# Natural Language Understanding, Generation, and Machine Translation

## Lecture 6: Modelling Data and Words

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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 |
| $\begin{matrix}0\\1\\2\\.\\1024\end{matrix}\;\begin{bmatrix}\text{the}\\\text{cat}\\\text{is}\\.\\\text{mat}\end{bmatrix}$ | $\begin{bmatrix}0\\1\\0\\.\\0\end{bmatrix}$ | $\begin{bmatrix}0.1\\0.3\\0.7\\0.5\end{bmatrix}$ |

# 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

# 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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- 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: 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
  - OSMANLILAŞTIRAMAYABİLECEKLERİIMİZDENMİSSŞINİZ
  - 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
  → computationally expensive
- compress representation based on information theory
  → byte pair encoding [Gage, 1994]
- repeatedly replace most frequent symbol pair ('A','B') with 'AB'
- hyperparameter: when to stop
  → 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

# Byte pair encoding for word segmentation

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vocabulary:

l o w e r n s t i d

**es**

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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
  → trade-off between text length and vocabulary size

’l o w e s t’

| | | |
|---|---|---|
| e s | → | es |
| es t | → | est |
| l o | → | lo |

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| | | |
|---|---|---|
| **e s** | → | **es** |
| es t | → | est |
| l o | → | lo |

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’l o w **est**’

| | | |
|---|---|---|
| e s | → | es |
| **es t** | → | **est** |
| l o | → | lo |

# Byte pair encoding for word segmentation

**why BPE?**

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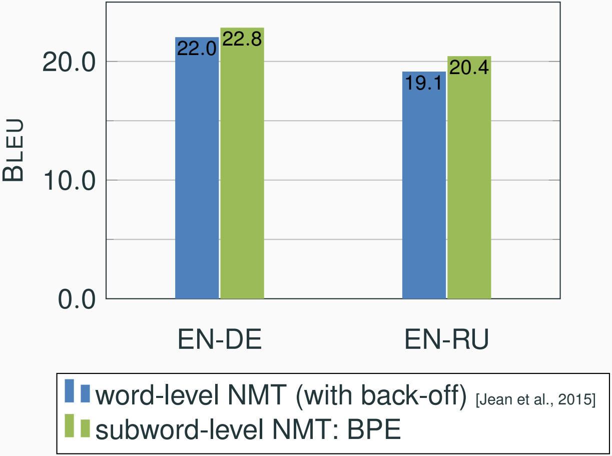
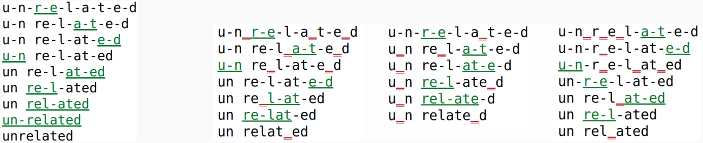
’**lo** w est’

| | | |
|---|---|---|
| e s | → | es |
| es t | → | est |
| **l o** | → | **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

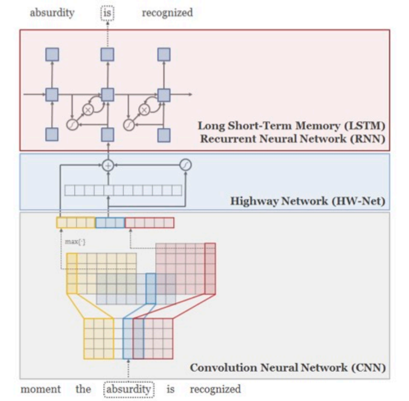
  [Provilkov et al., 2020]
- Adding stochastic noise to increase model robustness
- BPE: most frequent words are intact in vocabulary, learns how to compose with infrequent words
- If we sometimes forget to merge, we will learn how words compose, and better transliteration
- forget 1 in 10 times for most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

# Character-level Models

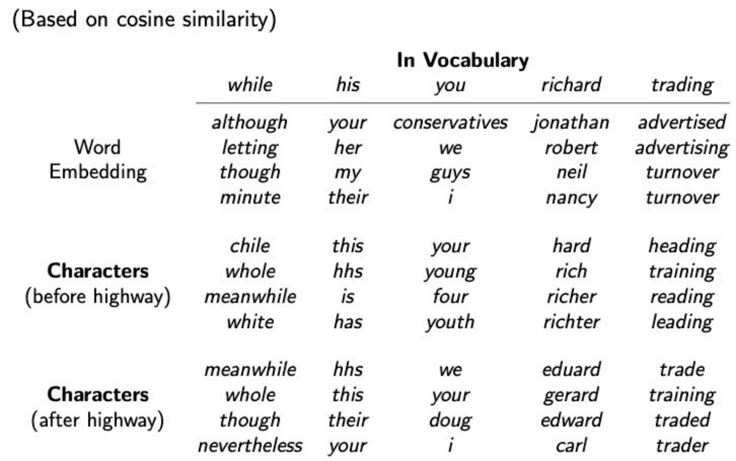
- advantages:
    - (mostly) open-vocabulary
    - no heuristic or language-specific segmentation
    - neural network can conceivably learn from raw character sequences
- drawbacks:
    - increasing sequence length slows training/decoding (reported x2–x8 increase in training time)
- open questions
    - 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


absurdity
is
recognized
Long Short-Term Memory (LSTM)
Recurrent Neural Network (RNN)
Highway Network (HW-Net)
max[·]
Convolution Neural Network (CNN)
moment
the
absurdity
is
recognized

# 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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