Transfer Learning for Unsupervised NMT

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Presentation Outline

1. Motivation for Transfer Learning
2. Recap: What we have learned so far
3. Transfer Learning for NMT
4. Transfer Learning for Unsupervised NMT
   - Motivation for Unsupervised Language Model Pretraining
   - A state-of-the-art Transformer Language Model: BERT
   - Cross-Lingual Language Model Pretraining
Motivation for Transfer Learning

**Problems** (especially in deep learning):
- Scarcity of labeled data
- Models trained on small datasets often fail to generalize in test data \(\rightarrow\) overfit

**Transfer learning:**
- Uses knowledge from a *learned* task to improve the performance on a *related* task
- Scarcity of labeled data \(\rightarrow\) implicit data augmentation
- Helps a model generalize \(\rightarrow\) avoid overfitting
Motivation for Transfer Learning

Natural language processing & Machine Translation

In Natural Language Processing tasks:

- **Out-of-context** pretrained word representations were used (word2vec, fasttext) to initialize the embedding layer.
Motivation for Transfer Learning

Natural language processing & Machine Translation

In Natural Language Processing tasks:

- **Out-of-context** pretrained word representations were used \((\text{word2vec, fasttext})\) to initialize the **embedding layer**
- Recently: **contextual** representations from language models \((\text{BERT, GPT OpenAI})\) are used to initialize the **full model**
Recap: What we have learned so far

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Supervised Learning methods in NMT work really well if a lot of parallel data available!

- We are provided the ground truth
- We use encoder-decoder models to
  - encode a sentence written in language x (hidden representation $s$)
  - provide $s$ to decoder, it generates the sentence in language $y \rightarrow y'$
  - compute training loss (by comparing translation $y'$ to ground truth $y$)

Figure: Seq2seq architecture for En-De NMT. Figure from https://smerity.com/articles/2016/google_nmt_arch.html
Recap: What we have learned so far

Why do we care about **Unsupervised Learning**?

- NMT models work very well, provided a lot of parallel data
- The size and domain of parallel data is limited
- **Monolingual** data is easier to acquire and abundant (for most lang.)
- **Goal**: uncover latent structure in unlabeled data
- **Unsupervised NMT** is not 100% realistic but...
- it serves as a very good baseline for extensions with parallel data (Semi-supervised Learning)
How does Unsupervised NMT work?

We use two new objectives:

1. Learn the structure of each language... How?
   Denoising auto-encoding
   (Language Model (LM) + noise + swap words)
How does Unsupervised NMT work?

We use **two** new objectives:

2. Force the representation to be good at translating too...without parallel data. How?

**Iterative backtranslation**

![Diagram of iterative backtranslation]

I am student <Fr> Je suis étudiant <EOS>
How does Unsupervised NMT work?

We use **two** new objectives:

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**Iterative backtranslation**

- First translate fr → en
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- First translate fr → en
- Then use as a **pseudo-supervised** example to train en → fr
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**Iterative backtranslation**

- First translate fr → en
- Then use as a *pseudo-supervised* example to train en → fr
- Why does this work? We initialize the model with *word translations* from a dictionary created with bilingual word embeddings - guides first iteration
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What happens when we don’t have enough parallel data to train an NMT model?
Transfer Learning for NMT

What happens when we don’t have enough parallel data to train an NMT model?

How can we build systems that provide accurate translations between low-resource languages?
Transfer Learning for NMT

Transferring a model trained on a **lot** of parallel data to a model that has only **small** amounts of parallel data gives a large performance boost! (e.g. Hindi-English $\rightarrow$ Marathi-English)
We can also use **pivot translation**!

We want to build an Italian-Romanian translation system (low-resource - we don’t have a lot of parallel corpora available)

We have **En-It** and **En-Ro** parallel corpora!

We can pretrain two NMT systems, that are then **transferred** to the final NMT system
Transfer Learning for NMT

- Transfer learning from an NMT system pretrained on large parallel corpora to an NMT system with small parallel corpora has limitations
- Parallel corpora are hard to find
- For some languages, there are no closely related high-resource languages
- How can we overcome this problem?
Transfer Learning for NMT

- Transfer learning from an NMT system pretrained on **large parallel corpora** to an NMT system with **small parallel corpora** has **limitations**

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- How can we overcome this problem?

  → **Unsupervised pretraining using monolingual data!**
Transfer Learning for NMT

Can we use transfer learning (and specifically unsupervised pretraining) to initialize an NMT model in a better way?

**Idea:**

1. Separately **Pretrain** Encoder and Decoder as **Language Models**
Transfer Learning for NMT

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**Idea:**

1. **Separately Pretrain** Encoder and Decoder as **Language Models**

2. **Then Train Jointly** on Bilingual Data (NMT)

(Figures from Kevin Clark’s talk)
Transfer Learning for Unsupervised NMT

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Motivation for Unsupervised Language Model Pretraining

Remember that we use **word translations** obtained by bilingual word embeddings to initialize the unsupervised NMT model.

How can we improve this?
Motivation for Unsupervised Language Model Pretraining

- Pretraining the encoder and decoder using two separate language models is not *directly* applicable to unsupervised NMT.
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  1. The encoder LM learns how to produce proper En sentences.
  2. The decoder LM learns how to produce proper Fr sentences.
- If we directly applied it to unsupervised NMT...

```
I traveled to Belgium
```

```
MT Model
```

```
Je suis étudiant
```

```
train
```

```
I traveled to Belgium
Translation: Je suis étudiant
```

```
MT Model
```
Motivation for Unsupervised Language Model Pretraining

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  1. The encoder LM learns how to produce proper En sentences.
  2. The decoder LM learns how to produce proper Fr sentences.
- If we directly applied it to unsupervised NMT...

The first sentence is in En, the second sentence is in Fr, but the Fr sentence is not a translation of the En sentence!
Motivation for Unsupervised Language Model Pretraining

Extension of idea, specifically for unsupervised NMT:

- Training two language models (LMs) separately does not permit “interaction” between the two languages
Motivation for Unsupervised Language Model Pretraining

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- Training one LM on two languages could be more helpful.
Motivation for Unsupervised Language Model Pretraining

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→ We want to pretrain a bilingual LM on **monolingual** data of 2 languages simultaneously to obtain better initial translations
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And not just a “regular” LM…but the state-of-the-art LM nowadays, called BERT
Motivation for Unsupervised Language Model Pretraining

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And not just a “regular” LM...but the state-of-the-art LM nowadays, called **BERT**

Not so fast... what is BERT?
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A state-of-the-art Language Model: BERT

- **Problem**: Word embeddings (like word2vec) do not encode context (bank has the same embedding, but two different meanings)

  ![Diagram of word embeddings]

- **Solution**: Ideally, representations should be *contextual*

  ![Diagram of contextual word embeddings]

(Figures from Jacob Devlin’s talk)
Previous approaches trained a **left-to-right** Transformer LM (OpenAI GPT)

or a **bi-directional** LSTM LM

**Problem 1:** Left-to-right Transformer LMs do not generate a well-formed probability distribution of words

**Problem 2:** Bi-directional LSTM LMs “see themselves” in a bi-directional encoder
**Solution**: Use a Transformer architecture (remember last week’s lecture), randomly mask out 15% of the input words, and then predict only the masked words by attending to all unmasked words.

BERT is trained using the following 2 objectives:

1. **LM**: At each time step, the LM predicts **only** the masked words.
2. **Next Sentence Prediction**: Predict whether Sentence B is actual sentence that proceeds Sentence A, or a random sentence.

```
Sentence A = The man went to the store.
Sentence B = He bought a gallon of milk.
Label = IsNextSentence

Sentence A = The man went to the store.
Sentence B = Penguins are flightless.
Label = NotNextSentence
```
A state-of-the-art Transformer Language Model: BERT

- The Masked LM is in fact an encoder Transformer

- Fine-tuning BERT to supervised tasks (NLI, sentiment analysis, question answering, and many others) gives \textbf{state-of-the-art} results
How does that change the way we handle NLP tasks?

**Before**, most models were trained **from scratch**, using pretrained embeddings (word2vec, fasttext) to initialize **only** the embedding layer:
Now, we fine-tune BERT to the supervised task and then we run the prediction:
Specifically for spam detection:

1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

2 - Supervised training on a specific task with a labeled dataset.

Figure: BERT fine-tuning example from http://jalammar.github.io/illustrated-bert/
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Following the same line of thought, we want to use transfer learning for unsupervised NMT.

A LM that provides *contextual* word representations in both languages we care about gives far better initial translations than a simple dictionary obtained from bilingual word embeddings.

Then, we can initialize an *unsupervised* encoder-decoder NMT model with the pretrained bilingual LM!
Cross-Lingual Language Model Pretraining

- **Pretrain BERT simultaneously on 2 languages** (without the next sentence prediction task)

Large amounts of training data:

**Not Parallel!!!**

**English**

**French**
We have a shared encoder and decoder (for both En→Fr and Fr→En)
We have a shared encoder and decoder (for both En→Fr and Fr→En) and we initialize the encoder and the decoder with a bilingual masked language model (pretrained on a lot of monolingual data)!
We have a shared encoder and decoder (for both En→Fr and Fr→En)

We train the NMT model using as training objectives (losses) **denoising auto-encoding** and **iterative backtranslation**
We have a shared encoder and decoder (for both En→Fr and Fr→En).

We train the NMT model using as training objectives (losses) **denoising auto-encoding** and **iterative backtranslation**.
Cross-Lingual Language Model Pretraining

- We have a shared encoder and decoder (for both En→Fr and Fr→En)
- We train the NMT model using as training objectives (losses) denoising auto-encoding and iterative backtranslation

![Diagram of Cross-Lingual Language Model Pretraining](image)
We have a shared encoder and decoder (for both En→Fr and Fr→En)

We train the NMT model using as training objectives (losses) denoising auto-encoding and iterative backtranslation

![Diagram of Cross-Lingual Language Model Pretraining](image-url)
## Cross-Lingual Language Model Pretraining

### Unsupervised NMT Results

<table>
<thead>
<tr>
<th>Model</th>
<th>En-Fr</th>
<th>En-De</th>
<th>En-Ro</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNMT</td>
<td>25.1</td>
<td>17.2</td>
<td>21.2</td>
</tr>
<tr>
<td>UNMT + Pre-Training</td>
<td>33.4</td>
<td>26.4</td>
<td>33.3</td>
</tr>
<tr>
<td>Current supervised State-of-the-art</td>
<td>45.6</td>
<td>34.2</td>
<td>29.9</td>
</tr>
</tbody>
</table>

Table from Kevin Clark’s talk.
Why does training an LM jointly on 2 languages (and transferring it to an encoder-decoder NMT model) provide good initial translations?

- The underlying reason is that we encode text in a subword level.
- Subword token improves the alignment of embedding spaces of two languages (especially if they share the alphabet or the digits).
- An example of phenomena for which subword information is useful:

Figure from Graham Neubig notes on MT class, Fall 2019.
Subword tokens provide useful cross-lingual information

- **Cognates**: words which share a common origin but have diverged at some point in the evolution of respective languages
- **Loan words**: words borrowed as-is from another language
- **Transliteration**: the process of converting words with identical or similar pronunciations from one script to another
- **Morphology**: systematic changing of word forms according to their grammatical properties such as tense, case, gender, part of speech
Cross-Lingual Language Model Pretraining

Limitations

- This pretraining method only works for similar languages, which have comparable corpora available (e.g. En Wikipedia and Fr News Corpus, not En Twitter and Fr Wikipedia)
Cross-Lingual Language Model Pretraining

Limitations

- There is only a **limited** number of languages that have **clean**, **comparable** monolingual data.
Cross-Lingual Language Model Pretraining

Limitations

- There is only a **limited** number of languages that have **clean, comparable** monolingual data
- but there are more than 6000 languages in the world...

Some Stats

- 6000+ languages in the world
- 80% of the world population does not speak English
- Less than 5% of the people in the world are native English speakers.
Thank You for your Attention! Questions?
References I


