GLUE: A MULTI-TASK BENCHMARK AND ANALYSIS PLATFORM FOR NATURAL LANGUAGE UNDERSTANDING

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ABSTRACT

For natural language understanding (NLU) technology to be maximally useful, it must be able to process language in a way that is not exclusive to a single task, genre, or dataset. In pursuit of this objective, we introduce the General Language Understanding Evaluation (GLUE) benchmark, a collection of tools for evaluating the performance of models across a diverse set of existing NLU tasks. By including tasks with limited training data, GLUE is designed to favor and encourage models that share general linguistic knowledge across tasks. GLUE also includes a hand-crafted diagnostic test suite that enables detailed linguistic analysis of models. We evaluate baselines based on current methods for transfer and representation learning and find that multi-task training on all tasks performs better than training a separate model per task. However, the low absolute performance of our best model indicates the need for improved general NLU systems.

1 INTRODUCTION

The human ability to understand language is *general*, *flexible*, and *robust*. In contrast, most NLU models above the word level are designed for a specific task and struggle with out-of-domain data. If we aspire to develop models with understanding beyond the detection of superficial correspondences between inputs and outputs, then it is critical to develop a more unified model that can learn to execute a range of different linguistic tasks in different domains.

To facilitate research in this direction, we present the General Language Understanding Evaluation (GLUE) benchmark: a collection of NLU tasks including question answering, sentiment analysis, and textual entailment, and an associated online platform for model evaluation, comparison, and analysis. GLUE does not place any constraints on model architecture beyond the ability to process single-sentence and sentence-pair inputs and to make corresponding predictions. For some GLUE tasks, training data is plentiful, but for others it is limited or fails to match the genre of the test set. GLUE therefore favors models that can learn to represent linguistic knowledge in a way that facilitates sample-efficient learning and effective knowledge-transfer across tasks. None of the datasets in GLUE were created from scratch for the benchmark; we rely on preexisting datasets because they have been implicitly vetted by the community to be challenging and interesting. Four of the datasets feature privately-held test data, which will be used to ensure that the benchmark is used fairly.

To understand the types of knowledge learned by models and to encourage linguistic-meaningful solution strategies, GLUE also includes a set of hand-crafted analysis examples for probing trained models. This dataset is designed to highlight common challenges, such as the use of world knowledge, logical operators, and lexical entailments, that models must handle to robustly solve the tasks.

To better understand the challenged posed by GLUE, we conduct experiments with simple baselines and state-of-the-art sentence representation models. We find that unified multi-task trained models slightly outperform comparable models trained on each task separately. Our best multi-task model makes use of ELMo (Peters et al., 2018), a recently proposed pre-training technique. However, this model still achieves a fairly low absolute score. Analysis with our diagnostic dataset reveals that our baseline models deal well with strong lexical signals but struggle with deeper logical structure.

Corpus	|Train|	|Test|	Task	Metrics	Domain
			Single-Sentence Tasks		
CoLA	8.5k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
			Similarity and Paraphrase Tasks		
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	**391k**	paraphrase	acc./F1	social QA questions
			Inference Tasks		
MNLI	393k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	108k	5.7k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	misc.
WNLI	634	**146**	coreference/NLI	acc.	fiction books

Table 1: Task descriptions and statistics. All tasks are single sentence or sentence pair classification, except STS-B, which is a regression task. MNLI has three classes; all other classification tasks have two. Test sets shown in bold use labels that have never been made public in any form.

In summary, we offer: (i) A suite of nine sentence or sentence-pair NLU tasks, built on established annotated datasets and selected to cover a diverse range of text genres, dataset sizes, and degrees of difficulty. (ii) An online evaluation platform and leaderboard, based primarily on privately-held test data. The platform is model-agnostic, and can evaluate any method capable of producing results on all nine tasks. (iii) An expert-constructed diagnostic evaluation dataset. (iv) Baseline results for several major existing approaches to sentence representation learning.

2 Related Work

Collobert et al. (2011) used a multi-task model with a shared sentence understanding component to jointly learn POS tagging, chunking, named entity recognition, and semantic role labeling. More recent work has explored using labels from core NLP tasks to supervise training of lower levels of deep neural networks (Søgaard & Goldberg, 2016; Hashimoto et al., 2016) and automatically learning cross-task sharing mechanisms for multi-task learning (Ruder et al., 2017).

Beyond multi-task learning, much work in developing general NLU systems has focused on sentence-to-vector encoders (Le & Mikolov, 2014; Kiros et al., 2015, i.a.), leveraging unlabeled data (Hill et al., 2016; Peters et al., 2018), labeled data (Conneau & Kiela, 2018; McCann et al., 2017), and combinations of these (Collobert et al., 2011; Subramanian et al., 2018). In this line of work, a standard evaluation practice has emerged, recently codified as SentEval (Conneau et al., 2017; Conneau & Kiela, 2018). Like GLUE, SentEval relies on a set of existing classification tasks involving either one or two sentences as inputs. Unlike GLUE, SentEval only evaluates sentence-to-vector encoders, making it well-suited for evaluating sentences *in isolation*. However, cross-sentence contextualization and alignment, such as that yielded by methods like soft-attention, are instrumental in achieving state-of-the-art performance on tasks such as machine translation (Bahdanau et al., 2014; Vaswani et al., 2017), question answering (Seo et al., 2016), and natural language inference (Rocktäschel et al., 2016). GLUE is designed to facilitate the development of these methods: It is model-agnostic, allowing for any kind of representation or contextualization, including models that use no vector or symbolic representations for sentences whatsoever.

GLUE also diverges from SentEval in the selection of evaluation tasks that are included in the suite. Many of the SentEval tasks are closely related to sentiment analysis, such as MR (Pang & Lee, 2005), SST (Socher et al., 2013), CR (Hu & Liu, 2004), and SUBJ (Pang & Lee, 2004). Other tasks are so close to being solved that evaluation on them is relatively uninformative, such as MPQA (Wiebe et al., 2005) and TREC question classification (Voorhees et al., 1999). In GLUE, we attempt to construct a benchmark that is both diverse and difficult.

McCann et al. (2018) introduce decaNLP, which also scores NLP systems based on their performance on multiple datasets. Their benchmark recasts the ten evaluation tasks as question answer-

ing, converting tasks like summarization and text-to-SQL semantic parsing into question answering using automatic transformations. That benchmark lacks the leaderboard and error analysis toolkit of GLUE, but more importantly, we see it as pursuing a more ambitious but less immediately practical goal: While GLUE rewards methods that yield good performance on a circumscribed set of tasks using methods like those that are currently used for those tasks, their benchmark rewards systems that make progress toward their goal of unifying all of NLU under the rubric of question answering.

3 TASKS

GLUE is centered on nine English sentence understanding tasks, which cover a broad range of domains, data quantities, and difficulties. As the goal of GLUE is to spur development of generalizable NLU systems, we design the benchmark such that good performance should require a model to share substantial knowledge (e.g., trained parameters) across all tasks, while still maintaining some task-specific components. Though it is possible to train a single model for each task and evaluate the resulting set of models on this benchmark, we expect that our inclusion of several data-scarce tasks will ultimately render this approach uncompetitive. We describe the tasks below and in Table 1. Appendix A includes additional details. Unless otherwise mentioned, tasks are evaluated on accuracy and are balanced across classes.

3.1 SINGLE-SENTENCE TASKS

CoLA The Corpus of Linguistic Acceptability (Warstadt et al., 2018) consists of English acceptability judgments drawn from books and journal articles on linguistic theory. Each example is a sequence of words annotated with whether it is a grammatical English sentence. Following the authors, we use Matthews correlation coefficient (Matthews, 1975) as the evaluation metric, which evaluates performance on unbalanced binary classification and ranges from -1 to 1, with 0 being the performance of uninformed guessing. We use the standard test set, for which we obtained private labels from the authors. We report a single performance number on the combination of in- and out-of-domain sections of the test set.

SST-2 The Stanford Sentiment Treebank (Socher et al., 2013) consists of sentences from movie reviews and human annotations of their sentiment. The task is to predict the sentiment of a given sentence. We use the two-way (*positive/negative*) class split, and use only sentence-level labels.

3.2 SIMILARITY AND PARAPHRASE TASKS

MRPC The Microsoft Research Paraphrase Corpus (Dolan & Brockett, 2005) is a corpus of sentence pairs automatically extracted from online news sources, with human annotations for whether the sentences in the pair are semantically equivalent. Because the classes are imbalanced (68% positive, 32% negative), we follow common practice and report both accuracy and F1 score.

QQP The Quora Question Pairs[1] dataset is a collection of question pairs from the community question-answering website Quora. The task is to determine whether a pair of questions are semantically equivalent. As in MRPC, the class distribution in QQP is unbalanced (37% positive, 63% negative), so we report both accuracy and F1 score. We use the standard test set, for which we obtained private labels from the authors.

STS-B The Semantic Textual Similarity Benchmark (Cer et al., 2017) is a collection of sentence pairs drawn from news headlines, video and image captions, and natural language inference data. Each pair is human-annotated with a similarity score from 1 to 5; the task is to predict these scores. Follow common practice, we evaluate using Pearson and Spearman correlation coefficients.

3.3 INFERENCE TASKS

MNLI The Multi-Genre Natural Language Inference Corpus (Williams et al., 2018) is a crowd-sourced collection of sentence pairs with textual entailment annotations. Given a premise sentence

[1] `data.quora.com/First-Quora-Dataset-Release-Question-Pairs`

and a hypothesis sentence, the task is to predict whether the premise entails the hypothesis (*entailment*), contradicts the hypothesis (*contradiction*), or neither (*neutral*). The premise sentences are gathered from ten different sources, including transcribed speech, fiction, and government reports. We use the standard test set, for which we obtained private labels from the authors, and evaluate on both the *matched* (in-domain) and *mismatched* (cross-domain) sections. We also use and recommend the SNLI corpus (Bowman et al., 2015) as 550k examples of auxiliary training data.

QNLI The Stanford Question Answering Dataset (Rajpurkar et al. 2016) is a question-answering dataset consisting of question-paragraph pairs, where one of the sentences in the paragraph (drawn from Wikipedia) contains the answer to the corresponding question (written by an annotator). We convert the task into sentence pair classification by forming a pair between each question and each sentence in the corresponding context, and filtering out pairs with low lexical overlap between the question and the context sentence. The task is to determine whether the context sentence contains the answer to the question. This modified version of the original task removes the requirement that the model select the exact answer, but also removes the simplifying assumptions that the answer is always present in the input and that lexical overlap is a reliable cue. This process of recasting existing datasets into NLI is similar to methods introduced in White et al. (2017) and expanded upon in Demszky et al. (2018). We call the converted dataset QNLI (Question-answering NLI).

RTE The Recognizing Textual Entailment (RTE) datasets come from a series of annual textual entailment challenges. We combine the data from RTE1 (Dagan et al., 2006), RTE2 (Bar Haim et al., 2006), RTE3 (Giampiccolo et al., 2007), and RTE5 (Bentivogli et al., 2009).[2] Examples are constructed based on news and Wikipedia text. We convert all datasets to a two-class split, where for three-class datasets we collapse *neutral* and *contradiction* into *not_entailment*, for consistency.

WNLI The Winograd Schema Challenge (Levesque et al., 2011) is a reading comprehension task in which a system must read a sentence with a pronoun and select the referent of that pronoun from a list of choices. The examples are manually constructed to foil simple statistical methods: Each one is contingent on contextual information provided by a single word or phrase in the sentence. To convert the problem into sentence pair classification, we construct sentence pairs by replacing the ambiguous pronoun with each possible referent. The task is to predict if the sentence with the pronoun substituted is entailed by the original sentence. We use a small evaluation set consisting of new examples derived from fiction books[3] that was shared privately by the authors of the original corpus. While the included training set is balanced between two classes, the test set is imbalanced between them (35% entailment, 65% not entailment). As with QNLI, each example is evaluated separately, so there is not a systematic correspondence between a model's score on this task and its score on the unconverted original task. We call converted dataset WNLI (Winograd NLI).

3.4 Evaluation

The GLUE benchmark follows the same evaluation model as SemEval and Kaggle. To evaluate a system on the benchmark, one must run the system on the provided test data for the tasks, then upload the results to the website for scoring. The benchmark site then shows per-task scores, as well as a macro-average of those scores to determine a system's position on the leaderboard. For tasks with multiple metrics (e.g., accuracy and F1), we use an unweighted average of the metrics as the score for the task when computing the overall macro-average. The website also provides fine- and coarse-grained results on the diagnostic dataset. See Appendix C for details.

4 Diagnostic Dataset

Drawing inspiration from the FraCaS suite (Cooper et al., 1996) and the recent Build-It-Break-It competition (Ettinger et al., 2017), we include a small, manually-curated test set for the analysis of system performance. While the main benchmark mostly reflects an application-driven distribution of examples, our diagnostic dataset highlights a pre-defined set of modeling-relevant phenomena.

[2] RTE4 is not publicly available, while RTE6 and RTE7 do not fit the standard NLI task.

[3] See similar examples at `cs.nyu.edu/faculty/davise/papers/WinogradSchemas/WS.html`

Tags	Sentence 1	Sentence 2	Fwd	Bwd
Lexical Entailment (Lexical Semantics), Downward Monotone (Logic)	The timing of the meeting has not been set, according to a Starbucks spokesperson.	The timing of the meeting has not been considered, according to a Starbucks spokesperson.	N	E
Universal Quantifiers (Logic)	Our deepest sympathies are with all those affected by this accident.	Our deepest sympathies are with a victim who was affected by this accident.	E	N
Quantifiers (Lexical Semantics), Double Negation (Logic)	I have never seen a hummingbird not flying.	I have never seen a hummingbird.	N	E

Table 2: Examples from the diagnostic set. *Fwd* (resp. *Bwd*) denotes the label when sentence 1 (resp. sentence 2) is the premise. Labels are *entailment* (E), *neutral* (N), or *contradiction* (C). Examples are tagged with the phenomena they demonstrate, and each phenomenon belongs to one of four broad categories (in parentheses). See Table 5 in Appendix A for a complete tag taxonomy.

Each diagnostic example is an NLI sentence pair with tags for the phenomena demonstrated. The NLI task is well-suited to this kind of analysis, as it can easily evaluate the full set of skills involved in (ungrounded) sentence understanding, from the resolution of syntactic ambiguity to pragmatic reasoning with world knowledge. We ensure the data is reasonably diverse by producing examples for a variety of linguistic phenomena and basing our examples on naturally-occurring sentences from several domains (news, Reddit, Wikipedia, academic papers). This approaches differs from that of FraCaS, which was designed to test linguistic theories with a minimal and uniform set of examples. A sample from our dataset is shown in Table 2. A full list of linguistic categories is in Appendix A.

Annotation Process We begin with a target set of phenomena, based roughly on those used in the FraCaS suite (Cooper et al., 1996). We construct each example by locating a sentence that can be easily made to demonstrate a target phenomenon, and editing it in two ways to produce an appropriate sentence pair. We make minimal modifications so as to maintain high lexical and structural overlap within each sentence pair and limit superficial cues. We then label the inference relationships between the sentences, considering each sentence alternatively as the premise, producing two labeled examples for each pair (1100 total). Where possible, we produce several pairs with different labels for a single source sentence, to have minimal sets of sentence pairs that are lexically and structurally very similar but correspond to different entailment relationships. The resulting labels are 42% *entailment*, 35% *neutral*, and 23% *contradiction*.

Evaluation Since the class distribution in the diagnostic set is not balanced, we use R_3 (Gorodkin, 2004), a three-class generalization of the Matthews correlation coefficient, for evaluation.

In light of recent work showing that crowdsourced data often contains artifacts which can be exploited to perform well without solving the intended task (Schwartz et al., 2017; Poliak et al., 2018, i.a.), we audit the data for such artifacts. We reproduce the methodology of Gururangan et al. (2018), training two fastText classifiers (Joulin et al., 2016) to predict entailment labels on SNLI and MNLI using only the hypothesis as input. The models respectively get near-chance accuracies of 32.7% and 36.4% on our diagnostic data, showing showing that the data does not suffer from such artifacts.

To establish human baseline performance on the diagnostic set, we have six NLP researchers annotate 50 sentence pairs (100 entailment examples) randomly sampled from the diagnostic set. Inter-annotator agreement is high, with a Fleiss's κ of 0.73. The average R_3 score among the annotators is 0.80, much higher than any of the baseline systems described in Section 5.

5 BASELINES

For baselines, we evaluate a multi-task learning model trained on the GLUE tasks, as well as several variants based on recent pre-training methods. We briefly describe them here. See Appendix B for details. We implement our models in the AllenNLP library (Gardner et al., 2017).

Model	Avg	Single Sentence CoLA	SST-2	Similarity and Paraphrase MRPC	QQP	STS-B	Natural Language Inference MNLI	QNLI	RTE	WNLI
Single-Task Training										
BiLSTM	62.0	15.7	85.9	69.3/79.4	81.7/61.4	66.0/62.8	70.3/70.8	60.8	52.8	62.3
+ELMo	66.2	**35.0**	90.2	69.0/80.8	85.7/65.6	64.0/60.2	72.9/73.4	69.4	50.1	**65.1**
+CoVe	62.4	14.5	88.5	73.4/81.4	83.3/59.4	67.2/64.1	64.5/64.8	64.8	53.5	61.6
+Attn	60.0	15.7	85.9	68.5/80.3	83.5/62.9	59.3/55.8	74.2/73.8	51.9	51.9	55.5
+Attn, ELMo	64.8	**35.0**	90.2	68.8/80.2	**86.5/66.1**	55.5/52.5	**76.9/76.7**	61.1	50.4	**65.1**
+Attn, CoVe	60.8	14.5	88.5	68.6/79.7	84.1/60.1	57.2/53.6	71.6/71.5	53.8	52.7	64.4
Multi-Task Training										
BiLSTM	63.5	24.0	85.8	71.9/82.1	80.2/59.1	68.8/67.0	65.8/66.0	71.1	46.8	63.7
+ELMo	64.8	27.5	89.6	76.2/83.5	78.5/57.8	67.0/65.9	67.1/68.0	66.7	55.7	62.3
+CoVe	62.2	16.2	84.3	71.8/80.0	82.0/59.1	68.0/67.1	65.3/65.9	70.4	44.2	**65.1**
+Attn	65.7	0.0	85.0	75.1/**83.7**	84.3/63.6	73.9/71.8	72.2/72.1	82.1	**61.7**	63.7
+Attn, ELMo	**69.0**	18.9	**91.6**	**77.3**/83.5	85.3/63.3	72.8/71.1	75.6/75.9	81.7	61.2	**65.1**
+Attn, CoVe	64.3	19.4	83.6	75.2/83.0	84.9/61.1	72.3/71.1	69.9/68.7	78.9	38.3	**65.1**
Pre-Trained Sentence Representation Models										
CBoW	58.9	0.0	80.0	73.4/81.5	79.1/51.4	61.2/58.7	56.0/56.4	75.1	54.1	62.3
Skip-Thought	61.5	0.0	81.8	71.7/80.8	82.2/56.4	71.8/69.7	62.9/62.8	74.7	53.1	**65.1**
InferSent	64.7	4.5	85.1	74.1/81.2	81.7/59.1	75.9/75.3	66.1/65.7	79.8	58.0	**65.1**
DisSent	62.1	4.9	83.7	74.1/81.7	82.6/59.5	66.1/64.8	58.7/59.1	75.2	56.4	**65.1**
GenSen	66.6	7.7	83.1	76.6/83.0	82.9/59.8	**79.3/79.2**	71.4/71.3	**82.3**	59.2	**65.1**

Table 3: Baseline performance on the GLUE tasks. For MNLI, we report accuracy on the matched and mismatched test sets. For MRPC and Quora, we report accuracy and F1. For STS-B, we report Pearson and Spearman correlation. For CoLA, we report Matthews correlation. For all other tasks we report accuracy. All values are scaled by 100. A similar table is presented on the online platform.

Architecture Our simplest baseline architecture is based on sentence-to-vector encoders, and sets aside GLUE's ability to evaluate models with more complex structures. Taking inspiration from Conneau et al. (2017), the model uses a two-layer, 1500D (per direction) BiLSTM with max pooling and 300D GloVe word embeddings (840B Common Crawl version; Pennington et al., 2014). For single-sentence tasks, we encode the sentence and pass the resulting vector to a classifier. For sentence-pair tasks, we encode sentences independently to produce vectors u, v, and pass $[u; v; |u - v|; u * v]$ to a classifier. The classifier is an MLP with a 512D hidden layer.

We also consider a variant of our model which for sentence pair tasks uses an attention mechanism inspired by Seo et al. (2016) between all pairs of words, followed by a second BiLSTM with max pooling. By explicitly modeling the interaction between sentences, these models fall outside the sentence-to-vector paradigm.

Pre-Training We augment our base model with two recent methods for pre-training: ELMo and CoVe. We use existing trained models for both.

ELMo uses a pair of two-layer neural language models trained on the Billion Word Benchmark (Chelba et al., 2013). Each word is represented by a contextual embedding, produced by taking a linear combination of the corresponding hidden states of each layer of the two models. We follow the authors' recommendations[4] and use ELMo embeddings in place of any other embeddings.

CoVe (McCann et al., 2017) uses a two-layer BiLSTM encoder originally trained for English-to-German translation. The CoVe vector of a word is the corresponding hidden state of the top-layer LSTM. As in the original work, we concatenate the CoVe vectors to the GloVe word embeddings.

Training We train our models with the BiLSTM sentence encoder and post-attention BiLSTMs shared across tasks, and classifiers trained separately for each task. For each training update, we sample a task to train with a probability proportional to the number of training examples for each

[4] `github.com/allenai/allennlp/blob/master/tutorials/how_to/elmo.md`

task. We train our models with Adam (Kingma & Ba, 2014) with initial learning rate 10^{-3} and batch size 128. We use the macro-average score as the validation metric and stop training when the learning rate drops below 10^{-5} or performance does not improve after 5 validation checks.

We also train a set of single-task models, which are configured and trained identically, but share no parameters. While this is generally an effective model for the tasks under study, to allow for fair comparisons with the multi-task analogs we do not tune parameter or training settings for each task, so these single-task models do not generally represent the state of the art for each task.

Sentence Representation Models Finally, we evaluate the following trained sentence-to-vector encoder models using our benchmark: average bag-of-words using GloVe embeddings (CBoW), Skip-Thought (Kiros et al., 2015), InferSent (Conneau et al., 2017), DisSent (Nie et al., 2017), and GenSen (Subramanian et al., 2018). See Appendix B for additional details. For these models, we only train task-specific classifiers on the representations they produce.

6 Benchmark Results

We train three runs of each model and evaluate the run with the best macro-average development set performance. For single-task and sentence representation models, we evaluate the best run for each individual task. We present performance on the main benchmark tasks in Table 3.

In most cases, using multi-task training over single-task training yields better overall scores, particularly among the parameter-rich attention models. Attention generally hurts performance in single task training, but helps in multi-task training. We see a consistent improvement in using ELMo embeddings in place of GloVe or CoVe embeddings, particularly for single-sentence tasks. Using CoVe slightly improves on GloVe for single task training but not for multi-task training.

Among the pre-trained sentence representation models, we observe fairly consistent gains moving from CBoW to Skip-Thought to Infersent and GenSen. Relative to the models trained directly on the GLUE tasks, InferSent is competitive and GenSen outperforms all but the two best.

Looking at results per task, we find that the sentence representation models substantially underperform on CoLA compared to the models directly trained on the task. Similarly, with the exception of InferSent, the sentence representation models are outperformed on SST by our BiLSTM and its non-CoVe variants. On the other hand, for STS-B, there is a significant gap between the models trained directly on the task and the best sentence representation model. Finally, there are tasks for which no model does particularly well. On WNLI, no model exceeds most-frequent-class guessing (65.1%). On RTE and in aggregate, even our best baselines leave room for improvement. These early results indicate that solving GLUE is beyond the capabilities of current models and methods.

7 Analysis

We analyze the baselines by evaluating each model's MNLI classifier on the diagnostic set to get a better sense of their linguistic capabilities. Results are presented in Table 4.

Coarse Categories Overall performance is low for all models: The highest total score of 28 still denotes poor absolute performance. Performance tends to be higher on Predicate-Argument Structure and lower on Knowledge, though numbers are not closely comparable across categories. Unlike on the main benchmark, the multi-task models are almost always outperformed by their single-task counterparts. This is perhaps unsurprising, since with our simple multi-task training regime, there is likely some destructive interference between MNLI and the other tasks. The models trained on the GLUE tasks largely outperform the pretrained sentence representation models, with the exception of GenSen. Using attention has a greater influence on diagnostic scores than using ELMo or CoVe, which we take to indicate that attention is especially important for generalization in NLI.

Fine-Grained Subcategories Most models handle universal quantification relatively well. Looking at relevant examples, it seems that relying on lexical cues such as "all" often suffices for good performance. Similarly, lexical cues often provide good signal in morphological negation examples.

		Coarse-Grained				Fine-Grained					
Model	**All**	**LS**	**PAS**	**L**	**K**	**UQuant**	**MNeg**	**2Neg**	**Coref**	**Restr**	**Down**
Single-Task Training											
BiLSTM	21	25	24	16	16	70	53	4	21	-15	**12**
+ELMo	20	20	21	14	17	70	20	**42**	33	-26	-3
+CoVe	21	19	23	20	18	71	47	-1	33	-15	8
+Attn	25	24	30	20	14	50	47	21	**38**	-8	-3
+Attn, ELMo	**28**	**30**	**35**	**23**	14	**85**	20	**42**	33	-26	-3
+Attn, CoVe	24	29	29	18	12	77	50	1	18	-1	**12**
Multi-Task Training											
BiLSTM	19	16	22	16	17	71	35	-8	26	**0**	8
+ELMo	19	15	21	17	**21**	70	**60**	15	26	**0**	**12**
+CoVe	17	15	21	14	16	50	31	-8	25	-15	**12**
+Attn	25	23	32	19	16	58	26	-5	28	-1	-20
+Attn, ELMo	23	24	30	17	13	78	27	37	30	-15	-20
+Attn, CoVe	20	16	25	15	17	78	37	14	31	-15	8
Pre-Trained Sentence Representation Models											
CBoW	9	6	13	5	10	3	0	13	28	-15	-11
Skip-Thought	12	2	23	11	9	61	6	-2	30	-15	0
InferSent	18	20	20	15	14	77	50	-20	15	-15	-9
DisSent	16	16	19	13	15	70	43	-11	20	-36	-09
GenSen	20	28	26	14	12	78	57	2	21	-15	**12**

Table 4: Results on the diagnostic set. We report R_3 coefficients between gold and predicted labels, scaled by 100. The coarse-grained categories are *Lexical Semantics* (**LS**), *Predicate-Argument Structure* (**PAS**), *Logic* (**L**), and *Knowledge and Common Sense* (**K**). Our example fine-grained categories are *Universal Quantification* (**UQuant**), *Morphological Negation* (**MNeg**), *Double Negation* (**2Neg**), *Anaphora/Coreference* (**Coref**), *Restrictivity* (**Restr**), and *Downward Monotone* (**Down**).

We observe varying weaknesses between models. Double negation is especially difficult for the GLUE-trained models that only use GloVe embeddings. This is ameliorated by ELMo, and to some degree CoVe. Also, while attention improves overall results, attention models tend to struggle with downward monotonicity. Examining their predictions, we found that the models were sensitive to hypernym/hyponym substitutions as signals of entailment, but predicted it in the wrong direction (as if the substituted word was in an upward monotone context). Restrictivity examples, which often depend on nuances of quantifier scope, are especially difficult for all models.

Overall, there is evidence that going beyond sentence-to-vector representations, e.g. with an attention mechanism, might aid performance on out-of-domain data, and that transfer methods like ELMo and CoVe encode linguistic information specific to their supervision signal. However, increased representational capacity may lead to overfitting, such as the failure of attention models in downward monotone contexts. We expect that our platform and diagnostic dataset will be useful for similar analyses in the future, so that model designers can better understand their models' generalization behavior and implicit knowledge.

8 Conclusion

We introduce GLUE, a platform and collection of resources for evaluating and analyzing natural language understanding systems. We find that, in aggregate, models trained jointly on our tasks see better performance than the combined performance of models trained for each task separately. We confirm the utility of attention mechanisms and transfer learning methods such as ELMo in NLU systems, which combine to outperform the best sentence representation models on the GLUE benchmark, but still leave room for improvement. When evaluating these models on our diagnostic dataset, we find that they fail (often spectacularly) on many linguistic phenomena, suggesting possible avenues for future work. In sum, the question of how to design general-purpose NLU models remains unanswered, and we believe that GLUE can provide fertile soil for addressing this challenge.

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Coarse-Grained Categories	Fine-Grained Categories
Lexical Semantics	Lexical Entailment, Morphological Negation, Factivity, Symmetry/Collectivity, Redundancy, Named Entities, Quantifiers
Predicate-Argument Structure	Core Arguments, Prepositional Phrases, Ellipsis/Implicits, Anaphora/Coreference Active/Passive, Nominalization, Genitives/Partitives, Datives, Relative Clauses, Coordination Scope, Intersectivity, Restrictivity
Logic	Negation, Double Negation, Intervals/Numbers, Conjunction, Disjunction, Conditionals, Universal, Existential, Temporal, Upward Monotone, Downward Monotone, Non-Monotone
Knowledge	Common Sense, World Knowledge

Table 5: The types of linguistic phenomena annotated in the diagnostic dataset, organized under four major categories.

A Additional Data Details

A.1 Dataset Construction

QNLI To construct a balanced dataset, we select all pairs in which the most similar sentence to the question was *not* the answer sentence, as well as an equal amount of cases in which the correct sentence was the most similar to the question, but another distracting sentence was a close second. Our similarity metric is based on CBoW representations with pre-trained GloVe embeddings. This approach to converting pre-existing datasets into NLI format is closely related to recent work by White et al. (2017), as well as to the original motivation for textual entailment presented by Dagan et al. (2006). Both argue that many NLP tasks can be productively reduced to textual entailment.

A.2 Diagnostic Data

We show the full label set used to tag the diagnostic set in Table 5.

B Additional Baseline Details

B.1 Attention Mechanism

We implement our attention mechanism as follows: given two sequences of hidden states $u_1, u_2, \ldots, u_M$ and $v_1, v_2, \ldots, v_N$, we first compute matrix H where $H_{ij} = u_i \cdot v_j$. For each u_i, we get attention weights α_i by taking a softmax over the ith row of H, and get the corresponding context vector $\tilde{v}_i = \sum_j \alpha_{ij} v_j$ by taking the attention-weighted sum of the v_j. We pass a second BiLSTM with max pooling over the sequence $[u_1; \tilde{v}_1], \ldots [u_M; \tilde{v}_M]$ to produce u'. We process the v_j vectors analogously to obtain v'. Finally, we feed $[u'; v'; |u' - v'|; u' * v']$ into a classifier.

B.2 Training

We train our models with the BiLSTM sentence encoder and post-attention BiLSTMs shared across tasks, and classifiers trained separately for each task. For each training update, we sample a task to train with a probability proportional to the number of training examples for each task. We scale each task's loss inversely proportional to the number of examples for that task, which we found to improve overall performance. We train our models with Adam (Kingma & Ba, 2014) with initial learning rate 10^{-3}, batch size 128, and gradient clipping. We use macro-average score over all tasks as our validation metric, and perform a validation check every 10k updates. We divide the learning rate by 5 whenever validation performance does not improve. We stop training when the learning rate drops below 10^{-5} or performance does not improve after 5 validation checks.

PRIMARY				AUXILIARY									
RankName	Model	URL	Score	CoLA	SST-2	MRPC	STS-B	QQP	MNLI-m	MNLI-mm	QNLI	RTE	WNLI
1 GLUE Baselines	BiLSTM+ELMo+Attn		68.9	18.9	91.6	77.3/83.5	72.8/71.1	83.5/63.3	75.6	75.9	81.7	61.2	65.1
	GenSen		66.6	7.7	83.1	76.6/83.0	79.3/79.2	82.9/59.8	71.4	71.3	82.3	59.2	65.1
	Single Task BiLSTM+ELMo		66.2	35.0	90.2	69.0/80.8	64.0/60.2	85.7/65.6	72.9	73.4	69.4	50.1	65.1
	BILSTM+Attn		65.7	0.0	85.0	75.1/83.7	73.9/71.8	84.3/63.6	72.2	72.1	82.1	61.7	63.7
	BiLSTM+ELMo		64.9	27.5	89.6	76.2/83.5	67.0/65.9	78.5/57.8	67.1	68.0	66.7	55.7	62.3
	Single Task BiLSTM+ELMo+Attn		64.8	35.0	90.2	68.8/80.2	55.5/52.5	86.5/66.1	76.9	76.7	61.1	50.3	65.1
	InferSent		64.7	4.5	85.1	74.1/81.2	75.9/75.3	81.7/59.1	66.1	65.7	79.8	58.0	65.1
	BiLSTM+CoVe+Attn		64.3	19.4	83.6	75.2/83.0	72.3/71.1	84.9/61.1	69.9	68.7	78.9	38.3	65.1
	BiLSTM		63.5	24.0	85.8	71.9/82.1	68.8/67.0	80.2/59.1	65.8	66.0	71.1	46.8	63.7
	Single Task BiLSTM+CoVe		62.4	14.5	88.5	73.4/81.4	67.2/64.1	83.3/59.4	64.5	64.8	64.8	53.5	61.6
	BiLSTM+CoVe		62.2	16.2	84.3	71.8/80.0	68.0/67.1	82.0/59.1	65.3	65.9	70.4	44.2	65.1
	DisSent		62.1	4.9	83.7	74.1/81.7	66.1/64.8	82.6/59.5	58.7	59.1	75.2	56.4	65.1
	Single Task BiLSTM		62.0	15.7	85.9	69.3/79.4	66.0/62.8	81.7/61.4	70.3	70.8	60.8	52.8	62.3
	Skip-Thought		61.5	0.0	81.8	71.7/80.8	71.8/69.7	82.2/56.4	62.9	62.8	74.7	53.1	65.1
	Single Task BiLSTM+CoVe+Attn		60.8	14.5	88.5	68.6/79.7	57.2/53.6	84.1/60.1	71.6	71.5	53.8	52.7	64.4
	Single Task BiLSTM+Attn		60.0	15.7	85.9	68.5/80.3	59.3/55.8	83.5/62.9	74.2	73.8	51.9	51.9	55.5
	CBOW		58.9	0.0	80.0	73.4/81.5	61.2/58.7	79.1/51.4	56.0	56.4	75.1	54.1	62.3

Figure 1: The benchmark website leaderboard. An expanded view shows additional details about each submission, including a brief prose description and parameter count.

B.3 Sentence Representation Models

We evaluate the following sentence representation models:

1. CBoW, the average of the GloVe embeddings of the tokens in the sentence.
2. Skip-Thought (Kiros et al., 2015), a sequence-to-sequence(s) model trained to generate the previous and next sentences given the middle sentence. We use the original pre-trained model[5] trained on sequences of sentences from the Toronto Book Corpus (Zhu et al. 2015, TBC).
3. InferSent (Conneau et al., 2017), a BiLSTM with max-pooling trained on MNLI and SNLI.
4. DisSent (Nie et al., 2017), a BiLSTM with max-pooling trained to predict the discourse marker (*because*, *so*, etc.) relating two sentences on data derived from TBC. We use the variant trained for eight-way classification.
5. GenSen (Subramanian et al., 2018), a sequence-to-sequence model trained on a variety of supervised and unsupervised objectives. We use the variant of the model trained on both MNLI and SNLI, the Skip-Thought objective on TBC, and a constituency parsing objective on the Billion Word Benchmark.

C Benchmark Website Details

GLUE's online platform is built using React, Redux and TypeScript. We use Google Firebase for data storage and Google Cloud Functions to host and run our grading script when a submission is made. Figure 1 shows the visual presentation of our baselines on the leaderboard.

[5] `github.com/ryankiros/skip-thoughts`