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Evaluating historical text normalization systems: How well do they generalize?

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Abstract

We highlight several issues in the evaluation of historical text normalization systems that make it hard to tell how well these systems would actually work in practice—i.e., for new datasets or languages; in comparison to more naïve systems; or as a preprocessing step for downstream NLP tools. We illustrate these issues and exemplify our proposed evaluation practices by comparing two neural models against a naïve baseline system. We show that the neural models generalize well to unseen words in tests on five languages; nevertheless, they provide no clear benefit over the naïve baseline for downstream POS tagging of an English historical collection. We conclude that future work should include more rigorous evaluation, including both intrinsic and extrinsic measures where possible.

1 Introduction

Historical text normalization systems aim to convert historical wordforms to their modern equivalents, in order to make historical documents more searchable or to improve the performance of downstream NLP tools. In historical texts, a single word type may be realized with several different orthographic forms, which may not correspond to the modern form. For example, the modern English word *said* might be realized as *sayed*, *seyd*, *said*, *sayd*, etc. Spellings change over time, but also vary within a single time period and even within a single author, since orthography only became standardized in many languages fairly recently.

Over the years, researchers have proposed normalization methods based on rules and/or edit distances (Baron and Rayson, 2008; Bollmann, 2012; Hauser and Schulz, 2007; Bollmann et al., 2011; Pettersson et al., 2013a; Mitankin et al., 2014; Pettersson et al., 2014), statistical machine translation (Pettersson et al., 2013b; Scherrer and Erjavec, 2013), and most recently neural network models (Bollmann and Søgaard, 2016; Bollmann et al., 2017; Korchagina, 2017). However, most of these systems have been developed and tested on a single language (or even a single corpus), and many have not been compared to the naïve but strong baseline that only changes words seen in the training data, normalizing each to its most frequent modern form observed during training. These issues make it hard to tell which methods generalize across languages and corpora, and how they compare to each other. Moreover, researchers have rarely examined whether their systems actually improve performance on downstream tasks.

This paper brings together best practices for evaluating historical text normalization systems, highlighting in particular the need to report results on unseen tokens and to consider the naïve baseline. We focus our evaluation on two recent neural models: one that has been previously tested only on a German collection that is not widely available (Bollmann et al., 2017), and one that is adapted from work on morphological re-inflection, but has not been used for historical text normalization (Aharoni et al., 2017). Both are encoder-decoder models; the former with soft attention, and the latter with hard monotonic attention.

We present results on five languages, for both seen and unseen words and for various amounts of training data. The soft attention model performs surprisingly poorly on seen words, so that its overall performance is worse than the naïve baseline and several earlier models (Pettersson et al., 2014). However, on unseen words (which we argue are what matters), both neural models do well.

Unfortunately, these positive results did not

\footnote{Some authors have focussed on *unsupervised* normalization, where the naïve baseline is to leave words unchanged (Mitankin et al., 2014; Hauser and Schulz, 2007). We consider only *supervised* systems in the remainder of this paper.}
We follow previous work in training our systems why, suppose 80% of test tokens were seen in train-forms. However, previous models have not addressed this the number of and test sets, researchers should not only report and experimental results. In describing the training system requires more complete dataset statistics that a full evaluation of any spelling normalization irrelevant that A scores higher overall than B. It is therefore critical to report both dataset statistics and experimental results for unseen tokens.

Unfortunately, some recent papers have only reported accuracy on all tokens, and only in comparison to other (non-baseline) systems (Bollmann and Søgaard, 2016; Bollmann et al., 2017; Korchagina, 2017). These figures can be misleading if systems underperform the naïve baseline on seen tokens (which we show does happen in practice). To see why, suppose 80% of test tokens were seen in training, and the baseline gets 90% of them right, while system A gets 80% and system B gets only 70%. Meanwhile the baseline gets only 50% of unseen tokens right, whereas systems A and B get 70% and 90%, respectively. A’s accuracy is higher overall than B’s (78% vs 74%), but both systems under-perform the baseline (82%). More importantly, the best system (90% accuracy overall) is achieved by applying the baseline to seen tokens, and the system that generalizes best (B) to unseen tokens; it is irrelevant that A scores higher overall than B.

Stemming from the reasoning above, we argue that a full evaluation of any spelling normalization system requires more complete dataset statistics and experimental results. In describing the training and test sets, researchers should not only report the number of types and tokens, but also the per-cent of unseen tokens in the test (or dev) set and the percentage of training items (h, m) where h = m. This last statistic measures the degree of spelling variation, which varies considerably between corpora.

As for reporting results, we have argued that accuracy should be reported separately for seen vs unseen tokens, and overall results compared to the naïve memorization baseline. Since historical spelling normalization is typically a low-resource task, systems should also ideally be tested with varying amounts of training data to assess how much annotation might be required for a new corpus (Pettersson et al., 2014; Bollmann and Søgaard, 2016; Korchagina, 2017). Finally, since these systems may be deployed on corpora other than those they were trained on, and used as preprocessing for other tasks, we advocate reporting performance on a downstream task and/or different corpus.

To our knowledge the only previous supervised learning system to do so is Pettersson et al. (2013b).

### 3 Models

We focus on two neural encoder-decoder models for spelling normalization, comparing them against the memorization baseline and to previous results from Pettersson et al. (2014). The first model (Bollmann et al., 2017) uses a fairly standard architecture with a bi-directional LSTM encoder and an LSTM decoder with soft attention (Xu et al., 2015), and is trained using cross-entropy loss.

The second model is a new approach to spelling normalization, which adapts the morphological re-inflection system of Aharoni et al. (2017). The reinflection model generates the characters in an inflected wordform (y_m), given the characters of its lemma (x_m) and a set of corresponding morphological features (f). Rather than using a soft attention mechanism that computes a weight vector over the entire sequence, this model exploits the generally monotonic character alignment between x and y and attends to only a single encoded input character at a time during decoding.

Architecturally, the model uses a standard bi-directional encoder. The decoder steps through the characters of the input and considers jointly the output of the previous step, the morphological features, and the currently attended encoded input. It outputs

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2 It would be possible to train on full texts rather than isolated tokens, which could improve results for ambiguous forms. However, previous models have not addressed this setting, nor do we, leaving this for future work.

3 Our version breaks ties by choosing the first m observed.

4 https://bitbucket.org/mbollmann/acl2017

5 https://github.com/roeeaharoni/morphological-reinflection
1. Because we do no hyperparameter tuning, we use the same datasets as Pettersson et al. (2014), we applied the models to a collection of unseen documents and then tagged them with the Stanford POS tagger, which comes pre-trained on modern English. The documents are from the Stanford project on Early English Correspondence (PCEEC) (Taylor et al., 2006), comprised of 84 letter collections from the 15th-17th centuries. (Our English normalization training data is from the 14th-17th centuries.) PCEEC contains roughly 2.2m manually POS-tagged tokens but no spelling annotation. Because it uses a large and somewhat idiosyncratic set of POS tags, we converted these to better match the Stanford tags before evaluating (though the match still isn’t perfect; accuracy would be higher in all cases if the tag sets were identical). Baselines are provided by tagging the unnormalized text and the output of the naïve normalization baseline.

Results: normalization accuracy Table 2 gives test set results for all models, broken down into seen and unseen items where possible. The split into seen/unseen highlights the fact that neither of the neural models does as well on seen items as the baseline; indeed the soft attention model is considerably worse in English and Hungarian, the two largest datasets. The result is that this model actually underperforms the baseline when applied to all tokens, although a hybrid model (baseline for seen, soft attention for unseen) would outperform the baseline. Nevertheless, the hard attention model performs best on unseen tokens in all cases, often by a wide margin, and also yields competitive overall performance.

We also compared the accuracy of the two neural models at different training data sizes starting from 1k tokens. On seen tokens, the baseline was best in all cases except for 1k tokens in Hungarian and Icelandic (where the soft attention model was slightly better) and the largest two data sizes in German (where the hard attention model was slightly better). This supports our claim that learned models should typically only be applied to unseen tokens.

Accuracy on unseen tokens is shown in Figure 1. Note that the set of unseen items gets smaller

<table>
<thead>
<tr>
<th></th>
<th>Tokens</th>
<th>h typ</th>
<th>m typ</th>
<th>%nc</th>
<th>%uns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eng</td>
<td>148/16/17k</td>
<td>19.4k</td>
<td>10.6k</td>
<td>73.9</td>
<td>8.6</td>
</tr>
<tr>
<td>Ger</td>
<td>39/5/5k</td>
<td>9.0k</td>
<td>8.4k</td>
<td>84.8</td>
<td>14.8</td>
</tr>
<tr>
<td>Hun</td>
<td>137/17/17k</td>
<td>45.5k</td>
<td>25.8k</td>
<td>15.4</td>
<td>24.1</td>
</tr>
<tr>
<td>Ice</td>
<td>52/6/6k</td>
<td>9.7k</td>
<td>8.5k</td>
<td>48.0</td>
<td>11.3</td>
</tr>
<tr>
<td>Swe</td>
<td>28/2/34k</td>
<td>8.3k</td>
<td>6.5k</td>
<td>65.9</td>
<td>22.4</td>
</tr>
</tbody>
</table>

Table 1: Dataset statistics: the number of tokens in train/dev/test sets; historical and modern word types and % of "no-change" tokens (h = m) in the training sets; and the % of dev set tokens that are unseen in training.

Either a character or an advance symbol (to advance the focus of attention for the next time step). It is trained on an oracle sequence of write/advance actions $s_{1,q}$ which are generated from an automatic alignment of the input and output sequences. The model maximizes $p(s_{1,q}|x_{1:m}, f)$. For details, see Aharoni et al. (2017).

We adapt the model to our purpose by removing the morphological features $f$, maximising only $p(s_{1,q}|x_{1:m})$. The monotonic assumption is well-suited to our task, since fewer than 0.4% of edit operations require non-monotonic alignments (i.e. character transpositions) in any of our datasets. Other than removing the need for morphological features from the hard attention model, and increasing the number of training epochs to 50 for both models, we did no further hyperparameter tuning, since our goal was to assess the "off-the-shelf" performance of these systems.

4 Experiments

We use the same datasets as Pettersson et al. (2014), with data from five languages over a range of historical periods. We use the same train/dev/test splits as Pettersson; dataset statistics are shown in Table 1. Because we do no hyperparameter tuning, we do not use the development sets, and all results are reported on the test sets.

Each system was tested as recommended above, with accuracy reported separately on seen and unseen items, and for different training data sizes. To evaluate the downstream effects of normalization, we applied the models to a collection of unseen documents and then tagged them with the Stanford POS tagger, which comes pre-trained on modern English. The documents are from the Stanford project on Early English Correspondence (PCEEC) (Taylor et al., 2006), comprised of 84 letter collections from the 15th-17th centuries. (Our English normalization training data is from the 14th-17th centuries.) PCEEC contains roughly 2.2m manually POS-tagged tokens but no spelling annotation. Because it uses a large and somewhat idiosyncratic set of POS tags, we converted these to better match the Stanford tags before evaluating (though the match still isn’t perfect; accuracy would be higher in all cases if the tag sets were identical). Baselines are provided by tagging the unnormalized text and the output of the naïve normalization baseline.

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6English: Markus (1999); German: Scheible et al. (2011); Hungarian: Simon (2014); Icelandic: Rögnvaldsson et al. (2012); Swedish: Fiebranz et al. (2011). For details of their dates and contents, see Pettersson et al. (2014).

8When we varied the training data sizes, we found that the soft attention model actually gets worse on seen tokens in all languages as the training data increases beyond a relatively small size. We have no good explanation for this, and it’s possible that tuning the parameters would help.
Table 2: Tokens normalized correctly (%) for each dataset. Upper half: results on (A)ll tokens reported by Pettersson et al. (2014) for a hybrid model (apply memorization baseline to seen tokens and an edit-distance-based model to unseen tokens) and two SMT models (which align character unigrams and bigrams, respectively). Lower half: results from our experiments, including accuracy reported separately on (S)een and (U)nseen tokens.

<table>
<thead>
<tr>
<th></th>
<th>English</th>
<th>German</th>
<th>Hungarian</th>
<th>Icelandic</th>
<th>Swedish</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>S</td>
<td>U</td>
<td>A</td>
<td>S</td>
</tr>
<tr>
<td>Hybrid</td>
<td>92.9</td>
<td>95.1</td>
<td>76.4</td>
<td>84.6</td>
<td>90.8</td>
</tr>
<tr>
<td>GIZA++ un</td>
<td>94.3</td>
<td>96.6</td>
<td>79.9</td>
<td>71.8</td>
<td>92.9</td>
</tr>
<tr>
<td>GIZA++ bi</td>
<td>92.4</td>
<td>95.5</td>
<td>80.1</td>
<td>71.5</td>
<td>92.5</td>
</tr>
<tr>
<td>Mem. baseline</td>
<td>91.5</td>
<td>96.9</td>
<td>94.1</td>
<td>96.9</td>
<td>80.3</td>
</tr>
<tr>
<td>Soft attention</td>
<td>89.9</td>
<td>93.7</td>
<td>94.3</td>
<td>98.1</td>
<td>79.8</td>
</tr>
<tr>
<td>Hard attention</td>
<td>93.0</td>
<td>96.6</td>
<td>96.5</td>
<td>99.3</td>
<td>88.0</td>
</tr>
</tbody>
</table>

Figure 1: Proportion of unseen tokens, and normalization accuracy on those tokens, as training data size is varied.

Figure 2: Average POS tagging accuracy on the unnormalized PCEEC texts (bottom of plot) and using three different normalization methods, as a function of the amount of data used to train the normalization systems.
intrinsic improvements do not always translate into extrinsic ones.

5 Conclusion

We have highlighted some important issues in the evaluation of historical text normalization systems: in particular, the need to report accuracy on unseen tokens and to compare performance to a naïve memorization baseline. Following these recommendations, we evaluated two neural models, one of which is new to this task. Across five languages, both models greatly outperformed the baseline on unseen tokens, with the soft attention model doing a bit better for smaller data sizes, and the hard attention model doing a bit better for larger ones. However, these improvements did not translate into clearly better POS tagging downstream.

Despite these mixed results, we hope that the evaluation guidelines presented here will help promote work in this area, in order to eventually provide better tools for working with historical text collections.

6 Acknowledgements

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