Natural Language Understanding, Generation, and Machine Translation

Lecture 18: Open-Vocabulary Models

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Based on slides by Rico Sennrich

Refresher

Text Representation

how do we represent text?

- 1-hot encoding
  - lookup of word embedding for input
  - probability distribution over vocabulary for output
- large vocabularies
  - increase network size
  - decrease training and decoding speed
- typical network vocabulary size: 10 000–100 000 symbols

	representation of "cat"	
vocabulary	1-hot vector	embedding
$\begin{matrix}0\\1\\2\\.\\1024\end{matrix} \begin{bmatrix}\text{the}\\\text{cat}\\\text{is}\\.\\\text{mat}\end{bmatrix}$	$\begin{bmatrix}0\\1\\0\\.\\0\end{bmatrix}$	$\begin{bmatrix}0.1\\0.3\\0.7\\0.5\end{bmatrix}$

Problem

NLU and NLG are open-vocabulary problems

- many training corpora contain millions of word types
- productive word formation processes (compounding; derivation) allow formation and understanding of unseen words
- names, numbers are morphologically simple, but open word classes
- Rest of this class we are going to focus on **translation**

Open-vocabulary models

Non-Solution: Ignore Rare Words

- replace out-of-vocabulary words with UNK
- a vocabulary of 50 000 words covers 95% of text
- this gets you 95% of the way...
  ... if you only care about automatic metrics

why 95% is not enough
rare outcomes have high self-information

source	Mr **Gallagher** has offered a ray of hope.
reference	Herr **Gallagher** hat einen hoffnungsstrahl ausgesandt .

Solution 1: Approximative Softmax

approximative softmax [Jean et al., 2015]
compute softmax over "active" subset of vocabulary

$\rightarrow$ smaller weight matrix, faster softmax

- at training time: vocabulary based on words occurring in training set partition
- at test time: determine likely target words based on source text
  (using cheap method like translation dictionary)

limitations

- allows larger vocabulary, but still not open
- network may not learn good representation of rare words

Solution 2: Back-off Models

back-off models [Jean et al., 2015, Luong et al., 2015]

- replace rare words with UNK at training time
- when system produces UNK, align UNK to source word, and translate this with back-off method

source	The **indoor temperature** is very pleasant.	
reference	Das **Raumklima** ist sehr angenehm.	
[Bahdanau et al., 2015]	Die **UNK** ist sehr angenehm.	✗
[Jean et al., 2015]	Die **Innenpool** ist sehr angenehm.	✗

limitations

- compounds: hard to model 1-to-many relationships
- morphology: hard to predict inflection with back-off dictionary
- names: if alphabets differ, we need transliteration
- alignment: attention model unreliable

Solution 3: Subword NMT

Subwords for NMT: Motivation

Subwords units could be meaningful units of translation

- compounding and other productive morphological processes
  - they charge a carry-on bag fee.
  - sie erheben eine Hand|gepäck|gebühr.
- names
  - Obama(English; German)
  - Обама (Russian)
- technical terms, numbers, etc.:
  - 10-12-2020.
  - December 10 2020.

Subword units

segmentation algorithms: wishlist

- **open-vocabulary NMT**: encode *all* words through small vocabulary
- encoding generalizes to unseen words
- small text size
- good translation quality

our experiments [Sennrich et al., 2016]

- after preliminary experiments, we propose:
  - character n-grams (with shortlist of unsegmented words)
  - segmentation via *byte pair encoding* (BPE)

Byte pair encoding for word segmentation

bottom-up character merging

- starting point: character-level representation
  $\rightarrow$ computationally expensive
- compress representation based on information theory
  $\rightarrow$ byte pair encoding [Gage, 1994]
- repeatedly replace most frequent symbol pair ('A','B') with 'AB'
- hyperparameter: when to stop
  $\rightarrow$ controls vocabulary size

word	freq
'**l o** w</w>'	5
'**l o** w e r</w>'	2
'n e w **e s t</w>**'	6
'w i d **e s t</w>**'	3

vocabulary:

l o w</w> w e r</w> n s t</w> i d

es est</w> lo

Byte pair encoding for word segmentation

why BPE?

- open-vocabulary:
  operations learned on training set can be applied to unknown words
- compression of frequent character sequences improves efficiency
  $\rightarrow$ trade-off between text length and vocabulary size

'**l o** w **e s t</w>**'

e s	$\rightarrow$	**es**
es t</w>	$\rightarrow$	**est</w>**
l o	$\rightarrow$	**lo**

Evaluation: data and methods

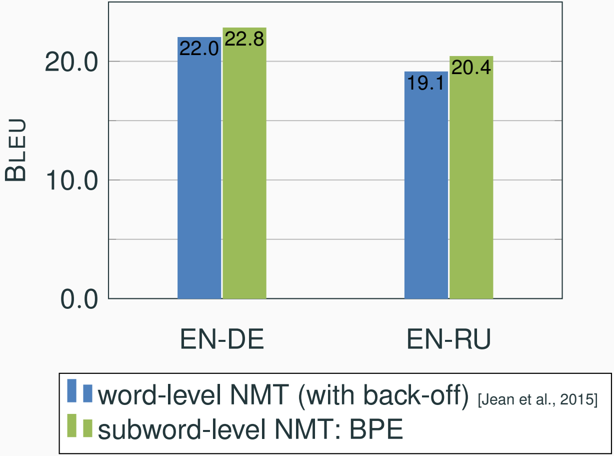
data

- WMT 15 English$\rightarrow$German and English$\rightarrow$Russian

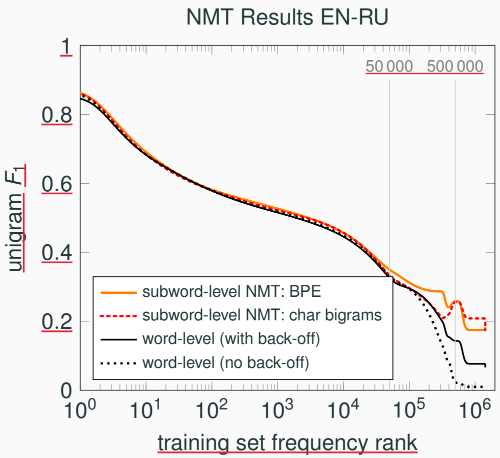
model

- attentional encoder–decoder neural network
- parameters and settings as in [Bahdanau et al, 2014]

Subword NMT: Translation Quality



Subword NMT: Translation Quality



Examples

system	sentence
source	health research institutes
reference	Gesundheitsforschungsinstitute
word-level (with back-off)	Forschungsinstitute
character bigrams	Fo|rs|ch|un|gs|in|st|it|ut|io|ne|n
BPE	Gesundheits|forsch|ungsin|stitute
source	rakfisk
reference	ракфиска (rakfiska)
word-level (with back-off)	rakfisk $\rightarrow$ UNK $\rightarrow$ rakfisk
character bigrams	ra|kf|is|k $\rightarrow$ ра|кф|ис|к (ra|kf|is|k)
BPE	rak|f|isk $\rightarrow$ рак|ф|иска (rak|f|iska)

Sharing BPE Vocabulary

- BPE merge operations for examples in previous slides are learned on concatenation of English and (romanized) Russian
- separate BPE can give inconsistent segmentations:
  rak|f|isk $\rightarrow$ пра|ф|иск (pra|f|isk)
- why? training data contains pair:
  p|rak|ri|ti$\rightarrow$пра|крит|и (pra|krit|i)
- with shared BPE, we get more consistent segmentation:
  pra|krit|i$\rightarrow$пра|крит|и (pra|krit|i)
- shared BPE has also proven useful for multilingual models

Subword Models: BPE-Dropout

- BPE-Dropout: Simple and effective Subword Regularizations [Provilkov et al., 2020]
- Adding stochastic noise to increase model robustness
- BPE: most frequent words are intact in vocabulary, learns how to compose with infrequent words
- If we sometimes forget to merge, we will learn how words compose, and better transliteration
- forget 1 in 10 times for most scripts, 6/10 in CKJ scripts
- Consistently give 1+ BLEU scores across language pairs - widely used

Subword Models: BPE-Dropout

```
u-n-r-e-l-a-t-e-d
u-n re-l-a-t-e-d
u-n re-l-at-e-d
u-n re-l-at-ed
un re-l-at-ed
un re-l-ated
un rel-ated
un-related
unrelated
```

(a)

```
u-n_r-e-l-a_t-e_d
u-n re-l_a-t-e_d
u-n re_l-at-e_d
un re-l-at-e-d
un re_l-at-ed
un re-lat-ed
un relat_ed
```

```
u-n-r-e-l-a_t-e-d
u_n re_l-a-t-e-d
u_n re-l-at-e-d
u_n re-l-ate_d
u_n rel-ate-d
u_n relate_d
```

```
u-n_r_e_l-a-t-e-d
u-n-r_e-l-at-e-d
u-n-r_e-l_at_ed
un-r-e-l-at-ed
un re-l_at-ed
un re-l-ated
un rel_ated
```

(b)

BPE

BPE dropout

From [Provilkov et al., 2020]

- Hyphen - possible merge
- merges performed - in green
- merges dropped - in red

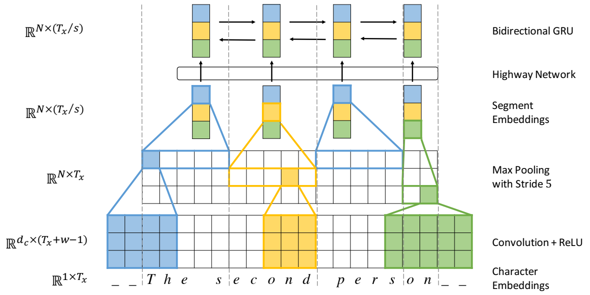
Solution 4: Character-level NMT

Character-level Models

- advantages:
  - (mostly) open-vocabulary
  - no heuristic or language-specific segmentation
  - neural network can conceivably learn from raw character sequences
- drawbacks:
  - increasing sequence length slows training/decoding (reported x2–x8 increase in training time)
- open questions
  - on which level should we represent meaning?
  - on which level should attention operate?

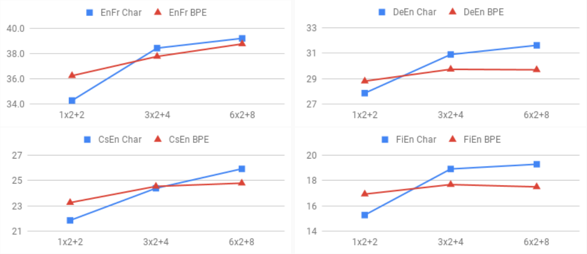
Fully Character-level NMT [Lee et al., 2016]

- goal: get rid of word boundaries
- source side: convolution and max-pooling layers
- character-level RNN on target side



Large-Capacity Character-level NMT [Cherry et al., 2018]

- train deep attentional LSTM encoder-decoders
- for shallow model, BPE is best quality
- for deep model, char-level model is better
- main problem for char-level: training time (8x slowdown)
- open challenge: compress representation without loss in quality



Beyond Character-level

- Massively multilingual settings character-level models can result in a very large vocabulary. eg. Unicode 143,859 codepoints
- Byte level input: better robustness to noise but longer training time ByT5: Towards a token-free future with pre-trained byte-to-byte models [Xue et al., 2021]
- Claim: token free - but really use fixed Unicode tokenisation which is not linguistically motivated
- Potentially unfair: Unicode characters beyond ASCII are much longer byte sequences - more expensive to model
- Pixel level: similarities that human readers might pick up on eg. to generalise to rare Chinese characters
- Makes translation significantly more robust to induced noise (including unicode errors) Robust Open-Vocabulary Translation from Visual Text Representations [Salesky et al., 2021]

Conclusion

- BPE and BPE-dropout is widely used
- There is no perfect method of handling tokenization.
- Opposing goals:
    - Decompose maximally for simple and robust processing
    - Desire to be computationally efficient in a way that is fair across languages
- Still not learning entities jointly with the rest of the model: separate preprocessing step
- How well these methods generalise from character strings to higher level of representation still to be fully studied

$\rightarrow$ next lecture: Pretrained language models and prompting

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