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TECHNICAL CONTRIBUTION

It's the Meaning That Counts: The State of the Art in NLP and Semantics

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Abstract
Semantics, the study of meaning, is central to research in Natural Language Processing (NLP) and many other fields connected to Artificial Intelligence. Nevertheless, how semantics is understood in NLP ranges from traditional, formal linguistic definitions based on logic and the principle of compositionality to more applied notions based on grounding meaning in real-world objects and real-time interaction. "Semantic" methods may additionally strive for meaningful representation of language that integrates broader aspects of human cognition and embodied experience, calling into question how adequate a representation of meaning based on linguistic signal alone is for current research agendas. We review the state of computational semantics in NLP and investigate how different lines of inquiry reflect distinct understandings of semantics and prioritize different layers of linguistic meaning. In conclusion, we identify several important goals of the field and describe how current research addresses them.

1 Introduction

The principle objects of research in Natural Language Processing (NLP), namely natural language and its semantics, are composed of units that can be combined to make a whole in a bottom-up fashion using intrinsic, formal properties, or in a top-down manner exploiting contextual information and external grounding. This complexity has brought about various approaches in computational semantics, in which a primary goal is to exploit meaning for certain tasks rather than to precisely model it.

Natural language is characterized by being *productive*: if a fluent speaker knows the words of a language and how to combine them, they can understand and produce sentences they have never encountered. This ability to derive the meaning of a whole linguistic utterance as a function of its parts and their mode of syntactic combination is known as *compositionality* [61, 134, 144] (§2.1); compositionality is thought to characterize not only language but human thought more generally [56, 57, 106], making it a central component of research into human knowledge. Such an innate human ability allows speakers to judge the grammaticality of nonce sentences independently of their meaning [34]. This ability goes hand-in-hand with *recursion*, the property of language that allows for the generation of a potentially infinite number of sentences as a result of a syntactic rule expanding to contain itself [33, 155]. In theory, if a speaker knows the rules of a language, they will be able to generate and understand any utterance they choose in that language.

Natural language is also inherently *interactive*: children acquire language through feedback and the setting of language-specific parameters [174], and speakers constantly adjust their style to their surroundings and interlocutors [105]. Although the literal or context-independent meaning of a linguistic utterance can be derived compositionally, context-dependent meaning varies from setting to setting [64, 151, 164]. Additionally, semantic content and the context of a linguistic utterance can influence each other in interaction, often to the point that the meaning of a sentence is crucially incomplete without contextual information. Indexicals and demonstratives whose references shift with context are paradigm cases of this: the utterance *'I am here now'* does not have a fully specified denotation without information about who the speaker is, when they are speaking, and where they are speaking. Context dependency is ubiquitous in language,

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which means that essentially all semantic theories rest on particular views of how to model contexts [92].

These questions of how to model language and potential contexts have been central to linguistic research and to the research and conversations in current computational semantic work. How humans *understand* language given its versatility proves difficult to translate to a computational setting in which all factors impacting language understanding need to be explicit. Such discussion has led to a new, albeit at times vague, conceptualization of *meaning* in natural language that is distinct from the meaning formal semanticists originally sought to model. Current computational semantic research is characterized by a dialectic between the need to model language in such a way as to respect its formal properties and be generalizable on one hand, and the desire to account for the interactive components of language that give words and utterances broader (if non-systematic) meaning on the other.

In this survey paper, we first define key terms essential to understanding various theories of meaning cited in computational semantics (§2). This discussion serves as the basis for understanding the central themes of computational semantic work that we review here and that are represented in this issue. We first look at representation in computational semantics (§3): lexical semantic representation (§3.2); logic and formal semantics (§3.3); meaning in the form of symbolic representations (§3.4); and multimodal representation (§3.5). We then turn to interactivity (§4), discussing further implications of multimodal work and simulated environments, as well as representations for pragmatics (§4.2). interpretability (§5.1), and argumentation (§4.3); ,

2 Defining Semantics and Meaning

The challenge of formalizing meaning is summarized by David Lewis in "General Semantics" [115]:

> I distinguish two topics: first, the description of possible languages or grammars as abstract semantic systems whereby symbols are associated with aspects of the world; and, second, the description of the psychological and sociological facts whereby a particular one of these abstract semantic systems is the one used by a person or population. Only confusion comes of mixing these two topics.

Corresponding to the two topics Lewis lays out are two distinct types of theory of meaning. A *semantic theory*, characteristic of formal linguistic work, is a specification of the meanings of the words and sentences of some symbol system. Words are characterized both by (i) *intensions*, or unchanging sets of attributes and conditions that are necessary and sufficient to define a word [58, 190]; and (ii) *extensions*, the set of real-world entities that a word refers or points to [102].[1] In contrast, a *foundational theory of meaning* attempts to explain some characteristic about a specific person or group that gives the symbols of their language the meanings that they have [175].

Theories and research in computational semantics often pick and chooses elements from both semantic and foundational theories of meaning. There are many reasons for this. A central reason is an oft-stated goal in computational semantics to build models that are "human-like" [50, 117, 183, 191]. Whether or not humans represent language as precisely as formal semantic theories posit, or if humans integrate semantic and more context-oriented levels of meaning in real time, is a central question in NLP work that seeks to emulate human-like linguistic ability [84, 145, 158]. An additional reason for blending semantic and foundational theories of meaning is that it is often practically unfeasible to precisely model distinct layers of meaning and all possible interpretations of ambiguous utterances [51]. Though practical, conflating semantic and foundational theories runs the risk of blurring *what* the semantic value of an expression is with *how* it comes to have that value [31]—processes that perhaps merit separate treatment in a computational setting. In what follows, we further define key terms to better assess the implications of this.

2.1 Key Terms

To understand the variety of approaches to semantics and meaning in NLP, it is important to define key concepts related to the meaning a natural language expression can convey. First and foremost, *semantics* is a general term that refers to the study of meaning. *Formal semantics* is a specific approach to meaning grounding in logic, linguistics, and the philosophy of language [144]. *Truth conditions* are a central part of formal semantics: to know the meaning of a sentence *S*, one must know the conditions that make it true [79]. Formal or truth-conditional semantics is sometimes called *model-theoretic semantics*. Here, the idea is that a sentence is true or false only with respect to a particular way things are or a particular model of what is reality. In some state of affairs, the sentence is true, and in some others it will be false. Such alternative state of affairs are often called a *possible world* [40, 116]. This characteristic of *displacement*—the ability to refer to worlds other than the actual here and now—is one of the principle design features of human language that differentiates it from animal language

[1] Simply stated, intensions refer to content and extensions to reference. So, while the intension of 'the current chancelor of Germany' is unchanging, its extension (currently, Angela Merkel) will change with time. Certain 'extensional' predicates can nevertheless be given intensional semantics: *smart* at a time *t* can be understood as $\lambda x \in D.x$ is smart at t.

[81, 190]; it is also perhaps one of the hardest to model computationally.

As noted earlier, formal semantics is centrally concerned with compositionality at the syntax–semantics interface, or how the meanings of larger constituents are built up from the meanings of their parts on the basis of their syntactic structure [61, 134]. Most formal semanticists treat meaning as mind-independent (and abstract), not as concepts "in the head"; formal semanticists distinguish semantics from knowledge of semantics [43, 115]. This sets formal semantics apart from approaches which view semantics as relating a sentence principally to a representation on another linguistic "level" (often referred to as the level of logical form) [126] or a representation in an innate "language of thought" [55] or "conceptual representation" [85].

The encoded semantic content of natural language utterances are nevertheless only the tip of the iceberg of what speakers actually communicate with these utterances [113]. In this sense, we can distinguish semantic *competence* from semantic *performance*: a crucial element of language for computational research is how language is used between speakers to communicate a representation of how the world is, or the activity (performance) that results from an ability (competence) [42]. *Pragmatics* complements semantics by studying how meaning arises from the use of a sentence in a particular context. The interpretation of linguistic utterances involves complex interactions among (i) semantic content, (ii) the context of utterance, and (iii) general pragmatic principles (e.g. Grice [73]) [146]. The starting point for a formal pragmatics is the observation that speakers agree to a remarkable extent on the interpretations of the utterances they hear, suggesting that there are deep regularities across speakers, utterance contexts, and sentence types in how (i)–(iii) interact.

3 Representation

In current NLP work, there is a tendency to conflate semantic and pragmatic levels of meaning, as well as to integrate extra-linguistic sources of knowledge that make linguistic meaning more robust. Bender et al. [15] note this as a conflation of *sentence meaning* and *speaker meaning*; Recanati [151] as a distinction between sentence meaning, what is said, and what is implicated; Gibbs Jr [64] as a distinction between what is psychologically real (speaker/listener meaning) and what is not (sentence meaning). In the context of NLP, Bender et al. [15] argue that while sentence meaning is compositional, any additional meaning is not; as such, they argue that NLP systems would benefit from reusable, automatically derivable, task-independent semantic representations which target sentence meaning, in order to capture exactly the information in the linguistic signal itself. Such compositional meaning representations offer better consistency, more comprehensiveness, greater scalability, and less duplication of effort for each new NLP application as their formal basis of representation is agnostic to any external contextual influence.

The representations discussed below exemplify a continuum from pure compositional representation to non-compositional representation, defined in (§3.1). Lexical semantic representations (§3.2) are concerned with atomic meaning and thus are not as concerned with the integration of the parts. Logic and formal semantics (§3.3), while in principle based on formal principles, have more recently trended towards emulating human performance over theoretical competence. Symbolic meaning representations (§3.4) seek to represent both syntactic and semantic structure, yet an emphasis on "meaning" over semantic principles often calls compositionality into question. Finally, multimodal representations (§3.4) integrate elements of all the aforementioned strategies with the goal to model human knowledge more broadly than linguistic principles.

3.1 Layers of Meaning

What kind of meaning representation is compositional? And which is not? Following Bender et al. [15], compositionality (as noted earlier) boils down to the relationships between the pieces of meaning contributed by the words. There is an additional principle, often tacitly assumed, that word-meaning pairings should not be superfluous: in the strictest form of this, word senses are only distinguished if the distinction interacts with the syntax and morphology [15, 176].

A compositional representation that is consistent with this principle can be further specialized with finer-grained word sense and semantic role information without changing its structure, and hence this amounts to a form of underspecification, rather than a strong claim about lexical meaning [76, 187]. Yet, though underspecification is useful to free semantic interpretation from a disambiguation burden [41], the driving force in most syntactic treebanks has been to assign the most plausible parse tree to a sentence for statistical reasons. Abzianidze and Bos [3] argue that this reasoning also makes sense for semantic representation and parsing: a corpus with the most plausible interpretation for sentences is preferred, as it is not straightforward to draw correct inferences with underspecified meaning representations [152]. For example, though a "sleeping bag" could be a bag that is asleep, this is very unlikely.

In contrast, non-compositional meaning can be understood to include layers that concern the individual substrates later used in compositional processes, including fine-grained word-sense tagging [148] and named entity tags. Additional non-compositional meaning requires additional computation over linguistic structure, equivalent to a type shift operation that allows natural language to be more expressive than first-order logic may allow [12]. This can be seen as including simple constraints on otherwise unspecified meaning representations that are not systematically regulated by the grammar. In current computational semantics, we find such work on quantifier scope ambiguity resolution [80], anaphora and coreference resolution [180], and the determination of the focus of negation [18, 135]. These methods build on partial constraints provided by the grammar while still allowing for interpretations in context that correspond to one (or a subset) of the possibilities allowed by the grammar [15].

3.2 Lexical Semantics

A fundamental problem in computational semantics is the meaning of individual words. This involves, for example, building lexical ontologies such as WordNet [129], which enumerate the different senses of lexical items and the semantic relations between them [171]. Word sense disambiguation (WSD) aims at classifying the sense of a lexical item in context [159], while lexical inference aims at recognizing the semantic relation between terms in an ontology or in context, as addressed by Shwartz [170] this issue], for example. Lexical semantics deals with all atomic meaning-bearing elements of language, including nouns, verbs and adjectives [161], but also prepositions, postpositions, circumpositions and morphological elements such as case markers, as shown by Prange and Schneider [148] this issue]. Another important issue is the historical evolution of the meaning of words, which is a particular aspect of diachronic language change [182].

3.3 Logic and Formal Semantics

Recent years have seen a surge of research activities that address machines' ability to perform deep language understanding which goes beyond what is explicitly stated in text and instead relies on reasoning and knowledge of the world. At the basic level, this work often boils down to recognizing textual entailment (RTE), a fundamental principle of natural language in which the truth on one sentence entails the truth of a related sentence [134]. Computational work on *natural language inference* (NLI) spans early efforts to model logical phenomena [39], to later statistical methods for modeling practical inferences needed for applications like information retrieval and extraction [44], to current work on learning common sense human inferences from hundreds of thousands of examples [24, 193].

The question of how to distinguish between semantic competence and peformance (Section 2.1) is central to work in NLI and logic-based representations. As Bender et al. [15] note, logic-based and compositional meaning representations afford better consistency, more comprehensiveness, greater scalability, and less duplication of effort for each new NLP application. Yet, such representations are often not reflective of human judgement: Pavlick and Kwiatkowski [145] note that current state-of-the-art NLI systems do not capture disagreement inherent in human judgements of textual inference by virtue of treating NLI as probabilistic and instead argue that NLI evaluation should explicitly incentivize models to predict distributions over human judgments. Current work in NLI similarly addresses the questions: which inference types are most common, which models have the highest performance on each reasoning type, and which types are the most challenging for state-of-the-art models [88, 138]? This work is extended to languages apart from English [36]. It has additionally motivated a wealth of research on probing what language models actually know about linguistic structure [96, 97, 127]. Herbelot & Copestake [76] this issue] present a novel take on this matter, integrating formal elements representative of semantic competence with performance-based representations that seek to limit possible ambiguities that may arise from, for example, scopal operators.

Storks et al. [177], in a survey of NLI benchmarks and evaluation measure, raise the central question (echoing the larger field of NLU) of whether current technologies developed are in fact pushing the state-of-the-art in natural language inference. The authors suggest the following directions important to pursue to ensure quality of research: 1. Greater emphasis on external knowledge acquisition and incorporation, instead of relying on large amounts of pre-training and training data to learn the model. Example tasks can be formed in the context of interactive task learning [32], embodied question answering [46, 71], or a physically embodied Turing test [142]. 2. Greater emphasis on reasoning, as models which exploit statistical biases in benchmark data have been shown to perform poorly when the biases are removed [139]. For machines to perform comprehensive commonsense reasoning, there is a critical need for methods that can automatically integrate many types of reasoning such as temporal reasoning, plausible reasoning, and analogy [47]. 3. Stronger justification and better understanding on design choices of models, rather than solely fine-tuning [120]. 4. Broader and multidimensional metrics for evaluation, including for task competence, efficiency, transparency, and generalization ability.

3.4 Symbolic Meaning Representations

Symbolic meaning representation frameworks express various semantic aspects of language in a uniform formalism. They include many different frameworks for abstractly representing the meaning of natural language expressions, and the interactions that bring about complex semantics beyond the meaning of individual words, abstracting away from formal and syntactic variation. They aim to assign similar structures to different constructions that have a similar meaning, and to assign different structures to constructions that have different meanings despite their surface similarity [2]. While theories of syntax-semantics interface view symbolic meaning representations as "gluing together" lexical semantics and syntactic structure to construct a compositional meaning, they additionally represent various compositional and non-compositional phenomena that are traditionally viewed as outside either lexical semantics or syntax [77, 78].

Meaning representation refers both to linguistically-motivated, broad-coverage, human-readable, typically graph-based, semantic representations of text, and to logic-based, executable, machine-readable representations [104], including database or knowledge-base queries, commands to robots or digital assistants, and even general-purpose programming languages [196]. However, current approaches are markedly different, as the former focus on broad coverage of possibly complex but still naturally occurring compositional expressions, and the latter on limited domains or tasks.

Meaning representation parsing, or semantic parsing, refers to the automatic construction of such representations from plain text or speech utterances. While symbolic meaning representation may provide an invaluable inductive bias for Machine Learning models in NLP, their use in NLP applications has so far been limited, mostly due to the low accuracy of semantic parsers. However, shared tasks (parsing competitions) have been driving the state-of-the-art in semantic parsing forward [141].

Semantic representation may encode information about named entities, argument structure, semantic roles, word sense and co-reference, among other phenomena. One central goal is to support lexical and logical inference in many languages, as, for example, targeted by Van Gysel et al. [187], this issue]. Linguistically-motivated meaning representation frameworks include graph-based meaning representations [198], including Universal Conceptual Cognitive Annotation [1], Abstract Meaning Representation [10], Minimal Recursion Semantics [41], as well as semantic formalisms converted into bilexical dependencies—directed graphs whose nodes are text tokens [54]. They also include non-graph-based meaning representations such as Discourse Representation Structures [23] and fine-grained sentence-structural representations like FrameNet [156].

In contrast, syntactic dependencies use bi-lexical trees, with edge labels representing syntactic relations. Universal Dependencies [140], for example, is a syntactic dependency scheme used in many languages, aiming for cross-linguistically consistent and coarse-grained treebank annotation. It does not attempt to represent semantics, although recent enhancement layers include deep syntactic relations [162]. Divergences between the content of semantic and syntactic representations have profound impact on the usefulness of each of the approaches for semantic tasks in NLP [77].

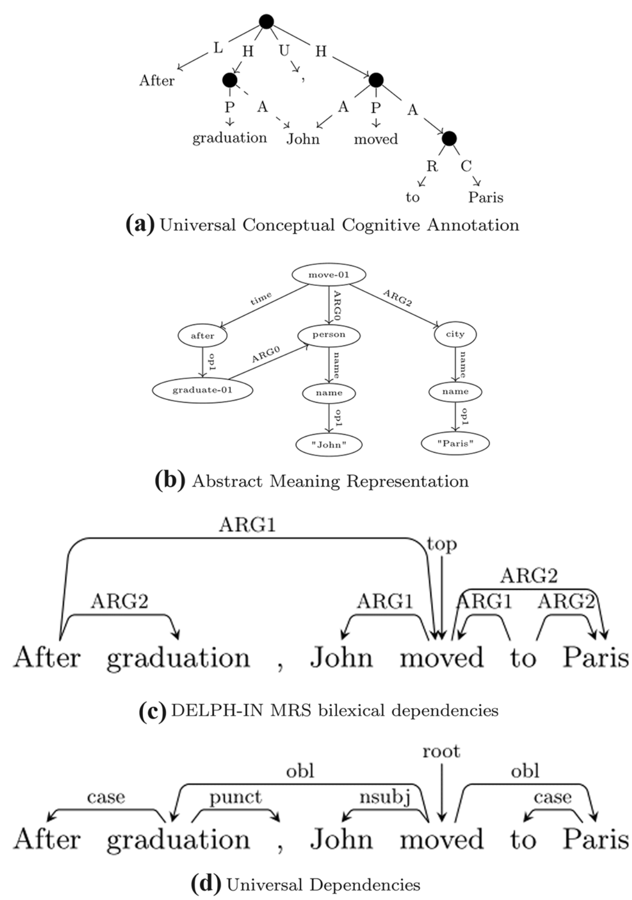

Fig. 1 Examples from different graph-based broad-coverage representation frameworks

Figure 1 presents the sentence "After graduation, John moved to Paris" annotated in four representations, demonstrating the annotation of predicate-argument structure, temporal links, and named entities.

Many differences between meaning representation frameworks are in fact superficial, as they can be normalized out [49]. However, an open research question is whether the comparison between meaning representations can be systematized to reach a "universal" representations that captures the core semantic elements of language.

3.5 Multimodal Representations

Language is grounded in experience, such that humans understand many basic words in terms of associations with perception and sensorimotor interactions with the environment. Theories of *grounded* or *embodied cognition* reject traditional views that human cognition is computation on amodal symbols in a modular system, independent of the brain's modal systems for perception, action, and introspection [11]. Instead, modal simulations, bodily states, and situated action underlie cognition [4, 166].

Multimodal semantic representations address these facts by grounding word and utterance meanings in some form of physical reality. Multimodal simulation of language, particularly motion expressions, brings together a number of existing lines of research from the computational linguistic, semantics, robotics, and formal logic communities, including action and event representation [48]; modeling gestural correlates to natural language expressions [99, 136] and emotion [98]; and action event modeling [100, 195]. Many representations and models are interactive and share commonalities with the frameworks described in Sect. 4.2.

Emerson [51], citing Harnad [75], notes that existing distributional[2] semantics models can be *grounded* in three ways. First, we can train a distributional model as normal, and then combine it with a grounded model. For example, Bruni et al. [25] concatenate distributional vectors and image feature vectors. This has also been applied to olfactory data [94], and visual and auditory data simultaneously [93]. However, while sensory dimensions include grounded information, concatenation leaves the distributional dimensions ungrounded. A second approach thus looks to find correlations between distributional and sensory features. For example, Bruni et al. [26] perform a Singular Value Decomposition (SVD) on concatenated vectors; Silberer and Lapata [172] train an autoencoder on concatenated vectors; and Lazaridou et al.[111] and Bulat et al.[27] learn a mapping from distributional vectors to visual vectors (and vice versa). However, there is no guarantee that every distributional feature will correlate with sensory features, and distributional features without correlations remain ungrounded. A third approach is joint learning: the parameters of a single model are defined and learned from both corpus and grounded data. For example, Feng and Lapata[53] train a Latent Dirichlet Allocation (LDA) model [19] for both words and "visual words" (clusters of visual features). Other methods use Skip-gram models to jointly predict both words and images [112] or embed text and image in a single space [101].

Grounding of natural language semantics is particularly important in interactive and collaborative scenarios with physical robots. To enable human-robot communication and collaboration, recent years have seen an increasing amount of works which aim to learn semantics of language that are grounded to agents' perception [72, 95, 118, 119, 185] and action [6, 124, 125, 130]. Physically grounded agents provide unique opportunities for and insight into language learning, as human acquisition of semantic representations does not occur based on pure language input. This is the basis for interactive learning approach that allows robots to learn models for grounded natural language semantics. To support learning of grounded verb semantics, early work relied on multiple instances of human demonstrations of corresponding actions [131, 167, 169]. Yet, such models often assumed perfect perception of environment by the robot; more recent methodologies based on findings from robotic learning [30] design robots to proactively engage in interaction with human partners by asking good questions to learn [168] or for help when they need [184] using a combination of graphical representations that emulate human knowledge and dialogue structure and reinforcement learning.

[2] *Distributional* models learn from the distribution of linguistic units in a text corpus, without necessitating external supervision.

4 Interactivity and Applications

Apart from the ability to accurately model linguistic phenomena, the utility of a meaning representation can be measured by its task-oriented success. Here we survey applications of representations in interactive settings to model distinct components of meaning.

4.1 Dialogue and HCI

An important layer of meaning and its representation concerns discourse and dialogue processing. For discourse, this includes the calculation of presupposition projection [157, 189, 199], coherence relations and rhetorical structure [109, 122], and the annotation of discourse moves, particularly as they relate to argumentation [62] and constructing speaker identities [194]. These aspects of meaning build on information provided during sentence-level processing, including lexically determined veridicality contexts as well as discourse connectives. In both cases, the grammatical structure links embedded clauses to the relevant lexical predicates. For dialogue, many semantic annotations attempt to capture (a) what speakers are trying to do with their speech acts and/or (b) what the effects on the dialogue are. This includes tasks like stance and hedge detection [160]; commitments to beliefs made by speakers in dialogue [188]; and dialogue acts, often in task-oriented human-human and human-agent dialogue [21, 28]. Typically these aspects of meaning are not anchored in the structure of sentences and may be annotated as a separate structure related to the goals of the speakers or the overall structure of the dialogue (cf. [20, 22]). Though these elements of meaning may appear to be non-compositional, work especially integrating multi-modal components of dialogue and interaction aims to develop compositional and aligned representation for language as well as modalities like gaze, gesture, and facial expression, as, for example, addressed by Pustejovsky & Krishnaswamy [149] this issue].

Additional approaches to multimodal semantics (§3.5) work in the realm of simulation, or environments that allow a user to interact with objects in a virtual or simulated world. Here, an interactive agent is embodied as a dynamic point-of-view or avatar in a proxy situation. Key to this work is encoding an elementary understanding of how objects behave relative to each other and as a consequence of some agent's actions on them into a simulated representation; this understanding of a *situated common ground* integrates elements of co-perception, co-attention, and general situational awareness [149]. When communications become multimodal, each modality in operation provides an orthogonal angle through which to probe the computational model of the other modalities, including the behaviors and communicative capabilities afforded by each [103]. Multimodal interactions thus require a unified framework and control language through which systems interpret inputs and behaviors and generate informative outputs. This is vital for intelligent and often embodied systems to understand the situation and context that they inhabit, whether in the real world or in a mixed-reality environment shared with humans.

More generally, the goal of the human-computer interaction (HCI) discipline is to reexamine and reform the input and output of personal computers and thus the ways users and computers communicate. It develops computational methods to enable the design of intelligent interfaces that make optimal use of people's abilities, skills, and experiences. A key goal is for interfaces to seamlessly integrate with our real world, as they adapt to a person's environment, preferences, or cognitive capacities in a way that is predictable and adjustable by end-users, as addressed by Bercher et al. [16] this issue].

4.2 Modeling Conversational Dynamics

A number of recent Bayesian models of pragmatics conceptualize language use as a recursive process in which abstract speaker and listener agents reason about each other to increase communicative efficiency and enrich the meanings of the utterances they hear in context-dependent ways [59, 60, 87]. Such models are based on the assumptions that (i) speakers choose their words to be informative in context, and (ii) listeners routinely make pragmatic inferences that go beyond the linguistic data to infer word meanings in otherwise ambiguous situations [165]. Probabilistic tools are used to formalize these kinds of informativeness inferences, essentially extending a model of pragmatic language comprehension to the acquisition and conversational settings. In such back-and-forth conversation, many phenomena characterized by Grice [73] as conversational implicatures emerge naturally as probabilistic inferences.

One thread of this work focuses on the Rational Speech Acts (RSA) paradigm [59, 69, 70], based on the theory that listeners assume that speakers choose their utterances close to optimally and then interpret an utterance by using Bayesian inference to "invert" this model of the speaker. RSA and its extensions have been applied to a wide range of pragmatic phenomena, including scalar implicatures [70, 147]; manner implicatures [17]; hyperbole [91]; and politeness [197]. RSA can additionally be cast as a machine learning model, thereby allowing the study of pragmatic reasoning in large corpora and complex environments [5, 132, 133] or used for NLG (Natural Language Generation) purposes [137]. Though standard RSA models are global in the sense that the pragmatic reasoning is defined over complete utterances, they can be adapted to local environments in which listeners reason word-by-word (or in terms of other, more-local linguistic units [35].

A subfield of work on dynamicity in interaction, or how information grows and updates the conversational context over time, is research on politeness. Danescu-Niculescu-Mizil et al. [45] establish a new corpus of requests annotated for politeness, which are used to evaluate aspects of politeness theory and to uncover new interactions between politeness markers and context. Similarly, Yamada [194] this issue] develops a Bayesian model of speaker usage of Japanese honorifics; this model can be extended to other languages that encode social hierarchy distinctions grammatically as politeness and to model persona of speakers, capturing "expressive" meaning of utterances in interaction separate from truth-conditional meaning [29, 128].

Finally, several semantic representations focus specifically on discourse structure and dynamic meaning in context. Rhetorical Structure Thoery (RST) [122], a theory of text organization designed for discourse analysis and text generation, has been applied to natural language generation, parsing, summarization, argument evaluation, machine translation, and essay scoring [181]. Segmented Discourse Representation Theory (SDRT) [109], an expansion of Discourse Representation Theory [90], is a dynamic semantic theory of discourse interpretation that uses rhetorical relations to model the semantics/pragmatics interface. In SDRT, discourse segments are linked with rhetorical relations reflecting different characteristics of textual coherence, such as temporal order and communicative intentions. Finally, Type Theory with Records (TTR) [38] is a type theoretical system developed for the analysis of natural language, in particular from the perspective of interaction and learning. TTR has been used to model incremental dialogue processing [66, 82], combine type theory with situation semantics [65], and model multimodal perception [37, 108].

4.3 Computational Argumentation

Computational argumentation aims at supporting human decision-making by retrieving, analyzing, summarizing and generating arguments [110]. It requires the integration of semantics, pragmatics, discourse, information retrieval and argumentation theory, going beyond the notion of meaning and addressing persuasiveness, framing and subjective opinions. Addressing these "softer" aspects of language is becoming increasingly important as AI agents take a greater role in human lives, and is indeed attracting growing attention from research and industry. For example, IBM recently developed a system capable of participating autonomously in competitive debates [173].

A central task in computational argumentation is argument mining, which consists of claim detection [114], evidence detection [154], evaluation of argument quality [67], and classification of the stance of an argument with respect to the debated topic [8]. This is related to sentiment analysis, but requires a deeper level of reasoning. It is important, for example, for identifying evidence of false information online, as shown by Schiller et al. [160] this issue].

5 Current Questions in Semantic NLP

As the pace of development for new language models and neural architectures increases, a growing number of researchers are pausing to ask whether our methods and research questions are meaningful themselves. Though continuous representations, and in particular neural representations, have consistently demonstrated their advantage in advancing the state-of-the-art in various NLP tasks, several questions have emerged as meta-themes for current computational semantics research: Are formal semantic notions of meaning sufficient for current computational semantic research? Is explicit meaning representation in any form necessary for language understanding? What is the role of interaction in learning meaning and its representation? Is the data we use for training our models representative of what we want our models to learn? Here we explore a few key questions before concluding.

5.1 Interpretability

Explainable Artificial Intelligence (XAI), an emerging field in the broader AI community, is important for facilitating human trust in AI systems such as deep learning models [86, 192], which are increasingly widespread but tend to be opaque with regard to their decision making. It is essential for ensuring their compliance with rules and regulations, but also for improving their correctness.

Explanations in NLP take the form of highlighting a subset of the words in the input text according to their (estimated) importance to the decision [143, 153], rules in the form of patterns, decision trees or programs [179, 200], or freely generated text [7, 150]. Arguments can also serve as a type of explanation, which is particularly appealing in the context of human-computer interaction, as the ability to articulate convincing and informative arguments is necessary for successful collaboration between humans and AI systems [9]. However, even complex explanations currently focus on surface features of the input, that is, word forms or their syntactic structure. Capturing semantics in a human-similar way is an important goal for explainable NLP.

5.2 Ethics

An important area that is playing an increasing role in NLP research and industry (and should take be even more central, many argue) targets the ethical aspects of deploying NLP systems trained on possibly biased data, risking perpetuating or exacerbating existing biases. Better understanding of current methods will allow detecting such bias, mitigating and even eliminating it [68, 74]. While most work in this area is on gender bias, other important factors are targeted as well, such as race [123] and linguistic diversity [89].

NLP and machine learning is starting to address these aspects, starting with defining the possible ethical issues, which include exclusion, overgeneralization, bias confirmation, topic under- and overexposure, and dual use [83]. Initiatives such as data statements [13] and datasheets for datasets [63] facilitate transparency and accountability by making it clear to dataset consumers what the characteristics of the data are.

Finally, energy considerations in researching, training and deploying models are starting to take a central role in the development of the field, aiming both to reduce environmental impact and to facilitate participation by actors with less economical means [163, 178].

5.3 Where We've Been and Where We're Going

The Association for Computational Linguistics (ACL) established a special theme track for papers in 2020 asking researchers to reflect on the progress of the field and what we as a community should be doing next. Many papers focused on computational semantics and the goals of "understanding" natural language and meaning. We highlight contributions of specific papers here, noting how they connect to the goals of this special issue.

Bender and Koller [14] question whether research in natural language understanding is "climbing the right hill": essentially, is the quantitative progress we see in our language models' abilities to "understand" language indicative of their abilities to actually capture "meaning"? Providing a cautious answer, the authors argue that a system trained only on form has a priori no way to learn meaning. Importantly, (linguistic) meaning is defined as the relation between a linguistic form and communicative intent where those intents are about something outside of language and grounded in the real world inhabited by the interlocuters. Though large language models can learn aspects of linguistic formal structure (for example, agreement and dependency structures), the authors argue, their apparent ability to "reason" is often a mirage built on leveraging form-based artifacts in the training data. The authors note that in order to accomplish bigger picture goals of building human-analogous natural language understanding systems, it is useful to distinguish cleanly between levels of linguistic representation–namely, form, conventional meaning, and communicative intent.

Emerson [51], in his assessment of the overarching goals of distributional semantics, asserts that while linguistic insights can guide the design of model architectures, future progress will require balancing the often conflicting demands of linguistic expressiveness and computational tractability. There is, he notes, a trade-off between expressiveness and learnability: the more structure we add, the more difficult it can be to work with our representations. Emerson nevertheless thinks the top-down goal of distributional semantics–the goal that we should design our language models to achieve–is to characterize the meaning of all utterances in a language. As this is a broad goal, Emerson identifies specific aspects of meaning he determines crucial to semantic tasks. Speaking of "meaning in the world," Emerson identifies two crucial aspects: (i) *grounding*, how to connect language to the world, including sensory perception and motor control; and (ii) distinguishing *concepts* (the meaning of a word) and *referents* (an entity the word can refer to) and therefore evaluate the *truth-conditions* of an expression based on the *extension* of a concept (i.e. its set of referents). For lexical meaning, Emerson identifies: (i) *vagueness* in lexical meaning; (ii) *polysemy* in lexical meaning; (iii) *hyponymy*.[3] For sentence meaning, Emerson identifies: (i) compositionality; (ii) logic; and (iii) context dependence.

Instead of addressing the goals of the field and assessing current progress, Trott et al. [186] dedicate their paper to expanding our understanding to include *construal*. The authors argue that the way something is expressed (for example, the difference between a passive and an active sentence) reflects different ways of conceptualizing or *construing* the information being conveyed. The notion of construal is rooted in frame-based and cognitive semantic traditions; specifically, the notion that words and other linguistic units evoke background scenes along with specific perspectives on those scenes is captured in Fillmore's (1977) idea that meanings are relativized to scenes. The authors define construal as a dynamic process of meaning construction, in which speakers and hearers encode and decode, respectively, some intended meaning in a given communicative context. To do so, they draw on their repertoire of linguistic and conceptual structures, composing and transforming them to build coherent interpretations consistent with the speaker's lexical, grammatical, and other expressive choices.

Linzen [117] addresses the question: are we making progress towards the classic goal of mimicking human linguistic abilities in machines–towards a model that acquires language as efficiently as humans, and generalizes it as humans do to new structures and contexts ("tasks")? The paper describes and critiques Linzen's self-termed Pretraining-Agnostic Identically Distributed (PAID) evaluation paradigm, which has become a central tool for measuring progress in natural language understanding. The paradigm consists of (1) pretraining a word prediction model on a corpus of arbitrary size; (2) fine-tuning (transfer learning) on a training set representing a classification task; and (3) evaluation on a test set drawn from the same distribution as that training set. Because it does not consider sample efficiency, this approach rewards models that can be trained on massive amounts of data, several orders of magnitude more than a human can expect to be exposed to. And because benchmark scores are computed on test sets drawn from the same distribution as their respective training sets, this paradigm favors models that excel in capturing the statistical patterns of particular data sets over models that generalize as a human would.

Finally, Tamari et al. [183] similarly expand conventional understandings of meaning and develop an approach to representation and learning based on the tenets of *embodied cognitive linguistics* (ECL) [107]. According to ECL, natural language is inherently executable (similar to programming languages): it is driven by mental simulation and metaphoric mappings over hierarchical compositions of structures and schemata learned through embodied interaction. The perception of a word form, whether through text, speech, or sign, is itself an elaborate neural computation, such that linguistic representations and other, higher-level cognitive functions are deeply grounded in neural modal systems [52]. The paper acts as a position paper, arguing that the use of grounding by metaphoric inference and simulation will greatly benefit NLU systems. The authors propose that work in computational semantics be treated as a *neural programming language* [121], or a "higher-level cognitive control system for systematically querying and inducing changes in the mental and physical states of recipients," with an executable model architecture in the paper.

6 Final Notes

Surveying the current state of computational semantics, the integration of semantic and foundational theories of meaning appears to be evolving into a more comprehensive modeling of human meaning as gleaned through not only language, but

[3] Basically defined, *vagueness* refers to a lexical item with more than one possible instantiation (e.g. "child"); *polysemy* to an item with different but related senses (e.g. "arms"); and *hyponomy* to an item that is a member of a broader class (e.g. "rose" to "flower").

additional modalities such as gesture, gaze, facial expression, and other embodied aspects of human communication. We expect future work to further highlight the usefulness of computational semantics as an infrastructure for better modeling of linguistic phenomena, as an interpretation method for probing linguistic knowledge, for fine-grained control and analysis, and as a research goal in itself.

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