Views of Text-Meaning in Computational Linguistics: Past, present, and future

Graeme Hirst
Department of Computer Science
University of Toronto
Toronto, Ontario, Canada M5S 3G4
gh@cs.toronto.edu

1 Introduction

The successes in recent years of computational linguistics, natural language processing, and human language technologies (CL, NLP, and HLT) through empirical methods based on statistics and lexical semantics have been achieved, at least in part, by changing the problem to be solved. Until the early 1990s, the central problem of computational linguistics was taken to be *natural language understanding*, a subproblem of *artificial intelligence*. Users' spoken or typed utterances, or complete documents, were to be "understood", in some deep sense of that term, by means of a full and correct syntactic parse followed by conversion into a "representation of meaning" from which all the necessary inferences could be drawn. It was easy to construct examples that showed that anything less than this kind of full "understanding" could and would lead to errors: the wrong flight booked, a misleading translation, a domestic robot washing the baby in the washing machine. Researchers built narrow but deep systems that could Do The Right Thing for a few "toy" examples, but the methods didn't scale up, often because they presupposed the existence of large knowledge resources, the creation of which was considered a separate, very long term problem.

The move away from this paradigm came with the growing realization that there were many useful natural-language applications in which some degree of error could be tolerated. These include text classification and document routing, text summarization, and finding answers to questions in a document collection.

The price of these successes, however, has been a diminished view of text-meaning and interpretation in computational linguistics. In this paper, I will discuss three computational views of text-meaning and how they have been tacitly used in computational linguistics research over the last three decades. I'll explain why the current view is a "diminished" one that needs to be

To appear in: *Computing, Philosophy, and Cognitive Science*, Gordana Dodig-Crnkovic and Susan Stuart, editors. Cambridge Scholars Press, Newcastle-upon-Tyne, 2006.

changed, and say a little about how recent work in my research group fits in with that.[1]

In this paper, I'll use the word *text* to denote any complete utterance, short or long. In a computational context, a text could be a non-interactive document, such as a news article, a legal statute, or a memorandum, that a *writer* or *author* has produced for other people and which is to undergo some kind of processing by a computer. Or a text could be a natural-language utterance by a *user* in a spoken or typewritten interactive dialogue with another person or a computer: a *turn* or set of turns in a conversation.[2] The term *text-meaning*, then, as opposed to mere *word-meaning* or *sentence-meaning*, denotes the complete in-context meaning or message of such texts at all levels of interpretation including subtext.

2 Three decades of text-meaning in computational linguistics

There are three distinct views on exactly where the meaning of a text can be found:

1. Meaning is in the text.
2. Meaning is in the writer.
3. Meaning is in the reader.

These different views of text-meaning often lead to heated debates in semiotics, literary theory, the philosophy of language, and semantics. In computational linguistics, however, all three views are found in the research literature, with different degrees of prominence at different times in the field's history, and researchers are rarely explicit as to which view they are taking — often they don't distinguish the views at all or they slide back and forth between them.

The varying prominence of the different views reflects the degree of prominence and success of different CL and NLP research paradigms and methods over the years. And perhaps surprisingly, as computational linguistics has developed, the predominant view has shifted from the one generally regarded as the most sophisticated to the one generally regarded as the least sophisticated. In more-cynical terms: the original problem was too hard, and so it was replaced by an easier problem.

---

[1] This paper is thus intended as an explicit response to these questions in the E-CAP 2005 call for papers: What are the philosophical underpinnings of computational linguistics? Are they (still) the right ones or do they need to be replaced? If so, with what? What are the philosophical implications of your current research?

[2] While this terminology emphasizes written language, I do not want to exclude spoken "texts"; the terms *writer* and *reader* should be taken to include *speaker* and *hearer.*

In this section, I'll look in more detail at each of the three views of text-meaning in computational linguistics, and, working backwards in time, show how each was associated with the milieu of (roughly) one decade of research.

2.1 1995–2005: Objective text-meaning

The dominant paradigm for the last decade or so in CL and NLP has been the application of statistical and machine-learning methods to large, non-interactive texts. The paradigm is exemplified and driven by books such as Manning and Schütze's *Foundations of Statistical Natural Language Processing* (1999). In this paradigm, the implicit view is that text-meaning is objectively "in" a text, and is determined solely by the combined effect of the words of the text, each as context for the others. That is, a text is a representation of its own meaning, just as much as any semantic formalism is; and this meaning is preserved, more or less, by operations such as summarization and translation to another natural language.

This view underlies, for example, applications that rely on statistically based lexical methods. If the user asks for articles about raptor migration in Colorado, then the statistical relationship of the words in the text to those in the query is determined, and the text is ranked accordingly for the degree of relevance of its meaning. A topic detection and tracking system for news stories, in determining that two stories are or aren't about the same event, is in effect making a judgement that the objective meaning of the texts is or isn't the same (at a certain level of granularity). The job of an extractive summarization system is to pick out the sentences in which the "important" meaning is concentrated. A system that monitors conversations in on-line chat rooms is looking out for sentences with "dangerous" meanings.

Thus a text is regarded as an *objet trouvé*, with little or no consideration of its author or its provenience. It just arrives from a wire service or from an anonymous user. Meaning is then "extracted" from the text by "processing" it.

2.2 1985–1995: Authorial intent

In the preceding decade, research in computational linguistics placed a much greater emphasis on interactive dialogue systems. A user was assumed to be conversing with the machine in pursuit of some task in which the machine played a role such as that of tutor, travel agent, or domestic servant. The computer's job was taken to be figuring out what it is that the user "really wants" from the "literal meaning" of what they say; for example, *I'd like a beer*, said to a domestic robot, means *Bring me a beer, and do it right now*. In effect, the computer has to read the user's mind. This research was marked by the application of Gricean and other theories of linguistic pragmatics to users' utterances, and by the development of models of the user that could be used to reason about the user's plans and goals. The more that was known about a specific user, the better their meaning could be determined. The paradigm was exemplified and driven by books such as Cohen, Morgan, and Pollack's *Intentions in Communication* (1990) and Kobsa and Wahlster's *User Models in Dialog Systems* (1989).

Thus, in this paradigm, the implicit view is that text-meaning is "in" the writer or user. A text or turn means whatever the user thinks it means or intends it to mean (i.e., humpty-dumptyism), and the reader (be it human or computer) might or might not determine what this is.

2.3 1975–1985: Subjective text-meaning

A view that is perhaps associated with literary criticism more than computational linguistics is that text-meaning is "in" the reader of the text. That is, a text means whatever the reader (or the "interpretive community") thinks it means. Generally in this view, the emphasis is not just on meaning but on *interpretation*, implying a perspective, a context, and an agenda that each reader brings to the act of reading any particular text. A consequence of this is that the meaning or interpretation depends, at least in part, on what the reader knows or believes (or doesn't know or believe); or, in computational terms, on what is or isn't in the system's knowledge base.

This view is implicit in the application-independent language-understanding research that dominated computational linguistics from the early-to-mid 1970s to the mid-to-late 1980s, which was rooted in the traditional knowledge-based artificial-intelligence paradigm of creating independent intelligent agents. Typically in this research, texts were seen to be massively ambiguous in both their syntax and their semantics, and the goal for the computer was to find the interpretation of the input that was most consistent with the knowledge that was already present in the system. The more the system knew, the more it would be able to understand. The paradigm was exemplified and driven by books such as Schank and Colby's *Computer Models of Thought and Language* (1973) and Sowa's *Conceptual Structures* (1984) (perhaps even Hirst's *Semantic Interpretation and the Resolution of Ambiguity* (1987)). This subjective view of text-meaning became very explicit in research such as that of Corriveau (1995), who additionally considered the question of how the interpretations produced by a language-understanding system are affected by the time constraints under which it operates.[3]

[3]Corriveau's work, though published in book form only in 1995, was carried out mostly in the late 1980s.

2.4 Vacillation

Thus, as the methods and applications changed, as the *weltanschauung* of CL and NLP changed from one in which computers were (would-be) independent intelligent agents to one in which humans *command* computers by means of natural language and then to one in which humans *use* computers to sift the information in the natural languages of the world, so too the predominant view of text-meaning tacitly changed. In the traditional intelligent-agent paradigm, the computer is trying to make sense of the linguistic utterances it finds in the world, increasing its knowledge and planning its actions accordingly; the subjective, in-reader view of text-meaning dominated. In the computer-as-servant paradigm, if the user asks the computer to do something — book a flight, fetch a beer — then it is the user's intent that is paramount in what the computer should actually do, regardless of how the request is phrased; the in-writer view dominated. And if the computer's task is to find information in text, then it is objective, in-text meaning that matters.

Computational linguistics and computational linguists thus vacillate between the three views of text-meaning, but don't generally notice that they are doing it and probably wouldn't care if they did notice: computational linguists are not normally students of philosophy, and therefore tend to be unaware of, or gloss over, the philosophical consequences of their work, the philosophical assumptions underlying it, and the philosophical issues that it raises.

Moreover, CL makes additional naive assumptions about meaning:

- that the writer or user is a perfect language user: they make no mistakes in their utterances (other than superficial performance errors of spelling and grammar), and when using interactive systems, they comprehend the system's utterances correctly;
- that meaning is conveyed only by or through what's present in the text and not what's omitted;
- that the system's agenda and the user's or author's agenda are complementary and they share the same goals: e.g., that the user wants to learn something that a tutoring system wants to teach; that the user wants to book the kind of trip that a travel assistant is able to arrange; that the system is looking for the overt information that the writer wishes to convey;
- that no distinction need be made between meaning and interpretation.

All of these assumptions will be challenged as computational linguistics proceeds. In the next section, I will show how forthcoming applications will remove the fourth assumption and implicitly the third. And in the subsequent section, I'll briefly discuss removal of the second assumption as one component of that. (For research on removing the first assumption, see Hirst et al (1994).)

3 2005–2015: Reclaiming the distinctions

What, then, of views of text-meaning in the next decade? How will new methods and new applications affect the view that computational linguistics takes? I believe that forthcoming applications will move CL to recognize the three views as distinct, but to embrace all three as complementary — as representative of different kinds of understanding that are needed, or expected, in different computational tasks. In particular, the in-writer and in-reader views will both come to the fore again, but not for the same reasons as in the past. Rather, in the new NLP applications that are now on the horizon, people will use computers to *interpret* the natural language of the world, not just to search it for information. Moreover, there will be two types of interpretation possible: interpretation on behalf of the user and interpretation on behalf of the writer.

The first of these, while the greater technical challenge, is the conceptually simpler; it is a straightforward extension of the current paradigm of searching, filtering, and classifying information. It requires the computer to consider a text from the point of view of the user, including his or her beliefs, goals, and agenda. For example, if the user wants the computer to find, say, evidence that society is too tolerant of intoxicated drivers or evidence that the government is doing a poor job or evidence that the Philippines has the technical resources to commence a WMD program, then a relevant text need not contain any particular set of words nor anything that could be regarded as a literal assertion about the question (though it might), and the writer of a relevant text need not have had any intent that it provide such evidence. In this paradigm, then, the computer is a surrogate for the user, and its job is to decide, as closely as it can, what some particular text would mean to the user, given the user's goals and anything else known about the user. For this kind of interpretation, the in-reader view of text-meaning becomes explicit: What's important to me in this text? In my view of the world, which camp does this opinion fall into?

The second kind of interpretative task requires the computer to consider a text from the point of view of its author, including his or her beliefs, goals, and agenda. It is a hermeneutic task, in which the user of the computer system wants to understand what it is that the author intends to say, or even what he or she is saying without intending to. Applications with this kind of interpretation include the analysis of opinion texts and of sentiment in text more generally, and the simplification of complex texts; it will also be a component of faithful, high-quality machine translation. In this paradigm, the computer, although working on behalf of some user, acts as a surrogate for the writer, and its job is to present, as closely as it can, what some particular text would mean to the writer. Thus, for this kind of interpretation, the in-writer view of text-meaning becomes explicit: What's this person trying to tell me? What are they up to? What are their implicit assumptions?

It's clear that applications of computational linguistics are moving towards both these kinds of interpretive tasks. Search engines have already turned the typical lay computer user into a researcher, but they have also shown the limitations of string-matching; interpretation remains solely the responsibility of the user. Automatic or assisted interpretation is thus the next great goal for computational linguistics. Many of the applications that are the subject of contemporary research, even if still using the in-text view, can be seen as preliminary steps in this endeavour: non-factoid question-answering, query-oriented summarization, and multi-document summarization; automatic classification of the sentiment or opinion expressed in a text; automatic essay scoring. Even machine translation, once construed solely as a tool to assist a professional human translator (or to replace them), is now also seen as a (still crude) interpretive tool for the ordinary user.

4 Knowing the alternatives

An important component of interpreting text is sensitivity to *nuances* in language and the choices that speakers make from the options that are available to them. Saussure (1916) wrote:

> In a given language, all the words which express neighbouring ideas help define one another's meaning. Each of a set of synonyms like *redouter* ('to dread'), *craindre* ('to fear'), *avoir peur* ('to be afraid'), has its particular value only because they stand in contrast to one another. If *redouter* did not exist, its content would be shared out among its competitors. (p. 114)

Nuance lies not only in near-synonyms, as in Saussure's example, but in all aspects of both content and style — from deciding what to say in the first place, through to the words and syntactic structures of its realization. If I tell you that I am *afraid* of my forthcoming exam, you can infer that my fear is not so great as to be *dread* (or at least, I'm not admitting that it is). If I concede that *a mistake was made* and you believe that it was in fact I who made the mistake, you can infer from my agentless passive that I'm avoiding taking any responsibility for the mistake.

Nuance in language thus arises from the speaker's or writer's deliberate (though not necessarily conscious) choice between close alternatives — from that which might have been said but wasn't. Sensitivity to nuance thus requires, for any particular utterance in its context, knowing what the possible alternatives were. Clearly, this kind of analysis requires both complex knowledge of the language and complex knowledge of the world. The latter may be arbitrarily hard — ultimately, it could imply, for example, a computational representation of a deep understanding of human motivations and behaviour that even many people do not achieve. The required linguistic knowledge is also difficult, but is at least in the territory of computational linguistics, and sets an agenda for research that has strongly influenced my own work for many years. If a computer system is to draw inferences from a writer's choice among a cluster of near-synonyms, it must first have a method of representing both the core meaning of the cluster and the distinctions among its members (Edmonds and Hirst 2002), and it must then have a lexical knowledge base that, using this method of representation, lists all this information for all the words of the relevant language or (in the case of machine translation) languages (Inkpen and Hirst 2006). If it is to draw inferences from the writer's choice of syntactic structures it must have a representation of the alternative structures available and the pragmatic consequences of each: e.g., emphasis or deliberate obfuscation (DiMarco and Hirst 1993).[4]

5 Conclusion

For its new and developing applications, computational linguistics needs to move away again from the solely objective in-text view of text-meaning that has dominated much of the statistically based work of the past decade, and reclaim both the subjective in-reader and authorial in-writer views. But the subjective view will now have purpose at its centre rather than idiosyncrasies of the system's knowledge; and the authorial view will be based not just on rules of pragmatics and implicature but also on a broader determination of what the author might have said but didn't.

Acknowledgements

The preparation of this paper was supported by the Natural Sciences and Engineering Research Council of Canada and by the Center for Spoken Lan-

[4] I have presented this argument from the perspective of language comprehension; but clearly language generation and the *creation* of text meaning by making the choices described above also require these kinds of knowledge. In computational linguistics, the primary work on this is undoubtedly still Hovy's (1987) system PAULINE, which tactfully adapted its political comments according to whom it was talking to and even shut up completely if it decided that it was a bad idea to say anything.

guage Research, University of Colorado at Boulder, where I was a guest at the time of its completion. For discussions and insights on this topic, I am grateful to Jane Morris (who first drew my attention to how the contemporary view in CL of the locus of text-meaning differs from that of the 1980s), Stephen Regoczei, Diana Inkpen, Philip Edmonds, Eduard Hovy, Nadia Talent, Jean-Pierre Corriveau, Chrysanne DiMarco, and Sergei Nirenburg.

References

Cohen, Philip R.; Morgan, Jerry; and Pollack, Martha E. (1990) (editors). *Intentions in communication*. Cambridge, MA: The MIT Press.

Corriveau, Jean-Pierre (1995). *Time-constrained Memory: A Reader-based Approach to Text Comprehension*. Mahwah, NJ: Lawrence Erlbaum Associates.

DiMarco, Chrysanne and Hirst, Graeme (1993). "A computational theory of goal-directed style in syntax." *Computational Linguistics*, 19(3), September 1993, 451–499.

Edmonds, Philip and Hirst, Graeme (2002). "Near-synonymy and lexical choice." *Computational Linguistics*, 28(2), June 2002, 105–144.

Hirst, Graeme (1987). *Semantic Interpretation and the Resolution of Ambiguity*. Cambridge University Press.

Hirst, Graeme; McRoy, Susan; Heeman, Peter; Edmonds, Philip; and Horton, Diane (1994). "Repairing conversational misunderstandings and non-understandings." *Speech Communication*, 15(3–4), 213–229.

Hovy, Eduard (1987). *Generating Natural Language under Pragmatic Constraints*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Inkpen, Diana and Hirst, Graeme (2006). "Building and using a lexical knowledge-base of near-synonym differences." *Computational Linguistics*, 32(2), June 2006.

Kobsa, Alfred and Wahlster, Wolfgang (eds.) (1989). *User Models in Dialog Systems*. Springer-Verlag.

Manning, Christopher and Schütze, Hinrich (1999). *Foundations of Statistical Natural Language Processing*. Cambridge, MA: The MIT Press.

Saussure, Ferdinand de (1916). *Course in General Linguistics*. (Translated by Roy Harris, 1983.) La Salle, IL: Open Court Press. [Page numbers refer to the English edition.]

Schank, Roger C. and Colby, Kenneth M. (1973). *Computer Models of Thought and Language*. San Francisco: W.H. Freeman.

Sowa, John F. (1984). *Conceptual Structures*. Reading, MA: Addison-Wesley.