CS 5740: Natural Language Processing

Contextualized Representations

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Slides adapted from Greg Durrett

Overview

- Motivation
- Context-dependent Representations with BERT
- Advanced tokenization for BERT (and elsewhere)
- Cross-modality representations

Motivation

- Word embeddings (e.g., word2vec, GloVe):
  - Learn a vector for each word type
  - Always the same vector
- Problem: each vector likely mixes multiple senses, regardless of how the specific instance of the word is used

Motivation

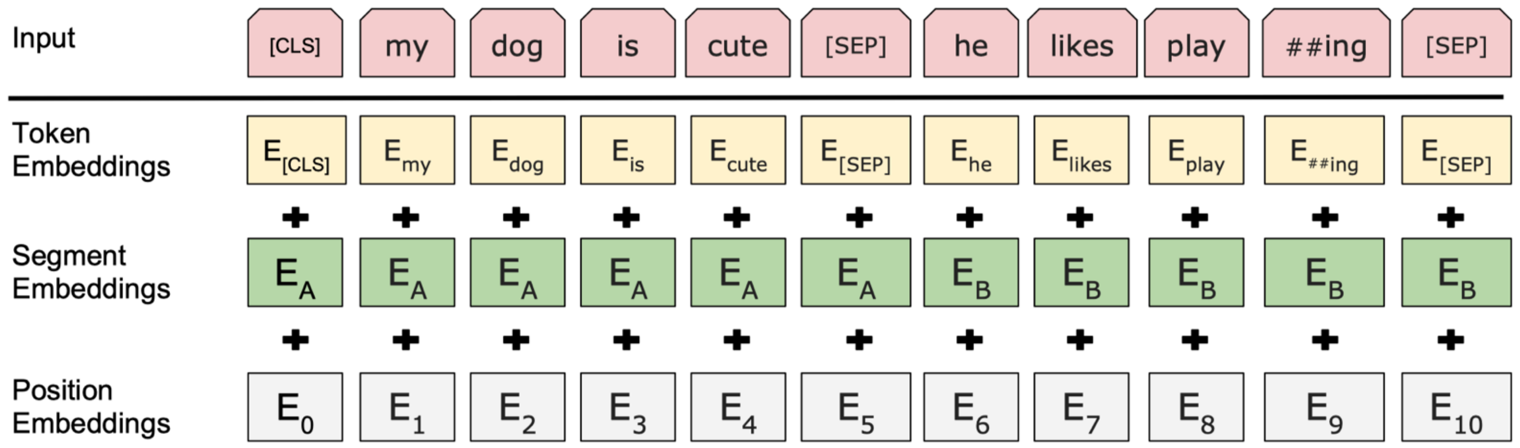
- Instead of a single vector: learn a different vector for each use of a word type
- Challenge: how do we define the space of uses? Isn’t it too large?
- Solution: use sentence encoders to create a custom vector for every instance of a word

Several Approaches

- Central Word Prediction Objective (context2vec) [Melamud et al. 2016]
- Machine Translation Objective (CoVe) [McMann et al. 2017]
- Bi-directional Language Modeling Objective (ELMo) [Peters et al. 2018]
- **Bidirectional Encoder Representations from Transformers (BERT) [Devlin et al. 2018]**
- Robustly Optimized BERT (RoBERTa) [Liu et al. 2019]

BERT

- Model: multi-layer self-attention (Transformer)
- Input: a sentence or a pair of sentences with a separator and subword representation
- Why do we need positional embedding?


Input
[CLS]
my
dog
is
cute
[SEP]
he
likes
play
##ing
[SEP]
Token Embeddings
$E_{[CLS]}$ E_{my} E_{dog} E_{is} E_{cute} $E_{[SEP]}$ E_{he} E_{likes} E_{play} $E_{\#\#ing}$ $E_{[SEP]}$
Segment Embeddings
E_A E_A E_A E_A E_A E_A E_B E_B E_B E_B E_B
Position Embeddings
E_0 E_1 E_2 E_3 E_4 E_5 E_6 E_7 E_8 E_9 E_{10}

[figure from Devlin et al. 2018]

Sub-word Tokenization

- BERT uses Word Piece tokenization
- Related models (e.g., for MT, language modeling, etc) use either Word Piece or Byte Pair Encoding tokenization
- Advantage: no unknown words problem
- Package: https://github.com/huggingface/tokenizers

Byte Pair Encoding (BPE) Tokenization

1. Start with every individual byte (basically character) as its own token

2. Count bigram token cooccurrences over words (potentially: weight according to corpus frequencies)

3. Merge the most frequent pair of adjacent characters to create a new token

- Vocabulary size is controlled by the number of merges

- With ~8000 tokens we get many whole words in English

[Sennrich et al. (2016)]

Word Piece Tokenization

1. Initialize with tokens for all characters

2. While vocabulary size is below the target size:

    1. Build a language model over the corpus (e.g., unigram language model)

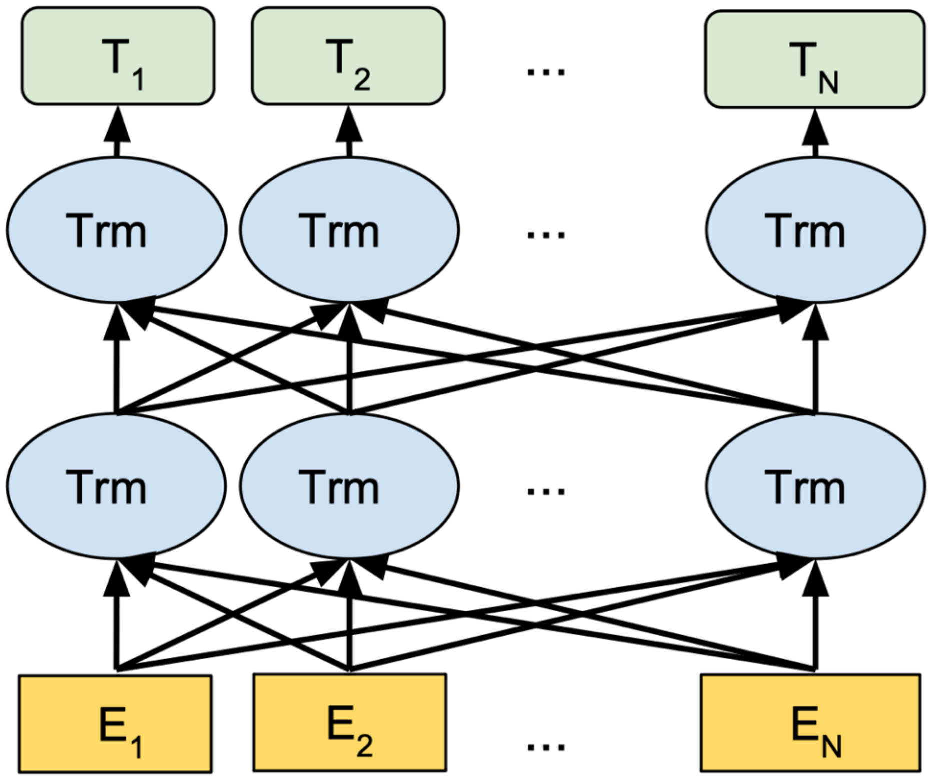
    2. Merge pieces that lead to highest improvement in language model perplexity

- Need to choose a language model that will make the process tractable
- Often a unigram language model (e.g., SentencePiece library)
- Particularly suitable for machine translation

[Schuster and Nakajima (2012), Wu et al. (2016), Kudo and Richardson (2018)]

BERT

- Model: multi-layer self-attention (Transformer)



[figure from Devlin et al. 2018]

BERT

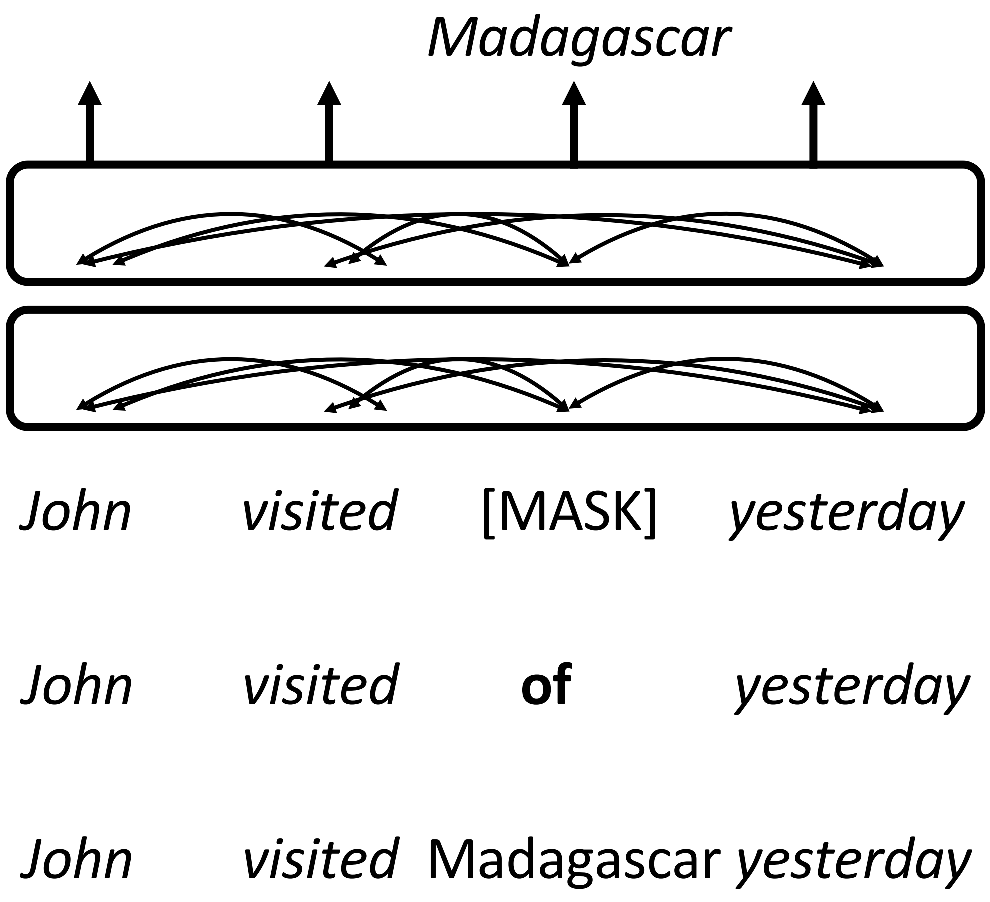
- Model: multi-layer self-attention (Transformer)
- BERT Base: 12 layers, 768-dim per word-piece token, 12 heads. Total parameters = 110M
- BERT Large: 24 layers, 1024-dim per word-piece token, 16 heads. Total parameters = **340M**
- RoBERTa: much more data (160GB of data instead of 16GB)

Training BERT

- Two objectives: masked language modeling and next sentence prediction
- Data: BookCorpus + English Wikipedia
- Later development with RoBERTa:
  - Much more data
  - Removed the next sentence prediction objective
  - Dynamic masking

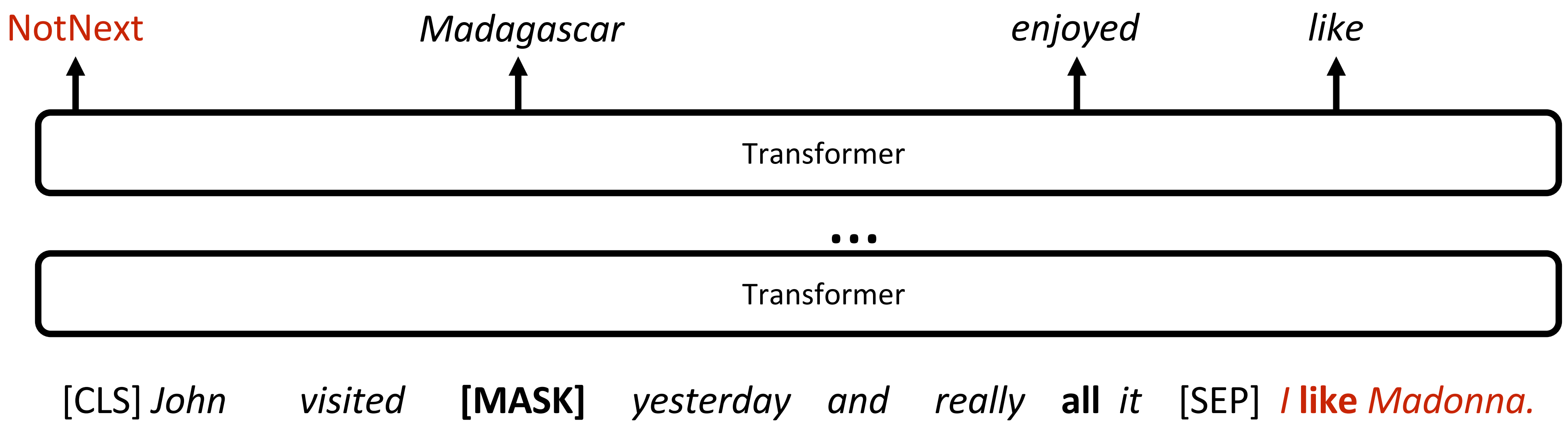
Masked Language Modeling

- Similar to predicting the next word for language modeling, but adapted for non-directional self-attention
- The BERT recipe: mask and predict 15% of the tokens
    - For 80% (of 15%) replace with the input token with [MASK]
    - For 10%, replace with a random token
    - For 10%, keep the same


Madagascar
John *visited* [MASK] *yesterday*
John *visited* **of** *yesterday*
John *visited* Madagascar *yesterday*

Next Sentence Prediction

- Input: [CLS] Text chunk 1 [SEP] Text chunk 2
- 50% of the time, take the true next chunk of text, 50% of the time take a random other chunk. Predict whether the next chunk is the "true" next

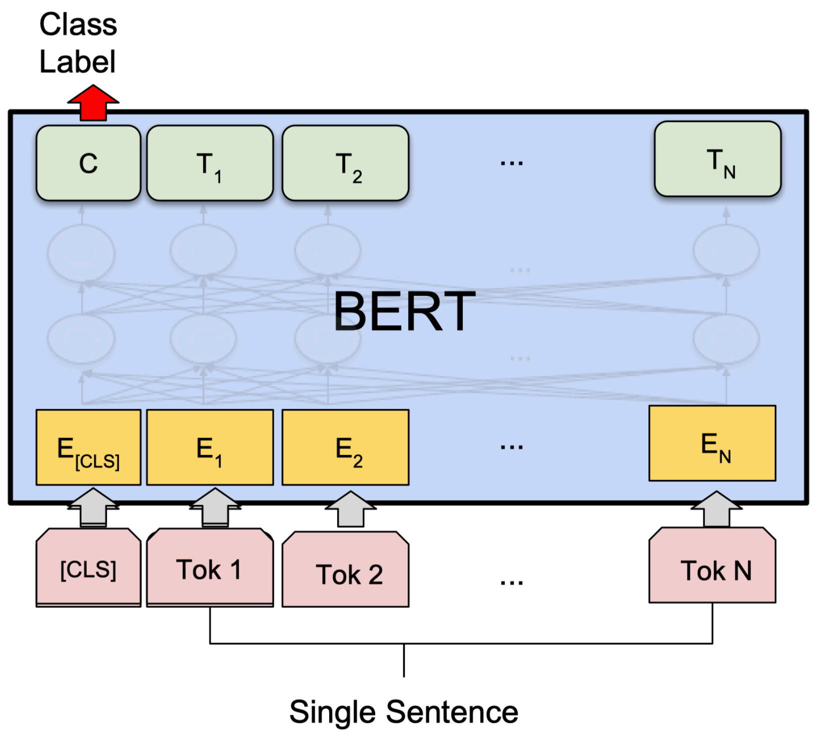

NotNext
Madagascar
enjoyed
like
Transformer
...
Transformer
[CLS] *John* *visited* **[MASK]** *yesterday* *and* *really* **all** *it* [SEP] *I* **like** *Madonna.*

Using BERT

- Use the pre-trained model as the first “layer” of your final model
- Train with fine-tuning using your supervised data
- Fine-tuning recipe: 1-3 epochs, batch size 2-32, learning rate 2e-5 - 5e-5
    - Large changes to weights in top layers (particularly in last layer to route the right information to [CLS])
    - Smaller changes to weights lower down in the transformer
    - Small learning rate and short fine-tuning schedule mean weights don’t change much
    - More complex recipes exist

Sentence Classification with BERT

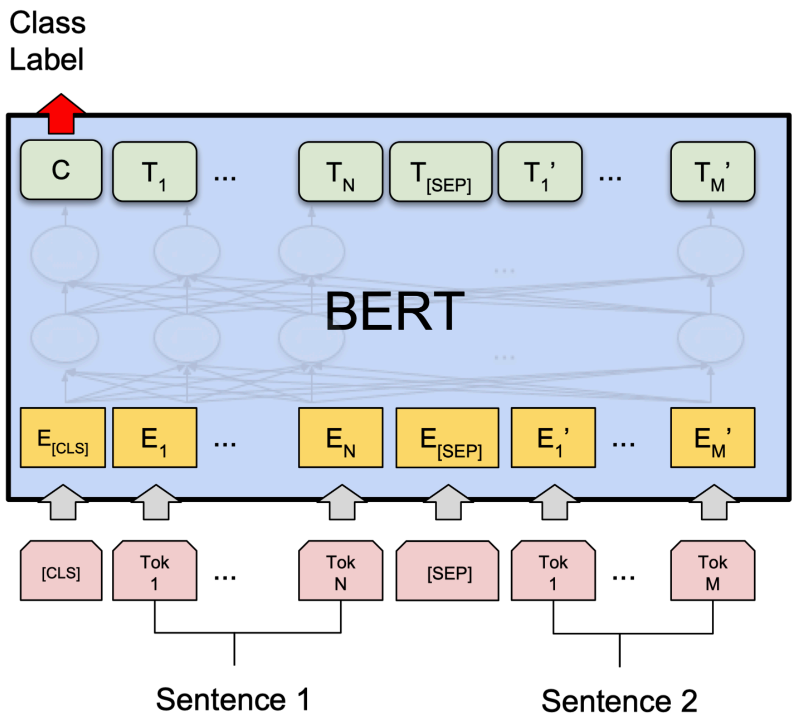
- CLS token is used to provide classification decision
- Example tasks:
  - Sentiment classification
  - Linguistic acceptability
  - Text categorization



[figure from Devlin et al. 2018]

Sentence-pair Classification with BERT

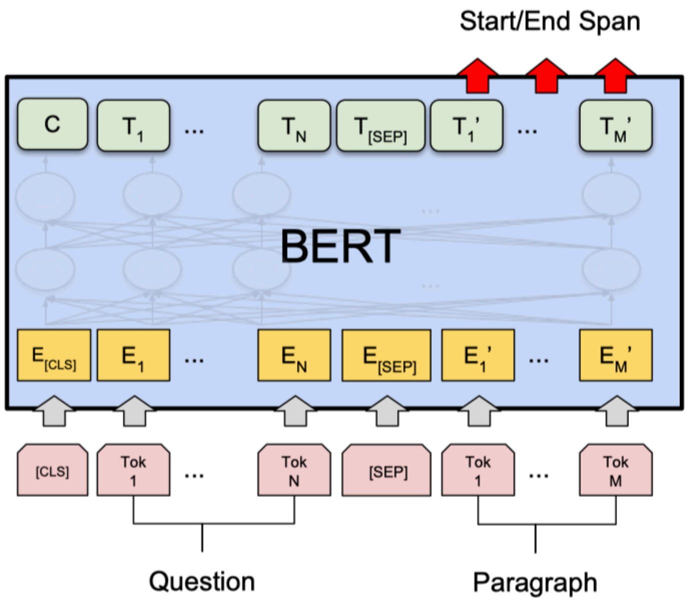
- Feed both sentences, and CLS token used for classification
- Example tasks:
  - Textual entailment
  - Question paraphrase detection
  - Question-answering pair classification
  - Semantic textual similarity
  - Multiple choice question answering

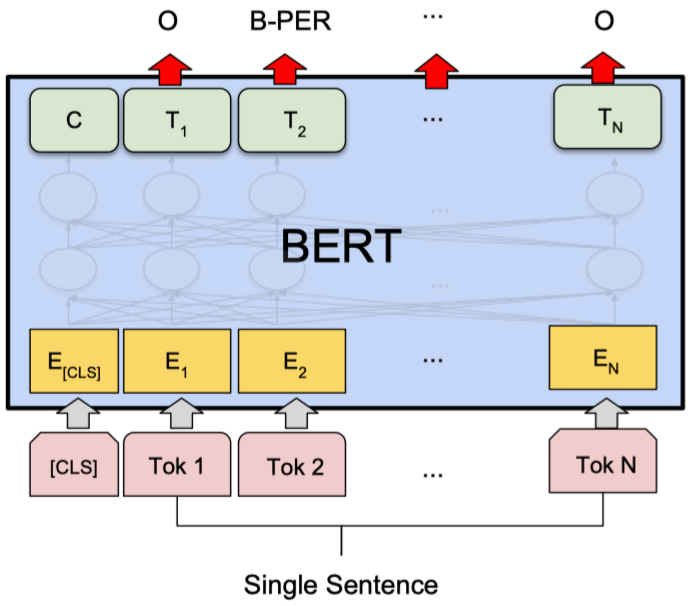


[figure from Devlin et al. 2018]

Tagging with BERT

- Can do for a single sentence or a pair
- Tag each word piece
- Example tasks: span-based question answering, name-entity recognition, POS tagging





[figure from Devlin et al. 2018]

Results

- Fine-tuned BERT outperformed previous state of the art on 11 NLP tasks
- Since then was applied to many more tasks with similar results
- The larger models perform better, but even the small BERT performs better than prior methods
- Variants quickly outperformed human performance on several tasks, including span-based question answering — but what does this mean is less clear
- Started an arms race (between industry labs) on bigger and bigger models

Hard to do with BERT

- BERT cannot generate text (at least not in an obvious way)
  - Not an autoregressive model, can do weird things like stick a [MASK] at the end of a string, fill in the mask, and repeat
- Masked language models are intended to be used primarily for “analysis” tasks

What does BERT Learn?

- A lot of recent work studying this problem
- Some very interesting results
- But, it’s not completely clear how to interpret them

What does BERT Learn?

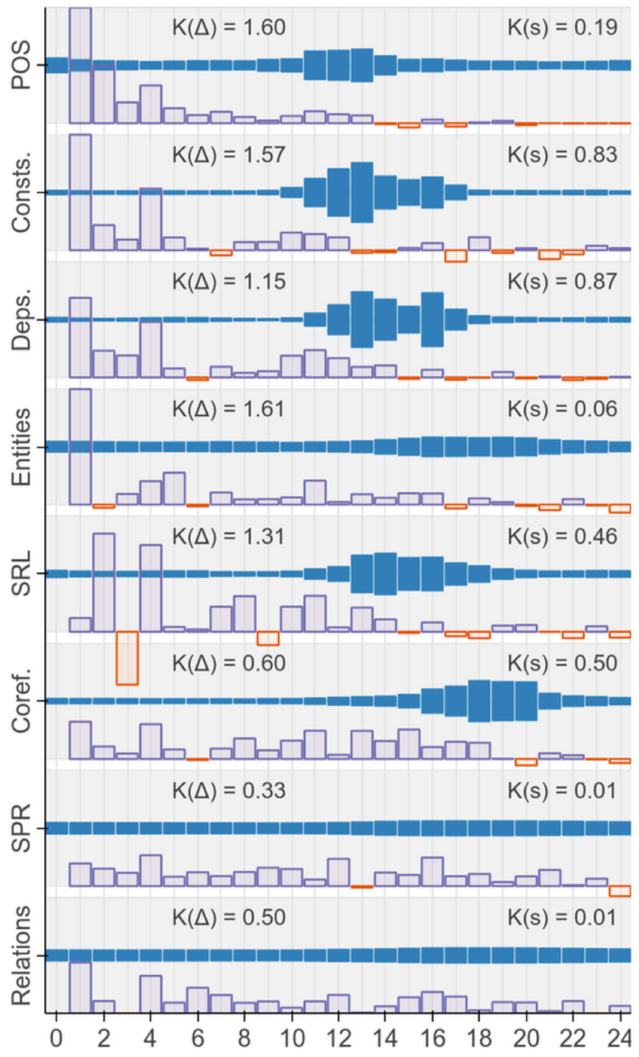
- Try to solve different linguistic tasks given each level
- Goal: see what information each new level adds
- Method: try to solve different tasks using mixing weights on levels
- Each task classifier takes a single mixed hidden representation $\mathbf{h}_{i,\tau}$ or a pair of representations

$$
\begin{aligned}
i &: \text{token index} \\
K &: \text{number of levels} \\
\tau &: \text{task} \\
\gamma_\tau &: \text{task parameter} \\
\mathbf{a}_\tau &: \text{mixing parameters} \\
\mathbf{s}_\tau &= \text{softmax}(\mathbf{a}_\tau) \\
\mathbf{h}_{i,\tau} &= \gamma_\tau \sum_{k=0}^{K} s_\tau^k \mathbf{h}_i^k
\end{aligned}
$$

[Tenney et al. (2019)]

What does BERT Learn?

- Each plot shows a task
- Plots show s_τ^k weights magnitude in blue, and the number of self-attention levels
- The performance delta when adding this layer is in purple
- Largely: higher level semantic tasks happen in later levels



[figure from Tenney et al. (2019)]

Where to get BERT?

- The Transformers library: https://github.com/huggingface/transformers
- Provides state-of-the-art implementation of many models, including BERT and RoBERTa
- Including pre-trained models

Vision-language Reasoning

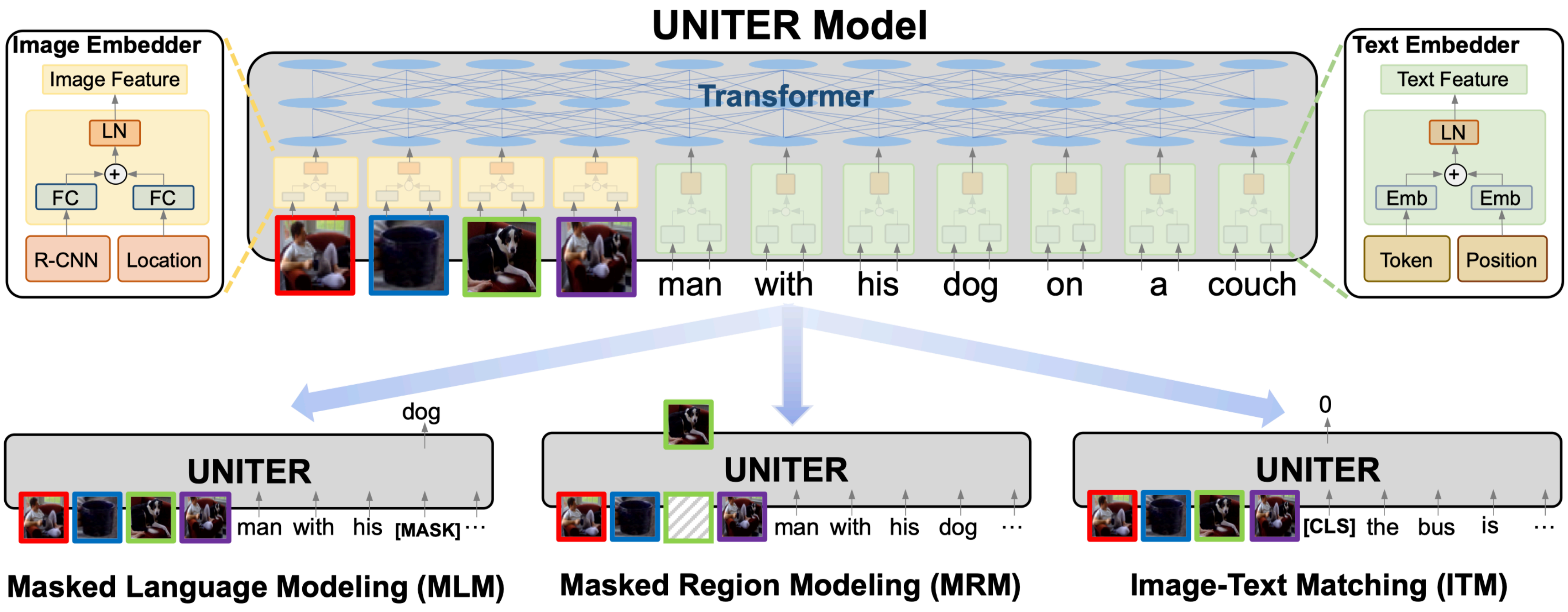
- Goal: pre-trained representations for language and vision, where the input is a sentence and image
- Self-attention in BERT allows attending between two sentences
- How can we extend that to a sentence paired with an image?

Vision-language Reasoning

- Solution: pre-process the image to extract bounding boxes around objects
- Now the image is an unordered list of discrete objects
- Objectives: masked language model + masked region modeling + image-text matching

[Li et al. 2019; Tan and Bansal 2019; Chen et al. 2019; and several other simultaneous papers]

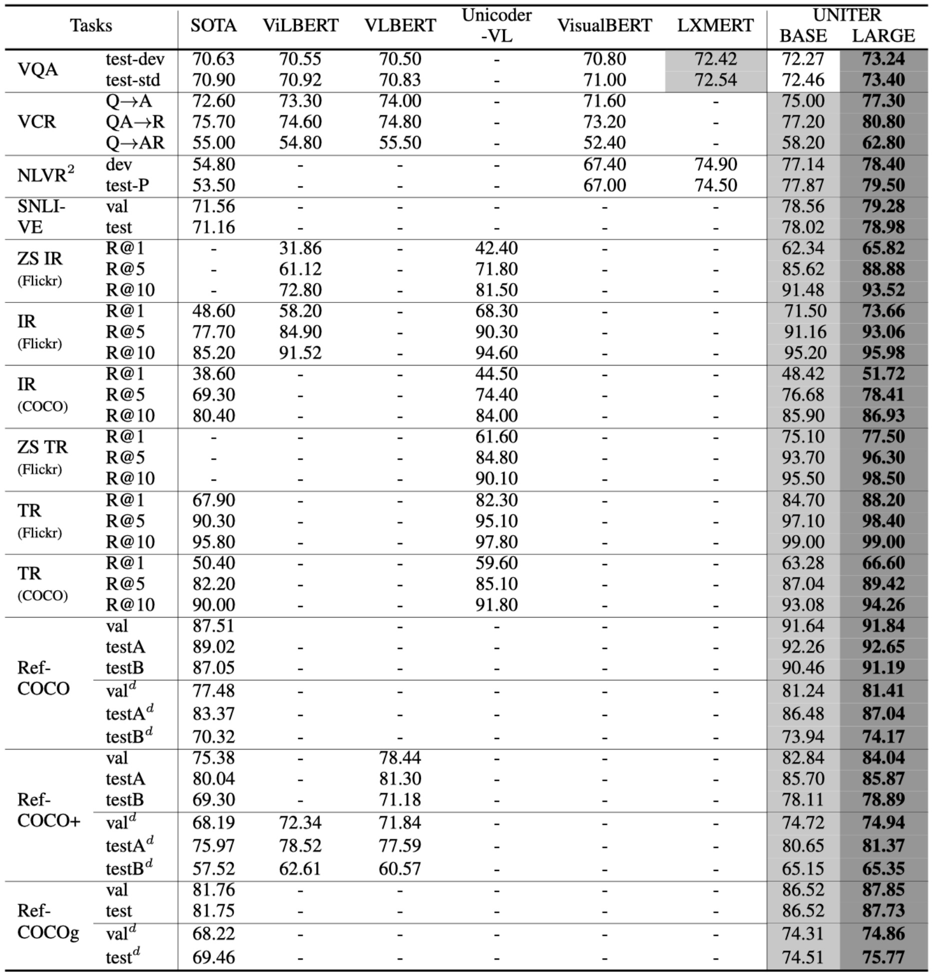
Vision-language Reasoning



[figure from Chen et al. 2019]

Results

- Similar trend to what we observe with BERT
- State of the art on 13 vision+language benchmarks
- Similar to BERT, there larger is better



Tasks		SOTA	ViLBERT	VLBERT	Unicoder -VL	VisualBERT	LXMERT	UNITER BASE	UNITER LARGE
VQA	test-dev	70.63	70.55	70.50	-	70.80	72.42	72.27	**73.24**
	test-std	70.90	70.92	70.83	-	71.00	72.54	72.46	**73.40**
VCR	Q→A	72.60	73.30	74.00	-	71.60	-	75.00	**77.30**
	QA→R	75.70	74.60	74.80	-	73.20	-	77.20	**80.80**
	Q→AR	55.00	54.80	55.50	-	52.40	-	58.20	**62.80**
NLVR^2	dev	54.80	-	-	-	67.40	74.90	77.14	**78.40**
	test-P	53.50	-	-	-	67.00	74.50	77.87	**79.50**
SNLI-VE	val	71.56	-	-	-	-	-	78.56	**79.28**
	test	71.16	-	-	-	-	-	78.02	**78.98**
ZS IR (Flickr)	R@1	-	31.86	-	42.40	-	-	62.34	**65.82**
	R@5	-	61.12	-	71.80	-	-	85.62	**88.88**
	R@10	-	72.80	-	81.50	-	-	91.48	**93.52**
IR (Flickr)	R@1	48.60	58.20	-	68.30	-	-	71.50	**73.66**
	R@5	77.70	84.90	-	90.30	-	-	91.16	**93.06**
	R@10	85.20	91.52	-	94.60	-	-	95.20	**95.98**
IR (COCO)	R@1	38.60	-	-	44.50	-	-	48.42	**51.72**
	R@5	69.30	-	-	74.40	-	-	76.68	**78.41**
	R@10	80.40	-	-	84.00	-	-	85.90	**86.93**
ZS TR (Flickr)	R@1	-	-	-	61.60	-	-	75.10	**77.50**
	R@5	-	-	-	84.80	-	-	93.70	**96.30**
	R@10	-	-	-	90.10	-	-	95.50	**98.50**
TR (Flickr)	R@1	67.90	-	-	82.30	-	-	84.70	**88.20**
	R@5	90.30	-	-	95.10	-	-	97.10	**98.40**
	R@10	95.80	-	-	97.80	-	-	99.00	**99.00**
TR (COCO)	R@1	50.40	-	-	59.60	-	-	63.28	**66.60**
	R@5	82.20	-	-	85.10	-	-	87.04	**89.42**
	R@10	90.00	-	-	91.80	-	-	93.08	**94.26**
Ref-COCO	val	87.51		-	-	-	-	91.64	**91.84**
	testA	89.02	-	-	-	-	-	92.26	**92.65**
	testB	87.05	-	-	-	-	-	90.46	**91.19**
	val^d	77.48	-	-	-	-	-	81.24	**81.41**
	testA^d	83.37	-	-	-	-	-	86.48	**87.04**
	testB^d	70.32	-	-	-	-	-	73.94	**74.17**
Ref-COCO+	val	75.38	-	78.44	-	-	-	82.84	**84.04**
	testA	80.04	-	81.30	-	-	-	85.70	**85.87**
	testB	69.30	-	71.18	-	-	-	78.11	**78.89**
	val^d	68.19	72.34	71.84	-	-	-	74.72	**74.94**
	testA^d	75.97	78.52	77.59	-	-	-	80.65	**81.37**
	testB^d	57.52	62.61	60.57	-	-	-	65.15	**65.35**
Ref-COCOg	val	81.76	-	-	-	-	-	86.52	**87.85**
	test	81.75	-	-	-	-	-	86.52	**87.73**
	val^d	68.22	-	-	-	-	-	74.31	**74.86**
	test^d	69.46	-	-	-	-	-	74.51	**75.77**