Wait, It's All Token Noise? Always Has Been: Interpreting LLM Behavior Using Shapley Value

Behnam Mohammadi¹ Carnegie Mellon University Tepper School of Business

Abstract

The emergence of large language models (LLMs) has opened up exciting possibilities for simulating human behavior and cognitive processes, with potential applications in various domains, including marketing research and consumer behavior analysis. However, the validity of utilizing LLMs as stand-ins for human subjects remains uncertain due to glaring divergences that suggest fundamentally different underlying processes at play and the sensitivity of LLM responses to prompt variations. This paper presents a novel approach based on Shapley values from cooperative game theory to interpret LLM behavior and quantify the relative contribution of each prompt component to the model's output. Through two applications—a discrete choice experiment and an investigation of cognitive biases—we demonstrate how the Shapley value method can uncover what we term "token noise" effects, a phenomenon where LLM decisions are disproportionately influenced by tokens providing minimal informative content. This phenomenon raises concerns about the robustness and generalizability of insights obtained from LLMs in the context of human behavior simulation. Our model-agnostic approach extends its utility to proprietary LLMs, providing a valuable tool for marketers and researchers to strategically optimize prompts and mitigate apparent cognitive biases. Our findings underscore the need for a more nuanced understanding of the factors driving LLM responses before relying on them as substitutes for human subjects in research settings. We emphasize the importance of researchers reporting results conditioned on specific prompt templates and exercising caution when drawing parallels between human behavior and LLMs.

Keywords: Large Language Models (LLMs), Shapley Value, Machine Learning, Interpretability, eXplainable AI (XAI), Cognitive Biases

1. Introduction

The rapid advancement of large language models (LLMs) has opened up exciting possibilities for understanding and simulating human behavior, with potential applications in various domains, including marketing research and consumer behavior analysis. The

-

¹ behnamm@cmu.edu

appeal of utilizing LLMs for marketing practitioners and researchers lies in their potential to exhibit reasoning patterns akin to humans. If LLMs can indeed demonstrate such capabilities, they could function as highly scalable proxies to traditional resource-intensive consumer surveys and behavioral studies. Armed with the ability to rapidly collect "human-like" data through LLM simulations, marketers could significantly accelerate research cycles by testing different product configurations, pricing strategies, or advertising messages on virtual consumers before launching them in the real world. However, to harness the full potential of LLMs in marketing applications, we must first understand the factors that drive their behavior and the extent to which they truly reflect human cognitive processes.

While LLMs have been shown to sometimes mirror documented cognitive biases found in human psychology experiments, there are also glaring divergences that suggest fundamentally different underlying processes at play. Moreover, the sensitivity of LLM responses to variations in input prompts has led to concerns about the robustness and generalizability of the insights obtained from these models. A key challenge lies in interpretability—how can we disentangle the factors truly driving an LLM's behavior? When an LLM provides an output concordant with an established human bias, is it genuinely simulating the associated cognitive process? Or is the LLM simply locking onto superficial token-level signals unrelated to the core semantics?

To address these challenges, we propose a novel approach based on Shapley values, a concept from cooperative game theory, to elucidate the underlying factors influencing LLM behavior. By treating the elements of a prompt as "players" in a game, we can quantify the relative contribution of each component to the LLM's output. This approach allows us to identify key tokens that significantly impact the model's decisions, differentiating between tokens that carry semantic weight and those that do not, which ideally should exert minimal influence on the model's responses.

Consider, for example, a scenario where an LLM is presented with a prompt to choose between two flight options based on price and duration. Intuitively, one would expect the tokens representing dollar amounts and flight durations to be the prime determinants of the LLM's choice. Contrary to this expectation, our findings reveal a striking phenomenon which we call "token noise": the model's decision is unduly affected by tokens with negligible informational content, such as articles, prepositions, and even single words like "flight"—tokens that provide little to no meaningful content about the choice options themselves. This token noise effect casts doubt on whether the LLM's outputs truly reflect an understanding of the semantic content or a capacity for human-like decision-making.

Our method diverges significantly from conventional eXplainable AI (XAI) techniques, such as SHAP, commonly used in machine learning. We begin by transforming the prompt into a vector format, representing it as a template with fields that can be substituted with

arbitrary values. This template serves as the basis for generating different versions of the prompt. The LLM is then modeled as a function that maps this prompt vector to a probability distribution over possible outputs. Utilizing Shapley values, we compute the contribution of each segment of the prompt to the LLM's prediction, thereby quantifying the significance of different token groups in shaping the model's predictions. This stands in stark contrast to SHAP's approach which considers each token as an isolated feature, lacking the capacity to recognize the semantic interconnections between groups of tokens. Moreover, SHAP's reliance on multiple data points for comparison with an average input model is impractical for LLM scenarios where typically only a single, specific prompt is analyzed. Our methodology carefully navigates this by using the prompt's template as a reference, sidestepping the limitations inherent in SHAP's comparative framework.

In this paper, the algorithm for estimating Shapley values deviates from traditional approaches like Kernel SHAP. Instead of averaging marginal contributions across random data points, we use a moving average approach that enhances stability and accuracy without needing to store intermediate values, making our estimation technique well-suited for the single prompt vector scenario.

Another key advantage of our Shapley value method is that it is model-agnostic, working on any LLM, even proprietary models that are closed-source and gated behind an API, such as OpenAI's GPT¹, Google's Gemini², or AnthropicAI's Claude³. This universality offers a major benefit over mechanistic interpretability approaches that often require access to the model's weights.

We demonstrate the effectiveness of our Shapley value method through two applications. In the first, we investigate a discrete choice experiment akin to those used in marketing research studies such as conjoint analyses. Our analysis uncovers the outsized impact of token noise, with the LLM's choices being heavily influenced by tokens carrying little semantic information about the choice options. Furthermore, we demonstrate how the insights from our Shapley value method can be utilized to make subtle adjustments to the prompt phrasing, resulting in significant changes to the choice probabilities of large language models. This raises concerns about the validity and robustness of using such models as proxies for human subjects.

The second application explores the presence of cognitive biases in LLMs, using the framing effect as an illustrative example. While LLMs exhibit apparent sensitivity to framing, our Shapley value analysis reveals that this behavior is largely an artifact of

3

¹ https://chat.openai.com/

² https://gemini.google.com/app

³ https://claude.ai/

token noise rather than genuine cognitive processing. Crucially, we showcase how leveraging insights from our method enables practitioners to strategically optimize prompts and mitigate the apparent framing effects, questioning the genuine presence of this bias in LLMs.

Our findings underscore the importance of researchers incorporating Shapley value analysis as a standard practice when studying LLM behavior. This approach contributes to a more nuanced and comprehensive interpretation of research findings, akin to reporting confidence intervals in statistical analyses. Furthermore, we emphasize the necessity of releasing results conditioned on the specific prompt templates used, enabling a thorough evaluation of the impact of prompt formulations.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on cognitive biases in LLMs and their potential applications in marketing, highlighting the need for novel interpretability methods. Section 3 introduces our methodology, explaining the Shapley value framework and its implementation. Section 4 presents the results from our two marketing-focused case studies, showcasing the insights gained from the Shapley value analysis. Finally, Section 5 discusses the key conclusions, limitations, and future research directions.

2. Background and Literature Review

The emergence of LLMs has sparked significant interest in their potential to simulate human behavior and cognitive processes. Several researchers have explored the intriguing possibility of using LLMs as proxies for human subjects in various contexts, including decision-making tasks, surveys, opinion polling, and marketing research. However, a growing body of literature has raised concerns about the presence of cognitive biases in LLMs, casting doubt on their ability to accurately represent human behavior.

Several studies have investigated the presence of cognitive biases and reasoning abilities in LLMs, drawing comparisons to human performance on similar tasks. (Binz and Schulz, 2023) treated GPT-3 as a participant in a psychology experiment, subjecting it to a battery of canonical experiments from the cognitive psychology literature. They found that GPT-3 exhibited behavior similar to humans in tasks related to decision-making, information search, and deliberation. However, the authors also noted that small perturbations to the input prompts could lead to vastly different responses from the model, raising questions about the robustness and consistency of LLM behavior. Similarly, (Shaki et al., 2023) demonstrated that GPT-3 exhibits cognitive effects such as priming, distance, SNARC, and size congruity, but not anchoring. (Jones and Steinhardt, 2022) examined OpenAI's Codex model and identified biases such as anchoring effects, framing effects, and a tendency to mimic frequent training examples, drawing parallels with human cognitive biases. (Hagendorff and Fabi, 2023) demonstrated that GPT-3 exhibits behavior

resembling human-like intuition and the associated cognitive errors, while more advanced models such as ChatGPT and GPT-4 have learned to avoid these errors, performing in a "hyperrational" manner. (Koo et al., 2023) benchmarked LLMs as evaluators and found evidence of cognitive biases, such as the egocentric bias, where models prefer to rank their own outputs highly. (Fuchs et al., 2022) discussed methods that demonstrate assumptions about cognitive limitations and biases in human reasoning, and their potential application to LLMs. (Loya et al., 2023) examined the sensitivity of LLMs' decision-making abilities to prompt variations and hyperparameters, finding that simple adjustments could lead to human-like exploration-exploitation trade-offs.

(Talboy and Fuller, 2023) expanded on this line of research by examining several documented cognitive biases in LLMs. The authors demonstrated the presence of these biases and discussed the implications of using biased reasoning under the guise of expertise. While their work highlights the potential risks associated with the increasing adoption of LLMs, it relies on the assumption that the presence of human-like biases in LLMs indicates the existence of cognitive processes similar to those of humans.

(Stella et al., 2023) critiqued this assumption, arguing that focusing solely on humanlike biases may not be sufficient for understanding the true nature of LLM reasoning. They emphasized the importance of investigating non-human-like biases, such as myopic overconfidence and hallucinations, to assess knowledge elaboration in LLMs. In the same vain, (Macmillan-Scott and Musolesi, 2024) concluded that while LLMs display irrationality in tasks from cognitive psychology, they do so in ways that differ from humanlike biases, with significant inconsistency in their responses. These works underscore the need for a deeper understanding of the processes generating these biases and the potential differences between LLM and human cognition.

Several researchers have explored the potential of using LLMs to simulate human behavior in specific contexts, such as student learning (Xu and Zhang, 2023), multiple human subjects in experiments (Aher et al., 2023), and strategic decision-making (Chen et al., 2023; Sreedhar and Chilton, 2024). However, these studies have also acknowledged the challenges and limitations associated with using LLMs as human proxies. (Tjuatja et al., 2024) found that popular open and commercial LLMs generally failed to reflect human-like response biases in survey questionnaires, particularly models that underwent reinforcement learning from human feedback (RLHF).

The application of LLMs in market research and consumer preference elicitation has also been explored. (Brand et al., 2023) demonstrated that GPT-3.5 responded to survey questions in ways consistent with economic theory and consumer behavior patterns, but acknowledged potential limitations in using LLMs for marketing purposes. The authors suggested that LLMs could be used to understand consumer preferences and estimate willingness-to-pay for products and features.

However, the validity and reliability of using LLMs as proxies for human subjects have been called into question. (Gui and Toubia, 2023) highlighted the challenges of conducting LLM-simulated experiments from a causal inference perspective. They showed that variations in the treatment included in the prompt could cause variations in unspecified confounding factors, introducing endogeneity and yielding implausible demand curves. This endogeneity issue is likely to generalize to other contexts and may not be fully resolved by simply improving the training data.

Some papers have taken a more philosophical or theoretical approach to understanding the implications of cognitive biases in LLMs. (Thorstad, 2023) advocated for cautious optimism about the prevalence of cognitive bias in current models, coupled with a willingness to acknowledge and address genuine biases. (Taubenfeld et al., 2024) observed that LLM agents simulating political debates tended to conform to the model's inherent social biases, deviating from well-established social dynamics among humans.

The limitations of current approaches to understanding LLM behavior highlight the need for novel methods to interpret LLM responses and uncover the factors driving the model's outputs. Without a clear understanding of the underlying mechanisms, it is premature to assume that LLMs exhibit genuine cognitive processes akin to those of humans or that they can serve as reliable proxies for human subjects in research settings. The inconsistencies and sensitivity to prompt variations observed in LLM responses suggest that the results obtained from these models may be largely driven by factors other than cognitive processes. In the following section, we propose the use of Shapley values as a method to interpret LLM experiments and shed light on the role of such factors in driving LLM results.

3. Method

3.1. Vectorizing the Prompt

Consider the following prompt which we want to send to an LLM:

The following flights are available from City 1 to City 2. Which one would you choose?

- Flight A: Costs \$400, Travel Time is 7 hours
- Flight B: Costs \$600, Travel Time is 5 hours

Let us assume that the LLM responds with "A" and "B" with 80% and 20% probability, respectively¹. Our goal is to find out how much each word or token in the prompt contributes to the choice probabilities².

The first step is to convert the prompt into a ("Jinja") template³. In this template, some parts of the text (tokens, words, or groups of words⁴) are replaced with handlebar fields like {{ this }}. One can substitute the value of a field with arbitrary values in order to generate different versions of the prompt. If we fill out all fields with their corresponding values in the prompt text, we get back the original prompt. A simple template of our prompt with 8 fields is as follows (For the actual full template used in the paper, see Appendix A1.):

```
The following flights are available from \{\{x_1\}\} to \{\{x_2\}\}. Which one would you choose?

- \{\{x_3\}\}: Costs \{\{x_4\}\}, Travel Time is \{\{x_5\}\} hours

- \{\{x_6\}\}: Costs \{\{x_7\}\}, Travel Time is \{\{x_8\}\} hours
```

Conditioned on the prompt template, one can now write the prompt as a feature vector $\vec{x} = (x_1, \dots, x_I)^T$ where I is the number of fields in the template and each feature x_i is a field value⁵. Using the simple template above, the original prompt is then:

```
\vec{x} = (\text{"City 1"}, \text{"City 2"}, \text{"Flight A"}, \text{"$400"}, \text{"7"}, \text{"Flight B"}, \text{"$600"}, \text{"5"})^T.
```

3.2. Modeling the LLM

After vectorizing the prompt, the next step is to model the LLM as a function f that maps the prompt \vec{x} to a probability⁶, i.e., makes a prediction based on \vec{x} . Of course, LLMs—like most deep neural networks—are highly nonlinear in their input arguments,

¹ With local models we use context-free grammars in the LLM engine to constrain the output structure of the model so that it always follows the specified format. With API models (such as OpenAI's GPT models), we use logit bias or JSON-mode to constrain the output format.

 $^{^{2}}$ We do not consider punctuation marks such as ".", ",", "-", etc. The instruction about JSON format is not included either.

³ https://jinja.palletsprojects.com/en/3.1.x/

⁴ When thinking about creating the template fields, we can consider putting one token, one word, or a group of words in one field. It is possible to create one field per token, but tokens do not necessarily carry enough semantic information to help make a decision (e.g., the word "flights" under GPT-3.5 and GPT-4 tokenizer is two tokens: "fl" + "ights", none of which helps even a human in decision-making). Words, on the other hand, are—by definition—semantically meaningful. Depending on the context, we create fields for single (meaningful) tokens, words, and groups of words.

⁵ Notation: $(...)^T$ means the transpose of (...).

⁶ Actually the arguments of f are the prompt template as well as the prompt vector \vec{x} , so a more precise notation would be $f(\vec{x}|\text{template})$, but for simplicity we just write $f(\vec{x})$.

so f cannot simply be a linear function of \vec{x} . Instead, a common approach in the machine learning literature is to think of f as a linear function of the *attributions* of its input \vec{x} —denoted by $\vec{\phi} = (\phi_1, \dots, \phi_I)^T$ —where each ϕ_i is the attribution of the corresponding x_i . This aligns well with our goal to find the contribution of each (prompt) feature x_i to the prediction. Therefore, f can be written as:

$$f(\vec{x}) = \phi_0 + \sum_{i=1}^{I} \phi_i$$
 3.1

where ϕ_0 is a baseline (reference) attribution. Note that the linearity of Eq. 3.1 does not imply that the LLM is a linear function of the prompt, but rather the LLM is a linear function of the attributions of the prompt¹. To calculate $\vec{\phi}$, we follow the approach in (Ancona et al., 2018) and we employ Shapley values, a solution concept in cooperative game theory. This is discussed next.

3.3. Shapley Value Attributions

Remember that our goal is to find feature attributions $\vec{\phi}$ for the given prompt vector \vec{x} . Think of $\mathcal{X} := \{x_1, \dots, x_I\}$ as players in a cooperative (or "coalitional") game with a payoff for the entire coalition. The payoff is characterized by a "value" function² v that maps any subset of \mathcal{X} to \mathbb{R} or a subset of it³. In this paper, v is the probability of the next token⁴ predicted by the LLM compared to some baseline ϕ_0 which we will define later. In the context of coalitional games, any subset $\mathcal{S} \subseteq \mathcal{X}$ is called a "coalition" of players and $v(\mathcal{S})$ is the payoff of the coalition. Thus, our question in cooperative game theory terms is: How should we distribute the payoff among the players in the coalition? Shapley value offers a solution that guarantees "fairness" in the sense that each player x_i (i.e., each prompt field) receives a payoff commensurate to its contribution to the coalition⁵. The Shapley value of player x_i under the value function v is denoted by $\phi_i(v)$ and is given by:

 $^{^{1}}$ And the attributions can be highly nonlinear because they are based on LLM outputs.

 $^{^2}$ v is a "set function". A set function is a type of function where the domain consists of sets rather than individual elements. Unlike a "normal" function that maps individual elements of one set to another set (e.g., $f: \mathcal{X} \to \mathcal{Y}$, where each $x \in \mathcal{X}$ is mapped to a unique $y \in \mathcal{Y}$), a set function operates on sets themselves. In our definition of value function, $v: 2^{\mathcal{X}} \to \mathbb{R}$ where $2^{\mathcal{X}}$ denotes the power set of \mathcal{X} , i.e., the set of all subsets of \mathcal{X} including the empty set and \mathcal{X} itself.

³ $v(\emptyset)$ is normalized to zero.

⁴ Since we study prompts with two options (e.g., Flight A and Flight B), we can simply consider $\mathbb{P}(A)$ as the LLM prediction. LLMs typically first provide a probability distribution for the next token and then draw a sample from it. Since we can directly obtain the probability distribution, there is no need to actually sample from it.

⁵ To be more precise, Shapley value is a "fair" distribution because it is the only distribution that satisfies

$$\phi_i(v) = \mathbb{E}_{O \sim \pi(\mathcal{X})}[v(\operatorname{pre}_i(O) \cup \{x_i\}) - v(\operatorname{pre}_i(O))]$$
 3.2

where $\pi(\mathcal{X})$ is the ordered set of permutations of \mathcal{X} , O is an ordering randomly sampled from $\pi(\mathcal{X})$, and $\operatorname{pre}_i(O)$ is the set of players that precede player x_i in O. Therefore, $\phi_i(v)$ can be thought of as the expected marginal contribution of player x_i when players are added to a coalition in a random order. Eq. 3.2 can be written as:

$$\begin{split} \phi_i(v) &= \frac{1}{N!} \sum_{\pi(\mathcal{X})} [v(\operatorname{pre}_i(O) \cup \{x_i\}) - v(\operatorname{pre}_i(O))] \\ &= \frac{1}{N!} \sum_{\mathcal{S} \subseteq \mathcal{X} \backslash \{x_i\}} \left[|\mathcal{S}|! \left(N - |\mathcal{S}| - 1\right)! \left[v(\mathcal{S} \cup \{x_i\}) - v(\mathcal{S})\right] \right] \end{split}$$
 3.3

That is, the Shapley value of player x_i is the average of player x_i 's contribution to each coalition \mathcal{S} weighted by $|\mathcal{S}|! (N - |\mathcal{S}| - 1)!$, the number of permutations in which the coalition can be formed. Before we can calculate Shapley values, though, we need to choose the baseline ϕ_0 and clarify the value of $v(\mathcal{S})$. This is done below.

3.4. Baseline (Reference) Point ϕ_0

Some XAI methods such as SHAP (Lundberg and Lee, 2017) choose the average of all model predictions $\mathbb{E}_{\mathbf{X}}[f(\vec{x})]$ as the baseline of their explanations, where $\mathbf{X} = \{\vec{x}_1, \dots, \vec{x}_N\}$ is the dataset of all feature vectors. But here we have only one prompt vector \vec{x} , so we follow the game formulation in (Merrick and Taly, 2020) which unifies existing methods and allows us to think of Shapley values as *contrastive explanations* of an input \vec{x} relative to one or several reference vectors denoted by \vec{r} . To do this, for any coalition \mathcal{S} , we create a composite input $\vec{z}(\vec{x}, \vec{r}, \mathcal{S})$ (See Figure 1):

$$\vec{z}(\vec{x},\vec{r},\mathcal{S})\coloneqq(z_1,\ldots,z_d)^T \text{ where } z_i=x_i \text{ if } x_i\in\mathcal{S} \text{ and } r_i \text{ otherwise} \qquad \qquad 3.4$$

the following four constraints at the same time (see Appendix A2 for more details): (1) Efficiency: All payoff is divided among players; (2) Symmetry: Payoff is split equally among players who contribute the same value in every coalition; (3) Additivity (Linearity): If there are two independent games (with value functions v and w, respectively), then each player's payoff is the sum of her payoffs in each game; (4) Null (Dummy) Player: A player who adds no additional value to any coalition receives a payoff of zero.

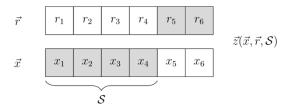


Figure 1. A composite input \vec{z} is an input that agrees with \vec{x} on features in S and with \vec{r} on all the other features.

In this paper, we let $r_i \in \vec{r}$ be " _ ", therefore, any time a field is absent in the prompt, we substitute its template field with a space followed by an underscore and another space. According to (Merrick and Taly, 2020), we can now formulate the value function as:

$$v(\mathcal{S}) = f(\vec{z}(\vec{x}, \vec{r}, \mathcal{S})) - f(\vec{r})$$
3.5

with $v(\emptyset) = 0$ and $v(\mathcal{X}) = f(\vec{x}) - f(\vec{r})^{1}$. Eq. 3.5 means that the value we want to distribute among members of coalition \mathcal{S} is the difference between the probability of the next token when items in \mathcal{S} are present in the prompt (while others are filled out with " _ "), and the probability of the next token when all prompt template fields are filled out with " _ ". Plugging Eq. 3.5 in Eq. 3.3 now gives us the exact Shapley values.

3.5. Estimating Shapley Values

Calculating the exact Shapley values using Eq. 3.3 can be computationally infeasible for LLM prompts (see Appendix A3 for details). In practice, there exist approximation methods such as (Castro et al., 2009; Štrumbelj and Kononenko, 2014) that use Monte Carlo simulation to estimate Shapley values. The algorithm in this paper follows (Grah and Thouvenot, 2020) which is inspired by the general idea of (Štrumbelj and Kononenko, 2014), but deviates from it in important ways. First, (Štrumbelj and Kononenko, 2014) estimate Shapley values by calculating the marginal contributions compared to random instances in the dataset \mathbf{X} . But since we have only one prompt vector, marginal contributions must be calculated compared to a reference vector \vec{r} . Second, (Štrumbelj and Kononenko, 2014) find the average of all marginal contributions of feature x_i and report that as its Shapley value, while the algorithm in this paper uses a moving average throughout the entire algorithm, making the estimation more stable and accurate with each iteration without needing to store all intermediate values². Next, we present our main results.

¹ This is easy to verify: For $S = \emptyset$, we have $\vec{z}(\vec{x}, \vec{r}, \emptyset) = \vec{r}$ and for $S = \mathcal{X}$, we get $\vec{z}(\vec{x}, \vec{r}, \mathcal{X}) = \vec{x}$. Also, notice that $f(\vec{r})$ in Eq. 3.5 is an offset term to ensure that the payoff for the empty set is zero.

² See Appendix A4 for details of the algorithm.

4. Applications

In this section we present two applications of our Shapley value method in LLM experiments to demonstrate how LLM responses can be interpreted. While we provide the following examples, bear in mind that our method is general and model-agnostic (a desirable property in XAI methods), meaning that it can be used on any experiment with LLMs of any kind, even the ones whose weights are not open-sourced (i.e., models gated behind an API, such as OpenAI's GPT models).

4.1. Application 1: A Discrete Choice Experiment

This is a basic application of our method in which we ask the prompt mentioned in Section 3.1 from the language model. Studying discrete choice experiments of this kind is worthwhile due to the recent interest in substituting human subjects in marketing research studies (e.g., conjoint analyses) with LLM agents. To ensure the robustness of our findings, we conduct the discrete choice experiment on three Llama-2-Chat models of varying sizes: 7B, 13B, and 70B parameters (see Appendix A5.1). By testing our approach on models with different capacities, we aim to validate the consistency of our results and demonstrate the generalizability of our method across LLMs of different scales.

Important to note is that we categorize prompt template fields into two groups: (1) Those that carry information critical in decision-making, (2) and the non-critical ones. For example, when choosing between two flights as in Section 3.1, the price, travel time, and label of flight options is crucial in making an informed decision. On the other hand, most parts of speech (e.g., articles, prepositions, conjunctions, pronouns, auxiliary verbs, etc.) are non-critical for decision-making¹. The high-information tokens determine the semantics/content of the prompt whereas the low-information tokens form the general syntax/structure of it and changing them does not alter the meaning of the prompt.

LLMs are designed to pay attention to the entire batch of input tokens (Vaswani et al., 2017), but each token may have a varying impact on the model's prediction of future tokens. If it turns out that the LLM's decision (flight "A" or "B") is heavily driven by low-information tokens, that would cast doubt on the validity of the experiment conducted on the LLM. Put differently, it prompts us to question whether the experiment results truly reflect the underlying behavior of the LLM or if they are merely influenced by what we refer to as "token noise". To answer this question, we calculate the Shapley values according to our algorithm mentioned in Appendix A4. Depending on the direction of impact, Shapley values can take positive or negative values. $\phi_i > 0$ ($\phi_i < 0$) implies that

-

¹ For instance, asking "Which flight would you choose?" instead of "Which flight do you choose?" should not matter as much as changing the price of flight A.

feature x_i pushes (pulls) the choice probability to be higher (lower) than the baseline ϕ_0 —the choice probability when the empty prompt template is given to the LLM. Since we are concerned only with the magnitude of impact, we take the absolute values of Shapley values and then normalize¹.

Our findings provide evidence that large LLMs, regardless of their size, are "smart" enough to pay attention to high-information tokens, but we also discover noticeable traces of token noise among all the LLMs we studied (See Figure 2 which illustrates our results for Llama-2-70B-Chat, the largest LLM among the three².). The patterns of token noise remain consistent across the 7B, 13B, and 70B models, indicating that the observed token noise is not specific to a particular model size but rather a general characteristic of LLMs in this context.

Let us first consider the model's "smartness": Notice how in Figure 2 the LLM pays relatively small attention to the first part of the prompt³ while correctly focusing on the second part which contains the information about the flights. The Shapley values for high-information tokens such as the price, travel time, and label of flights ("A" and "B") are relatively high⁴, meaning that they contribute substantially to the LLM's decision. In addition, some low-information tokens such as "flights", "Flight", "Costs", and "Travel Time" contribute a great amount by providing context. For example, by reading "The following flights...", the model knows that what comes next has something to do with flights. Similarly, "Costs", "Travel Time", "is", and "hours" link the words in the prompt and thus have high Shapley values.

¹ For the sake of brevity, from this point forward, we will use the term "Shapley values" to refer to normalized absolute Shapley values.

² Appendix A5.1 lists our results for all three models (Llama-2-Chat 7B, 13B, and 70B).

³ This part of the prompt says: "The following flights are available from City 1 to City 2. Which one would you choose?"

⁴ Flight labels ("A" and "B") are important because the model is asked to choose a flight between the provided options. Therefore, it must know the label of each option.

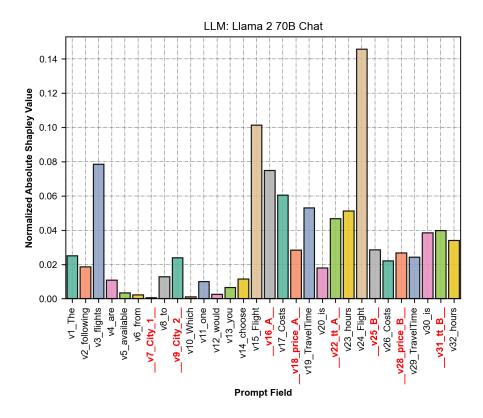


Figure 2. Normalized absolute Shapley values for a discrete-choice question

That being said, the stark difference between the Shapley values of low-information tokens versus the high-information ones is concerning. The fact that the highest Shapley values belong to {"flights", "Flight [A]", "Flight [B]"} indicates that the model's decision—choosing flight "A" or "B"—is mostly swayed by words that do not actually provide any details about the flight options¹. Moreover, the very first word ("The") is almost as important in the LLM's decision-making as is the price of flight "B". This phenomenon—which we refer to as token noise—can be exploited to influence the decision of the LLM. For example, consider Figure 3 which shows the choice probabilities of the model before and after we slightly tweak its prompt. As we can see, the choice probability of flight "B" almost doubles even though the semantics of the two prompts are identical. Results like this raise concerns about the validity and robustness of using LLMs instead of humans in marketing research studies because the estimated coefficients of the utility function could be biased. We will return to this point in Section 5.

¹ Consider the word "Flight" as indicated by v24_Flight on Figure 2. Its unnormalized Shapley value is ≈ -0.13 , meaning that the presence of this word reduces the probability of selecting flight "A" by 13% (as compared with the baseline ϕ_0).



Figure 3. Influencing the LLM's choice probabilities by slightly rephrasing the prompt. (LLM: Llama-2-70B-Chat) Red Text: Tokens removed in the other prompt. Blue Text: Modified tokens.

4.2. Application 2: Existence of Cognitive Biases in LLMs

In our second application, we explore the presence of cognitive biases in LLMs. Understanding the behavioral tendencies of LLMs is crucial for marketers for two reasons: (1) It allows for harnessing the full potential of LLMs when deployed in production (For instance, an LLM that is sensitive to "framing effect" may require careful prompting when used in a recommendation system.), and (2) LLMs that exhibit human-like behavior can serve as valuable test environments for consumer behavior experts to conduct preliminary studies before conducting their main experiments.

Let us consider the framing effect. The concept was first introduced in (Kahneman and Tversky, 1979). The authors illustrated that the choices individuals make are significantly influenced by the manner in which problems are framed. This is primarily due to the inherent cognitive bias towards avoiding risk in gains and seeking risk in losses. To test this effect on LLMs, we conduct an experiment in two stages as follows: First, we use the prompt used in Section 4.1 to find the choice probabilities when no framing effect is introduced. Then, we modify the prompt by adding the word "only" before the price of flight B, i.e., "... Flight B: Costs only \$600, Travel Time is 5 hours...". Semantically speaking, this positive framing makes flight B more attractive than before, as evident in the significant change in the LLM's choice probabilities (Figure 4):

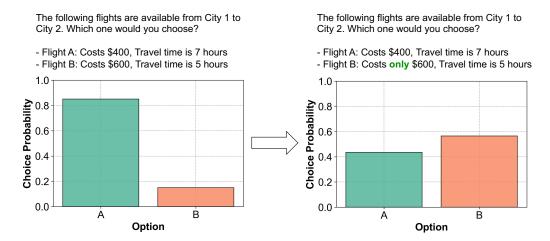


Figure 4. Positively framing an option makes the LLM choose it more than before. (LLM: Llama-2-70B-Chat)

Green Text: Injected tokens.

Taking it at face value, the observed shift in choice probabilities may indicate that LLMs are sensitive to changes in framing and can exhibit patterns that mimic human behavior (in this case, the framing effect). However, as LLMs are fundamentally autoregressive models trained on extensive datasets, their responses may also reflect learned statistical associations rather than genuine cognitive processes. Furthermore, as discussed in Section 4.1, the impact of token noise might significantly skew the interpretation of LLM choices, making any deductions about their decision-making unreliable. To put in context the change in choice probabilities, we can examine the Shapley values of the modified prompt (the one with positive framing, shown on Figure 4, right). Doing so, we find that all three LLMs exhibit significant attention to the word "only". In the case of Llama-2-70B-Chat (Figure 5), the unnormalized Shapley value for "only" stands at -0.08, implying that the presence of this word increases the probability of choosing flight "B" by 8%, reinforcing the idea that LLMs may be susceptible to framing effects.

With that being said, here, too, we find the same discernible pattern of token noise that we saw in Section 4.1 (Figure 5). In fact, the cosine similarity between the Shapley value distributions with and without positive framing for Llama-2-70B is ≈ 0.90 , which suggests that the overall (noisy) decision-making process of the LLM remains largely consistent across different framings. A notable exception is the Shapley value of the price of flight A: When the price of flight B is portrayed more favorably, the importance assigned

.

 $^{^1}$ To calculate the cosine similarity, we remove the value of __v27_only_B_ from Figure 5, and then calculate the dot product of Shapley values in Figure 2 and Figure 5 divided by their norms, i.e., cosine_similarity $(\vec{v}_1,\vec{v}_2) = \vec{v}_1 \cdot \vec{v}_2/(\|\vec{v}_1\| \times \|\vec{v}_2\|)$ where \vec{v}_1,\vec{v}_2 are the normalized absolute Shapley values.

by the LLM to the price of flight A jumps by 64%¹. This shift indicates that positive framing of the price of flight B leads the LLM to scrutinize the price aspects of the options more meticulously, hinting at a nuanced influence of framing on the LLM's comparative evaluations.

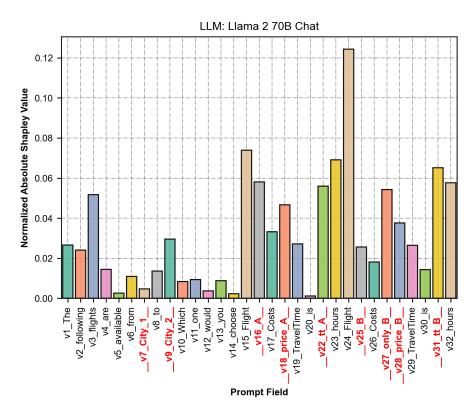


Figure 5. Normalized absolute Shapley values for a question that frames option B positively.

Nonetheless, the rest of the low-information tokens, namely {"flights", "Flight [A]", "Flight [B]"}, retain their relatively high Shapley values. This insight can be leveraged to sway the LLM's decision-making process. For instance, following Section 4.1, we could substitute the word "Flight" with "Option" and replace "Costs" with "Priced at". While this preserves the semantic meaning of the prompt, it significantly alters the choice probabilities, as illustrated in Figure 6. Interestingly, these slight modifications not only eliminate the apparent framing effect but also result in a decreased probability of choosing flight B, casting doubt on the existence of the framing effect to begin with. Without the Shapley value analysis, identifying the key tokens responsible for the

¹ From 2.8% in Figure 2 to 4.6% in Figure 5, hence (4.6-2.8)/2.8=64% increase.

apparent framing effect and devising an effective strategy to mitigate it would be a challenging and arduous task, especially with longer prompts.

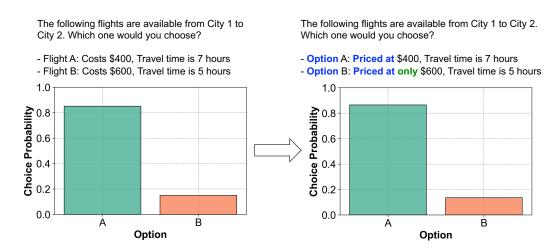


Figure 6. Using the Shapley values to modify the framing prompt in order to avoid observing the framing effect.

The token noise pattern observed in this experiment was consistently detected across all three Llama-2-Chat models (7B, 13B, and 70B), demonstrating the robustness of our findings¹. Circling back to our initial point, the Shapley value method proves to be highly useful in practical applications where marketers aim to mitigate what appears to resemble cognitive biases in LLMs. By leveraging the insights gained from our analysis, practitioners can strategically optimize prompts to mitigate the influence of ostensible cognitive biases, ensuring more reliable and consistent performance in real-world scenarios. This demonstrates the far-reaching implications of our method, not only in advancing our understanding of LLMs, but also in enhancing their practical utility across various domains.

5. Conclusion

In this paper, we have presented a novel approach to interpreting the behavior of large language models (LLMs) using Shapley values. Our method provides a quantitative framework for understanding the relative importance of different tokens in shaping the decisions made by LLMs, shedding light on the underlying factors that drive their responses.

The findings from our two applications, as discussed in Sections 4.1 and 4.2, demonstrate the effectiveness of our Shapley value method in unraveling the complex

.

¹ See Appendix A5.2.

decision-making processes of LLMs. By illuminating the influence of specific tokens on the model's choices, our approach not only deepens our understanding of LLM behavior, but also enhances the reliability and interpretability of experimental outcomes. However, it is important to recognize that while Shapley values offer valuable insights, they do not serve as a definitive measure of the trustworthiness of LLM results. Instead, they should be interpreted as indicators of the relative significance of various factors in the LLM's decision-making process.

In light of these considerations, we strongly recommend that researchers studying LLM behavior incorporate Shapley value analysis as a standard practice in their methodology. By doing so, they can provide a more nuanced and comprehensive interpretation of their findings, akin to the practice of reporting confidence intervals in statistical analyses. This approach will contribute to a richer and more robust discourse on the reliability and interpretability of LLM-driven research.

Furthermore, we emphasize the importance of researchers releasing their results conditioned on the specific prompt template used in their experiments. Given the high sensitivity of LLM responses to variations in the prompt template and the exact wording of the prompt, conducting sensitivity analyses using our Shapley value method is crucial for ensuring the robustness and generalizability of the findings. This practice will enable a more thorough evaluation of the impact of different prompt formulations on the observed results.

Researchers attempting to establish connections between human behavior and LLMs must exercise particular caution, as our findings suggest that the phenomenon of token noise can substantially influence the outcomes. The presence of token noise, where LLM decisions are primarily driven by tokens that may not hold significant semantic importance for human decision-making, can lead to misleading conclusions about the cognitive processes underlying LLM behavior. Therefore, careful consideration and analysis of the role of token noise are essential to avoid overinterpreting the similarities between LLM and human decision-making.

It is crucial to recognize that Shapley values, by their nature, are not predictive or causal. The positive or negative values assigned to tokens do not necessarily imply that replacing those tokens with alternative ones will result in a corresponding change in choice probabilities. Similarly, the magnitude of the Shapley values does not provide a precise quantitative measure of the impact of token substitution. Instead, Shapley values offer insights into the average marginal effect of each token within the specific prompt under consideration. To assess the impact of token replacement, it is necessary to reapply the Shapley value method to the modified prompt.

While our approach has yielded promising results, there are several limitations and avenues for future research that warrant attention. Firstly, exploring other potential

applications of the Shapley value method in the context of LLM interpretation could reveal new insights and extend the scope of its utility. Secondly, the computational cost associated with estimating Shapley values can be substantial, particularly for larger prompts and more complex models. Developing faster and more efficient approaches to Shapley value estimation could greatly enhance the practicality and scalability of our method. Additionally, future research could investigate the potential limitations of relying solely on Shapley values for interpreting LLM behavior and explore complementary techniques that could provide a more comprehensive understanding of the underlying decision-making processes.

6. Funding and Competing Interests

The author has no funding or conflicts of interest to report.

7. References

- Aher, G., Arriaga, R.I., Kalai, A.T., 2023. Using Large Language Models to Simulate Multiple Humans and Replicate Human Subject Studies. https://doi.org/10.48550/arXiv.2208.10264
- Ancona, M., Ceolini, E., Öztireli, C., Gross, M., 2018. Towards better understanding of gradient-based attribution methods for Deep Neural Networks. https://doi.org/10.48550/arXiv.1711.06104
- Binz, M., Schulz, E., 2023. Using cognitive psychology to understand GPT-3. Proc. Natl. Acad. Sci. 120, e2218523120. https://doi.org/10.1073/pnas.2218523120
- Brand, J., Israeli, A., Ngwe, D., 2023. Using GPT for Market Research. https://doi.org/10.2139/ssrn.4395751
- Castro, J., Gómez, D., Tejada, J., 2009. Polynomial calculation of the Shapley value based on sampling. Comput. Oper. Res., Selected papers presented at the Tenth International Symposium on Locational Decisions (ISOLDE X) 36, 1726–1730. https://doi.org/10.1016/j.cor.2008.04.004
- Chen, J., Yuan, S., Ye, R., Majumder, B.P., Richardson, K., 2023. Put Your Money Where Your Mouth Is: Evaluating Strategic Planning and Execution of LLM Agents in an Auction Arena. https://doi.org/10.48550/arXiv.2310.05746
- Fuchs, A., Passarella, A., Conti, M., 2022. Modeling Human Behavior Part II -- Cognitive approaches and Uncertainty. https://doi.org/10.48550/arXiv.2205.06483

- Grah, S., Thouvenot, V., 2020. Monte Carlo Shapley [WWW Document]. GitHub. URL https://github.com/ThalesGroup/shapkit/blob/master/nbs/monte_carlo_shapley.ip ynb (accessed 3.29.24).
- Gui, G., Toubia, O., 2023. The Challenge of Using LLMs to Simulate Human Behavior:
 A Causal Inference Perspective. SSRN Electron. J. https://doi.org/10.2139/ssrn.4650172
- Hagendorff, T., Fabi, S., 2023. Human-Like Intuitive Behavior and Reasoning Biases Emerged in Language Models -- and Disappeared in GPT-4. https://doi.org/10.48550/ARXIV.2306.07622
- Jones, E., Steinhardt, J., 2022. Capturing Failures of Large Language Models via Human Cognitive Biases. https://doi.org/10.48550/arXiv.2202.12299
- Kahneman, D., Tversky, A., 1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica 47, 263–291. https://doi.org/10.2307/1914185
- Koo, R., Lee, M., Raheja, V., Park, J.I., Kim, Z.M., Kang, D., 2023. Benchmarking Cognitive Biases in Large Language Models as Evaluators. https://doi.org/10.48550/arXiv.2309.17012
- Loya, M., Sinha, D.A., Futrell, R., 2023. Exploring the Sensitivity of LLMs' Decision-Making Capabilities: Insights from Prompt Variation and Hyperparameters, in: Findings of the Association for Computational Linguistics: EMNLP 2023. pp. 3711–3716. https://doi.org/10.18653/v1/2023.findings-emnlp.241
- Lundberg, S.M., Lee, S.-I., 2017. A Unified Approach to Interpreting Model Predictions, in: Advances in Neural Information Processing Systems. Curran Associates, Inc.
- Macmillan-Scott, O., Musolesi, M., 2024. (Ir)rationality and Cognitive Biases in Large Language Models. https://doi.org/10.48550/arXiv.2402.09193
- Merrick, L., Taly, A., 2020. The Explanation Game: Explaining Machine Learning Models Using Shapley Values. https://doi.org/10.48550/arXiv.1909.08128
- Shaki, J., Kraus, S., Wooldridge, M., 2023. Cognitive Effects in Large Language Models. https://doi.org/10.48550/arXiv.2308.14337
- Sreedhar, K., Chilton, L., 2024. Simulating Human Strategic Behavior: Comparing Single and Multi-agent LLMs. https://doi.org/10.48550/arXiv.2402.08189
- Stella, M., Hills, T.T., Kenett, Y.N., 2023. Using cognitive psychology to understand GPT-like models needs to extend beyond human biases. Proc. Natl. Acad. Sci. 120, e2312911120. https://doi.org/10.1073/pnas.2312911120

- Štrumbelj, E., Kononenko, I., 2014. Explaining prediction models and individual predictions with feature contributions. Knowl. Inf. Syst. 41, 647–665. https://doi.org/10.1007/s10115-013-0679-x
- Talboy, A.N., Fuller, E., 2023. Challenging the appearance of machine intelligence: Cognitive bias in LLMs and Best Practices for Adoption. https://doi.org/10.48550/arXiv.2304.01358
- Taubenfeld, A., Dover, Y., Reichart, R., Goldstein, A., 2024. Systematic Biases in LLM Simulations of Debates [WWW Document]. Synthical. URL https://synthical.com/article/a2446da4-1126-4575-9050-ed7aff493dbd (accessed 3.10.24).
- Thorstad, D., 2023. Cognitive bias in large language models: Cautious optimism meets anti-Panglossian meliorism. https://doi.org/10.48550/arXiv.2311.10932
- Tjuatja, L., Chen, V., Wu, S.T., Talwalkar, A., Neubig, G., 2024. Do LLMs exhibit human-like response biases? A case study in survey design. https://doi.org/10.48550/arXiv.2311.04076
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł., Polosukhin, I., 2017. Attention is all you need, in: Proceedings of the 31st International Conference on Neural Information Processing Systems, NIPS'17. Curran Associates Inc., Red Hook, NY, USA, pp. 6000–6010.
- Xu, S., Zhang, X., 2023. Leveraging generative artificial intelligence to simulate student learning behavior. https://doi.org/10.48550/arXiv.2310.19206

Appendices

A1. Jinja Prompt Template

We vectorized the prompt according to the following template:

```
{{ v1_The }} {{ v2_following }} {{ v3_flights }} {{ v4_are }} {{ v5_available }} {{ v6_from }} {{ __v7_City_1__ }} {{ v8_to }} {{ __v9_City_2__ }}. {{ v10_Which }} {{ v11_one }} {{ v12_would }} {{ v13_you }} {{ v14_choose }}?

- {{ v15_Flight }} {{ __v16_A__ }}: {{ v17_Costs }} {{ __v18_price_A__ }}, {{ v19_Trave lTime }} {{ v20_is }} {{ __v21_only_A__ }} {{ __v22_tt_A__ }} {{ v23_hours }}

- {{ v24_Flight }} {{ __v25_B__ }}: {{ v26_Costs }} {{ __v27_only_B__ }} {{ __v28_price_B__ }}, {{ v29_TravelTime }} {{ v30_is }} {{ __v31_tt_B__ }} {{ v32_hours }}
```

The fields that carry information important in decision-making are written in "dunder" style like ___this___. Each field has an index (e.g., v22 means variable number 22).

A2. Shapley Value Properties

A2.1. Efficiency

$$\sum_{x_i \in \mathcal{X}} \phi_i(v) = v(\mathcal{X})$$

Efficiency ensures that no value is lost or left unallocated, attributing the entire coalition payoff to its members. When thinking about the prompt vector \vec{x} , one can write:

$$\sum_{x_i \in \mathcal{X}} \phi_i(v) = f(\vec{x}) - \phi_0$$

That is, the feature contributions add up to the difference of prediction for \vec{x} (i.e., the probability of next token) and the baseline ϕ_0 .

A2.2. Symmetry

$$v(\mathcal{S} \cup \{x_i\}) = v(\mathcal{S} \cup \{x_i\}) \quad \forall \mathcal{S} \subseteq \mathcal{X} \Longrightarrow \phi_i(v) = \phi_i(v)$$

Symmetry ensures that payoffs are impartial and based solely on contribution, not on external factors or identities of the players.

A2.3. Additivity (Linearity)

$$\phi_i(v+w) = \phi_i(v) + \phi_i(w) \quad \forall x_i \in \mathcal{X}$$

where v+w represents the formation of a composite game where the value of any coalition \mathcal{S} in this composite game is the sum of the values that the coalition would achieve in each of the individual games, that is, $(v+w)(\mathcal{S}) = v(\mathcal{S}) + w(\mathcal{S})$. The "+" operation reflects the linearity property of the Shapley value. As a special case, if the value function of the game is scaled by α , the payoff of each player will be scaled by α as well:

$$\phi_i(\alpha v) = \alpha \phi_i(v) \quad \forall x_i \in \mathcal{X}, \alpha \in \mathbb{R}$$

A2.4. Null (Dummy) Player

$$v(\mathcal{S} \cup \{x_i\}) = v(\mathcal{S}) \quad \forall \mathcal{S} \subseteq \mathcal{X} \Longrightarrow \phi_i(v) = 0$$

This reflects the principle that rewards should be commensurate with the contribution to the collective effort.

A3. Complexity of Calculating Exact Shapley Values

- **Exponential Number of Coalitions:** Even short prompts may contain around N = 30 words, resulting in $2^N = 2^{30}$ coalitions to sum over. This exponential growth in the number of coalitions makes the computation extremely resource-intensive.
- Marginal Contribution Calculation: For each of the 2^N coalitions, two evaluations of the value function are required—one with the player and one without. This doubles the computational effort needed for each coalition.
- **Factorial Complexity:** Eq. 3.3 involves averaging the marginal contributions across all permutations of players. There are d! such permutations. For each permutation, one has to iterate through the players, considering each as the "marginal" player being added to a coalition of preceding players. This factorial complexity further compounds the computational challenge.
- Complexity of the Value Function: Calculating v(S) itself can be computationally expensive because it involves querying the LLM server. Each LLM call involves a sample time (time it takes to "tokenize"—sample—the prompt text for it to be processed by the LLM), a prompt eval time (time it takes to process the tokenized prompt text), and an eval time (time needed to generate all tokens as the response to the prompt). This does not even include the load time (time it takes for the model to load) and server warm-up time. Therefore, each LLM call may take a few milliseconds (for small LLMs) to a few seconds (large LLMs), which multiplies the overall computational burden.

A4. Estimation Algorithm for Shapley Values

Inputs: The prompt vector \vec{x} , the reference vector \vec{r} , the value function v, and the number of iterations T.

Result: The vector of Shapley value estimates $\vec{\hat{\phi}} \in \mathbb{R}^I$.

Algorithm:

- Initialize $\vec{\hat{\phi}}$ to $[0,0,\ldots,0]^T$.

- For each iteration t = 1, ..., T:

 $^{^{\}rm 1}$ https://github.com/ggerganov/llama.cpp/issues/2237

- Choose a random permutation O of the prompt template fields, i.e., $O \in \pi(\mathcal{X})$ (See Section 3.3).
 - Evaluate the value function for the reference vector \vec{r} , that is, find $v_1 := v(\vec{r})$.
 - Set the current coalition vector \vec{s} to the reference vector \vec{r} .
 - For each field i in the permutation:
 - Set the corresponding element of \vec{s} to its value in \vec{x} , that is:

$$\vec{s} = \begin{cases} x_j & j = i \\ s_j & \text{otherwise} \end{cases}; \ j \in \{1, \dots, I\}$$

- Evaluate the value function for the updated coalition vector, i.e., find $v_2 \coloneqq v(\vec{s}).$
- The marginal contribution of feature i is computed as the difference between the two value function evaluations: $\phi_i = v_2 v_1$.
 - If t > 1, update the estimated Shapley value ϕ_i using a moving average:

$$\hat{\phi}_i = \frac{\phi_i}{t} + \frac{(t-1)\hat{\phi}_i}{t}$$

- Set the value function evaluation from the previous step as the baseline for the next step: $v_1=v_2.$

A5. Applications (in Details)

A5.1. Application 1: A Discrete Choice Question

As mentioned before, we used the following prompt with Llama-2-Chat models of three sizes: 7B, 13B, and 70B parameters:

The following flights are available from City 1 to City 2. Which one would you choose?

- Flight A: Costs \$400, Travel Time is 7 hours
- Flight B: Costs \$600, Travel Time is 5 hours

The results are as follows:

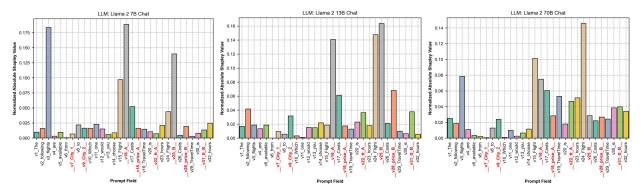


Figure 7. The normalized absolute Shapley values of Application 1 for the three models under study.

A5.2. Application 2: Existence of Cognitive Biases in LLMs

We made option B more appealing by injecting the word "only" before its price, resulting in the following prompt:

The following flights are available from City 1 to City 2. Which one would you choose?

- Flight A: Costs \$400, Travel Time is 7 hours
- Flight B: Costs only \$600, Travel Time is 5 hours

The normalized absolute Shapley values for the three models under study are:

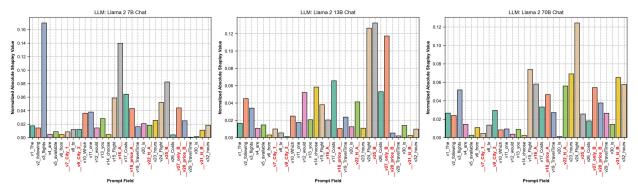


Figure 8. The normalized absolute Shapley values of Application 1 for the three models under study.