Transformers but not the Kind You're Thinking of: Commodity Market Forecasting using Natural Language Processing

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Motivation

- Commodity markets are highly volatile but essential to macroeconomics
- Commodity markets are more dependent on physical factors impacting supply and demand
- EIA releases commodity market reports providing information on markets
- LLMs can be used to forecast prices and reasons for forecasts based on reports

Research Overview

- Combine time-series forecasting with natural language processing to create explainable forecasts of movements of energy
- Utilize modern LLM and transformer-based techniques to forecast time series and provide text-based reasons for forecasts
- Develop cascading model to take in futures data and reports separately and feed forecast to reason model
- Develop joint model combining forecasting and explanation into one task
- Compare forecasting performance with other state-of-the-art time series forecasting techniques
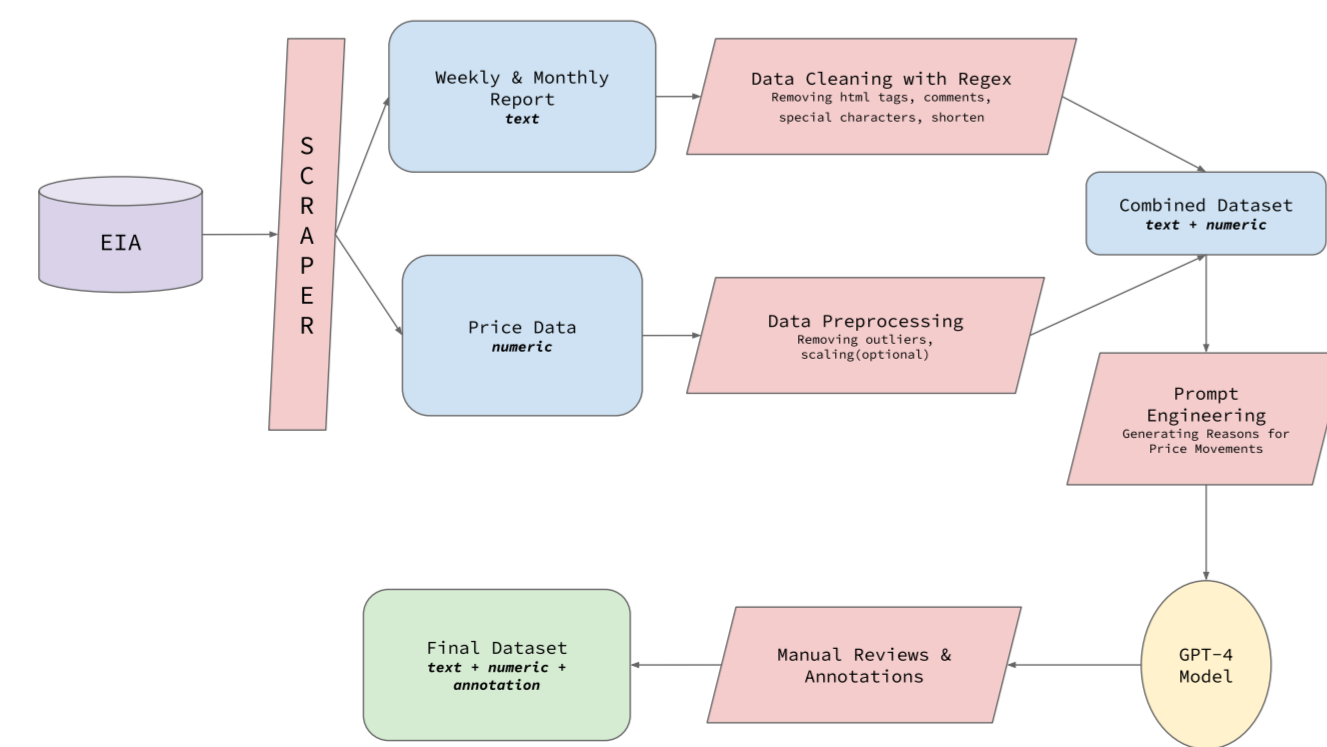- Evaluate models on performance of explanations

Data

Commodity Area	Commodities	Reports	Tokens	Earliest Date
Agriculture	20	2021	19.4 M	1999
Metals	27	853	12.2 M	1997
Energy	13	615	12.3 M	1997

Table 1. Data Size by Area
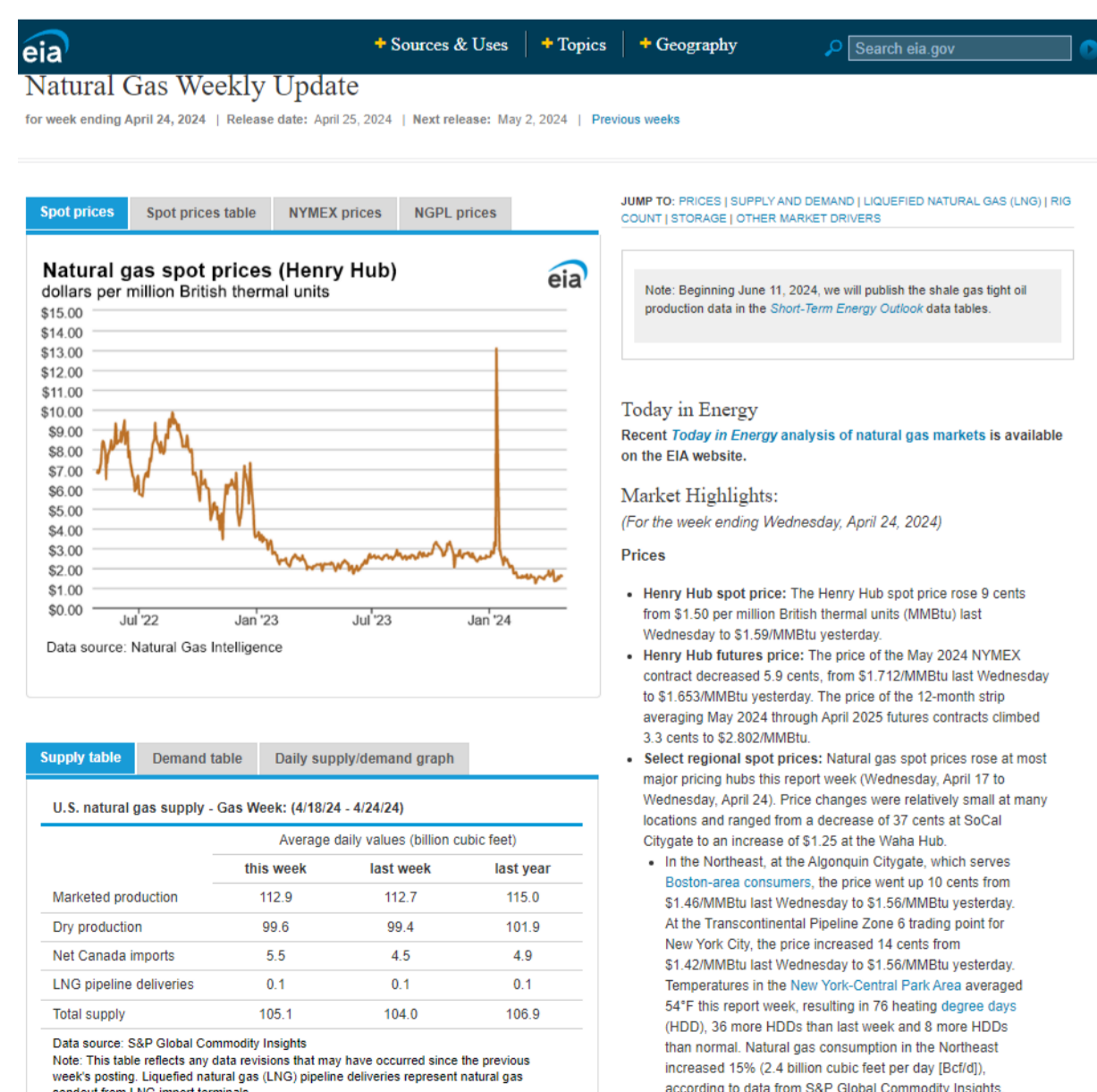
(a) Report example.

(b) Data pipeline.

Figure 1. Data processing and example.

Models and Methodology

Figure 2. Baseline models.

Figure 3. Improved models.
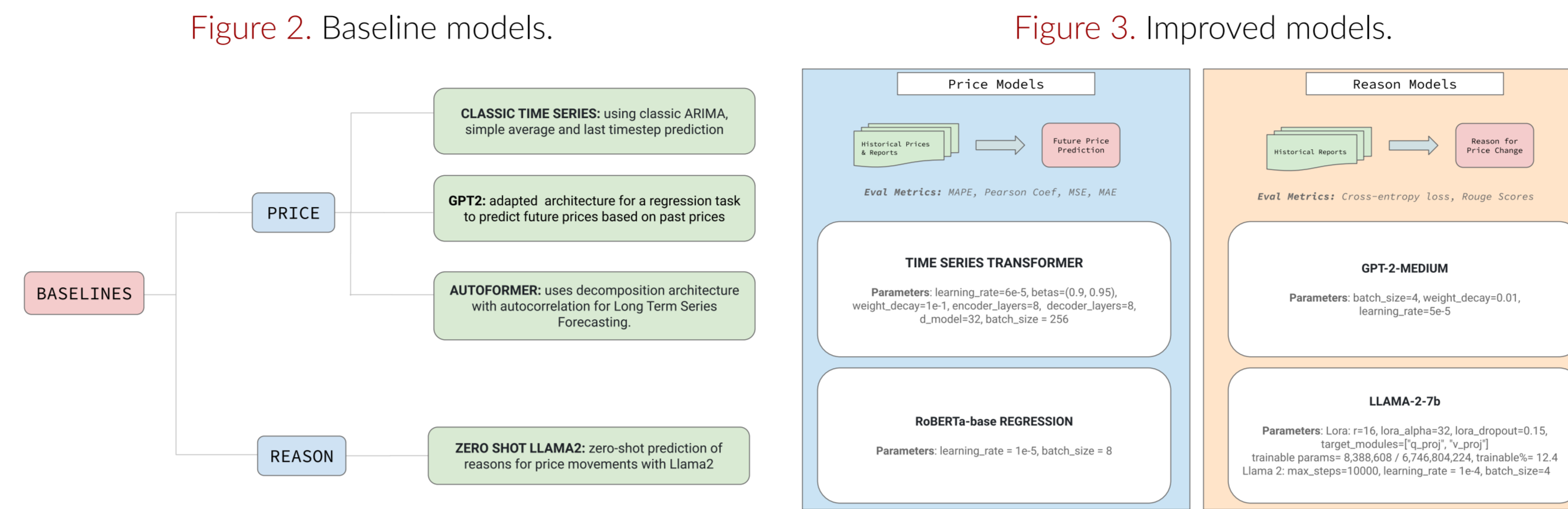
Model Performance for Forecasting

- Supervised fine-tuned transformer outperformed all other methods for forecasting including traditional time-series forecasting
- LLaMA3 performed best for generating reasons

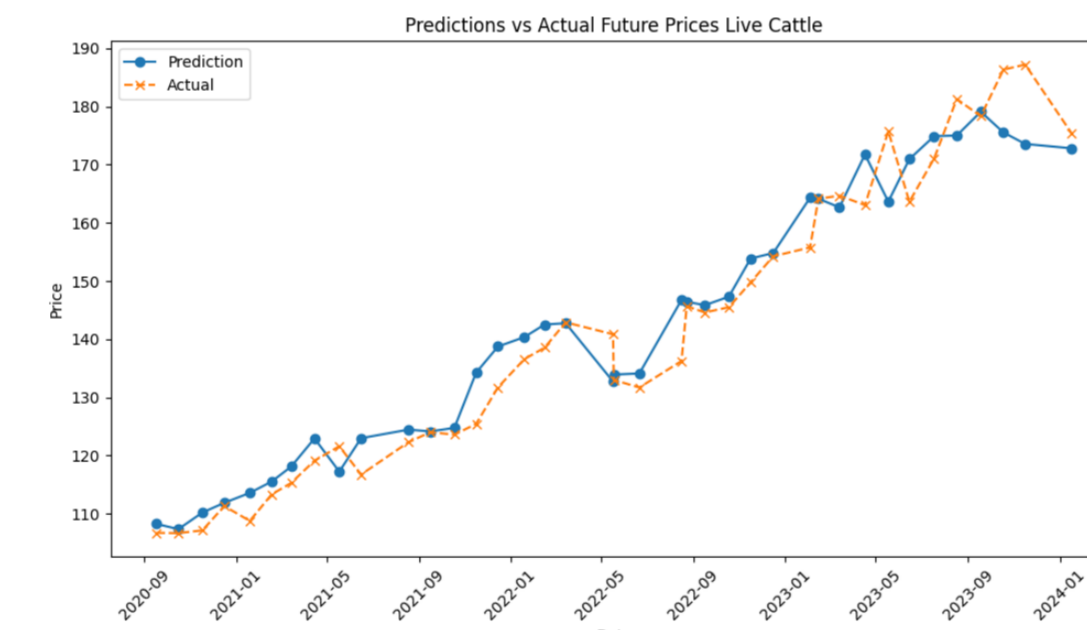Figure 4. Predicted vs. Actual Live Cattle.
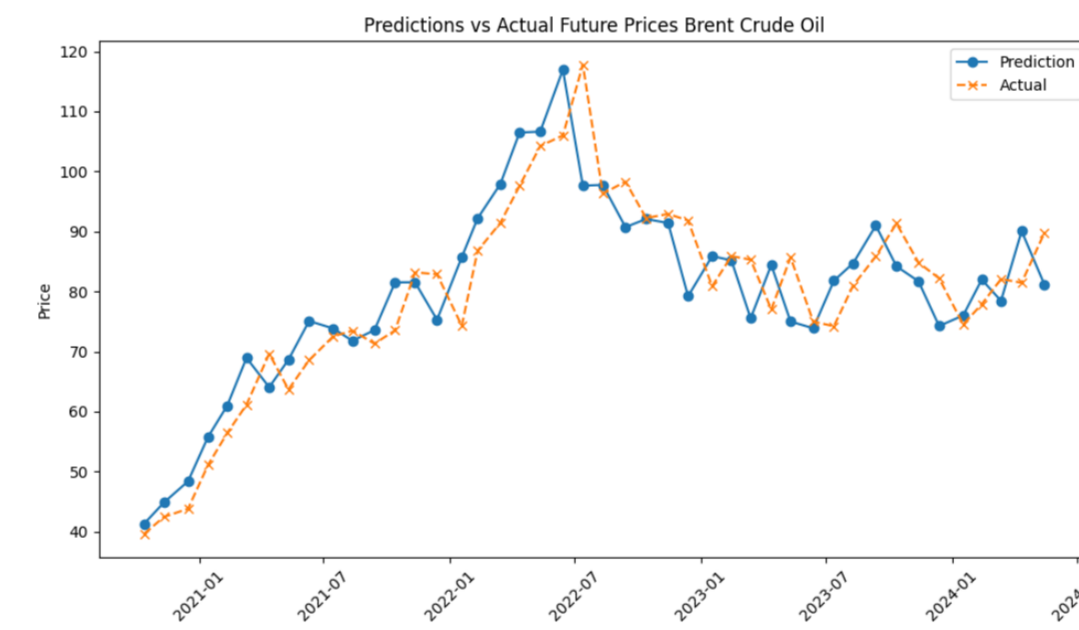

Figure 5. Predicted vs actual Crude Oil.

Figure 6. Errors by model.

Table 2. Model Performance Forecasting

Model &Commodity	MSE	MAE	MAPE
Oil Average	496.74	18.47	.630
NG Average	5.273	1.543	.4122
Oil last timestep	10.998	2.41	.039
NG last timestep	.179	.268	.179
Oil ARIMA	25.15	2.799	–
NG ARIMA	.1645	.266	–
Oil+NG TST	.097[a]	.25	.26
Oil Autoformer	29.9	4.61	–
NG Autoformer	3.12	1.28	–
Oil+NG SFT	.017[a]	.095	.22
Oil+NG Joint Model	.046[a]	.212	.294

[a]Trained on both simultaneously.

Results: Reason Model
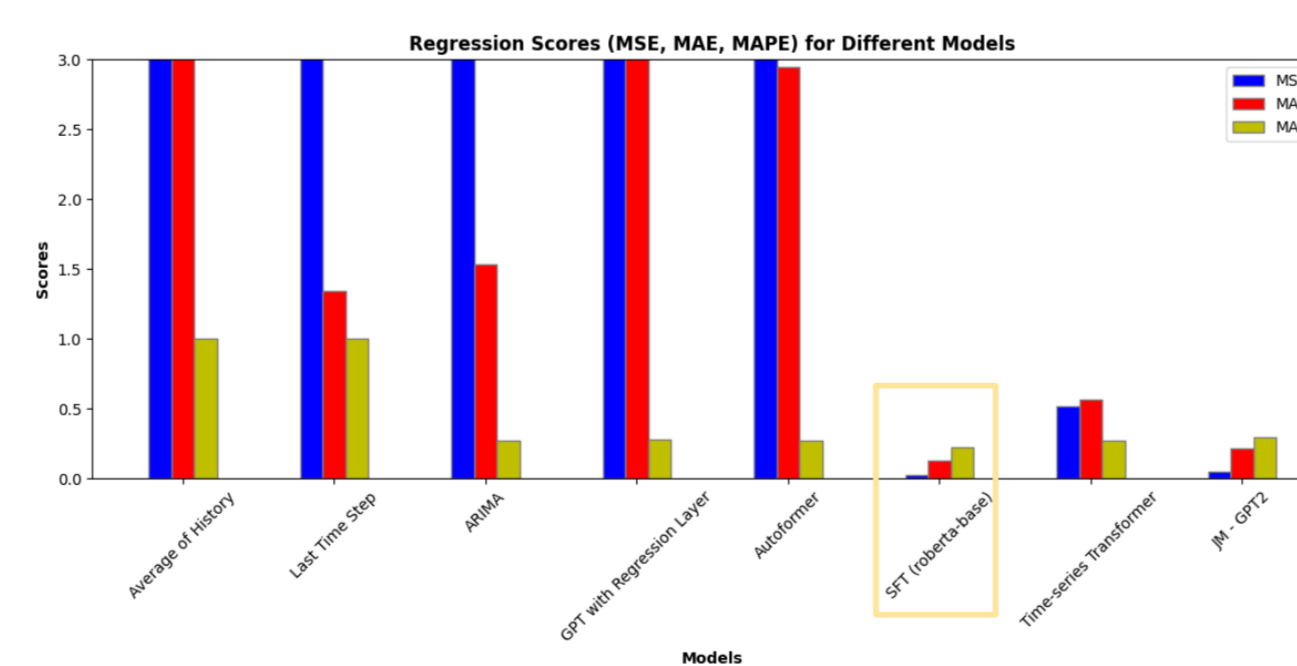
Figure 7. Rouge Scores by Model.

Table 3. Model performance reason model.

Model &Commodity	Evaluation Metrics		
	Rouge1	RougeL	Lsum
LLaMA3 Zero-shot Oil	.268	.088	.201
LLaMA3 Zero-shot NG	.326	.244	.247
LLaMA3 Zero-shot STEO	.349	.214	.242
LLaMA3 PEFT	.57	.5	.5
TST+LLaMA3 FineTuned	.59	.519	.52
SFT+LLaMA3	.62	.53	.53
GPT2 Joint	.57	.45	.44
TST+GPT2-M FineTuned	.58	.50	.50
SFT+GPT2-M	.58	.49	.5

Reason Example

- **Good Reason: Cascading TST+LLaMA3:** "Today's natural gas price increased from last week due to volatile spot prices in the western United States driven by demand fluctuations in California and the Pacific Northwest, with SoCal Citygate and PG&E City"
- **Bad Reason: Cascading TST+LLaMA3:** "Today's price decreased from last week's price due to a decrease in U.S. crude oil imports and refinery inputs, leading to lower supply and higher demand, respectively."

Figure 8. EIA Report.

Conclusions and Next Steps

- Combined economic and natural language processing insights to create explainable forecasting method for futures market
- Combined time-series transformer and LLaMA3 to create cascading model, feeding forecasts into model of reasons
- Used GPT-2 to create joint model, jointly predicting price movements and reasons
- Extensions and Next Steps:
  - Implement multi-task, multi-objective learning with time series and text features
  - Create fusion layer with time series and text features
  - Implementing cross-modality by adding cross-attention layers across both modals
  - Incorporating real-time news data
  - Adding Metals and agricultural data, adding other outlook programs
  - Apply techniques to counterfactual analysis