Large Language Models (LLMs) for Machine Translation Adaptation

Suzanna Sia and Kevin Duh
Johns Hopkins University
Or: Trying to make sense of all the talk around ChatGPT
Serious question: What does an NLP Ph.D student work on nowadays with the presence of closed source GPT models that beat anything you can do in standard academic lab?

Sasha Rush @srush_nlp · Mar 15
Replying to @andriy_mulyar @sleepinyinourhat and 3 others
It's certainly a very active topic of conversation. I don't have a one-size-fits-all answer, but I can say that I have seen surprising differences in reactions among academics.

Sasha Rush @srush_nlp · Mar 15
Replying to @andriy_mulyar @sleepinyinourhat and 3 others
I've seen:
* This is boring, I'll go do something else
* This is scary, how will my students get jobs
* This is amazing, now NLP really starts
* This is a distraction, my goal was never building an artifact.
My reaction to LLMs (currently)

• This is both exciting and risky. I’m hedging my bets (25% effort)

• Will off-the-shelf LLM replace dedicated Machine Translation (MT)?
  • I think not
  • LLM BLEU scores are surprisingly good, but dedicated MT trained in a supervised way on bitext still better in terms of accuracy and cost.

• Does LLM enable new applications in translation?
  • Yes.
  • Focus of this talk: Explore On-the-Fly adaptation
Domain Adaptation

• A well-established method for domain adaptation is fine-tuning, but:
  • Requires pre-specified definition of domain
  • Generates a new model per domain

  General-Domain MT Model

  MT for Social Media  fine-tune  MT for Patents  fine-tune  MT for Domain X  fine-tune

  input sentence  translation

• This is static; can’t prepare too many adapted models in practice.
The Promise of On-the-Fly Adaptation via In-Context Learning

• “In-Context Learning” is the ability of LLM to perform new tasks when given a few examples in the prompt.

• Only one model. Enables fine-grained domains and personalization

example sentence pairs in domain X

[en]: It’s really cool. [fr]: C'est vraiment génial.
[en]: It’s pretty glum [fr]:

[en]: Molecular weight [fr]: Masse moléculaire
[en]: an iodine crystal [fr]:

Il est assez lugubre

un cristal d'iode
Outline

1. Brief background on LLMs

2. Two experiments in on-the-fly adaptation
   - Domain adaptation
   - Document-level adaptation

3. Improving LLMs for MT
   - Soft prompt tuning

4. Discussion
BERT vs GPT-3

• Both trained as “Language Models” but something seems fundamentally different

Pre-train on large data
+ Fine-tune on Task A
= Great performance on Task A

Pre-train on large data
+ Scale Up
= Emergent ability on many tasks (AGI?)
“There’s this idea of emergence that caught me and also, I think, many researchers, by surprise – that you can just train a language model, predict the next token on a tons of raw text, and then it can answer questions, it can summarize documents, have dialogue, translate, classify text, learn all sorts of different kind of pattern manipulation, format dates, and so on. It was just really eye-opening …”

– Percy Liang (Stanford), 2022/06
https://web.stanford.edu/class/cs224u/podcast/liang/
Why do these abilities emerge? I dunno

- Large scale?
- Overparameterization?
- Instruction tuning?
- Training on code?
- RLHF?
- Magic?

Recommended read: Blogpost by Yao Fu, Hao Peng, Tushar Khot. May 2023. How does GPT Obtain its Ability? Tracing Emergent Abilities of Language Models to their Sources
In-Context Learning

Translate English to French

[en]: A discomfort which lasts.  
[fr]: Un malaise qui dure

[en]: HTML is a language for formatting  
[fr]: HTML est un langage de formatage

[en]: After you become comfortable with formatting  
[fr]:

Zero Shot

Few Shot (w/ Instruction)

Few Shot (Example only)
Evaluation: dedicated MT vs off-the-shelf LLM

Difference in BLEU scores on WMT21/22 test sets: WMTBestSystem – GPT3 5-Shot

- surprisingly small gap in some cases, considering GPT is not specially designed for translation
- But: GPT is still far behind in many cases


GPT3: text-davinci-003, with in-context examples from WMT training data with high LaBSE scores
Aside: Test set leakage

LLM evaluation may be challenging because they are trained on so much data. Need to check for (partial) overlap with test.

Potential solution: Membership Inference e.g. See Hisamoto, Duh, Post. Membership Inference Attacks on Sequence-to-Sequence Models: Is My Data In Your MT System? (TACL 2020)
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My current thinking

• Will off-the-shelf LLM replace dedicated Machine Translation (MT)?
  • No
  • Even if accuracy gap reduces, development & deployment cost is still big
  • Is academia best situated to tackle these challenges?

• Does LLM enable new applications in translation?
  • Yes
  • We’ll explore: On-the-fly adaptation.
  • Goal: no need to pre-specify domains, one model but personalization for all
Domain Adaptation: Experiment Setup

• 4 test domains: FLORES, MED, MTNT, TED
• Vary the examples given to LLM
• Research questions:
  • Do in-domain translation examples improve results?
  • Do results vary by the LLM implementation?
## Open-access LLMs used in experiments

<table>
<thead>
<tr>
<th></th>
<th>GPTNeo 2.7B</th>
<th>XGLM 2.9B</th>
<th>BLOOM 3B</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Citation</strong></td>
<td>Black et al., 2021 (EleutherAI)</td>
<td>Lin et al. 2021 (Meta)</td>
<td>Scao et al. 2022 (BigScience)</td>
</tr>
<tr>
<td><strong>Reason</strong></td>
<td>Meant to replicate GPT3 2.7B</td>
<td>Advertised as multilingual</td>
<td>Advertised as multilingual</td>
</tr>
<tr>
<td><strong>Architecture</strong></td>
<td>32 layers, 2560 hidden dim</td>
<td>38 layers, 2048 hidden dim</td>
<td>30 layers, 2560 hidden dim</td>
</tr>
<tr>
<td><strong>Data &amp; Languages</strong></td>
<td>Mainly English: 97% estimated. 420B tokens</td>
<td>30 languages from CC100XL. English 49%, Russian 9%, Chinese 8%, German 5%, Spanish 5%, French 4%. 500B tokens</td>
<td>45 natural languages, 12 programing languages. English 31%, Chinese 18%, Code 13%, French 13%, Spanish 11%, Portuguese 5%. 350B tokens</td>
</tr>
<tr>
<td><strong>Compute</strong> (not comparable, just reference)</td>
<td>?</td>
<td>The XGLM 7.5B model was trained on 256 A100 GPUs for about 3 weeks</td>
<td>18 weeks of 52 nodes of 8 80GB A100 GPUs (for all models?)</td>
</tr>
</tbody>
</table>

GPT-3 175B (96 layers, 12k hidden dim) is trained on ~300B tokens.
## En-Fr MT BLEU results

<table>
<thead>
<tr>
<th>Prompt / Test</th>
<th>GPTNeo2.7B</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Bloom3B</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>XGLM2.9B</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FLORES</td>
<td>MED</td>
<td>MTNT</td>
<td>TED</td>
<td></td>
<td>FLORES</td>
<td>MED</td>
<td>MTNT</td>
<td>TED</td>
<td></td>
<td>FLORES</td>
<td>MED</td>
<td>MTNT</td>
</tr>
<tr>
<td>FLORES</td>
<td>24.6</td>
<td>19.7</td>
<td>23.1</td>
<td>24.6</td>
<td></td>
<td>36.7</td>
<td>28.5</td>
<td>28.5</td>
<td>31.1</td>
<td></td>
<td>29.3</td>
<td>20.9</td>
<td>24.7</td>
</tr>
<tr>
<td>MED</td>
<td>23.0</td>
<td>19.2</td>
<td>21.1</td>
<td>23.2</td>
<td></td>
<td>34.5</td>
<td>28.7</td>
<td>26.2</td>
<td>29.5</td>
<td></td>
<td>27.5</td>
<td>21.4</td>
<td>22.9</td>
</tr>
<tr>
<td>MTNT</td>
<td>23.7</td>
<td>18.6</td>
<td>22.4</td>
<td>23.7</td>
<td></td>
<td>35.5</td>
<td>27.7</td>
<td>29.1</td>
<td>30.6</td>
<td></td>
<td>27.9</td>
<td>21.2</td>
<td>25.0</td>
</tr>
<tr>
<td>TED</td>
<td>23.2</td>
<td>18.6</td>
<td>22.1</td>
<td>23.6</td>
<td></td>
<td>36.1</td>
<td>27.9</td>
<td>29.1</td>
<td>31.2</td>
<td></td>
<td>27.8</td>
<td>21.1</td>
<td>24.2</td>
</tr>
</tbody>
</table>

- **Diagonal tend to be best:** in-domain examples improve translation quality (1-2 BLEU)
- **Results make less sense here.**
- **e.g. Prompt with 5 MED examples, test on FLORES**
Document-level Adaptation: Motivation

• Domain boundaries are fuzzy and coarse-grained
• Document is a more clear-cut unit
  • Internally coherent, e.g. one sense per discourse
  • Many practical translation tasks are document-based

Each TED talk is translated as a whole

source: www.ted.com
Document-level Adaptation: Experiment Setup

- Re-split TED talks data:
  - 120 test documents, 100-120 sentence each → in-doc examples
  - The rest are used “out-doc” prompt examples

- Research question: are in-doc examples better out-doc examples?
Document Adaptation Results (3 language pairs)

For out-doc examples, little difference among:
- random sampling
- sentence retrieval by nearest neighbor embedding (nn) or BM25
- submodular optimization (with BM25 like objective)

<table>
<thead>
<tr>
<th>In/outdoc</th>
<th>GPTNeo2.7B(BLEU)</th>
<th></th>
<th></th>
<th>Bloom3B(BLEU)</th>
<th></th>
<th></th>
<th>XGLM2.9B(BLEU)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>en↔fr</td>
<td>en-pt</td>
<td>en-de</td>
<td>en-fr</td>
<td>en-pt</td>
<td>en-de</td>
<td>en-fr</td>
<td>en-pt</td>
<td>en-de</td>
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<tr>
<td>random</td>
<td>26.3</td>
<td>27.1</td>
<td>16.6</td>
<td>35.2</td>
<td>35.5</td>
<td>7.9</td>
<td>27.1</td>
<td>26.7</td>
<td>18.9</td>
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<tr>
<td>nn</td>
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<td>26.9</td>
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<td>8.2</td>
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<tr>
<td>bm25</td>
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<td>bm25-s</td>
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<td>window</td>
<td>28.1</td>
<td>28.3</td>
<td>17.9</td>
<td>36.9</td>
<td>37.0</td>
<td>8.8</td>
<td>28.6</td>
<td>31.6</td>
<td>21.2</td>
</tr>
</tbody>
</table>

Random In-doc examples and especially Sliding Window of previous in-doc examples perform well
Preliminary Conclusions

• Domain Adaptation
  • On-the-fly adaptation to domain is possible, but results are mixed

• Document-level Adaptation
  • Good fit for LLMs
  • In-doc examples are better than out-doc examples
  • Next step: use predicted translations (not oracle) in prompts
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Motivation: Are there general techniques to improve the translation capability of LLMs?

• During LLM construction:
  • Better selection of multilingual corpora
  • Fine-tuning during the Instruction Tuning / RLHF phase

• After LLM construction (cannot rely on too much data):
  • Adaptors
  • Prompt Engineering
  • Soft Prompt Tuning or Prefix Tuning
  • Etc
Soft Prompt Tuning

Train embeddings for this token
1. We can do train this just on monolingual French:
   [fr] f1 f2 f3  
   [fr] f4 f5
   *by fixing all LLM parameter except [fr] token*
2. We can also then fine-tune on a bit of bitext
   [en] e1 e2 e3 [fr] f1 f2 f3
   [en] e4 e5 [fr] f4 f5

Few Shot Setup

[en]: A discomfort which lasts.
[fr]: Un malaise qui dure

[en]: HTML is a language for formatting
[fr]: HTML est un langage de formatage

[en]: After you become comfortable with formatting [fr]:

E1: Example1
E2: Example2
T: Test Input
Soft prompt tuning results

• Setup: GPTNeo-2.7B, similar to domain adaptation experiments previously but use 20 in-domain examples as prompts

• We observe slight improvements (esp bilingual soft prompt tuning)
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For more information, refer to:
- Sia & Duh (2023). In-context Learning as Maintaining Coherency: A Study of On-the-fly MT Using LLMs
- Sia & Duh (2022). Prefix Embeddings for In-Context MT
Summary

• My current bet: LLMs won’t replace dedicated MT but they will enable new niche applications
• Example: On-the-fly adaptation, esp. at document-level
• From academia, we can’t easily build or work with the largest LLM, but there are some knobs we can tune (e.g. soft prompt tuning)
• The challenge is to figure out which niche applications + knobs
Discussion questions

• Do you think LLMs will become a true “foundation model”, part of every NLP system?
• Are there new applications of in-context learning for translation?
• What should we work on, if multilingual LLM is our ultimate goal?
• How much effort would you put into LLM vs non-LLM research?