Human Intelligence and Value of Machine Advancements in Cognitive Science A Design thinking Approach

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Abstract – Latent Semantic Analysis (LSA) is an approach used for expressing and extracting textual meanings using statistical evaluations or modeling applied to vast corpora of text, and its development has been a major motivation for this study to understand the design thinking approach. We introduced LSA and gave some instances of how it might be used to further our knowledge of cognition and to develop practical technology. Since LSA's inception, other alternative statistical models for meaning detection and analysis in text corpora have been created, tested, and refined. This study demonstrates the value that statistical models of semantics provide to the study of cognitive science and the development of cognition. These models are particularly useful because they enable researchers to study a wide range of problems pertaining to knowledge, discourse perception, text cognition, and language using expansive representations of human intelligence.

Keywords – Latent Semantic Analysis, Human Cognition, Human Intelligence, Statistical Models, Working Memory, Design Thinking, Man and Machine.

I. INTRODUCTION

Understanding the development of human intelligence within an adaptive context is crucial because it suggests that the foundations of complex cognitive design skills lie in the architecture and function of the vertebrate brain. Evolutionary innovations are the result of natural selection and are based on the pre-existing structure of the brain. This is not like new building blocks that appear by magic; instead, enhancements and adjustments are made to the pre-existing framework. Therefore, we may discover that the system we are employing for one cognitive performance has little resemblance to its initial building blocks. The left hemisphere dominance, for instance, may have been extended to support the grammatical building block underlying language function, since it is responsible for creating regular, goal-oriented sequences of motor movements. On the other hand, it is possible that the right hemisphere dominance that was developed to help humans escape environmental dangers has been expanded to aid in the complex emotional processing inherent in contemporary human social cognition (e.g., in press).

Humans and other animals' lateralized motor functions give a novel approach to studying the development and origins of cognition across and within species in the context of a common evolutionary past. Higher cognitive capacities in humans scaffold, construct upon, and bootstrapping early perceptual and motor capacities, which are driven by brain lateralization of function. However, ontogeny does not literally repeat phylogeny (the development of the species). In humans, the most fundamental cognitive processes are those involved in basic sensory and motor activities. (See **Fig 1**). A common theme in theories of human intelligence is that humans rely heavily on their Working Memory (WM) systems [1] to store and manipulate information. There is not a single WM model that everyone agrees on, but we do know that they all need to handle a few critical problems. One of the most important is the fact that there is a restriction on how much information can be kept in mind at once, while there are also constraints in processing power that are unique to certain modalities (such as verbal and visual-spatial information). Information actively preserved in WM primarily influences the subsequent set of cognitive processes to be undertaken, which is why the idea of WM is very intimately related to the executive control functions of cognition (e.g. the role of WM in the ACT-R model).

Memory-scanning tests, short-term recall tasks, and the N-back task are just few of the many that have been used to explore SD's impact on WM because to its essential role in explaining human performance. In addition to maintaining and manipulating information in WM, the process of acquiring new pieces of data and making decisions in response to new information may have a significant impact on overall performance across all WM activities. Decreased performance on such tasks may be indicative of Working Memory (WM) issues, but only if the individual examines the task's constituent parts and uses performance indices that separate out the processes of interest.

Using a memory-scanning task similar to the ones used in Sternberg's classic experiments, we can readily show the task impurity issue in WM tasks. Several research examining the impact of SD on WM have employed variants of this test. In the Sternberg task, the participant's memory is tested by presenting them with a set of stimuli—typically a string of numbers or letters—whose size varies between trials. A probing stimulus is shown after the memory set has been hidden from view. The goal is to rapidly determine whether the probe item is part of the memory set. The RT of the task develop in a linear manner with the dimensions of the memory set. The efficiency of scanning WM may be quantified using a pretty clean metric, the slope of the RT function in relation to set size. However, the time it takes to encode the probe, make a choice, and execute the reaction are all included in the total mean RT on Sternberg trials. However, a number of the studies that have been used to support the claim that SD negatively affects WM either did not adjust set size or employed a control condition in which stimulus encoding and memory load differed among conditions.

In order to get a better understanding of the human mind, scientists often analyze our written communication. Modern tools provide researchers the ability to analyze dialogue on massive sizes, making it easier to accomplish these goals. Large linguistic corpora (collections of written text) are analyzed using statistical models in order to determine the text's meaning and, by extension, to get insight into the human mind. All of these pieces share the premise that writing is a window into human intelligence. Scientists are able to extract insights from texts and, as a result, investigate numerous elements of the human culture and mind that emerge in language thanks to the availability of large text corpora and the development of computer approaches for analyzing these corpora. This issue of topics is mostly focused on defending the use of corpus analytical methods for studying thought.

Latent Semantic Analysis (LSA) is a fundamental approach for using statistics to infer meaning from text. Basic information regarding LSA and some instances of its usage in elucidating the nature of cognition and advancing applied technologies were presented by [2]. With LSA, we may infer a word's meaning by looking at who else uses it in big collections of texts; this is a revolutionary approach. Sentence meanings, paragraph meanings, and document meanings are all collections of word meanings. Specifically, provided a wide-range text corpus with numerous documents, a matrix is structured to display the words' context. In order to understand the meaning of a word, it must be placed in the larger whole of the text, sentences, or paragraph in which it appears. The definition of a phrase or word is the vector, which represents a 1D value array of different texts in which that word or phrase occurs.

The majority of words appear in a small number of documents, making this a sparse matrix, but the high number of terms present in a wide range of documents gives it a big size. This allows the matrix's hidden features to be revealed via reduction. To do this, LSA employs Singular Value Decomposition (SVD) and reduces the dimensions such that the matrix has hundreds rather than thousands of elements [3]. This procedure generates a high-dimensional LSA space in which each phrase has a specific position. Cosine similarity measures between words or word sets reveal their degree of relatedness. When the cosine between two words is large, it means that they are highly connected to one another. To deduce the meanings of words, phrases, and texts, we must first discover the hidden connections between them.

Since its inception, Latent Semantic Analysis (LSA) has proven to be an invaluable tool for scholars seeking to get a deeper grasp of a variety of theoretical concerns pertaining to meaning and for scaling up theoretical discoveries to practical tasks. But LSA is not the only topic we will be covering in this edition of Topics. In this article, we will explore possibilities beyond LSA. The highlighted papers in this section discuss novel applications of LSA, in addition to additional mathematical and computational techniques that are at least as effective as, and in some cases beyond, LSA. Instead of reiterating LSA's many applications, we want to highlight how recent studies have expanded beyond LSA's original scope. The remaining part of this article is organized as follows: **Section II** presents a review of the statistical semantic models, which **Section III** focuses on a comparison of the semantic models. In **Section IV**, an improvement of the semantic models is described. **Section V** focuses on a discussion of embodiment and representation of knowledge. **Section VI** presents a discussion of textual meanings. Lastly, **Section VII** draws a conclusion to the article.

II. STATISTICAL SEMANTIC MODELS

The [4] have been developing statistical models of semantics for more than fifty years. However, advancements in technology allowed the discipline of semantics to expand into higher dimensional spaces and process larger data sets. The upsurge in interest in and implementation of statistical modeling of semantics may be traced back to LSA, which was driven by these technological developments. Aside from its theoretical successes, LSA was also quite useful in practice. Despite its evident usefulness and effectiveness, LSA and other semantic model development and improvement efforts have received significant academic attention. This goal is addressed in most of the pie5ces included here. Semantic models have proliferated over the last several decades, thus there is a wide variety of them that can (roughly) correctly extract meaning from text. The [5] offer nine distributional models of semantic statistics as illustrated in **Fig 2.**

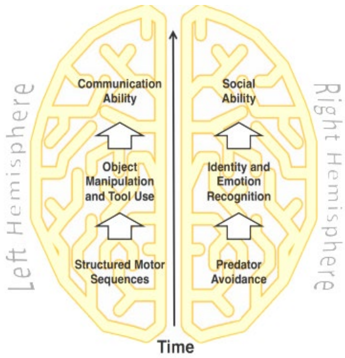

Fig 1. Representation of the Left and the Right Hemisphere

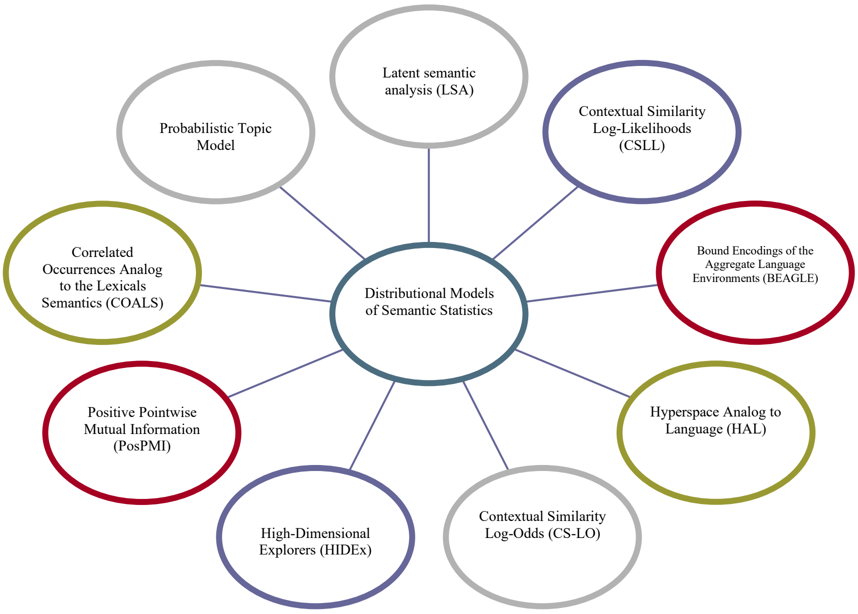

Fig 2. Distributional Design Thinking Models of Semantic Statistics

Bound Encoding of the Aggregate Language Environment (BEAGLE) describe three additional models: (i) Constructed Semantics Model (CSM), (ii) Vectorspace Model, and (iii) Sparse Nonnegative Matrix Factorization (SpNMF). In addition, [6] detail how they adapted the Temporal Context Model (TCM) used in the research of memory into their own method of semantic modeling called the predictive Temporal Context Model (pTCM). There are two more categories that may be used to categorize semantic models; these are context phrase and contextual area. The first category differs from the second in terms of the type of matrices it employs. Term-by-term (Word-by-word) matrices are used in context word models, with the matrices being created by a "moving window" method. The scope of the page is narrowed down to only the words around the search term.

The matrices are made up of all the times the same word appears in a certain range (such two or more consecutive words). Models vary in terms of window size and whether or not the window takes into account both proceeding and following words. Furthermore, the co-occurrences of the terms are given varying weights (Co-occurrence matrices may be used to calculate weights, for instance, by multiplying them with a weight matrix). They could be assigned more or less weight depending on how close they are to the target words (HAL, COALS), how often they appear in the corpus (HIDEx), or the conditions under which they occur (condcoocc) (COALS, CS-LO, CS-LL, PosPMI). Using convolution, BEAGLE compresses the n-gram information that is used to capture syntactic (word sequence) and semantics (context) data, making it comparable to other contextual word frameworks.

The Vectorspace framework, LSA, Topics, pTCM, CSM and SpNMF, are just a few of the context area models that make use of term-by-document (or word-by-context) matrices. In frameworks e.g., Vectorspace, the Latent Semantic Analysis, and the SpNMF, contexts of words represent texts in which is tends to occur; as was discussed before, this document might be a single phrase, a paragraph, or the full text. Context is determined by latent themes extracted from the corpus in the Topic model. The likelihood of each document's topics and the words that make up each topic are both distributed uniformly. Vector representations of words are weighted in LSA and SpNMF in a manner similar to that used in the Vectorspace model; this weighting technique involves multiplying the vectors by the occurrence of word and its logs within texts and scale in IDF (Inverse Document Frequency) to provide more weight to more significant terms while giving less weight to more frequent ones (as a result, they have fewer identifying details). The LSA method used SVD to collapse matrices down to their latent dimensions, which was a departure from the Vectorspace concept. In contrast to other models, SpNMF can only store positive numbers.

In contrast to existing models of the context area, the CSM model employs retrieval processes rather than dimension reduction methods. Modeling of episodic memory retrieval in CSM is taken from the MINERVA 2 framework. For this reason, we may define the content of our recollections of past events as feature-based representations, which are then kept as discrete traces or episodes. Each occurrence or object is represented in the database as a vector of values linked to features, each of which is assigned a probability value or learning rate. Rules of matching based on similarity and prior probability are essential to the retrieval process. CSM determines semantic similarity by measuring the degree to which a probe vector resonates with the context vectors. The final result is influenced more by the context vectors that have a higher resonance with the probe. CSM is unique among distributional models since it is an iterative training algorithm in which the representation is modified as the sequences of words is provided.

Similar incremental improvements are made to the representation in the pTCM proposed by [7]. pTCM is a model of episodic memory that builds on TCM. Time Context Memory (TCM) is a decentralized memory framework that defines how past events influence present-day recall (word-list memorization is a common cognitive skill). TCM offers an explanation for memory phenomena like primacy and recency that does not rely on co-occurrences but rather on processes linked to contextual retrieval and contextual drift. This is because TCM, like LSA, makes assumptions about the influence of context on learning and memory. In order to anticipate the next word to be given, pTCM frameworks semantic memory by accumulating the semantic representations of previously presented items and utilizing that weighted total as a cue. To determine a word's semantic representation, we use the mean of the predictions made before we ever see the word. Unlike traditional semantic memory models, which use a single, comprehensive representation of a text, this one builds its representations progressively over time (the model takes a while to execute, which is an inconvenience). When it comes to finding pairs of words that have similar meanings, the pTCM model does just as well as LSA, as shown by [8]. The model's use of an episodic memory framework is an obvious strength, and the results of this investigation show that similar structures may be put to work for both types of memory storage (episodic and semantic), but the length of time needed to run the model is a limitation (see also the BEAGLE model).

Xie, Wang, Li, Lai, and Pei's deep generative model is repeatedly trained and is motivated by cognitive models, much like the other semantic concepts mentioned in [9]. The nonlinear, multilayer model described and evaluated by Hinton and Salakhutdinov produces binary codes that may be used to characterize the meaning of texts. When training a model, a Restricted Boltzman Machine is used to iteratively create the model's bottom layers, which are hidden layers with distributed representations. Once a layer's features have been learnt, those vectors are sent into the next hidden layer to be trained. Through repeated training, an encoder network is developed that efficiently encodes the word-count vectors. Aftermath, the word count vector is transferred to RBM (Restricted Boltzman Machine) that operates as a network of a decoder to restore the original values and form a multilayer autoencoder network. The result is refined repeatedly using backpropagation solution, a gradual method of education. In contrast, after solutions have been learned, retrieval speed is quite high, considerably higher than with approaches like LSA. With big data set, it is possible to see this difference. Iteratively feeding the fresh data into the network allows the machine to keep learning. This method would be ideal for dealing with massive corpora like the one housed in the Wikipedia. While adding additional data during training would slow things down significantly, subsequent retrieval based on meaning would be lightning quickly.

III. COMPARING SEMANTIC MODELS

As scientists work to refine computer models of semantics, one open challenge concerns how to best describe meaning and cognition. Among the research presented here are two that tested different models' abilities to explain certain types of mental activity. Maslak, University of Wolverhampton, UK, Mitkov, and University of Wolverhampton, UK in [10] evaluate the accuracy of six models in determining paragraph similarity (CSM, Vectorspace, Topic-JS, Topic, SpNMF, and LSA). One model that employed the cosine between phrase frequency vectors was found to perform the best of all the ones tested. In other words, the model that relied on the overt, non-concealed representation of the text came the closest to accurately reproducing human assessments of paragraph similarity. Latent models, however, fared better when trained on more limited, topic-specific corpora. Limiting the scope of available information helps keep the knowledge base clean from the contamination of words with various meanings in different settings. For example, most predictive methods of semantics would extract all interpretations of words, yet individuals can quickly determine that "bank" has a monetary sense. The issue of obtaining numerous meanings of words that are likely unnecessary is therefore avoided in more concentrated, topic-specific settings.

The capacity of models to capture semantic clusters was compared to human evaluations of concept characteristics by authors in [11]. They tested nine models and discovered that a context word model, COALS, did a better job of capturing the semantic clusters than any of the others. The success of the approach may be traced back to the way in which it uses conditional logic to account for word combinations. COALS is derived from HAL, but it lessens the weight of common terms like articles and articles that have no meaningful purpose in a sentence (e.g., the, a, that) in favor of less common words. The conditional co-occurrence rate is then determined (i.e., co-occurrence rates relative to those of similarly occurring terms). Specifically, COALS do this by square rooting the positive values in a correlation matrix and discarding the negative ones (to increase their weight). However, other models also account for the possibility of word pairs occurring by accident, and almost all models account for the frequency with which certain words appear, thus this argument for COALS' greater performance may not give a wholly persuasive explanation. That being said, it is still unclear why this model performed so well in this regard.

The [12] implementation of COALS lends credence to [13]'s observation that "words are like the people with whom they are most closely associated," implying, however, that this association is limited to immediate neighbors rather than all acquaintances. As a result, a lot of meaning may be gleaned from the co-occurrence of words in a given context (after accounting for randomness). The nonlatent word overlap model outperformed the other six statistical models, as determined by [14]. An essential question is whether or not meaning may be recovered just as effectively from the words themselves, or whether or not a latent or second-order representation is required.

IV. IMPROVING DESIGN SEMANTIC MODELS

When we compare semantic models, we get insight into what features of the models are most important for accurate meaning extraction. Supplementing statistical models with other approaches is another way to improve ways of extracting meaning from text. This is achieved by [15] by integrating the Topic model with subjective evaluations. They argue that employing corpus approaches to represent the learner's prior knowledge may improve models of the learning process. Since statistically computed connections may augment human-oriented concepts by refilling in errors and omissions, combining relevant data from databases and human data can demonstrate the relative significance of pre-existing knowledgebase and retrieved knowledge from texts.

The analysis performed with their output and the interpretation of the findings provides yet another opportunity for development. Multidimensional scaling (MDS) is used by Wang et al. to derive the representations generated by the LSA analysis, which might include flattening what could be hundreds of variables into a 2D representation. MDS (and related approaches) is useful since it shows how far off ideas are from one another. This method allows Louwerse to see the chronological and geographical connections between the texts. The MDS technique is also used by [16] to explain the composition of various conceptual groups. Clusters are ranked according to their resemblance to one another by their distance from one another; a cluster's height denotes its internal consistency; and its area reflects the amount of phrases included inside it. Thus, MDS may aid in providing supplementary data and interpreting hidden patterns in the data. This method has also been used by many other researchers. For example [17] used MDS in conjunction with LSA to probe the connections between various sections of a research contribution. In their research, MDS is employed as a statistical method for determining the distances between text portions and the groupings of related concepts within the text, similar to factor analysis and PCA.

Multidimensional Scaling (MDS)

As a method for representing the degree of similarity between examples in a dataset, multidimensional scaling (MDS) is a useful tool. In MDS, "information about the pairwise 'distances' among a collection of textstyle ntextstyle n objects or persons" is transformed into a set of textstyle ntextstyle n points in an abstract Cartesian space. In the context of data visualization, multidimensional scaling (MDS) refers to a family of ordination methods for representing distance matrices. Non-linear dimensionality reduction describes this method. In order to preserve the inter-object distances as much as possible, a Multidimensional Scaling (MDS) method uses a distance matrix that lists the distances between every pair in a set and a fixed number of aspects, N, to place each object in N-dimensional area (a lower-dimensional characterizations). The resultant points may be plotted on a scatter diagram for the values of N = 1, 2, and 3 as seen in **Fig 3**. James Ramsay of McGill University is widely recognized as the father of functional data analysis and made significant theoretical contributions to MDS [18]. The Republicans in the House are all denoted by red dots, whereas the Democrats are all denoted by blue dots.

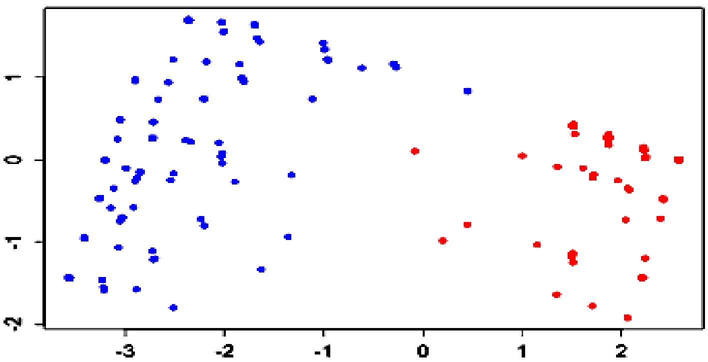

Fig 3. Use of Conventional Multidimensional Scaling to Analyze House of Representatives Vote Trends.

Latent Semantic Analysis (LSA)

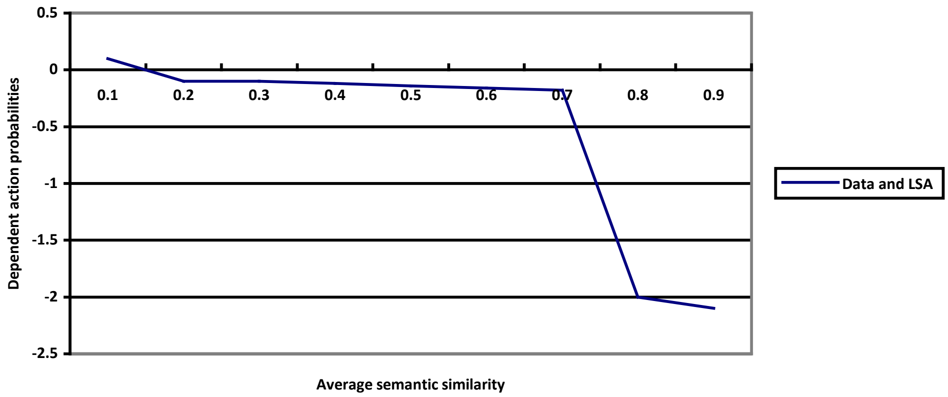

Fig 4. Conditional Response Probabilities and their Semantic Relatedness of Design Thinking for Data and LSA

Latent Semantic Analysis (LSA) is an approach that, such as HAL, uses investigations of huge corpora to produce a high-dimensional vector representation of text. To do a corpus-wide analysis of co-occurrence, however, LSA employs a predetermined context window (such as the text level). Singular value deconstruction, which is a factor analytic technique, is then used in the co-occurrence matrix to reduce the number of variables to a more workable level (typically 300 to 500). As a result of this dimensionality reduction, words that have similar meanings but are employed in different contexts end up sharing similar vectors. Even though the words "house" and "home" are often used combined with the word "roof," they are seldom used interchangeably in speech. However, in LSA, their vector representations would be quite similar. Vectors assigned to individual words in LSA may be added together to provide a sense of the significance of whole passages or sections of text. That means that a paragraph's meaning is equal to the total of the vectors of the words inside it. Larger units of text may be compared on this basis, including the meaning of individual words, paragraphs, and even whole works. **Fig 4 and Fig 5** represent Data and LSA and eSAM and LSA respectively portrays plots of dependent action probabilities vs. average semantic similarity (bottom).

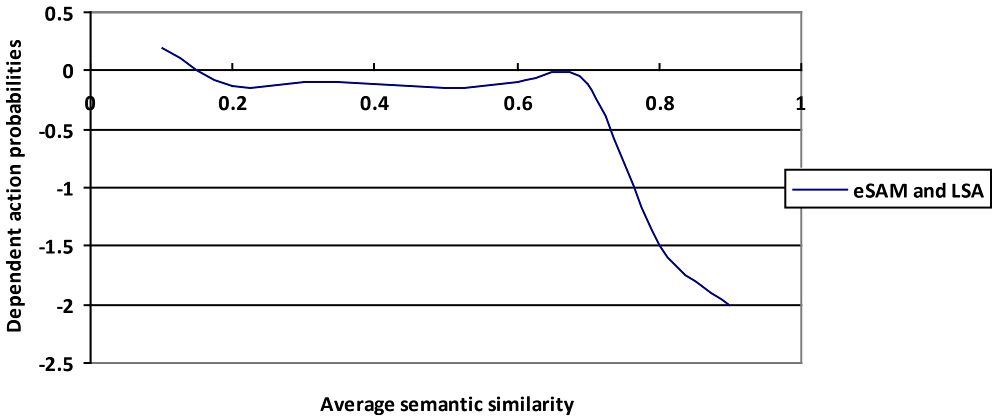

Fig. 5: Conditional Response Probabilities and their Semantic Relatedness of Design Thinking for eSAM and LSA

Free recall output order may be predicted using LSA or WAS (word association space) semantic similarity values. To ensure that each bin had an equal number of pairings, the distribution of pairwise semantic relatedness was binned (1,000 bins for WAS, 200 bins for LSA). We determined the average similarity value of recall the relative transitions between two words that fell into each bin and the likelihood of a recall the relative transitions between words with similarity values, which fell into each bin. Each bin's mean posterior distribution and similarity value are shown together with its collapsed classification into one of five similarity dimensions (less than 0.4-1, 0.3-0.4, 0.2-0.3, 0.1-0.2, 0.1).

From vast samples of language that toddlers and adults might have experienced to specialized domain corpora, such as those covering certain course subjects, LSA has been used to a wide variety of corpora. When applied to larger corpora, it generates a semantic representation of information that is broadly applicable, much like the broad knowledge that individuals accumulate over the course of their lives. When applied to domain-specific corpora, it produces a representation more like to that of domain experts. LSA has served as both a theoretical model and practical instrument for characterizing the semantic relatedness of linguistic units. LSA has been employed as a theoretical model to measure textual coherence and learnability by individual students, and its results overlap those of humans on conventional vocabulary and subject matter examinations, word sorting, and category judgements. LSA's vector form is flexible enough to be used in a variety of other theoretical frameworks. The Construction-Integration model is a symbolic connectionist framework for the study of language; it includes a representation for propositions based on vectors obtained from the LSA. LSA has been applied in a variety of contexts, including as a knowledge measurement tool, in information retrieval to better match user queries to relevant resources, and in automated discourse segmentation to better understand the relationships between different topics being discussed.

V. EMBODIMENT AND KNOWLEDGE REPRESENTATION

The senses, according to recent theories of knowledge representation, simulate the referent of a word in order to construct an internal model of that word's meaning. Several studies of sentence processing have lent credence to this idea, showing that readers create perceptual simulations of events that are modality-specific during reading and comprehension. For instance [19] found that people identified images of objects in certain orientations (such a pen held vertically) more rapidly if they had just read a statement that inferred a similar orientation for the photographed item (John inserted the pencil into the mug). Evidence in [20] suggests that readers also engage in mental motor reconstructions of the actions depicted in texts. Perceptual simulations are shown to contribute to conceptual object evaluations by [21]. Even though in their experiment just visually presented word stimuli were used, they found that a subjective simulation associated with various paradigms may still occur. Soap-perfumed was confirmed more rapidly by participants after they had verified another olfactory characteristic (musty, old book) than after they had validated a property connected to a different modality (television-noisy).

The preceding research shows that quick, accurate assessments also include perceptual representations. Perceptual simulations may have long-lasting effects on memory, however the evidence is limited. Such outcomes might be useful in elucidating the potential functions that perceptual simulations play in the cognitive process. These embodiment impacts in the tasks associated with language processing may be partly explained by the recent argument of [22] that linguistic features of word stimuli reflect embodied interactions in the environment. Thus, it is not easy to determine whether or not perceptual simulations have any cognition-at-large effects, or whether or not language representations also contribute specifically to embodiment effects. This research used perceptual simulations to test the hypothesis that linguistic properties of the word stimuli account, at least in part, for performance on instantaneous relatedness assessments and long-term memory for different words.

The term "spatial iconicity effect" was created by [23] to describe the observation that while making assessments of semantic relatedness, readers often resort to mental simulations based on the iconic geographical placements of words. In Experiment 1, participants made snap decisions about the degree to which they were semantically related to pairs of terms like "car-road" displayed either in a geographically iconic alignment (car on the screen's top and street on the bottom) or in a noniconic alignment (car on the bottom of the screen and street on the top) (the road is at the top of the screen, and a car is at the bottom). Participants' ability to make relatedness judgments more quickly whenever the words were displayed in an iconic configuration was seen by Saunders and Quinto-Pozos as proof that the respondents had created perceptual models of the usual spatial orientations of the words. This result has been seen in different contexts. When an item word was shown on the screen in a position that corresponded to its regular location in the environment (eagle on the top), participants made living-nonliving judgments more quickly than when the words were displayed in random positions (eagle on the bottom). Subjects' discrimination of a non-related target face (X or O) was impaired when the objective word (eagle) was centered on the screen, as opposed to the typical, iconic location of that term (i.e., top).

Authors of [24] reasoned that hearing the denotative term for an object would direct one's focus to the location where one could typically find it, so evoking a mental image of the thing being referred to. Given that the simulated object (an eagle) and X had few attributes, participants had to ignore the active but superfluous perception simulations in order to recognize the objective, which was X. This demonstrates that the iconicity of space associated with object terms affects not just language processing but also where one's focus goes. Memory encoding may be improved under focused attention, thus the object phrases presented in their usual context may be more deeply stored and, therefore, more easily retrieved, as has been proven in previous studies. The spatial iconicity effect may not be fully explicable by perceptual simulation alone. In general, writers argue, linguistic representations code data drawn from our sensory experiences. Response times improve when "car" shows at the screen's top and "road" shows at the bottom, suggesting that the order of these words is more similar to how they occur in normal conversation. Unlike the embodied explanation, which denies the existence of perceptual simulation, this one claims that language representations may be just as good as, if not better than, the latter at predicting performance in timed tasks. Indeed, the authors argue that prelinguistic, perceptive models of real world occurrences (such as the fact that a vehicle is often found at the road's beginning) impact our linguistic interpretations (e.g., word-order frequencies of cars-roads).

Due to the sequence in which a language is acquired, embodied interactions are written into language. In [25] reexamined the word stimuli created by [26] and discovered that the spatial iconicity of words is connected with their order in the stimulus. Their regression studies confirmed the findings of Swann, Daliri, and Honeycutt, which noticed that the word-order occurrence predicted the "spatial iconicity" impact in relatedness judgements more accurately than spatial iconicity alone. Furthermore [27] demonstrated that extracting geographically precise city locations from word co-occurrence within text corpora is possible. One of the aims of the current research was to reproduce [28] relatedness judgment results, for which we employed their paradigm and altered [29] analytic methodologies.

Perceptual simulation has been proven to affect not just immediate assessments but also the quality of episodic memories later on. In a property verification test [30] found that participants remembered an image of an item (apple) better after the name of the object was associated with a visual feature (apple is shiny) compared to after the name of the object was associated with a nonvisual attribute (apple-tart). When the feature of an apple was verified, a modality-specific simulations occurred (the portraying of a glossy apple), leading the authors to infer that the image of a shiny apple effectively stimulated the participants' recollections. In fact, the recognition memory gap between object names validated with visual vs. nonvisual attributes disappeared when the word (apple) was employed as the test item rather than the image. The [31] adapted paradigm to isolate the processes of text comprehension and image recognition. In the research phase, they discovered that people remembered more information when the photos' object orientations and shapes matched the sentence's indicated object orientations and shapes. This impact was seen whether the memory challenge was administered right away or after a 45-minute wait.

In computational semantics [46], there is a lot of interest in the function that embodied mental representations and simulated sensory experiences perform in cognitive processing. Most people understand that the environment and our bodies' capacities place limits on our experiences. In this way, our tangible world experiences mold our minds and the way we think. It follows that our mental representations of the environment and our experiences within it are often analog in nature, taking the shape of images. It has been stated that trying to define human cognition based on symbolic or quantitative abstractions is futile due to the fact that they ignore the vital role that embodiments serves in the conceptual process. Furthermore, there are many who argue that retrieving meaning from representation such as text is impossible since language, being vocal and representational, cannot offer an accurate depiction of human cognition. This extreme viewpoint has helped to spark discussion, which may be seen as a positive outcome. In addition, some academics try to push the limits of how far a basic model may go them by looking for "beautiful" models. Many things may be learned about the phenomena by testing the limitations of basic models.

However, most agree that both points of view have merit. Abstract, and symbolic, verbal reasoning and thought, as well as embodied and concrete representations, are all components of cognition, as is generally agreed upon by researchers and theorists. In simple terms, the idea that our minds can only use one type or the other to encrypted meanings is ridiculous. There are two literature works here that deal with this subject. In this book [32] evaluate the relative efficacy of two different approaches to representing semantic clusters: distributional and symbolic models (such as LSA) and feature-oriented models (which rely on subjective assessments of characteristics). Some researchers have proposed that feature-based models, which describe word insights based on their descriptive properties rather than solely symbolic, distributional models like LSA, better accurately portray perception and action in cognition. These characteristics are seen to more closely resemble sensory experiences, which are therefore thought to form a basic part of the meanings of words.

In [33] evaluate the nine aforementioned distributional models and compare them to feature-based models (i.e., BEAGLE, LSA, PosPMI, HIDEx, HAL, COALS, CS-LO, Topic, and CS-LL). Nine models are compared against human-generated norms on word characteristics to see how well they can extract semantic clusters. Using the TASA corpus as a training set, the first two investigations examined the models' performance in clustering words using WordNet's semantic class labels. They were compared to the McRae aspect standards for lexical items in the first experiment and Wu, Motamed, Srivastava, and De la Torre's feature standards for adjectives and verbs in the second. The third study used semantic categories from the MacArthur-Bates Expressive Developmental Questionnaire to assess the performance of classifiers on the CHILDES dataset of caregivers language (adult statements to toddlers, 12-48 months).

Several models were shown to be competitive with human-based feature norms across all three investigations conducted by [34]. In contrast, COALS was the most reliably determined to be on par with the feature-based standards when it came to recreating semantic classes across datasets. Nonetheless, they came to the conclusion that the stipulations pertaining to distribution and features were not redundant. Distributed models were good at identifying events and contexts, but they were less sensitive to sensory details e.g., texture or color. However, the distributional framework’s capacity to potentially leverage language cues in languages was comparable to that attained by feature standards (produced by humans). This study suggests that a distributional strategy combined with human-derived norms may provide better results. This study shows that statistical algorithms can detect certain information related to embodied mind, however not as well as humans.

To complete the image of human cognition, both symbolic and embodied processing are necessary, as [35] argues. The Symbol Interdependency hypothesis, as he calls it, holds that both the production and understanding of language are predicated on the mutual dependencies of abstract linguistic symbols and the allusions to perception and action that these symbols imply. Furthermore, he presents evidence that what the embodied theorists have dismissed as just symbolic in text corpora may in fact be used to extract perceptual and modal components of cognition. Lundblom, Cohn, and Tindall Covert’ research [36] (and thus problem of topiCS) rests on the premise that our thoughts are reflected in the language we choose to express them. So, language may be used to infer the impact of perceptual and motor processes, or embodied thinking, on mental processing.

The many findings that have been used to bolster the embodied viewpoint may be reproduced using methods such as LSA [37] demonstrates. The authors showed that the LSA cosines of word pairs belonging to the same sensory modality (motoric, olfactory, auditory, gustatory, tactile, and visual) are greater than those of word pairs belonging to other modalities. Additionally, the LSA cosine values show a more robust association between ideas and their characteristics or features than between concepts and qualities describing other concepts. The [38] demonstrates, in the same viewpoint as Lam, Toai, and Vaclav [39], that characteristics may be recognized using computational models such as LSA, even though such traits would be deemed embodied and hence beyond computation by many scholars.

VI. TEXTUAL MEANINGS

Taking the premise that language has meaning, we look to the individual units of text (words, phrases, paragraphs, etc.) for clues as to what that meaning is. Still, one may wonder whether and where the text's meaning is located. The challenge is whether the terms and their comparative co-occurrences (i.e., the business they maintain) are enough to infer the whole meaning, or whether additional context and data, such semantics or data collected from humans, are necessary. Most, if not all, frameworks of text comprehensions imply that understanding takes place on many levels, which work in tandem to form the reader's mental image. The Construction-Integration framework, for instance, presupposes not one but three layers of representations: the surface codes (grammar or words), the propositional database (significance of the text's hidden meaning), and the scenario framework (using both the text and one's own background knowledge). Due to the multifaceted nature of readers' understanding, a more accurate image is painted when it is evaluated on numerous dimensions (e.g., employing both textual analysis and hypothetical scenarios).

Mechanisms of cognitive processing may explain why there are different degrees of understanding. However, the signal itself is a third factor. Language is multifaceted because it contains information on many different levels. When attempting to extract meaning from text using statistical models, it is prudent to consider that distinct degrees of meaning exist within language. For instance [40] showed that semantic models may better account for a variety of cognitive events when they include syntactic (word order) information. As with the parameters of an algorithm, distinct parts of a representation might be highlighted in this way. To determine whether or not modifying these variables would improve the system's performance, Sun, Wang, Che, Wu, Chen, and Liu evaluated several iterations of the LSA approach: the relative weight given to high- and low-frequency words, and the level of similarity required between words. The research concluded that the depth of investigation affects which algorithms are best suited to discover changes in meaning.

Accordingly, the efficacy and suitability of various algorithms may vary depending on the specific cognitive processes under investigation. In fact, Coh-Metrix relies on this same premise. Coh-Metrix gives data regarding language levels to bolster research into when and where each level is used. Word frequency, homonymy, concreteness, polysemy, noun phrase density, sentence length, and the number of terms preceding the key verb are only few of the indicators that Coh-Metrix delivers (referential cohesion, semantic cohesion, and lexical diversity). Cohesion refers to how well the various parts of a text work together; it measures how well the various parts of a text (such as sentences, paragraphs, and even whole chapters) are connected to one another. If we think of text as a network of connections and nodes, they nodes could stand in for individual words or grammatical units. A text's vocabulary may be mostly abstract or concrete; it can also be primarily known or unknown; and it can be primarily ambiguous or unambiguous. The words have these traits because of the context they were placed in.

In [41] articles provide credence to the idea that a text's meaning may be gleaned from its words alone. Meaning may be recovered from the nonlatent information accessible in big text corpora, as shown [42]. By revealing that a text may be broken down into its component parts that make up latent representations, which include the basics of textual semantics, Latent Semantic Analysis (LSA) was a game-changing approach. However, reducing the number of dimensions is not always necessary for extracting significance. This is in accordance with the argument made by [43], who contends that the capacity to extract meaning from text does not originate in computational models like LSA but rather in the structure of language. One facet of the structure is cohesion, along with connection. Cohesion is the adhesive that keeps the thoughts from flopping about. Word units link phonemes and morphemes at the surface level, while syntax binds the words together at the deeper level. Verbs act as cement at the textbase level, joining thoughts to construct whole sentences. Sentences that include similar wording or concepts help to bind the arguments together [47].

Similarly, at the level of the scenario model, connectives highlight the interconnections of ideas and the broader concepts being communicated in the text. In addition, the text or speech is united as a coherent whole through rhetorical devices, pragmatic considerations, and indications for global coherence [48]. The lack of cohesiveness signals in the text forces the reader to make inferences based on reasoning and past knowledge or to recall earlier material in order to fill in the gaps in understanding [49]. The most comprehensive image of language may be obtained by combining data from words, phrases, and relations [50]. Therefore, the multiple features of how those terms are connected undoubtedly have a part in reading the multidimensional nature of text and its subtext, regardless of their precise attributes, closeness, or co-occurrence (latent or nonlatent).

If meaning exists on different planes, a more detailed statistical framework of semantics could benefit from including these different planes. In [44] approach incorporates syntactic data as well as matrices connecting context words to regions. An updated version of the Construction-Integration model of understanding incorporates these many forms of data (CI-II). In contrast to the surface-level processing represented by the word-word matrix, the relational, gist information (called the gist trace) provided by the Topic Model-generated word-document matrix is more informative (called the explicit relational trace). Dependency grammar parsers provide syntactic information in the form of two distinct and parallel tracks (at least one on each side of the dependent components). Therefore, grammatical information and text representations at both the textbase (gist) and surface (explicit) levels may be captured by this paradigm. The CI-II algorithm takes irrational samples from the straight-lined, explicitly recorded data, requiring only that they be semantically and syntactically meaningful. In a variety of lexical, semantic, and sentential tasks [45] indicate that conditionalized integrations of three are superior than using just one or two sources or LSA.

Similar emphasis on context for meaning is included in the CI-II model. While it's possible to store several meanings of a word in Long-Term Memory (LTM), a detailed framework is needed to eliminate unnecessary meanings when a word is grasped in the context of text and speech. Although words like "band" may be remembered in a variety of contexts, their meanings in phrases like "He played in a rock band" and "He wore his wrist band" are limited. By combining the conditional probabilities from numerous sources, The CI-II model limits how words may be used in different settings. It functions similarly to the prediction model. Through this method, the contextualized meaning of words may arise in a circular fashion inside working memory. This is especially significant when trying to explain more advanced forms of thought, such the ability to use metaphors.

VII. CONCLUSION

The previous two decades have seen a proliferation of models and variants on models, with an uptick in interests and research during the previous decade. Semantic models, which utilize statistical methodologies employed in larger text corpora, substantially assist in the process of extracting meaning from text. An Design thinking Technology advancements over the last two decades have made it possible to examine big data that accurately reflect a vast amount of human knowledge. It has been argued that "bag of words" approaches may fail to capture essential features of human cognition. In this paper, however, even non-latent approaches to textual evaluation are capable of effectively capturing much of what is thought to go beyond the words in text. The authors identified in this paper demonstrate how latent and non-latent (i.e. LSA) prediction approaches may be used to replicate many of the findings described by embodiment theorists.

Second, integrating human-generated data, including word arrangement or syntax, and accounting for distinct cognitive processing degree are all ways to enhance semantic modeling. It seems that for modeling to account for diversified cognitive data, it is necessary to include several sources of data and to assume multiple levels of processing. Semantic models are often used to mimic human knowledge because of how immobile it is in long-term memory. The text included in the area may be used to change the model's knowledge base. One may, for instance, employ literature and conversation that a normal 8-year-old might have been exposed to in order to imitate an 8-year-old. Semantic models fare better when the textual corpora utilized to build the contextual space are restricted in terms of both breadth and depth. The capacity of semantic models to mimic human cognition is both practically and theoretically valuable, and ignoring this would be irresponsible. However, it is difficult for these frameworks to outperform the state-of-the-art in lexical similarity detection because of statistical limits in corpora that are in turn tied to specific statistical traits. Synonymy, paraphrase, metaphor, and coherence are all examples of complicated cognitive events that need to be accounted for in semantic models. In fact, a few of the researchers included here have done precisely that, or at least laid the groundwork for doing so in future studies. Semantic modeling seems to need a mix of diverse strategies to account for performances across a broad range of activities and go beyond merely replicating knowledge.

First, memories, supervised learning, and semantics cognition may all be explained by models that incorporate hypotheses relevant to both types of memory and cognition. And second, including sources of data descriptive of syntax (e.g., word ordering, linguistic connections) enhances model performance since syntactic information is often significant in the interpretation of text and speech. Third, comprehension involves several levels of processing, such as the surface, textbase, and scenario model layers; hence, it may be required to combine different data sources to account for the whole spectrum of interpretations, memory, and learning strategies. In addition to grammatical and lexical information, latent representations recovered by statistical methods like LSA are used in a wide variety of practical contexts. Depending on context and the dependent variable of interest, it may not always be clear that multilevel models are necessary. For instance, in many cases, the reader's pre-existing knowledge is so extensive that it obscures any new insights gained from the text (besides the frequency of words). Similarly, whenever the intended structure is a document's or a global text's comprehension, the impacts of syntax could be determined by the words' and texts' meanings. Resultantly, it's conceivable that statistical models like LSA that disregard syntax may effectively extract meaning from text even when they do not take into account the most basic layers of text meaning. However, several, complementary methods will be necessary to extract the whole meaning of text, including all of its glorious multidimensionality. More important than picking a single successful model is learning how to combine several approaches. As additional dimensions of meaning are quantified, better, more detailed semantics models are projected to emerge.

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No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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