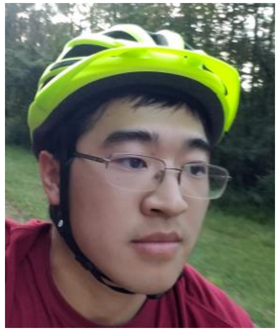
Which *BERT?

A Survey Organizing Contextualized Encoders

Patrick Xia Shijie Wu Benjamin Van Durme



JOHNS HOPKINS UNIVERSITY

CENTER FOR LANGUAGE AND SPEECH PROCESSING

Background

History of Text Representations | Who is BERT? | About BERT and friends

A History of Text Representations

- Co-occurrence statistics
  - Brown Clusters
  - Count vectors, TF-IDF vectors, co-occurrence matrix decomposition
- Predictive
  - word2vec, GloVe, CBOW, Skip-Gram, etc
- Contextualized language models
  - Representation of word *changes* based on context
  - CoVE, ELMo, GPT, BERT, etc

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Who is BERT? 

BERT is a 12 (or 24) layer Transformer language model trained on two pretraining tasks, masked language modeling (fill-in-the-blank) and next sentence prediction (binary classification), and on English Wikipedia and BooksCorpus.

About BERT  and friends

Why this size and architecture?

-base, -large, -small, -xl, etc.

How much "language"?

linguistic probing tasks, attention, few-shot evaluation

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Why these tasks?

XLNet, ELECTRA, SpanBERT, LXMERT, etc.

Other languages?

mBERT, XLM, XLM-R, mT5, RuBERT, etc

What's special about this data?

BioBERT, Covid-Twitter-BERT, etc

Using these *BERTs

- Pretrain → finetune
  - *Pretrain* encoders on pretraining tasks (high-resource/data, possibly unsupervised)
  - *Finetune* encoders on target task (low-resource, expensive annotation)
- Primary method of evaluation: Natural Language "Understanding" (NLU)
  - Question Answering and Reading Comprehension
  - Commonsense
  - Textual Entailments

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The story so far...

Pretraining | Efficiency | Data | Interpretability | Multilinguality

Pretraining

- Quantitative improvements in downstream tasks are made through pretraining methods

Predict tokens in text

- Masked language modeling
  - Masked token/word/span prediction
  - Replaced word prediction

Predict other signals

- Next sentence/segment prediction
- Discourse relations
- Grounding
  - To KB
  - Visual/multimodal

Pretraining

- Masked language modeling

What is natural language processing ?

What is natural language [mask]?

Masked token prediction

What is [mask] processing?

Masked span prediction

Who is natural language processing?

Replaced word prediction

Pretraining

- Predict other signals
  - Next “sentence” prediction
  - Discourse markers/relations
  - Real-world knowledge: knowledge base/IR scores
  - Visual and multimodal grounding

Efficiency

- Training:
  - Faster convergence with improved optimizers, hardware
- Inference size/time:
  - Large → small: knowledge distillation, pruning
  - Start small: parameter sharing/factorization, quantization
- Are these techniques compared equally?
  - Do we care about %parameter reduction? Memory? Inference time? These don't necessarily correlate
  - Do we care about all tasks or just downstream one(s)?

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Data

- Quantity: more data is better
  - Are comparisons across encoders fair?
- Quality: clean, *in-domain*, data is better
  - What are our test sets?
- Where is our data coming from??
  - Do we know what biases the contextualized encoders learn?
  - Should we use biased model in real systems?

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Interpretability

- Task probing
  → Finetune pretrained models to test specific linguistic phenomenon
- Model weight inspection
  → Visualize weights for important words in input or layers in model
- Input Prompting
  → Force language models to fill in or complete text
- None of these methods are perfect
  - Task probing: more finetuning
  - Weight inspection: not reliable
  - Prompting: picking the prompt is critical

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Multilinguality

- A single encoder on multilingual text with shared input vocabulary
- These models do well! Why?
  - Shared vocabulary
  - Shared (upper) layers
  - Deep networks
  - Embeddings across languages can be aligned
- When are multilingual models good?

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Shortcomings

Leaderboards | Overfitting our understanding | Expensive evaluations

Leaderboards without a leader

- There's good science in 2nd place: who is responsible for publishing when reviewers demand 1st?
  - Publicize and publish negative results
- Leaderboard *owners* should be responsible for frequently surveying submissions
- A leaderboard is not just a dataset: it's an unending shared task
  - Shared tasks need summaries discussing all the methods

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Overfitting our understanding

- We know so much about English Wikipedia + BooksCorpus, 12-layer and 24-layer BERT.
  - What about 8-layer BERT? Or distilled BERT?
  - Simple English Wikipedia + RoBERTa?
  - BooksCorpus (subgenres) + XLNet?
- Draw more conclusions across *models* in addition to across *tasks*
  - At what point (#params) does a model outperform humans on X?
  - How much of Wikipedia does a model need to outperform on Y?

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Expensive evaluations

- GLUE: 9 tasks, SuperGLUE: 10 tasks, SQuAD: 150K QA pairs
  - Finetuning cost for every task is high
- If a researcher is focused on distilling encoders with several novel methods:
  - Finetune all tasks → unrelated effort and time running “evaluation”
  - Stick with a few tasks → unfair comparisons, angry reviewers
- How can we make evaluation easier?
- Unit testing models for practical applications?

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So, which *BERT?

What is your … task | data | language | goal ?

What is your task?

- Not all tasks benefit from the shiniest encoder!
  - Some pretrained systems work well with just BERT
  - Encodings are just inputs to complex systems that are further tuned
- Finetuning and retraining entire models may not be feasible or even justified for your task

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- Does the domain of your data overlap with that of the encoder?
- Is there are specialized pretrained encoder for your domain or data?
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- Is your language low-resource?
  - Use the best general-purpose model
  - Again, depends on your task and data
- Is there a competitive monolingual contextualized encoder?
  - Chinese, French, etc
  - Monolingual data curation may be better
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- Encoder research?
  - Build off great recent ideas
  - Incorporate “beta” and “nightly” ideas!
- Product development, fast deployment, something that works?
  - Pick well-documented models
  - HuggingFace Transformers uses a single interface; models can be easily upgraded later

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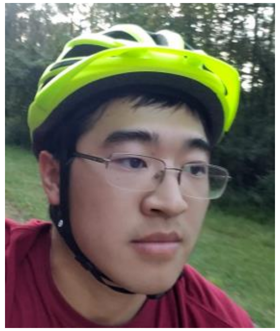
Summary

- Contextualized encoders have transformed research and thinking in NLP in just a couple years
- Areas we are focusing on:
  - Pretraining, efficiency, data, interpretability, and multilinguality
- Are we making progress?
- Which model should you use?
  - Depends on task, data, language, and objective

Patrick Xia



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Thank you

Please join the Q&A for discussion

See paper for more details and references

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