# arXiv:2310.18038v1 [cs.CL] 27 Oct 2023

# **On General Language Understanding**

**David Schlangen** 

Computational Linguistics / Department of Linguistics University of Potsdam, Germany david.schlangen@uni-potsdam.de

### Abstract

Natural Language Processing prides itself to be an empirically-minded, if not outright empiricist field, and yet lately it seems to get itself into essentialist debates on issues of meaning and measurement ("Do Large Language Models Understand Language, And If So, How Much?"). This is not by accident: Here, as everywhere, the evidence underspecifies the understanding. As a remedy, this paper sketches the outlines of a model of understanding, which can ground questions of the adequacy of current methods of measurement of model quality. The paper makes three claims: A) That different language use situation types have different characteristics, B) That language understanding is a multifaceted phenomenon, bringing together individualistic and social processes, and C) That the choice of Understanding Indicator marks the limits of benchmarking, and the beginnings of considerations of the ethics of NLP use.

### **1** Introduction

In early 2019, Wang et al. (2019b) released the "General Language Understanding Evaluation" (GLUE) benchmark, with an updated version (Wang et al., 2019a) following only a little later. Currently, the best performing model on the updated version sits comfortably above what the authors calculated as "human performance" on the included tasks.<sup>1</sup> This can mean one of two things: Either General Language Understanding in machines has been realised, or these benchmarks failed to capture the breadth of what it constitutes. The consensus now seems to be that it is the latter (Srivastava et al., 2022; Liang et al., 2022).

In this paper, I try to take a step back and ask what "General Language Understanding" (GLU) implemented in machines could mean. The next



Figure 1: A Space of Language Use Situation Types

section dives into the *general* part of GLU, Section 3 into the *understanding*, as a cognitive process. Section 4 zooms out, and looks at conditions under which a *model* of GLU ceases to be *just* a model. In the course of the discussion, I will derive three desiderata for models of GLU and their evaluation.

### 2 Types of Language Use

Language can be used for many purposes (e.g., ordering dinner, teaching, making small talk with friends) and via various types of media (e.g., letters, computerised text messages, face-to-face).<sup>2</sup> As Fillmore (1981, p. 152) observed, one setting appears to be primary, however: "The language of face-to-face conversation is the basic and primary use of language, all others being best described in terms of their manner of deviation from that base." A detailed, multi-dimensional categorisation of these deviations can be found in (Clark and Brennan, 1991; Clark, 1996); for our purposes here, this can be collapsed into two dimensions, as in Figure 1. Along the vertical axis, we move from high interactivity as it can be found in live interaction, to low- or non-interactive language use, as it is made possible by technical mediation (via

<sup>&</sup>lt;sup>1</sup>At 91.3, compared to the 89.8 in the paper; https: //super.gluebenchmark.com/leaderboard, last accessed 2023-06-09.

<sup>&</sup>lt;sup>2</sup>Where these purposes all come with their specific constitutive constraints on the language use, see e.g. (Bakhtin, 1986), (Wittgenstein, 1953/84, §23)).

writing or recorded messages). What are the consequences of the changes? The increase in mediation comes with a loss of immediacy, which reduces opportunities of the addressee to influence the formulation of the message, or in general to contibute. Consequently, low-immediacy use situations are appropriate more when it is one language producer who wants to convey a larger contiguous message, and not when language is used to guide collaborative action. It is reasonable to expect this difference to have an effect on the *form* of the language that is produced, and indeed this is what is typically found (Miller and Weinert, 1998; Halliday, 1989). Differences can also be found in the range of its functions: the range of speech acts that can be found in high-interactivity settings is larger, and includes all kinds of interaction management acts (Asher and Lascarides, 2003; Ginzburg, 2012; Bunt, 1996), the understanding of which requires reference to the state of the interaction. On the horizontal axis, we move from language use between speakers who share an extensive history of previous interactions and/or a rich shared situational context, to use between speakers who do not. Consequently, the kind of background information that the speakers can presuppose changes, leading to a need to make much more of the presuppositions explicit in the "low shared context" setting. This leaves us with a quadrant (top-right) where a lot of the "understanding work", at least if the language production is good, has to be "front-loaded" by the language producer, who cannot rely on the addresse intervening (bottom row) or the availability of much shared context (left column).

We can use this diagram to make several observations. First, while the ontogenetic trajectory takes the human language learner from the strongest kind of the "basic and primary" form of language—namely child/caretaker face-to-face interaction (Clark, 2003)—outwards into regions of which some are only accessible via formal education (writing in general, then technical/scientific writing), the trajectory for Natural Language Understanding in NLP takes the exact opposite direction, only now moving from the top-left corner of processing formal writing further towards the origin (Bisk et al., 2020).<sup>3</sup> This does not have to mean anything, but it is worth noting—however humans do it, the fact that the more abstract types of language production found in the top-right quadrant come less easy to them may indicate that the methods that humans use to process language are taxed harder by them. (We might term the question of whether this is an essential or incidental feature the *acquisition puzzle.*)

Second, we can note that, as a consequence of this development trajectory, all of the extant large scale, "general" evaluation efforts (Srivastava et al., 2022; Liang et al., 2022) target this top-right quadrant. No standard methods have yet been proposed for evaluating models that increase interactivity and/or context dependency.<sup>4</sup> This might be due to the factor that an increase in context-dependence requires concrete, and hence, less general setups; but given the agenda-forming function of benchmarks, this is concerning for the emergence of a field of true GLU. (We might term this the *coverage problem*.) We derive from this discussion the first desideratum.

Desideratum 1: Models of "General Language Understanding" must be general also with respect to language use situation types, and must cover situated as well as abstracted language use.

# **3** Understanding as a Cognitive Process: Inside the Understander

The previous section looked at generality in terms of coverage of language use situations. This section will look at one aspect of the *understanding* part in "General Language Understanding". What is understanding? The classic view in NLP is well represented by this quote from a seminal textbook: "*[the understanding system] must compute some representation of the information that can be used for later inference*" (Allen, 1995, p.4).

Taking up this "actionable representation" view, and at first focussing on "text understanding", Figure 2 (left column) shows an attempt to compile out of the vast literature on language understanding, both from NLP, but also from linguistics and psycholinguistics, a general (if very schematic) picture—a picture that at this level of detail would not be incomprehensible to the contemporary reader of Allen (1995). The model assumes that the language understander possesses a model

<sup>&</sup>lt;sup>3</sup>Note that while there is renewed interest in "embodied" language use in NLP (Duan et al., 2022; Gu et al., 2022), outside of the small interactions with the neighbouring field of social robotics, there is little work on actual embodiment that could lead to models of "face-to-face" interaction.

<sup>&</sup>lt;sup>4</sup>For evidence that the increase in interactivity is inconsistent, see (Doğruöz and Skantze, 2021). A theoretical proposal for an evaluation method is given by (Schlangen, 2023), with a first realisation attempted by (Chalamalasetti et al., 2023).

of the language in which the material that is to be understood is formulated; here in the more narrow sense that it is a model of a mapping between form and meaning (representation), roughly of the *scope* aimed at by the formalisations such as those of Chomsky (1957) or Pollard and Sag (1994).<sup>5</sup> This model interfaces with world knowledge at least in the lexicon (Pustejovsky and Batiukova, 2019), via knowledge of *concepts* (Murphy, 2002; Margolis and Laurence, 2015). The *world model*, however, in this view more generally needs also to contain "common sense knowledge" about the workings of the world (e.g., as script knowledge, common sense physics, etc.; Allen and Litman (1990); Nunberg (1987)).

The central representation however in this model is the *situation model* representing the described situation, in the broadest sense (which may or may not be congruent with the reporting situation; Johnson-Laird (1983); van Dijk and Kintsch (1983)). To give an example, Winograd schema sentences (Levesque et al., 2012) such as (1) (taken from (Wang et al., 2019a)) can in this scheme be understood as inducing a situation model, for which *language* and *world model* suggest a preferred understanding (namely, that it was the table, as the patient of the breaking event, that was built out of the fragile material).

(1) The large ball crashed right through the table because it was made of styrofoam.

To be able to separate between elements of the situation model that may have been implied and those that have been explicitly mentioned, a representation of the discourse is required (Heim, 1983; Kamp, 1981). Its structure moreover can constrain what can be inferred, as in (2-a), where 'car' is not available as antecedent for the pronoun.

- (2) a. The nearly bankrupt company did not own a car. It was on the verge of collapse.
  - b. The nearly bankrupt company did own a car. It was on the verge of collapse.

(We will skip over the agent model for now.)

That "language understanding" is internally structured and draws on various types of knowledge is implicitly acknowledged also in modern attempts at evaluating the performance of NLU



Figure 2: A Model of Understanding as a Cognitive Process

models, for example in the diagnostic dataset included in SuperGLUE (Wang et al., 2019a), or in the checklists of Ribeiro et al. (2020). This assumption also underlies the fertile field of representation probing (e.g., (Marvin and Linzen, 2018; Belinkov, 2022; Loáiciga et al., 2022; Schuster and Linzen, 2022)), which tests for mapping between such theoretically motivated assumptions and empirical findings on processing models. However, the underlying assumptions are rarely made explicit, not even to the degree that it is done here (but see (Trott et al., 2020; Dunietz et al., 2020)) which, I want to claim here, should be done, in the interest of *construct validity* of measurement (Flake and Fried, 2020).

But we are not done. What I have described so far may capture text understanding, but once we move outwards from the top-right quadrant of Figure 1, the collaborative nature of interaction, and with it the importance of the *agent model*; and in general the processual nature, and with it the importance of the various anchoring processes shown in Figure 2 on the right, come into focus. In order: Where it might be possible to understand text, particularly of the de-contextualised kind described above, without reference to its author, the further one moves towards the origin of the language use space (Figure 1), the clearer it becomes that the understander needs to represent its beliefs about the interacting agent. This is indicated by the agent model in Figure 2, where the segment for the partner contains information about which parts of the other models the understander deems to be shared (Bratman, 1987; Cohen et al., 1990). The model of Clark (1996) makes building up this common ground the point of understanding, and the process of managing this common ground via interaction,

<sup>&</sup>lt;sup>5</sup>Which is not to imply that an implemented language understanding system should be *based on* such formalisations.



Figure 3: A Model of Understanding as a Social Process

conversational grounding, its central element. In conversational grounding, not only processes of repair (asking for clarification) are subsumed, but also "positive" indicators of understanding (such as producing a relevant continuation). This process is made possible by the fact that processing of material happens, very much unlike the current assumptions in NLP, in an incremental fashion (Levinson, 2010; Christiansen and Chater, 2016; Schlangen and Skantze, 2009), allowing for timely adaptations and interventions. Another natural phenomenon in interaction is covered by the process of incremental learning (Hoppit and Laland, 2013; Harris, 2015): If, in the course of an interaction, I am introduced to a fact previously unknown to me, and I accept it through conversational grounding, I am expected to be able to later draw on it. The final process is the only one that has seen some attention recently in NLP, multimodal grounding; which here however is meant not just to cover the word-world relation (Harnad, 1990; Chandu et al., 2021), but also the grounding of meaning-making, in face-to-face situations, in multimodal signals from the speaker (Holler and Levinson, 2019; Mc-Neill, 1992; Kendon, 2004).

The takeaway from this shall be our second desideratum.

# Desideratum 2: Attempts at measuring performance in "General Language Understanding" must be clear about their assumptions about the underlying construct.

(Where the model sketched in this section provides one example of how to be explicit about such assumptions.)

# 4 Understanding as a Social Process: The Understanding Indicator

The discussion from the previous section suggests a picture where a language understanding system receives a stimulus and delivers a response, which we take as an indicator of understanding. And this is indeed how typical evaluation of such a system works: The response is compared to the known, expected response, and the assumed quality of the model is a function of this comparison. This, however, is not how understanding in real use situations works: Here, we do not care about understanding as symptom (reflecting an inner state), but rather as understanding as signal (offering a social commitment). In most use situations, "computer says no" (Britain, 2004) is not good enough (or at least, should not be good enough): We want to know why it says this, and we want to know who takes responsibility if the reasons are found to be not good enough.<sup>6</sup> In other words, and as indicated in Figure 3, in this view, the understanding indicator is embedded in practices of receiving challenges and providing justifications (Toulmin, 2003 [1958]), as well as making commitments (Brandom, 1998; Lascarides and Asher, 2009); in other words, it underlies the constraints holding for the speech act of assertion (Goldberg, 2015; Williamson, 2000).

I can only scratch the surface of this discussion here, to make a few notes: A) The target of "normal" evaluation-improving the reliability of the understanding symptoms-certainly stands in some relation to improving the quality of the understanding signal, but it is not entirely straightforward to see what this relation is, and what its limits are. B) While the process of giving justifications when challenged may be within the range of "normal" work in NLP, and indeed is addresses by some work in "explainable AI" (Miller, 2019), whether the notion of *commitment* can ever be abstracted away from human involvement is more than questionable. C) There is a long tradition of work making similar points, coming to them from a different angle (e.g., inter alia, Bender et al. (2021)). I just note here that considerations originating from the philosophy of language about how meaning is underwritten by the "game of giving and asking for reasons" (Sellars, 1956) only strengthen these concerns.

Desideratum 3: Uses of models of Language Understanding must be clear about their understanding of the Understanding Indicator, and how it is warranted.

<sup>&</sup>lt;sup>6</sup>A right which famously recent EU regulation (Regulation, 2016, recital 71, "right to explanation") indeed codifies, at least in principle.

# 5 Conclusions

This short paper is an invitation to debate what the meaning of "general language understanding" (in machines) could, and ought to, be. Ultimately, it may be that the answer to "can large language models *model* language understanding" is *yes*, while the answer to "can large language models understand language" has to be *no*.

## Limitations

This paper does not report on any empirical work. Is it hence out of place at a conference on "empirical methods"? I would argue that it is not, as, in the words of Dewey (1960, p.85) "all experiment involves regulated activity directed by ideas". To not be empty, empirical methods must be guided by theoretical considerations, and it is to this that this paper wants to contribute.

A limitation might be that this text was written with the thought that language understanding by machines is done for humans, and that thus the human-likeness of the understanding is crucial, because only it guarantees that generalisations go in expected directions. The thoughts developed here might not apply if the goal is to evolve machine communication that only superficially resembles natural language.

# **Ethics Statement**

While the paper discusses some possible limits to language understanding by machines, it does not per se question whether "general language understanding" by machines is a worthwhile, ethical goal. This should be discussed; for now, elsewhere.

### References

- James C. Allen. 1995. *Natural Language Understanding*, 2nd edition. Benjamin/Cummings, Redwood City, USA.
- James F. Allen and Diane J. Litman. 1990. Discourse processing and common sense plans. In (Cohen et al., 1990).
- Nicholas Asher and Alex Lascarides. 2003. Logics of Conversation. Cambridge University Press.
- Mikhail M. Bakhtin. 1986. Speech Genres and Other Late Essays. University of Texas Press Slavic Series. University of Texas Press.
- Yonatan Belinkov. 2022. Probing Classifiers: Promises, Shortcomings, and Advances. Computational Linguistics, 48(1):207–219.

- 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, page 610–623, New York, NY, USA. Association for Computing Machinery.
- 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. EMNLP 2020 - 2020 Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference, pages 8718–8735.
- Robert Brandom. 1998. *Making it Explicit: Reasoning, Representing, and Discursive Commitment*. Harvard University Press, Harvard, MA, USA.
- Michael E. Bratman. 1987. Intentions, Plans, And Practical Reason. Harvard University Press, Cambridge, Massachusetts, USA.
- Little Britain. 2004. Computer says no. British Broadcasting Company.
- Harry Bunt. 1996. Interaction management functions and context representation reqirements. In *Dialogue Management in NL Systems: Proceedings of the 11th Twente WS on Language Technology*, pages 187–198, Enschede, The Netherlands.
- Kranti Chalamalasetti, Jana Götze, Sherzod Hakimov, Brielen Madureira, Philipp Sadler, and David Schlangen. 2023. clembench: Using game play to evaluate chat-optimized language models as conversational agents. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, Singapore. Association for Computational Linguistics.
- Khyathi Raghavi Chandu, Yonatan Bisk, and Alan W Black. 2021. Grounding "Grounding" in NLP. In *Findings of ACL-IJCNLP 2021*.
- Noam Chomsky. 1957. *Syntactic Structures*. Mouton & Co.
- Morten H Christiansen and Nick Chater. 2016. The Now-or-Never bottleneck: A fundamental constraint on language. *Behavioral and Brain Sciences*, 39:e62.
- Eve Clark. 2003. *First Language Acquisition*. Cambridge University Press, Cambridge, UK.
- Herbert H. Clark. 1996. *Using Language*. Cambridge University Press, Cambridge.
- Herbert H. Clark and Susan E. Brennan. 1991. Grounding in communication. In L. B. Resnick, J. Levine, and S. D. Behrend, editors, *Perspectives on Socially Shared Cognition*, pages 127–149. American Psychological Association Books, Washington D.C., USA.

- Philip R. Cohen, Jerry Morgan, and Martha E. Pollack, editors. 1990. *Intentions in Communication*. MIT Press, Cambridge, Mass.
- John Dewey. 1960. On Experience, Nature, and Freedum. Liberal Arts Press, New York, USA.
- A. Seza Doğruöz and Gabriel Skantze. 2021. How "open" are the conversations with open-domain chatbots? a proposal for speech event based evaluation. In Proceedings of the 22nd Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 392–402, Singapore and Online. Association for Computational Linguistics.
- Jiafei Duan, Samson Yu, Hui Li Tan, Hongyuan Zhu, and Cheston Tan. 2022. A Survey of Embodied AI: From Simulators to Research Tasks. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 6(2):230–244.
- Jesse Dunietz, Greg Burnham, Akash Bharadwaj, Owen Rambow, Jennifer Chu-Carroll, and Dave Ferrucci. 2020. To test machine comprehension, start by defining comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7839–7859, Online. Association for Computational Linguistics.
- Charles Fillmore. 1981. Pragmatics and the description of discourse. In Peter Cole, editor, *Radical Pragmatics*. Academic Press.
- Jessica Kay Flake and Eiko I. Fried. 2020. Measurement Schmeasurement : Questionable Measurement Practices and How to Avoid Them. *Advances in Methods and Practices in Psychological Science*, 3(4):456– 465.
- Jonathan Ginzburg. 2012. *The Interactive Stance: Meaning for Conversation*. Oxford University Press, Oxford, UK.
- Sanford Goldberg. 2015. Assertion: On the Philosophical Significance of Assertoric Speech. Oxford University Press.
- Jing Gu, Eliana Stefani, Qi Wu, Jesse Thomason, and Xin Wang. 2022. Vision-and-language navigation: A survey of tasks, methods, and future directions. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 7606–7623, Dublin, Ireland. Association for Computational Linguistics.
- M.A.K. Halliday. 1989. Spoken and Written Language. Oxford University Press, Oxford.
- Stevan Harnad. 1990. The symbol grounding problem. *Physica D*, 42:335–346.
- Paul L. Harris. 2015. *Trusting What You're Told: How Children Learn from Others*. Harvard University Press, Harvard, Mass., USA.

- Irene Heim. 1983. File Change Semantics and the Familiarity Theory of Definiteness. In R. Bäuerle, Ch. Schwarze, and Arnim von Stechow, editors, *Meaning*, *Use and Interpretation of Language*, pages 164–189. De Gruyter, Berlin, Germany.
- Judith Holler and Stephen C. Levinson. 2019. Multimodal Language Processing in Human Communication. *Trends in Cognitive Sciences*, pages 1–14.
- William Hoppit and Kevin N. Laland. 2013. Social Learning: An Introduction to Mechanisms, Methods, and Models. Princeton University Press.
- Philip Nicholas Johnson-Laird. 1983. *Mental Models: Towards a Cognitive Science of Language, Inference, and Consciousness.* Cognitive science series. Harvard University Press.
- Hans Kamp. 1981. A theorie of truth and representation. In J.A.G. Groenendijk, T.M.V. Janssen, and M.B.J. Stokhof, editors, *Formal Methods in the Study* of Language, number 135 in Mathematical Centre Tracts, pages 277–322. University of Amsterdam, Amsterdam.
- Adam Kendon. 2004. *Gestures*. Cambridge University Press, Cambridge, UK.
- Alex Lascarides and Nicholas Asher. 2009. Agreement, Disputes and Commitments in Dialogue. *Journal of Semantics*, 26(2):109–158.
- Hector J. Levesque, Ernest Davis, and Leora Morgenstern. 2012. The Winograd schema challenge. *Proceedings of the International Workshop on Temporal Representation and Reasoning*, pages 552–561.
- Stephen C Levinson. 2010. Interactional Foundations of Language: The Interaction Engine Hypothesis. In Peter Hagoort, editor, *Human language: From genes* and brain to behavior, chapter 14, pages 189–200. MIT Press, Cambridge, MA, USA.
- Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, Benjamin Newman, Binhang Yuan, Bobby Yan, Ce Zhang, Christian Cosgrove, Christopher D. Manning, Christopher Ré, Diana Acosta-Navas, Drew A. Hudson, Eric Zelikman, Esin Durmus, Faisal Ladhak, Frieda Rong, Hongyu Ren, Huaxiu Yao, Jue Wang, Keshav Santhanam, Laurel J. Orr, Lucia Zheng, Mert Yüksekgönül, Mirac Suzgun, Nathan Kim, Neel Guha, Niladri S. Chatterji, Omar Khattab, Peter Henderson, Qian Huang, Ryan Chi, Sang Michael Xie, Shibani Santurkar, Surya Ganguli, Tatsunori Hashimoto, Thomas Icard, Tianyi Zhang, Vishrav Chaudhary, William Wang, Xuechen Li, Yifan Mai, Yuhui Zhang, and Yuta Koreeda. 2022. Holistic evaluation of language models. CoRR, abs/2211.09110.
- Sharid Loáiciga, Anne Beyer, and David Schlangen. 2022. New or old? Exploring how pre-trained language models represent discourse entities. In *Proceedings of the 29th International Conference*

*on Computational Linguistics*, pages 875–886, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.

- Eric Margolis and Stephen Laurence, editors. 2015. *The Conceptual Mind: New Directions in the Study of Concepts.* MIT Press, Cambridge, Massachusetts, USA.
- Rebecca Marvin and Tal Linzen. 2018. Targeted syntactic evaluation of language models. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1192–1202, Brussels, Belgium. Association for Computational Linguistics.
- David McNeill. 1992. *Hand and Mind: What Gestures Reveal about Thought*. University of Chicago Press, Chicago, IL, USA.
- Jim Miller and Regina Weinert. 1998. Spontaneous Spoken Language. Clarendon Press, Oxford.
- Tim Miller. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267:1–38.
- Gregory L. Murphy. 2002. *The Big Book of Concepts*. MIT Press, Cambridge, MA, USA.
- Geoffrey Nunberg. 1987. Position paper on commonsense and formal semantics. *Proceedings of the 1987 Workshop on Theoretical Issues in Natural Language Processing, TINLAP 1987*, pages 129–133.
- Carl Pollard and Ivan Sag. 1994. *Head-Driven Phrase Structure Grammar*. CSLI / The University of Chicago Press, Chicago and London.
- James Pustejovsky and Olga Batiukova. 2019. *The Lexicon*. Cambridge Textbooks in Linguistics. Cambridge University Press.
- EU Regulation. 2016. REGULATION (EU) 2016/679 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation).
- Marco Tulio Ribeiro, Tongshuang Wu, Carlos Guestrin, and Sameer Singh. 2020. Beyond accuracy: Behavioral testing of NLP models with CheckList. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4902– 4912, Online. Association for Computational Linguistics.
- David Schlangen. 2023. Dialogue games for benchmarking language understanding: Motivation, taxonomy, strategy. CoRR, abs/2304.07007.
- David Schlangen and Gabriel Skantze. 2009. A general, abstract model of incremental dialogue processing.

In Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics (EACL 2009), pages 710–718, Athens, Greece.

- Sebastian Schuster and Tal Linzen. 2022. When a sentence does not introduce a discourse entity, transformer-based models still sometimes refer to it. In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 969–982, Seattle, United States. Association for Computational Linguistics.
- Winfrid Sellars. 1956. *Empiricism and the Philosophy of Mind*. Harvard University Press, Cambridge, Mass., USA.
- Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R. Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, Agnieszka Kluska, Aitor Lewkowycz, Akshat Agarwal, Alethea Power, Alex Ray, Alex Warstadt, Alexander W. Kocurek, Ali Safaya, Ali Tazarv, Alice Xiang, Alicia Parrish, Allen Nie, Aman Hussain, Amanda Askell, Amanda Dsouza, Ameet Rahane, Anantharaman S. Iyer, Anders Andreassen, Andrea Santilli, Andreas Stuhlmüller, Andrew M. Dai, Andrew La, Andrew K. Lampinen, Andy Zou, Angela Jiang, Angelica Chen, Anh Vuong, Animesh Gupta, Anna Gottardi, Antonio Norelli, Anu Venkatesh, Arash Gholamidavoodi, Arfa Tabassum, Arul Menezes, Arun Kirubarajan, Asher Mullokandov, Ashish Sabharwal, Austin Herrick, Avia Efrat, Aykut Erdem, Ayla Karakas, and et al. 2022. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. CoRR, abs/2206.04615.
- Stephen E. Toulmin. 2003 [1958]. The Uses of Argument. Cambridge University Press.
- Sean Trott, Tiago Timponi Torrent, Nancy Chang, and Nathan Schneider. 2020. (Re)construing meaning in NLP. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5170–5184, Online. Association for Computational Linguistics.
- T.A. van Dijk and W. Kintsch. 1983. *Strategies of Discourse Comprehension*. Monograph Series. Academic Press.
- Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019a. SuperGLUE: A Stickier Benchmark for General-Purpose Language Understanding Systems. In *NeurIPS*, July, pages 1–30.
- Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019b. GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding. In *ICLR* 2019, pages 1–20.

- Timothy Williamson. 2000. *Knowledge and its Limits*. Oxford University Press.
- Ludwig Wittgenstein. 1953/84. Tractatus Logicus Philosophicus und Philosophische Untersuchungen, volume 1 of Werkausgabe. Suhrkamp, Frankfurt am Main.