Adversarial Evaluation for Models of Natural Language

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Abstract

We now have a rich and growing set of modeling tools and algorithms for inducing linguistic structure from text that is less than fully annotated. In this paper, we discuss some of the weaknesses of our current methodology. We present a new abstract framework for evaluating natural language processing (NLP) models in general and unsupervised NLP models in particular. The central idea is to make explicit certain adversarial roles among researchers, so that the different roles in an evaluation are more clearly defined and performers of all roles are offered ways to make measurable contributions to the larger goal. Adopting this approach may help to characterize model successes and failures by encouraging earlier consideration of error analysis. The framework can be instantiated in a variety of ways, simulating some familiar intrinsic and extrinsic evaluations as well as some new evaluations.

1 Introduction

This paper presents a new approach to evaluating computational models of natural language, based on adversarial roles performed by different researchers or their models. We begin in §2 with a brief review of current evaluation strategies in NLP. We then turn to coupled adversarial evaluations inspired by perplexity (§3) and the traditional roles of linguists (§4). The two-performer setup is formalized in §5. We then consider the origins of the data and growing awareness of the importance of context on language use (§6) and provide a three-performer setup, in which a third performer manages data selection (§7). We close with a few open questions (§8).

2 Current Evaluation Strategies in NLP

At present, NLP models are primarily evaluated in three ways: intrinsic evaluations, in which model predictions are compared to manually produced “gold-standard” output; extrinsic evaluations, in which output is passed downstream to an application whose performance can in turn be evaluated; algorithm competitions with predefined, formal criteria for success (less typical in NLP but used

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in some related areas); and (for probabilistic models) perplexity evaluations, in which the model is used to assign a likelihood score to unseen data, and this score is compared to other models’ scores. We assume the reader is familiar with these styles of evaluation and consider their strengths and weaknesses in turn.

2.1 Intrinsic Evaluations: MATCHLINGUIST

Models can be evaluated by comparing their predictions on input data to which they have never previously been exposed to the predictions of human experts (known as “gold-standard” linguistic annotations). This is the dominant intrinsic evaluation approach in NLP. In Smith and Eisner's (2005) introduction of the term “MATCHLINGUIST” to refer to the task of automatically reproducing gold-standard linguistic annotations.

The strength of intrinsic evaluations is that, once gold-standard annotations are provided, they can be reused forever. Once a scoring algorithm is agreed upon, many researchers can evaluate their models on the same data, making quantitative comparison easy. Unfortunately, this makes it difficult to draw conclusions about how well performance results generalize to other linguistic samples (e.g., in different genres, topics, dialects, languages, etc.). Indeed, some have conjectured that long-term reuse of an annotated test dataset can lead to community-wide “overfitting” to the peculiarities of the data and the conventions used in annotating it. Wagstaff (2012) recently expressed concern over this trend in the field of machine learning, emphasizing the gap between such datasets and “real world” problems.) The recent trend of developing new, small testing datasets, often in a range of languages or genres, helps to alleviate this problem (e.g., the CoNLL dependency parsing shared tasks; Buchholz and Marsi, 2006).

A major problem with intrinsic evaluations is that they assume the phenomenon of interest is already well-enough understood that linguistic experts have identified the best representation and trained annotators to produce it accurately. Anyone who has worked on an annotation project, however, knows that interaction with the data always leads to evolution within the annotation scheme. Intrinsic evaluation further commits the fallacy that human evaluations are worthy of replication. Annotators are only human, and we have very restricted ways of evaluating them (e.g., inter-annotator agreement). These annotator evaluations are often incomplete, ignoring major factors like the kind and amount of training annotators have been subjected to and the learning curve of the annotators. A model that succeeds at the MATCHLINGUIST task can be said to have reproduced what a particular set of annotators, with a particular kind of training, on a particular kind of data, within a particular amount of time, would generate on the test set. Our view is that drawing stronger conclusions about the quality of such a model may be too bold.

Even if we accept human annotations as correct, the intrinsic evaluation strategy only permits comparison between models that produce similar output. We cannot use it to test two divergent theories of linguistic structure without introducing more automation or manual effort. We also cannot use it to test models of the interaction of different levels of structure (e.g., morphology and syntax), unless all levels of interest are part of the human annotation effort or all models make use of the same preprocessing mechanisms, whether manual or automatic. The more we are forced to incorporate pre- and post-processing in order to evaluate our models, the more narrow our claims must be.

Finally, the cost of employing linguistic experts to annotate data is often cited as one of the main motivating factors for unsupervised NLP. When we consider that any annotation project used

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1 For an example of this problem, consider the literature on unsupervised part-of-speech tagging. A whole range of evaluation scores for this problem exist, each proposing a different way of dealing with the incommensurability of categories that come from linguistic annotators or various unsupervised learning models.
to evaluate an unsupervised NLP model has been necessarily limited in how much data annotators could annotate and how many iterations they could make over the data, it seems that using these cost-constrained annotations as a gold-standard to match is misguided. Unsupervised automatic learners should be able to reason about far more data far more consistently; should matching what resource-limited humans can do really be our aim? As noted by Alex Clark (personal communication), linguists really perform two tasks in creating an annotated dataset, and the labor is likely divided. One task is defining the formalism: what is the set of analyses that are possible for each input? The other is selecting the correct one for each input. Supervised NLP models focus only on the latter task, while unsupervised NLP models may perform both tasks, depending on the underlying assumptions.

Though it has not been consistently articulated this way, and not all NLP researchers are likely to agree, perhaps we should consider the goal of doing linguistics—describing and explaining the phenomena of human language, or defining formalisms, as above—in ways that unaided humans cannot. Indeed, as long as the mark of success for an unsupervised linguistic learner is to closely match what annotation scheme designers and annotators believe they already know about language, we cannot claim that MATCHLINGUIST-evaluations of unsupervised NLP models have anything to do with advancing the scientific study of language.

### 2.2 Extrinsic Evaluations: Passing the Buck

Extrinsic evaluations are attractive because they allow NLP modelers to make claims of “usefulness” about their models. Real-world applications that use NLP models of various kinds include machine translation systems, search engines, information extraction systems, and question answering systems. Insofar as evaluation of these systems’ quality is uncontroversial, there is little to be said against an argument for the usefulness of a model whose output improves the downstream state of the art. Unfortunately, system evaluation remains fraught with debate for most of these downstream applications.

There is also a practical concern: evaluating an NLP model in a downstream system requires the ability to incorporate that model’s functionality within such a system. The open-source versions of such applications do not generally provide a “plug-and-play” architecture for linguistically annotated input, and if they do, there are strong assumptions about what kind of annotation is to be provided. How to use a particular linguistic annotation within any given application is itself a research question. Further, as in intrinsic evaluations, models that make use of different kinds of representations will not generally be comparable in downstream applications, since much will depend on the process of incorporating the annotations into the application. Finally, applications change fast. There is value in having stable mechanisms to compare models; yet the community tends to show little interest in performance gains in a downstream application that is no longer the state of the art, since the results may not generalize to newer, better systems.

All is not hopeless, and extrinsic evaluations should continue to provide evidence for model quality. However, we are not optimistic that downstream applications can serve as the primary evaluation mechanism for NLP models, due to these challenges of access and stability.

### 2.3 Algorithm Competitions

Some research agendas lead naturally to the design of competitions in which a well-defined problem is stated formally and benchmarks to test an algorithm’s success are constructed by experts. A notable example is the Omphalos competition (Starkie et al., 2004), in which competitors constructed context-free grammar learning algorithms. Theoretical and practical matters were taken quite seri-
ously; datasets were designed to be provably sufficient for identifying the language but beyond the capabilities of the state of the art at the time. Some of the benchmarks were constructed around natural language phenomena. Though our proposed adversarial evaluations here seek to drive natural language modeling research, not formal language acquisition, much of what was done by the Omphalos designers and competitors focused on the construction of negative examples, which also play a key role here.

2.4 Perplexity

The idea of using model likelihood on test data to compare probabilistic models arose in the speech recognition community, where it was applied to the evaluation of language models. It provides a simple way to compare any models that properly assign probability mass to linguistic data. Perplexity evaluations were mostly abandoned in the 1990s when it became clear that perplexity reductions did not correlate with word error rate reductions on speech recognition tasks. In general, it is widely known that having a good probabilistic model of data need not have anything to do with having a model that performs well in intrinsic or extrinsic evaluations. Perplexity’s use as a scientific tool is less controversial, though it is not widespread or widely accepted in computational linguistics today, with the possible exception of the Bayesian topic modeling subcommunity (see, e.g., Blei et al., 2003).

There are also some key difficulties. First, only probabilistic models define perplexity scores. While probabilistic modeling has many attractions, requiring that researchers adopt that framework in order to compare with other work is unnecessarily exclusionary. Second, two models’ perplexity scores are only comparable if they define exactly the same event space. In practice, this means prior agreement on the vocabulary and on handling of out-of-vocabulary terms. This must be done with great care, because events that are assigned very low probability by a model can have a large effect on the model’s perplexity score. (Assigning zero, in particular, leads to infinite perplexity. Perplexity offers no way to rank two models that have infinite perplexity, no matter how sharp their differences on the non-zero-probability instances.) Focusing on perplexity can lead to over-attention to smoothing algorithms, the details of which may be less important in large-data settings (Brants et al., 2007). And finally, many models in use today involve latent structures, so that perplexity—which is calculated by marginal inference—can only be calculated approximately. Conclusions based on approximate perplexity comparisons, with each researcher deciding on his or her own approximations, are suspect at best.

3 Improving Perplexity: Claude, the Chooser

Perplexity, in its most general form, requires the performer to define a probability distribution $p$ over some event space $\mathcal{X}$. During the evaluation period, a series of events $\langle x_1, \ldots, x_N \rangle$ are assumed to be drawn i.i.d. from the “true” distribution, which we denote by $p^*$. The estimated perplexity is given by:

$$\exp_2 \left( -\frac{1}{N} \sum_{n=1}^{N} \log_2 p(x_n) \right) \approx \exp_2 \left( -\sum_{x \in \mathcal{X}} p^*(x) \log_2 p(x) \right)$$  \hspace{1cm} (1)

(On the right is the true perplexity, approximated on the left using a test sample. We use $\exp_2(a)$ to more clearly denote $2^a$.) As we have noted, the event space $\mathcal{X}$, is often an infinitely large discrete

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2We gratefully acknowledge Alex Clark for bringing this to our attention.

3Even in that community, the usefulness of perplexity has been brought into question; Chang et al. (2009) found that topic models with better perplexity may infer relatively less semantically meaningful topics.
space (e.g., the space of strings for a given alphabet). Performers must assign nonzero probability to all $x \in \mathcal{X}$, and be able to compute that probability, to be able to compete.

Suppose we replace the calculation with a choice between two elements of $\mathcal{X}$, $x$ and $y$, the former being true data from $p^*$, and the latter being contrived or synthesized data. These two elements would be presented in random order, hiding the provenance of each. Performers might use probabilistic models to make this decision (e.g., choosing $x$ iff $p(x) > p(y)$, and choosing $y$ otherwise), but they need not do so. Any approach could be applied to make the choice. Insofar as the ability to distinguish real data from contrived data is of scientific or practical interest, we would prefer a model with greater average accuracy on this binary task.

We will conflate the engineer of such a model and the model itself, calling both “Claude.”

Claude takes as input two instances from $\mathcal{X}$—sentences in the language modeling case—denoted by $x$ and $y$. $x$ is assumed to be drawn from a true linguistic sample, and the other, $y$, to be contrived by an adversary who is given access to $x$, and whom we call “Zellig.”

We will return to Zellig in §4, for now taking it for granted that Zellig’s role can be meaningfully performed.

We remark on a few observations about this task:

- The accuracy score is easy to calculate, objective, and does not hinge on any human input beyond the choice of the test data $\langle x_1, \ldots, x_N \rangle$ and the machinations of Zellig to construct confusion instances $\langle y_1, \ldots, y_N \rangle$.

- Comparing Claude to an alternative, competing model “Chloe” is straightforward, regardless of their internal operations and representations of the data. In particular, they need not use the same theory (or any theory), and they need not use probabilistic models. They only need to distinguish true data from contrived data.

- Zellig’s role is crucial. If Zellig creates $y$ through some “safe,” trivial operation on $x$ (e.g., replacing common words with common words of the same syntactic category, or, worse, just copying $x$; or selecting instances from a corpus that closely approximates the same $p^*$ whence $x$ is drawn), then for reasonably large $N$ no Claude will be able to achieve better than 50% accuracy. On the other hand, if Zellig is built to be completely ignorant (e.g., sampling from a character $n$-gram distribution), it should be easy for any Claude to achieve very high performance.

### 4 Zellig, Transformer of Data

It quickly becomes clear that the quality of a Zellig must be defined in terms of contemporary Claudes (and vice versa). A good Zellig, in short, is one that stumps the Claudes of the day, but not all to the same degree. In some sense, Zellig is like an extrinsic task evaluation, except that rather than taking a model of language’s predictions as output, we imagine that it challenges that model to be aware of phenomena that hold in real linguistic data but not in corrupted versions of those data.

We consider next three kinds of Zelligs, each suggesting a different research goal that is interesting regardless of its role in stumping Claudes.

#### 4.1 Human Zellig

A human linguistic expert who has a theory of language might manually corrupt a real linguistic utterance $x$ to create an ill-formed similar utterance $y$. The minimal pair then represents a prediction

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4 After Claude Shannon (1916–2001), the father of information theory.
5 After Zellig Harris (1909–1992), linguist and methodologist of science.
of Zellig’s theory. Supporting evidence for the theory might come from a fluent (or native-speaker) human Claude, who selects which of the two utterances is ill-formed. In this setup, if Claude performs well (across many instances), Zellig’s theory is given some credence. This is simply an experiment for testing claims about well-formedness in natural languages. A more useful variation might compare Zellig to another expert, Zelda, to see whose theory better predicts native speaker judgments.

This alters the role of a linguist from annotator (§2.1) to creative illustrator. Rather than constructing theories that seek to account “horizontally” for all phenomena at a particular level of description in a natural language (e.g., syntax), the linguistic expert is free to consider “vertical” interactions among any levels at all that are appropriate to identifying selected phenomena in a language.

4.2 Model of Language Zellig

It is, of course, a small step to imagine that human Zellig would write a program to perform the $x \mapsto y$ transformation. Indeed, many existing models of language can be used to construct a Zellig. For example, a probabilistic language model might be queried to find a string that has high probability and low (but nonzero) “distance” from $x$:

$$y = \arg \max_{x' \in X : 1 \leq \Delta(x', x) \leq \delta} p(x')$$

where $\Delta(x', x)$ might be the Hamming distance or some other metric on strings. A model of linguistic constraints might identify the constraints holding in $x$, then make a change that violates one of them. A little-discussed property that any computational model of language might be expected to have is the ability to produce instances in violation of the underlying theory. We propose that explicit construction of algorithms for this use-case is motivated as a new way to validate models in computational linguistics, and further may lead to new insights about computational models of linguistic phenomena. Note further that the same model, if it provides algorithms for both kinds of queries, might serve as Zellig or Claude in different evaluations.

4.3 Text-Generating System Zellig

Another kind of Zellig can be constructed as an NLP system that generates text as output. For example, suppose that each $x_n$ is a sentence in English that was translated (by a human) from French. Assume $x_n$ comes packaged with metadata, which we will denote $m_n$, which is comprised of the original French sentence. If Zellig is a machine translation system, then $y_n$ will be an automatic translation of French sentence $m_n$. Another scenario might consider question answering: $m_n$ is a question, $x_n$ its human answer, and $y_n$ the answer from a system. Two versions might be considered here, one where Claude observes $m_n$ (encouraging evaluation of adequacy of translation or correctness of question answering), and one where it is kept hidden (judging only fluency).

The setup therefore provides a new way to perform system evaluations, exploiting models of language that seek to pass distinguishability tests.

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6In past work evaluated within the MATCHLINGUIST paradigm, we considered functions that generated large “neighborhood” sets of strings similar to $x$ but perturbed in ways expected to corrupt linguistic quality. The corrupting function was heuristic and served the definition of a “contrastive” objective function for learning. See, for example, Smith and Eisner (2005).
5 Defining the Two-Performer Evaluation

A formal definition of the basic adversarial evaluation follows; Figure 1 provides an illustration.

We assume a random source of linguistic instances, the probability distribution $p^*$. Each instance $x_n$ is drawn from $p^*$. Optionally, $p^*$ defines a joint distribution over the instance random variable $X$ and a metadata random variable $M$. We assume that instances are generated at fixed periodic intervals of length $t$.

The evaluation involves two performers, Zellig and Claude, who—though in an adversarial relationship—are not in direct competition with each other. Zellig can be compared to other performers of the $Z$-task, defined below, using the same sample and Claude. Claude can be compared to other performers of the $C$-task, defined below, using the same sample and Zellig.

On each iteration (indexed by $n$), Zellig takes $x_n$ (and optionally $m_n$) and constructs an object $y_n$, purportedly from the support of $p^*$. If there is metadata $m_n$, then Zellig should seek $y_n$ that is well-paired with $m_n$. It is to Zellig’s advantage to choose $y_n \neq x_n$. Zellig must perform all necessary computation within time $t$, before the next iteration. This is the $Z$-task.

On each iteration, the pair $(x_n, y_n)$ is permuted uniform-randomly and presented to Claude. Claude must guess which element is the false instance $y_n$; all necessary computation must be within time $t$, before the next iteration. We denote by $z_n$ Claude’s choice. (It is helpful to think of Claude as one step behind Zellig, so that at an arbitrary point in time, Zellig is generating $y_n$ and Claude is guessing between $x_{n-1}$ and $y_{n-1}$.) This is the $C$-task.

Over $N$ instances, the score is defined by:

$$S = \frac{1}{N} \sum_{n=1}^{N} 1\{z_n = y_n\} \approx E_{p^*(X)}[1\{Z = Y\}]$$

(3)

For two competing performers of the $Z$-task, the one achieving the lower $S$ is the winner; this is a

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Footnotes:

7 If Zellig does not provide $y_n$ in time $t$, a reasonable default is to set $y_n = x_n$, thereby giving a free point to Claude.

8 If Claude does not make a choice in time $t$, then a uniform-random choice should be made.
Zellig who more successfully deceived Claude. For two competing performers of the \( C \)-task, the one achieving the higher \( S \) is the winner; this is a Claude who has more successfully distinguished real data from corrupted data.

**A connection to cryptography.** Our \( C \)-task bears some similarity to a particular notion of security of an encryption scheme called “indistinguishability of encryptions” \cite{Bellareetal1998}\. To highlight the similarity, we will employ Claude as an analyst and Zellig as an encryption oracle within a particular kind of attack known as “chosen ciphertext.” In this evaluation, Claude chooses two plaintext messages and sends both to Zellig. Zellig chooses one at his discretion, encrypts it, and sends the ciphertext to Claude. Zellig succeeds—and the scheme declared secure—if Claude can do no better than chance at guessing which message Zellig chose. Returning to our linguistic setup, for Zellig to have this ability would be evidence for “strong linguistic knowledge.” Much like the notion of “provable security,” “strong linguistic knowledge” should perhaps be regarded with skepticism; a scheme can be considered secure only until it is broken, and a Zellig remains respectable only as long as the state-of-the-art Claudes cannot consistently perform well on his output. (Note, however, that the evaluation we have proposed does not allow Claude any control over the inputs to Zellig.)

**Spam detection.** Several members of the audience at the June 7 talk noticed the similarity between Zellig and Claude’s activities and the adversarial relationship between spammers and spam detection software. Of course, spammers are constrained by the speech act they seek to execute through the message \( y \), and they have no analogue to “\( x \),” unlike Zellig. Successful spam detection systems presumably exploit this (and metadata \( m \)) heavily. (For an interesting recent discussion of spammer strategy, specifically considering the linguistic choices involved, see \cite{Herley2012}.)

**Game theory.** We have deliberately avoided discussing the proposed evaluation in game-theoretic terms. On reading a draft of this proposal, economist Bryan Routledge exclaimed, “I want this data,” seeing long-term transcripts of the choices by Claudes and Zelligs as inherently interesting in studying the dynamics of “co-evolution” in evolutionary game theory \cite{Weibull1995}. We leave this possible point of exploration for future work.

### 6 On Context

The reader may have noticed the introduction of a largely underspecified element, metadata \( m_n \) on each iteration, in §4.3. The importance of context—encoded in our setup as metadata—to interpretation and generation of language has been noted with increasing intensity in recent discourse about NLP. Context can include well-studied variables like the dialect or genre in which language is produced, or simply “co-text” (a term used in a recent presentation by Graeme Hirst to refer to nearby text), or farther-removed representations of the situation in which the text arose. In recent research efforts, we and others have made the prediction of contextual information from text a task of its own, often predicting future contextual variables from text in a forecasting setup (e.g., \cite{Koganelal2009}).

\[ A \text{ strong statement of the importance of context is to claim that } p^* \text{ is such an over-simplification} \]

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\*We gratefully acknowledge Amber Wilcox-O’Hearn for introducing this connection in personal communication.

\[9\] Social media platforms offer a rich set of possibilities for the last of these, since messages are broadcast from an identifiable individual with a history, to a set of identifiable individuals connected to her, at a known timestamp, etc.
of reality as to be useless. Indeed, all corpora currently used to construct and evaluate NLP systems come with some description of the provenance of the text. The community already views the construction of contextualized linguistic resources as a valuable research effort; what we lack are frameworks for objectively evaluating the quality of such datasets or their relevance to scientific or engineering efforts, and the early incorporation of this information into our models. The evaluation framework proposed here offers a first step toward imposing the same kind of rigorous evaluation on data selection methods as on data modeling methods.

We noted that one role of linguistic experts in this framework is as a human Zellig performer who contrives corrupted instances \( y \) from observed linguistic instances \( x \). By introducing a third performer, called “John,” we propose another role for linguistic experts—the curation of linguistic datasets with contextual descriptions, and the construction of systems to perform this task. We have reached a time when raw text data is available in massive amounts, often with metadata as *objets trouvés*; the collection and further description of such data (adding to the metadata) naturally feeds the adversarial evaluations we have proposed so far.

A useful by-product of John’s performance is the generation of metadata that enables error analysis. Many researchers desire understanding of the kinds of systematic “mistakes” that NLP systems make, but we have very few methodological tools for this kind of characterization. Many researchers resort to fine-grained statistics on errors or selection of illustrative examples, but these do little to show the way forward for future research. Correlating errors to well-defined phenomena marked in metadata may be a more useful tool in gaining an understanding of what a given model (performing either as Zellig or as Claude) solves or does not solve.

### 7 Defining the Three-Performer Evaluation

The full three-performer adversarial evaluation is illustrated in Figure 2. Claude and Zellig are exactly as before (§5). We introduce performer John, who replaces “\( p^* \)” as a source of pairs \((x_n, m_n)\).

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11 After John Sinclair (1933–2007), a corpus linguist.
| Name          | Task                              | Evaluation |
|--------------|-----------------------------------|------------|
| \( C \)-task (Claude) | distinguish data from non-data     | high \( S \) |
| \( Z \)-task (Zellig)  | generate corruptions of data      | low \( S \) |
| \( J \)-task (John)   | select data to exemplify phenomena of interest | high \( S \) |

**Table 1:** Summary of the three performers.

John’s contribution is to collect data that reveal phenomena on contextualized natural language, or to implement algorithms that collect such data. Researchers performing this task—the \( J \)-task—are expected to justify the relevance of the selection method for scientific exploration and/or engineering NLP systems. Further, John can be compared to another \( J \)-task performer “Jennifer” by selecting a Zellig-Claude pair and measuring the scores \( S \) as achieved before. John is said to outperform Jennifer, given Zellig and Claude, if Zellig’s task has been made harder with John’s data than with Jennifer’s (i.e., a higher score results).

Any evaluation on the three tasks (\( C \)-task, \( Z \)-task, and \( J \)-task) requires the presence of the other two performers. Just as evaluations on multiple datasets with different properties are often used to make stronger arguments in NLP, an evaluation can be strengthened by considering a range of other performers. For example, in evaluating Claude, we might compare his performance against a baseline Chloe on a range of evaluations \( \mathcal{Z} \times \mathcal{J} \), where \( \mathcal{Z} \) is a set of existing Zelligs and \( \mathcal{J} \) a set of existing Johns. Higher-level analysis can be performed by relating \( S \) to properties of the Zelligs or Johns. The wider the range of other performers, the more confident we can be that an evaluation result is not due to idiosyncrasies.

The discussion has been fairly abstract; we have deliberately avoided making assumptions about what kinds of resources a performer might have access to constructing the algorithm or model to perform a task. The original idea was conceived out of skepticism toward evaluations for unsupervised NLP models, but we believe the framework is appropriate regardless of the level of supervision. Indeed, the framework forces us to differentiate two different kinds of supervision:

1. Supervision from the MATCHLINGUIST perspective, in which expert annotations are provided in support of the task.

2. Supervision within the task:
   - In the \( C \)-task, observations of tuples \((m_n, x_n, y_n)\), with \( X \) and \( Y \) labeled as such (rather than randomly permuted), for a given John-Zellig pair.
   - In the \( Z \)-task, observations of a given Claude’s choices in response to the generated \( y_n \), given each \((m_n, x_n)\) pair from a given John.
   - In the \( J \)-task, observations of the generated \( y_n \) from a given Zellig and \( z_n \) from a given Claude in response to each \((m_n, x_n)\) produced by the performer.

We call a round of evaluation \( n \) “transparent” from the perspective of a given performer if that performer can see the other performers’ actions clearly in the round.

From each performer’s perspective, MATCHLINGUIST supervision, though perhaps useful, is indirect. From a learning perspective, it is the second kind of supervision that is expected to give the most information. Given the framework, it is easy to explain supervised, semi-supervised, and...

\[12\] An extremely adversarial variant of the evaluation might allow all performers some transparent rounds. While entertaining, we believe such a scenario begins to lose attraction as a way to objectively compare systems in a highly controlled, understandable setting.
unsupervised versions of the evaluation. We must simply specify the schedule of observations—
transparent and non-transparent—that occur before evaluation takes place. A few interesting cases
include:

- zero observation rounds prior to evaluation;
- a fixed number of transparent rounds (“supervised”) prior to evaluation;
- a fixed number of transparent rounds followed by a fixed number of non-transparent rounds
  (“semi-supervised”) prior to evaluation; or
- a fixed number of non-transparent rounds (“unsupervised”) prior to evaluation.

- Orthogonal to all of the above, performers might adapt their performance during the evaluation’s non-transparent rounds.

Regardless of which framework is selected, the explanation of any performer should clarify what
resources were used to construct it, and how, as in current NLP research. For frameworks that
involve adaptation, reporting how the score changes over time (e.g., as a time series) would be
useful for comparing convergence rates.

Finally, we suggest again that any of the roles might be played by humans. Such an exercise
might be useful in establishing human “upper bounds” (risking the problems underlying MATCH-
LINGUIST), or in training any of the performers. An example suggested by Amber Wilcox-O’Hearn
is a human Claude who provides supervision for a supervised learner Zellig.

8 Open Questions

Collusion. We have assumed that, for clarity’s sake, collusion among performers should not be allowed. However, collusion between any pair might lead to more challenging evaluations for the third performer and might be worth considering.

Cheating. Is it possible to cheat? Validity of evaluations in this framework may rest on limiting
the resources available to some performers. We believe, for example, that it is possible to cheat if
John does not have access to external data sources unavailable to Zellig and Claude.

Should we do it? A reasonable concern, raised by Dan Bikel, is that the collective actions of a
community of Johns, Zelligs, and Claudes might not lead to improved models of natural language.
The ideas laid out here are intended to refocus our evaluations so as to build better models of the
phenomena inherent in language. Yet it is not hard to imagine that researchers would collectively
over-attend to $S$ (Equation 3) and lose sight of those phenomena.

We therefore propose a modest start. A few straightforward John, Zellig, and Claude performers
should be publicly released, perhaps through an API allowing inspection of all data, algorithms, and
scores. If the API is extended to allow new performers to join in and test performance, we conjecture
that the adversarial framework will begin to be used to provide evidence for the quality of newly
developed models. Whether this evidence is judged meaningful by the research community will
depend, of course, on the particulars. We believe, though, that a critical assessment of our evaluation
practices, and the introduction of some new ones, can only benefit future research.
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