

# Navigating Opinion Space: A Study of Explicit and Implicit Opinion Generation in Language Models

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**Abstract.** The paper focuses on testing the use of conversational Large Language Models (LLMs), in particular chatGPT and Google models, instructed to assume the role of linguistics experts to produce opinionated texts, which are defined as subjective statements about animates, things, events or properties, in contrast to knowledge/evidence-based objective factual statements. The taxonomy differentiates between Explicit (Direct or Indirect), and Implicit opinionated texts, further distinguishing between positive and negative, ambiguous, or balanced opinions. Examples of opinionated texts and instances of explicit opinion-marking discourse markers (words and phrases) we identified, as well as instances of opinion-marking mental verbs, evaluative and emotion phraseology, and expressive lexis, were provided in a series of prompts. The model demonstrated accurate identification of Direct and Indirect Explicit opinionated utterances, successfully classifying them according to language-specific properties, while less effective performance was observed for prompts requesting illustrations for Implicitly opinionated texts. To tackle this obstacle, the Chain-of-Thoughts methodology was used. Requested to convert the erroneously recognized opinion instances into factual knowledge sentences, LLMs effectively transformed texts containing explicit markers of opinion. However, the ability to transform Explicit Indirect, and Implicit opinionated texts into factual statements is lacking. This finding is interesting as, while the LLM is supposed to give a linguistic statement with factual information, it might be unaware of implicit opinionated content. Our experiment with the LLMs presents novel prospects for the field of linguistics.

## 1 Introduction

The present paper aims to discuss testing results with reference to the use of conversational Large Language Model (LLM), in particular chatGPT and Google models, instructed to assume the role of linguistics expert in our testing exercises.

## 2 ChatGPT applications

### 2.1 Language-focused LLM applications

Language has been the first system and communication medium which has been subject to Artificial Intelligence applications.

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### 2.1.1 Translation

is the first linguistic skill that was the forerunner of other machine-instructed applications. Researchers perform various studies to apply LLMs to machine translation tasks and evaluate their performance. One of the most recent ones uses automatic retrieval or human feedback as supervision signals to enhance the LLM's translation through in-context learning [23].

### 2.1.2 Language education

Since the first attempts of its systematic studies, language education has been an object of investigation and applicational attempts by various types of e-learning Computer-Assisted Language Learning systems. At present, LLMs are particularly widely used in education generally, and in language education in particular, proved to be especially relevant for teachers to devise work plans, curricula, language exercises and testing.

A significant step in the development of **automatised linguistic application systems** has been performed since first attempts to collect large language corpora [4]. Compiled by Henry Kučera and W. Nelson Francis at Brown University, in Rhode Island, USA, the so-called Brown Corpus, contained 500 samples of, predominantly written, American English (ca one million words). Since then, corpus linguistics, aided in the following years by computational linguistics, has begun its career in linguistics and its applications, particularly in lexicology, morpho-syntax, and discourse studies and, with the development of spoken corpora – in phonetics and phonology. The findings have been applied to lexicography, and more recently, to the identification of figurative meanings and implicit senses in semantics.

LLMs have paved the way towards communicative natural conversation applications, not to mention the areas of multilanguage and multimodal applications.

ChatGPT's naturally occurring **conversational skills**, fluent, human like, and coherent, are particularly attractive to the millions of users. And yet, although e.g., ChatGPT's conversational behaviour is considered structurally correct in the majority of tests, it equally often happens to be pragmatically unconventional, due to some excessive length, not following what are considered 'conversational routines', lacking context-sensitivity and conventional pragmatic competences.

### 2.1.3 Academic editing

Academic editing is by far most frequently used application of chatGPT [1]. It is used both by lecturers in humanities and in STEM, as well as in student writing. There it may well serve language education objectives. There are also attempts to make ChatGPT write original poems, though its products typically lack refinement and finesse.

During the last few months lexicographic testing, comments, descriptions, research projects, have also appeared in larger numbers, particularly relevant to **dictionary making and ontoterminological system building** [15, 12].

There are also attempts to automatically identify in the corpora rather **vague and implicit categories of meaning** (e.g., [5]). One of such categories, opinions, the topic of the present paper, is not a particularly frequent object to be satisfactorily identified by means of LLMs.

## 3 Language of Opinions

Language of opinionated texts is characterized by some properties which make it potentially distinguishable from fact-based statements. On the other hand, the class of implicit opinionated texts is particularly problematic to identify outside of context, because of the absence of a set of criterial, ever present universal markers. Therefore, we assume that some of the tasks to identify this and some other categories of opinion text, will also cause identification and illustration problems for LLM models.

### 3.1 Definitions of Opinion

In the paper by [7] definitions of opinion were scrutinized and the conclusion was reached that opinion is a subjective statement, containing judgement about THINGS (Human/Animal), which can be expressed in language or multimodally, about OBJECTS (people or things), EVENTS or PROPERTIES (Lewandowska-Tomaszczyk et al. 2023:461). The property of truth concerning expressing of an opinion is suspended – it is not known whether what is proposed is true or not [2].

To reach a contextually based definition, we proposed a cognitive-social understanding of opinion, perceiving it not as a single word, or sentence, but rather as an Opinion (Speech) Event (Lewandowska-Tomaszczyk et al. 2023:471) considered a semiotic act, which is embedded in a social-cultural context, and expresses an opinion holder's judgement on a person, animal, property or event. One additional caveat must be added to the definition of opinions, with reference to the emotional and evaluative language used in opinionated texts, dubbed as 'private state' expressions. Wiebe et al. [21] view private states in terms of their functional components as "states of experiencers holding attitudes optionally toward targets. For example, for the private state expressed in the sentence John hates Mary, the experiencer is John, the attitude is hate, and the target is Mary" (Wiebe et al. p.4). If the private states (including emotions, beliefs, etc.) are expressed with reference to direct experiences (e.g., I love Mary) they either cannot be treated as prototypical opinions or can fall out entirely of the definitional characteristics of opinions. Opinions can be private state expressions though expressed only towards so-called nested (or linguistically embedded) constructions, hence e.g., 'I love John' is not an opinion, 'I love skiing', can be considered a marginal opinion, while 'Russia fears war escalation' is an opinion due to the fact that the experience of the target 'other X fears war escalation' is a nested Speech Event.

In that paper we also proposed a typology of context-immersed opinions postulating a basic distinction between Explicit, which can be Direct or Indirect as opposed to Implicit opinionated texts. These categories are further subdivided into positive and negative opinions, ambiguous in this respect, and balanced opinions.

### 3.2 Taxonomy of Opinions

1. **Explicit – introduced by semantically transparent structural/semantic opinionated markers:** *Syntactic framing* imposes the order of linguistic elements used an opinion and together with *Semantic framing* identifies degrees of certainty and conviction by particular Agents: e.g., My/Our opinion is.../According to me... Lexical framing is marked by relevant lexical items, as e.g., Cognitive verbs (e.g., I think, I believe, I feel), Modifiers (adjectives slow, adverbs slowly) that express evaluation or judgement (e.g., good/bad, worthy, valuable; slowly), in the three comparison degrees: positive pretty, comparative prettier (than), and superlative the prettiest (of...), as well as expressions that convey personal feelings or experiences (e.g., I/they... love, I/they hate, I/they enjoy...).
2. **Explicit indirect opinion markers:** Opinions may be reinforced with persuasive language, such as rhetorical questions, appeals to authority, and emotional appeals [16], often accompanied by offensive and vulgar language. **Indirectly conveyed opinions:** he said/I've heard. Those opinionated texts which are introduced by means of unambiguous opinion markers such as 'I think/I don't think/I do not think', 'in my opinion' or 'according to me' or else by indirect Explicit Opinionated Texts heard/repeated from outside sources or via intermediaries. Contrasted with pragmatically expressed opinions, which are context-identifiable are Implicit Opinions.
3. **Implicit Opinions** Implicit opinions are typically used unaccompanied by any explicit opinion markers. However, they may include reference to targets that are vague.

## 4 Computational opinion identification and GPT at work

### 4.1 Previous attempts

In a report by Pew Research Center, Mitchell et al. [13] propose that in real life it is political awareness, digital savviness and trust in the media that all play large roles in the ability to distinguish between factual and opinion news statement. In digital methodology, the situation is not so simple. Rather modest numbers of publications focusing on the topic of opinion as opposed to factual knowledge statements is not direct. Rather they uncover opinions by the identification of opinion holders (e.g., [6]), or else most of the efforts focus on opinion mining that can analyse opinions from many information sources automatically and extract opinions, along with determining primarily their positive or negative (or else neutral) polarities, holders, strength, and possibly targets, typically by heuristic rule based and machine learning based methods.

A particularly problematic issue in opinion research, characteristic in fact of all language study, is the identification of vagueness and implicit language. There have been numerous attempts towards achieving this goal. It is also particularly important for the purposes of our study to investigate methods of identifying uncertainly, implicitness and vagueness in textual data as an important category of opinionated texts.

Original works by Wiebe et al. [22] with collaborators [20, 21] laid foundations on the development of a gold standard dataset for subjectivity classifications, subjectivity, which is a criterial property of opinionated statements (Lewandowska-Tomaszczyk et al. 2023). As the next step, there have been attempts at rather indirect ways to get to the sense of the concept of opinion. Yu and Hatzivassiloglou [24] investigated it via looking answers to opinion questions and, in this way, identify the polarity of opinion sentences. There are attempts at uncovering distinctions between general and specific types of text e.g., Louis and Nenkova [11] who investigated identifying general and specific sentences in news articles by exploring the feasibility of using existing annotations of discourse relations as training data for a general/specific classifier. This tool relies on classes of features that capture lexical and syntactic information, as well as word specificity and polarity. Dinu et al. [3] proposed an entirely different approach: hermeneutic introspection towards the intrinsic vagueness of analyzed texts, particularly for research on historical documentation. The author also presented limitations of annotation approaches in this respect.

In an extensive, detailed study on textual uncertainty Zerva [25] examined options of its automatic identification in to provide a more informative weighting of extracted knowledge, representing the confidence of the author in a statement. The author develops a set of uncertainty cues, grouped according to category Strong/Weak speculation where such words and expressions as WEAK certainty is represented by such forms as indicate, suggest, speculate, while admission to lack of knowledge by the words such as unknown/unclear; strong: hypothesize, propose, potent, while the medium level as there is evidence/it is known to be). Particular word clouds were generated by using the relative frequencies of cues in the corpora. The author used an adaptation of subjective logic theory in order to frame each event mention as an opinion model, in this way capturing potentially varying classification of uncertainty schemes.

In recent papers context-focused considerations have been applied e.g., Lian et al. [10] propose an approach of the  $F_{vague}$  detector to automatically detect vagueness in the text. According to their analysis, a large part of individual vague sentences have at least one clarifying sentence in the documents. The experiments showed good performance of high recall and precision.

With the advent of LLM generative tools, attempts at their use to identify and generate linguistically complex utterances have risen, e.g., in their paper on the identification of implicit toxicity in texts, Wen et al. [18] show that LLMs generate implicit toxic outputs that are exceptionally difficult to detect via simply zero-shot prompting.

#### 4.1.1 Our approach

We implemented the chain-of-thought prompting (CoT) methodology [17]. CoT enhances the reasoning capacity of LLMs by incorporating systematic step-by-step reasoning procedures into the demonstration. CoT prompting enhances the model’s comprehension of the question’s complexities and the process of reasoning. In addition, the model produces a series of logical stages, providing us with a clear understanding of the model’s cognitive process, hence improving its interpretability.

## 4.2 Prompts

White et al. [19] provided a comprehensive collection of efficient engineering methods, organized in a pattern format, that have been

applied to address typical challenges encountered during interactions with LLMs. We used the following patterns in our experiment:

1. The Persona Pattern – we asked the LLMs to act as a linguistic expert, i.e., somebody who uses and knows the language very well, and provide outputs that such a persona would.
2. The Reflection Pattern - we successfully accomplished the objective of the reflection pattern, which involves prompting the model to automatically explain the rationale behind provided replies to the user. This was achieved by integrating the persona pattern with a request to provide a range of diverse examples that exemplify various linguistic phenomena.
3. The Cognitive Verifier Pattern - Research literature has established that LLMs demonstrate improved reasoning abilities when a question is broken into sub-questions, with their respective replies merged to form the overall solution to the original question [26]. Therefore, we attempted to apply this pattern as well. The description of explicit and indirect explicit opinionated texts encompasses various illustrative instances. For example, in explicit opinionated texts lexical framing is characterized by the use of pertinent lexical items, such as cognitive verbs and modifiers. We executed two queries. Initially, we solicited instances of lexical framing including cognitive verbs, and subsequently, we asked cases of lexical framing with modifiers. Nevertheless, the LLMs were unsuccessful in achieving the separation and, as a result, produced a combination of both types for the two queries. By employing a comprehensive and intricate definition of direct opinionated texts, encompassing a wide range of examples, the LLM models demonstrated superior performance. It not only generated more effective examples without repetition, but also categorized them based on the language phenomena they showed.
4. The Context Manager Pattern – we specify context for a conversation with the LLMs. We have enhanced the model by providing extra context, including a description of the category of opinionated text together with integrated relevant examples, instead of simply requesting examples based on a specific category name. The LLMs were then requested to provide examples that adhere to the category’s rule.

It is observed that the utilization of the template pattern, which enables the user to specify a template for the output, was unnecessary in this case, as the bulleted list was already obtained in response to the examples request.

In addition, we incorporated an emotional stimulus into our prompt based on prior research [8] indicating that LLMs possess emotional intelligence and that their performance can be enhanced by the use of emotional prompts.

Given that LLMs tend to be chatty and have a tendency to engage in a ‘question and answer’ format by inventing their own questions [14], we explicitly urged the LLMs to avoid such behavior.

In one session, we used the conversational LLMs, to execute the following conversation:

1. We requested the LLMs to provide instances for the initial category of explicit opinionated text, based on the concept of the category that was explained with illustrations.
2. Following the LLMs’ successful presentation of accurate examples demonstrating its comprehensive grasp of the category, the LLMs were then presented with the subsequent description of indirect explicit opinionated text and tasked with providing appropriate examples for this newly introduced category.
3. The LLMs provided accurate illustrations and received the definition of the final classification of implicit opinionated text.

4. The LLMs provided some incorrect examples and offered new examples of explicit direct and indirect opinionated content. In order to discern between factual and opinionated content, we requested the LLMs to transform the generated instances from the previous stage into factual statements.

```

system = ("You are a linguistic expert.") ①
prompt_text = '''
② Context: {context}
③ Examples: {example}
④ Task: {task}
⑤ My job depends on how good
and diverse these examples are.
⑥ Don't be chatty,
give me only the output format I asked for
'''
prompt = ChatPromptTemplate.from_messages([
    ("system", system),
    ("human", prompt_text)])

```

Figure 1. Prompt Structure

Figure 1 illustrates the structure of our prompt. #1 is the persona pattern "You are a linguistic expert". #2 is the context, the category definition presented in the taxonomy. #3 includes examples. This option was exclusively utilized for the implicit category. Other categorized examples were presented in the context. #4 is the task: "Give me 50 diverse examples that represent different linguistic phenomena of opinionated sentences which follow this rule." (the rule, category definition, is provided in the context). #5 is the emotional prompt "My job depends on how good and diverse these examples are", and #6 is an instruction to avoid chatty behavior: "Don't be chatty, give me only the output format I asked for".

By applying the specified prompting method, we effectively provided examples for each of the preset categories of opinionated text, which proved challenging for corpus linguistic techniques [7].

### 4.3 Results

In this section we report the results of two popular conversational LLMs: OpenAI's ChatGPT-4<sup>2</sup> and Google's Gemini<sup>3</sup>. Both models were given identical prompts. Next, we detail the examples extracted for each category in the taxonomy of opinions.

#### 4.3.1 Explicit opinions

Both LLMs successfully extracted 50 accurate examples as requested. Nevertheless, Gemini autonomously categorized them into distinct linguistic phenomena. Table 1 displays the various categories along with two examples for each category. In the semantic framing category, all the examples consisted of the first person singular/plural. This type can be considered as a peripheral opinion type. The fundamental semantic framework is centered around the concept of a person (excluding the first person singular/plural). The expected structure would be: You/He/She/It/They... strongly believe(s) (present simple or past simple tense). The ten examples of expressions of personal feelings or experiences are not opinions. At most, they can be considered extremely peripheral opinions, as they do not

convey a nested target, as previously explained. While all the examples of the other linguistic phenomena category are correct, the majority of them do not establish a distinct category but rather offer supplementary illustrations for existing categories.

Table 1. Categories of explicit opinions by Gemini

Type	Ex1	Ex2
General	"In my view, the United States should withdraw from the Paris Agreement."	"I am convinced that the Earth is flat."
Semantic Framing	"I am somewhat skeptical of the claims that the new drug is effective."	"I am indifferent to the outcome of the election."
Lexical Framing	"The new tax policy is a disaster."	"College tuition is too expensive."
Expressions of Personal Feelings or Experiences	"I love my country."	"I am grateful for all that I have."
Other Linguistic Phenomena	"I believe that the media is biased against conservatives, don't you?"	"According to me, the best way to solve the climate crisis is to invest in renewable energy, and I am confident that it will work."

#### 4.3.2 Explicit indirect opinions

As requested, both LLMs extracted fifty accurate examples successfully. However, while ChatGPT utilized rhetorical questions to emphasize opinions in all the extracted examples (such as "Can't you see the blatant injustice in our legal system?", "How can we deny the suffering of the homeless people in our city?", and "He said that our company's stocks are plummeting. Isn't it a sign of weak leadership?"), Gemini extracted a diverse range of examples that employed various forms of persuasive language and indirectly conveyed opinions. Gemini additionally offered a clarification, enclosed in parentheses, for each of the examples.

- "Isn't it obvious that this new policy is a disaster waiting to happen?" (Rhetorical question)
- "If you don't support this bill, you're clearly heartless and don't care about the poor." (Emotional appeal)
- "My boss told me that if I don't meet my sales target this month, I'm out of a job." (Text heard/repeated from an intermediary)
- "This movie is so bad, it's almost funny." (Sarcasm)
- "If you don't like it here, then leave." (Appeal to ignorance)
- "If you don't vote for me, you're throwing your vote away." (Appeal to fear)
- "She's not exactly a beauty queen, but she's got a great personality." (Backhanded compliment)
- "I'm not saying he's a bad person, but I wouldn't trust him with my wallet." (Damning with faint praise)
- "I'm not ageist, but I don't think older people should be allowed to drive." (Ageism)
- "You're so stupid, you don't even know what you're talking about." (Ad hominem attack)

#### 4.3.3 Implicit opinions

Despite being requested to provide 50 examples, the LLM only provided 25 and 30 examples for ChatGPT and Gemini respectively. All

<sup>2</sup> <https://chat.openai.com>

<sup>3</sup> <https://deepmind.google/technologies/gemini/>

**Table 2.** Implicit opinionated examples converted to facts

Type	Opinion	Fact
Implicit → Implicit	"Her research is groundbreaking - it could revolutionize the field."	"Her research has significant potential to make a major impact on the field."
	"That politician just talks the talk, but never delivers on their promises."	"The politician's pronouncements often fail to translate into concrete actions or outcomes."
Explicit Indirect → Explicit Indirect	"What a stunning view from this mountaintop!"	"The panorama from the mountaintop offers breathtaking visuals."
	"You should definitely come to the party tonight, it'll be a blast!"	"Many people are looking forward to the party tonight."
Implicit → Explicit Indirect	"The movie was just meh, not really worth the hype."	"The movie received mixed reviews."
	"I wouldn't mind trying that new restaurant - everyone says it's amazing!"	"Many people are praising the new restaurant."
	"He's certainly got a way with words, that's for sure."	"The movie received mixed reviews."
	"Her artwork is so bold and daring, I love it"	"Her artwork is characterized by its use of vivid colors and unconventional techniques."

the examples provided by ChatGPT consisted of explicit opinionated texts containing clear markers of opinion. The erroneous instances of implicit opinionated texts were effectively transformed into factual statements. For example, "I think that the movie was fantastic." was converted to "The movie received positive reviews", "I suppose the concert ended late" was converted to "The concert ended at midnight", and "My opinion is that the law should be revised" was converted to "The law is under review."

Gemini excelled in producing implicit opinionated texts. 28 of the 30 examples were accurate. Additionally, the typology identification gave promising results. The generated distinction between the categories of Implicit and Explicit Indirect types can be presented in the following format: out of the 30 exemplary instances, generated as Implicit Opinions to be converted to Factual statements, less numerous instances are Implicit to Implicit opinions (3 examples), and Explicit Indirect converted to synonymous Explicit Indirect opinions. The most numerous category are Implicit opinions converted to Explicitly Indirect ones (25 instances), which can be considered a big step towards the full clarification of opinion typology content. Examples are presented in Table 2. Some of the examples may be considered taxonomically ambiguous due to independent reasons: the missing reference to the contextually-anchored Opinion Event context that would disambiguate the taxonomy type. As discussed in the first sections of the present paper (p. 2), opinion is proposed to be defined as an event with the identification of opinion holder, its sources, target, effects, relation to evidence data, etc. With no such reference available, options to identify opinionated samples from factual statements are lower. This is not unique to LLM system's performance. Similarly, human language users experience identical problems with implicit opinion identification. The reason is that in terms of language, implicit opinions most often adopt a linguistic form identical

to that used for factual statements, i.e., with the absence of evident linguistic clues that would make it possible to differentiate between the two types. The context-free utterance such as e.g., "It is raining", when said to another person on the phone, cannot be verified by the addressee as to its factual content. The sentence is referentially ambiguous between two conflicting scenarios. It can either convey a factual statement uttered in the outdoors context in a heavy rain, or else it can be produced in a cosy room, when the speaker sees water falling from the roof outside. The statement "It is raining" in the latter context is an implicit opinion, a shorthand for the complete (opinionated) form "I think it is raining". Both in the former and the latter scenarios, the contextual information on the event would clarify the ambiguity. One can thus conjecture that LLM systems would exploit its fuller taxonomic options when provided with the information on the Opinion Event contextual clues. Our next section will focus on attempts to refine a series of prompts towards making the opinion event contextual clues more transparent to incorporate such them into a system of contextual information transfer.

**Contextual clues** The search for entity context has recently been an important topic of inquiry in computational linguistics. Although existing corpus-based methods have achieved some progress, they still rely on annotated corpora to obtain the context patterns through the position of the entity in a sentence. There are attempts to overcome the annotation dilemma some authors such as Li et al. [9] explore an approach based on Entity Set Expansion (ESE) and its newer version GAPA (GenerAted PATterns) to expand target entities, which are corpus-independent to automatically generate high-quality context patterns for entities.

To generate sufficient contextual clues by ChatGPT and Gemini to identify and produce implicit opinions we refined our prompts to urge the LLMs to generate some context for Implicit Opinion Events with the sentences provided.

Prompt: Generate a few sentences of context to make the following sentence an opinionated text, the context should include the sentence itself. The sentences are provided in the first column of Table 3:

## 5 Discussion

It is important to note that LLMs are nondeterministic models, meaning they exhibit different behaviors each time they are executed. Executing the identical prompt can yield varying instances. In addition, we did not optimize the prompts for any of the models. Customizing the prompt for each LLM individually may lead to improved outcomes. However, provision of more detailed, contextually specific condition types for each possible implicit opinion scenario might be considered time and effort consuming, especially when a series of similar forms would need to be sequentially generated, with reference to distinct objects or domains. A cumulative prompt admitting variance would be needed in such cases which would constitute an adequate prompting signal for the system. This level of opinion analysis is typically influenced by the context around the sentence and is considered decisive for applications dealing with various types of text - from social networks, political comments and casual conversations. Its aim is to determine language users' opinions about various phenomena, people, objects, properties and states and possibly confront them with the actual states of affairs in the outside reality. In order to perform this level of analysis, it is essential to identify both the linguistic context and the actual situational scene entities mentioned and their respective properties related to the words produced. From there, the judgment concerning a distinction between factual

**Table 3.** Implicit opinionated examples in context

Sentence	ChatGPT	Gemini
It is raining.	"It is raining outside," she muttered with a sigh, annoyed by the incessant downpour that seemed to dampen her plans every time she dared to make them. In her opinion, rainy days were nothing but a nuisance, disrupting outdoor activities and leaving everything soggy and gloomy. She couldn't fathom why some people found solace or romance in the pitter-patter of raindrops; to her, it was simply an inconvenience that warranted staying indoors with a hot cup of tea and a good book.	I peeked out the window and groaned. It is raining. Perfect. With this downpour, there's no way I'll be able to wear my new sandals today. Looks like it's boots again.
Her research is groundbreaking - it could revolutionize the field.	"Her research is groundbreaking - it could revolutionize the field," exclaimed Professor Thompson, his eyes gleaming with excitement as he discussed the latest findings in the faculty lounge. In his opinion, her work represented a paradigm shift, challenging long-held assumptions and opening up new avenues of exploration that could redefine the boundaries of their discipline. He couldn't help but feel a sense of awe at the sheer innovation and potential impact of her discoveries, envisioning a future where her ideas would shape the trajectory of their field for years to come.	For years, scientists have been searching for a way to create a more sustainable energy source. Many have tried and failed, but Dr. Amelia Rose's latest research is different. Her research is groundbreaking - it could revolutionize the field by creating a way to harness solar energy even more efficiently. With this new technology, we could see a dramatic reduction in our reliance on fossil fuels.
That politician just talks the talk, but never delivers on their promises.	"That politician just talks the talk, but never delivers on their promises," grumbled Sarah, her frustration evident as she flipped through the channels, each one featuring the same empty rhetoric and hollow pledges. In her opinion, this particular politician was a master of spin, adept at crafting persuasive speeches and making grandiose commitments during campaign season, only to backtrack or conveniently forget once elected. She couldn't understand how so many people continued to support someone who consistently failed to follow through on their word, lamenting the state of politics and longing for leaders who prioritized integrity and accountability over empty platitudes.	The election cycle is in full swing, and promises are being thrown around like confetti. But one politician in particular, [politician's name], seems to be all talk and no action. That politician just talks the talk, but never delivers on their promises. It's a shame, because they have some good ideas, but their lack of follow-through makes them untrustworthy in my eyes.
The movie was just meh, not really worth the hype.	"The movie was just meh, not really worth the hype," sighed Emily, disappointed as she left the theater with her friends. In her opinion, the film fell short of its lofty expectations, failing to deliver the gripping storyline and memorable performances that had been promised in the trailers and early reviews. She couldn't help but feel let down by the hype surrounding it, wishing she had spent her time and money on a more captivating cinematic experience instead.	Everyone was raving about this new movie, calling it a masterpiece. I was excited to see it, but after finally sitting down to watch it, I was left feeling disappointed. The movie was just meh, not really worth the hype. The plot was predictable, the characters lacked depth, and the special effects were underwhelming. I'd rather have spent my time watching something else.
I wouldn't mind trying that new restaurant - everyone says it's amazing.	"I wouldn't mind trying that new restaurant - everyone says it's amazing," remarked Mark, his curiosity piqued by the enthusiastic reviews he had heard from friends and colleagues. In his opinion, the widespread acclaim surrounding the eatery hinted at an exceptional dining experience just waiting to be savored. He couldn't resist the allure of exploring new culinary delights, eager to indulge his taste buds and see if the restaurant truly lived up to its stellar reputation.	Dating nights have been feeling a little repetitive lately. We keep going to our usual Italian place, and while it's good, I'm craving something new. I wouldn't mind trying that new restaurant on Elm Street - everyone says it's amazing. It's a little pricier than we usually go for, but for a special occasion, it could be perfect!
He's certainly got a way with words, that's for sure.	"He's certainly got a way with words, that's for sure," chuckled Sarah, impressed by her colleague's eloquence during the presentation. In her opinion, his ability to articulate complex ideas with such clarity and flair was nothing short of remarkable. She couldn't help but admire his skillful communication style, which effortlessly captivated their audience and left a lasting impression.	I wasn't sure about attending the presentation at first, but then I heard who the speaker was. He's certainly got a way with words, that's for sure. People say he can take the driest topic and make it fascinating. I figured even if the content wasn't the most exciting, at least his delivery would be entertaining.
Her artwork is so bold and daring, I love it.	"Her artwork is so bold and daring, I love it," exclaimed Mia, her eyes sparkling with admiration as she gazed at the vibrant canvases adorning the gallery walls. In her opinion, the artist's fearless exploration of color and form challenged conventional boundaries, evoking a sense of excitement and inspiration. She couldn't help but feel drawn to the raw energy and emotion infused into each brushstroke, finding herself captivated by the bold creativity on display.	Galleries these days are filled with safe, predictable pieces. I crave art that pushes boundaries and makes a statement. Her artwork is so bold and daring, I love it! The way she uses color and texture is unlike anything I've seen before. It's truly refreshing to see an artist unafraid to take risks.

statements and opinions generally and possible implicit opinions, targeted at each of the identified entity or property, can be determined. It has been shown in the present paper that in the case of LLM generative tools more explicit prompts at the training phase that would indicate contextual variants of opinion scenario types might constitute materials leading to more satisfactory outcomes. In this way, a more effective functioning of the current models in this areas of their activity were obtained, particularly for implicit opinions, especially with Gemini LLMs.

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