Building a Corpus from Handwritten Picture Postcards: Transcription, Annotation and Part-of-Speech Tagging

Kyoko Sugisaki, Nicolas Wiedmer, Heiko Hausendorf

German department, University of Zurich
Schönberggasse 9, 8001 Zurich, Switzerland
{sugisaki, nicolas.wiedmer, heiko.hausendorf}@ds.uzh.ch

Abstract

In this paper, we present a corpus of over 11,000 holiday picture postcards written in German and Swiss German. The postcards have been collected for the purpose of text-linguistic investigations on the genre and its standardisation and variation over time. We discuss the processes and challenges of digitalisation, manual transcription, and manual annotation. In addition, we developed our own automatic text segmentation system and a part-of-speech tagger, since our texts often contain orthographic deviations, domain-specific structures such as fragments, subject-less sentences, interjections, discourse particles, and domain-specific formulaic communicative routines in salutation and greeting. In particular, we demonstrate that the CRF-based POS tagger could be boosted to a domain-specific text by adding a small amount of in-domain data. We showed that entropy-based training data sampling was competitive with random sampling in performing this task. The evaluation showed that our POS tagger achieved a F1 score of 0.93 (precision 0.94, recall 0.93), which outperformed a state-of-the-art POS tagger.

Keywords: postcard corpus, POS tagging, German

1. Introduction

In this paper, we report the construction of the language resource Ansichtskartenkorpus (janko), 'picture postcard corpus', containing over 11,000 holiday postcards written in Standard German and Swiss German. They were manually transcribed and annotated with structural and discourse-related information, and then automatically annotated with text segmentation, lemma and part-of-speech (POS) information.

We will first characterise the texts contained in the resource (Section 2), and then describe their manual transcription and annotation before outlining the development of an NLP toolkit for text segmentation and POS annotation (Section 3).

2. Data Source

The holiday postcards were collected at the University of Zurich from 2009 to present day for the purpose of text-linguistic investigations on the genre and its standardisation and variation over time. The postcards included in our corpus were sent by post from people on holiday, mainly from Switzerland but also from Italy, Germany and other European countries to their family, friends, colleagues and neighbours living in the German-speaking area of Switzerland. About 95% of the cards (11,760 cards) were written mainly in Standard German. The remaining part of the corpus is comprised of postcards written mainly in Swiss German. Although the postcards were sent from 1898 to 2016, the majority were written in the 1980s (22%) and 1990s (19%). On average, a post card contains 50 words, while individual post cards vary from one to 350 words.

3. Corpus Construction

In this section, we describe the process of digitalisation, transcription, and annotation carried out manually and automatically to build the corpus of the collected postcards.

3.1. Overall Pipeline: From Digitalisation to XML with Linguistic Annotation

Because the collected holiday postcards were in paper format, we first scanned the front and back of each card. We then considered using an optical character recognition (OCR) system to extract the texts from the scanned images. However, the postcards were handwritten in German, and OCR systems do not work well for handwritten texts in languages other than English. Therefore, we decided on manual transcription for which we developed a web-based tool. The user interface is illustrated in Figure 3.2. Each scanned card was integrated into the tool. The tool displayed the front and back images of each card on the left side and the transcription and annotation forms on the right side. Thus, the transcribers could directly transcribe handwriting, mark paragraphs, note textual discourse structures (e.g. greetings) and enter metainformation (e.g. dates). The data were then saved in a MySQL database, which we then converted to an XML representation. We then incorporated our automatic annotations in the XML: 1) text segmentation, 2) lemma and 3) POS tags.

3.2. Transcription and Manual Annotation

The picture postcards written in Standard German were transcribed and annotated by four transcribers in a typing office in Germany. The Swiss German postcards were transcribed and annotated by a student whose native language is Swiss German. To ensure the quality of the transcription and the manual annotation, during the process of transcription and annotation, three students checked samples, corrected them manually and gave feedback to the typing office.

Our corpus consisted of the main texts as primary data and textual properties as metadata. A picture postcard consists of two sides – the front side and the back side. The front side of a modern postcard typically includes images of tourist attractions and landscapes, including the name of the location, whereas the back side consists of an address field on the
3.3. Automatic Text Segmentation

The primary texts were segmented into paragraphs, sentences and words. The segmented texts were then structured in a XML representation.

Generally in German, punctuation segments a text into sentences, and spaces are used to segment a sentence into words. However, this rule of thumb was not always applicable to the sentence segmentation of the postcards, particularly with regard to the following cases: 1) punctuation was a part of a token with preceding characters; and 2) punctuation was absent. Case 1 refers to abbreviations (e.g. z.B. instead of zum Beispiel or ‘for example’) and brand or proper names (e.g. Sat.1), which is also common in Standard German orthography. Case 2 refers to freestanding lines, which typically ended with a wide blank space or extra line spacing, and which often omitted punctuation, such as titles, subtitles, addresses, dates, greetings, salutations and signatures (Official German Orthography, 2006). Dates, greetings, salutations and signatures belong to the core text zones of postcards. In addition, freestanding lines were often extended to the end of the paragraph in the texts of the postcards. Furthermore, the following use of punctuations is also common in postcards, which differs from Standard German orthography: (a) repeated punctuation (e.g., !!!, ???, .......) in order to emphasise words, phrases and sentences; (b) the use of emotional punctuation is also common in postcards. Furthermore, based on these peculiarities, we developed a statistical sequential sentence segmentation system that differentiates punctuations into Case (1) and the sentence boundary, and deliberately handles Case (2) (Sugisaki, 2017).

With regard to tokenisation, the texts of the postcards showed a frequent use of contractions, which is also common in internet-based and computer-mediated communication (Hartz et al., 2013). In the contractions, the verb was often combined with the pronoun es, ‘it’, and delimited by an apostrophe (e.g. gib’s instead of gib es, ‘gives it’). The apostrophe was sometimes omitted (e.g. gibts). Nonetheless, not only verbs are concatenated with the pronoun, but also in ‘wh question’ words (wenn’s/wo’s instead of wenn es/wo es, ‘when/where it’) and prepositions (auf’s instead of aufs or auf das, ‘on the’). Based on this observation, we developed a simple rule-based tokeniser in which ‘s was separated from the remaining part of the token if it was not a noun. If it was a noun, the ‘s was considered a genitive marker and part of the token. We used TreeTagger (Schmid, 1995) to obtain the POS information. However, in the case of contractions without apostrophes, TreeTagger does not provide an accurate POS tag. Contractions without apostrophes do not belong to standard orthographies, which might cause this difficulty. We observed that frequently used verbs, such as give, be and have often occurred with the reduced pronoun s without an apostrophe. Therefore, we created a list of these verbs and some wh question words in order to separate s from them.

\[\text{http://ansichtskartenprojekt.de}\]
3.4. Part-of-speech Tagging

The segmented tokens were further annotated with POS tags that were integrated into the XML representation. We developed a POS tagger for the postcards. The texts comprised a mixture of Standard German and Swiss German. In addition, the targeted texts were in written form, but conceptually, they were in near-oral language (Koch and Oesterreicher, 2008; Dürscheid, 2016). An off-the-shelf POS tagger is typically trained on a corpus of newspapers written in Standard German. A newspaper article belongs to the category of a prototypical written language in both form and concept. Furthermore, it contains fewer orthographical deviations. Therefore, we experimented with features and training data to determine the best method for optimising the accuracy of the tagger applied to the postcard text in this study.

3.4.1. Experimental Setting

In the experiments, we used the tagging method of conditional random fields (CRF) (Lafferty et al., 2001). CRF is a supervised machine learning method for sequences. For the experiments, we created the following three data sets:

1. TüBa-D/Z v. 10, Tübingen Baumbank des Deutschen/Zeitungskorpus (Telljohann et al., 2012), which is a German newspaper corpus (1,787,801 tokens, henceforth TüBa). In our first experiments, approximately 80% of the TüBa (803,040 tokens, henceforth, TüBa80) were used as training data, and 20% of the TüBa tokens were used as test data (252,784 tokens, henceforth TüBa20). In the second experiment, we used all the TüBa (TüBa100) tokens as training data. In addition, we used a cross-validation data set (2,239 tokens) in all experiments.

2. NOAH’s Corpus of Swiss German Dialects (henceforth, NOAH) (Hollenstein and Aepli, 2014) is a Swiss German corpus (94,306 tokens) that contains a variety of texts (blogs, reports, Wikipedia, etc.). In our experiments, we used the corpus as training data.

3. From the Ansichtskartenkorpus, or ‘picture postcard corpus’ (henceforth, ANKO), we first manually annotated 200 postcards to derive the test data. The test data were sampled randomly from the corpus and divided into two sets: 100 cards for the experiment (5,048 tokens, henceforth ANKO-TEST) and 100 cards for the evaluation (5,341 tokens, henceforth ANKO-EVAL). In addition, we manually annotated 1,500 sentences for the experiments. The sentences were used as training data, and they were sampled in three ways: 1) 300 sentences were selected randomly (henceforth, ANKO-R); 2) 1,200 sentences were selected based on word 4-gram-based entropy scores according to four measurements. We describe the entropy sampling method in Section 3.4.3. In our experiments, we used the Standard German sub-corpus of ANKO.

The set of linguistic features used in our experiments is provided in Table 1. The features were divided into (A) word and lemma, (B) POS features generated by the POS tagger TreeTagger (Schmid, 1995) and the Stanford POS Tagger (toutanova et al., 2003), and (C) semantic clusters generated by unsupervised machine learning methods, that is, Brown clustering (Brown et al., 1992), Mikolov et al., 2013) and fasttext (Bojanowski et al., 2016).

In the following subsections, we describe the experiments using the set of linguistic features and the data sets.

3.4.2. Features

We trained CRF models on the training set of TüBa and tested them on the test set of TüBa and ANKO. We trained four different types of features (A to C in Table 1) separately and all features in context window 0 (i.e., current tokens). The results are shown in Table 2. As expected, tagging accuracy (F1 score) was lower if the training data and test data were derived from different domains. Regardless of the test data, the best features were the word and lemma features (A). The morphosyntactic analysis using the existing POS taggers showed a lower performance, and the semantic features (B) did not achieve high accuracy. However, the combination of these three types of features outperformed the word/lemma features. We extended the feature sets of (A), (B) and (C) from context window 0 (current tokens) to 5 left and right context windows. The results are shown in Table 2. The main finding was that the window side did not affect the accuracy as much as expected. However, the wider context window size slightly improved the accuracy of the test set of TüBa. Therefore, we conducted further experiments using the combination of the feature sets (A), (B) and (C) in context windows 0 to 5.

3.4.3. Training Data

In this section, we investigate the following challenges: 1) how to boost the tagging accuracy in texts with mixed languages and 2) whose domain and morphosyntactic distribution were different from newspapers.

To handle the first challenge, we added the Swiss German training data, NOAH. The results are shown in Table 3. The addition of the Swiss German training data produced results that were similar to those of the model that was trained only on TüBa100, but it did not improve the tagger.

To address the second challenge, we added small amounts of five types of training data from ANKO to the TüBa100 and NOAH training data. The first in-domain training data were randomly selected from ANKO. The remaining data sets were selected using a cross entropy score. Cross entropy is a variant of perplexity that is used to compare different probability models. The score is measured as follows (Jurafsky

\[2\text{For Brown clustering, we used the implementation of P. Liang. To create 100 clusters, we trained the model on TüBa100, NOAH, ANKO (normalized word form). The first 4 digits and all digits are used as features.}
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\[3\text{For word2vec, we used gensim with parameters skip-gram, 500 dimensions, context window 5. For K-means clustering, we used the scikit-learn to create 30 clusters.}
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\[4\text{We used the fasttext with parameters, CBOW, 200 dimensions, context window 5, 5 word ngrams. For K-means clustering, we used the scikit-learn to build 20 clusters.}
\]
The goal of the in-domain training data selection was the automatic selection of a small number of in-domain sentences that might improve the tagging accuracy. Ideally, the in-domain sentences to be selected were not observed in the training in TuBa and NOAH but were typical in ANKO. We considered two methods: 1) ranking-based entropy scoring (henceforth, method [A]) and 2) difference-based entropy scoring (henceforth, method [B]). Ranking-based entropy scoring is a measurement of how informative in-domain sentences are based on a language model trained on out-of-domain data. The entropy scores were ranked in order from high to low. In this method, in-domain sentences with high entropy scores were assumed distinct from the out-of-domain data and thus more informative. This method is compatible with Axelrod and Gao (2011) in which perplexity was used instead of cross entropy. We inspected the top 300 sentences. They included salutations, greetings, signatures and dates. These discourse types are typical in postcards but are rarely included in a newspaper corpus. In contrast, difference-based entropy is a measurement of differences in entropy scores based on a language model trained on both out-of-domain and in-domain sentences. In-domain sentences were considered informative if the difference in score was large. This method is based on Moore and Lewis (2010). We inspected the top 300 sentences. These sentences were similar to those selected by the ranking-based entropy scores, and they were a mixture of typical discourse structures.

However, the selected sentences did not include in-domain interpersonal and fragmental sentence patterns typically used in private communication. Thus, we did not find any sentences whose subject was in the first or second person, such as Danke für Deine Karte. (‘Thank you for your card’) or fragments such as sind glücklich hier oben gelandet (‘happily landed up here above’). Here, we found that the variance in higher entropy scores was high in TuBa (mean: 10, variance: 914) and low in ANKO (mean: 1, variance: 3), which indicated that the difference-based entropy scores were mainly guided by the TuBa scores. Therefore, these two methods selected similar sentences.

To detect typical main sentences in ANKO, we introduced two methods: in-domain ranking-based entropy score (henceforth, method [C]) and a difference-ranking-based entropy score (henceforth, method [D]). Method (C) was used to select the sentences with lowest entropy scores based on a language model trained on the in-domain data. In method (D), we simply ranked the entropy scores trained on TuBa and on ANKO, and we ordered the difference in ranking from high to low.

Table 2: Experiments with features in context window 0, 0-1, 0-3, 0-5: Training data =TuBa80:F1 score (precision, recall)

| Context window | 0 | 0-1 | 0-3 | 0-5 |
|----------------|---|-----|-----|-----|
| Feature A      | TuBa-Test 968 (.968, 968) | 967 (.967, 967) | 961 (.961, 961) | 931 (.893, 891) |
|                | ANKO-Test 883 (.886, 881) | 848 (.850, 846) | 795 (.796, 794) | 893 (.891, 894) |

\[
H(w_1 \ldots w_n) = -\frac{1}{N} \log P(w_1 \ldots w_n)
\]

Table 3: Experiments with training data with features (A), (B), and (C), and test on the ANKO-TEST: F1 score (precision, recall)

| Training data | Test |
|---------------|------|
| TuBa100       | .899 (.902, 897) |
| TuBa100 + NOAH| .898 (.901, 896) |
| TuBa100 + NOAH + 100 ANKO-A | 910 (.913, 908) |
| TuBa100 + NOAH + 100 ANKO-B | 908 (.911, 906) |
| TuBa100 + NOAH + 100 ANKO-C | 922 (.924, 920) |
| TuBa100 + NOAH + 100 ANKO-D | 926 (.928, 924) |
| TuBa100 + NOAH + 100 ANKO-R | 931 (.934, 929) |
| TuBa100 + NOAH + 300 ANKO-R/A/B/C/D | 941 (.943, 939) |

The goal of the in-domain training data selection was the automatic selection of a small number of in-domain sentences that might improve the tagging accuracy. Ideally, the in-domain sentences to be selected were not observed in the training in TuBa and NOAH but were typical in ANKO. We considered two methods: 1) ranking-based entropy scoring (henceforth, method [A])

4. Conclusion

In this paper, we described the process of digitalising, transcribing and annotating of over 11,000 handwritten postcards. In particular, we demonstrated that the POS tagger could be boosted to a domain-specific text by adding a small amount of in-domain data. We showed that entropy-based training data sampling was competitive with random sampling in performing this task. In future work, we will test our POS tagger on text that is written in Swiss German.

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