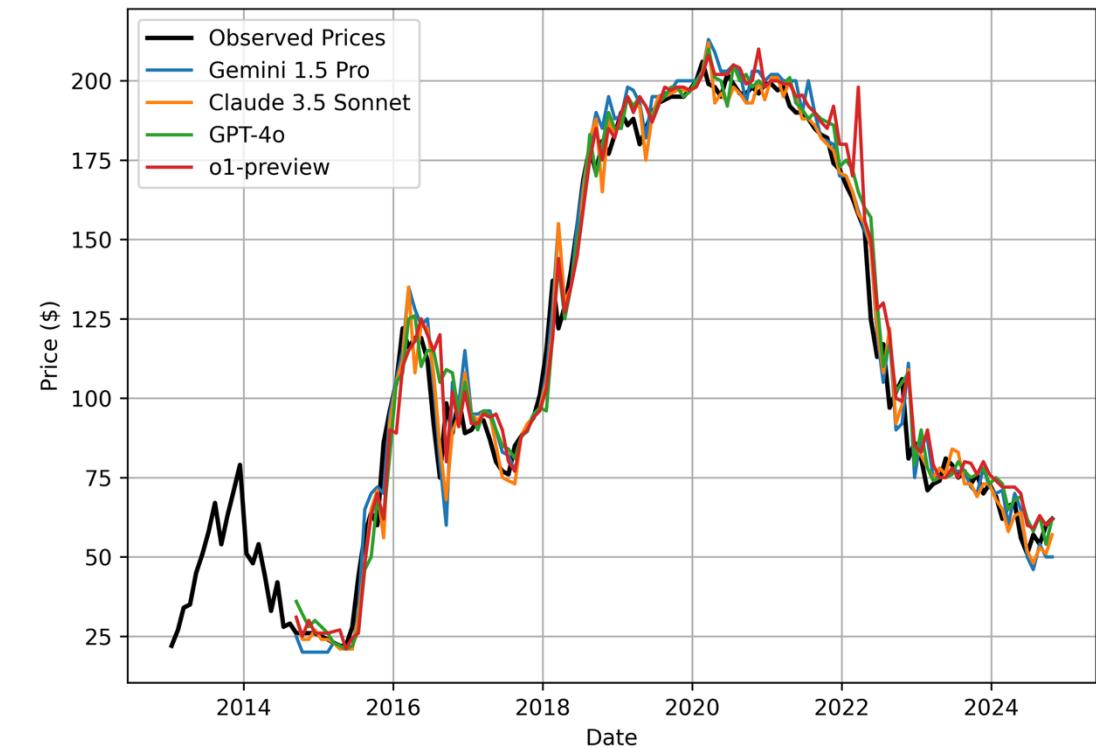
- Sentiment-assisted analysis: news → LLM → score → models → price
- LLM-based analysis: news + data → LLM → price prediction

News Sentiment Assisted Prediction

- Sentimental score assisted: ARIMAX, XGBoost, LSTM, and TFT
- Gemini 1.5 pro, Claude 3.5 Sonnet, GPT-4o, and o1-preview



Sentiment-assisted prediction using previous models



Direct LLM-based forecasting

Performance of Sentiment Aided Analysis

Methods	MSE	MPA (%)	F1 Score	MDA (%)
ARIMAX (+sentiment)	75.9338	93.21	0.3400	48.76
XGBoost (+sentiment)	112.1775	91.00	0.3405	48.76
LSTM (+sentiment)	<u>65.5611</u>	<u>93.80</u>	0.3347	47.93
TFT (+sentiment)	158.9985	90.47	<u>0.3463</u>	<u>49.59</u>
Gemini 1.5 Pro	94.7669	92.44	0.3732	42.98
Claude 3.5 Sonnet	<u>81.9726</u>	<u>93.62</u>	<u>0.4317</u>	<u>49.59</u>
GPT-4o	87.9907	92.41	0.3897	49.59
o1-preview	113.1193	92.08	0.3395	42.98

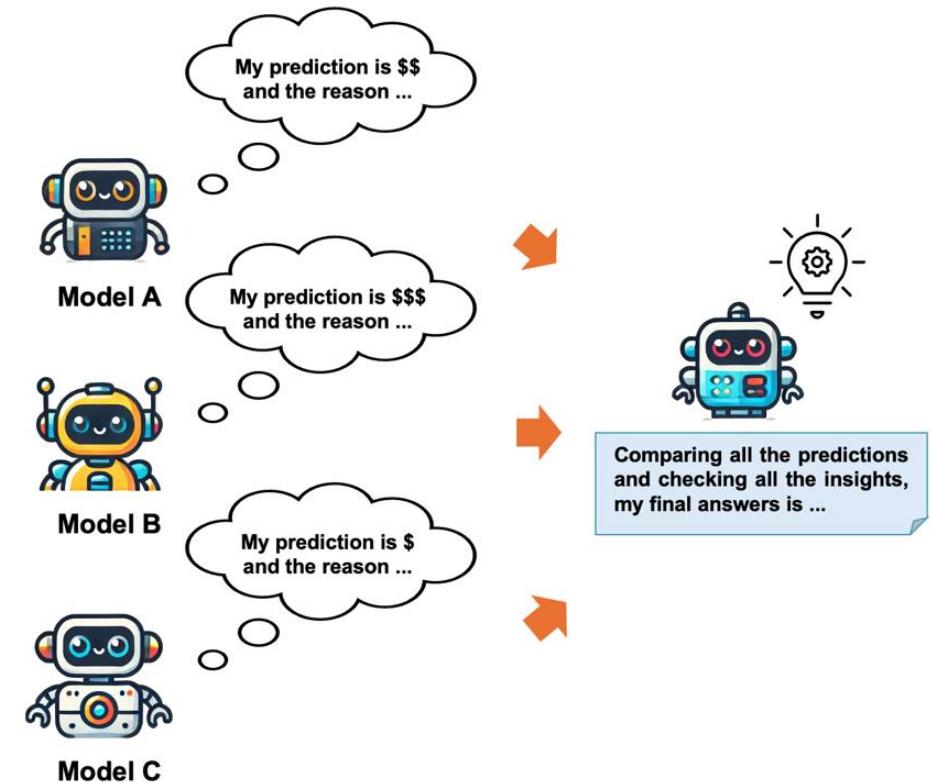
Reasoning with Prediction

Methods	Predicted Price	Reasoning
Gemini 1.5 Pro	\$170	<p>The LCFS price is expected to decrease slightly ... Recent news (2021-22) shows a significant increase in investment and development of carbon capture, utilization, and storage (CCUS) technologies, along with increased adoption of renewable fuels and electrification. This suggests a potential increase in the future supply of LCFS credits ...</p>
Claude 3.5 Sonnet	\$171	<p>Several factors suggest a moderate decline in LCFS prices: ...</p> <p>2. Recent news indicates increasing investment in carbon capture and alternative fuel technologies, which could increase credit supply:</p> <ul style="list-style-type: none"> - Multiple announcements of new CCS (Carbon Capture and Storage) projects - Growing investments in renewable diesel and alternative fuels - Increasing adoption of electric vehicles and charging infrastructure ...
GPT-4o	\$173.0	<p>... Recent news articles show strong industry initiatives toward carbon management and clean technologies, which generally bolster LCFS markets. However, it's worth noting that despite this sentiment, the largest demand factors stemming from compliance goals have been largely met in recent periods, as depicted by consistent high prices flattening ...</p>
o1-preview	\$180	<p>... Recent price movements indicate a decrease from 195.0 to 174.0, matching an overarching trend seen across the current year. Although there is ongoing compliance and adaptation within the LCFS market, as evident in the news, there is no substantial evidence of immediate policy shifts or compliance crises to fuel a price rebound ...</p>

An example predictions for December 21, 2021. The true price is \$172 indicating a small decrease from \$174 (November) and \$182 (October)

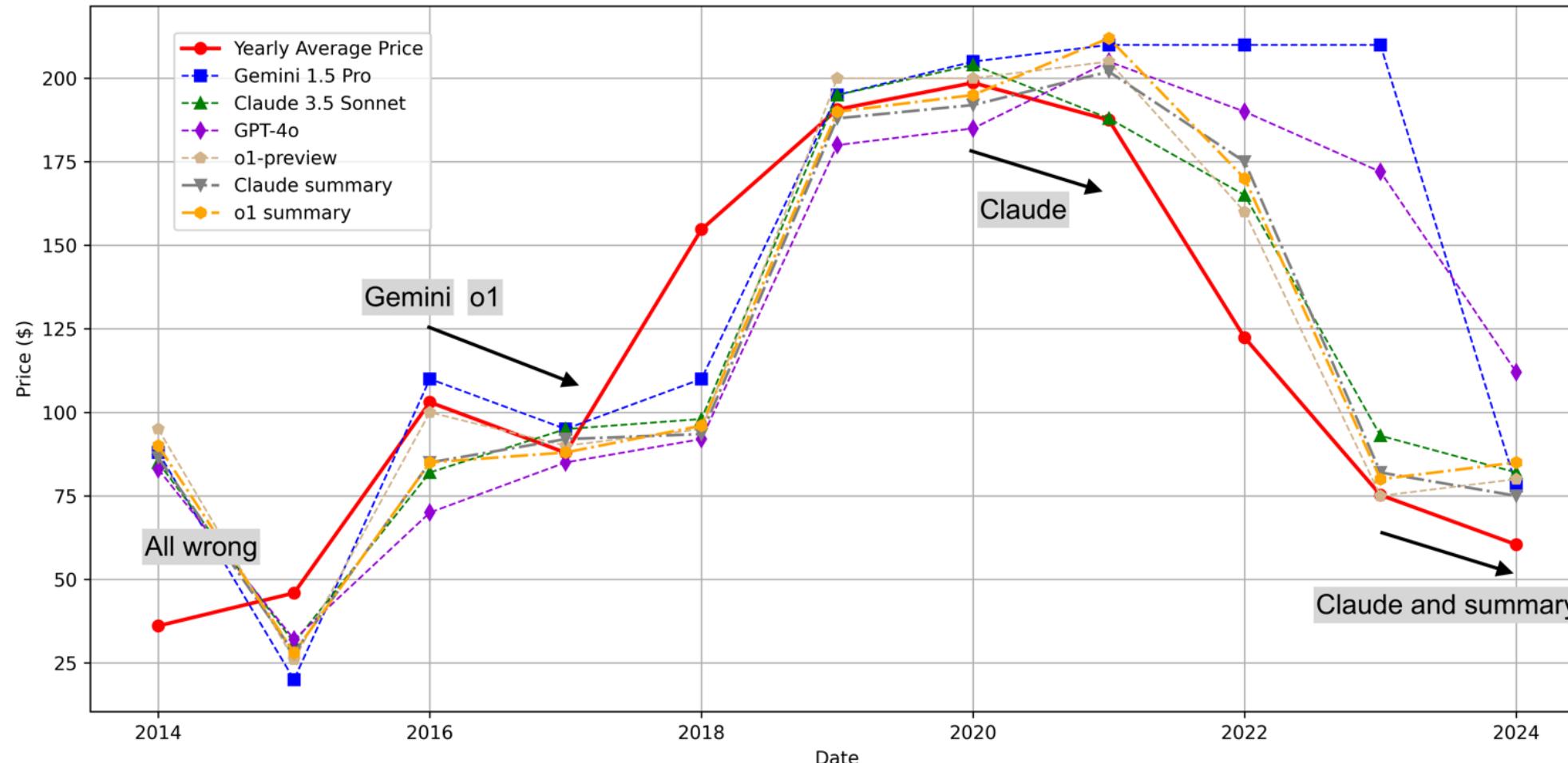
IV. Capture Long-Term Price Dynamics

- Yearly average price to be predicted
- History yearly averaged price, total volume, all the news, and other long-term indicators including:
 - 1) California **gasoline and diesel prices** data
 - 2) California **carbon emissions** data
 - 3) Annual **electric vehicle (EV) sales** in California
 - 4) Annual California **Cap-and-Trade (CaT) carbon tax** prices from 2012 to 2024
 - 5) Annual EU **ETS carbon prices** from 2011 to 2024
 - 6) Canada **federal fuel charge** from 2019 to 2024



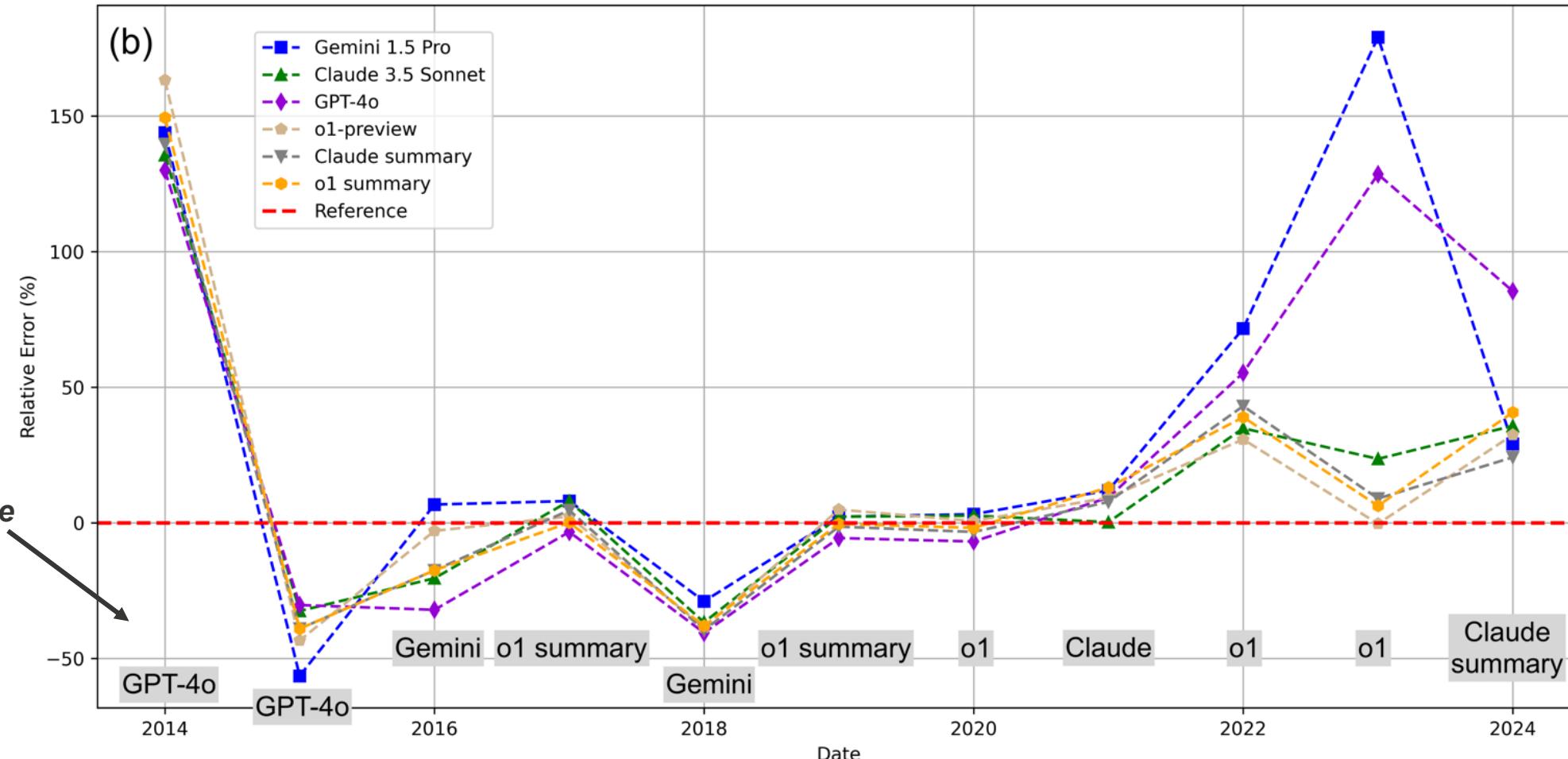
Schematic of LLMs' consensus-based prediction.
A model makes final decisions by aggregating prediction and insight from multiple prior models

Performance of Long-Term Price Prediction



Predicted prices compared to the actual yearly average prices

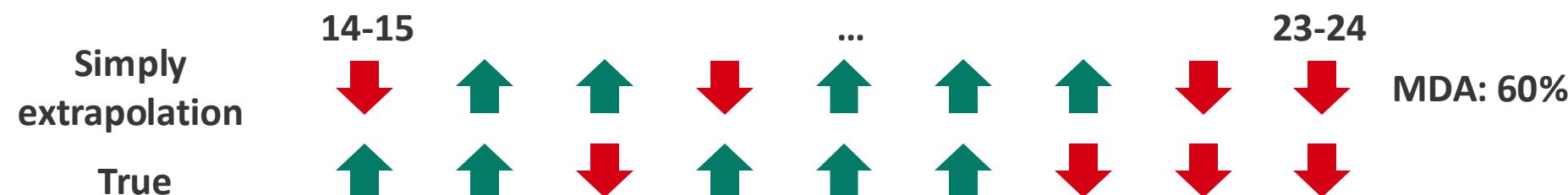
Performance of Long-Term Price Prediction



Relative percentage error between predicted prices and actual yearly average prices

Direction Prediction Using Different Models

Methods	MSE	MPA (%)	F1 Score	MDA (%)
Gemini 1.5 Pro	2926.0173	50.78	0.4333	60.0
Claude 3.5 Sonnet	<u>816.1840</u>	69.76	<u>0.8000</u>	<u>80.0</u>
GPT-4o	2240.0749	52.06	0.6970	70.0
o1-preview	877.2355	<u>70.09</u>	0.4222	60.0
Claude summary	931.8718	70.08	0.6970	70.0
o1 summary	956.2506	68.61	0.5833	60.0



Example – Predict 2024 Price by Claude 3.5 Sonnet

	Key Factors
Recent Price	- The LCFS price has shown a clear downward trend from its peak of ~200 in 2021 to around 73 by end of 2023
Trajectory	- The decline has been gradual but consistent, suggesting a structural market adjustment rather than temporary volatility
Supply-Side Factors	<ul style="list-style-type: none"> - Increased EV adoption in California (441,283 sales in 2023, up from 308,268 in 2022) is generating more credits - Recent news about "50% of California diesel fuel being replaced by clean fuels" (Aug 2023) indicates massive credit generation - Growing renewable diesel and sustainable aviation fuel projects are adding to credit supply
Policy & Regulatory	<ul style="list-style-type: none"> - CARB's November 2023 update to LCFS indicates program adjustments to rebalance the credit market - The new proposal aims to stabilize prices while maintaining program effectiveness
Environment	<ul style="list-style-type: none"> - Federal support for clean fuels and CCS projects provides additional momentum for credit generation - Credit bank remains well-supplied
Market Fundamentals	<ul style="list-style-type: none"> - Trading volumes have remained robust, indicating market liquidity - Recent stabilization around \$70-80 range suggests market finding equilibrium
External Market Influences	<ul style="list-style-type: none"> - Lower natural gas prices reducing compliance costs - EU ETS prices stabilizing around €90-100/ton - California's Cap-and-Trade program showing mature price signals

Conclusion

- LLMs match fine-tuned models in predictive performance and outperform in handling diverse inputs and generating interpretable reasoning.
- LLMs still struggle with short-term price oscillations but perform well in long-term trend forecasting through capturing broader context inputs

Future Work

- Expand data coverage to broader range of sources
- From passive input to AI agent actively search for relevant news, filings, and regulatory updates across the web as well as evaluation

Data and code available at



<https://github.com/geoz-lab/Carbon-Market-Insights-with-LLM>

Ethical Discussion

- **Reasonable Pricing:** The carbon market aims to combat climate change, but its success relies on fair pricing that reflects the environmental cost of emissions.
- **AI Cost:** LLMs require significant computational resources, raising concerns about their carbon footprint. Is it justifiable to use energy-intensive technologies to predict prices in a market focused on reducing emissions? Could this trade-off be mitigated by adopting carbon-neutral data centers?
- **New Regulations?** Who is accountable if LLM predictions lead to harmful economic or environmental outcomes? Should regulations govern their use in carbon market forecasting?

Acknowledgement

GZ acknowledges that part of the work presented in this paper was conducted as part of the Stanford CS229: Machine Learning final project, which also benefited from valuable suggestions from R. Li.

The API of several LLMs including from Google, Anthropic, and OpenAI are utilized in this research.

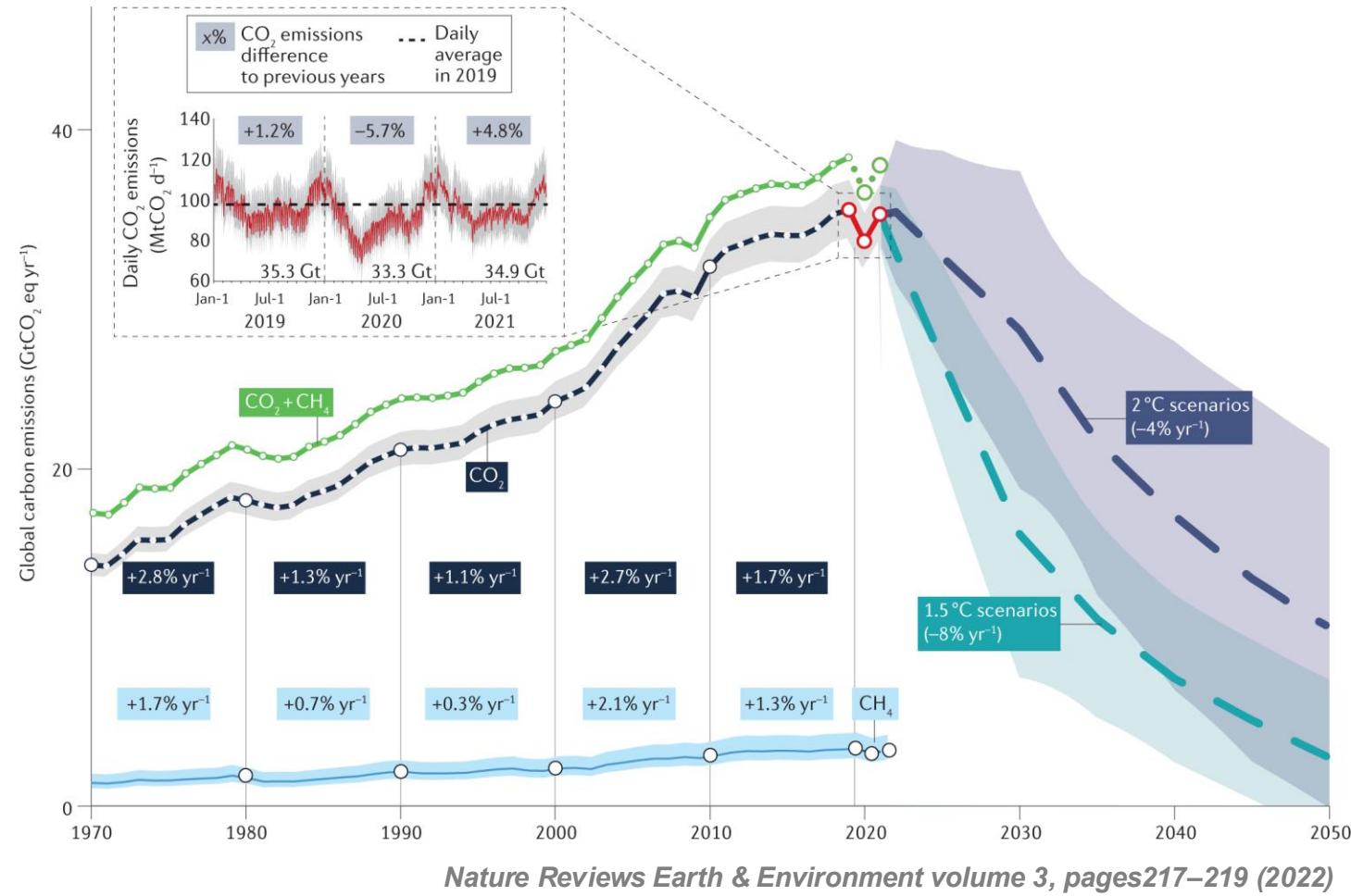
Additionally, we acknowledge that manuscript preparation benefited from writing suggestions and grammar checks provided by ChatGPT.



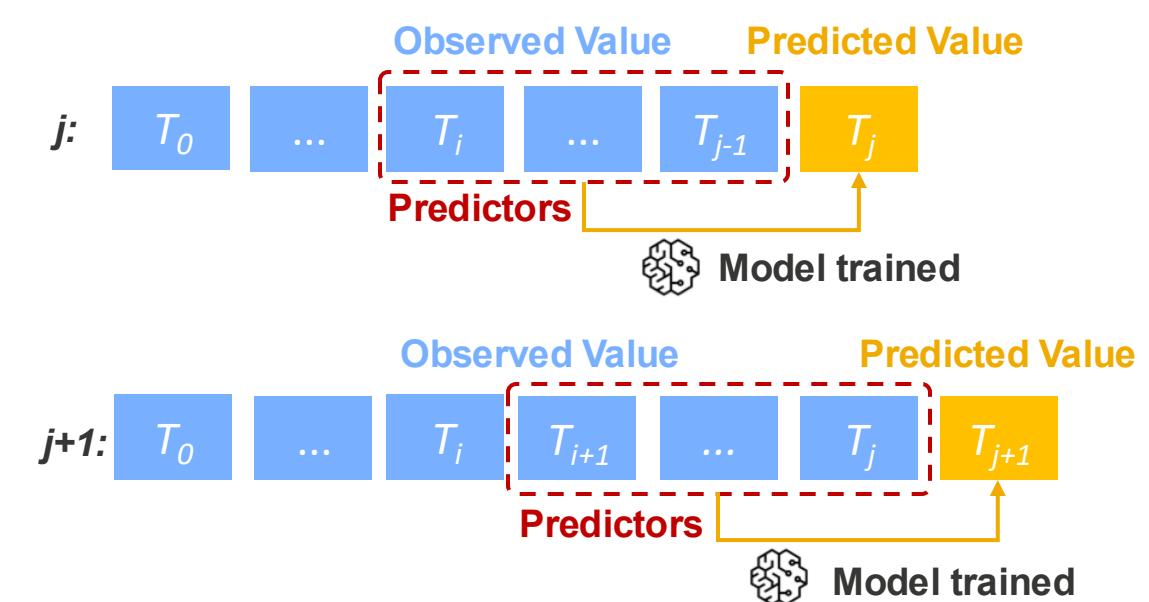
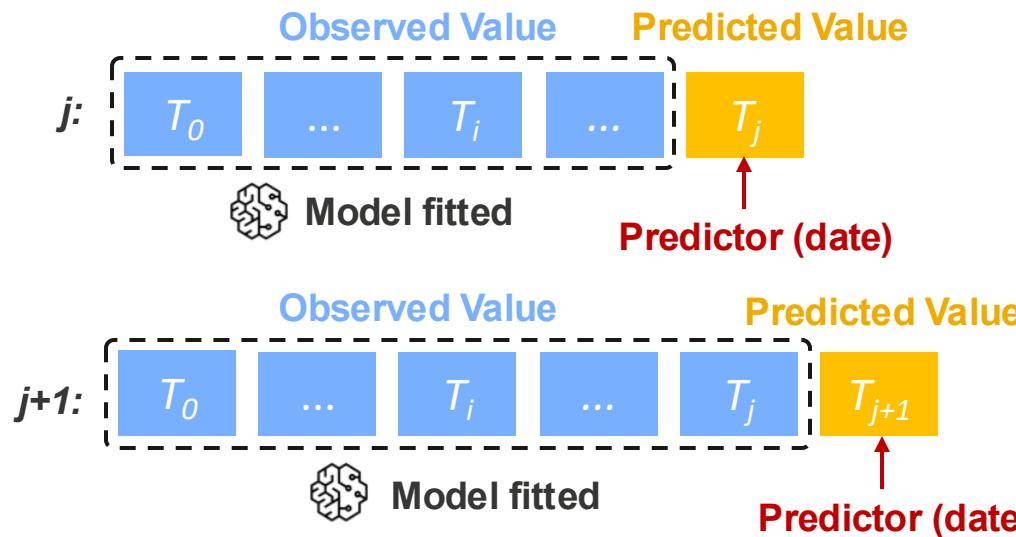
Key References/Data Source

- 1) Anthropic. 2024. Claude 3.5 Sonnet. Accessed [November 10, 2024], from <https://www.anthropic.com/news/clause-3-5-sonnet>
- 2) Brown, T., Mann, B., Ryder, N., et al. 2020. *Advances in neural information processing systems*33: 1877-1901.
- 3) California Air Resources Board. 2024a. LCFS Data Dashboard. Data last updated [October 31, 2024]. Retrieved [November 1, 2024] from <https://ww2.arb.ca.gov/resources/documents/lcfs-data-dashboard>
- 4) California Air Resources Board. 2024b. Low Carbon Fuel Standard: News. Data last updated [November 8, 2024]. Retrieved [November 10, 2024] from <https://ww2.arb.ca.gov/our-work/programs/low-carbon-fuel-standard/news>
- 5) California Air Resources Board. 2024c. Current California GHG Emission Inventory Data. Data last updated [2024]. Retrieved [December 15, 2024] from <https://ww2.arb.ca.gov/ghg-inventory-data>
- 6) California Air Resources Board. 2024d. Cap-and-Trade Program Data. Data last updated [December 9, 2024]. Retrieved [December 15, 2024] from <https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/cap-and-trade-program-data>
- 7) California Energy Commission. 2024. New ZEV Sales in California. Data last updated [November 19, 2024]. Retrieved [December 15, 2024] from <https://www.energy.ca.gov/files/zev-and-infrastructure-stats-data>
- 8) Chevallier, J. 2013. Carbon Price Drivers: An Updated Literature Review. *International Journal of Applied Logistics (IJAL)*4 (4): 1–7.
- 9) Herzen, J., Lässig, F., Piazzetta, S. G., et al. 2022. Darts: User-Friendly Modern Machine Learning for Time Series. *Journal of Machine Learning Research*23 (124): 1–6.
- 10) Metz, B., Davidson, O., De Coninck, H., et al. 2005. *IPCC Special Report on Carbon Dioxide Capture and Storage*. Cambridge: Cambridge University Press.
- 11) Society of Petroleum Engineers. 2024. Search Results for [Carbon] under categories [Business, Carbon capture and storage, Decarbonization, and Energy Transition]. Data last updated [November 4, 2024]. Retrieved [November 8, 2024] from <https://jpt.spe.org/searchjpt>
- 12) Sperling, D., Yeh, S. 2009. Low Carbon Fuel Standards. *Issues in Science and Technology*25 (2): 57–66.
- 13) Gemini Team, Georgiev, P., Lei, V. I., et al. 2024. Gemini 1.5: Unlocking Multimodal Understanding across Millions of Tokens of Context. *arXiv preprint arXiv:2403.05530*.
- 14) Thomson Reuters. 2024. Search Results for [Low carbon fuel standard]. Data last updated [November 1, 2024]. Retrieved [November 1, 2024] from <https://www.reuters.com/site-search/>
- 15) U.S. Energy Information Administration. 2024. Gasoline and Diesel Fuel Update. Data last updated [December 12, 2024]. Retrieved [November 15, 2024] from <https://www.eia.gov/petroleum/gasdiesel/>
- 16) World Bank Group. 2024. State and Trends of Carbon Pricing Dashboard. Data last updated [December 2024]. Retrieved [December 15, 2024] from <https://carbonpricingdashboard.worldbank.org/compliance/price>

Greenhouse Gases Emission



Rolling Prediction



Models

(a) Kalman Filtering

1. Prediction: State Equation (Estimates the next state based on the previous state)

$$x_t = F \cdot x_{t-1} + G \cdot u_t + w_t$$

2. Update: Observation Equation (Incorporates observed data to correct the predicted state)

$$z_t = H \cdot x_t + v_t$$

Autoregressive (AR) Model (hyperparameter p)

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \dots + \phi_p y_{t-p} + \epsilon_t$$

Fitting to determine ϕ_i

Moving Average (MA) Model (hyperparameter q)

$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

Fitting to determine θ_i

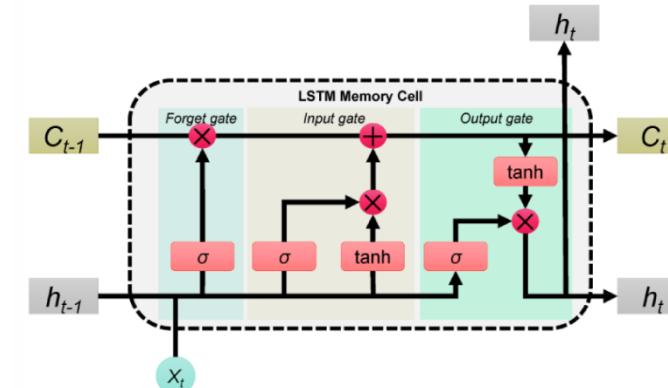
Integrated (I) Part

-- Perform differencing, **d** means the differencing steps to make the series stationary

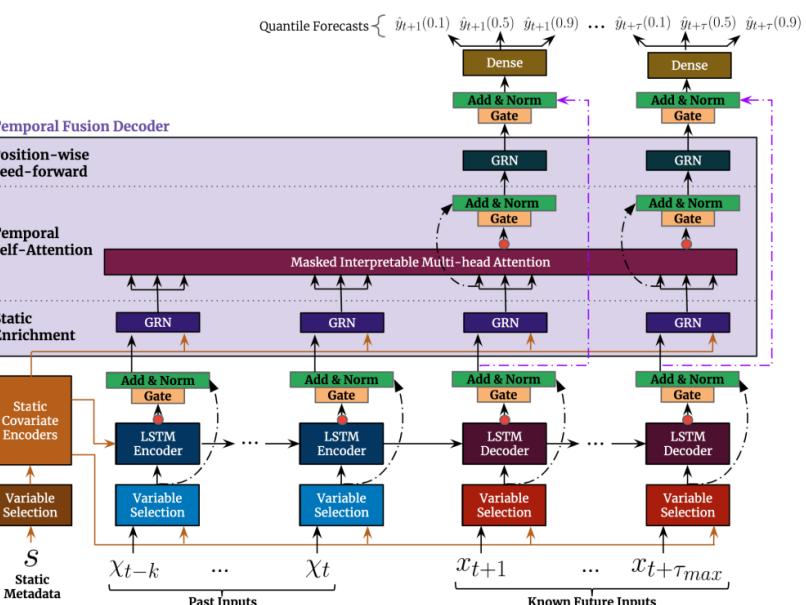
ARIMA Model (Combining AR, I, and MA)

$$y'_t = c + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \dots + \phi_p y'_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

where **AR** part models the dependency on previous values and **MA** part models the dependency on past forecast errors.



<https://mlarchive.com/deep-learning/understanding-long-short-term-memory-networks/>



<https://doi.org/10.48550/arXiv.1912.09363>

Prompts

```
prompt = [{"role": "system",  
"content": (  
    f"You are an expert in carbon marketing analysis and LCFS carbon  
    price forecasting.\n"  
    f"Your task is to predict the LCFS price for the next time  
        step based on the following inputs:\n"  
    f"1. Historical prices, volumes, and values of LCFS credits.\n"  
    f"2. Relevant news articles impacting the LCFS market dynamics.\n"  
    f"Consider these factors:\n"  
    f"1. Analyze historical trends in prices, volumes, and values.\n"  
    f"2. Incorporate the impact of news articles on LCFS market  
        conditions (e.g., policy changes, supply/demand shifts).\n"  
    f"3. Predict the next price while considering both historical  
        data patterns and news impact.\n"  
    f"4. Make reasoning of your prediction.\n"  
    f"Output the prediction in the format:\n"  
    f"(Price: <price>, Reason: <reason>)"  
)  
,  
{"role": "user",  
"content": (  
    f"Here is the data to evaluate:\n"  
    f"Historical prices, volumes, values, and related news\n"  
    f"Hisrotical dates list: {list(date_range)},\n"  
    f"Corresponding prices list: {list(history_prices)},\n"  
    f"Corresponding volumes list: {list(history_volumes)},\n"  
    f"Corresponding values list: {list(history_values)}.\n\n"  
    f"Here are relevant News:\n"  
    f"{news_to_current_date}.\n"  
    f"Please predict the LCFS price for the next time step and  
        make reasoning in the format: \n"  
    f"(Price: <price>, Reason: <reason>)."  
)  
}]
```