

We went to look for meaning and all we got were these lousy representations: aspects of meaning representation for computational semantics

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Abstract

In this paper we examine different meaning representations that are commonly used in different natural language applications today and discuss their limits, both in terms of the aspects of the natural language meaning they are modelling and in terms of the aspects of the application for which they are used.

1 Introduction

A crucial component to produce a “successful” NLP system is sufficiently expressive representations of meaning. We consider a sufficiently expressive meaning representation to be one that allows a system’s output to be considered acceptable to native speakers given the task. In this paper we present several features of meaning and discuss how different methods of deriving meaning representations capture these features. This list is by no means exhaustive. It might be viewed as a first attempt to discuss ways of establishing a general methodology for evaluating meaning representations and characterising what kinds of applications they might be useful for. The features we will discuss are:

compositionality The ability to compute the meaning of phrases on the basis of the meanings of their immediate sub-constituents.

logic-based inference The ability to derive conclusions based on logical inference, including logical inferences based on the semantics of logical constants such as **and**, **not** and logical quantifiers and also consequences that follow from additional axioms or “meaning postulates”.

discourse semantics This involves giving meaning representations for units larger than a sentence.

underspecification Underspecified meaning rep-

resentations are single representations which cover several meanings in cases where there is systematic ambiguity.

model theory Model theory deals with representing the relationship between language and the world.

dialogue Dialogue semantics is sometimes thought of as part of discourse semantics. However, there are many phenomena that occur in conversations with two or more participants that do not occur in texts. These include fragmentary utterances, repair phenomena, utterances split between different dialogue participants and overlap (dialogue participants speaking at the same time). This seems to warrant dialogue being treated as a feature separate from discourse.

similarity of meaning In addition to meaning relations such as entailment there is a notion of words, phrases and sentences having similar meanings in various respects.

robust non-logical inference This type of inference is discussed in e.g. the work on textual entailment. Rather than representing something that follows logically, it corresponds to what conclusions people might draw from a given utterance or text, is often reliant on background knowledge and is to a large extent defeasible.

dynamic changes of meaning The meaning of words and phrases can change over time and during the course of a text or dialogue.

grounding meaning in action and perception While model theory purports to relate language and the world it tells us little about how we relate our perception of the world and action in the world to the meaning of words and phrases. Such issues become important, for example, if we want to put natural language on board a robot.

multimodality The multimodal nature of commu-

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nication becomes obvious when you begin to think of meaning in terms of action and perception.

The rigour of the work on semantics by Richard Montague (Montague, 1973; Partee, 1976) inspired early work on computational semantics (perhaps the earliest was Friedman and Warren, 1978; Friedman et al., 1978). Two high-points of the literature on computational semantics based on Montague are Blackburn and Bos (2005), using logic programming, and van Eijck and Unger (2010), using functional programming. Montague’s semantic techniques have also played an important role in semantic treatments using Combinatory Categorical Grammar (CCG, Bos et al., 2004).

One problem with Montague’s treatment of semantics was that it was limited to the level of the sentence. It could not, for example, deal with cross-sentence anaphora such as *A dog_i barked. It_i was upset by the intruder.* This, among several other things, led to the development of Discourse Representation Theory (DRT, Kamp and Reyle, 1993; Kamp et al., 2011) and other variants of *dynamic* semantics such as Heim (1982) and Groenendijk and Stokhof (1991). Here “dynamic” is meant in the sense of treating semantic content as context change potential in order, among other things, to be able to pass referents from one sentence to a subsequent sentence in the discourse. This is a much less radical notion of dynamic interpretation than we discuss in Section 3, where the meaning associated with a word or phrase may change as a dialogue progresses. DRT has played an important role in computational semantics from early work on the Verbmobil project (Bos et al., 1996) to work by Johan Bos and others on the Groningen Meaning Bank (<http://gmb.let.rug.nl/>) and the Parallel Meaning Bank (<https://pmb.let.rug.nl/>).

What do we get from this body of work? Here are some of the features that we can get in a compositional semantics based on this work.

compositionality Compositionality is one of the cornerstones of Montague’s approach.

logic-based inference The ability to derive conclusions based on logical inference and the ability to characterise “meaning postulates” is a central feature of semantics in the Montague tradition. Defeasible reasoning has been added to this kind of framework (e.g., Asher and Lascarides, 2003) and systems have been connected to theorem provers and model builders (Blackburn and Bos, 2005).

discourse semantics The variants of dynamic se-

mantics discussed above gave us the ability to treat discourse phenomena (that is, phenomena occurring in texts or utterances of more than a single sentence, including cases of discourse anaphora).

underspecification While there is some work on underspecification of meaning in the theoretical literature (Reyle, 1993), the most interest has been devoted to it in computational work based on formal semantics (such as Alshawi, 1992; Bos, 1996; Copestake et al., 2005).

model theory Model theory associated with a formal approach to semantics can in computational terms relate to database query (Blackburn and Bos, 2005; van Eijck and Unger, 2010).

What we have sketched above might be called the classical canon of formal semantics as it relates to computational semantics. There is much that we would like to have for a computational semantics that is still lacking here. To some extent more recent developments address these gaps and to some extent they are addressed by other kinds of meaning representations we discuss later in the paper, though often at the expense of giving up on (or at least having difficulty with) the features that we listed above. Features lacking in the classical canon include:

dialogue The notion that language is actually used in interaction between agents engaging in communication came quite late to formal semantics though there is now a significant body of theoretical work such as Ginzburg (1994, 2012). This gave rise to the Information State Update approach to dialogue systems (Larsson, 2002). TTR (a type theory with records, Cooper, 2005, *in prep*) has played an important role in this.

similarity of meaning The kind of meaning similarity that is discussed in connection with vector semantics (see Section 2) is hard to recreate in a formal meaning representation, though the use of record types in TTR suggests that a connection could be made.

robust non-logical inference The kind of inference that is represented, for example, in work on textual entailment is hard to square with the logic-based inference discussed above. However, the work on topoi by Breitholtz (2020), perhaps coupled with probabilistic TTR (Cooper et al., 2015), is suggestive of a computational approach to this.

dynamic changes of meaning Notions of meaning negotiation and coordination have become cen-

tral in the literature on formal approaches to dialogue. We discuss this in Section 3.

grounding meaning in action and perception

This has become central to theories such as TTR and Dynamic Syntax (Kempson et al., 2016) and we discuss this in Section 4.

multimodality The multimodal nature of communication becomes obvious when you begin to think of meaning in terms of action and perception. We discuss this in Section 5.

Above we have mentioned examples of formal approaches which attempt to incorporate features which are not present in the classical canon. An alternative strategy is to try to incorporate features from the classical canon in non-formal approaches (for example, Coecke et al., 2010) or to combine aspects of non-formal and formal approaches in a single framework (for example, Larsson, 2013; Erk and Herbelot, 2020).

2 Distributional meaning representations

Distributional representations of meaning can be traced back to Wittgenstein (1953), but was popularised by Firth (1957). The idea at its core is that the meaning of a word is given by its context. Wittgenstein (1953) primarily speaks about meaning in relation to the world, or some game, while Firth (1957) speaks about language in relation to language. The second notion of meaning, is the basis for distributional semantics. This notion is both realised in the world (for example if someone say “grab” sufficiently often when grabbing things), and in language where if two words occur in the same context, e.g. a and b occur in the context of “colour”, we know that they relate to colour.

The two predominant approaches to constructing distributional meaning representations today is using deep learning to construct distributed word representations and contextualised word representations (Chrupała and Alishahi, 2019). In these approaches, the meaning of a word is encoded as a dense vector of real valued numbers. The values of the vector is determined by the task used for training and the corpus used to train.

Distributed word representations focus on building static representations of words given a corpus. Popular techniques for obtaining these representations are BoW (Bag-of-Words) or SGNS (Skip Gram with Negative Sampling), popularised by (Mikolov et al., 2013a). Distributed representations construct a representation of a word x such

that given a context C we are able to select x from a vocabulary V . The results of such models is a matrix of size (N, D) where the row n_i is the meaning representation of word $x_i \in V$. Contextualised representations on the other hand attempt to build a model which gives a word different representations given its context (i.e. dynamic representations). The main difference between the two methods of meaning representations is that in contextualised methods the matrix (N, D) is accompanied by a model f , typically a language model, which yields word representations given a *sentence*.

With distributed representations we may also reason analogically about words and about combinations of concepts, e.g. “Russia” + “River” = “Volga” (Mikolov et al., 2013b). That is, we may construct complex meaning by combining simpler parts. By adding the representation for “Russia” and “river” we obtain some vector z which contains information about the contexts of both “Russia” and “river”. By querying the vector space for words with a *similar* representation to that of z we find other words with similar context, where we find rivers in Russia and among them, Volga. The success of distributed meaning representations, both static and contextualised, can in part be attributed to the ability of a model to predict *similarity* between units of language. Because meaning is defined as the context in which language occurs, two vector representations can be compared and their similarity measured. (Conneau and Kiela, 2018; Vulic et al., 2020). This similarity, in the case of words, indicate whether they occur in similar context. Or, in the case of sentences, indicate whether they have similar sentence meaning. For example, the sentences (1) “*the price is 1 dollar*” and (2) “*the amount to pay is 100 cents*” are essentially equivalent. If we consider the sentence “*the price is 2 dollars*” it’s arguably more similar to (1) and (2) than “*the cat sat on the mat*”. This problem has been explored in the STS (Semantic Textual Similarity) shared tasks (Cer et al., 2017).

The ability to model similarity allows models to discover relationships between units of language. It allows models to transfer knowledge between languages. For example, unsupervised word translation can be done by aligning monolingual vector spaces. (Lample et al., 2018; Artetxe et al., 2018). The transformer models (Vaswani et al., 2017) have also enabled zero-shot and transfer learning, e.g. by learning English word representations and evaluat-

ing on a task in another language (Pires et al., 2019). The simplicity of static and contextualised meaning representations allows us to construct meaning representations for *any* unit of language, be it words, sentences (Conneau et al., 2018), documents (Lau and Baldwin, 2016) or languages (Östling and Tiedemann, 2017).

But a word, or a sentence may mean different things depending on the context. For example a sentence in different domains will express different meanings even if the words are exactly the same. This presents a problem for distributed representations, as our observation of a word or sentence in the real world may differ from what we have seen in the data. However, the effects of different domains may be counteracted by *domain adaptation* techniques (Jiang and Zhai, 2007). The same holds for words, where a word may mean different things depending on the sentence it occurs in. This is a problem for static embeddings where a word is associated with one and only one meaning representation. The problem is mitigated in contextualised representations that construct the meaning representations based on the context. That is, “mouse” will have a different representation when “animal” or “computer” is in the sentence. This does not solve the problem but goes some way in disentangling the different meanings.

Distributed representations enjoy success across a wide variety of NLP tasks. However, a consequence of automatically learning from a corpus results in some inherent shortcomings. A corpus is a snapshot of a subset of language and only captures language as it was used then and there. This means that the meaning representations do not model language as it changes (see Section 3). Additionally, the meaning representations are created from observing language use, not from language use in the world. A consequence of this is that distributional meaning representations don’t capture the state-of-affairs in the world, i.e. the context, in which the language was used. In practical terms this means that for tasks that depends on the state-of-affairs in the world, such as robot control, dialogue or image captioning, a system needs to gather this information from elsewhere.

3 Dynamic meaning representations

Meaning is context dependent in (at least) two different ways. To see how, we can make the distinction between *meaning potential* and *situated mean-*

ing (Norén and Linell, 2007). The situated meaning of a word is its disambiguated interpretation in a particular context of use. Meaning potential (or *lexical meaning*) is the system of affordances (Gibson, 1966; Gregoromichelaki et al., 2020) that a word offers for sense-making in a given context. In this conception, situated meaning is context dependent by construction, but we also claim that the meaning potential of a word depends on context of a certain kind. In particular, it depends on what is *common ground* (Stalnaker, 2002) between a speaker and their audience.

At a linguistics conference, a speaker might use words like *attention* or *modality*— words that would mean something completely different (or nothing at all) at a family dinner. The conference speaker expects to be understood *based on* their and their audience’s joint membership in the computational linguistics community, where they (rightly or wrongly) consider certain specialised meanings to be common ground. The communities that serve as a basis for semantic common ground can be as broad as *speakers of Spanish* (grounding the “standard” Spanish lexicon), or as small as a nuclear family or close group of friends (grounding specialised meanings particular to that group of people) (Clark, 1996).

Recent work in NLP has demonstrated the value of modelling context, including sentential (Section 2) and multimodal context (Section 4). in the representation of situated meanings. Very little work has been done to model the *social context*, which provides the basis for semantic common ground. As a result, NLP models typically assume that words have a single, fixed lexical meaning. We identify three related sources of lexical fluidity that might be accounted for with dynamic meaning representations by incorporating social context of different kinds.

Variation As demonstrated in the conference example, lexical meaning is community dependent. This doesn’t necessarily mean that every NLP application needs to mimic the human ability to tailor our semantic representations to the different communities we belong to, but some applications may serve a broader set of users by doing so. Consider, for example, an application that serves both the general public and experts in some domain.

Even where variation is not explicitly modelled, it is an important factor to consider on a meta level. In practice, NLP models typically target the most

prestigious, hegemonic dialect of a given language, due in part to biases in what training data is easily available on the internet (Bender et al., 2021). This results in applications that favour users who are more comfortable with the dominant language variety.

Furthermore, many applications *assume* a single variety of a given language, when in fact the training data of the models they rely on is rather specific. The standard English BERT model, for example, is trained on a corpus of unpublished romance novels and encyclopedia articles, but is applied as if it represents English written large.

Alignment Semantic common ground is not only based on joint community membership— it can also be built up between particular agents through interaction. Additions or modifications to existing common ground can take place implicitly (through *semantic accommodation*) or explicitly, as in *word meaning negotiation* (Myrendal, 2015). Experiments have shown that pairs of speakers to develop shorter lexicalised referring expressions in when they need to repeatedly identify a referent (Mills and Healey, 2008).

There is some hope for developing models that dynamically update their meaning representations based on interaction with other agents. Larsson and Myrendal (2017) suggest an inventory of semantic update functions that could be applied to formal meaning representations based on the results of an explicit word meaning negotiation. On the distributional side, one- or few-shot learning may eventually allow models to generalise from a small number of novel uses by drawing on existing structure in the lexicon (Lake et al., 2019). One question that remains unexplored in both these cases is which updates to local (dialogue or partner-specific) semantic ground should be propagated to the agent’s representation of the communal common ground (and to which community). This naturally brings up the issue of community-level semantic change.

Change How words change in meaning has long been an object of study for historical linguists (e.g., Paul, 1891; Blank, 1999). Historical change may not seem like a particularly important thing for NLP applications to model. After all, we can accommodate for changes over decades or centuries by simply retraining models with more current data, but significant *semantic shift* can also take place over a much shorter timeline, especially in smaller speech communities (Eckert and McConnell-Ginet,

1992). The issue of semantic change also intersects with that of variation, since coinages and shifts in meaning that take place in one community can cause the lexical common ground to diverge from another community. Conversely, variants in one community may come to be adopted by another (possibly broader) community.

The recent widespread use of distributional semantics to study semantic change suggests that distributional representations are capable of capturing change.¹ Diachronic distributional representations have been used to study semantic change on both a historic/language level (e.g., Dubossarsky et al., 2015; Hamilton et al., 2016) and on a short-term/community level (Rosenfeld and Erk, 2018; Del Tredici et al., 2019).

While social context is not often taken into account in meaning representations, ongoing research on semantic variation and change suggests that such dynamic representations are possible as extensions of the formal and distributional paradigms.

4 Grounded meaning representations in action and perception

The meaning of words is not merely in our head. It is grounded in our surroundings and tied to our understanding of the world (Regier, 1996), particularly through visual perception (Mooney, 2008). Mapping language and vision to get **multi-modal** meaning representations imposes an important challenge for many real-world NLP applications, e.g. conversational agents. This section describes how different modalities are typically integrated to get a meaning representation for **language-and-vision (L&V)** tasks and what is still missing in the respective **information fusion** techniques.

Historically, modelling of situated language has been influenced by ideas from language technology, computer vision and robotics, where a combination of top-down rule-based language systems was connected with Bayesian models or other kinds of classifiers of action and perception (Kruijff et al., 2007; Dobnik, 2009; Tellex et al., 2011; Mitchell et al., 2012). In these approaches, most of the focus was on how to ground words or phrases in representations of perception and action through classification. Another reason for this hybrid approach has also been that such models are partially interpretable. Therefore, they have been a preferred

¹See Tahmasebi et al. (2018), Tang (2018), and Kutuzov et al. (2018) for recent surveys.

choice in critical robotic applications where security is an issue. The compositionality of semantic representations in these systems is ensured by using semantic grammars, while perceptual representations such as SLAM maps (Dissanayake et al., 2001) or detected visual features (Lowe, 1999) provide a model for interpreting linguistic semantic representations. Deep learning, where linguistic and perceptual features are learned in an interdependent manner rather than engineered, has proven to be greatly helpful for the task of image captioning (Vinyals et al., 2015; Anderson et al., 2018a; Bernardi et al., 2016) and referring expression generation (Kazemzadeh et al., 2014).

A more in-depth analysis of how meaning is represented in these models is required. Ghanimifard and Dobnik (2017) show that a neural language model can learn compositionality by grounding an element in the spatial phrase in some perceptual representation. In terms of methodology for understanding what type of meaning is captured by the model, attention (Xu et al., 2015; Lu et al., 2017) has been successfully used. Lu et al. (2016) have shown that co-attending to image and question leads to a better understanding of the regions and words the model is focused on the most. Ilinykh and Dobnik (2020) demonstrate that attention can struggle with fusing multi-modal information into a single meaning representation based on the human evaluation of generated image paragraphs. This is because the nature of visual and linguistic features and the model’s structure significantly impact what representations can be learned when using attention mechanism. Examining attention shows that attention can correctly attend to objects, but once it is tasked to generate relations (such as prepositional spatial relations and verbs), attention visually disappears as these relations are non-identifiable in the visual features utilised by the model. This leads several researchers to include specifically geometric information in image captioning models (Sadeghi et al., 2015; Ramisa et al., 2015). On the other hand, it has also been shown that a lot of meaning can be extracted solely from word distributions. Choi (2020) demonstrates how linguistic descriptions encode common-sense knowledge which can be applied to several tasks while Dobnik and Kelleher (2013); Dobnik et al. (2018) demonstrate that word distributions are an important contributing part of the semantics of spatial relations.

Interactive set-ups such as visual question an-

swering (VQA) (Antol et al., 2015; de Vries et al., 2017) or visual dialogue (Das et al., 2017) make first attempts in modelling multi-modal meaning in multi-turn interaction. However, such set-ups are asymmetric in terms of each interlocutor’s roles, which leads to homogeneous question-answer pairs with rigid word meaning. *Conversational games* have been proposed as set-ups in which the meaning of utterances is agreed upon in a collaborative setting. These settings allow for modelling meaning coordination and phenomena such as clarification requests (Schlangen, 2019). Ilinykh et al. (2019) propose a two-player coordination game, MeetUp!, which imposes demands on a conversational agent to utilise dialogue discourse and visual information to achieve a mutual understanding with their partner. Haber et al. (2019) introduce the PhotoBook task, in which the agent is required to be able to track changes in the meaning of referring expressions, which is continually changing throughout the dialogue.

Examining L&V models and representations they learn points to several significant and interesting challenges. The first relates to the structure of both datasets and models. Many corpora contain prototypical scenes where the model can primarily optimise on the information from the language model to generate an answer without even looking at the image (Cadene et al., 2019). Secondly, information captured by a language model is more compact and expressive than patterns of visual and geometric features. Thirdly, common-sense language model and visual information is not enough (Lake et al., 2017; Bisk et al., 2020; Tenenbaum, 2020): we also rely on mental simulation of the scene’s physics to estimate, for example, from the appearance and position of a person’s body that they are making a jump on their skateboard rather than they are falling over a fire hydrant. Such representations are necessary for modelling *embodied agents* (Anderson et al., 2018b; Das et al., 2018; Kottur et al., 2018). Fourthly, adding more modalities and representations puts new requirements on inference procedures and more sophisticated models of attention (Lavie et al., 2004) that weighs to what degree such features are relevant in a particular context. In recent years we have seen work along these lines implemented with a transformer architecture (Lu et al., 2019; Su et al., 2020; Herdade et al., 2019). However, the issue of interpretability in terms of how individual parts (self-attentions) of large-scale

models process information from different modalities is still an open question.

5 Representations of meaning expressed with our body

In this section we attempt to raise awareness of the role of our bodies in meaning creation and perception in a bidirectional way. This includes how meanings can result in bodily reactions and, conversely, how meanings can be expressed with our bodies, including non-verbal vocalisations, gaze and gestures.

5.1 Emotions

Our view of emotions is two-fold. On one hand, meanings perceived from the environment can change our emotional states and be expressed in bodily reactions. For instance, evaluating events as intrinsically unpleasant may result in gaze aversion, pupillary constriction and some of the other components listed by Scherer (2009). On the other hand, our emotional states can be expressed and the expressions can be adjusted by emotional components, such as mood (Marsella et al., 2010).

Over the last years *appraisal theories* became the leading theories of emotions (for overview, see Oatley and Johnson-Laird, 2014). These theories posit that emotion arises from a person's interpretation of their relationship with the environment. The key idea behind cognitive theories is that emotions not only reflect physical states of the agents but also emotions are judgements, depending on the current state of the affairs (depending on a certain person, significance/urgency of the event etc.). Such an evaluation is called *appraisal*. In our view, linguistic events can as well enter the calculation of appraisal on the level of information-state of the agent and the formal theories of emotions can be implemented to model this process. For instance, following the view of Oatley and Johnson-Laird (2014) we can distinguish emotions as either free-floating or requiring an object, whereas in the latter case the object can be a linguistic entity, entity in the environment or a part of agent's information-state (e.g., obstruction of the agent's goal can lead to anger or irritation, and, vice versa, agent's sadness can lead to the search for a new plan).

5.2 Non-verbal vocalisations

Non-verbal vocalisations, such as laughter, are ubiquitous in our everyday interactions. In the

British National Corpus laughter is a quite frequent signal regardless of gender and age—the spoken dialogue part of the British National Corpus contains approximately one laughter event every 14 utterances. In the Switchboard Dialogue Act corpus non-verbally vocalised dialogue acts (whole utterances marked as non-verbal) constitute 1.7% of all dialogue acts and laughter tokens make up 0.5% of all the tokens that occur in the corpus.

A much debated question is to what extent laughter is under voluntary control. Despite a very particular bodily reaction (laughter causes tensions and relaxations of our bodies), it is believed that we laugh in a very different sense from sneezing or coughing (Prusak, 2006). Many scholars agree that we laugh for a reason, *about* something. One of the most prominent arguments against involuntary laughter is its social function, that is well-documented (e.g., Mehu, 2011): laughter is associated with senses of closeness and affiliation, establishing social bonding and smoothing away discomfort. Even the “primitive” case of tickling not only requires the presence of the other (self-tickling is much less efficient), but also tickling stimulation is likely to elicit laughter if subjects have close relationships (Harris, 1999). Therefore, it is hard to claim that the behaviour that is highly socially dependent can be involuntary.

This leads us to the conclusion that the meaning of laughter ought to be represented, which would allow an artificial agent to understand it and react accordingly (Maraev et al., 2018). Maz-zocconi (2019) presents a function-based taxonomy of laughter, distinguishing, for example, such functions as indication of pleasant incongruity or smoothing the discomfort in conversation. Ginzburg et al. (2020) propose an account for formal treatment of laughter within the information-state of dialogue participants, which includes potential scaling up to other non-verbal social signals, namely, smiling, sighing, eye rolling and frowning.

5.3 Gaze

Gaze is one of the non-verbal signals with many functions. It can dictate attention, intentions, and serve as a communicative cue in interaction. Gaze following can infer the object people are looking at. While scanning a visual scene, the brain stores the fixation sequences in memory and reactivated it when visualising it later in the absence of any perceptual information (Brandt and Stark, 1997).

Scan-path theory illustrations indicate the meaning representations on areas scanned depended on the semantics of a sentence (Bochynska and Laeng, 2015). The existence of semantic eye fixations supports the view of mental imagery that is intrinsically flexible and creative. Although it is grounded on particular previous experiences, by selecting the past episode it is able to generalise the past information to novel images that share features with the novel item (Martarelli et al., 2017). The spatial representations associated with semantic category launch eye movements during retrieval (Spivey et al., 2000).

For dialogue participants gaze patterns act as resources to track their stances. Interlocutors engage in mutual gaze while producing agreeing assessments (Haddington, 2006). Gaze shifts sequentially follow a problematic stance and are followed by a divergent stance by the person who produced the gaze shift. Gaze patterns are not meaningful themselves but become so in dialogue, when combined with linguistic and other interactional practices.

Eye movement patterns, EEG signals and brain imaging are some of the techniques that have been widely used to augment traditional text-based features. Temporal course and flexibility with respect to speakers eye gaze can be used to disambiguate referring expressions in spontaneous dialogue. Eye tracking data from reading provide structural signal with fine-grained temporal resolution which closely follows the sequential structure of speech and is highly related with the cognitive workload associated with speech processing (Barrett and Holenstein, 2020).

Also, CNN has been used to learn features from both gaze and text to classify the input text yielding better classification performance by leveraging the eye movements obtained from human readers to tackle semantic challenges better (Mishra and Bhat-tacharyya, 2018). For multimodal and multiparty interaction in both social and referential scenarios, Somashekarappa et al. (2020) calls for categorical representation of gaze patterns.

5.4 Gestures

Gestures are the hand and body movements that help convey information (Kita and Özyürek, 2003). The observational, experimental, behavioural and neuro-cognitive evidence indicate that language and gestures are tightly linked in comprehension and production (Wilkins, 2006; Willems et al.,

2007). Speech and gestures are semantically and temporally coordinated and therefore involved in co-production of meaning.

Meanings are conveyed by gestures through iconicity and spacial proximity providing information that are not necessarily expressed in speech (e.g., size and shape). Even though the shaping of gestures is related to the conceptual and semantic aspects of accompanying speech, gestures cannot be unambiguously interpreted by naïve listeners (Hadar and Pinchas-Zamir, 2004). While Morett et al. (2020), showed that the semantic relationship between representational gestures and their lexical affiliates are evaluated similarly regardless of language modality.

The mentions of referents for the first time in discourse are often accompanied by gestures. Debreslioska and Gullberg (2020) report that “entity” gesture accompanies referents expressed by indefinite nominals. The clause structures specialise for the introduction of the referents, which contrasts the representation of “action” gestures that co-occur with inferable referents expressed by definite nominals.

Fixing gesture functions, integrating the representations originating from different modalities and determining their composite meanings is challenging. To develop an agent system, multimodal output planning is crucial and timing should be explicitly represented. Lücking (2016) approaches some of the challenges from type-theoretic perspective, representing iconic gestures in TTR (Cooper, 2005) and linking them with linguistic predicates.

6 Conclusions

We surveyed formal, distributional, interactive, multi-modal and body-related representations of meaning used in computational semantics. Overall, we conclude, they are able to deal with compositionality, under-specification, similarity of meaning, inference and provide an interpretation of expressions but in very different ways, capturing very different kinds of meaning. While this works well in practice for individual systems, a challenge arises when we try to combine representations. What do joint representations represent? How they can be transferred across-contexts of language use?

In line with this we suggest that future work should focus on developing benchmarks that compare and test these representations. We hope that this paper points to some of the aspects of repre-

sentations that need to be taken into account.

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References

- Hiyan Alshawi, editor. 1992. *The Core Language Engine*. MIT Press.
- P. Anderson, X. He, C. Buehler, D. Teney, M. Johnson, S. Gould, and L. Zhang. 2018a. [Bottom-up and top-down attention for image captioning and visual question answering](#). In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6077–6086.
- P. Anderson, Q. Wu, D. Teney, J. Bruce, M. Johnson, N. Sünderhauf, I. Reid, S. Gould, and A. van den Hengel. 2018b. [Vision-and-language navigation: Interpreting visually-grounded navigation instructions in real environments](#). In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3674–3683.
- Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. 2015. VQA: Visual Question Answering. In *International Conference on Computer Vision (ICCV)*.
- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018. [A robust self-learning method for fully unsupervised cross-lingual mappings of word embeddings](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 1: Long Papers*, pages 789–798. Association for Computational Linguistics.
- N Asher and A Lascarides. 2003. *Logics of conversation*. Cambridge University Press.
- Maria Barrett and Nora Hollenstein. 2020. [Sequence labelling and sequence classification with gaze: Novel uses of eye-tracking data for natural language processing](#). *Language and Linguistics Compass*, 14.
- Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. [On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜](#). In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, FAccT '21*, pages 610–623, New York, NY, USA. Association for Computing Machinery.
- Raffaella Bernardi, Ruket Cakici, Desmond Elliott, Aykut Erdem, Erkut Erdem, Nazli Ikizler-Cinbis, Frank Keller, Adrian Muscat, and Barbara Plank. 2016. Automatic description generation from images: A survey of models, datasets, and evaluation measures. *J. Artif. Int. Res.*, 55(1):409–442.
- Yonatan Bisk, Ari Holtzman, Jesse Thomason, Jacob Andreas, Yoshua Bengio, Joyce Chai, Mirella Lapata, Angeliki Lazaridou, Jonathan May, Aleksandr Nisnevich, Nicolas Pinto, and Joseph Turian. 2020. [Experience grounds language](#). *arXiv*, arXiv:2004.10151 [cs.CL].
- Patrick Blackburn and Johan Bos. 2005. *Representation and Inference for Natural Language: A First Course in Computational Semantics*. CSLI Studies in Computational Linguistics. CSLI Publications, Stanford.
- A. Christian Blank. 1999. Why do new meanings occur? A cognitive typology of the motivations for lexical semantic change. In Andreas Blank and Peter Koch, editors, *Historical Semantics and Cognition*. De Gruyter Mouton.
- Agata Bochynska and Bruno Laeng. 2015. [Tracking down the path of memory: eye scanpaths facilitate retrieval of visuospatial information](#). *Cognitive processing*, 16 Suppl 1.
- J. Bos. 1996. Predicate logic unplugged. In *Proceedings of the Tenth Amsterdam Colloquium*, pages 133–143, Amsterdam. ILLC/Department of Philosophy, University of Amsterdam.
- Johan Bos, Stephen Clark, Mark Steedman, James R Curran, and Julia Hockenmaier. 2004. Wide-coverage semantic representations from a CCG parser. In *COLING 2004: Proceedings of the 20th International Conference on Computational Linguistics*, pages 1240–1246.
- Johan Bos, Björn Gambäck, Christian Lieske, Yoshiki Mori, Manfred Pinkal, and Karsten Worm. 1996. Compositional semantics in Verbmobil. *arXiv preprint cmp-lg/9607031*.
- Stephan Brandt and Lawrence Stark. 1997. [Spontaneous eye movements during visual imagery reflect the content of the visual scene](#). *Journal of cognitive neuroscience*, 9:27–38.
- Ellen Breitholtz. 2020. *Enthymemes in Dialogue*. Brill.
- Remi Cadene, Corentin Dancette, Matthieu Cord, and Devi Parikh. 2019. [RUBi: Reducing unimodal biases for visual question answering](#). In *NeurIPS*, pages 841–852.
- Daniel M. Cer, Mona T. Diab, Eneko Agirre, Iñigo Lopez-Gazpio, and Lucia Specia. 2017. [Semeval-2017 task 1: Semantic textual similarity - multilingual and cross-lingual focused evaluation](#). *CoRR*, abs/1708.00055.

- Yejin Choi. 2020. [Intuitive reasoning as \(un\)supervised language generation](#). Seminar, Paul G. Allen School of Computer Science and Engineering, University of Washington and Allen Institute for Artificial Intelligence, MIT Embodied Intelligence Seminar.
- Grzegorz Chrupała and Afra Alishahi. 2019. Correlating neural and symbolic representations of language. *arXiv preprint arXiv:1905.06401*.
- Herbert H. Clark. 1996. *Using Language*. Cambridge University Press.
- Bob Coecke, Mehrnoosh Sadrzadeh, and Stephen Clark. 2010. Mathematical foundations for a compositional distributional model of meaning. *arXiv preprint arXiv:1003.4394*.
- Alexis Conneau and Douwe Kiela. 2018. [Senteval: An evaluation toolkit for universal sentence representations](#). In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation, LREC 2018, Miyazaki, Japan, May 7-12, 2018*. European Language Resources Association (ELRA).
- Alexis Conneau, Germán Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. 2018. [What you can cram into a single \$\\$&!#*\$ vector: Probing sentence embeddings for linguistic properties](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 1: Long Papers*, pages 2126–2136. Association for Computational Linguistics.
- Robin Cooper. 2005. Records and record types in semantic theory. *Journal of Logic and Computation*, 15(2):99–112.
- Robin Cooper. in prep. [From perception to communication: An analysis of meaning and action using a theory of types with records \(TTR\)](#). Draft of book chapters available from <https://sites.google.com/site/typetheorywithrecords/drafts>.
- Robin Cooper, Simon Dobnik, Shalom Lappin, and Staffan Larsson. 2015. Probabilistic Type Theory and Natural Language Semantics. *Linguistic Issues in Language Technology*, 10(4):1–45.
- Ann Copestake, Dan Flickinger, Carl Pollard, and Ivan A Sag. 2005. Minimal recursion semantics: An introduction. *Research on language and computation*, 3(2):281–332.
- Abhishek Das, Samyak Datta, Georgia Gkioxari, Stefan Lee, Devi Parikh, and Dhruv Batra. 2018. Embodied Question Answering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
- Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José M.F. Moura, Devi Parikh, and Dhruv Batra. 2017. Visual Dialog. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
- Sandra Debreslioska and Marianne Gullberg. 2020. [What’s new? gestures accompany inferable rather than brand-new referents in discourse](#). *Frontiers in Psychology*, 11.
- Marco Del Tredici, Raquel Fernández, and Gemma Boleda. 2019. Short-Term Meaning Shift: A Distributional Exploration. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics*, volume 1 (Long and Short Papers), pages 2069–2075, Minneapolis, Minnesota. Association for Computational Linguistics.
- M. W. M. G. Dissanayake, P. M. Newman, H. F. Durrant-Whyte, S. Clark, and M. Csorba. 2001. A solution to the simultaneous localization and map building (SLAM) problem. *IEEE Transactions on Robotic and Automation*, 17(3):229–241.
- Simon Dobnik. 2009. *Teaching mobile robots to use spatial words*. Ph.D. thesis, University of Oxford: Faculty of Linguistics, Philology and Phonetics and The Queen’s College, Oxford, United Kingdom.
- Simon Dobnik, Mehdi Ghanimifard, and John D. Kelleher. 2018. [Exploring the functional and geometric bias of spatial relations using neural language models](#). In *Proceedings of the First International Workshop on Spatial Language Understanding (SpLU 2018) at NAACL-HLT 2018*, pages 1–11, New Orleans, Louisiana, USA. Association for Computational Linguistics.
- Simon Dobnik and John D. Kelleher. 2013. [Towards an automatic identification of functional and geometric spatial prepositions](#). In *Proceedings of PRE-CogSsci 2013: Production of referring expressions – bridging the gap between cognitive and computational approaches to reference*, pages 1–6, Berlin, Germany.
- Haim Dubossarsky, Yulia Tsvetkov, Chris Dyer, and Eitan Grossman. 2015. A bottom up approach to category mapping and meaning change. *NetWords 2015 Word Knowledge and Word Usage*, page 5.
- Penelope Eckert and Sally McConnell-Ginet. 1992. Communities of practice: Where language, gender, and power all live. *Locating Power, Proceedings of the 1992 Berkeley Women and Language Conference*, pages 89–99.
- Jan van Eijck and Christina Unger. 2010. *Computational Semantics with Functional Programming*. Cambridge University Press.
- Katrin Erk and Aurelie Herbelot. 2020. How to marry a star: probabilistic constraints for meaning in context. *arXiv preprint arXiv:2009.07936*.
- J. R. Firth. 1957. *Papers in Linguistics, 1934-1951*. Oxford University Press, London.

- Joyce Friedman, Douglas B. Moran, and David S. Warren. 1978. Two Papers on Semantic Interpretation in Montague Grammar. *American Journal of Computational Linguistics*. Microfiche 74.
- Joyce Friedman and David S Warren. 1978. A parsing method for Montague grammars. *Linguistics and Philosophy*, 2(3):347–372.
- Mehdi Ghanimifard and Simon Dobnik. 2017. [Learning to compose spatial relations with grounded neural language models](#). In *Proceedings of IWCS 2017: 12th International Conference on Computational Semantics*, pages 1–12, Montpellier, France. Association for Computational Linguistics.
- James J Gibson. 1966. *The senses considered as perceptual systems*. Mifflin, New York [u.a.
- Jonathan Ginzburg. 1994. An update semantics for dialogue. In *Proceedings of the 1st International Workshop on Computational Semantics*, Tilburg University. ITK Tilburg.
- Jonathan Ginzburg. 2012. *The Interactive Stance: Meaning for Conversation*. Oxford University Press, Oxford.
- Jonathan Ginzburg, Chiara Mazzocconi, and Ye Tian. 2020. Laughter as language. *Glossa: a journal of general linguistics*, 5(1).
- Eleni Gregoromichelaki, Stergios Chatzikyriakidis, Arash Eshghi, Julian Hough, Christine Howes, Ruth Kempson, Jieun Kiaer, Matthew Purver, Mehrnoosh Sadrzadeh, and Graham White. 2020. Affordance Competition in Dialogue: The Case of Syntactic Universals. In *Proceedings of the 24th Workshop on the Semantics and Pragmatics of Dialogue - Full Papers*.
- Jeroen Groenendijk and Martin Stokhof. 1991. Dynamic predicate logic. *Linguistics and Philosophy*, pages 39–100.
- Janosch Haber, Tim Baumgärtner, Ece Takmaz, Lieke Gelderloos, Elia Bruni, and Raquel Fernández. 2019. [The PhotoBook dataset: Building common ground through visually-grounded dialogue](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1895–1910, Florence, Italy. Association for Computational Linguistics.
- Uri Hadar and Lian Pinchas-Zamir. 2004. [The semantic specificity of gesture](#). *Journal of Language and Social Psychology - J LANG SOC PSYCHOL*, 23:204–214.
- Pentti Haddington. 2006. [The organization of gaze and assessments as resources for stance taking](#). *Text & Talk - TEXT TALK*, 26:281–328.
- William L. Hamilton, Jure Leskovec, and Dan Jurafsky. 2016. [Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1489–1501, Berlin, Germany. Association for Computational Linguistics.
- Christine R Harris. 1999. The mystery of ticklish laughter. *American Scientist*, 87(4):344.
- Irene Heim. 1982. *The Semantics of Definite and Indefinite NPs*. Ph.D. thesis, University of Massachusetts at Amherst.
- Simao Herdade, Armin Kappeler, Kofi Boakye, and Joao Soares. 2019. [Image captioning: Transforming objects into words](#). In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.
- Nikolai Ilinykh and Simon Dobnik. 2020. [When an image tells a story: The role of visual and semantic information for generating paragraph descriptions](#). In *Proceedings of the 13th International Conference on Natural Language Generation*, pages 338–348, Dublin, Ireland. Association for Computational Linguistics.
- Nikolai Ilinykh, Sina Zarriß, and David Schlangen. 2019. [Meet up! a corpus of joint activity dialogues in a visual environment](#). In *Proceedings of the 23rd Workshop on the Semantics and Pragmatics of Dialogue - Full Papers*, London, United Kingdom. SEMDIAL.
- Jing Jiang and ChengXiang Zhai. 2007. [Instance weighting for domain adaptation in NLP](#). In *ACL 2007, Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics, June 23-30, 2007, Prague, Czech Republic*. The Association for Computational Linguistics.
- Hans Kamp, Josef van Genabith, and Uwe Reyle. 2011. [Discourse Representation Theory](#). In Dov Gabbay and Franz Guentner, editors, *Handbook of Philosophical Logic*, volume 15. Springer Science+Business Media B.V. .
- Hans Kamp and Uwe Reyle. 1993. *From Discourse to Logic*. Kluwer, Dordrecht.
- Sahar Kazemzadeh, Vicente Ordonez, Mark Matten, and Tamara L. Berg. 2014. Referit game: Referring to objects in photographs of natural scenes. In *EMNLP*.
- Ruth Kempson, Ronnie Cann, Eleni Gregoromichelaki, and Stergios Chatzikyriakidis. 2016. Language as Mechanisms for Interaction. *Theoretical Linguistics*, 42(3-4):203–276.
- Sotaro Kita and Asli Özyürek. 2003. [What does cross-linguistic variation in semantic co-ordination of speech and gesture reveal?: Evidence of an interface representation of spatial thinking and speaking](#). *Journal of Memory and Language*, 48:16–32.

- Satwik Kottur, José M. F. Moura, Devi Parikh, Dhruv Batra, and Marcus Rohrbach. 2018. [Visual coreference resolution in visual dialog using neural module networks](#).
- Geert-Jan M. Kruijff, Hendrik Zender, Patric Jensfelt, and Henrik I. Christensen. 2007. Situated dialogue and spatial organization: what, where... and why? *International Journal of Advanced Robotic Systems*, 4(1):125–138.
- Andrey Kutuzov, Lilja Øvrelid, Terrence Szymanski, and Erik Velldal. 2018. Diachronic word embeddings and semantic shifts: A survey. In *Proceedings of the 27th International Conference on Computational Linguistics*, pages 1384–1397, Santa Fe, New Mexico, USA. Association for Computational Linguistics.
- Brenden M. Lake, Tal Linzen, and Marco Baroni. 2019. [Human few-shot learning of compositional instructions](#). *arXiv:1901.04587 [cs]*.
- Brenden M. Lake, Tomer D. Ullman, Joshua B. Tenenbaum, and Samuel J. Gershman. 2017. [Building machines that learn and think like people](#). *Behavioral and Brain Sciences*, 40:e253.
- Guillaume Lample, Alexis Conneau, Marc’Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2018. [Word translation without parallel data](#). In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings*. OpenReview.net.
- Staffan Larsson. 2002. *Issue-based Dialogue Management*. Ph.D. thesis, University of Gothenburg.
- Staffan Larsson. 2013. [Formal semantics for perceptual classification](#). *Journal of Logic and Computation*, 25(2):335–369.
- Staffan Larsson and Jenny Myrendal. 2017. [Dialogue Acts and Updates for Semantic Coordination](#). In *SEMDIAL 2017 (SaarDial) Workshop on the Semantics and Pragmatics of Dialogue*, pages 52–59. ISCA.
- Jey Han Lau and Timothy Baldwin. 2016. [An empirical evaluation of doc2vec with practical insights into document embedding generation](#). In *Proceedings of the 1st Workshop on Representation Learning for NLP, Rep4NLP@ACL 2016, Berlin, Germany, August 11, 2016*, pages 78–86. Association for Computational Linguistics.
- Nilli Lavie, Aleksandra Hirst, Jan W de Fockert, and Essi Viding. 2004. [Load theory of selective attention and cognitive control](#). *Journal of Experimental Psychology: General*, 133(3):339–354.
- David G Lowe. 1999. [Object recognition from local scale-invariant features](#). In *Computer vision, 1999. The proceedings of the seventh IEEE international conference on*, volume 2, pages 1150–1157. IEEE.
- J. Lu, C. Xiong, D. Parikh, and R. Socher. 2017. [Knowing when to look: Adaptive attention via a visual sentinel for image captioning](#). In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3242–3250.
- Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. 2019. [Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks](#). In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.
- Jiasen Lu, Jianwei Yang, Dhruv Batra, and Devi Parikh. 2016. Hierarchical question-image co-attention for visual question answering. In *Proceedings of the 30th International Conference on Neural Information Processing Systems, NIPS’16*, page 289–297, Red Hook, NY, USA. Curran Associates Inc.
- A. Lücking. 2016. Modeling co-verbal gesture perception in type theory with records. In *2016 Federated Conference on Computer Science and Information Systems (FedCSIS)*, pages 383–392.
- Vladislav Maraev, Chiara Mazzocconi, Christine Howes, and Jonathan Ginzburg. 2018. [Integrating laughter into spoken dialogue systems: preliminary analysis and suggested programme](#). In *Proceedings of the FAIM/ISCA Workshop on Artificial Intelligence for Multimodal Human Robot Interaction*, pages 9–14.
- Stacy Marsella, Jonathan Gratch, Paolo Petta, et al. 2010. Computational models of emotion. *A Blueprint for Affective Computing—A sourcebook and manual*, 11(1):21–46.
- Corinna Martarelli, Sandra Chiquet, Bruno Laeng, and Fred Mast. 2017. [Using space to represent categories: insights from gaze position](#). *Psychological Research*, 81.
- Chiara Mazzocconi. 2019. *Laughter in interaction: semantics, pragmatics and child development*. Ph.D. thesis, Université de Paris.
- Marc Mehu. 2011. Smiling and laughter in naturally occurring dyadic interactions: Relationship to conversation, body contacts, and displacement activities. *Human Ethology Bulletin*, 26(1):10–28.
- Tomás Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013a. [Efficient estimation of word representations in vector space](#). In *1st International Conference on Learning Representations, ICLR 2013, Scottsdale, Arizona, USA, May 2-4, 2013, Workshop Track Proceedings*.
- Tomás Mikolov, Ilya Sutskever, Kai Chen, Gregory S. Corrado, and Jeffrey Dean. 2013b. [Distributed representations of words and phrases and their compositionality](#). In *Advances in Neural Information Processing Systems 26: 27th Annual Conference on Neural Information Processing Systems 2013. Proceedings of a meeting held December 5-8, 2013, Lake Tahoe, Nevada, United States*, pages 3111–3119.

- Gregory Mills and Pat Healey. 2008. Semantic negotiation in dialogue: The mechanisms of alignment. *Proceedings of the 9th SIGdial Workshop on Discourse and Dialogue*, pages 46–53.
- Abhijit Mishra and Pushpak Bhattacharyya. 2018. *Scanpath Complexity: Modeling Reading/Annotation Effort Using Gaze Information: An Investigation Based on Eye-tracking*, pages 77–98. Springer, Singapore.
- Margaret Mitchell, Xufeng Han, Jesse Dodge, Alyssa Mensch, Amit Goyal, Alex Berg, Kota Yamaguchi, Tamara Berg, Karl Stratos, and Hal Daumé III. 2012. Midge: Generating image descriptions from computer vision detections. In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*, pages 747–756. Association for Computational Linguistics.
- Richard Montague. 1973. The Proper Treatment of Quantification in Ordinary English. In Jaakko Hintikka, Julius Moravcsik, and Patrick Suppes, editors, *Approaches to Natural Language: Proceedings of the 1970 Stanford Workshop on Grammar and Semantics*, pages 247–270. D. Reidel Publishing Company, Dordrecht.
- Raymond J. Mooney. 2008. Learning to connect language and perception. In *Proceedings of the 23rd National Conference on Artificial Intelligence - Volume 3, AAAI’08*, page 1598–1601. AAAI Press.
- Laura Morett, Sarah Hughes Berheim, and Raymond Bulger. 2020. [Semantic relationships between representational gestures and their lexical affiliates are evaluated similarly for speech and text](#). *Frontiers in Psychology*, 11.
- Jenny Myrendal. 2015. *Word Meaning Negotiation in Online Discussion Forum Communication*. PhD Thesis, University of Gothenburg, University of Gothenburg.
- Kerstin Norén and Per Linell. 2007. [Meaning potentials and the interaction between lexis and contexts: An empirical substantiation](#). *Pragmatics*, 17(3):387–416.
- Keith Oatley and P.N. Johnson-Laird. 2014. [Cognitive approaches to emotions](#). *Trends in Cognitive Sciences*, 18(3):134–140.
- Robert Östling and Jörg Tiedemann. 2017. [Continuous multilinguality with language vectors](#). In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 644–649, Valencia, Spain. Association for Computational Linguistics.
- Barbara H. Partee, editor. 1976. *Montague Grammar*. Academic Press.
- Hermann Paul. 1891. *Principles of the History of Language*. London ; New York : Longmans, Green.
- Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. [How multilingual is multilingual BERT?](#) In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4996–5001, Florence, Italy. Association for Computational Linguistics.
- Bernard G Prusak. 2006. The science of laughter: Helmut plessner’s laughing and crying revisited. *Continental philosophy review*, 38:41–69.
- Arnau Ramisa, Josiah Wang, Ying Lu, Emmanuel Dellandrea, Francisc Moreno-Noguer, and Robert Gaizauskas. 2015. [Combining geometric, textual and visual features for predicting prepositions in image descriptions](#). In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 214–220, Lisbon, Portugal. Association for Computational Linguistics.
- Terry Regier. 1996. *The human semantic potential spatial language and constrained connectionism*. Neural network modeling and connectionism. MIT Press, Cambridge.
- Uwe Reyle. 1993. Dealing with ambiguities by underspecification: Construction, representation and deduction. *Journal of Semantics*, 10(2):123–179.
- Alex Rosenfeld and Katrin Erk. 2018. [Deep Neural Models of Semantic Shift](#). In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 474–484, New Orleans, Louisiana. Association for Computational Linguistics.
- Fereshteh Sadeghi, Santosh K Kumar Divvala, and Ali Farhadi. 2015. [Viske: Visual knowledge extraction and question answering by visual verification of relation phrases](#). In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1456–1464.
- Klaus R Scherer. 2009. The dynamic architecture of emotion: Evidence for the component process model. *Cognition and emotion*, 23(7):1307–1351.
- David Schlangen. 2019. [Grounded agreement games: Emphasizing conversational grounding in visual dialogue settings](#).
- Vidya Somashekarappa, Christine Howes, and Asad Sayeed. 2020. [An annotation approach for social and referential gaze in dialogue](#). In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 759–765, Marseille, France. European Language Resources Association.
- Michael Spivey, Daniel Richardson, Melinda Tyler, and Ezekiel E Young. 2000. Eye movements during comprehension of spoken descriptions. In *Proceedings of the 22nd Annual Meeting of the Cognitive Science Society*.

- Robert Stalnaker. 2002. Common Ground. *Linguistics and Philosophy*, 25(5-6):701–721.
- Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. 2020. [Vi-bert: Pre-training of generic visual-linguistic representations](#). In *International Conference on Learning Representations*.
- Nina Tahmasebi, Lars Borin, and Adam Jatowt. 2018. [Survey of Computational Approaches to Diachronic Conceptual Change](#). *arXiv:1811.06278 [cs]*.
- Xuri Tang. 2018. [A state-of-the-art of semantic change computation](#). *Natural Language Engineering*, 24(5):649–676.
- Stefanie Tellex, Thomas Kollar, Steven Dickerson, Matthew Walter, Ashis Banerjee, Seth Teller, and Nicholas Roy. 2011. [Understanding natural language commands for robotic navigation and mobile manipulation](#). *Proceedings of the AAAI Conference on Artificial Intelligence*, 25(1).
- Joshua B. Tenenbaum. 2020. [Cognitive and computational building blocks for morehuman-like language in machines](#). Acl 2020 keynote, Center for Brains, Minds and Machines, MIT.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. [Attention is all you need](#). In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 5998–6008.
- Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. 2015. [Show and tell: A neural image caption generator](#).
- Harm de Vries, Florian Strub, Sarath Chandar, Olivier Pietquin, Hugo Larochelle, and Aaron Courville. 2017. [Guesswhat?! visual object discovery through multi-modal dialogue](#).
- Ivan Vulic, Simon Baker, Edoardo Maria Ponti, Ulla Petti, Ira Leviant, Kelly Wing, Olga Majewska, Eden Bar, Matt Malone, Thierry Poibeau, Roi Reichart, and Anna Korhonen. 2020. [Multi-simlex: A large-scale evaluation of multilingual and cross-lingual lexical semantic similarity](#). *CoRR*, abs/2003.04866.
- David Wilkins. 2006. [Adam kendon \(2004\). gesture: Visible action as utterance](#). *Gesture*, 6.
- Roel Willems, Asli Özyürek, and Peter Hagoort. 2007. [When language meets action: The neural integration of gesture and speech](#). *Cerebral cortex (New York, N.Y. : 1991)*, 17:2322–33.
- Ludwig Wittgenstein. 1953. *Philosophical Investigations*. Basil Blackwell, Oxford.
- Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhudinov, Rich Zemel, and Yoshua Bengio. 2015. [Show, attend and tell: Neural image caption generation with visual attention](#). In *Proceedings of the 32nd International Conference on Machine Learning*, volume 37 of *Proceedings of Machine Learning Research*, pages 2048–2057, Lille, France. PMLR.