Analyzing and Tackling Challenges in NMT

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in collaboration with: M. Auli, A. Conneau, S. Edunov, L. Denoyer, D. Grangier, H. Jegou, G. Lample, M. Ott
Machine Translation

• Case-study for sequence to sequence transduction.
• It works in practice and has lots of applications.
• Some challenges:
  • input and output are discrete sequences of variable length
  • alignment
  • large vocabulary, large hypothesis space, need to search
  • one-to-many mapping / uncertainty, metric
  • domain shift
  • some language pairs may have little parallel data

Six challenges for neural machine translation, Koehn et al. Workshop NMT, ACL 2017
Machine Translation

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Six challenges for neural machine translation, Koehn et al. Workshop NMT, ACL 2017
Goal

To propose:

• Tools to analyze such challenges.

• Methods to tackle some of these challenges,
Neural Machine Translation
(in 3 slides)

Example:

ITA (source) : Il gatto si e’ seduto sul tappetino.

EN (target) : The cat sat on the mat.

Approach:

Have one RNN/CNN to encode the source sentence, and another RNN/CNN/MemNN to predict the target sentence. The target RNN learns to (soft) align via attention.

Neural machine translation by jointly learning to align and translate, Bahdanau et al. ICLR 2015
Y. LeCun’s diagram
1) Represent source

Source Encoder (RNN/CNN)

il gatto si e' sedutosul tappetino
2) score each source word (attention)
Source Encoder (RNN/CNN) \[ \text{Sum} \]

\[ \ast \rightarrow \text{softmax} \]

10 the cat sat

Source

il gatto si e' sedutosul tappetino

Target

3) combine target hidden with source vector

M. Ranzato
NMT Training & Inference

**Training**: predict one target token at the time and minimize cross-entropy loss.

**Inference**: find the most likely target sentence (approximately) using beam search.

**Evaluation**: BLEU at inference time.
Lecture Outline

• Exposure bias/Loss Mismatch: Training at the Sequence Level.
  • how do classical structured prediction losses fare against recent proposals?
  • how much to be gained by fixing this inconsistency?

• Analyzing Uncertainty: model fitting and effects on search.
  • why do larger beam perform worse?
  • why is the model under-estimating rare words?

• Training Without Supervision.
  • how to leverage monolingual data?
  • can we learn without any parallel sentence?
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*Classical Structured Prediction Losses for Sequence to Sequence Learning*
Sergey Edunov*, Myle Ott*, Michael Auli, David Grangier, Marc'Aurelio Ranzato
NAACL 2018
https://arxiv.org/abs/1711.04956
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credit: Several slides borrowed from Sergey.
Problems

• Exposure bias: training and testing are inconsistent. At training time, model has never observed its own predictions at input.

• At training time, we optimize for a different loss.

• Evaluation criterion is not differentiable.
Selection of Recent Literature

- RL-inspired methods
  - MIXER
  - Actor-Critic
- Using beam search at training time:
  - BSO
  - Distillation based

Ranzato et al. ICLR 2016
Bahdanau et al. ICLR 2017
Wiseman et al. ACL 2016
Kim et al. EMNLP 2016
Question

How do classical structure prediction losses compare against these recent methods?

Classical losses were often applied to log-linear models and/or other problems than MT.

Bottou et al. “Global training of document processing systems with graph transformer networks” CVPR 1997
Collins “Discriminative training methods for HMMs” EMNLP 2002
Taskar et al. “Max-margin Markov networks” NIPS 2003
Tsochantaridis et al. “Large margin methods for structured and interdependent output variables” JMLR 2005
Och “Minimum error rate training in statistical machine translation” ACL 2003
Smith and Eisner “Minimum risk annealing for training log-linear models” ACL 2006
Gimpel and Smith “Softmax-margin CRFs: training log-linear models with cost functions” ACL 2010
Energy-Based Learning

During training

score

target
prediction
space of possible predictions

Energy-Based Learning

After training

score

space of possible predictions

target=prediction

Energy-Based Learning

Key questions if we want to extend this to structured outputs:

- how to search for most likely output? Enumeration & exact search are intractable.
- how to deal with uncertainty?
- what if target is not reachable?
Notation

\[ \mathbf{x} = (x_1, \ldots, x_m) \quad \text{input sentence} \]
Notation

\( x \) input sentence

\( t \) target sentence
Notation

\[ \begin{align*}
  x & \quad \text{input sentence} \\
  t & \quad \text{target sentence} \\
  u & \quad \text{hypothesis generated by the model}
\end{align*} \]
Notation

\( x \)  
input sentence

\( t \)  
target sentence

\( u \)  
hypothesis generated by the model

\( u^* = \arg \min_{u \in U(x)} \text{cost}(u, t) \)  
oracle hypothesis
Notation

\( x \) \hspace{1cm} \text{input sentence}

\( t \) \hspace{1cm} \text{target sentence}

\( u \) \hspace{1cm} \text{hypothesis generated by the model}

\( u^* \) \hspace{1cm} \text{oracle hypothesis}

\( \hat{u} \) \hspace{1cm} \text{most likely hypothesis}
Baseline: Token Level NLL

\[ \mathcal{L}_{\text{TokNLL}} = - \sum_{i=1}^{n} \log p(t_i | t_1, \ldots, t_{i-1}, \mathbf{x}) \]

for one particular training example and omitting dependence on model parameters.
Sequence Level NLL

\[ \mathcal{L}_{\text{SeqNLL}} = -\log p(u^* \mid x) + \log \sum_{u \in \mathcal{U}(x)} p(u \mid x) \]

The sequence log-probability is simply the sum of the token-level log-probabilities.
Sequence Level NLL

\[ \mathcal{L}_{\text{SeqNLL}} = -\log p(u^*|x) + \log \sum_{u \in U(x)} p(u|x) \]

The sequence log-probability is simply the sum of the token-level log-probabilities.

Two key differences: choice of target and hypothesis set.

Homework: compute gradients of loss w.r.t. inputs to token level softmaxes.
Sequence Level NLL

\[
\mathcal{L}_{\text{SeqNLL}} = - \log p(u^* | x) + \log \sum_{u \in \mathcal{U}(x)} p(u | x)
\]
Example

Source:
Wir müssen unsere Einwanderungspolitik in Ordnung bringen.

Target
We have to fix our immigration policy.

Beam:

<table>
<thead>
<tr>
<th>BLEU</th>
<th>Model score</th>
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<tbody>
<tr>
<td>75.0</td>
<td>-0.23</td>
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Observations

• Important to use oracle hypothesis as surrogate target as opposed to golden target. Otherwise, the model learns to assign very bad scores to its hypotheses but is not trained to reach the target.

• Evaluation metric only used for oracle selection of target.

• Several ways to generate $U(x)$.

• Similar to token level NLL but normalizing over (subset of) hypotheses. Hypothesis score: average token level log-probability.
Expected Risk

\[ \mathcal{L}_{\text{Risk}} = \sum_{u \in \mathcal{U}(x)} \text{cost}(t, u) \frac{p(u|x)}{\sum_{u' \in \mathcal{U}(x)} p(u'|x)} \]

• The cost is the evaluation metric; e.g.: 100-BLEU.

• REINFORCE is a special case of this (a single sample Monte Carlo estimate of the expectation over the whole hypothesis space).

Homework: compute gradients of loss w.r.t. inputs to token level softmaxes.
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(expected BLEU=69)
Example

$\mathcal{U}(x)$ set of hypotheses reachable by the model

$hypothesis$ $space$}

$\overset{\uparrow}{\mathcal{U}}(x)$

gradients

$t u^*$

hypothesis $space$
Max-Margin

\[ \mathcal{L}_{\text{MaxMargin}} = \max \left[ 0, \text{cost}(t, \hat{u}) - \text{cost}(t, u^*) - s(u^*|x) + s(\hat{u}|x) \right] \]

- The score is average token level log-probability (or un-normalized score).
- The cost is our evaluation metric; e.g.: 100-BLEU.
- Increase score of oracle hypothesis, while decreasing score of most likely hypothesis.

Homework: compute gradients of loss w.r.t. inputs to token level softmaxes.
Max-Margin

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Max-Margin

- log p

gradients

$\{ u(x) \}$ set of hypotheses reachable by the model

hypothesis space
Check out the paper for more examples of sequence level training losses!
Practical Tips

• Start from a model pre-trained at the token level. Training with search is excruciatingly slow…

• Even better if pre-trained model had label smoothing.

• Accuracy VS speed trade-off: offline/online generation of hypotheses.

• Cost rescaling.

• Mix token level NLL loss with sequence level loss to improve robustness.

• Need to regularize more.
## Results on IWSLT’14 De-En

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<td>SeqNLL</td>
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</tr>
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<td>Risk</td>
<td>32.9</td>
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<tr>
<td>Max-Margin</td>
<td>32.6</td>
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Observations

• Sequence level training does improve evaluation metric (both on training and) on test set.

• There is not so much difference between the different variants of losses. Risk is just slightly better.

• In our implementation and using the same computational resources, sequence level training is 26x slower per update using online beam generation of 5 hypotheses.
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• In our implementation and using the same computational resources, sequence level training is 26x slower per update using online beam generation of 5 hypotheses.

• *Hard comparison since each paper has a different baseline!*
# Fair Comparison to BSO

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These methods fare comparably once the baseline is the same…
On WMT’14 En-Fr, TokNLL gets 40.6 while Risk gets 41.0. The stronger the baseline, the less to be gained.
Conclusion

• Sequence level training does improve, but with diminishing returns. It’s computationally very expensive.

• The particular method to train at the sequence level does not really matter.

• It’s important to use as target the hypothesis in the reachable set that is closest to the reference, as opposed to the reference itself which may not be reachable.

• Sequence level training is more prone to overfitting.

• We should expect big improvements when search is crippled by token level optimization, or if model puts mass int the wrong place or if there is little uncertainty… *but, is this true in NMT?*
Questions?
Вопросы?
¿Preguntas?
Lecture Outline

• Exposure bias/Loss Mismatch: Training at the Sequence Level.
  • how do classical structured prediction losses fare against recent proposals?
  • how much to be gained by fixing this inconsistency?

• Analyzing Uncertainty: model fitting and effects on search.
  • why do larger beam perform worse?
  • why is the model under-estimating rare words?

• Training Without Supervision.
  • how to leverage monolingual data?
  • can we learn without any parallel sentence?
Lecture Outline

• Analyzing Uncertainty: model fitting and effects on search.
  • why do larger beam perform worse?
  • why is the model under-estimating rare words?

Analyzing uncertainty in neural machine translation
Myle Ott, Michael Auli, David Grangier, Marc'Aurelio Ranzato
https://arxiv.org/abs/1803.00047
Questions

• what are the sources of uncertainty in the data?
• do NMT models capture such uncertainty?
• does uncertainty hinder search?
• what tools can we use to measure uncertainty?
Goal

BETTER UNDERSTANDING

E.g.:

- rare word under-estimation
  - artifact of beam search (argmax)?
  - due to exposure bias?
  - due to poor estimation?
- wider beam degradation
  - due to heuristic nature of beam search?
  - is the model poorly trained?
- model fitting
  - are NMT models calibrated?
  - what do NMT models over/under-estimate?
## Datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Nr. Sentences</th>
<th>Vocab Size (BPE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WMT14 En-De</td>
<td>4.5M</td>
<td>40K</td>
</tr>
<tr>
<td>WMT17 En-De</td>
<td>5.9M</td>
<td>40K</td>
</tr>
<tr>
<td>WMT14 En-Fr</td>
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Model

- Convolutional NMT with attention
- 15 layers
- 768D embeddings
- ~250M parameters
Evaluating NMT

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<tr>
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<td>train PPL</td>
<td>2.54</td>
<td>5.14</td>
</tr>
<tr>
<td>valid PPL</td>
<td>2.56</td>
<td>6.36</td>
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<tr>
<td>test BLEU</td>
<td>41.03</td>
<td>24.78</td>
</tr>
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<td><strong>Human evaluation (pairwise)</strong></td>
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<td>Ref &gt; Sys</td>
<td>42.0%</td>
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Table 1: Automatic and human evaluation on a 500 sentence subset of the WMT’14 En-Fr and En-De test sets. Models generalize well in terms of perplexity and BLEU. Our human evaluation compares (reference, system) pairs for beam 5.
Evaluating NMT

Model is very well trained, particularly in En-Fr dataset.

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Outline

• Data uncertainty
• Search
• Analyzing the model distribution
Data Uncertainty

• Intrinsic

  • there are many semantically equivalent translations of the same sentence. E.g.: style, skipping prepositions, choice of words, structural choices (active/passive tense), etc.

EXAMPLE

Source: The night before would be practically sleepless.

Target #1: La nuit qui précède pourrait s’avérer quasiment blanche.
Target #2: Il ne dormait pratiquement pas la nuit précédente.
Target #3: La nuit précédente allait être pratiquement sans sommeil.
Target #4: La nuit précédente, on n’a presque pas dormi.
Target #5: La veille, presque personne ne connaîtra le sommeil.
Data Uncertainty

• Intrinsic
  • there are many semantically equivalent translations of the same sentence. E.g.: style, skipping prepositions, choice of words, structural choices (active/passive tense), etc.
  • under-specification. E.g.: gender, tense, number, etc.

EXAMPLE
Source: nice.
Target #1: chouette.
Target #2: belle.
Target #3: beau.
Data Uncertainty

• Intrinsic
  • there are many semantically equivalent translations of the same sentence. E.g.: style, skipping prepositions, choice of words, structural choices (active/passive tense), etc.
  • under-specification. E.g.: gender, tense, number, etc.

• Extrinsic
  • noise in the data. E.g.: partial translation, copies of the source, etc.

Example: on WMT between 1 and 2% of the training target sentences are copies of the source.
Data Uncertainty

• Intrinsic

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  HOW DOES THIS AFFECT NMT?

• Extrinsic

  • noise in the data. E.g.: partial translation, copies of the source, etc.
Outline

• Data uncertainty

• Search

• Analyzing the model distribution
Search

Search aims at finding the most likely sequence according to the model: $\arg \max_y p(y|x; \theta)$

Preliminary questions:

• is beam search effective?
• is beam search efficient?
• are there better search strategies?
Beam search is very effective; only 20% of the tokens with probability < 0.7 (despite exposure bias)!
Search

- Increasing the beam width does not increase BLEU, while probability increases.

- Sampling can find hypotheses with similar logprob but:
  - lower BLEU
  - it's more than 10x more inefficient
• Increasing the beam width does not increase BLEU, while probability increases.

• Sampling can find hypotheses with similar logprob but:
Increasing the beam width does not increase BLEU, while probability increases.

Sampling can find hypotheses with similar logprob but:

- lower BLEU

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Increasing the beam width does not increase BLEU, while probability increases.

Sampling can find hypotheses with similar logprob but:

- lower BLEU
- it’s 20x less efficient
• Increasing the beam width does not increase BLEU, while probability increases.

• Sampling can find hypotheses with similar logprob but…

• Among the generated hypotheses, there exist at least one that is pretty close to the reference.
Beam search is very effective and efficient. However, large beams yield worse BLEU!
• Beam 200/sampling 10K cover only about 22% of the total probability mass; where is the rest?
Search

Model distribution has a lot of uncertainty.
Puzzling Observations

- Increasing beam width after a certain point hurts performance in terms of BLEU.

- Large beam accounts only for fraction of total probability mass.
Hint: Scatter Plot of Samples
Hint: Scatter Plot of Samples

Homework: take 10 random sentences from a WMT dataset and a trained NMT model. Plot a similar scatter plot and analyze the clusters (if any).
Hint: Scatter Plot of Samples

Source #2375 (purple): 
*Should this election be decided two months after we stopped voting?*

Target #2375 (purple): 
Cette élection devrait-elle être décidée deux mois après que le vote est terminé?

High-BLEU sample: 
Cette élection devrait-elle être décidée deux mois après l'arrêt du scrutin?

Low-BLEU sample: 
Ce choix devrait-il être décidé deux mois après la fin du vote?
Hint: Scatter Plot of Samples

Source #2375 (purple):
Should this election be decided two months after we stopped voting?

Target #2375 (purple):
Cette élection devrait-elle être décidée deux mois après que le vote est terminé?

High-BLEU sample:
Cette élection devrait-elle être décidée deux mois après l'arrêt du scrutin?

Low-BLEU sample:
Ce choix devrait-il être décidé deux mois après la fin du vote?

BLEU is just a poor metric.
Source #115 (red):
The first nine episodes of Sheriff [unk]'s Wild West will be available from November 24 on the site [unk] or via its application for mobile phones and tablets.

Target #115 (red):
Les neuf premiers épisodes de [unk] [unk]'s Wild West seront disponibles à partir du 24 novembre sur le site [unk] ou via son application pour téléphones et tablettes.

High-logp low BLEU sample:
The first nine episodes of Sheriff [unk]'s Wild West will be available from November 24 on the site [unk] or via its application for mobile phones and tablets.
The first nine episodes of Sheriff [unk]'s Wild West will be available from November 24 on the site [unk] or via its application for mobile phones and tablets.

Les neuf premiers épisodes de [unk] [unk] s Wild West seront disponibles à partir du 24 novembre sur le site [unk] ou via son application pour téléphones et tablettes.

Model generates copies of source sentence! Why does beam find this?
Uncertainty $\leftrightarrow$ Search

- Hard to characterize how uncertainty affects search in general.

- We can however simulate (extrinsic) uncertainty:
  - add fraction of “copy noise” and check effects on search.
Large beams are more prone to copy the source, hence the lower BLEU.
Uncertainty $\leftrightarrow$ Search

• **Source**: The first nine episodes of Sheriff $\langle \text{unk} \rangle$’s Wild West will be available from November 24 on the site $\langle \text{unk} \rangle$ or via its application for mobile phones and tablets.

• **Target (reference)**: Les neuf premiers épisodes de $\langle \text{unk} \rangle$ $\langle \text{unk} \rangle$’s Wild West seront disponibles à partir du 24 novembre sur le site $\langle \text{unk} \rangle$ ou via son application pour téléphones et tablettes.

• **Sample**: The first nine episodes of Sheriff $\langle \text{unk} \rangle$’s Wild West will be available from November 24 on the site $\langle \text{unk} \rangle$ or via its application for mobile $\langle \text{unk} \rangle$ and tablets.
Uncertainty $\leftrightarrow$ Search

• **Source**: The first nine episodes of Sheriff <unk> ’s Wild West will be available from November 24 on the site <unk> or via its application for mobile phones and tablets.

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• **Sample**: The first nine episodes of Sheriff <unk> s Wild West will be available from November 24 on the site <unk> or via its application for mobile <unk> and tablets.

Inductive bias alert: NMT + attention has easy time to learn how to copy!
Initial tokens pay big penalty, but afterwards copying the source is cheap. Only large beams can discover this.
Uncertainty \leftrightarrow\text{ Search}

On WMT’14 En-Fr, we estimate that \sim2\% of the training target sentences are copies of the corresponding source.

Beam@1 yields copies 2.6\% of the times.
Beam@20 yields copies 3.5\% of the times.
Fixing Search

- Filtering the data with model trained on “clean data” to remove copies from training set.

- Constraining beam search not to output too many words from the source sentence.
Fixing Search

![Graph showing BLEU scores for different beam sizes and conditions. The graph compares original, filtered, clean, original (no copy), filtered (no copy), and clean (no copy) scenarios.]

M. Ranzato
Search & Uncertainty

• Search works very well, i.e. beam finds likely hypotheses according to the model.

• However, it can find spurious sentences (model is wrong), that are merely due to noise in the data collection process.

• This explains why BLEU deteriorates for large beams.

• There are easy fixes.
Puzzling Observations

• Increasing beam width after a certain point hurts performance in terms of BLEU.

• Large beam accounts only for fraction of total probability mass.
Outline

• Data uncertainty

• Preliminaries

• Search

• **Analyzing the model distribution**
Model Distribution

• Checking match between model and data distribution is challenging because:

  • For a given source sentence, we typically observe only one sample from the data distribution (the provided reference).

  • Enumeration of all possible sequences using the data distribution is intractable anyway.
Model Distribution

We would like to:

• check how closely model and data distribution match

• understand when they differ and why
Anecdotal Example

In the training set there are some source sentences that appear multiple times. Use corresponding targets to estimate the underlying distribution!

**EXAMPLE**

**Source:** (The president cutoff the speaker).

Appears 798 times on the training set with 36 unique translations.

For this source sentence, model and data distribution match very well!
Analysis Tools

• Token level fitting
• Sentence level calibration
• Set level calibration
• Other necessary conditions
Token Level: Matching Unigram Stats

Model grossly under-estimate rare words. Beam over-estimates frequent words, as expected.
Model grossly under-estimate rare words. Beam over-estimates frequent words, as expected.
WMT’17 En-De news-comm. portion

- ~300K parallel sentences
- 21 BLEU on test
- median freq. in 10% bin: 12

WMT’14 En-Fr

- ~35M parallel sentences
- 41 BLEU on test
- median freq. in 10% bin: 2500

More data & better model close the gap, but rare words are still under-estimated.
Token Level: Matching Unigram Stats

WMT’17 En-De news-comm. portion

- ~300K parallel sentences
- 21 BLEU on test
- median freq. in 10% bin: 12

WMT’14 En-Fr

- ~35M parallel sentences
- 41 BLEU on test
- median freq. in 10% bin: 2500

Match may look better than it is if model shifts probability mass within each of these buckets, let’s take a closer look then…

M. Ranzato
Model fits fairly well at the token level for mid-frequency words. Beam under/over-estimates.
Sentence Level Calibration

Copy source sentences at a given rate during training, check whether probability assigned by the model to copies matches the copy production rate.

NMT model under-estimates copy probability at low rates, while it over-estimates it at high rates. Model spills probability mass on partial copies.
Sentence Level Calibration

Copy source sentences at a given rate during training, check whether probability assigned by the model to copies matches the copy production rate.

NMT model under-estimates copy probability at low rates, while it over-estimates it at high rates. Model spills probability mass on partial copies.
Set Level Calibration

\[ \mathbb{E} \left[ \mathbb{1}\{ x \in S \} \right] = p_m(S) \]

where \( S \) is the set of hypotheses produced by beam.

NMT model is very well calibrated at the set level.
Distance Matching

$$\mathbb{E}_{y \sim p_d, y' \sim p_d} [BLEU(y, y')] = \mathbb{E}_{y \sim p_m, y' \sim p_m} [BLEU(y, y')]$$

<table>
<thead>
<tr>
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<th>En-Fr</th>
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<tbody>
<tr>
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<tr>
<td>NMT</td>
<td>28.6</td>
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</tbody>
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NMT model produces samples that have low BLEU and that are too diverse. Model spreads probability mass.
Distance Matching

\[ \mathbb{E}_{y \sim p_d, y' \sim p_d} \left[ \text{BLEU}(y, y') \right] \overset{?}{=} \mathbb{E}_{y \sim p_m, y' \sim p_m} \left[ \text{BLEU}(y, y') \right] \]

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NMT model produces samples that have low BLEU and that are too diverse. Model spreads probability mass.
Multi-Reference Experiments

We collected 10 additional references for 500 randomly selected source sentences from the test set.

We then measure:

- BLEU with *oracle reference*, which is the reference yielding the largest BLEU score.

- BLEU of *average oracle*: compute the above for every hypothesis produced by beam/sampling, and then average.

- *coverage*: number of unique references hypotheses are matched to.
## Multi-Reference Experiments

<table>
<thead>
<tr>
<th></th>
<th>Beam@5</th>
<th>Beam@200</th>
<th>200 Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>single reference</strong></td>
<td>41.4</td>
<td>36.2</td>
<td>38.2</td>
</tr>
<tr>
<td><strong>oracle reference</strong></td>
<td>70.2</td>
<td>61.0</td>
<td>64.1</td>
</tr>
<tr>
<td><strong>average oracle</strong></td>
<td>65.7</td>
<td>56.4</td>
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Beam produces outputs close to an actual reference. Lower scoring hypotheses are not far from a reference. However, they often map to the same reference.
## Multi-Reference Experiments

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Sampling is more diverse but several samples poorly match any given reference. Mass is spread too much.
## Multi-Reference Experiments

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Homework: if two continuous and uniform p.d.f. matched, how many samples would we need to draw in order to get full coverage with high probability?
Model/Data Distribution Match

• they do not match in general, although anecdotally they might.

• model spreads probability mass too much (see results using sampling and pair-wise BLEU, for instance):
  
  • it’s impossible for NMT to assign 0 probability to any sequence; low coverage of probability mass.
  
  • spill-over to “nearby” hypotheses.

• [conjecture] although model may under-estimate copies at low rates, these may be on the top of the beam, just because probability mass is too spread.

• copy noise is over-estimated at high rates.

• model’s most likely outputs (or their proxy) are usually very concentrated (little diversity), possibly also due to probability spread over similar hypotheses.
Conclusions

• Uncertainty in data: intrinsic/extrinsic

• Search: works really well. For large beams, beam finds spurious modes, but we know how to fix it! [not so surprising, since we did model selection using beam search!]

• Model & Data distribution: model is surprisingly well calibrated. In general, it spreads probability mass too much compared to the data distribution.

• More parallel data helps a lot…
Actionable Items

- There are easy fixes to the copy problem [done]

- It would be interesting to find ways to manipulate the model to avoid the spread of probability mass while diversifying beam. [ongoing]
Questions?
Вопросы?
¿Preguntas?
Lecture Outline

• Exposure bias/Loss Mismatch: Training at the Sequence Level.
  • how do classical structured prediction losses fare against recent proposals?
  • how much to be gained by fixing this inconsistency?

• Analyzing Uncertainty: model fitting and effects on search.
  • why do larger beam perform worse?
  • why is the model under-estimating rare words?

• Training Without Supervision.
  • how to leverage monolingual data?
  • can we learn without any parallel sentence?
Lecture Outline

Word Translation Without Parallel Data
Alexis Conneau*, Guillaume Lample*, Marc’Aurelio Ranzato, Ludovic Denoyer, Herve Jegou
ICLR 2018

Unsupervised Machine Translation Using Monolingual Corpora Only
Guillaume Lample, Alexis Conneau, Ludovic Denoyer, Marc'Aurelio Ranzato
ICLR 2018
https://arxiv.org/abs/1711.00043

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Lecture Outline

*Word Translation Without Parallel Data*
Alexis Conneau*, Guillaume Lample*, Marc’Aurelio Ranzato, Ludovic Denoyer, Herve Jegou
ICLR 2018
https://arxiv.org/abs/1710.04087  
CODE: [https://github.com/facebookresearch/MUSE](https://github.com/facebookresearch/MUSE)

*Unsupervised Machine Translation Using Monolingual Corpora Only*
Guillaume Lample, Alexis Conneau, Ludovic Denoyer, Marc'Aurelio Ranzato
ICLR 2018
https://arxiv.org/abs/1711.00043

credit: several slides borrowed from Guillaume.
Motivation

• NMT models work very well, provided a lot of parallel data.

• For many language pairs, parallel data is however very scarce, or even inexistent.

• Professional translators are very expensive and hard to find for some language pairs.

• We need a scalable approach to be able to translate in any language pair.
Motivation

• Resources we could use:
  • Limited amount of parallel data.
  • Parallel data from other language pairs.
  • Large amount of monolingual data, which is often more easily available.
Goal

• Training an NMT system without supervision, using monolingual data only.

  • Admittedly, unrealistic but…

  • Baseline for extensions using parallel data (from language pair of interest or others).

  • Scientific endeavor, towards our quest for a good unsupervised learning algorithm.
Unsupervised Word Translation

• Motivation: A pre-requisite for unsupervised sentence translation.

• Problem: given two monolingual corpora in two different languages, estimate bilingual lexicon.

• Hint: the context of a word, is often similar across languages since each language refers to the same underlying physical world.
Method

1) learn word embeddings (word2vec) separately on each language using lots of monolingual data.
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2) learn a rotation matrix to roughly align the two domains.

E.g., via adversarial training: pick a word at random from each language, embed them, project one of the two, and make sure distributions match.

- $x_i$ embedding i-th word in En
- $y_j$ embedding j-th word in It
- $W$ orthogonal matrix

\[
\mathcal{L}_D(\theta_D|W) = -\mathbb{E}_x [\log p(\text{En}|Wx; \theta_D)] - \mathbb{E}_y [\log p(\text{It}|y; \theta_D)]
\]

\[
\mathcal{L}_W(W\theta_D) = -\mathbb{E}_x [\log p(\text{It}|Wx; \theta_D)] - \mathbb{E}_y [\log p(\text{En}|y; \theta_D)]
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2) learn a rotation matrix to roughly align the two domains.
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\[ L_W(W\theta_D) = -\mathbb{E}_x [\log p(\text{It}|W x; \theta_D)] - \mathbb{E}_y [\log p(\text{En}|y; \theta_D)] \]
3) Iterative refinement via orthogonal Procrustes, using the most frequent words.

Pick most frequent words, translate them via nearest neighbor, solve least square, and iterate.

\( \mathbf{x}_i \) embedding i-th word in En

\( \mathbf{y}_j \) embedding j-th word in It

\( W_t = \arg \min ||W_{t-1}X - Y||^2 \), s.t. \( W_t W_t^T = I \)

\( W \) orthogonal matrix
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$W$ orthogonal matrix
4) Build lexicon using metric that compensates for hubness.

There are words that have lots of neighbors, while others that are not neighbors of anybody.

\[ x_i \] embedding i-th word in En
\[ y_j \] embedding j-th word in It
\[ W \] orthogonal matrix

\[ \text{CSLS}(Wx, y) = 2 \cos(Wx, y) - r_{En}(Wx) - r_{It}(y) \]

\[ r_{En}(Wx) = \frac{1}{K} \sum_{y_t \in \mathcal{N}(Wx)} \cos(Wx, y_t) \]
4) Build lexicon using metric that compensates for hubness.
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\[ x_i \text{ embedding i-th word in En} \]
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\[
\begin{align*}
\text{CSLS}(W x, y) &= 2 \cos(W x, y) - r_{\text{En}}(W x) - r_{\text{It}}(y) \\
r_{\text{En}}(W x) &= \frac{1}{K} \sum_{y_t \in \mathcal{N}_{\text{En}}(W x)} \cos(W x, y_t)
\end{align*}
\]
More results on several language pairs, analysis and other tasks in the paper. By using more anchor points and lots of unlabeled data, we even outperform supervised approaches!
Results on Word Translation

Homework 1: how accurate does the adversarial alignment need to be? Can more refinement steps compensate for poor initial alignment?

Homework 2: apply the same method to sentences from the Multi30K-Task1 image caption dataset.
Key Idea

• Learn representations of each domain.
• Force representations to match in order to translate.
• How to apply this principle to sentences?
Naïve Application

• In general, this may not work on sentences because:

  • Without leveraging compositional structure, space is exponentially large.
  
  • Need good sentence representations.
  
  • Unlikely that a linear mapping is sufficient to align sentence representations of two languages.
From Words to Sentences

How to learn good sentence representations?
We want to train usual sep2seq architecture (as that achieves the best MT results), but without supervision.
From Words to Sentences

How to learn good sentence representations?
We want to train usual sep2seq architecture (as that achieves the best MT results), but without supervision.

Solution: denoising autoencoding task.

Noise: word drop and word swap.

Ref: Arizona was the first to introduce such a requirement.

Drop
- Ref: Arizona was the first to introduce such a requirement.
- Arizona was first to introduce such a requirement.

Swap
- Ref: Arizona the first was to introduce a requirement such.
- Arizona was the to introduce first such requirement a.
From Words to Sentences

How to learn good sentence representations?
We want to train usual sep2seq architecture (as that achieves the best MT results), but without supervision.

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Swap
Ref: Arizona was the first to introduce such a requirement.
Arizona the first was to introduce a requirement such.
Arizona was the to introduce first such requirement a.

Even with attention, the model has to learn regularities in the input (not just copy but a good language model).
Denoising Auto-Encoding

**It DAE**

\[ x + n \xrightarrow{\text{encoder}} h_{it}(x + n) \xrightarrow{\text{decoder}} \tilde{x} \xrightarrow{\text{NLL}} x \]

**En DAE**

\[ y + n \xrightarrow{\text{encoder}} h_{en}(y + n) \xrightarrow{\text{decoder}} \tilde{y} \xrightarrow{\text{NLL}} y \]
Constraining the Latent Representation

Add adversarial term between the two latent representations.
Constraining the Latent Representation

It DAE

\[ x + n \xrightarrow{\text{encoder}} h_{it}(x + n) \xrightarrow{\text{decoder}} \tilde{x} \]

\[ \text{NLL} \]

En DAE

\[ y + n \xrightarrow{\text{encoder}} h_{en}(y + n) \xrightarrow{\text{decoder}} \tilde{y} \]

\[ \text{NLL} \]

Share encoder and decoder parameters, just swap embeddings.
Constraining the Latent Representation

It DAE

\[ \hat{x} \rightarrow \text{encoder} \rightarrow h_{it}(\hat{x}) \rightarrow \text{decoder} \rightarrow \tilde{x} \]

En DAE

\[ y + n \rightarrow \text{encoder} \rightarrow h_{en}(y + n) \rightarrow \text{decoder} \rightarrow \tilde{y} \]

NLL

Adversarial

Force the representation to be good at translating too. But, we do not have parallel sentences. What to feed?
Recap

• Method is a combination of several ingredients:
  - denoising autoencoders
  - translation from artificially generated pairs
  - adversarial loss in latent space
  - parameter sharing
  - initialization from word translation model.

• It’s crucial to:
  - somehow share the same latent representation, and
  - to use noise close to actual translation noise.

• If the above two conditions were satisfied and denoising worked well, we could guarantee improvement as we iterate.
An Alternative View

Since what we are ultimately interested in translation, we can start our construction from the back-translation model and artificially generate parallel sentences.
An Alternative View

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An Alternative View

Since what we are ultimately interested in translation, we can start our construction from the back-translation model and artificially generate parallel sentences.

How to constrain the intermediate sentence to be a valid Italian sentence? It has to be a valid sentence and it has to be a translation.
Since what we are ultimately interested in translation, we can start our construction from the back-translation model and artificially generate parallel sentences.

How to constrain the intermediate sentence to be a valid Italian sentence?
- we could add some language modeling constraints directly on $\hat{x}$, but it would be hard to bprop and would be weak constraint on translation.
- instead, we constraint the latent space.
Adding Language Modeling

Since inner decoders are shared between the LM and MT task, it should constraint the intermediate sentence to be fluent.
Adding Language Modeling

Since inner decoders are shared between the LM and MT task, it should constraint the intermediate sentence to be fluent. But that’s not enough:
- translation noise cannot be exactly reproduced (without parallel data).
- latent representation may not be robust to translation noise
Since inner decoders are shared between the LM and MT task, it should constraint the intermediate sentence to be fluent. But that’s not enough:

- translation noise cannot be exactly reproduced (without parallel data).
- latent representation produced by the “other” inner encoder may be different.

NMT won’t know how to translate.
Since inner decoders are shared between the LM and MT task, it should constraint the intermediate sentence to be fluent.

But that’s not enough:

- translation noise cannot be exactly reproduced (without parallel data).
- latent representation produced by the “other” inner encoder may be different. **WE NEED TO SHARE LATENT REPRESENTATIONS.**
Since inner decoders are shared between the LM and MT task, it should constraint the intermediate sentence to be fluent. But that’s not enough:
- translation noise cannot be exactly reproduced (without parallel data).
- latent representation produced by the “other” inner encoder may be different. WE NEED TO SHARE LATENT REPRESENTATIONS.
Sharing Representations

Straightforward methods to induce representation sharing between inner encoders when fed with different languages:
- parameter sharing
- adversarial term in latent space.
- Initializing embeddings with word translation mapping.
Methodology

Take commonly used parallel corpus.
Methodology

Split training set into two non-overlapping parts to generate monolingual corpora.
Methodology

Train using composite loss
(denoising autoencoding, cross-coding, adversarial)
Methodology

Test on original test set.
Datasets

- Multi30k-Task1: En-Fr, En-De (without using images)
  - 14.5K captions in each language for training
  - eval on test set

- WMT’14 En-Fr
  - 15M sentences in each language for training
  - eval on newstest2014

- WMT’16 En-De
  - 1.8M sentences in each language for training
  - eval on newstest2016
Results on Multi30K-Task1

<table>
<thead>
<tr>
<th>Language Pairs</th>
<th>Iteration 1</th>
<th>Iteration 2</th>
<th>Iteration 3</th>
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<tbody>
<tr>
<td>en-fr</td>
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<tr>
<td>de-en</td>
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<td>en-de</td>
<td>5.39</td>
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<td>21.16</td>
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</table>

Supervised

Word-by-word

BLEU
Results on WMT

<table>
<thead>
<tr>
<th>Language Pair</th>
<th>Supervised</th>
<th>Word-by-word</th>
<th>Iteration 1</th>
<th>Iteration 2</th>
<th>Iteration 3</th>
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<td>15.05</td>
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<td>de-en</td>
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Supervised Word-by-word Iteration 1 Iteration 2 Iteration 3
## Improvements by Iterating

<table>
<thead>
<tr>
<th>Source</th>
<th>une femme aux cheveux roses habillée en noir parle à un homme.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iteration 0</td>
<td></td>
</tr>
<tr>
<td>Iteration 1</td>
<td></td>
</tr>
<tr>
<td>Iteration 2</td>
<td></td>
</tr>
<tr>
<td>Iteration 3</td>
<td></td>
</tr>
<tr>
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## Improvements by Iterating

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<tr>
<td>Iteration 0</td>
<td>a woman at hair roses dressed in black speaks to a man.</td>
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<td></td>
</tr>
<tr>
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</tr>
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<td></td>
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<tr>
<td>Reference</td>
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</table>

Iteration 0 is word-by-word translation using the unsupervised word translation model.
# Improvements by Iterating

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<td>Iteration 0</td>
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<td></td>
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Improvements by Iterating

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<tr>
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<td>a woman at hair roses dressed in black speaks to a man.</td>
</tr>
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<td>Iteration 1</td>
<td>a woman at glasses dressed in black talking to a man.</td>
</tr>
<tr>
<td>Iteration 2</td>
<td>a woman at pink hair dressed in black speaks to a man.</td>
</tr>
<tr>
<td>Iteration 3</td>
<td>a woman with pink hair dressed in black is talking to a man.</td>
</tr>
<tr>
<td>Reference</td>
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</tbody>
</table>
Supervised VS Unsupervised

BLEU vs number of parallel training sentences

- En->Fr
- Fr->En
- De->En
- En->De
## Ablation Study on Multi30K-Task1

<table>
<thead>
<tr>
<th></th>
<th>en-fr</th>
<th>fr-en</th>
<th>de-en</th>
<th>en-de</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full</strong></td>
<td>27.48</td>
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<td>$\lambda_{cd} = 0$</td>
<td>25.44</td>
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- $\lambda_{cd}$ cross-domain loss coefficient. No translation task.
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- $\lambda_{cd}$: cross-domain loss coefficient. No translation task.

On this dataset, it’s important to either initialize the embeddings or to add the translation task.
Ablation Study on Multi30K-Task1

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<tr>
<td>Without noise, $C(x) = x$</td>
<td>16.76</td>
<td>16.85</td>
<td>16.85</td>
<td>14.61</td>
</tr>
<tr>
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- $\lambda_{cd}$: cross-domain loss coefficient. No translation task.

Noise is important to learn good representations.
Ablation Study on Multi30K-Task1

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<tr>
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- $\lambda_{cd}$ cross-domain loss coefficient. No translation task.
# Ablation Study on Multi30K-Task1

<table>
<thead>
<tr>
<th>Condition</th>
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<th>de-en</th>
<th>en-de</th>
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<td>19.32</td>
</tr>
</tbody>
</table>
Summary

• To some extent, we can learn to translate without any supervision, using monolingual data only.

• It’s key to constrain the model to produce valid intermediate sentences. We did so in the feature space.
  
  • Use noise that is proxy of translation noise.
  
  • Induce sharing of latent representations.
Future Work

• Figure out which constraints are universally useful and efficient.

• Leverage small amounts of labeled data, and large amounts of labeled data from other language pairs.

• Test method on languages for which we really do not have labeled data.
Summary of the Lecture

- To understand what is worth working on, we need to come up with better tools to analyze current models.

- Some well-known challenges of NMT can be easily explained and resolved.

- In general, model fitting needs more attention than search. Training at the sequence level works better but with diminishing returns as the baseline model gets stronger.

- The same principle of aligning domains in feature space can be used to translate words and sentences in a fully unsupervised manner; but there is a lot of room for improvement.
References

[1] **Classical Structured Prediction Losses for Sequence to Sequence Learning**
Sergey Edunov, Myle Ott, Michael Auli, David Grangier, Marc'Aurelio Ranzato
NAACL 2018
https://arxiv.org/abs/1711.04956

Myle Ott, Michael Auli, David Granger, Marc’Aurelio Ranzato
submitted
https://arxiv.org/abs/1803.00047

[3] **Word Translation Without Parallel Data**
Alexis Conneau, Guillaume Lample, Marc’Aurelio Ranzato, Ludovic Denoyer, Herve Jegou
ICLR 2018

Guillaume Lample, Ludovic Denoyer, Marc'Aurelio Ranzato
ICLR 2018
https://arxiv.org/abs/1711.00043
Collaborators

Myle Ott

Sergey Edunov

Michael Auli

David Grangier

Guillaume Lample

Alexis Conneau

Herve Jegou

Ludovic Denoyer
THANK YOU
Questions?
Вопросы?
¿Preguntas?