What you can cram into a single $\&!#* vector: Probing sentence embeddings for linguistic properties

Alexis Conneau, German Kruszewski, Guillaume Lample, Loïc Barrault, Marco Baroni

Facebook AI Research     Université Le Mans (LIUM)

ACL 2018
The quest for universal sentence embeddings

|                      | Words Embed. | Sentences Embed. |
|----------------------|--------------|------------------|
| **Strong baselines** | FastText     | Bag-of-Words     |
| **State-of-the-art** | ELMo         |                  |

- **Unsupervised**
  - Uses unannotated or weakly-annotated dataset
  - Skip-Thoughts
  - Quick-Thoughts
  - DiscSent
  - Google's dialog input-output

- **Supervised**
  - Uses annotated dataset
  - InferSent
  - Machine translation

- **Multi-task learning**
  - Uses several annotated or unannotated datasets
  - MILA/MSR's General Purpose Sent.
  - Google's Universal Sentence Enc.

*Courtesy: Thomas Wolf blogpost, Hugging Face*
Now-famous Ray Mooney’s quote

You can’t cram the meaning of a single $&!#* sentence into a single $!#&* vector!

• While not capturing meaning, we might still be able to build useful transferable sentence features
• But what can we actually cram into these vectors?
The evaluation of universal sentence embeddings

• Transfer learning on many other tasks

• Learn a classifier on top of pretrained sentence embeddings for transfer tasks

• SentEval downstream tasks:
  • Sentiment/topic classification
  • Natural Language Inference
  • Semantic Textual Similarity
The evaluation of universal sentence embeddings

- Downstream tasks are complex
- Hard to infer what information the embeddings really capture
- "Probing tasks" to the rescue!
  - designed for inference
  - evaluate simple isolated properties
Probing tasks and downstream tasks

Probing tasks are simpler and focused on a single property!

| Subject Number probing task | Natural Language Inference downstream task |
|------------------------------|--------------------------------------------|
| **Premise:** A lot of people walking outside a row of shops with an older man with his hands in his pocket is closer to the camera. |

| Hypothesis: A lot of dogs barking outside a row of shops with a cat teasing them. |
|---|
| **Label:** contradiction |

**Sentence:** The hobbits waited patiently.

**Label:** Plural (NNS)
Our contributions

An extensive analysis of sentence embeddings using probing tasks

• We vary the architecture of the encoder (3) and the training task (7)

• We open-source 10 horse-free classification probing tasks.

• Each task being designed to probe a single linguistic property

Shi et al. (EMNLP 2016) - Does string-based neural MT learn source syntax?
Adi et al. (ICLR 2017) - Fine-grained analysis of sentence embeddings using auxiliary prediction tasks
Probing tasks: understanding sentence embeddings content
Probing tasks

What they have in common:

• Artificially-created datasets all framed as classification

• … but based on natural sentences extracted from the TBC (5-to-28 words)

• 100k training set, 10k valid, 10k test, with balanced classes

• Carefully removed obvious biases (words highly predictive of a class, etc)
Probing tasks

Grouped in three categories:

• Surface information
• Syntactic information
• Semantic information
Probing tasks (1/10) – Sentence Length

- **Goal**: Predict the length range of the input sentence (6 bins)

- **Question**: Do embeddings preserve information about sentence length?

She had not come all this way to let one stupid wagon turn all of that hard work into a waste!  

MLP classifier

Surface information
• **Goal**: 1000 output words. Which one (only one) belongs to the sentence?

• **Question**: Do embeddings preserve information about words?

Adi et al. (ICLR 2017) - Fine-grained analysis of sentence embeddings using auxiliary prediction tasks

Surface information
Probing tasks (3/10) – Top Constituents

- **Goal**: Predict top-constituents of parse-tree (20 classes)

- **Note**: 19 most common top-constituent sequences + 1 category for others

- **Question**: Can we extract grammatical information from the embeddings?

Shi et al. (EMNLP 2016) - Does string-based neural MT learn source syntax?

Syntactic information
Probing tasks (4/10) – Bigram Shift

- **Goal**: Predict whether a bigram has been shifted or not.

- **Question**: Are embeddings sensible to word order?

```
This new was information .
```

```
We 're married getting .
```

MLP classifier

Syntactic information
Probing tasks – 5 more

- 5/10: **Tree Depth** (depth of the parse tree)

- 6/10: **Tense prediction** (main clause tense, past or present)

- 7-8/10: **Object/Subject Number** (singular or plural)

- 9/10: **Semantic Odd Man Out** (noun/verb replaced by one with same POS)
Probing tasks (10/10) – Coordination Inversion

They might be only memories, but I can still feel each one

I can still feel each one, but they might be only memories.

• **Goal**: Sentences made of two coordinate clauses: inverted (I) or not (O)?

• **Note**: human evaluation: 85%

• **Question**: Can extract sentence-model information?

| Input | Output |
|-------|--------|
| They might be only memories, but I can still feel each one | 0 |
| I can still feel each one, but they might be only memories. | 1 |

Semantic information
Experiments and results
Experiments
We analyse almost 30 encoders trained in different ways:

• Our baselines:
  • Human evaluation, Length (1-dim vector)
  • NB-uni and NB-uni/bi with TF-IDF
  • CBOW (average of word embeddings)

• Our 3 architectures:
  • Three encoders: BiLSTM-last/max, and Gated ConvNet

• Our 7 training tasks:
  • Auto-encoding, Seq2Tree, SkipThought, NLI
  • Seq2seq NMT without attention En-Fr, En-De, En-Fi
## Experiments – training tasks

| task          | source                                                                 | target                                                                 |
|---------------|------------------------------------------------------------------------|------------------------------------------------------------------------|
| AutoEncoder   | I myself was out on an island in the Swedish archipelago, at Sandhamn. | I myself was out on an island in the Swedish archipelago, at Sand@ ham@ n. |
| NMT En-Fr     | I myself was out on an island in the Swedish archipelago, at Sandhamn. | Je me trouvais ce jour là sur une île de l’archipel suédois, à Sand@ ham@ n. |
| NMT En-De     | We really need to up our particular contribution in that regard.       | Wir müssen wirklich unsere spezielle Hilfsleistung in dieser Hinsicht aufstocken. |
| NMT En-Fi     | It is too early to see one system as a universal panacea and dismiss another. | Nyt on liian aikaita nostaa yksi järjestelmä ja@ usta@ ile ja antaa jollekin toiselle huono arvo@ sana. |
| SkipThought   | the old sami was gone, and he was a different person now.              | the new sami didn’t mind standing barefoot in dirty white, sans ra@ y-@ bans and without beautiful women following his every move. |
| Seq2Tree      | Dikoya is a village in Sri Lanka.                                      | (ROOT (S (NP NNP) NP (VP VBZ (NP (NP DT NN) NP (PP IN (NP NNP NNP) NP) NP) VP . )S )ROOT |

Source and target examples for seq2seq training tasks

Sutskever et al. (NIPS 2014) - Sequence to sequence learning with neural networks  
Kiros et al. (NIPS 2015) - SkipThought vectors  
Vinyals et al. (NIPS 2015) - Grammar as a Foreign Language
Baselines and sanity checks

Probing task evaluation baselines

| Feature | Hum. | NB-uni-tfidf | NB-bi-tfidf | CBOW | Majority vote |
|---------|------|--------------|-------------|------|---------------|
| SentLen | 66.6 | 84.1         | 63.8        | 53.2 | 50.8          |
| WC      | 95.1 | 98.8         | 65.4        | 59.8 | 50            |
| TopConst| 1    | 5            | 68.1        | 5    | 5             |
| BShift  | 20   | 79.8         | 87.0        | 87.0 | 50            |
| ObjNum  | 23   | 84.1         | 67.6        | 67.6 | 23            |
Impact of training tasks
Impact of model architecture

Average accuracies for different models

| Model      | SentLen | WC | TopConst | BShift | ObjNum | CoordInv |
|------------|---------|----|----------|--------|--------|----------|
| BiLSTM-max | 81.2    | 46.2 | 72.9     | 72.6   | 72.9   | 73.1     |
| BiLSTM-last| 83.9    | 40.3 | 79.2     | 62.4   | 83.9   | 73.1     |
| GatedConvNet | 87.5 | 35  | 79.7     | 73     | 86.6   | 72.6     |

BiLSTM-max, BiLSTM-last, and GatedConvNet are the model architectures compared.

- **SentLen**: Sentence length
- **WC**: Word count
- **TopConst**: Top constant
- **BShift**: Backshift
- **ObjNum**: Object number
- **CoordInv**: Coordination inversion
Evolution during training

• Evaluation on probing tasks at each epoch of training

• What do embeddings encode along training?

• NMT: Most increase and converge rapidly (only SentLen decreases). WC correlated with BLEU.
Correlation with downstream tasks

• Strong correlation between WC and downstream tasks

• Word-level information important for downstream tasks (classification, NLI, STS)

• If WC good predictor -> maybe current downstream tasks are not the right ones?
Take-home messages and future work

• Sentence embeddings need not be good on probing tasks

• Probing tasks are simply meant to understand what linguistic features are encoded and to designed to compare encoders.

• Future work
  • Understanding the impact of multi-task learning
  • Studying the impact of language model pretraining (ELMO)
  • Study other encoders (Transformer, RNNG)
Thank you!
Thank you!

• Publicly available in SentEval

• Automatically generated datasets (generalize to other languages)

• Natural sentences from Toronto Book Corpus

• Used Stanford parser for grammatical tasks

https://github.com/facebookresearch/SentEval/tree/master/data/probing
Probing tasks – Semantic Odd Man Out

• **Goal:** Predict whether a sentence has been modified or not: one verb/noun randomly by another verb/noun with same POS

• **Note:** preserved bigrams frequency, human eval.: 81.2%

• **Question:** Can we identify well-formed sentences (sentence model)?