GLUE:
Toward Task-Independent Sentence Understanding

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NAACL GenDeep Workshop

NYU
ML²
Machine Learning
for Language

Today: GLUE

The General Language Understanding Evaluation (GLUE):

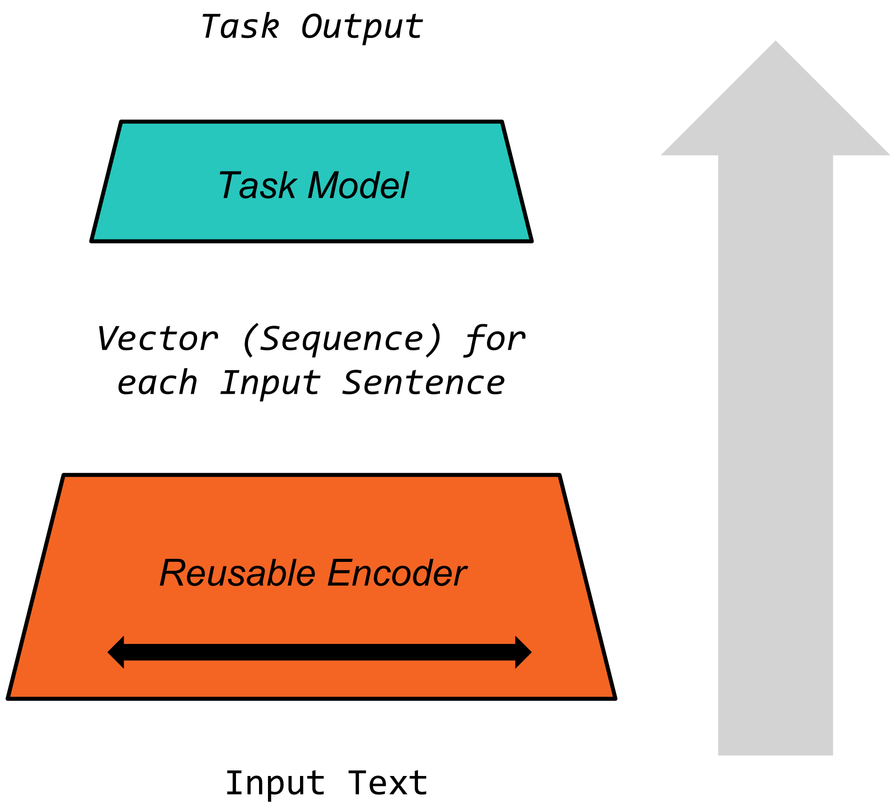
An open-ended competition and evaluation platform for sentence representation learning models.

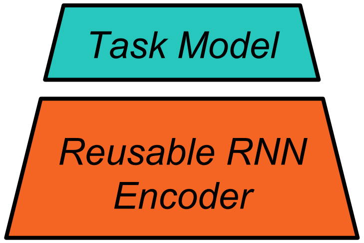
Background: Sentence Representation Learning

The Long-Term Goal

To develop a general-purpose sentence encoder which produces substantial gains in performance and data efficiency across diverse NLU tasks.

A general-purpose sentence encoder



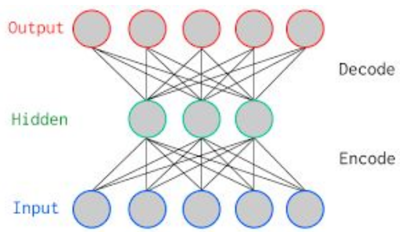


A general-purpose sentence encoder

Roughly, we might expect effective encodings to capture:

- Lexical contents and word order.
- (Rough) syntactic structure.
- Cues to idiomatic/non-compositional phrase meanings.
- Cues to connotation and social meaning.
- Disambiguated semantic information of the kind expressed in a semantic parse (or formal semantic analysis).

$$\forall x[\text{patient}'(x) \rightarrow \exists y[\text{doctor}'(y) \wedge \text{treat}'(y, x)]]$$



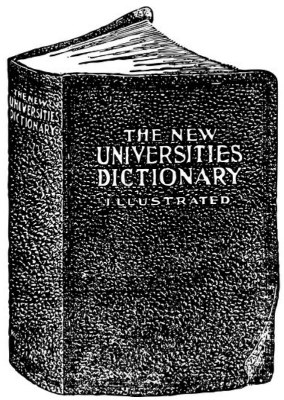
Progress to date: Sentence-to-vector

Unsupervised training on single sentences:

- Sequence autoencoders (Dai and Le ‘15)
- Paragraph vector (Le and Mikolov ‘15)
- Variational autoencoder LM (Bowman et al. ‘16)
- Denoising autoencoders (Hill et al. ‘16)

Unsupervised training on running text:

- Skip Thought (Kiros et al. ‘15)
- FastSent (Hill et al. ‘16)
- DiscSent/DisSent (Jernite et al. ‘17/Nie et al. ‘17)



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Supervised training on large corpora:

- Dictionaries (Hill et al. ‘15)
- Image captions (Hill et al. ‘16)
- Natural language inference data (Conneau et al. ‘17)
- Multi-task learning (Subramanian et al. ‘18)

The Standard Evaluation: SentEval

- Informal evaluation standard formalized by Conneau and Kiela (2018).
- Suite of ten tasks:
    - MR, CR, SUBJ, MPQA, SST, TREC, MRPC, SICK-R, SICK-E, STS-B
- Software package automatically trains and evaluates per-task linear classifiers using supplied representations.

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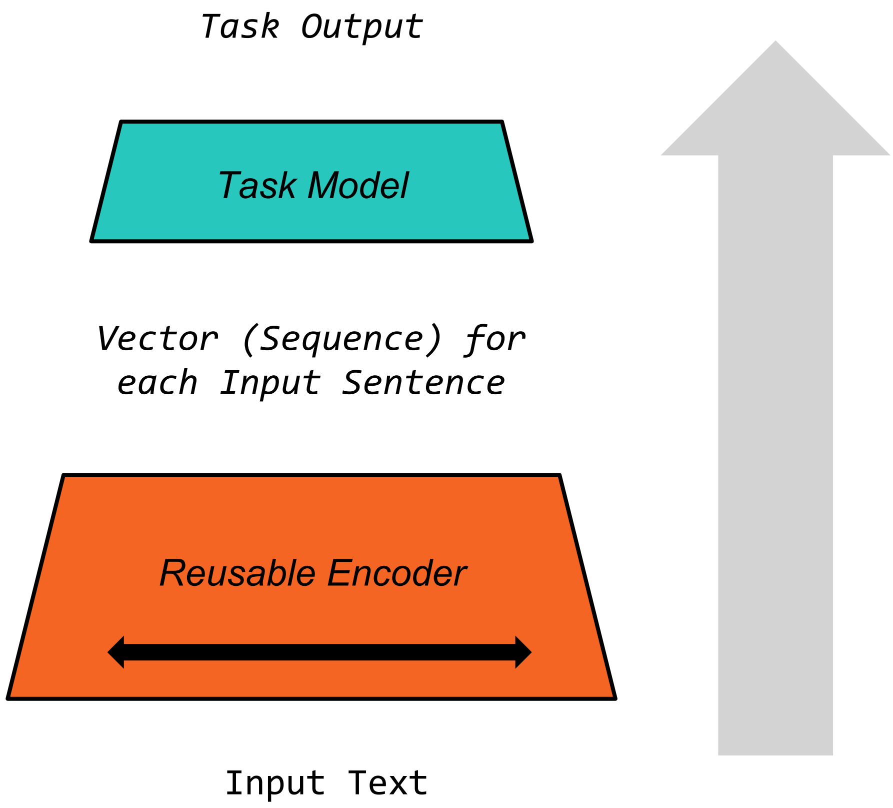
- Limited to sentence-to-vector models.
- Heavy skew toward **sentiment-related** tasks.

Subramanian et al. '18

Progress to date: SentEval

Model	MR	CR	SUBJ	MPQA	SST	TREC	MRPC	SICK-R	SICK-E	STSB	Δ
Transfer approaches											
FastSent	70.8	78.4	88.7	80.6	-	76.8	72.2/80.3	-	-	-	-
FastSent+AE	71.8	76.7	88.8	81.5	-	80.4	71.2/79.1	-	-	-	-
NMT En-Fr	64.7	70.1	84.9	81.5	-	82.8	-	-	-	-	-
CNN-LSTM	77.8	82.1	93.6	89.4	-	92.6	76.5/83.8	0.862	-	-	-
Skipthought	76.5	80.1	93.6	87.1	82.0	92.2	73.0/82.0	0.858	82.3	-	-
Skipthought + LN	79.4	83.1	93.7	89.3	82.9	88.4	-	0.858	79.5	72.1/70.2	-
Word Embedding Average	-	-	-	-	82.2	-	-	0.860	84.6	-	-
DiscSent + BiGRU	-	-	88.6	-	-	81.0	71.6/-	-	-	-	-
DiscSent + unigram	-	-	92.7	-	-	87.9	72.5/-	-	-	-	-
DiscSent + embed	-	-	93.0	-	-	87.2	75.0/-	-	-	-	-
Byte mLSTM	**86.9**	**91.4**	**94.6**	88.5	-	-	75.0/82.8	0.792	-	-	-
Infersent (SST)	(*)	83.7	90.2	89.5	(*)	86.0	72.7/80.9	0.863	83.1	-	-
Infersent (SNLI)	79.9	84.6	92.1	89.8	83.3	88.7	75.1/82.3	0.885	86.3	-	-
Infersent (AllNLI)	81.1	86.3	92.4	90.2	**84.6**	88.2	76.2/83.1	0.884	86.3	75.8/75.5	0.0
Our Models											
+STN	78.9	85.8	93.7	87.2	80.4	84.2	72.4/81.6	0.840	82.1	72.9/72.4	-2.56
+STN +Fr +De	80.3	85.1	93.5	90.1	83.3	92.6	77.1/83.3	0.864	84.8	77.1/77.1	0.01
+STN +Fr +De +NLI	81.2	86.4	93.4	90.8	84.0	93.2	76.6/82.7	0.884	87.0	79.2/79.1	0.99
+STN +Fr +De +NLI +L	81.7	87.3	94.2	90.8	84.0	**94.2**	77.1/83.0	0.887	87.1	78.7/78.2	1.33
+STN +Fr +De +NLI +L +STP	82.7	88.0	94.1	91.2	84.5	92.4	77.8/83.9	0.885	86.8	78.7/78.4	1.44
+STN +Fr +De +NLI +2L +STP	82.8	88.3	94.0	**91.3**	83.6	92.6	77.4/83.3	0.884	87.6	**79.2/79.1**	1.47
+STN +Fr +De +NLI +L +STP +Par	82.5	87.7	94.0	90.9	83.2	93.0	**78.6/84.4**	**0.888**	**87.8**	78.9/78.6	**1.48**
Approaches trained from scratch on these tasks											
Naive Bayes SVM	79.4	81.8	93.2	86.3	83.1	-	-	-	-	-	
AdaSent	83.1	86.3	95.5	93.3	-	92.4	-	-	-	-	
TF-KLD	-	-	-	-	-	-	80.4/85.9	-	-	-	
Illinois LH	-	-	-	-	-	-	-	-	84.5	-	
Dependency tree LSTM	-	-	-	-	-	-	-	0.868	-	-	
Neural Semantic Encoder	-	-	-	-	89.7	-	-	-	-	-	
BLSTM-2DCNN	82.3	-	94.0	-	89.5	96.1	-	-	-	-	

A general-purpose sentence encoder



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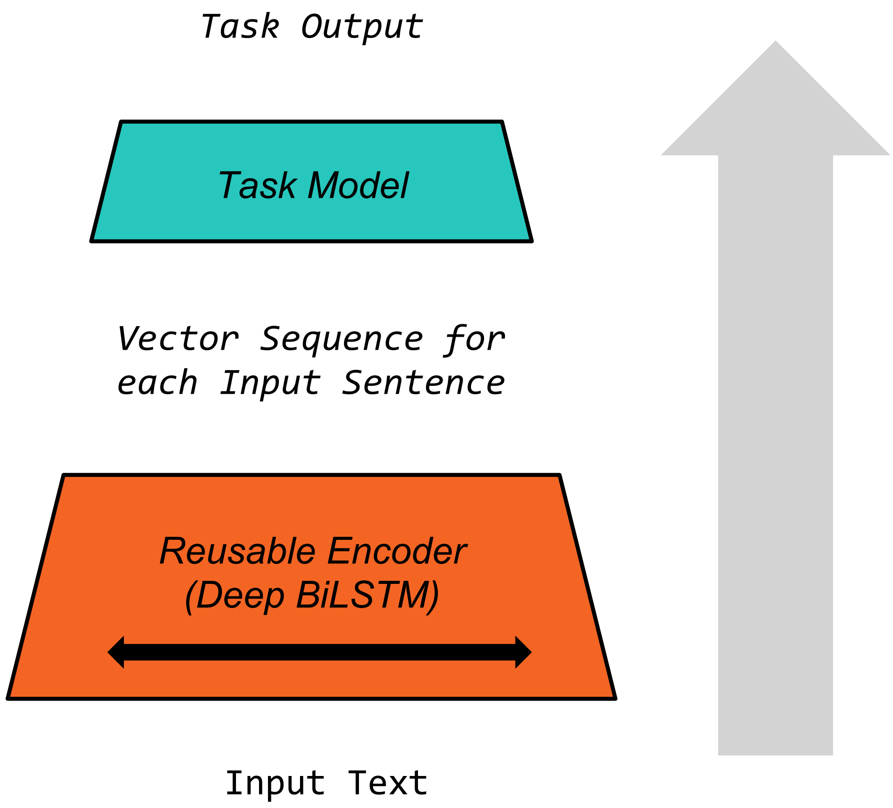
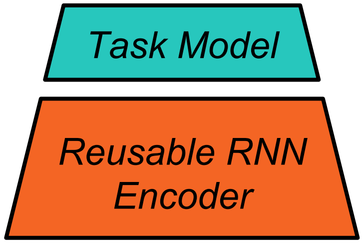




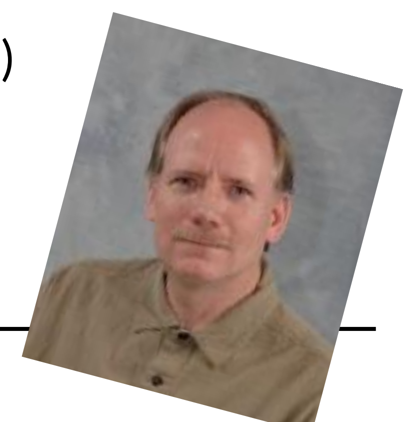
A general-purpose sentence encoder

General-purpose sentence representations probably won't be fixed length vectors.

- For most tasks, a sequence of vectors is preferable.
- For others, you can pool the sequence into one vector.

"You can't cram the meaning of a whole %&!$# sentence into a single $&!#* vector!"

—Ray Mooney (UT Austin)



Progress to date: Beyond $&!#* Vectors

Training objectives:

- Translation (CoVe; McCann et al., 2017)
- Language modeling (ELMo; Peters et al., 2018)

Evaluation:
Beyond $&!#* Vectors

Dataset	Random	GloVe	GloVe+ Char	CoVe-S	CoVe-M	CoVe-L	Cha
SST-2	84.						
SST-5	48.						
IMDb	88.						
TREC-6	88.						
TREC-50	81.						
SNLI	82.						
SQuAD	65.						

TASK	PREVIOUS SOTA		OUR BASELIN
SQuAD	Liu et al. (2017)	84.4	81.1
SNLI	Chen et al. (2017)	88.6	88.0
SRL	He et al. (2017)	81.7	81.4
Coref	Lee et al. (2017)	67.2	67.2
NER	Peters et al. (2017)	91.93 ± 0.19	90.15
SST-5	McCann et al. (2017)	53.7	51.4

GLUE

GLUE, in short

- Nine sentence understanding tasks based on existing data, varying widely in:
  - Task difficulty
  - Training data volume and degree of training set /test set similarity
  - Language style/genre
  - (...but limited to classification/regression outputs.)
- No restriction on model type—must only be able to accept sentences and sentence pairs as inputs.
- Kaggle-style evaluation platform with private test data.
- Online leaderboard w/ single-number performance metric.
- Auxiliary analysis toolkit.
- Built completely on open source/open data.

GLUE: The Main Tasks

Corpus	**|Train|**	**|Dev|**	**|Test|**	**Task**	**Metrics**	**Domain**
				Single-Sentence Tasks		
CoLA	8.5k	1k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	872	1.8k	sentiment	acc.	movie reviews
				Similarity and Paraphrase Tasks		
MRPC	3.7k	408	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.5k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	40k	**391k**	paraphrase	acc./F1	social QA questions
				Inference Tasks		
MNLI	393k	20k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	108k	5.7k	5.7k	QA/NLI	acc.	Wikipedia
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Bold = Private

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The Tasks

The Corpus of Linguistic Acceptability (Warstadt et al. ‘18)

- *Binary acceptability judgments* over strings of English words.
- Extracted from articles, textbooks, and monographs in formal linguistics, with labels from original sources.
- Test examples include some topics/authors not seen at training time.

✓ *The more people you give beer to, the more people get sick.*

* *The more does Bill smoke, the more Susan hates him.*

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The Stanford Sentiment Treebank (Socher et al. ‘13)

- *Binary sentiment judgments* over English sentences.
- Derived from IMDB movie reviews, with crowdsourced annotations.

\+ *It's a charming and often affecting journey.*

\- *Unflinchingly bleak and desperate.*

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The Microsoft Research Paraphrase Corpus (Dolan & Brockett, 2005)

- *Binary paraphrase judgments* over headline pairs.

    - *Yucaipa owned Dominick's before selling the chain to Safeway in 1998 for $2.5 billion.*

      Yucaipa bought Dominick's in 1995 for $693 million and sold it to Safeway for $1.8 billion in 1998.

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The Semantic Textual Similarity Benchmark (Cer et al., 2017)

- *Regression* over non-expert similarity judgments on sentence pairs (labels in 0–5).
- Diverse source texts.

4.750 *A young child is riding a horse.*
A child is riding a horse.

2.000 *A method used to calculate the distance between stars is 3 Dimensional trigonometry.*
You only need two-dimensional trigonometry if you know the distances to the two stars and their angular separation.

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The Quora Question Pairs (Cer et al., 2017)

- *Binary classificitation* for pairs of user generated questions. Positive pairs are pairs that can be answered with the same answer.

\+ *What are the best tips for outlining/planning a novel?*
How do I best outline my novel?

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The Multi-Genre Natural Language Inference Corpus (Williams et al., 2018)

- *Balanced classification* for pairs of sentences into *entailment*, *contradiction*, and *neutral*.
- Training set sentences drawn from five written and spoken genres. Dev/test sets divided into a matched set and a *mismatched* set with five more.

neutral *The Old One always comforted Ca'daan, except today.*
Ca'daan knew the Old One very well.

Corpus	Tra					n
				Tasks		
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The Question Natural Language Inference Corpus (Rajpurkar et al., 2018/us)

- *Balanced binary classification* for pairs of sentences into *answers question* and *does not answer question.*
- Derived from SQuAD (Rajpurkar et al., 2018), with filters to ensure that lexical overlap features don't perform well.

- *What is the observable effect of W and Z boson exchange?*
  The weak force is due to the exchange of the heavy W and Z bosons.

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CoLA						
SST-2						movie reviews
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The Recognizing Textual Entailment Challenge Corpora (Dagan et al., 2006, etc.)

- *Binary classification* for expert-constructed pairs of sentences into *entailment* and *not entailment* on news and wiki text.
- Training and test data from four annual competitions: RTE1, RTE2, RTE3, and RTE5.

entailment *On Jan. 27, 1756, composer Wolfgang Amadeus Mozart was born in Salzburg, Austria.*
Wolfgang Amadeus Mozart was born in Salzburg.

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The Winograd Schema Challenge, recast as NLI (Levesque et al., 2011/us)

- *Binary classification* for expert-constructed pairs of sentences, converted from coreference resolution to NLI.
- Manually constructed to foil superficial statistical cues.
- Using new private test set from corpus creators.

not_entailment *Jane gave Joan candy because she was hungry.*
Jane was hungry.

entailment *Jane gave Joan candy because she was hungry.*
Joan was hungry.

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The Diagnostic Data

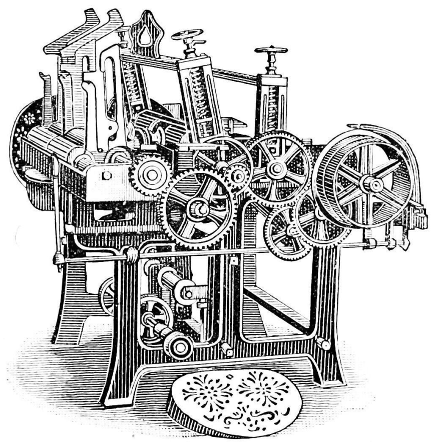
The Diagnostic Data

- Hand-constructed suite of 550 sentence pairs, each made to exemplify at least one of 33 specific phenomena.
- Seed sentences drawn from several genres.
- Each labeled with NLI labels in both directions.

The Diagnostic Data

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

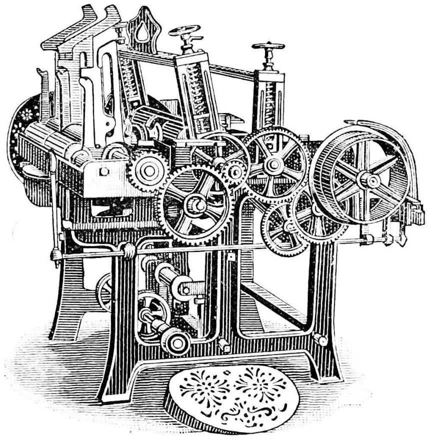
Baselines



Baseline Models

Three model types:

- Existing pretrained **sentence-to-vector encoders**
  - Used as-is, no fine-tuning.
  - Train separate downstream classifiers for each GLUE task.
- Models trained primarily on GLUE tasks
  - Trained either on each task separately (**single-task**) or on all tasks together (**multi-task**)



Model Architecture

- Our architecture:
  - Two-layer BiLSTM (1500D per direction/layer)
  - Optional attention layer for sentence pair tasks with additional shallow BiLSTM (following Seo et al., 2016)
- Input to trained BiLSTM any of:
  - GloVe (840B version, Pennington et al., 2014)
  - CoVe (McCann et al., 2017)
  - ELMo (Peters et al., 2018)
- For multi-task learning, need to balance updates from big and small tasks.
  - Sample data-poor tasks less often, but make larger gradient steps.

Results

		Single Sentence		Similarity and Paraphrase			Natural Language Inference			
Model	Avg	CoLA	SST-2	MRPC	QQP	STS-B	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**

Results

Model	Avg	Single Sentence		Similarity and Paraphrase			Natural Language Inference			
		CoLA	SST-2	MRPC	QQP	STS-B	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**

Results

Model	Avg	Single Sentence		Similarity and Paraphrase			Natural Language Inference			
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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
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+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**
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+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**
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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**

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+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
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+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**
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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**

Results on Diagnostic Data (MNLI classifier)

Model	All	Coarse-Grained LS	PAS	L	K	Fine-Grained 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**

Results on Diagnostic Data (MNLI classifier)

		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**

Results on Diagnostic Data (MNLI classifier)

		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
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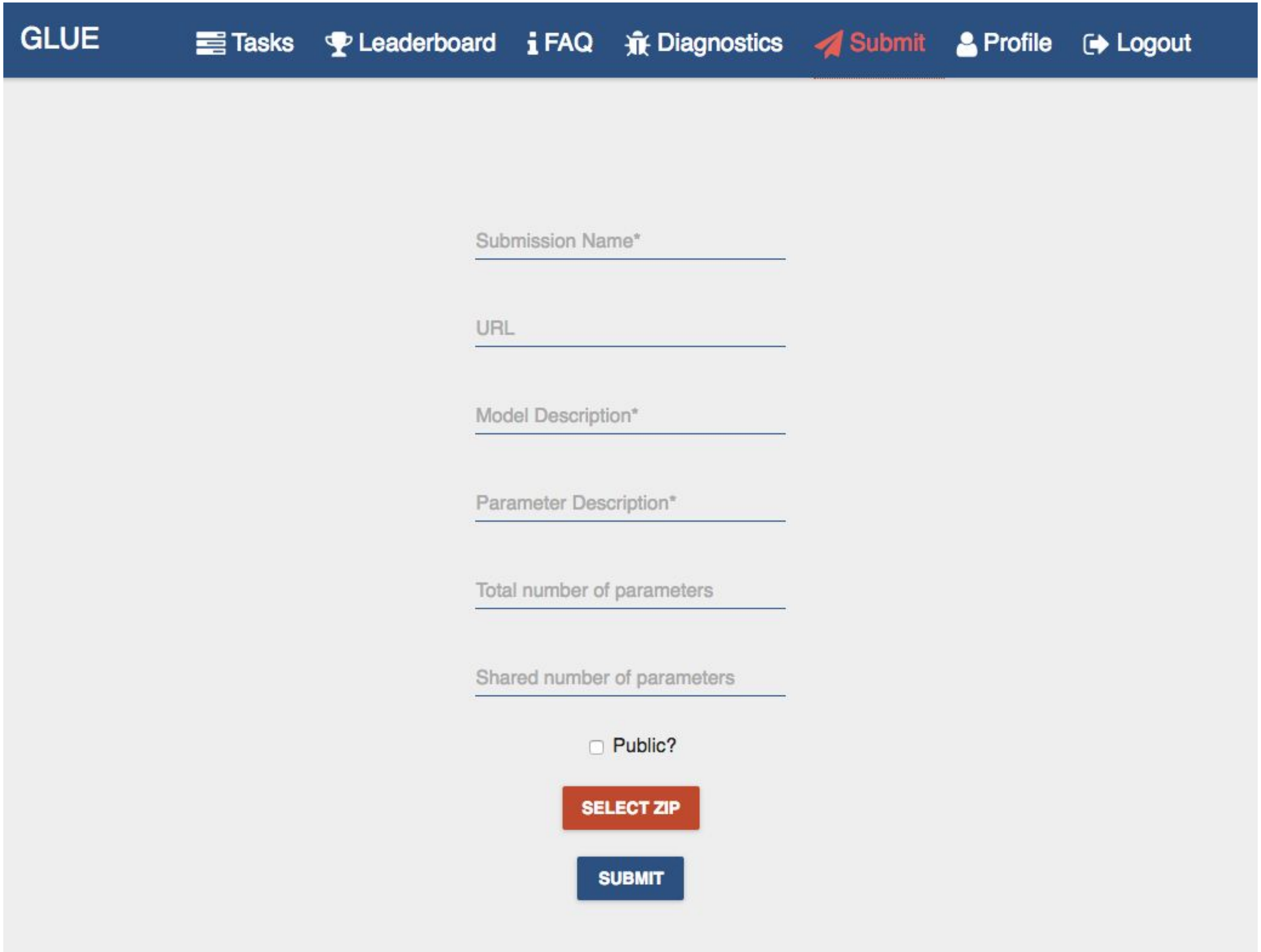
+Attn, CoVe	24	29	29	18	12	77	50	1	18	-1	**12**
					Multi-Task Training						
BiLSTM	19	16	22	16	17	71	35	-8	26	**0**	8
+ELMo	19	15	21	17	**21**	70	**60**	15	26	**0**	**12**
+CoVe	17	15	21	14	16	50	31	-8	25	-15	**12**
+Attn	25	23	32	19	16	58	26	-5	28	-1	-20
+Attn, ELMo	23	24	30	17	13	78	27	37	30	-15	-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**

Limitations

- GLUE is built only on English data.
  - Sentence representation learning may look quite different in lower-resource languages!
- GLUE does not evaluate text *generation*, and uses only small amounts of context.
  - Isolates the problem of extracting sentence meaning, but avoids other hard parts of NLP.
- GLUE uses naturally occurring and crowdsourced data.
  - Models trained on the GLUE training set generally acquire biases and world knowledge that we may not want them to.
  - Models that reflect these biases may do better on GLUE.

The Site


GLUE
Tasks
Leaderboard
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Diagnostics
Submit
Profile
Logout
Submission Name*
URL
Model Description*
Parameter Description*
Total number of parameters
Shared number of parameters
Public?
SELECT ZIP
SUBMIT

The Site

PRIMARY									AUXILIARY						
Rank	**Name**	**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+Att		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	

Take-Aways

- Sentence representation learning is a hard open problem.
- GLUE offers some tools to evaluate sentence representation learning models:
  - Broad sample of training set sizes, genres, task formats, and degrees of difficulty.
  - Private test sets ensure fairness.
  - Minimal constraints on model design.
  - Automatic linguistic analysis.
- Multi-task learning models with ELMo outperform simple single-task baselines, but don't do well in absolute terms.

Closing Comments

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Customers who viewed this item also viewed

- Suchin Gururangan and Swabha Swayamdipta's poster here on artifacts in NLI.

- Kelly Zhang's manuscript comparing translation and language modeling in depth. (Contact me!)

Thanks!

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