# Encoder-decoder methods for text normalization

## Swiss German WhatsApp messages

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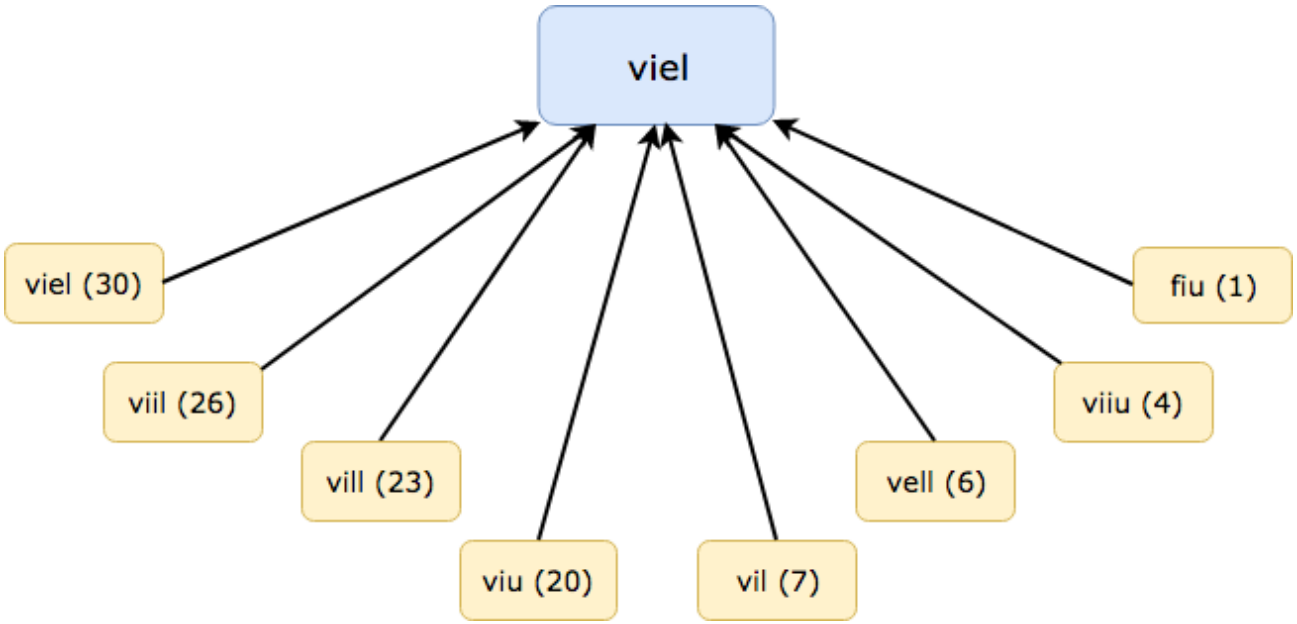
# Why text normalization?

- Historical texts
- Dialects and languages with no orthographic standard
- Computer-mediated communication (CMC)

# Variation in the source text: the dialect factor

Many different spelling variants for the same source word.



# Variation in the source text: the CMC factor

- **Vowel reduplication**
  *gaaaanz* → *ganz* 'all, whole'

- **Omitted vowels**
  *vllt* → *vielleicht* 'maybe'

- **Typos, unconventional casing and abbreviations**

# State of the art

Text normalization as a machine translation task.

Statistical Machine Translation (SMT)
vs.
Neural Machine Translation (NMT)

# The corpora: composition

| Corpus | | Messages | Alignment units |
|---|---|---|---|
| **WUS** | What's up, Switzerland?[1] | 5,345 | 54,229 |
| **SMS** | Swiss SMS corpus[2] | 10,674 | 262,494 |

[1] Corpus: Stark et al., 2014; Documentation: Ueberwasser and Stark, 2017
[2] Corpus: Stark et al., 2015; Documentation: Ueberwasser, 2015

# The corpus: alignment units

- **one-to-one**
  *hüt* → *heute* 'today'
- **one-to-many**
  *hämmers* → *haben wir es* 'have we ... it'
- **many-to-one**
  *aweg riise* → *wegreissen* 'tear away'
- **many-to-many**
  *über chunts* → *überkommt es* 'receives it'

# Methods: baseline

**Baseline**

For each word in the test set we choose its most frequent normalization form in the training set. Unseen words are copied.

| | Baseline | |
|---|---|---|
| **Word category** | **Proportion** | **Accuracy** |
| Unique | 55.05 | 98.43 |
| Ambiguous | 32.70 | 81.22 |
| New | 12.25 | 30.27 |
| Total | 100 | 84.45 |

# Methods: character-level approach

1. Statistical Machine Translation (cSMT)
2. Neural Machine Translation (cNMT)

- **Formally similar word pairs**
  *Sunne* → *Sonne* 'sun'

- **Regular transformation patterns** (e.g., *ii* → *ei*)
  *Ziit* → *Zeit* 'time'
  *wiiter* → *weiter* 'further'
  *Priis* → *Preis* 'price'

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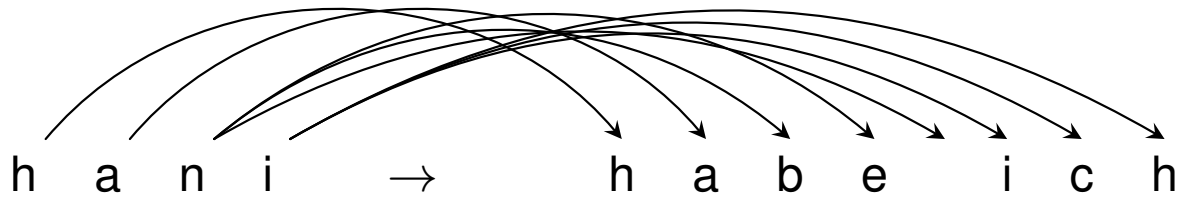
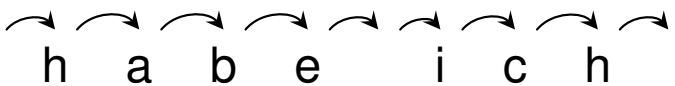
# cSMT

Translation model: $p(normalised|source)$



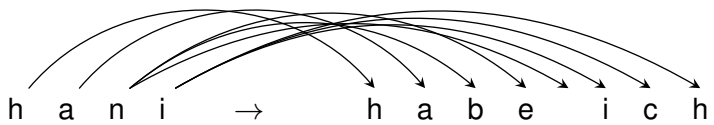

Language model: $p(normalised_i|normalised_{i-1})$



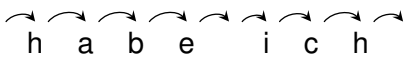
# cSMT vs cNMT

**cSMT:**

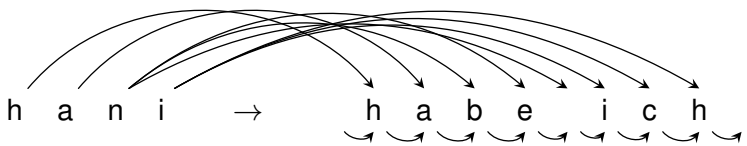
TM: $p(normalised|source)$



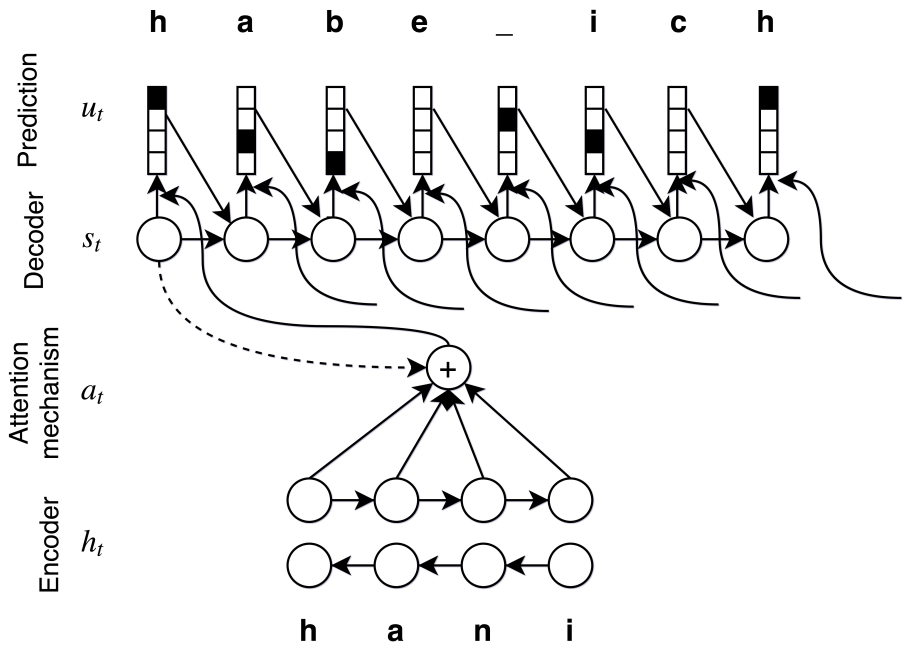

LM:
$p(normalised_i|normalised_{i-1})$




**cNMT:**



# cNMT




- LSTM decoder & bidirectional encoder
  Hochreiter and Schmidhuber, 1997, Sutskever et al., 2014
- Soft Attention
  Bahdanau et al., 2014

$$p(u_t) = f(s_t, c_t)$$
$$c_t = \sum_i a_t^i h_i$$
$$a_t = \phi(s_t, h_{1:N})$$

# cNMT mistakes

cNMT search for *'idere'*:

||| ideren ||| nmt= -4.341753 - *NMT prediction*
||| in dieser||| nmt= -29.94 - *correct form*
||| ider einer||| nmt= -30.29

- Word *'ideren'* does not appear in the target side of the corpus while *'in'* and *'dieser'* do

→ give more signal about word frequencies and rerank?

→ combine cNMT scores over chars with LM scores over words

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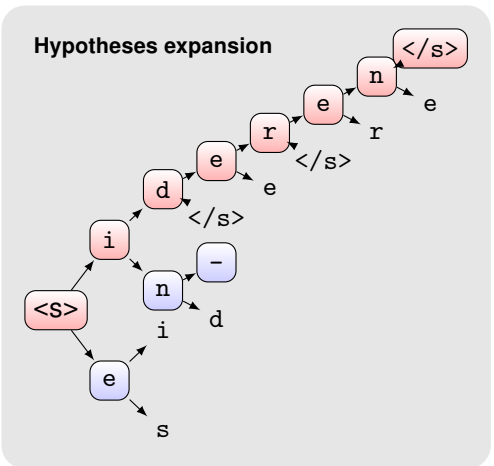
# cNMT + LM: synchronized decoding

## Ruzsics and Samardžić, 2017

**idere → in dieser**

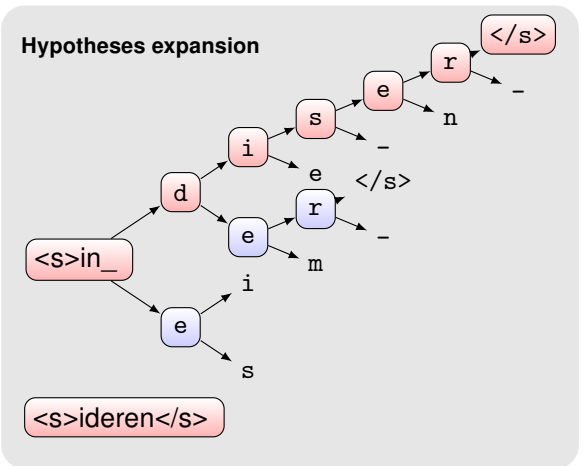
Iteration 1:




**Scores Synchronization**

| Hypothesis | NMT score | Combined score |
|---|---|---|
| ideren</s> | **-4** | -5 |
| in_ | -8 | **-2** |

Iteration 2:




**Scores Synchronization**

| Hypothesis | cED score | Combined score |
|---|---|---|
| in_dieser</s> | -30 | **-3** |
| in_der</s> | -35 | -9 |
| ideren</s> | **-4** | -5 |

- Hypos generation on char level
- Scores are combined at word boundaries (synchronization)
- char-level NMT scores
- word-level LM scores
- MERT optimization for weights

# CNMT + LM: experimental setup

## LM training settings:

- REUSE:

  cNMT + LM_wus :word

- ADD:

  cSMT + LM_sms:char
  cNMT + LM_sms:char

- REUSE+ADD:

  cNMT + LM_wus+sms:word

## Corpus:

- Original

  emojiQfaceWithTearsOfJoy → emojiQfaceWithTearsOfJoy

- Modified

  😂 → 😂

# Results

| System | | Corpus | |
|---|---|---|---|
| | | Original | Modified |
| REUSE+ADD | **cNMT + LM_wus+sms:word** | **87.61** | 87.07 |
| ADD | cNMT + LM_sms:char | 87.27 | 86.55 |
| REUSE | cNMT + LM_wus :word | 87.14 | 86.55 |
| | cNMT (ensemble 5) | 87.03 | 86.50 |
| ADD | cSMT + LM_sms:char | 86.35 | 86.43 |
| | cSMT | 85.30 | 85.85 |
| | Baseline | 84.45 | 84.45 |

Table: Text normalization accuracy scores.

# Results: error analysis

| Group | Source | cSMT Error | cNMT and Reference | English gloss |
|---|---|---|---|---|
| dissimilar reference | hb | hb | hauptbahnhof | 'train station' |
| | òmu | ömel | jedenfalls | 'anyway' |
| | gäbig | gebung | praktisch | 'useful' |
| | eig | eig | eigentlich | 'actually' |
| foreign word | feedback | feichtback | feedback | 'feedback' |
| | cream | kream | cream | 'cream' |
| > 1 target word | hanise | hanise | habe ich sie | 'have I ... her' |
| | meini | meine | meine ich | 'I mean' |
| | nonig | nonung | noch nicht | 'not yet' |
| | söuis | sollte es | soll ich es | 'shall I ... it' |

Table: Improvements of the cNMT over cSMT.

# Conclusion

- Neural frameworks can achieve state-of-the-art performance in the task of text normalization, when the training corpus is of limited size.
- This can be achieved by exploiting their flexibility in integrating additional components, such as language models trained on different tokenization levels.

# Future work

- include context
- learn the predictor weights as a part of NN
- introduce copy for unseen characters

Thank you for your attention!

# References I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