Natural Language Processing RELIES on Linguistics

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Abstract

Large Language Models (LLMs) have become capable of generating highly fluent text in certain languages, without modules specially designed to capture grammar or semantic coherence. What does this mean for the future of linguistic expertise in NLP? We highlight several aspects in which NLP (still) relies on linguistics, or where linguistic thinking can illuminate new directions. We argue our case around the acronym RELIES that encapsulates six major facets where linguistics contributes to NLP: Resources, Evaluation, Low-resource settings, Interpretability, Explanation, and the Study of language. This list is not exhaustive, nor is linguistics the main point of reference for every effort under these themes; but at a macro level, these facets highlight the enduring importance of studying machine systems vis-à-vis systems of human language.

1 Introduction

It is 2024. ChatGPT has been an international sensation for over a year, a focal point in the ongoing public hype, enthusiasm, and concern about "generative AI." NLP conferences are awash in papers about prompting *Large Language Models* that have gobbled zillions of words of text and can produce eerily fluent language (in English, anyway). These models have been refined with corrective feedback on conversational outputs, but (so far as we know) no direct inductive biases about natural language grammaticality or compositional meaning. Like BERT and company an NLP research epoch before—or word embeddings an epoch before that—they have elicited both fascination and hand-wringing in scientific circles.

Do these developments spell the end of the relevance of linguistics to NLP?² After all, linguistic theories positing elaborate models of syntax are presented as necessary for explaining grammaticality, but are not incorporated into NLP models which nevertheless generate fluent text.

In this piece, we will argue that ideas from linguistics, even if not overtly framed as such, actually continue to underlie much of what we do in NLP. We highlight six facets where linguistics continues to play a major role, and for each facet, point to NLP work which has benefited from (or has been founded on) linguistic knowledge. We hope our survey will resonate with audiences representing a range of expertise—those with technology-oriented perspectives as well as human language perspectives, and their meeting point within the field of NLP.

1.1 What do we mean by "linguistics", "NLP", and "CL"?

Before developing our argument, we need to define our terms (while acknowledging that our definitions will not be perfectly crisp, as disciplinary boundaries are inherently fuzzy).

Linguistics is the study of systematicity and variation in communication between humans, as transmitted via speech, sign, and writing. Linguists may specialize in how knowledge of forms is organized and deployed to symbolize meanings; how linguistic behaviors emerge, drawing on human cognitive and social capacities; and how language varies over time (ontogeny, phylogeny), geography, identity group, etc.

Adjacent to the core field of linguistics are a range of fields of study and practice that center on language, including language education, translation, documentation, rhetoric, communications, and philosophy of language. Below, the term "lin-

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¹For example, we did not find any such linguistic biases in the reported Llama 3.1 training procedure, though parts of the training targeted code (Llama Team, 2024).

²We are hardly the first to ask some version of this question: see §2.

guistics" covers these (non-AI) "language fields", broadly defined.

Natural Language Processing (NLP) is the field concerned with developing technology for sophisticated computational processing of text, and especially, computational understanding or generation of individual sentences, documents, or conversations (as opposed to drawing inferences about entire collections).³ Contemporary NLP research is organized around a paradigm of empirical evaluation of systems on tasks, whether connected with general user applications (like question answering, translation, summarization) or more granular and focused on aspects of the language system (like parsing and coreference resolution). In recent years, the dominant concern of NLP has been the design, interpretation, and application of pretrained transformer language models such as BERT and GPT. Pretrained models of considerable scale are often called Large Language Models (LLMs).

Today, **Computational Linguistics** (CL) has two definitions: a broad one (roughly, 'computation and natural language') that includes technologically-oriented NLP, and a narrower one that focuses on computational formalization and processing for the end goal of studying how language works. We use "**cL**" for this narrower goal whose chief motivation is to answer questions about language, rather than questions about technology, though methods and sub-questions often overlap between cL and NLP, and consequently both can be found at CL conferences.

1.2 Where would NLP be without linguistics?

Linguistics is no longer front and center in the way we build NLP systems for practical tasks (§2). Gone are the days when machine translation engines consisted of rules painstakingly crafted by linguists. But engineering the behavior of a system is only one component of the NLP research or development/deployment lifecycle, and there are ways expertise in linguistics continues to be essential in NLP—that is to say, there are ways NLP RELIES ON LINGUISTICS.

Imagine what the field would be like without linguistics, assuming for the sake of argument that current modeling approaches (word embeddings, transformers, LLMs) had somehow been developed with only a cursory understanding of how language works. Many of the systems might look similar, but the field would look very different. The field would have only the shallowest attention to linguistic analysis (i.e. tasks that focus on representing regularities in linguistic systems beyond the information communicated in a particular application setting). Even for objectives not primarily tied to linguistic analysis, our toolbox would be all the poorer. We explore six facets of NLP research, organized under the mnemonic "RELIES." Indeed, without linguistics

- Resources: We would not have carefully curated datasets such as lexicons and corpora, with an appreciation for variation between languages, dialects, genres and styles, etc. We would not have gold standard annotations of language-system phenomena, only of application-oriented phenomena.
- Evaluation: Not only would we not have gold standard evaluations for linguistic tasks, but for applied tasks, we would also lack expertise for designing effective human evaluations, interrogating automatic metrics, and characterizing the linguistic phenomena that challenge systems (such as anaphora or dialect variation).
- Low-resource settings: We would struggle more to understand why approaches that work well for English or French might not work well for Swahili or Arapaho. We would not have the knowledge that would allow us to test linguistic inductive biases in neuro-symbolic models for greater accuracy.
- Interpretability and Explanation: It would be harder to develop and test hypotheses about how black box systems such as LLMs process language across domains, and we would lack appropriate metalanguage for describing many observed patterns.
- Study of language: Classic cL tasks such as parsing, coreference resolution, and textual entailment/natural language inference would not exist within our community. An NLP devoted purely to commercial technology would

³Text mining, information retrieval, and speech processing are studied in separate research communities, though there is some overlap, as evidenced by dedicated tracks in NLP conferences such as ACL. These area, in combination with prototypical NLP applications such as machine translation and summarization, constitute *language technologies*. The shifting technological landscape may be opening up opportunities for greater unification of these fields (e.g., Chrupała, 2023).

also be indifferent to applications connected with scholarly or community-driven linguistic work, such as documenting endangered languages.

In what follows, we give a sampling of the ways linguistics continues to play a role in NLP, organized under the RELIES categories listed above: resources (§3), evaluation (§4), low-resource settings (§5), interpretability/explainability (§6), and study of language (§7). It is worth emphasizing that these categories and the literature review are meant to be illustrative, not exhaustive; that we are speaking at a macro level; and that we are not claiming that linguistics is the only or necessarily the single most important source of expertise for working with language data and systems. We conclude by discussing pertinent challenges for the NLP community which involve linguistic expertise (§8).

2 Background

Today it is not a given that theories and representations from linguistics will form a direct foundation of NLP technologies. Given the current state of the field, it is possible to do research in NLP without traditional training in linguistics. As was the case in the age of the "statistical revolution" of NLP (Johnson, 2009; Uszkoreit, 2009; Church, 2011), the neural era has brought on skepticism towards the role of linguistics in NLP engineering tasks, offering ways to do language processing 'from scratch' (Collobert et al., 2011). The field also saw the introduction of pre-trained word embeddings (Mikolov et al., 2013) and then pre-trained contextualized language models (Howard and Ruder, 2018), with the well-known inflection points of ELMo and BERT (Peters et al., 2018; Devlin et al., 2019). With such milestones as ChatGPT (Open AI, 2022) in 2022/23, the past couple of years have seen LLMs with billions of parameters that can be accessed by a wide range of users through a natural language interface ('prompting').

Do these developments prove the 'bitter lesson' (Sutton, 2019) that AI for language is best achieved by funneling data on a massive scale into rather

general machine learning architectures? What role does linguistics play nowadays in NLP? Triggered by these and similar questions, we analyze the role of linguistics in the current LLM regime of NLP.

We are not the only researchers that have studied these apparently tectonic shifts. Relatedly, Ignat et al. (2024) collect interesting topics for PhD students, particularly evaluation, and Saphra et al. (2023) hypothesize a cyclical historic model that then would suggest that familiar problems will resurface.

The relationship between Linguistics and NLP (as well as the relationship between Linguistics and AI) has been a topic of discussion for some time (e.g., Lakoff, 1978; Raskin, 1985; Nirenburg, 1986). Within the ACL community, it has been explicitly on the agenda of fora such as the EACL 2009 Workshop on the Interaction between Linguistics and Computational Linguistics: Virtuous, Vicious or Vacuous? (Baldwin and Kordoni, 2009), the ACL 2010 Workshop on NLP and Linguistics: Finding the Common Ground (Xia et al., 2010), and more recently the NAACL 2022 panel entitled "The Place of Linguistics and Symbolic Structures" (Carpuat et al., 2022, p. xxxiv).

In this paper, we want to look more generally at the overlap between the concerns of linguistics and the concerns of contemporary NLP as well as their relationship. In the sections that follow, we tackle each of the six facets of NLP research which make up the mnemonic "RELIES," for which we argue that linguistics has enduring relevance.

3 Resources

The field of NLP is committed to an empirical methodology wherein machine learning models are trained and evaluated on language data. This paradigm requires linguistic expertise on several fronts. Resources are supported by various degrees of linguistic knowledge—ranging from proficiency in a language to formal training in linguistics.

Creation of resources for general NLP tasks

By "general NLP tasks" we mean tasks that closely relate to applications in widespread demand, such as machine translation (MT), entity linking, and sentiment classification. Studying these tasks in an empirical way requires corpus resources. Even if we can do without some of these resources in the *training* of NLP systems, they remain relevant for testing and studying systems, ensuring sound behavior.

⁴That is, the RELIES facets highlight ways that linguistics *can* be useful in individual projects, and has a role to play in the field at large, alongside other kinds of expertise. We are not claiming that advanced training in linguistics is always a prerequisite for engaging with the RELIES facets (it depends on the nature of the study).

Linguistic expertise contributes to the development of resources at the first step of building a dataset: selecting data. The **selection and curation of data is often informed by language expertise**, even if the data is raw text.

Linguistic expertise is important in moving away from a language ideology which sets some fluent text as more "high quality" than others and ripe for inclusion in training data. For example, awareness of various sociolinguistic factors can inhibit bias in model training and use: Gururangan et al. (2022) showed that US school newspaper data is more likely to be marked as "high quality" via GPT-3 if it comes from a school in a wealthier zip code.

Issues that arise in selection/curation of raw text include language diversity, variation amongst dialects/speakers, genre variation, code-switching, social biases, and undesirable content (e.g. hate speech). This is particularly important because of the wide variability of human language and the subjectivity of core NLP tasks; for example, Sasidharan Nair et al. (2024) explores the reliability and reproducibility of sentiment annotations of codemixed data, and Abercrombie et al. (2023) investigates the impact of source language on hate speech labeling.

Data selection may involve shallow linguistic heuristics such as the analysis of word/sentence counts, or linguistically advanced techniques that increase and validate the diversity and language phenomena coverage of the data (Dryer, 1989; Rijkhoff et al., 1993). For example, Ravichander et al. (2022) select data with sufficient prepositions and complementizers, and Ponti et al. (2020) inform their data selection with a language typology index (Littell et al., 2017). Statistical induction of dataset properties is possible through assessing its broader linguistic features, as shown by (Monteiro et al., 2024) that characterize datasets with psycholinguistic features such as readability index (Anderson, 1983) or content word frequency (Baayen et al., 1995).

In the annotation process, advanced linguistic knowledge of annotators can also be important. For example, people skilled at language analysis are needed to ensure meaningful evaluation of machine translation systems. As such, paraphrasing references with linguists increases their quality and diversity (Freitag et al., 2020), and professional translators (Freitag et al., 2021a) offer annotations that provide correct system rankings (in both stud-

ies, crowd-workers were not able to make the cut). For consistent annotation of sentiment, Taboada (2016) outline that it is necessary to understand and conceptualize linguistic phenomena, such as discourse patterns. Since not all tasks may be suitable for crowdsourcing without extensive experimentation, linguistically trained annotators can also help reduce annotation cost (Gillick and Liu, 2010).

Further, the design and execution of crowdsourcing and annotation protocols depend on (advanced) linguistic knowledge of designers. This is due to the challenging nature of establishing communication that will elicit accurate judgments from lay people facing diverse natural language data (Ambati et al., 2012); an agreed-upon linguistic metalanguage and vocabulary is required to invoke a consensual view on the setting and the linguistic object of interest. This holds true even for tasks such as entity linking, which though less subjective, calls for a precise definition of named entity that resolves "lexical, syntactic, semantic, and pragmatic" ambiguities (Berry, 2007; Bouarroudj et al., 2022). 5 As such, the linguistic knowledge that both or either the designer and annotator have is (either explicitly or implicitly) relevant to the creation of the dataset, even if it's not a "linguistic" task.⁶

Dataset development Annotation is a complex endeavor that with insufficient care can easily produce misleading data, and thus misleading conclusions (Tedeschi et al., 2023). This is especially true with crowdsourcing, given the difficulty of controlling the annotation quality. As such, irreproducible and low-quality crowdsourced datasets often emerge (Karpinska et al., 2021).

Therefore, each aspect of the process of language resource creation requires careful consideration (Rehm, 2016; Ide and Pustejovsky, 2017; Klie et al., 2024), including the development and documentation of data. One step towards consistent data use is standardized documentation of the characteristics and intended uses of datasets (Gebru et al., 2021; McMillan-Major et al., 2024).

Resources for endangered languages According to some predictions, half of the world's spo-

⁵Even less subjective tasks like named entity annotation elicit annotation disagreement (Peng et al., 2024) and dataset creators and analyzers must take care to consider the range of backgrounds and perspectives which contribute to disagreement (Wein et al., 2023; Prabhakaran et al., 2024).

⁶For more on metalanguage, see also Interpretability and Explanation (§6).

ken languages might be on the brink of extinction (UNESCO, 2023), prompting the development of computational tools to document and revitalize endangered languages (e.g., van Esch et al., 2019; Levow et al., 2021; San et al., 2022). The lack of existing language resources in endangered languages can also frustrate the development of NLP technologies that could serve communities with ties to such languages.

To counteract the ongoing depletion of the world's languages, collaborations involving community members, linguists, and NLP practitioners seem particularly promising. Linguistic expertise is relevant for structurally collecting and documenting language data, as well as helping to distill and compress knowledge about the language into human dictionaries and rules. This linguistic knowledge may also be relevant then when building parallel corpora from which we might even then create machine translation methods to compress language knowledge into a neural network's parameters, as hypothesized by Bird and Chiang (2012); Abney and Bird (2010).

Such projects are by nature highly interdisciplinary, as NLP experts and linguists rely on each others' input. Recent work has brought community members and NLP practitioners together for the purpose of language documentation through provisioning access to speech tools such as ASR (San et al., 2022), building datasets on online platforms (Zuckermann et al., 2021; Everson et al., 2019; Dunham et al., 2014), analysis of phonetic data (Kempton, 2017), and linguistic feature structures to describe "particularly morphologically complex, low-resource languages" (Van Gysel et al., 2021). As endangered languages tend to be underresourced, we return to this topic in §5.

Resources with linguistic annotations These encompass datasets of various sorts of grammatical and semantic structures. Linguistically detailed resources prominent in current NLP research include Universal Dependencies treebanks, with morphosyntactic annotations for over a hundred languages (UD; Nivre et al., 2016), and Abstract Meaning Representation, which is a framework for describing semantic graphs that now underlies datasets in several languages (AMR; Banarescu et al., 2013; Wein and Schneider, 2024). Linguistic knowledge and awareness is, of course, needed for designing these frameworks, but also for conducting annotation and verifying model output. UD and

AMR are *applied linguistic theories* (in the sense of Raskin, 1985, p. 275).

Research in and with such frameworks continues apace, with numerous recent workshops in the ACL community focused on grammar and semantic frameworks (Bonial and Tayyar Madabushi, 2023; Dakota et al., 2023; Bonn and Xue, 2023; Grobol and Tyers, 2023; Rambow and Lareau, 2023) and more than 100 publications addressing applications of the AMR framework alone.⁷ Recent areas of NLP where integration of AMR has seen success include, i.a., machine translation (Song et al., 2019; Nguyen et al., 2021; Li and Flanigan, 2022), human-robot interaction (Bonial et al., 2019; Abrams et al., 2020; Bonial et al., 2020, 2021, 2023), and information extraction (Garg et al., 2016; Wang et al., 2017; Rao et al., 2017; Zhang et al., 2021; Yi et al., 2024). For a comprehensive overview of AMR applications, we refer the reader to two recent surveys: Wein and Opitz (2024) and Sadeddine et al. (2024).

Still, though interest in structured linguistic representations does not seem to be receding, it is not clear yet which avenues will be most fruitful for downstream application of formal representations. While some approaches have successfully leveraged explicit linguistic structures alongside neural models for applications (e.g., Kapanipathi et al., 2021; Li and Flanigan, 2022), neuro-symbolic approaches do not consistently outperform strictly neural approaches (Hamilton et al., 2022; Shwartz, 2023). We consider the utility of such formal representations for evaluating and interpreting models (e.g., Xu et al., 2021; Opitz and Frank, 2022) to be an exciting path. Another exciting application lies in using NLP models for studying questions about language, which we will continue to discuss below.

4 Evaluation

We illustrate where linguistic influence is useful to successfully *evaluate* an NLP system, that is, to describe the degree to which a system conforms to our expectations of accuracy on a task.

A common practice in NLP system evaluation is to apply one or several **automatic metrics** that

⁷https://nert-nlp.github.io/AMR-Bibliography/

⁸Still, as two interesting recent developments regarding neuro-symbolic models, we see the creation of challenging datasets that reveal the need for their application (Fodor et al., 2024), and abstract symbolic cross-lingual representations that even enable *fully-symbolic* cross-lingual comparison (Zhang et al., 2024b).

assess model output against a reference, ideally supplemented by a **human evaluation**. As we discussed in §3, expertise in computational linguistics can be important to designing crowdsourcing protocols which lead to collection of accurate reference annotations. Similarly, human evaluation studies require language knowledge that ensure effective error analysis and quality assessment (Freitag et al., 2021a).

Gold standard evaluation Linguistic resources, particularly so-called gold standard annotations, play an important role in the evaluation of NLP technologies. For instance, they contribute to the comprehensive benchmarking of general AI systems (Tenney et al., 2019b; Pimentel et al., 2020a), where many of the tasks packaged in the Beyond the Imitation Game Benchmark (BIG-bench), a large test-suite for tracing AI development (Srivastava et al., 2023), are linguistic tasks, such as bridging resolution and detecting common morphemes. In low-resource and extinct languages, models are benchmarked with linguistic puzzles (Bean et al., 2024); this draws a connection to another area where NLP relies on linguistics (low-resource settings), which we will cover later in more detail (reLies, §5).

Linguistic resources are also crucial for **system diagnostics** which is a part of evaluation, but does not necessarily have the aim to achieve a "global ranking" (benchmarking) of AI systems. Instead, diagnostic methods help find more targeted perspectives for system improvement, with possible relevance even to broader society, since linguistic phenomena are often contingent with issues of societal interest, as is the case of coreference and gender bias (Rudinger et al., 2018) or question answering with social biases Parrish et al. (2022).

Overall, linguistic diagnostics can come in many forms, and here we give a non-comprehensive overview. E.g., with their 'CheckList' approach, Ribeiro et al. (2020) test NLP systems in various categories, leveraging linguistic features (negation, part of speech, sentiment, etc.) to build templates. In a similar style, Song et al. (2022) create a data set for assessing LLM performance on various Chinese linguistic phenomena, and Parcalabescu et al. (2022) employ linguistic knowledge to design image-caption foils that reveal the behavior and understanding of V&L systems in different visual-linguistic aspects. Moore (2009) outlines examples of challenges for models which require linguistic

knowledge to unpack, such as structural parallelism and translation of "WH" questions.

Automatic diagnostics for text generation systems can be conducted through controlled and targeted measurements on parsed semantic role (Lo and Wu, 2011; Fan et al., 2023) or semantic (sub)graph structures (Birch et al., 2016; Opitz and Frank, 2021; Opitz, 2023) (which calls for research to improve the intrinsic NLP task of parsing). Finally, there is the large area of probing systems with linguistic structures (Tenney et al., 2019c; Rama et al., 2020; Pimentel et al., 2020b; Starace et al., 2023), possibly tailored at certain linguistic branches, e.g., psycholinguistics (Gauthier et al., 2020).

In sum, linguistics helps to take a system's fingerprint, evaluate a system in particular categories, fosters understanding of complex models by binding observed behavior to interpretable linguistic categories (cf. Interpretability, §6), and helps to build resources (cf. Resources, §3).

Human evaluation Despite being an important component of model evaluation, human evaluation practices are currently varied. The combination of varied human evaluation practices with progress towards highly fluent models has led to a degradation of human evaluations, meaning that not all human evaluation studies are useful measures of model output (Clark et al., 2021; Freitag et al., 2021a).

Whether making use of implicit linguistic knowledge held by native speakers (e.g. judging the fluency of system output) or more explicit linguistic training (e.g. assessing the syntactic diversity of system output), human evaluations serve a crucial role in reliably assessing the state of the field (Michael et al., 2016; Callison-Burch et al., 2008), especially as systems continue to improve (Ma et al., 2019); this therefore motivates the use of human evaluation and its standardization with regard to design and terminology (Howcroft et al., 2020; Belz et al., 2020; van der Lee et al., 2019).

Meta-evaluation In addition to their use in human evaluation studies, human judgments are often used to train metrics as well as to judge the quality of automatic metrics themselves ("meta-evaluation"). Typically, this is done by correlating agreement between the human judgments and the automatic metric scores, a protocol that has been used for numerous automatic metrics, e.g., in the Machine Translation metric shared tasks (Ma

et al., 2019; Mathur et al., 2020), the WebNLG challenge (Gardent et al., 2017; Zhou and Lampouras, 2020), generation of medical notes (Moramarco et al., 2022), and generation of meaning graphs (Manning et al., 2020).

To design a meta-evaluation framework for metrics that assess generated language, expertise in linguistic theories may be required for some tasks, and possibly offer general value due to training in abstract thinking. For instance, similar to how training in *mathematics* would help in solving *machine* learning problems, training in linguistics can help study and diagnose complex behavior of models and metrics that produce and evaluate language data; this is because the specific linguistic phenomena which may be more challenging for the models need to be understood in order to be identified, such as in the case of probing BERT via psycholinguistic diagnostics (Ettinger, 2020). Further, in their WMT shared task overview paper on MT metrics, Freitag et al. (2021b) find that most metrics struggle to handle complex semantic phenomena as well as to appropriately punish the reversal of sentiment or negation; this is established through the use of test sets which assess specified linguistic features, such as negation and sentiment polarity.

One way to circumvent the need for metaevaluation is with a 'human user in the loop' (Bodén et al., 2021), though downstream evaluations may be costly and irreproducible in many circumstances.

New metrics In some cases, linguistic information in the form of annotations can help build strong automatic metrics. For instance, entailment data is used to build accurate and efficient neural NLG evaluation metrics (Chen and Eger, 2023), including metrics that address the problem of checking whether a generated text is factual (Xie et al., 2021; Scialom et al., 2021; Honovich et al., 2022; Steen et al., 2023). For finer classification, pragmatics-informed annotations of veridicality could be crucial (de Marneffe et al., 2012).

Finally, we observe that measures for biases of

other sorts, like social biases, have drawn upon the efforts of linguists. For example, Steen and Markert (2024) propose bias evaluation measures that leverage socio-linguistic lexicons (gender, race) and OntoNotes (Pradhan et al., 2013) for template creation. This work also highlights the potential use of linguistically annotated corpora in constructing evaluation data and evaluation measures.

5 Low-Resource Settings

The term "low-resource" can have multiple meanings (Hedderich et al., 2021). In NLP and ML generally, an important problem is efficiently learning to generalize to new tasks, domains, and languages, where the term "new" is not to be understood in a strict way, but can in this context also indicate a situational lack of information, e.g., little, or no available training data or lack of feedback of some other sorts. Specifically, "new" languages would include endangered languages (as discussed in §3 above), and extinct languages, as well as languages that are widely used but not as commercially prioritized for language technologies (Joshi et al., 2020; Petrov et al., 2023; Khanuja et al., 2023; Hu et al., 2023), i.e., all global and historic languages. In such settings, often we lack the direct feedback that we usually use to train or create NLP system in higher-resource settings. As an edge case, we'd have only archaeological fragments and perhaps dictionaries available.

Next, within the broader field of computer science, the term *low-resource* can mean that a method can be run with **strictly limited compute-resources**. These methods would, e.g., offer quicker inference, or have a smaller energy footprint.

Finally, we touch on the need for **linguistically** sensitive supervision when it comes to developing language technologies for under-resourced languages, as it concerns the native speakers of the language.

Processing of global and historic languages Linguistics is crucial in situations where the amount of data is limited, e.g., when developing technologies for languages with a limited amount of available recordings or written data. This could include languages that lack digitized text (and/or even) audio/video recordings, or have only a few and noisy transcriptions of recordings (Bird, 2020). The only few bits of information readily at our hands could consist of, e.g., archaeological frag-

⁹Even though entailment annotations may come from non-linguists, the notion of textual entailment was inspired by traditions from logic and formal semantics (Dagan et al., 2006; Bowman et al., 2015).

¹⁰Factual text generation is a fundamental problem that may rise in importance against the backdrop of new risks through LLMs (De Angelis et al., 2023; Gupta et al., 2023; Li et al., 2023), in particular with regard to the phenomenon of *hallucination* (Xu et al., 2024).

ments or descriptions of the language and contexts, for instance in the form of dictionaries written by (field-)linguists. In these and similar scenarios, using linguistic input can improve generalization performance across an array of LLM models, as demonstrated by Zhang et al. (2024a) who exploit linguistic features and Lu et al. (2024) who use dictionaries for balanced data augmentation; these findings also generalize to audio (Kim et al., 2024).

What may appear first as a potential 'linguisticsfree' avenue for addressing some of these extremely low resource-scenarios, is Tanzer et al.'s (2024) study that seems to show that LLMs can to a certain extent translate an under-resourced language from only one linguist's grammar book, seemingly calling into question the assumption that "language models would have to wait for a usable language corpus to be created" (Lewis, 2023). Still, this work relies on linguistics in several crucial aspects: a linguist is required to reasonably assess LLM performance (here, to establish an upper bound), and even the largest LLMs considerably underperform relative to a linguist that has read the book but was unfamiliar with the language. Of course, it is also the case that this fundamental resource was created by a linguist.

Processing particular types of language/ particular languages can also pose challenges that require input from linguistics. For examples, polysynthetic languages such as those spoken in Canada (Gupta and Boulianne, 2020a,b) pose problems for automatic speech recognition (ASR): if 'word' is taken as the basic unit for recognition (which makes sense for most languages, but not these ones) the out-of-vocabulary (OOV) rate on new data is extreme. As a result, ASR researchers need linguistic knowledge in order to effectively design their systems to account for the diversity of global languages—e.g. by breaking long polysyllabic words up into morphemes or syllables. Note that this isn't the only problem for NLP with indigenous polysynthetic languages—many are also under-resourced. Finite-state methods can be superior to machine learning methods for many polysynthetic and other morphologically rich languages, at least with respect to their precision (Forbes et al., 2021). They can also provide the groundwork for leveraging neural advances by generating silver annotations (Rueter and Hämäläinen, 2020; Rueter et al., 2023).

Furthermore, even in the case where there is

much (but not abundant data) available, linguistics can be of value: It can inform data selection in multi-lingual pre-training (Ogunremi et al., 2023), or enable more language-balanced tokenization with morphemes (Creutz and Lagus, 2002; Limisiewicz et al., 2024). While it may be possible to pretrain multilingual LLMs on data from hundreds of languages (e.g., Imani et al., 2023), experiments on unseen languages indicate that "simply scaling up the number of languages [...] in the pre-training is unhelpful" for out-of-sample generalization (Adelani et al., 2024), and "bigger is not always better" (Wilcox et al., 2024), suggesting the models may benefit from incorporation of a linguistic signal. It may also be possible to leverage auxiliary linguistic structures to improve upon a pretrained language model (Prange et al., 2022).

Compute restriction Systems that require less compute power, particularly at inference time, are also of increasing interest. Critically, off-the-shelf conventional parsers/taggers clearly defend their status as the go-to method in targeted situations, in academia and industry. They are ideal for conducting a lightweight data analysis or fast (and affordable) processing of huge corpora, e.g., up until extracting relation networks with linguistic machinery (Angeli et al., 2015; Martinez-Rodriguez et al., 2018), justifying future work into improving the breadth and quality of the computational linguistic tool box.

More generally, there are several scenarios where we might want to reduce the time of inference (Treviso et al., 2023) or the size/energy footprint of a model (Strubell et al., 2019). For many end-user applications, sending data to an LLM (or hosting an LLM locally) may also simply not be practical, due to issues of connectivity, privacy, and runtime.

Some effective approaches to computational efficiency are pure engineering solutions, such as quantization (Dettmers et al., 2022) or low-rank adaptation (Hu et al., 2022) of LLMs. However, soft inductive linguistic biases might be complementary, or an alternative in specific situations (we refer back to the paragraph above for examples). To find a right balance of linguistic biases and pure LLM engineering, new evaluation metrics might be useful that facilitate such investigations into resource-performance tradeoffs (Zhou et al., 2022).

Linguistically sensitive supervision Developers of technologies for under-resourced languages (e.g., a QA dialog system for a language with only a handful of speakers) are bound to not only encounter data scarcity, but also scarcity of input from native speakers who could help oversee a system's design and application. An outcome that should be prevented is triggering ethical issues in local communities that can arise when technology is released in a top-down fashion (Bird, 2022; Doğruöz and Sitaram, 2022).

To reduce the risk of harmful biases or misunderstandings, and when applied with care, *linguistic* sensitivity through pragmatics and field linguistics can help to better become aware of the diverse cultural contexts of local language communication situations. Thus, while in §3 we outlined the importance of (interdisciplinary) linguistics for collecting and documenting data to *preserve* under-resourced languages, here we argue that *developing and applying text technologies* for under-resourced languages also profits from linguistic input.

6 Interpretability and Explanation

How can we efficiently understand, reason about, and explain observations of observed language phenomena, language systems, and processes of language? For this, it is necessary to have a **shared terminology and metalanguage**, onto which we can bind our observations, and develop **binding methods** that relate model processes and internals to human-understandable concepts. We argue that linguistics provides valuable tools for helping with both aspects.

We find that NLP is already permeated by a **lin**guistic metalanguage. This metalanguage is employed by researchers, laypeople, and users to talk and reason about their observations, such as model predictions, and hypothesizing explanations. As a simple example, take the grammatical concept of noun: even if we all may not agree in every instance on what a noun exactly is, the approximations that we have of this concept constitute a common ground that can be useful, e.g., to describe observed model behavior ("the model is mostly attending to *nouns* for its predictions"). While *noun* is a concept familiar to anybody who has used a dictionary, exposure to linguistics enriches one's lexicon with terms like syntactic ambiguity, presupposition, code-switching, and polysynthetic language. These terms of art reflect a level of understanding of language systems—how they are organized, how they vary, and so on.

Fundamentally, with a precise metalanguage for the inner workings of language, it is possible to formulate more rigorous hypotheses and claims about language models. This can be seen in the literature in observations like "phonemic representations exhibit higher similarities between languages compared to orthographic representations" (Jung et al., 2024) and "difficult to score [in MT evaluation] are the transitive past progressive, multiple connectors, and the ditransitive simple future I for English to German, and pseudogapping, contact clauses, and cleft sentences for English to Russian" (Avramidis et al., 2024).

For understanding computational models of language such as LLMs with billions and trillions of parameters, directed binding methods are being developed that learn to relate model internals and processes to specific human-understandable descriptions, that often lie within our vocabulary of linguistic meta-language. We will consider a few examples of such methods that particularly use a linguistic notion of binding: Rassin et al. (2023) bind linguistic concepts in V&L diffusion models leveraging syntax trees and attention maps; Haviv et al. (2023) show how to understand transformer memories with idioms, or detecting linguistic feature representations in LLMs with prompts (Di Marco et al., 2023; Jumelet and Zuidema, 2023); Opitz and Frank (2022) enforce binding in a transformer model by relating parts of neural representations to semantic features, for greater interpretability of decisions. Explanations and binding can also adopt an outside, behavioral view (Beguš et al., 2023; Behzad et al., 2023; Chang and Bergen, 2024). E.g., Muñoz-Ortiz et al. (2023) contrast linguistic patterns in human- and LLM-generated text in morphological, syntactic, and sociolinguistic aspects. Since such methods can be also seen as diagnostic methods, the section on Evaluation (§4) is also relevant.

Indeed linguistics, and binding observed behavior to said meta-language, can help us understand, or establish hypotheses, for what happens in complex NLP systems, and how they differ. A popular example is the hypothesis that a text Transformer model can be viewed through the lens of a classical NLP pipeline, which has received arguments for and against (Tenney et al., 2019a; de Vries et al., 2020; Niu et al., 2022). Alternatively, neu-

ral decisions can be viewed as constructed from interpretable concepts in a vocabulary (Geva et al., 2022), or the learning trajectory of LLMs can be examined through a linguistic lens, such as noting the point when a model acquires syntax (Chen et al., 2024).

Tying interpretability more immediately back to Resources (§3), we can use data sets that elicit linguistic phenomena to "open the black box" of LLMs down to the level of single neurons, as exemplified by Niu et al. (2024), who study neuron-level knowledge with the BLiMP corpus of linguistic minimal pairs (Warstadt et al., 2020). Through designing a resource using linguistically informed counterfactuals, Wang et al. (2024) show that BERT-like models primarily focus on sentencelevel features, whereas LLMs such as GPTand Llama are sensitive to conventions, accuracy, language complexity, and organization. Experiments with complex and simple language structures can illuminate the settings in which LLMs learn successfully (Qin et al., 2024).

Linguistically-agnostic interpretability approaches can be mechanics-based, i.e., formalizing the algorithms learned by neural networks (Weiss et al., 2021); or eliciting attributions to input features, e.g., by employing integrated gradients (Sundararajan et al., 2017), classifiers (Ribeiro et al., 2016), or Shapley values (Shapley, 1951). However, still, for interpreting and evaluating the results of such methods, we depend on linguistic analysis (Schuff et al., 2022; Feldhus et al., 2023; Moeller et al., 2024), to verify that a computational interpretability method "outputs meaningful explanations" (Mardaoui and Garreau, 2021) or "emphasize[s] specific types of linguistic compositions" (Kobayashi et al., 2024). This means that linguistic analyses can be used to validate interpretability methods whose algorithms do not explicitly incorporate such representations.

Finally, at the thousand-foot view, we see ideas from linguistics and adjacent fields take center stage in debates about how to *interpret* what NLP models are capable of representing—like how to define machine 'understanding' (Dunietz et al., 2020; Ray Choudhury et al., 2022) and whether grounding is required for a model to capture meaning (e.g., Bender and Koller, 2020; Merrill et al., 2021; Pavlick, 2023).

7 Study of Language

Our last facet highlights linguistics (and related areas) as the application domain. That is, those who study language, but are not necessarily computational linguists themselves, are a user base that can motivate NLP tasks and tools. ¹¹ These *language-system-focused* applications can be distinguished from most contemporary NLP applications, which seek to make *content* more accessible through language (for example, by translating it, summarizing it, or reasoning about it).

Classic cL tasks like parsing have applications to corpus linguistics: in order to study a linguistic pattern, it is often important to query not just strings, but with grammatical abstractions like tags, dependencies, and phrases. This was not the original goal of parsing researchers: parsing was a cL topic before the days of substantial digital corpora, and was studied to examine computational capacity to model natural language grammar. Now, the tools produced have found a secondary application in corpus linguistics, with parser outputs accessible through corpus search engines (Resnik and Elkiss, 2005; Ghodke and Bird, 2012; Krause and Zeldes, 2016; Guillaume, 2021; Hundt et al., 2012; Kulick et al., 2022). ¹² The application to corpus linguistics perhaps motivates new angles on parsing research (e.g., syntactically searching a large text collection without having to pre-parse it in its entirety, or in a way that accounts for parser uncertainty).

Documentary and historical linguistics also motivate and contribute to NLP advancement. In documentary and historical linguistics, data may be sparse, fragmented, primarily in image or audio form (without transcriptions), and lacking a standard orthography; the basic grammar of the language may still be a mystery; and the language may have few or no living speakers. (The case of endangered language documentation was discussed above in §3.) The exigencies of such settings call for considerably more noise-tolerance

¹¹Unlike the previous categories, which highlight ways that linguistics contributes to NLP, we view this category as bidirectional: language study motivates research towards developing NLP tools which can then contribute to the study of language. We focus here on NLP *tools* in the sense of off-the-shelf text analysis software, not NLP models and representations generally, but see e.g. Beguš et al. (2023); Mahowald et al. (2024); Chang and Bergen (2024) on the potential relevance of LLMs to broader linguistics and cognitive science.

¹²Search engines allowing users to query parsed corpora may also be motivated by information extraction applications (Shlain et al., 2020).

and interactivity than run-of-the-mill NLP tasks. Pure-text tasks like normalization (Robertson and Goldwater, 2018), as well as signal processing capabilities like OCR for historical documents (Berg-Kirkpatrick et al., 2013) or low-resource speech processing (Duong et al., 2016; Anastasopoulos et al., 2017; Liu et al., 2022), are important here. Still, algorithms and software infrastructure to assist humans engaging in multiple tasks collaboratively (elicitation, transcription, annotation, discovering grammatical generalizations, and developing usable resources for scholars and community members) in limited-data multimodal conditions are needed, and there is a long way to go before they can be used seamlessly by non-computational linguists (Gessler, 2022; Moeller and Arppe, 2024).

Language teaching, as studied in the field of Applied Linguistics and practiced in classrooms as well as other modes of instruction and technological support, is another area ripe for further engagement with NLP. The research that exists in the NLP community tends to be formulated in narrow tasks like grammatical error correction (as a generation task) or essay scoring (as a regression task) (Burstein and Chodorow, 1999; Massung and Zhai, 2016; Wang et al., 2021; Klebanov and Madnani, 2022). Applications with richer contexts—for example, technologies that would monitor student progress over time and deliver adaptive pedagogical experiences—are more difficult to study, but could enhance student learning more holistically.

Finally, we note the potential for NLP to embrace applications facilitating language-focused study in fields beyond linguistics proper, including literature (Jakobson, 1987), education, law (Marmor, 2014), communications (Miller, 1951), translation studies (Gambier and Van Doorslaer, 2009), history (Piotrowski, 2012), argumentation (Cohen, 1987), and lexicography (McArthur, 1998). In the NLP community, these fields are associated and developed with active workshops, e.g., LaTeCH-CLfL (CL for Cultural Heritage, Social Sciences, Humanities and Literature—8th iteration in 2024) (Bizzoni et al., 2024); BE(ducational)A (19th iteration) (Kochmar et al., 2024); Argument Mining (11th iteration) (Ajjour et al., 2024); and NL(egal)LP (3rd iteration) (Aletras et al., 2024), among others. Important objectives featured in these workshops include creating structured resources, increasing interpretability, evaluating models and resources, and coping with low-resource settings, underpinning not only how language studies rely on NLP, but also how NLP relies on linguistics.

8 Challenges for the community

Having reviewed both obvious and subtle ways in which NLP relies on linguistic knowledge (highlighting Resources, Evaluation, Low-resource settings, Interpretability, Explainability, and Study of language), we now consider the future of NLP vis-à-vis linguistics.

A longstanding priority in NLP has been the development of linguistic resources including annotated datasets and linguistic processors (taggers, parsers, etc.). For a long time, automating analysis into linguistically-based representations was undertaken in part with the aim of paving the path towards NLU, building modules that capture features of language based on human conceptualizations (expressed in the form of manually crafted rules, or latent rules induced through training on annotations). Today, for some settings, LLMs offer an alternative path. However, there remain strong reasons for continuous improvement of linguistic resources. These reasons include some major engineering applications (Low-resource), but also goals that don't immediately lie on the path towards NLU accuracy via scale. Among these other reasons are compute-constrained as well as targeted evaluation and data analysis settings, where taggers and parsers could shine with advantageous features such as efficiency, task-specificity (controllability) and precision. Moreover, for answering cL questions (as part of the study of language; §7), we require accurate, fast, and robust linguistic resources.

Beyond continuing to develop cL resources, our review has highlighted **other pertinent challenges for the NLP community**, namely:

- Efforts towards preserving the world's languages. This requires cooperation between linguists, machine learning experts, and language communities (RLS).
- Language learning applications and computational models of language acquisition, with potential for both the use and analysis of linguistic phenomena in NLP (ELIES).
- Tasks that benefit from the integration of symbolic representations into models for *inter-pretability and explanation* (IE). This appears

as a fruitful avenue for future work, while the broader application of neuro-symbolic modeling for *performance* is still an open debate (Hamilton et al., 2022; Shwartz, 2023).

- Avenues where linguistics helps define and assess model facility and desiderata (Evaluation and Interpretability). Examples are linguistic calibration (Mielke et al., 2022; Zhou et al., 2024), linguistic conventions (Hawkins et al., 2020; Hua and Artzi, 2024), and exploring metalinguistic behavior (Behzad et al., 2023; Beguš et al., 2023; Hu and Levy, 2023; Thrush et al., 2024). Research progress in these areas may also open doors to improving models.
- As the quality of generated output improves, the focus of evaluation may shift increasingly away from linguistic form and toward function, including social meaning. We see great potential for sociolinguistics in creating resources and evaluation measures, studying the use of generated language in different social settings, understanding challenges, and helping develop solutions (Grieve et al., 2024) in all RELIES categories (and beyond).

9 Conclusion

Given the recent emergence of powerful LLMs that leverage huge amounts of data to recognize patterns in text, the question of the relationship between natural language processing and linguistics, in particular how linguistic knowledge benefits work in natural language processing, is a pressing one. In this paper, we have illustrated the role of linguistics when compiling resources and conducting system evaluations (RE-); when building systems in lowresource settings (-L-); when pursuing granular interpretation or control of large-data systems (-IE-); and when connecting NLP to the study of human language (-S). While explicit linguistic knowledge is not necessary to achieve high accuracy on all NLP tasks, in this work we have highlighted the engineering utility of varying degrees of language knowledge.

We hope that this study will promote future work that leverages collaboration and connections between linguistics and computer scientists with the aim of NLP progress in diverse domains.

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