Natural Language Understanding, Generation, and Machine Translation

Lecture 6: Modelling Data and Words

Alexandra Birch

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School of Informatics
University of Edinburgh
a.birch@ed.ac.uk

Based on slides by Rico Sennrich

Refresher

Input Representation

how do we represent input?

- 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
$\begin{array}{c} 0 \\ 1 \\ 2 \\ . \\ 1024 \end{array} \begin{bmatrix} \text{the} \\ \text{cat} \\ \text{is} \\ . \\ \text{mat} \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \\ 0 \\ . \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0.1 \\ 0.3 \\ 0.7 \\ 0.5 \end{bmatrix}$

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

Problem

Research: we can download a clean corpus eg. Hansard, Europarl, Penn Treebank
Real life: nothing like this

- What if we need data that is not available publically? medical, financial, conversational
- What if it is for a low-resource language and none available?
- What if data we have is very noisy?
- What if there are very long dependencies over many sentences?

Modelling Data

Language Identification

Many datasets are crawls from the internet: CommonCrawl (250B pages) or the Internet Archive (850B pages)

- First step is Language Identification: LID
- What languages are these?
  - ndiyahamba (I'm going)
  - This is lekker bru (This is lovely)
- Generally solved task for high-resource languages
- Challenge with low resource, closely related language, code-switched or noisy data
- Solution: Fast lightweight classifiers
- Fasttext - Pre-trained models for 157 different languages

Sentence Splitting

Real data comes unsegmented into sentences.

- Sentence Segmentation:
  ! ? Mostly unabiguous but "." is very ambiguous (eg. the U.N.)
- Many scripts do not have end of sentence marker
- Speech is often not easy to segment into complete sentences
- Clean sentences - normally what models are trained on can struggle with shorter/longer sequences
- Solution: Language specific rules

Tokenisation

What is a word?

- Lookup in dictionary - but morphology makes this harder
- Thing between spaces - what about language without spaces or Finnish?
- Punctuation? Contractions? “that’s” $\rightarrow$ “that” “’s”
- Solution: For languages with spaces use spaces + punctuation + rules
- For Chinese etc. large dictionaries, punctuation + rules

Modelling Data

Critical for input to neural network - what is the input?
What sequence?

- Document, sentence, window, turn or utterance in a conversation

Sequence of what?

- Words, tokenized words, word stems, morphemes

Very long sequences are harder to model.
Vocabulary size needs to be limited as it has a huge effect on model size and efficiency.

Modelling words - 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

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

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

Subwords for NMT: Motivation

Subwords units could be meaningful useful for translation

- compounding and other productive morphological processes
  - they charge a carry-on bag fee.
  - sie erheben eine Hand|gepäck|gebühr.
- names
  - Edinburgh(English)
  - Edimburgo(Spanish)
- Morphological variation: slightly exaggerated eg. Turkish
  - OSMANLILAŞTIRAMAYABİLECEKLERİIMİZDENMİSŞINİZ
  - OSMAN-LI-LAŞ-TIR-AMA-YABİL-ECEK-LER-İIMİZ-DEN-MİS-ŞINİZ
- 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'	5
'l o w e r'	2
'n e w e s t'	6
'w i d e s t '	3

vocabulary:
l o w e r n s t i d

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vocabulary:

l o w e r n s t i d

es

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word	freq
'l o w'	5
'l o w e r'	2
'n e w **est**'	6
'w i d **est** '	3

vocabulary:

l o w e r n s t i d

es **est**

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word	freq
'**lo** w'	5
'**lo** w e r'	2
'n e w **est**'	6
'w i d **est** '	3

vocabulary:
l o w e r n s t i d
es est **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’

e s	$\rightarrow$	es
es t	$\rightarrow$	est
l o	$\rightarrow$	lo

Byte pair encoding for word segmentation

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e s	$\rightarrow$	**es**
es t	$\rightarrow$	est
l o	$\rightarrow$	lo

Byte pair encoding for word segmentation

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'l o w **est**'

e s	$\rightarrow$	es
es t	$\rightarrow$	**est**
l o	$\rightarrow$	lo

Byte pair encoding for word segmentation

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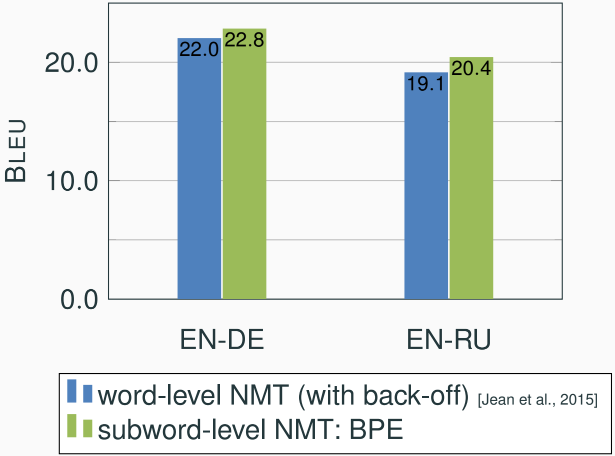
'**lo** w est'

e s	$\rightarrow$	es
es t	$\rightarrow$	est
l o	$\rightarrow$	**lo**

Subword NMT: Translation Quality



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

Subword Models: BPE-Dropout

- BPE-Dropout: Simple and effective Subword Regularizations

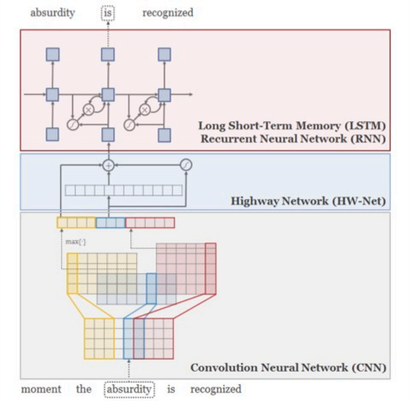
  [Provilkov et al., 2020]
- Adding stochastic noise to increase model robustness
- BPE: most frequent words are intact in vocabulary, learns how to compose with infrequent words
- If we sometimes forget to merge, we will learn how words compose, and better transliteration
- forget 1 in 10 times for most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

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?

Character Aware Neural Language Model [Kim et al., 2016]

- goal: vocabulary over character set
- Convolution over characters, highway network over words, and LSTM layers



Character Aware Neural Language Model [Kim et al., 2016]

(Based on cosine similarity)

	In Vocabulary				
	while	*his*	*you*	*richard*	*trading*
Word Embedding	*although*	*your*	*conservatives*	*jonathan*	*advertised*
	letting	*her*	*we*	*robert*	*advertising*
	though	*my*	*guys*	*neil*	*turnover*
	minute	*their*	*i*	*nancy*	*turnover*
Characters (before highway)	*chile*	*this*	*your*	*hard*	*heading*
	whole	*hhs*	*young*	*rich*	*training*
	meanwhile	*is*	*four*	*richer*	*reading*
	white	*has*	*youth*	*richter*	*leading*
Characters (after highway)	*meanwhile*	*hhs*	*we*	*eduard*	*trade*
	whole	*this*	*your*	*gerard*	*training*
	though	*their*	*doug*	*edward*	*traded*
	nevertheless	*your*	*i*	*carl*	*trader*

Beyond Character-level

- Massively multilingual settings character-level models can result in a very large vocabulary. eg. Unicode 1,112,064 codepoints
- Byte level:
  - 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

- Understand how your data was preprocessed
- Important to model it correctly
- 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

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