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

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Facebook AI Research     Université Le Mans (LIUM)

ACL 2018
The quest for universal sentence embeddings

<table>
<thead>
<tr>
<th>Strong baselines</th>
<th>Words Embed.</th>
<th>Sentences Embed.</th>
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<tr>
<td>FastText</td>
<td>Bag-of-Words</td>
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<tr>
<th>State-of-the-art</th>
<th>ELMo</th>
<th>Unsupervised</th>
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<tr>
<td></td>
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<td>Uses unannotated or weakly-annotated dataset</td>
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<td>Skip-Thoughts</td>
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<td>DiscSent</td>
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<td>Google’s dialog input-output</td>
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<th>Supervised</th>
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<tr>
<td>Uses annotated dataset</td>
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<tr>
<th>InferSent</th>
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<tr>
<td>Machine translation</td>
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<tr>
<th>Multi-task learning</th>
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<tbody>
<tr>
<td>Uses several annotated or unannotated datasets</td>
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</tbody>
</table>

| 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!

<table>
<thead>
<tr>
<th>Subject Number probing task</th>
<th>Natural Language Inference downstream task</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sentence:</strong> The hobbits waited patiently.</td>
<td><strong>Premise:</strong> 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.</td>
</tr>
<tr>
<td><strong>Label:</strong> Plural (NNS)</td>
<td><strong>Hypothesis:</strong> A lot of dogs barking outside a row of shops with a cat teasing them.</td>
</tr>
<tr>
<td></td>
<td><strong>Label:</strong> contradiction</td>
</tr>
</tbody>
</table>
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

21-25

Surface information
**Probing tasks (2/10) – Word Content**

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

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

---

Helen took a pen from her purse and **wrote** something on her cocktail napkin.

MLP classifier

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 .

<table>
<thead>
<tr>
<th>Input</th>
<th>MLP classifier</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>This new was information .</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>We 're married getting .</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

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

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

- **Note**: human evaluation: 85%

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

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

MLP classifier output

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

input

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

<table>
<thead>
<tr>
<th>task</th>
<th>source</th>
<th>target</th>
</tr>
</thead>
<tbody>
<tr>
<td>AutoEncoder</td>
<td>I myself was out on an island in the Swedish archipelago, at Sandhamn.</td>
<td>I myself was out on an island in the Swedish archipelago, at Sandhamn.</td>
</tr>
<tr>
<td>NMT En-Fr</td>
<td>I myself was out on an island in the Swedish archipelago, at Sandhamn.</td>
<td>Je me trouvais ce jour là sur une île de l’archipel suédois, à Sandhamn.</td>
</tr>
<tr>
<td>NMT En-De</td>
<td>We really need to up our particular contribution in that regard.</td>
<td>Wir müssen wirklich unsere spezielle Hilfsleistung in dieser Hinsicht aufstocken.</td>
</tr>
<tr>
<td>NMT En-Fi</td>
<td>It is too early to see one system as a universal panacea and dismiss another.</td>
<td>Nyt on liian aikaista nostaa yksi järjestelmä jalustaa 1le ja antaa jollekin toiselle huono arvo sana.</td>
</tr>
<tr>
<td>SkipThought</td>
<td>the old sami was gone, and he was a different person now.</td>
<td>the new sami didn’t mind standing barefoot in dirty white, sans ra y Bans and without beautiful women following his every move.</td>
</tr>
<tr>
<td>Seq2Tree</td>
<td>Dikoya is a village in Sri Lanka.</td>
<td>(ROOT (S (NP NNP) (VP VBZ (NP (NP DT NN) NP (PP IN (NP NNP NNP) NP) NP) NP) NP) VP . )S )ROOT</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Baseline</th>
<th>SentLen</th>
<th>WC</th>
<th>TopConst</th>
<th>BShift</th>
<th>ObjNum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hum. Eval</td>
<td>66.6</td>
<td>95.9</td>
<td>1</td>
<td>98.0</td>
<td>87.0</td>
</tr>
<tr>
<td>NB-bi-tfidf</td>
<td>65.4</td>
<td>63.8</td>
<td>5.0</td>
<td>50.85</td>
<td>50.0</td>
</tr>
<tr>
<td>NB-uni-tfidf</td>
<td>79.8</td>
<td>91.6</td>
<td>1.0</td>
<td>95.0</td>
<td>100.0</td>
</tr>
<tr>
<td>CBOW</td>
<td>20.0</td>
<td>53.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Majority vote</td>
<td>23.0</td>
<td>5.0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ACCURACY values are shown for each baseline across different features.
Impact of training tasks

Probing tasks results for BiLSTM last trained in different ways

<table>
<thead>
<tr>
<th>Task</th>
<th>CBO</th>
<th>Autoencoder</th>
<th>NMT En-Fr</th>
<th>NMT En-Fi</th>
<th>Seq2Tree</th>
<th>SkipThought</th>
</tr>
</thead>
<tbody>
<tr>
<td>SentLen</td>
<td>66.6</td>
<td>82.4</td>
<td>75.9</td>
<td>75.9</td>
<td>94.7</td>
<td>99.3</td>
</tr>
<tr>
<td>WC</td>
<td>23.3</td>
<td>52.6</td>
<td>47.3</td>
<td>47.3</td>
<td>60.1</td>
<td>58.8</td>
</tr>
<tr>
<td>TopConst</td>
<td>23.3</td>
<td>52.6</td>
<td>47.3</td>
<td>47.3</td>
<td>60.1</td>
<td>58.8</td>
</tr>
<tr>
<td>BShift</td>
<td>50.8</td>
<td>62</td>
<td>54.5</td>
<td>54.5</td>
<td>60.1</td>
<td>58.8</td>
</tr>
<tr>
<td>ObjNum</td>
<td>66.6</td>
<td>82.4</td>
<td>75.9</td>
<td>75.9</td>
<td>94.7</td>
<td>99.3</td>
</tr>
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</table>
Impact of model architecture

Average accuracies for different models

- SentLen: BiLSTM-max = 81.2, BiLSTM-last = 83.9, GatedConvNet = 87.5
- WC: BiLSTM-max = 46.2, BiLSTM-last = 40.3, GatedConvNet = 35
- TopConst: BiLSTM-max = 79.2, BiLSTM-last = 79.7, GatedConvNet = 78.3
- BShift: BiLSTM-max = 72.9, BiLSTM-last = 73, GatedConvNet = 86.1
- ObjNum: BiLSTM-max = 86.6, BiLSTM-last = 83.9, GatedConvNet = 86.1
- CoordInv: BiLSTM-max = 72.6, BiLSTM-last = 68.7, GatedConvNet = 73.1
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

No one could see this Hayes and I wanted to know if it was real or a spoonful (orig: “ploy”)

• **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)?