Seeing the Shift: Keep an Eye on Semantic Changes in Times of LLMs

Raphael Buchmüller Friedericke Körte Daniel Keim

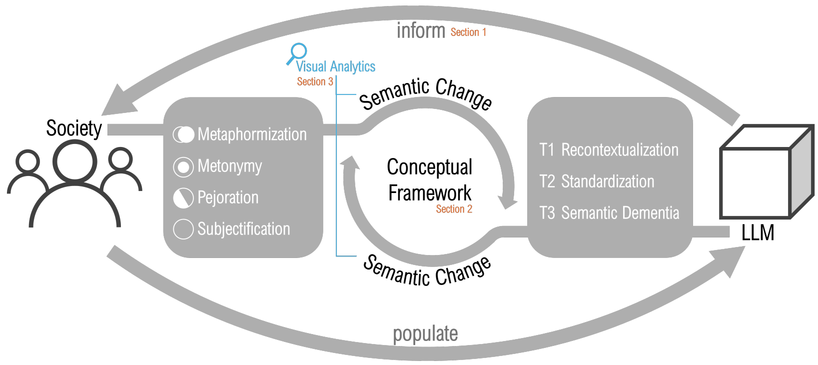

Fig. 1: Our research examines the growing interdependency between socio-linguistic mental models and large language models (LLMs) as influencers of semantic change. Traditionally driven by socio-linguistic mechanisms such as metaphorization, we now introduce the theories of recontextualization, standardization, and semantic dementia to conceptualize the impact of LLMs on our general, conceptual framework. We further propose Visual Analytics as a tool to monitor and explain these ongoing semantic changes.

Abstract— This position paper discusses the profound impact of Large Language Models (LLMs) on semantic change, emphasizing the need for comprehensive monitoring and visualization techniques. Building on linguistic concepts, we examine the interdependency between mental and language models, highlighting how LLMs and human cognition mutually influence each other within societal contexts. We introduce three primary theories to conceptualize such influences: **(T1) Recontextualization**, **(T2) Standardization**, and **(T3) Semantic Dementia**, illustrating how LLMs drive, standardize, and potentially degrade language semantics. Our subsequent review categorizes methods for visualizing semantic change into frequency-based, embedding-based, and context-based techniques, being first in assessing their effectiveness in capturing linguistic evolution: Embedding-based methods are highlighted as crucial for a detailed semantic analysis, reflecting both broad trends and specific linguistic changes. We underscore the need for novel visualization tools to explain LLM-induced semantic changes, ensuring the preservation of linguistic diversity and mitigating biases, while providing essential insights for the research on semantic change visualization and the dynamic nature of language evolution in the times of LLMs.

Index Terms—Computation and Language, Visualization, Semantic Change, Word Embeddings, Large Language Models

Human language is a constantly evolving phenomenon. New word senses emerge and existing ones change or disappear due to social, cultural, and technological influences. This dynamic nature of semantics has captivated NLP researchers, leading to extensive investigations into the diachronic aspects of language. Some studies focus on developing and refining theories of meaning change from psycholinguistic and sociolinguistic perspectives [17, 20, 41, 55] to understand the underlying mechanisms driving language evolution. Others explore the historical evolution of word meanings [14, 32] to trace cultural and societal changes reflected in language. Additionally, research tracking current transformations in public discourse [2, 50] helps identify shifts in language use relevant to applications like sentiment analysis and media monitoring. Visualizing semantic change helps detect and address biases, as shifts in word meanings can reflect underlying biases or stereotypes. By identifying these changes, it is possible to mitigate their impact and promote fairer language modeling. Recent efforts have focused on creating adaptive learning systems that evolve with human language and improve predictions beyond their training period [60].

• *Raphael Buchmüller, Friedericke Körte and Daniel Keim are with the University of Konstanz. E-mail: raphael.buchmueller@uni-konstanz.de, friedericke.koerte@uni-konstanz.de, keim@uni-konstanz.de.*

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Conversely, **Large Language Models (LLMs) such as GPT [44] change the way we produce and process information.** Transformer models outperform traditional methods in tasks of natural language processing, including prediction and decision-making through fine-tuning and adaptation. Pre-trained on vast numbers of text documents they can learn intricate language patterns without supervision. LLMs like GPT are embedded into various contexts including business domains, medical diagnostics, and language translation. Additionally, platforms and integrations such as ChatGPT [44] or GitHub Copilot [9] assist users with tasks like content creation, correction, and question answering.
The pervasive use of LLMs underscores the urgency of assessing their impact on our collective knowledge within our digital ecosystem. Following the former discussion of Nannini [40], these models do not just alter language patterns; they have the potential to reshape the collective knowledge ecosystem and impair linguistic diversity and the richness of our collective knowledge. To mitigate risks of homogenization and semantic erosion, it is crucial to foster critical engagement and (visual) exploration with AI-generated content and training data. Proactive strategies are required while leveraging LLM capabilities for enhanced communication and knowledge dissemination.
Semantic change in natural language offers a unique lens through which we can observe and understand the profound impact of LLMs. The utilization of LLMs influences our linguistic patterns as shown by Liang et al. [35] in AI conference peer reviews: The study revealed that LLMs have altered the linguistic landscape of review texts, evidenced by a noticeable shift in the frequency of certain adjectives. For instance, adjectives like “commendable,” “meticulous,” and “intricate” saw a significantly increased use. Similarly, research by Bender

et al. [4] on the language used in social media platforms highlights a trend towards more formal and elaborate expressions, reducing the prevalence of slang and colloquial terms. Another relevant study by Youvan [59] on academic writing shows that AI tools have led to a broader range of vocabulary and more varied syntactic structures in scholarly papers.

Our research hints towards diverging socio-linguistic influences initiated by LLM usage: LLMs tend to use a more varied and sophisticated vocabulary compared to the writing style of an individual across given domains. This shift is not merely cosmetic; a single user's vocabulary can be enriched and diversified. The user can gain word senses or linguistic patterns through **(T1) recontextualization** by LLM agent interaction. However, our language and consequently our conceptual framework runs into the risk of being **(T2) standardized** and homogenized towards linguistic convergence meanwhile reducing linguistic diversity and **(T3) semantic dementia**. Methods of visualization and Visual Analytics (VA) proved to be effective in exploring semantic changes as further discussed. **We, therefore, call on the visualization community to monitor current socio-linguistic changes.** We particularly argue for the application of such towards understanding the epimistic impacts caused by LLMs.

This paper discusses the possible impacts of Large Language Models (LLMs) on linguistic diversity and semantic shifts in particular, emphasizing the need to visually examine these changes to understand their epistemic impacts. We present the first comprehensive review of techniques for visualizing semantic shifts, identifying established methods for capturing such language dynamics to tackle discussed challenges. Our contributions include a discussion of previous works on semantic change and the epimistic impact of LLM usage converging into three theories. This work provides a foundation for leveraging visualization to mitigate LLM-induced semantic erosion and promote language-preserving modeling.

1 How do LLMs drive Semantic Change? On the Interdependency between Semantic and Language Models

Semantic Models are human, subjective, and adaptable. Mental models, as described by Jones et al. [29], are personal, internal representations of external reality used for interaction with the world essential for reasoning, decision-making, and filtering new information. As a subpart, semantic models represent our understanding and use of language being subjective, shaped by an individual's background, experiences, perceptions, and the applied context. For instance, a car is conceptualized differently by a mechanic compared to a driver, just as the meaning of words can vary between individuals based on their unique experiences. In Human-Computer Interaction (HCI) research, it is noted that mental models evolve through system interaction [42]. Similarly, our mental model of language evolves with learning and experiences. Early education builds foundational models of semantics and syntax, which are continuously updated. Acquiring a second language as an adult extends this model, contrasting with pre-existing knowledge.

Semantic change is influenced by context, cognition, and society. Semantic change, a key area in linguistic evolution, involves the transformation of word meanings over time due to cognitive, social, and contextual factors as depicted in Figure 1. This process is driven by socio-linguistic motivations as presented by Tragott [52]: metaphorization, metonymy, pejoration, and subjectification. **Metaphorization** transfers meaning based on perceived similarities between concepts, creating new, often abstract, meanings. For example, "doughnut" metaphorically describes an inept person, using the concrete image to convey incompetence [22]. **Metonymy** shifts meaning based on associative links; For example "Number 10" representing the British Prime Minister, where a part (the address) stands for the whole (the office and its occupant) [26]. **Pejoration** (and melioration) alter a word's connotation towards more negative or positive meanings, respectively. "Silly," which originally meant "blessed," now connotes "foolish" [26], while "rude" has shifted from "unmannered" to "attractive" in certain contexts [10]. **Subjectification** involves meanings becoming more subjective over time, influenced by personal perspectives. The term "very" transitioned from meaning "true" to its modern function as an intensifier, exemplifying this mechanism [52]. Subjectification suggests meanings tend to become more subjective, reflecting broader cognitive and social trends [19]. These mechanisms interact, reflecting the complex interplay between cognitive processes and linguistic contexts within society.

Similar to discussed societal factors, we believe that the increasing use of LLMs drives semantic change. To the best of our knowledge, there are few studies apart from initial indications as discussed in Section 1. The following section presents three theories as depicted in Figure 1 on the impact of LLMs on semantic change grounded by further, initial indications:

Theory 1: Recontextualization
Large language models generate textual outputs that make learned forms of language accessible to diverse contexts. LLMs can simulate various text styles and contexts, which could foster the dissemination of semantic concepts. By generating text that introduces new terms or repurposes existing ones, LLMs contribute to the evolution of our conceptual framework.
Observations suggest that LLMs have played a critical role in the spread and normalization of terms like "delve" by disseminating and recontextualizing them [11]. Further, Radford et al. [46] demonstrate how LLMs can generate contextual text that popularizes new terminology. Brown et al. [7] as well as Floridi and Chiriatti [12] discuss the extensive capability of models to adapt and introduce new language patterns in social networks.

Theory 2: Standardization
LLMs, through their widespread use, can lead to the standardization and homogenization of language. The general use of models without variations or tuning can impose uniform language patterns, potentially stifling linguistic diversity and creativity. Caines et al. [8] highlight that uniformity of LLM text generation can lead to a loss of regional dialects and unique linguistic expressions. This standardization can contribute to a homogenized language framework by reducing the richness of linguistic variation.
Studies confirm that our language runs the risk of being standardized towards linguistic convergence reducing linguistic diversity. Bender and Koller [4] discuss how the widespread use of uniform LLMs can suppress linguistic variation. Prabhu and Birhane [45] highlight concerns over the loss of cultural and regional linguistic nuances due to LLMs' homogenizing effects.

Theory 3: Semantic Dementia
The extensive use of LLMs can lead to the phenomenon of Semantic Dementia. Semantic Dementia refers to the gradual degradation of language quality caused by LLMs propagating biased, erroneous, or oversimplified models. This process can provoke semantic changes by provoking inaccuracy within the conceptual framework. The phenomenon emerges when LLMs generate misleading language patterns of word meanings and their usage.
Studies by Prabhu and Birhane [45] highlight the risks of training LLMs on biased data, potentially perpetuating inaccuracies. Vincent and Hecht [53] discuss how the propagation of oversimplified models by LLMs can erode nuanced terminology, particularly in scientific discourse, leading to the misuse of precise terms and thereby reducing communication effectiveness. Demonstrations of semantic dementia are provided by recent studies of LLM translations [1, 57] and cultural awareness [36].

			Corpus					Language							Detection Method						Visual Approach			Semantic Shift								Visualization														
															Conceptual			Contextual																												
Author	Citation	Year	Google Ngram	COHA	TIME	Other	Temporal Interval	English	German	Dutch	French	Spanish	Chinese	Others	Co-Occurence	Static Embeddings	Dynamic Embedding	Contextualized Embed.	Topic Modelling	Contextual	Frequency	Embedding	Context	Top Similarity Words	Word Re-Occurence	Similarity Degree	Continuity	Metaphorization	Metonymy	Pejoration	Subjectification	Change Visible	Motion Component	Interactive	Versatile	Scatterplot	Line Chart	Bar Chart	Heatmap	Word Cloud	Graph	Projection	Tabular View	Extra	Detection Focus	Visualization Focus
Hilpert and Gries	[23]	2009			●		1920-2000	●							●						●							●							●	●	●							Dendrogram, Screen Plot	●	
Rohrdantz et al.	[47]	2011			●		1987-2007	●							●				●	●			●	●	●	●	●	●	●			●			●	●	●									●
Wijaya and Yeniterzi	[54]	2011	●				1500-2008	●	●		●	●	●	●	●				●			●	●	●	●		●	●	●	◐		●			●		●				●				●	
Heylen et al.	[22]	2012				●	1999-2005			●					●				●			●	●	●		◐			◐			◐	◐	●	●	●								Motion Chart		●
Odijk and Santucci	[43]	2012					1800-1994			●											●			●				●	●					●	●			●						RadViz		●
Kim et al.	[31]	2014	●				1850-2009	●								●							●	●	●	●	●	●	◐			●			●		●						●		●	
Jatowt and Duh	[27]	2014	●	●			1810-2009	●							●	●			●	●			●	◐	●	◐	●	●				●			●		●		●				●			●
Hilpert and Perek	[24]	2015		●		●	1810-2009	●							●	●					●	●	●	●				●				◐	●	●		●								Motion Chart		●
Xu and Kemp	[56]	2015	●				1890-1999	●							●						●	●	●	●	●			●	◐		◐	●			●			●				●			●	
Theron and Fontanillo	[51]	2015				●	1732-2001					●													●		●				●	●		●										Parallel Coordinate Plot		●
Kulkarni et al.	[33]	2015	●			●	-	●							●	●					●	●	●	●	●		●	●			●	●			●		●					●			●	
Hamilton et al.	[20]	2016	●	●			1800-1999	●	●		●		●		●	●						●	●	●	●			●				●			●							●			●	
Frerman and Lapata	[13]	2016				●	1700-2010	●							●	●			●	●			●	●	●		●	●	●	◐	●	●			●			●					●	Stacked Bar Chart	●	
Martinez-Ortiz et al.	[39]	2016				●	1950-1990			●						●					●	●	●	●	●		●	●				●		●	●						●			Stream Graph, Network Graph		●
Benito et al.	[5]	2016				●	-		●												●							●					●	●				●								●
Mahmood et al.	[37]	2016				●	-	●								●						●	●	●				◐							●	●								Story Lines		●
Xu and Crestani	[56]	2017			●	●	1900-200	●								●							●	●	●	●	●	●	●			●			●				●	●						●
Bamler and Mandt	[3]	2017	●				1850-2008	●									●						●	●	●	●	●	●	●			●			●		●								●	
Rudolph and Blei	[49]	2018				●	1858-2015	●									●					●	●	●	●		●	●	◐			●			●		●					●	●		●	
Rosenfeld and Erk	[48]	2018	●				1900-2009	●									●						●	◐	●	●	●	●	◐		●	●			●		●								●	
Yao et al.	[58]	2018			●		1990-2016	●									●					●	●	●	●		◐	●	●		◐	●			●							●			●	
Jatowt et al.	[27]	2018	●	●			1600-2010	●							●	●				●	●		●	●	●	●	●	●	●			●		●	●		●			●				Tree		●
Hellrich et al.	[21]	2018	●	●		●	-	●	●						●	●							●		●	●	●		●	●		●			●		●									●
Giulianelli et al.	[15]	2020					1910-2009	●										●					●		●		●		●			●			●			●						Stacked Bar Chart	●	
Martinc et al.	[38]	2020				●	2011-2019	●						●				●					●	◐		●	●		◐		◐	●				●	●								●	
Hofmann et al.	[25]	2021				●	2000-2020	●									●	●				●			●	●			●		●	◐			●						●				●	
Li et al.	[34]	2021				●	1800 - 1950	●								●						●		●	●	●	●	●	●			●			●		●				●				●	
Gruppi at al.	[18]	2022				●	-	●	●					●		●						●		●					●			●		●	●	●										●
Kazi et al.	[30]	2022				●	1970-2020	●								●							●	●	●	●	●	●	●		●	●		●	●		●	●		●	●			Spiral Line Chart, Radial Bar Chart		●

Table 2: Our review analyzes techniques for visualizing semantic changes. We extracted information on the corpus, temporal interval, language, detection method, visual approach, semantic shift, and applied visualization techniques. Our findings indicate that embedding-based techniques are most effective for visualizing the impacts of LLM usage, though further approaches are needed to explain upcoming changes.

The continuous development and fine-tuning of LLMs through iterative improvement mechanisms can further impact semantic change. As LLMs evolve through training and feedback, their internal representations and outputs also change, reflecting and influencing linguistic trends. This iterative process can further support shifts in word meanings and usage patterns. By adapting to new data and refining their outputs, LLMs continuously align with evolving language norms, thus playing an active role in shaping and being shaped by semantic change [8, 52].

2 How can we detect Semantic Change?

This section introduces key approaches to the computational detection of semantic shifts, focusing on two primary categories: **conceptual** and **semantic** methods. Collecting those techniques, we are further able to monitor upcoming changes in our linguistic, conceptual framework.

Conceptual methods include approaches such as co-occurrence analysis and neural embeddings. One subpart is co-occurrence-based approaches that identify frequently co-occurring words. By capturing textual distances, co-occurrence matrices map relationships between word pairings. More recent methods use **static neural embeddings** representing words as numerical vectors with distances reflecting semantic similarity [31]. In contrast, **Dynamic word embeddings** are generated by continuous training to capture temporal information without splitting data into discrete temporal bins. This allows its adaption and evolution over time thereby reflecting the dynamic nature of language. According to Bamler and Mandt [3], the method generates more accurate embeddings for conceptualizing semantics.

Contextual methods focus on identifying changes in the meanings of words using techniques such as topic modeling, clustering, and contextualized embeddings. Traditional **Topic-based models** apply algorithms like Latent Dirichlet Allocation (LDA) [6] to group words into clusters based on their co-occurrence patterns. These clusters represent thematic areas, tracking the topics associated with the word in different periods. Further, there exists a variety of **further contextual models** to cluster context information to detect and model word senses in text [27]. Present approaches use **Deep contextualized embeddings** to capture both the individual meanings of words and their context within sentences. Techniques like those by Giulianelli et al. [16] use pre-trained language models to generate these embeddings. The transformer architecture processes each word while considering its surroundings, resulting in embeddings of higher informativeness inheriting relations between a word to its given context.

3 How can we visualize Semantic Change?

We provide the first review of existing methods for visualizing semantic shifts to motivate future developments. We bridge insights from NLP and Visual Analytics collecting approaches for Semantic Change visualizations.

Survey Methodology - A literature survey was conducted finding seed papers via Google Scholar and ConnectedPapers, identifying 45 papers on visualizing semantic shifts, with 29 meeting the inclusion criteria. These studies, spanning IEEE Transactions on Visualization and Computer Graphics (TVCG, including IEEE VIS proceedings) and Computer Graphics Forum (EuroVis and EuroVA), were selected for their relevance to both visualization and linguistic perspectives. We focused on publications from the past 15 years (2006 to 2023), complemented by snowball sampling.

Next to discussed semantic detection methods and aspects of semantic shifts, we extracted the used input data in terms of corpus, language, and temporal span of the studies as relevant parameters. Drawing from both fields, NLP and VA, we distinguish between linguistic and semantic focus for reviewing the used visualization techniques.

Techniques

We present the revised techniques, categorized into frequency-based, embedding-based, and context-based visualization methods:

Frequency-based visualization techniques leverage word usage frequency over time to identify semantic shifts. **Dendrograms** by Hilpert and Gries [23] use variability-based neighborhood clustering (VNC) to detect stability and change, highlighting relevant semantic shifts.

Bar charts by Odijik and Santucci [43], Benito et al. [5], and Xu and Kemp [56] visualize word frequency over time, aiding detection when combined with other techniques. **Motion charts** by Hilpert and Perek [24] dynamically represent word frequency in a semantic vector space. **Stream graphs** by Martinez-Ortiz et al. [39] show term frequency with varying stream widths over time. **Line charts** by Kulkarni et al [33], Theron and Fintanillo [51] and Jatowt et al. [27] plot word frequency, often integrated into temporal word clouds for context.

Embedding-based techniques visualize semantic changes through word embeddings in a semantic space. **Scatter plots** by Heylen et al. [22] and Martinc et al. [38] illustrate semantic distances and relationships over time. Gruppi et al. [18] present SenSE, comparing semantic differences across corpora. **Projections** using PCA and t-SNE, applied by Xu and Kemp [56], Kulkarni et al. [33], Hamilton et al. [20], and Yao et al. [58], visualize word trajectories and contextual relationships in a lower-dimensional space. **Graphs** by Wijaya and Yeniterzi [54] and Li et al. [34] model semantic changes using topic models, representing senses as nodes and their co-occurrence frequencies as edges. Martinez-Ortiz et al. [39] use graph visualization in ShiCo, relating words within semantic spaces of different periods while Hofman et al. [25] analyze social and temporal dynamics.

Content-based techniques visualize word context to identify semantic changes. **Bar charts** by Frerman and Lapata [13] and Giulianelli et al. [16] use stacked bars to show context evolution over time. Kazi et al. [30] propose radial bar charts for similarity within time periods. **Line charts** by Rohrdantz et al. [47], Wijaya and Yeniterzi [54], and others [3, 21, 31, 34, 48] plot cosine similarity and context density, revealing temporal semantic shifts. Li et al. [34] aggregate contexts to show average change over time. **Table views** by Kim et al. [31] and Rudolph and Blei [49] list similar words at different times. **Word clouds** by Xu and Crestani [55], Jatowt et al. [28], and Kazi et al. [30] size words by similarity, displaying semantic associations. **Heat maps** by Jatowt and Duh [27] and Xu and Crestani [56] show context similarity over time, with color indicating the degree of similarity.

Discussion

This section evaluates the applicability of techniques formerly introduced, focusing on their effectiveness in detecting and visualizing semantic changes. The summarized findings are detailed in Table 2.

We find that the studies use different text corpora, including Google Books Ngram, the Historical American English Corpus (COHA), and the TIME Magazine Corpus. Some studies find that word developments vary depending on the text corpus used showing strong dependencies on the actual input data. While Google Books NGram proves to be the most comprehensive entity, one needs to extend the input at least towards typically applied areas of LLMs such as text generation for scientific publication or social media as that field. Most studies focus on English, with some exploring semantic changes in other languages. As formerly discussed, the area of automatic translation is prone to trigger Semantic Dementia. Future work should consider the extension towards multi-lingual approaches. Frequency-based techniques, such as **dendrograms** [23], **bar charts** [5, 43], **motion charts** [23], **stream graphs** [39], and **line charts** [27, 33], proof to be quite basic but useful for identifying periods of rapid change in word frequency but appear to ineffective when used as a stand-alone visualization approach. These methods are best combined with other techniques for a comprehensive overview and also finding more complex patterns of LLM - while standardization might be highlighted, recontextualization and semantic dementia might be overlooked due to the simplistic approaches. Embedding-based techniques, including **scatter plots** [18, 22, 37, 38], **projections** [20, 33, 55, 58], and **graphs** [25, 34, 39, 54], capture semantic relationships and their changes over time. These methods are powerful for exploring the direction of semantic change, allowing visualization of both broad and specific similarities in meaning. They require dimensionality reduction or vector space representation, making them suitable for analyzing semantic shifts in a high-dimensional space. Given the complexity and richness of embeddings, these techniques are particularly relevant for LLM-driven semantic change detection and have the potential to display recontextualization of semantics. Content-based techniques focus on visualizing the context associated with a word to recognize changes in meaning. **Bar charts** [13, 15, 30], **line charts** [3, 21, 31, 34, 38, 47, 48, 54], **table views** [31, 49], **word clouds** [27, 30, 55], and **heat maps** [27, 55] provide insights into how the contexts of word usage evolve over time. These methods help identify the emergence of new meanings or the decline of old ones, offering the possibility to reveal patterns of semantic dementia.

We further find a variety of visualization techniques applied for visualizing semantic change. Besides more usual methods such as scatter plots, line - and bar charts, rarer visualizations are applied such as motion charts [24] or storylines [37]. While metaphormization and metonymy proofs to be well covered by existing approaches, pejoration appears to be more represented in the related field sentiment visualization.

In general, we find that embedding-based techniques will be crucial for understanding the impacts of LLMs on semantic change. These methods provide detailed and accurate representations of semantic relationships and their evolution over time. Scatter plots, projections, and graphs effectively capture the dynamics of semantic change, reflecting both broad trends and specific shifts in language usage [18, 22, 34, 38, 54, 55]. Also, we rarely find actual dashboards applied towards a more detailed investigation. By that, the highlighted change often lacks context as is discussed in the context of the publication but not actually demonstrated by inherent visualizations. We believe the still-growing impact and continuous development of LLMs will further impact semantic change. Therefore, novel, custom visual approaches are needed for not only monitoring semantic changes but also for explaining how these changes happened in tracing back sources toward the actual origins to distinguish sociological from technical impact. As LLMs evolve through updates feedback, their internal representations and outputs also change, reflecting and likewise influencing linguistic trends. This iterative process can lead to shifts in word meanings and usage patterns and resolve in interdependency effects. LLMs can continuously align with evolving language norms, thus playing an active role in shaping and being shaped by semantic change - examining such alignments will be the task of the Visual Analytics community not only showing these changes but also explaining and retracing them as a first step towards model validation.

4 Conclusion

This paper discusses the growing impact of Large Language Models (LLMs), emphasizing the need for monitoring semantic change to detect possible influences of **(T1) recontextualization**, **(T2) standardization**, and **(T3) semantic dementia** resulting from the interdependency between mental models and language models. We find that embedding-based techniques will be crucial for understanding the impacts of LLMs on semantic change. These methods provide detailed and accurate representations of semantic relationships and their evolution over time. Techniques like scatter plots, projections, and graphs effectively capture the dynamics of semantic change, reflecting both broad trends and specific shifts in language usage [18, 22, 34, 38, 54, 55]. However, the lack of comprehensive dashboards in current approaches limits the contextual understanding of these changes. We believe the ongoing impact and continuous development of LLMs will further influence semantic change. Therefore, novel, custom visual approaches are needed not only for examining semantic changes but also for explaining the origins and tracing the sources of these changes. Distinguishing sociological from technical impacts will be essential. As LLMs evolve through updates and epistemic feedback, their internal representations and outputs change, influencing and reflecting linguistic trends. The Visual Analytics community will play a vital role in monitoring these alignments, not only showing these changes but also explaining and retracing them as a step toward model validation. Future research should prioritize embedding-based visualizations and develop interactive visualization tools that adapt to new data, particularly in the context of LLM applications, to offer insights into current language evolution.

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