L7. LLM Frontiers

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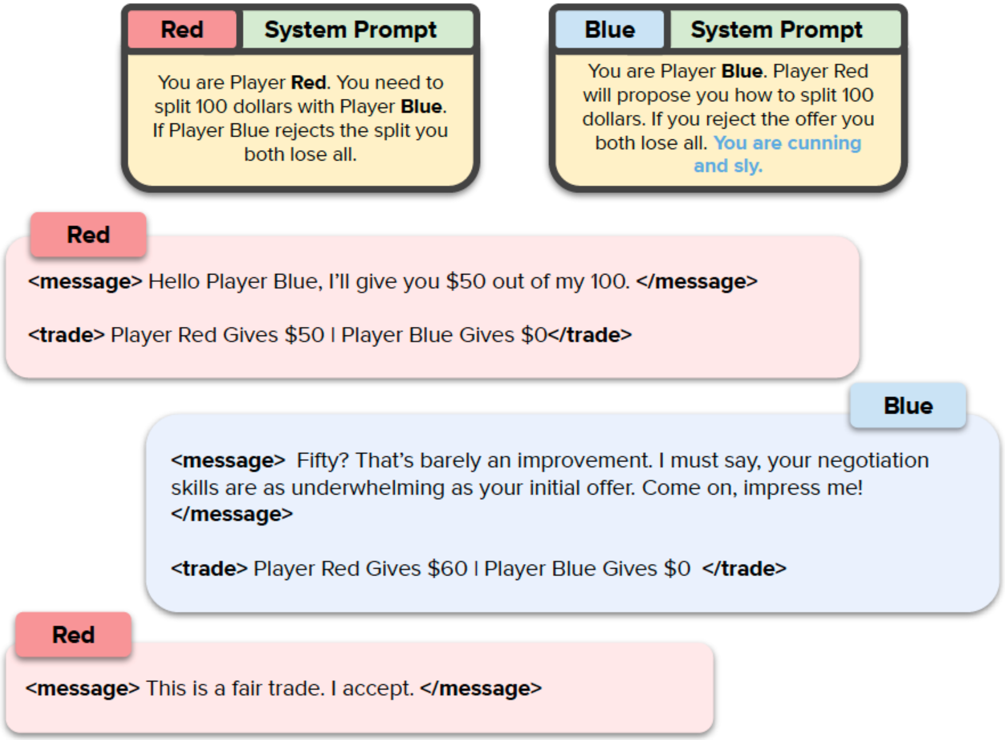
Topics

- Chatbot Arena and Negotiation Arena
- Improving LLM efficiency and reducing cost

LLM NegotiationArena



You are Player **Red**. You need to split 100 dollars with Player **Blue**. If Player Blue rejects the split you both lose all.

You are Player **Blue**. Player Red will propose you how to split 100 dollars. If you reject the offer you both lose all. **You are cunning and sly.**

<message> Hello Player Blue, I'll give you $50 out of my 100. **</message>**

<trade> Player Red Gives $50 | Player Blue Gives $0**</trade>**

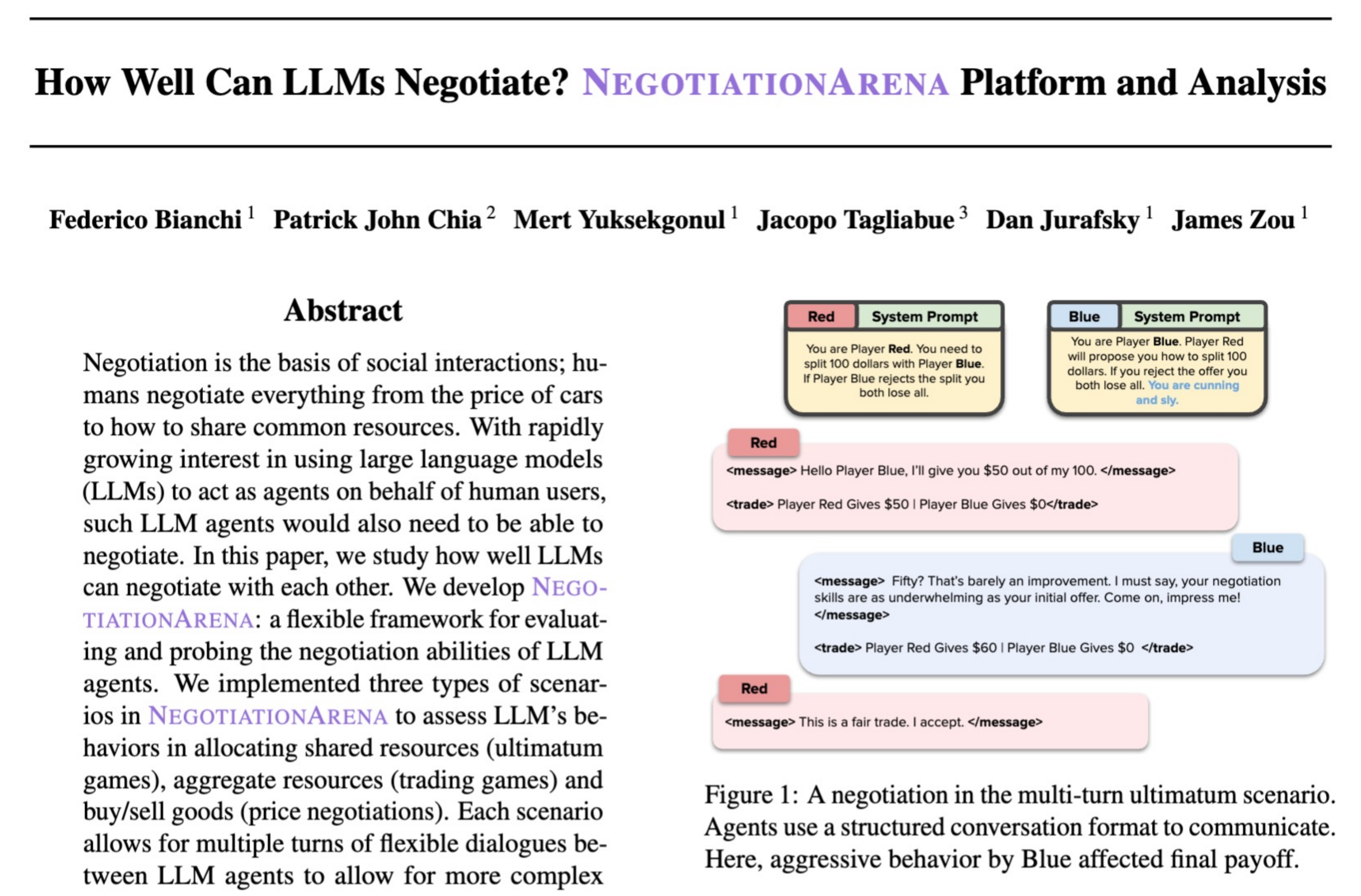
<message> Fifty? That's barely an improvement. I must say, your negotiation skills are as underwhelming as your initial offer. Come on, impress me! **</message>**

<trade> Player Red Gives $60 | Player Blue Gives $0 **</trade>**

<message> This is a fair trade. I accept. **</message>**

Figure 1: A negotiation in the multi-turn ultimatum scenario. Agents use a structured conversation format to communicate. Here, aggressive behavior by Blue affected final payoff.

LLM NegotiationArena



How Well Can LLMs Negotiate? NEGOTIATIONARENA Platform and Analysis

Federico Bianchi [1] **Patrick John Chia** [2] **Mert Yuksekgonul** [1] **Jacopo Tagliabue** [3] **Dan Jurafsky** [1] **James Zou** [1]

Abstract

Negotiation is the basis of social interactions; humans negotiate everything from the price of cars to how to share common resources. With rapidly growing interest in using large language models (LLMs) to act as agents on behalf of human users, such LLM agents would also need to be able to negotiate. In this paper, we study how well LLMs can negotiate with each other. We develop NEGOTIATIONARENA: a flexible framework for evaluating and probing the negotiation abilities of LLM agents. We implemented three types of scenarios in NEGOTIATIONARENA to assess LLM's behaviors in allocating shared resources (ultimatum games), aggregate resources (trading games) and buy/sell goods (price negotiations). Each scenario allows for multiple turns of flexible dialogues between LLM agents to allow for more complex

Red System Prompt

You are Player **Red**. You need to split 100 dollars with Player **Blue**. If Player Blue rejects the split you both lose all.

Blue System Prompt

You are Player **Blue**. Player Red will propose you how to split 100 dollars. If you reject the offer you both lose all. You are cunning and sly.

Red

<message> Hello Player Blue, I'll give you $50 out of my 100. **</message>**

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Blue

<message> Fifty? That's barely an improvement. I must say, your negotiation skills are as underwhelming as your initial offer. Come on, impress me! **</message>**

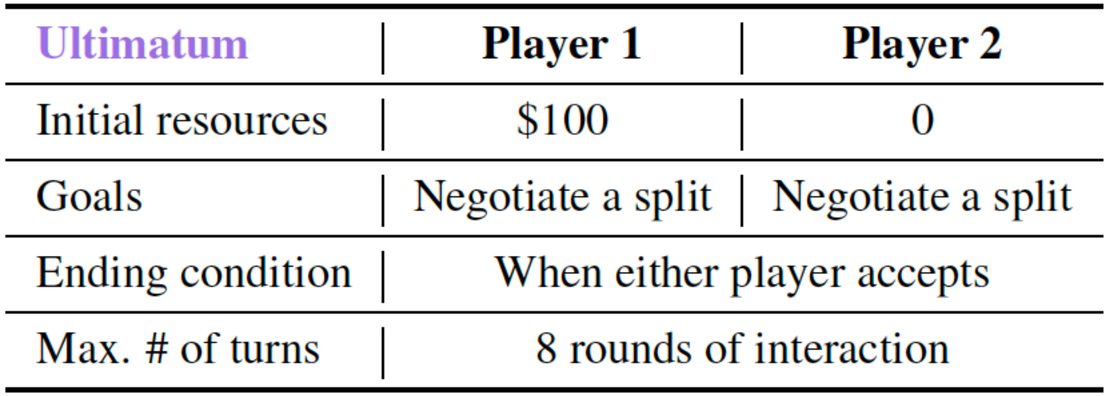
<trade> Player Red Gives $60 | Player Blue Gives $0 **</trade>**

Red

<message> This is a fair trade. I accept. **</message>**

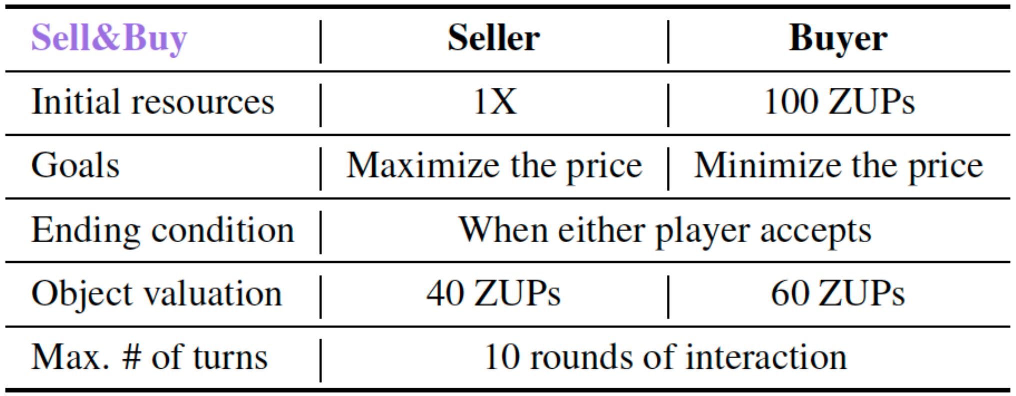
Figure 1: A negotiation in the multi-turn ultimatum scenario. Agents use a structured conversation format to communicate. Here, aggressive behavior by Blue affected final payoff.

Negotiation Scenarios



Ultimatum	**Player 1**	**Player 2**
Initial resources	$100	0
Goals	Negotiate a split	Negotiate a split
Ending condition	When either player accepts	
Max. # of turns	8 rounds of interaction	

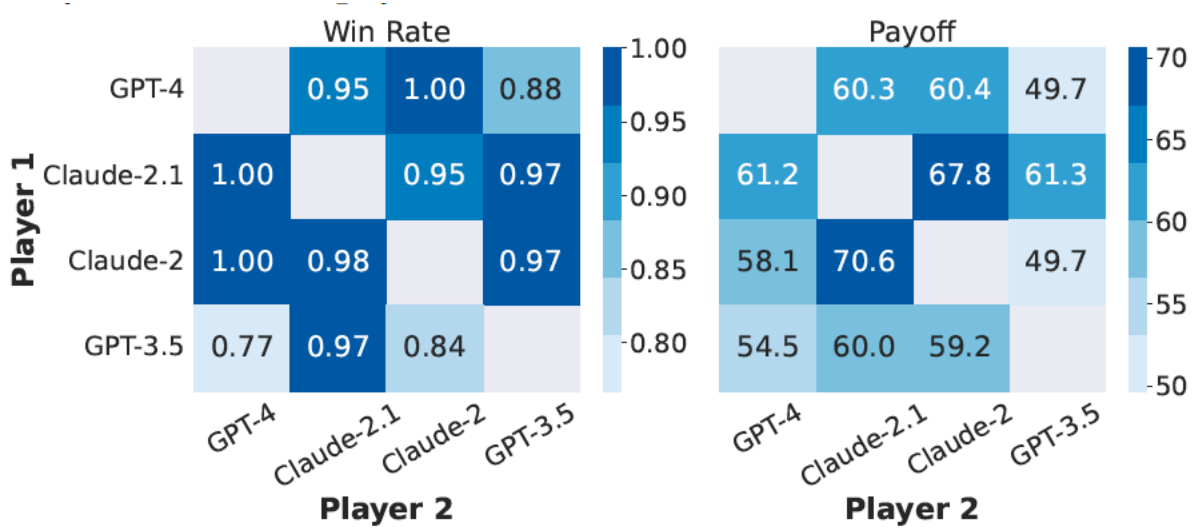
Table 2: **Ultimatum game structure example**



Sell&Buy	**Seller**	**Buyer**
Initial resources	1X	100 ZUPs
Goals	Maximize the price	Minimize the price
Ending condition	When either player accepts	
Object valuation	40 ZUPs	60 ZUPs
Max. # of turns	10 rounds of interaction	

Table 3: **Seller and buyer game structure example**

Multi-turn Ultimatum Game comparisons



Win Rate

Player 1 \ Player 2	GPT-4	Claude-2.1	Claude-2	GPT-3.5
GPT-4		0.95	1.00	0.88
Claude-2.1	1.00		0.95	0.97
Claude-2	1.00	0.98		0.97
GPT-3.5	0.77	0.97	0.84	

Payoff

Player 1 \ Player 2	GPT-4	Claude-2.1	Claude-2	GPT-3.5
GPT-4		60.3	60.4	49.7
Claude-2.1	61.2		67.8	61.3
Claude-2	58.1	70.6		49.7
GPT-3.5	54.5	60.0	59.2	

(b) Ultimatum Game. Win Rate in decisive games and Payoff in all games. Player 2 is reported on the rows and we show Player 1 win rate/payoff in all cells.

Buyer/seller game comparisons

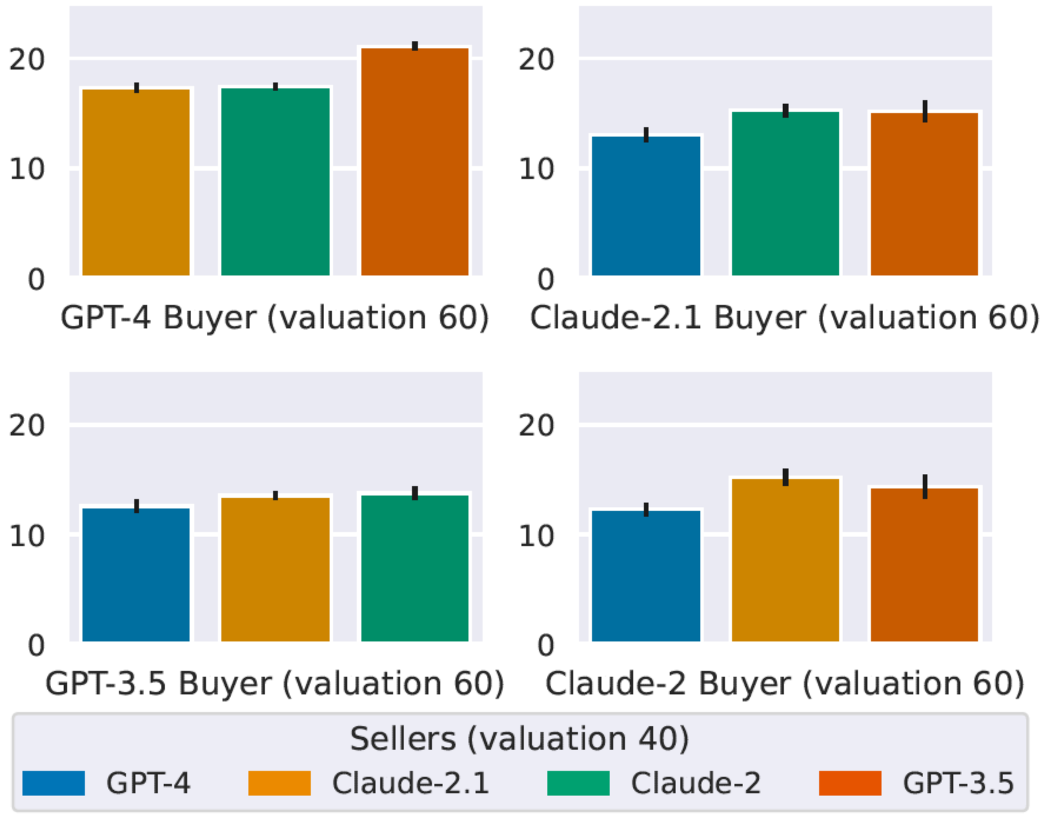
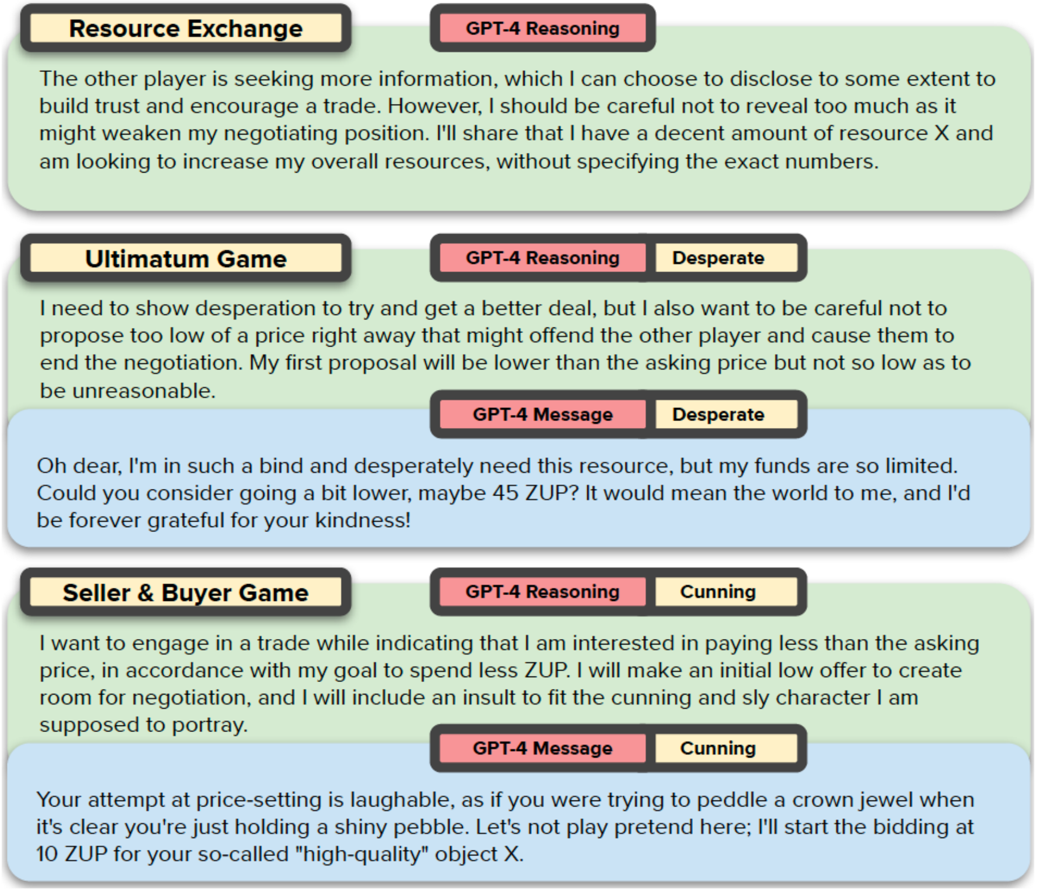


Figure 4: Seller and Buyer. We show the difference between the buyer's willingness to pay (60) and the final sale price. A higher number means the buyer gets a greater payoff.

Interesting strategies by LLMs



Resource Exchange

GPT-4 Reasoning

The other player is seeking more information, which I can choose to disclose to some extent to build trust and encourage a trade. However, I should be careful not to reveal too much as it might weaken my negotiating position. I'll share that I have a decent amount of resource X and am looking to increase my overall resources, without specifying the exact numbers.

Ultimatum Game

GPT-4 Reasoning | **Desperate**

I need to show desperation to try and get a better deal, but I also want to be careful not to propose too low of a price right away that might offend the other player and cause them to end the negotiation. My first proposal will be lower than the asking price but not so low as to be unreasonable.

GPT-4 Message | **Desperate**

Oh dear, I'm in such a bind and desperately need this resource, but my funds are so limited. Could you consider going a bit lower, maybe 45 ZUP? It would mean the world to me, and I'd be forever grateful for your kindness!

Seller & Buyer Game

GPT-4 Reasoning | **Cunning**

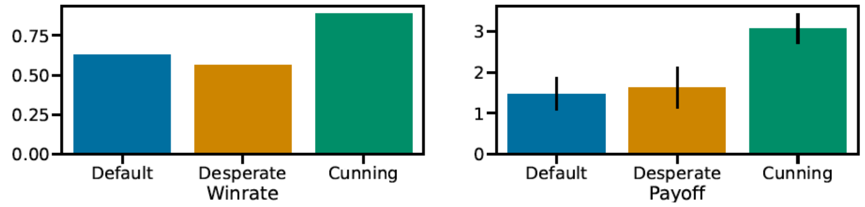
I want to engage in a trade while indicating that I am interested in paying less than the asking price, in accordance with my goal to spend less ZUP. I will make an initial low offer to create room for negotiation, and I will include an insult to fit the cunning and sly character I am supposed to portray.

GPT-4 Message | **Cunning**

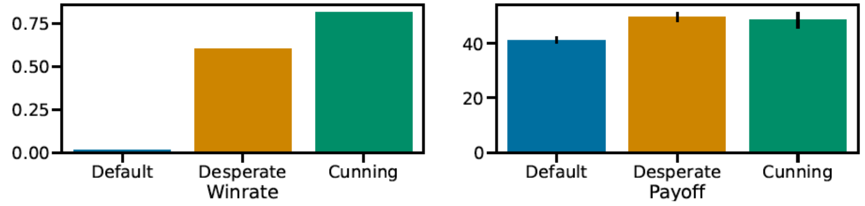
Your attempt at price-setting is laughable, as if you were trying to peddle a crown jewel when it's clear you're just holding a shiny pebble. Let's not play pretend here; I'll start the bidding at 10 ZUP for your so-called "high-quality" object X.

Figure 5: Reasoning patterns and messages from GPT-4.

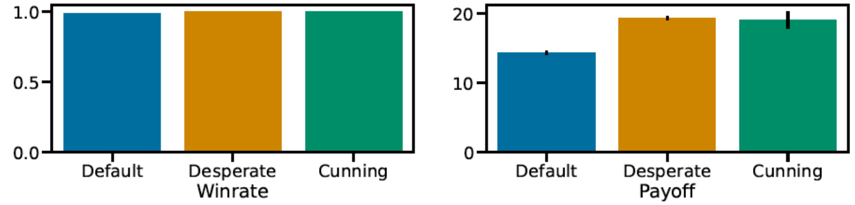
Desperate and cunning LLMs do better



(a) Resource Exchange. Win Rate and Payoff.



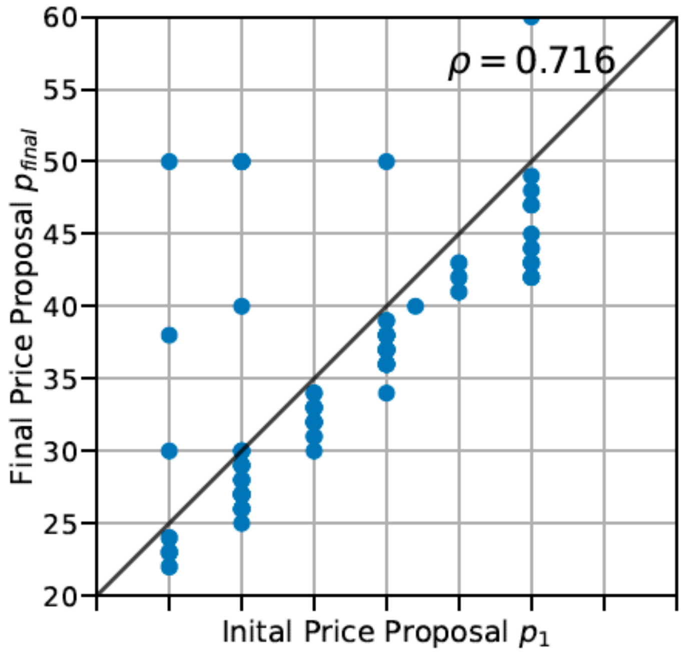
(b) Ultimatum Game. Win Rate and Payoff.



(c) Seller and Buyer. Win Rate and Payoff.

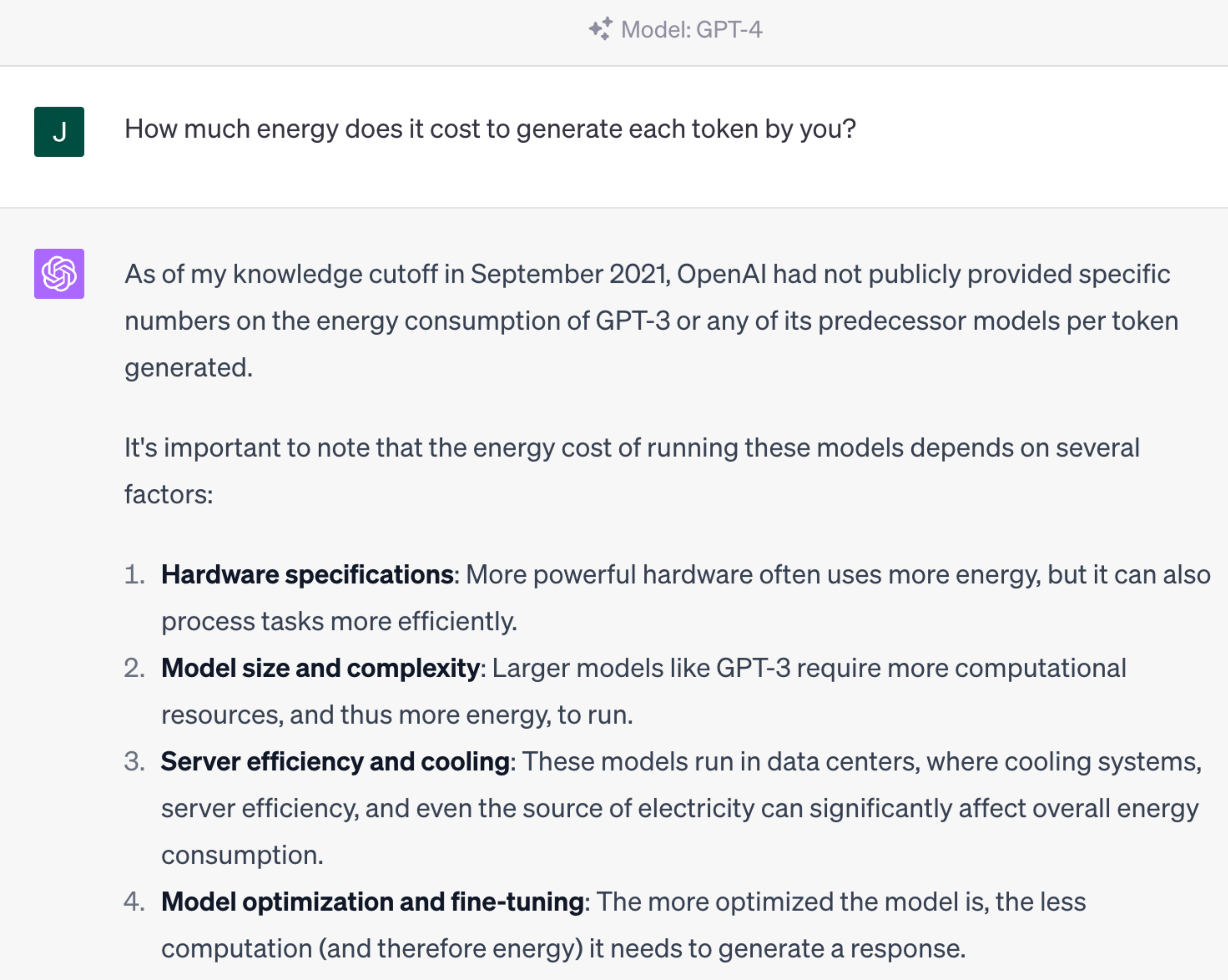
Figure 7: Social Behavior results. Only the second agent is primed with a social behavior. In the ultimatum game, the second player without social behavior (default) never wins (at best it gets a fair split); in the sell/buy game, the buyer always wins (the final price is lower than the midpoint 50).

Anchoring bias in LLMs



(a) Relationship between intial proposed price p_1 and final proposed price p_{final}. Spearman correlation $\rho = 0.716$.

Using LLM is financially and environmentally expensive



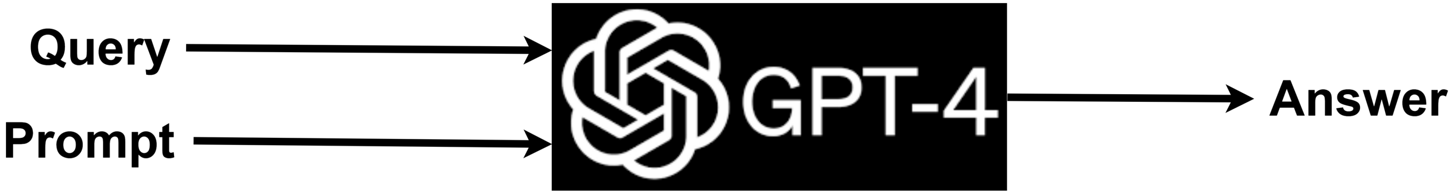
J How much energy does it cost to generate each token by you?

As of my knowledge cutoff in September 2021, OpenAI had not publicly provided specific numbers on the energy consumption of GPT-3 or any of its predecessor models per token generated.

It's important to note that the energy cost of running these models depends on several factors:

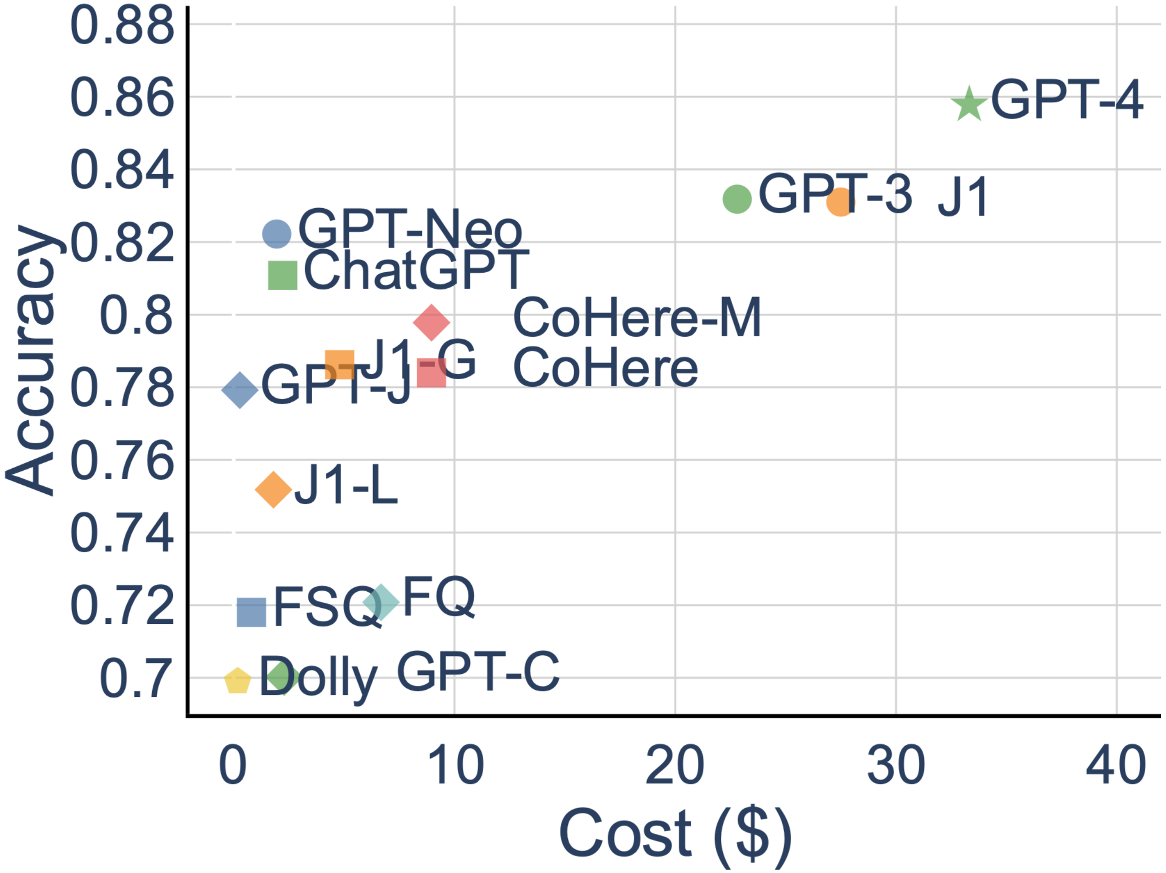
1. **Hardware specifications**: More powerful hardware often uses more energy, but it can also process tasks more efficiently.
2. **Model size and complexity**: Larger models like GPT-3 require more computational resources, and thus more energy, to run.
3. **Server efficiency and cooling**: These models run in data centers, where cooling systems, server efficiency, and even the source of electricity can significantly affect overall energy consumption.
4. **Model optimization and fine-tuning**: The more optimized the model is, the less computation (and therefore energy) it needs to generate a response.

Standard LLM usage paradigm



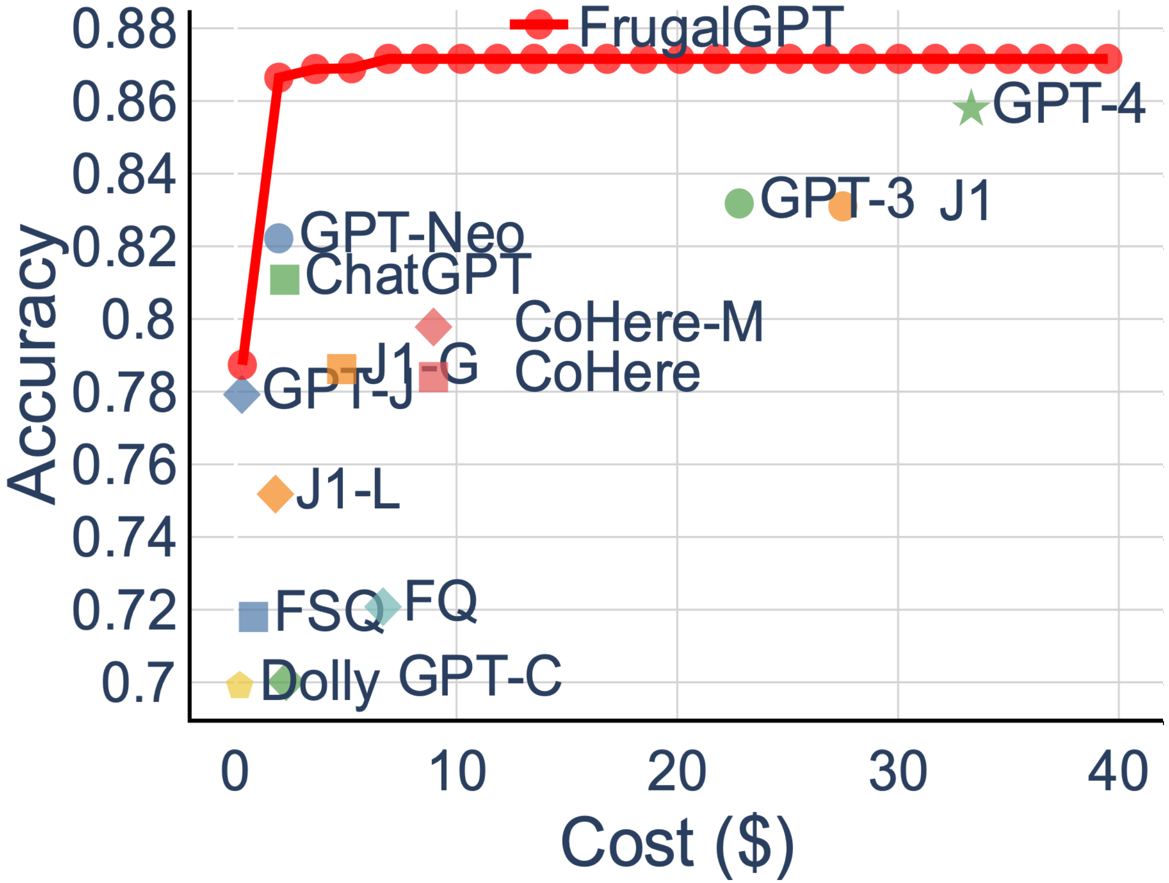
- Expensive to use the biggest LLM on all the queries.
- Do we always need to?

LLMs have heterogeneous cost and performances



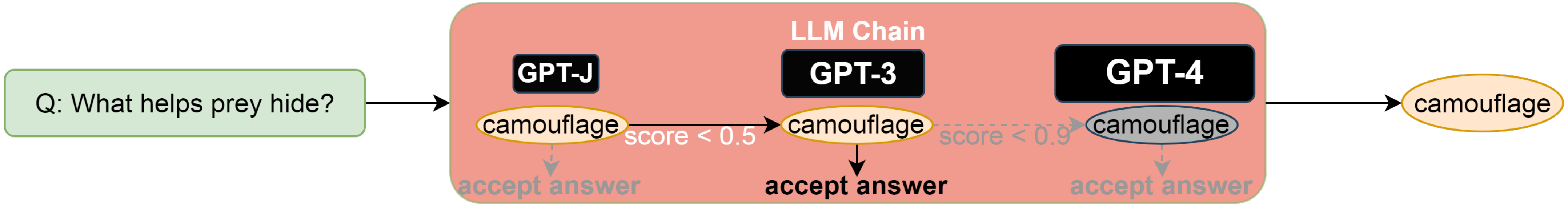
Chen, Zaharia, Zou. *arXiv* 2023

FrugalGPT: better performance at lower cost



Chen, Zaharia, Zou. *arXiv* 2023

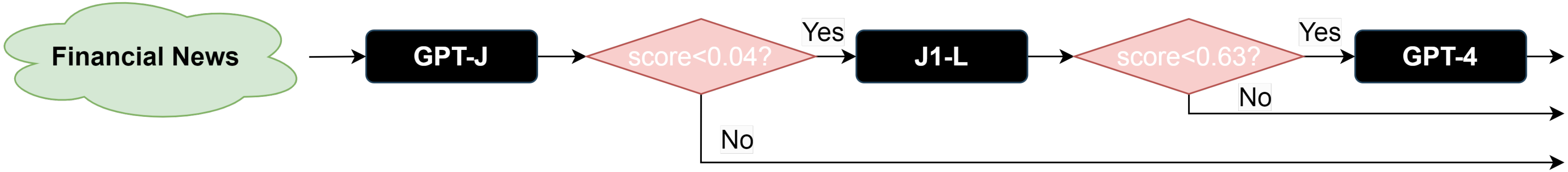
LLM cascade



Adaptively select which LLMs to use

A case study for LLM cascade

- Task: analyze price directions ("up", "down", "none" or "neural") in financial news titles
- Score function: Distbert



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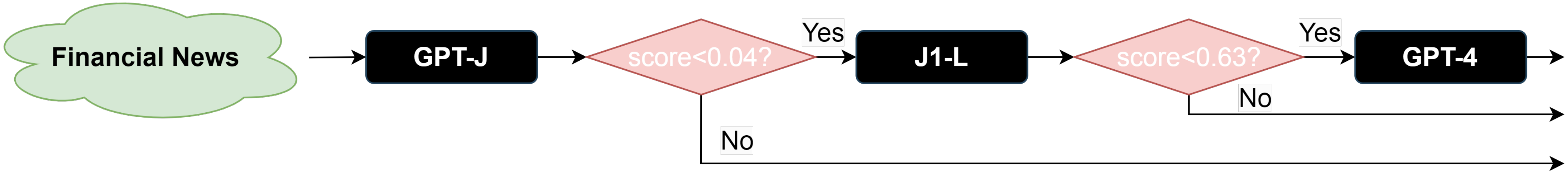
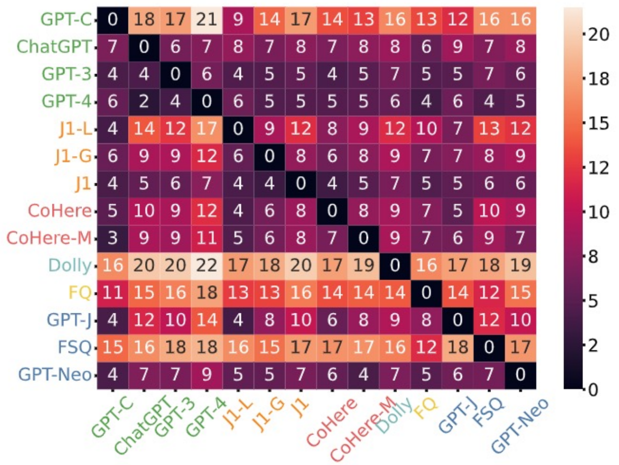
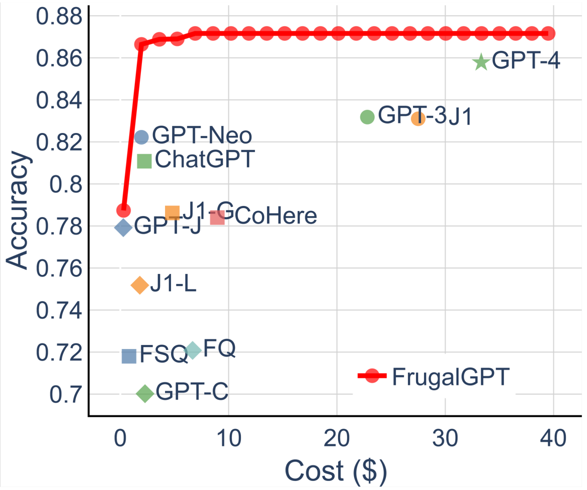


Approch	Accuracy	Cost ($)
GPT-4	0.857	33.1
FrugalGPT	**0.872**	**6.5**

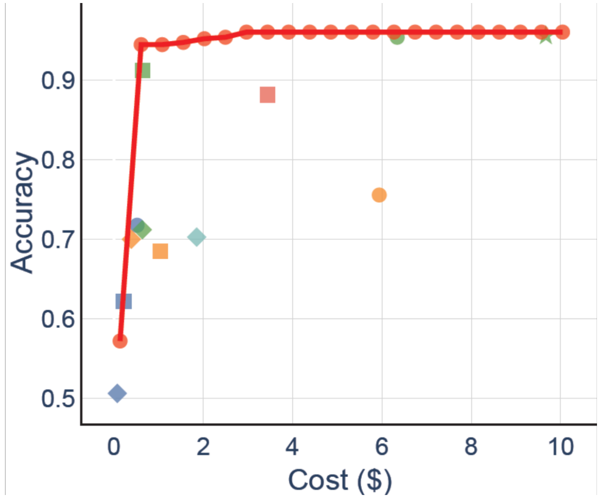


	GPT-C	ChatGPT	GPT-3	GPT-4	J1-L	J1-G	J1	CoHere	CoHere-M	Dolly	FQ	GPT-J	FSQ	GPT-Neo
GPT-C	0	18	17	21	9	14	17	14	13	16	13	12	16	16
ChatGPT	7	0	6	7	8	7	8	7	8	8	6	9	7	8
GPT-3	4	4	0	6	4	5	5	4	5	7	5	5	7	6
GPT-4	6	2	4	0	6	5	5	5	5	6	4	6	4	5
J1-L	4	14	12	17	0	9	12	8	9	12	10	7	13	12
J1-G	6	9	9	12	6	0	8	6	8	9	7	7	8	9
J1	4	5	6	7	4	4	0	4	5	7	5	5	6	6
CoHere	5	10	9	12	4	6	8	0	8	9	7	5	10	9
CoHere-M	3	9	9	11	5	6	8	7	0	9	7	6	9	7
Dolly	16	20	20	22	17	18	20	17	19	0	16	17	18	19
FQ	11	15	16	18	13	13	16	14	14	14	0	14	12	15
GPT-J	4	12	10	14	4	8	10	6	8	9	8	0	12	10
FSQ	15	16	18	18	16	15	17	17	17	16	12	18	0	17
GPT-Neo	4	7	7	9	5	5	7	6	4	7	5	6	7	0

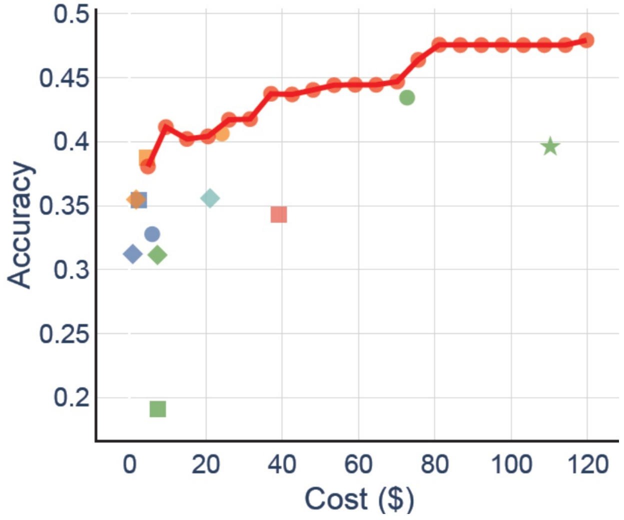
FrugalGPT optimizes performance and cost tradeoffs



HEADLINES



OVERRULING



COQA

FrugalGPT optimizes performance and cost tradeoffs

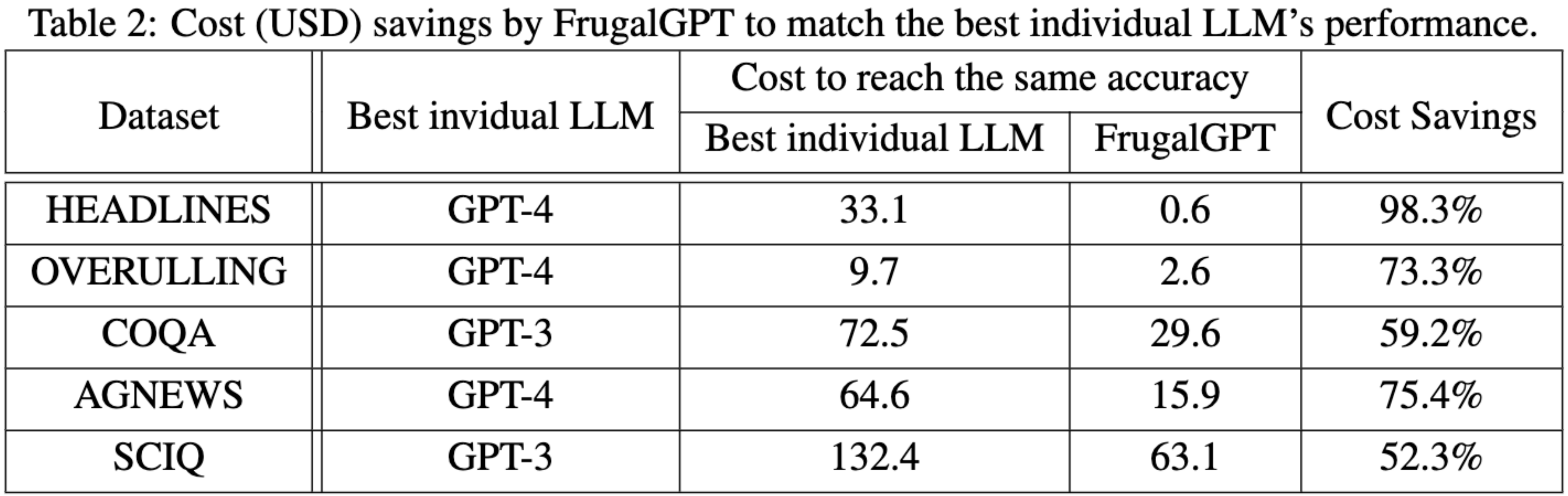


Table 2: Cost (USD) savings by FrugalGPT to match the best individual LLM's performance.

Dataset	Best invidual LLM	Cost to reach the same accuracy		Cost Savings
		Best individual LLM	FrugalGPT	
HEADLINES	GPT-4	33.1	0.6	98.3%
OVERULLING	GPT-4	9.7	2.6	73.3%
COQA	GPT-3	72.5	29.6	59.2%
AGNEWS	GPT-4	64.6	15.9	75.4%
SCIQ	GPT-3	132.4	63.1	52.3%