A Part-of-Speech Tagger for Yiddish

Seth Kulick and Neville Ryant
Linguistic Data Consortium
University of Pennsylvania
{skulick,nryant}@ldc.upenn.edu

Beatrice Santorini
Department of Linguistics
University of Pennsylvania
beatrice@sas.upenn.edu

Joel Wallenberg
Department of Language
and Linguistic Science
University of York
joel.wallenberg@york.ac.uk

Assaf Urieli
Joliciel Informatique
Foix, France
assaf@joli-iciel.com

Abstract

We describe the construction and evaluation of a part-of-speech tagger for Yiddish. This is the first step in a larger project of automatically assigning part-of-speech tags and syntactic structure to Yiddish text for purposes of linguistic research. We combine two resources for the current work - an 80K-word subset of the Penn Parsed Corpus of Historical Yiddish (PPCHY) (Santorini, 2021) and 650 million words of OCR’d Yiddish text from the Yiddish Book Center (YBC). Yiddish orthography in the YBC corpus has many spelling inconsistencies, and we present some evidence that even simple non-contextualized embeddings trained on YBC are able to capture the relationships among spelling variants without the need to first “standardize” the corpus. We also use YBC for continued pretraining of contextualized embeddings, which are then integrated into a tagger model trained and evaluated on the PPCHY. We evaluate the tagger performance on a 10-fold cross-validation split, showing that the use of the YBC text for the contextualized embeddings improves tagger performance. We conclude by discussing some next steps, including the need for additional annotated training and test data.

1 Introduction

Treebanks - text corpora annotated for part-of-speech (POS) and syntactic information - have been important resources for both natural language processing (NLP) and research on language change. For NLP, corpora such as the Penn Treebank (PTB) (Marcus et al., 1993), consisting of about 1 million words of modern English text, have been crucial for training machine learning models intended to automatically annotate new text with POS and syntactic information.

For research on language change, a family of treebanks of historical English (Taylor et al., 2003; Kroch et al., 2000b; Taylor et al., 2006; Kroch et al., 2016) and other languages (Wallenberg et al., 2011; Galves et al., 2017; Martineau et al., 2021; Kroch and Santorini, 2021), with a shared annotation philosophy and similar guidelines across languages, has formed the basis for reproducible studies of language change (Kroch et al., 2000a; Ecay, 2015; Wallenberg, 2016; Galves, 2020; Wallenberg et al., 2021).

The Penn Parsed Corpus of Historical Yiddish (PPCHY) (Santorini, 2021), developed mostly in the late 1990s, is an early example of such a treebank developed for linguistic research. It consists of about 200,000 words of Yiddish dating from the 15th to 20th centuries, annotated with POS tags and syntactic trees. The corpus grew out of a collection of linguistically relevant examples for research on the changing syntax of subordinate clauses in the history of Yiddish (Santorini, 1989, 1992, 1993).

While the PPCHY contains a relatively small amount of treebanked Yiddish text, there is a large amount of unannotated Yiddish text available. In particular, the Yiddish Book Center (YBC) has applied Yiddish-specific Optical Character Recognition (OCR)\(^1\) to their book collection, resulting in about 650 million words of Yiddish text (Markey, 2012; Urieli and Vergez-Couret, 2013; Kutzik, 2019).

We describe here the development of a POS-tagger bringing these resources together - using the PPCHY as training and evaluation material, and using the YBC corpus to train word embeddings, which encode distributional similarities among words and which we integrate into the tagger train-
ing. The use of embeddings can improve a model’s performance beyond the immediate annotated training data and has resulted in great advances in NLP over the last few years. We also present evidence that the embeddings implicitly encode information on spelling variations, thereby allowing us to bypass a step of standardizing the large number of spelling variants in the YBC texts.

This POS tagger is the first step in a larger project of (1) expanding PPCHY to one million words of manually annotated text, and (2) training a POS tagger and syntactic parser for Yiddish to automatically annotate a large and historically diverse corpus of Yiddish, including the YBC itself. This would allow for a next phase in corpus-based diachronic research on Yiddish by increasing the amount of annotated text beyond what could be manually annotated. We also hope that the steps in this work can result in additional search capabilities on the YBC and the PPCHY. Sections 6 and 7 discuss the problem of needing a common representation for the two sources and our solution to that problem. Section 8 describes the creation of the embeddings using the YBC. Sections 9 and 10 discuss the POS tagger model\(^2\) and the results, and Section 11 is the conclusion.

2 **Yiddish Orthography**

This section summarizes some aspects of Yiddish orthography that are referred to in following sections. For more details on these issues, see Kahn (2017, pp. 667-670), Jacobs (2005, pp. 46-52, 301-303), and Gold (1977).

Yiddish is in general written with Hebrew characters, although the representation of vowels and the use of diacritics is significantly different than in Hebrew. Yiddish can be roughly considered to consist of German and Hebrew/Aramaic components, with two different spelling systems, and each present important aspects to be considered for NLP work.

**Spelling inconsistency for the German component** This component is considered “phonetic” in that there is a mapping from the orthography to the pronunciation. However, the spelling has varied in quite a few ways over time, sometimes reflecting efforts to follow German spelling (“daytshmerish orthography”) or reflecting dialect pronunciations. In Section 8 we give some examples of these spelling variations, and show how the word embeddings reflect them.

There have been proposals for a standardized orthographic system, in particular by the YIVO Institute for Jewish Research in 1936, which we will refer to as “Standard YIVO Orthography” (SYO). While this has in some respects come to be the standard for contemporary Yiddish, most of the text in the YBC corpus predates this proposal, and even subsequent text doesn’t necessarily follow it.

**“Non-phonetic” component** While the spelling of words from the Hebrew/Aramaic component is less variable, they are represented by what is in essence a second orthographic system. For example, some letters only appear in these words. The frequency of words from this component can vary considerably depending on the material.\(^3\) For the tagger described here, their identification is important because the tagset has tags for Hebrew words used as particles and for quoted Hebrew text.

**Romanization** There is a relatively standard transliteration from the Yiddish script, particularly from SYO orthography, to Latin letters. For the phonetic component, the mapping from the Yiddish script to the romanization and back is fairly straightforward (modulo spelling differences in the Yiddish script). This not always the case, though. For example, \(\text{alts}\) can be \(\text{אַלְט} \text{אַלָנִים}\) ‘all’ or \(\text{אַלְט} \text{סְדָר}\) (a form of ‘old’). However, for the non-phonetic component, the mapping is not simple and in effect requires listing each such case.\(^4\) There are also

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\(^2\)The software for the resulting POS tagger is at [https://github.com/skulick/yiddishtag](https://github.com/skulick/yiddishtag).

\(^3\)Weinreich (2011, p. 66) writes that it can sometimes exceed 15 percent.

\(^4\)Saleva (2020) notes that the Hebraic words were problematic for the romanized-to-SYO transliteration model, since the
ambiguities where different words from the two components may be transliterated as the same romanization. For example, the romanization Šem can be the “non-phonetic” noun שם ‘reputation’ or the “phonetic” verbal stem שמש ‘be shy’.

Such ambiguities are an important concern for this work, since the PPCHY files discussed in Section 5, unlike the YBC texts, are romanized and must be converted to Yiddish script in order to prepare the training and evaluation material for the tagger, as discussed in Sections 6 and 7.

3 Related Work

Kirjanov et al. (2014), Blum (2015), and Saleva (2020) all discuss the problem of normalizing Yiddish text to a standard form. Blum (2015) experiments with a number of approaches to convert Yiddish text to SYO (including Kirjanov et al. (2014)). It is noteworthy that the training and evaluation data for this work are an earlier form of the OCR output used for YBC, although much smaller (16 documents and 37,902 tokens), with OCR mistakes manually excluded. The work used a list of standardized forms for all the words in the texts, experimenting with approaches that match a variant form to the corresponding standardized form in the list. Saleva (2020) uses a corpus of Yiddish nouns scraped off Wiktionary and consisting of 2,750 word forms to create transliteration models from SYO to the romanized form, from the romanized form to SYO, and from the “Chasidic” form of the Yiddish script to SYO, where the former is missing the diacritics in the latter.

We view these works as complementary to the current work. The work described below involves 650 million words of text which is internally inconsistent between different orthographic representations, along with the inevitable OCR errors, and we do not have a list of the standardized forms of all the words in the YBC corpus. However, it is possible that continued work on the YBC corpus will further development of transliteration models.

There are two sources of word embeddings for Yiddish currently available. Non-contextualized embeddings for Yiddish have been created by Grave et al. (2018) as part of the fastText word embeddings for 157 languages. The fastText embeddings were in general created using Wikipedia and CommonCrawl, although the specific sources or quantity were the Yiddish embeddings are not clear. The multilingual XLM-roberta-base contextualized embeddings (Conneau et al., 2020) include training on 34M Yiddish tokens (0.3 GB). We return to the use of these embeddings in Section 8.1.

4 The Yiddish Book Center Corpus

We describe here the main steps we took to generate the YBC corpus. See Appendix A for more details.

Downloading and text extraction To assemble the YBC corpus, we downloaded 9,925 OCR html files from the Yiddish Book Center site, performed some simple character normalization, extracted the OCR’d Yiddish text from the files, and filtered out 120 files due to rare characters, leaving 9,805 files to work with.

Conversion to ASCII The files were in the Unicode representation of the Yiddish alphabet. For ease of processing, we preferred to work with a left-to-right version of the script within strict ASCII. We therefore defined a bidirectional mapping between the Unicode and ASCII and converted the YBC text to this ASCII representation. We omit the details here of the definition of the notational variant, except to say that we tested it by converting all of the download text from the Unicode to ASCII and back again.

Tokenization and sentence segmentation With the text now in a more convenient representation, we also did some simple tokenization, separating out most cases of punctuation (e.g., “.ברך” becomes “ברך”). We did not, however, split words on apostrophes, given its frequent and inconsistent use in Yiddish. For example, the word מֵמ/דרֹו emes ‘truth’, with an inflectional ending n, appears 27,129 times as מ/דרו and 12,743 times as מ/דרו.

We split the lines into sentences based on the presence of period, question mark, or exclamation mark.

Result This process resulted in 9,805 files with 653,326,190 whitespace-delimited tokens, in our ASCII equivalent of the Unicode Yiddish script.6

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6We did not attempt at this stage to account for abbreviations with a period, and currently the period is incorrectly separated in abbreviations, which also affects the sentence segmentation.

6Some of these tokens are punctuation marks, due to the tokenization process. In what follows we will use the terms token and word interchangeably.
There were 10,642,884 distinct tokens. In Appendix B we discuss some aspects of how our use of the YBC corpus might be improved, in particular with respect to the OCR errors that will inevitably occur in uncorrected OCR of a corpus of this size.

5 The Penn Parsed Corpus of Historical Yiddish

As mentioned in the introduction, the PPCHY contains text from the 15th to 20th centuries. While most of the files contain varying amounts of running text, in some cases containing only subordinate clauses (because of the original research question motivating the construction of the treebank), the largest contribution comes from two 20th-century texts, Hirshbein (1977) (15,906 tokens) and Olsvanger (1947) (67,551 tokens). These are the two files from the PPCHY that we use in the work reported here.

An example tree from the PPCHY is shown in (1) for the sentence (2), from Hirshbein (1977).

(1) (IP-MAT
(META (NPR rokhl:))
(NP-SBJ (NPR elkone))
(PUNC ,)
(CP-QUE-MAT-PRN
(IP-SUB (VBF meyns@)
(NP-SBJ (PRO @tu))))
(PUNC ,)
(VLF volt)
(NEG nisht)
(VB veln)
(NP-ACC (NPR hersh-bern))
(PP (P far)
(NP (D an) (N eydem)))
(PUNC ?))

(2) רוחל: אלוקה , מיטמס , ואלמ נשמ עולם וורס ברן

(Rokhl: Elkone, do you think, would not want Hersh-Ber for a son-in-law?)

Text representation One of the reasons we focus on the two files mentioned is that they use a romanization that mostly corresponds to the SYO (which is not always true for the older Yiddish text). This is evident in the representation of the words in (1), which also contains an example of the slight modification from the usual romanized form, in that what are usually written as single words are sometimes split apart for purposes of the POS and syntactic annotation. Specifically, meynst is written as two separate tokens meyns and tu, with the split indicated by the trailing and leading “at” signs. This allows tu to be annotated as the pronoun subject, while meyns is the finite verb.8 Other common cases of this tokenization in the PPCHY concern the separation of stressed verbal prefixes and contractions with an apostrophe, such as s‘iz, which are split after the apostrophe.

Syntactic and POS annotation The text in the PPCHY has been annotated in a similar style to that of other treebanks for historical research, such as the Penn Parsed Corpus of Historical English (Kroch, 2020) and the Icelandic Parsed Historical Corpus (Wallenberg et al., 2011).

Without going into full detail, the tree shows the usage of the POS tags NPR (proper noun), VBF (ordinary finite verb), PRO (pronoun), VLF (finite form of VOLN), VB (infinitive), P (preposition), N (noun), NEG (negation), and PUNC (punctuation). The syntactic annotation on top of the POS tags also shows that meyns tu is a parenthetical question, that elkone is the subject, hersh-bern is the accusative object, and far an eydem is a prepositional phrase.9

6 The Need for a Common Representation

The two main resources for this work are, to this point, in different representations. The YBC, discussed in Section 4, is in Yiddish script, while the PPCHY, discussed in Section 5, is in a romanized form, with some whitespace-delimited tokens split into two. We need to have a common representation for the two, in order to allow the embeddings trained on the YBC to be used in the model trained on the PPCHY, so that it can assign POS tags to the YBC and other text. There are two choices:

(A) Convert the PPCHY to the Yiddish script. An example would be going from the representation of the text in the tree (1) to the sentence (2). This would need to be done for all the words in the two files from the PPCHY.

(B) Convert the YBC to SYO and then a romanized representation. An example would be converting sentence (2), if it occurred in the YBC, to

8The verb is actually meynat, but the t is in effect shared between the two separated tokens.
9For more details, the general annotation style is at https://www.ling.upenn.edu/~beatrice/annotation/index.html. See Santorini (2021) for Yiddish-specific details.
the representation of the words in the tree (1). This would need to be done for all 650 million words in the YBC (and any text from other sources to be tagged and parsed in the future).

While the second alternative is maybe possible in principle, it would be very problematic to carry out. It would need to be done automatically for the 650 million words, with their many alternate spellings and the inevitable OCR errors.

In contrast, the first alternative requires the conversion of only a comparatively small amount of text from the PPCHY, which to a certain extent can be checked manually. The first alternative also results in a tagger trained on standard Yiddish script, and therefore ready to use on new text in that form, without requiring further conversions.\footnote{Another possibility is to train a tokenizer to first split apart the words and then POS tag words with modified tokenization, such as "ֶדנֵמיינסֶדרוּו." We prefer to use a single model for the related tasks of tokenization and POS tagging, and so we leave this possibility aside for now.}

7 Converting PPCHY to Yiddish Script

The conversion of the two PPCHY files just discussed to Yiddish script poses two problems, described in the following two subsections.

7.1 Generating the original tokenization

As discussed in Section 5, the tokens forming the leaves in the syntactic trees are sometimes modified forms of words from the original text. The first aspect of the problem is to undo these modifications.

Recombining words  Section 5 showed an example of how some words were split apart for purposes of annotation. We restored such cases based on information in the treebank about which words had been split. For example, in the tree (2), meyns and tu are combined as meynstu.

Each word must have a single associated POS label to be used in training/evaluation data for the POS tagger, and so we connect the labels for each of the two split words with a ~. In the example at hand, (VBF meyns) and (PRO tu) are combined as (VBF~PRO meynstu). There are 53 such combined tags, which occur on 2,405 words. Table 1 shows the 20 most common such cases, accounting for 96.34% of the 2,405 words with combined tags.

Splitting words  Sometimes, the inverse of the previous case occurs, in which the source text had two separate words that were combined as one

| tag      | count | example word |
|----------|-------|--------------|
| P~D      | 648   | oyf~n        |
| RP~VBN   | 435   | on~gehoynbn  |
| RP~VB    | 249   | on~heybn     |
| ADV~VBN  | 219   | avek~geshtelt|
| ADV~VB   | 140   | aroys~kumen  |
| VBF~PRO  | 105   | bistu        |
| MDF~PRO  | 76    | vestu        |
| PRO~VBF  | 75    | kh'hob       |
| PRO~HVF  | 59    | kh'hob       |
| PRO~MDV  | 51    | kh' vel      |
| NEG~ADV  | 49    | nit~o        |
| P~WPRO   | 41    | far~vos      |
| RP~TO~VB | 33    | oyf~tsu~shteyn|
| WADV~Q   | 27    | vi~fl        |
| RP~VAN   | 25    | on~geton     |
| HVF~PRO  | 19    | hostu        |
| VBI~PRO  | 19    | lo~mir       |
| ES~VBF   | 18    | s'iz         |
| ADV~TO~VB| 16    | avek~tsu~geyn|
| BEF~PRO  | 13    | bistu        |

Table 1: The 20 most common cases of combined POS tags. We also include the most common word for each combined tag. In some cases we have inserted a ~ in the word as well, to indicate where it was originally split. kh'hob appears twice since hob can be HVF (auxiliary) or VBF (main verb). Likewise bistu appears twice since bist can be BEF (auxiliary) or VBF (main verb).

in the treebank. An underscore in the word indicates words that were so combined, as in (W ADV vi~azoy), ‘how so’ (literally ‘how so’). To generate the original tokenization for such cases, we simply split apart the words at the underscore, and append a _S0 and _S1 to the label that is appropriate for the joined word. In this case, that results in the two tokens (WADV S0 vi) and (WADV S1 azoy).

There are 34 new tags, resulting from 236 originally separate words that were combined into one in the treebank. The words that occur more than 10 times, accounting for 64% of all such cases, are shown in Table 2.

Results  The processing in this section, with the combining and splitting of PPCHY tokens, resulted in 82,675 tokens (compared to the 83,457 before). The steps of recombining and splitting words resulted in a substantial increase in the total number of different POS tags, from 68 to 155. Some of the combinations are very infrequent, and this is an area that will be revisited in future work. See
Table 2: The six most common cases of words that were combined in the treebank and then split to generate the original tokenization. They account for 64% of all cases.

Appendix C for the complete tagset.

7.2 Conversion to Yiddish script

At this point, with the creation of appropriate tokens, all that remains is to convert them to the original Yiddish script. As discussed in Section 2, the conversion from the romanized form to Yiddish script is not so straightforward, in significant part because there is no simple correspondence between the romanized form of a “non-phonetic” component word and its representation in Yiddish script. Another example of this in (1), with the romanized name rokhš, corresponding to רוקחל. Applying the rules for the “phonetic” component to rokhš would result in the incorrect רוקחלדרו, which has an extra vowel and uses the ד character instead of ה for kh.

We carried out the conversion with a wrapper around calls to the yiddish Python library.11 The library includes code for converting between the different representations, utilizing an extensive list of such non-phonetic cases. The wrapper overrides the results in some cases. For example, in some cases we used the POS tag of a word to determine the correct conversion, such as for the shem case mentioned in Section 2. This is discussed, along with the some more details of our usage of the yiddish package, in Appendix D.12

8 Embeddings Trained on the YBC

8.1 Contextualized embeddings

As mentioned in Section 3, the XLM-roberta-base multilingual embeddings include a (relatively) small amount of Yiddish in their training data. We carry out continued pretraining using YBC, for 1, 2, 5, and 10 epochs. For more details of the training of the embeddings, see Appendix E.

8.2 Non-contextualized embeddings

Non-contextualized embeddings such as GloVe (Pennington et al., 2014), where every occurrence of a word has a single vector, perform worse than contextualized embeddings such as XLM-roberta-base, where each occurrence of a word may have a different vector. However, non-contextualized embeddings can still be useful to illustrate the relations among embeddings. Here we use GloVe embeddings trained on the YBC corpus, with a dimension of 300. See Appendix F for further details on the training of these embeddings.

Table 3 shows four examples of the embedding relationships. For each of the examples, we have selected one word and identified the two most “similar” words by finding the words with the highest cosine similarity to them based on the GloVe embeddings. The last column is the number of occurrences of that word in the YBC corpus.
8.2.1 Embeddings identifying alternate spellings

The first word listed is *badaytung* ‘significance, meaning’. The two closest words to it are alternate spellings. In the first, *badeytung*, *ay* (‘*) is written as *ey* (*’), without the diacritic marker below, as is often the case. In fact, while *badeytung* is the correct spelling, the version without the diacritic is far more common (12,082 vs. 788). The next word, *baditung*, is another nonstandard spelling, though a very infrequent one (141).

This example shows how the embeddings can capture relationships among alternate spellings without requiring prior “standardization” of the texts. The second example is another such case. The word is the nonstandard spelling for *ehnlikh* ‘similar’. The word closest to it by cosine similarity is *enlekh*, which is actually the “standard” form, and in this case it is far more frequent than the nonstandard form, which differs both in the vowel (*i* for *e*), and in the extra *h*, added by analogy to the spelling of the cognate word in German. The next word, *enlikh*, is yet another variant spelling.

The third example returns to the example mentioned in Section 4. The two variants, *ems’n* and *emsn*, are in a close relationship, as we hoped would be the case. In addition, our procedures identifies yet another variant, *ems’en*, with an extra *e* before the final *n*.13,14

8.2.2 Embeddings identifying OCR errors

The fourth example is somewhat different. Here the word *bur* ‘ignoramus, boor’ is an actual word, as is the word closest to it, *bud* ‘shop, stall’. However, given their distributional similarity and the similarity in the final letters, which could be easily confused, what seems far more likely is that these are OCR errors for the next word closest to them, *bukh* ‘book’, and this is indeed the case for the instances of *bur* and *bud* that we have spot-checked.

This example shows the potential for word embeddings trained on the YBC collection to help find OCR errors for correction. Ideally, integrating contextualized embeddings into an OCR detection system could find such cases on a sentence-by-sentence basis - that is, deciding for each occurrence of *bur* or *bud* if it is a likely OCR error in that sentence or a genuine instance of the word (Nguyen et al., 2021; Rigaud et al., 2019).

9 POS Tagger Training and Evaluation

We trained a tagger using five versions of the XLM-roberta-base embeddings - the standard version and four variants with different amounts of continued pretraining on YBC, as discussed in Section 8.1. For completeness, we also also trained the tagger using the GloVe embeddings discussed in Section 8.2.

Our POS tagger is implemented using the Flair library (Akbik et al., 2019), slightly adapting their sample script for training. The XLM-roberta-base embeddings are used in a model consisting of a linear layer on top of the transformer embeddings, predicting a score for each POS tag. Additionally, we incorporate parameters for the transitions between each pair of POS tags so that the resulting model has the form of a linear chain conditional random field (CRF). Training is conducted using a sentence-level CRF loss computed using forward-backward, while Viterbi decoding is used for inference at test time. The model using the GloVe embeddings is similar, with the addition of another linear layer and bidirectional LSTM on top of the embeddings before the linear layer and CRF. See Appendix G for further details.

The amount of training and evaluation data we have (82,675 tokens) is very small compared e.g. to POS taggers trained on the 1 million words of the PTB. With such a small amount of data for training and evaluation, and that from only two sources, we used a 10-fold stratified split. Each of the 10 splits has 90% of the text for training, 5% for validation, and 5% for testing. The validation section is used to select the best model during training. The training, validation, and test sections are all balanced between the two sources, with 79% from Olsvanger (1947) and 21% from Hirshbein (1977).

10 Results

10.1 Results on the PPCHY evaluation

Table 4 shows the results for each of the six configurations and for the validation and test sections. Each cell shows the mean and standard deviation across the 10 splits. Unsurprisingly, the results using GloVe are below the results using XLM-roberta-
Table 4: Cross-validated POS tagging results, for the six configurations of the POS tagger, differing on the embeddings used. The first row shows the results with GloVe embeddings, and the other rows show the results using the XLM-roberta-base with the number of epochs of continued pretraining on YBC in parentheses. The row xlm-rb (0) is XLM-roberta-base without any continued pretraining. Each cell shows the mean and standard deviation of the POS accuracy over the 10 validation or test sections.

| embeddings | validation | test |
|------------|------------|------|
| glove      | 96.71 (0.39) | 96.35 (0.25) |
| xlm-rb (0) | 98.06 (0.27) | 97.71 (0.29) |
| xlm-rb (1) | 98.40 (0.28) | 98.23 (0.25) |
| xlm-rb (2) | 98.46 (0.26) | 98.26 (0.23) |
| xlm-rb (5) | 98.50 (0.22) | 98.21 (0.23) |
| xlm-rb (10)| 98.44 (0.20) | 98.21 (0.26) |

10.2 Limitations of the evaluation

The evaluation just presented is significantly incomplete because of the limited amount and range of gold-standard annotated data. The test sections all come from the PPCHY corpus. As discussed above, we aim to tag and parse the YBC corpus, the one epoch of continued pretraining further improves the results, and further pretraining results in incremental increases and then a dropoff.

To get a better idea of the performance and improvement on particular tags, in Table 5 we break down the (xlm-rb(0), ‘test’) and (xlm-rb(2), ‘test’) cells from Table 4 into F1 scores. The first line has the totals, just as in Table 4. Since PUNC, the most common tag, has an almost perfect score, the second line shows the score for all tags excluding PUNC. We were also particularly interested in how well the tagger does on the complex tags with a tilde separating the components (as discussed in Section 7.1), and this result is shown in the third row. While the total w/o PUNC increases by 0.66 (97.21 to 97.87) with two epochs of pretraining, the combined tags increase by 1.44 (from 94.76 to 96.20). Below those three lines, we show the scores for the individual tags. They show a general increase, with a few exceptions, across all tags with the two epochs of pretraining.

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Table 5: A breakdown of the accuracy scores for the test section for the xlm-rb (0) and xlm-rb (2) configurations from Table 4, showing the mean and standard deviation F1 scores for each tag over the 10 test sections. The “count” column reports the mean number of occurrences of the POS tag over the 10 test sections.

| count | xlm-rb (0) | xlm-rb (2) |
|-------|------------|------------|
| Total | 4145.40 | 97.71 (00.29) | 97.26 (00.23) |
| no PUNC | 3391.50 | 97.21 (00.34) | 97.87 (00.28) |
| tilde | 123.40 | 94.76 (01.98) | 96.20 (01.49) |
| PUNC | 753.90 | 99.99 (00.02) | 99.99 (00.02) |
| N | 523.90 | 97.45 (00.53) | 98.19 (00.50) |
| PRO | 598.50 | 99.30 (00.20) | 99.49 (00.29) |
| D | 333.50 | 99.64 (00.29) | 99.62 (00.30) |
| ADV | 244.60 | 97.79 (00.65) | 98.50 (00.51) |
| F | 193.60 | 98.06 (00.83) | 98.56 (00.72) |
| NPR | 136.80 | 98.44 (01.53) | 98.62 (01.62) |
| VBN | 132.00 | 99.30 (00.62) | 99.20 (00.74) |
| VB | 119.00 | 97.64 (00.98) | 98.58 (00.68) |
| HVF | 104.60 | 99.85 (00.24) | 99.96 (00.14) |
| ADJ | 100.40 | 90.92 (02.66) | 94.11 (01.87) |
| MDF | 84.20 | 98.29 (01.23) | 98.35 (01.32) |
| C | 70.80 | 96.45 (01.55) | 97.07 (01.68) |
| NEG | 57.80 | 99.20 (00.71) | 99.47 (00.58) |
| BEF | 51.20 | 98.77 (00.93) | 98.73 (00.99) |
| Q | 45.90 | 96.73 (01.76) | 97.53 (01.27) |
| WPRO | 43.30 | 96.21 (02.14) | 97.34 (01.06) |
| INTJ | 35.90 | 93.52 (02.89) | 94.85 (03.31) |
| P~D | 35.50 | 97.87 (01.54) | 98.67 (01.53) |
| H | 24.70 | 84.46 (10.13) | 85.45 (09.24) |
| PROS | 24.10 | 98.95 (01.52) | 100.00 (00.00) |
| VBI | 23.00 | 89.69 (05.16) | 93.11 (05.85) |
| RP~VBN | 21.80 | 97.80 (02.78) | 98.18 (01.83) |

11 Conclusion and Next Steps

We have presented here the first steps toward the larger goal of training a POS tagger and syntactic parser to automatically annotate a large cor-
pus of Yiddish. We trained embeddings on the YBC corpus and created a unified representation for the annotated data from the PPCHY and the unannotated YBC. Using the framework based on a cross-validation split for training and evaluating a POS tagger trained on the PPCHY, we showed that even with such limited training and evaluation data, continued pretraining on embeddings using YBC resulted in improved performance.

11.1 Future work

As discussed in Section 10.2, we require more gold POS-annotated text to evaluate the tagger on. We plan to create the requisite data by tagging samples from the YBC corpus and manually correcting the predicted POS tags.

We will also be training and evaluating a syntactic parser in addition to the POS tagger, using the PPCHY annotation. This will mostly follow the training/evaluation framework established above. Just as with the POS tagger, we will need additional evaluation data, this time manually annotated with gold syntactic trees. Given the greater complexity of a parser, the need for gold data is correspondingly more pressing.

We are also interested in POS-tagging the YBC corpus and in exploring the possibility mentioned at the end of the introduction and in Section 8.2.2 of using the methodology and results reported here to augment the search capabilities on the YBC, to identify variant spellings, and to locate OCR errors for correction.

12 Acknowledgments

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A The Yiddish Book Center Corpus

A.1 Initial downloading and text extraction

We first carried out the following steps:

1. We downloaded 10,970 MARC files from the nationalyiddishbookcenter collection on the internet archive.

2. For each such MARC file $<id>$, we downloaded the corresponding html file at https://ocr.yiddishbookcenter.org/contents?doc=<id>.

3. 9,925 of the MARC files had a corresponding html file with the OCR text.

4. We extracted the OCR content from each file, removing the header and footer and so on. We retained the page number indicators.

5. We normalized all the files with NFC normalization, and also did some additional minor normalization, such as changing occurrences of “no-break space” (unicode a0) to a regular space, and the em dash (2014) to a hyphen.

6. We removed 120 files containing very rare characters, leaving 9,805 files to work with.

While extracting the OCR content, we also stored each line as two tab-delimited fields, where the second is the actual text, and the first is a sentence identifier with the page number of the source pdf (extracted from the page number attribute in the html), together with the line number within that page. This proved useful for looking up particular cases of words.

B Aspects of the YBC

B.1 Apostrophes as commas

It is sometimes the case that an apostrophe is OCR’d as a comma - e.g. in one instance $ךַרַג$ is OCR’d as $ך,רג$. In future processing we will adjust the tokenization to account for such cases.

B.2 Pointed Yiddish characters

There are some files in which the Yiddish script has extensive use of diacritics to (redundantly) represent vowels, lowering the OCR accuracy for such files. For example, an instance of $ךַרַג$ is OCR’d as $ך,רג$. In future processing we will adjust the tokenization to account for such cases.

B.3 Unusual words and OCR errors

We sorted all the word tokens by frequency (after the tokenization step described in Section 4) and examined some cases that seemed unexpected. There were two types of cases we looked at, as described below in Sections B.3.1 and B.3.2. We made no further study of the unexpected character sequences beyond the cursory checking described. Our goal was to start exploring how combining this sort of analysis with cases such as the fourth example in Section 8 and some combination of manual and automated correction might be used for post-OCR text correction.

B.3.1 Words with a word-medial final form

There are five characters in the Yiddish script with a form that only appears at the end of a word (or before a hyphen in a compound). A search of the word list for exceptions to this rule revealed 269,814 different words, 2.5% of the 10,642,884 different words in the corpus. They totalled 427,855 occurrences, 0.07% of the 653,326,190 words in the corpus. 237,926 of the 269,814 words (88.2%) occur only once in the corpus.

While such cases are relatively infrequent, we were curious as to what they could be. Some of the most common cases were not OCR errors, but rather resulted from the joining of words split over a line. For example, the second most common case was ר��דראס ארצדישר ‘land of Israel’ with the final form ר in the middle of the word. Spot-checking a few revealed that they arose from רלדראס ארצדישר split over a line, with a hyphen originally ending the line and being removed at some point.

Other cases were genuine OCR errors. The example above in Section B.2 with the pointed Yiddish characters is one such case, with the incorrect word-medial ר in the incorrect OCR word. There are a variety of other cases. As another example, in one instance רע א ‘and a’ was OCR’d as רע,א.

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The html files were downloaded on April 9, 2021.
B.3.2 Low-frequency words

We also carried out some cursory spot-checking of low-frequency words that seemed suspect. For example, הָדַנְיָה groyee occurs 73 times, and checking the first such instance, the word in the source text is actually הָדַנְיָה groyse 'big'.

C Tagset

Table 6 shows the final tagset after the combining and splitting of words described in Section 7.1.

D Conversion to Yiddish Script

The default conversion for each word uses the yiddish package call:

```
yiddish.detransliterate(<word>, loshn_koydesh=True)
```

where <word> is the romanized word. The loshn_koydesh flag indicates that it should convert to a Hebrew/Aramaic word if there is one corresponding to <word>.

In addition, for words with a hyphen, our wrapper converts the individual components separately - e.g. (P~N~P) far-peysekh ‘before Passover’, with the results joined together. In general (but not always, as mentioned below), the hyphenated words need to be split apart and converted separately to obtain the correct conversion.

D.1 Handing special cases

There are a variety of special cases, mostly resulting from minor discrepancies between the romanization in PPCHY and what was required by yiddish.detransliterate. See the code convert_to_script.py in the ppchyprep package mentioned in footnote 12 for complete details, but roughly:

1. For some (word, pos) cases, the loshn_koydesh flag is set to False, when the Hebrew word was not the one desired - e.g. (VBI shem) (the example from Section 2).

2. For some words with a hyphen, the hyphen needs to first be removed to return the correct conversion - e.g., (N eyn-hore) ‘evil eye’.

3. In other cases, words with a hyphen need to be passed in as a unit instead of the default of being done separately - e.g. (N beys-hamigdesh)‘Temple in Jerusalem’.

4. Miscellaneous cases in which we hard-coded the correct conversion, without calling detransliterate. A number of these cases include Hebrew words quoted in the material and not included in the yiddish conversion.

5. There are a number of cases in which the romanization in the PPCHY was not quite the same as what was expected by yiddish, and in such cases we simply modify the word before passing it to detransliterate - e.g. changing (RP-H maskim)) to (RP-H maskem))

D.2 Testing the conversion

In earlier work, we had implemented our own conversion of the romanization to Yiddish script and tested the algorithm by comparing the converted version of Hirshbein (1977) to the original Yiddish script source text of the play. While the exact edition used for the treebank is not part of the YBC corpus, we used an earlier edition (Hirshbein, 1951). We carried out a Smith-Waterman alignment between the words in the two versions and manually inspected it to verify the correctness of the conversion. This procedure caught a number of the non-phonetic words that had not been converted properly.

While we are now using the yiddish package instead of that earlier conversion code, we compared all cases where the yiddish package gave different results from our earlier conversion code. While in some cases the new conversion was correct, that was not always the case, and this process identified a number of the cases that were then handled as discussed in Section D.1. In future work we will again directly compare the converted version to the Yiddish script source text using Smith-Waterman.

The other text that we are using, from Olsvanger (1947), lacks an original source text in Yiddish script, since the source text was written in a romanized dialect representation. We are in effect converting it to a non-existent Yiddish script source. In the earlier version, we tested the conversion by reasoning that if a non-phonetic word was incorrectly converted from the romanized form to Yiddish script, the resulting ”word” would likely never appear in the YBC corpus, and so we checked whether each converted word exists in the YBC corpus. In future work we can test the current conversion in the same
| tag       | count | tag       | count | tag       | count |
|-----------|-------|-----------|-------|-----------|-------|
| PUNC      | 15,107| QR        | 46    | RP-H_S0   | 4     |
| N         | 10,305| RP-ADJ    | 42    | RP-H_S1   | 4     |
| PRO       | 7,981 | P-WPRO    | 41    | TO-VB     | 4     |
| D         | 6,651 | Q_S0      | 39    | WPRO5     | 4     |
| VBF       | 4,940 | Q_S1      | 39    | C-NEG     | 3     |
| ADV       | 4,193 | ADVR      | 36    | LS        | 3     |
| P         | 3,813 | RDN       | 35    | NUM_S3    | 3     |
| NPR       | 2,706 | NEG_S0    | 34    | N_S0      | 3     |
| VBN       | 2,603 | NEG_S1    | 34    | N_S1      | 3     |
| CONJ      | 2,505 | RP-TO-VB  | 33    | P-N       | 3     |
| VB        | 2,364 | NPRS$     | 31    | WADV-FP   | 3     |
| HVF       | 2,084 | RP-N      | 31    | NPR_S0    | 2     |
| ADJ       | 2,055 | X         | 29    | NPR_S1    | 2     |
| MDF       | 1,663 | VAG       | 28    | NPR_S2    | 2     |
| ADV~VB    | 1,414 | VX        | 27    | P-D-N     | 2     |
| NEG       | 1,151 | WADV-Q    | 27    | ADJ_S0    | 1     |
| BEF       | 1,013 | RP-VAN    | 25    | ADJ_S1    | 1     |
| Q         | 936   | WD        | 25    | ADV-1     | 1     |
| WPRO      | 864   | FW        | 24    | ADV-FP    | 1     |
| INTJ      | 685   | NUM_S0    | 21    | ADV-VAG   | 1     |
| P-D       | 648   | NUM_S1    | 21    | C_S0      | 1     |
| PROS      | 496   | HVF-PRO   | 19    | C_S1      | 1     |
| H         | 486   | VBI-PRO   | 19    | DR+P_S0   | 1     |
| VBI       | 456   | ES-VBF    | 18    | DR+P_S1   | 1     |
| RP~VBN    | 435   | ADV~TO-VB | 16    | ES-BEF    | 1     |
| NUM       | 395   | BE        | 16    | ES-HVF    | 1     |
| RP        | 370   | RD        | 15    | FP-ADV    | 1     |
| WADV      | 363   | RP-V      | 15    | FP-D      | 1     |
| ES        | 252   | WADV_S0   | 15    | H_S2      | 1     |
| RP~VB     | 249   | WADV_S1   | 15    | MD-IPP    | 1     |
| FP        | 245   | BEF-PRO   | 13    | MDF-ADJ   | 1     |
| TO        | 245   | BEN       | 13    | MDF-NEG   | 1     |
| MDN       | 221   | WPRO-FP   | 13    | MDF-VB    | 1     |
| ADV~VBN   | 219   | VBD-BL    | 12    | NEG-VAG   | 1     |
| RP-H      | 147   | H_S0      | 10    | P-DBL-DR+P| 1     |
| ADV~VB    | 140   | H_S1      | 10    | P-NPR     | 1     |
| VLF       | 133   | NUM_S2    | 9     | F-PRO-VB  | 1     |
| RP-ADV    | 107   | ES-MDF    | 7     | QTP       | 1     |
| VBF-PRO   | 105   | P-DDBL    | 7     | Q-D       | 1     |
| DR+P      | 96    | P_S0      | 7     | RP-N-VBN  | 1     |
| ADV_S0    | 93    | P_S1      | 7     | RP-VAG    | 1     |
| ADV_S1    | 93    | PRO-BEF   | 6     | VB-1      | 1     |
| MDF-PRO   | 76    | RP-ADV-VB | 6     | VB-DL-RSP | 1     |
| PRO-VBF   | 75    | ADV-VAN   | 5     | VB-LFD    | 1     |
| VAN       | 68    | HVN       | 5     | VBI-FP    | 1     |
| PRO-HVF   | 59    | PRO-VLF   | 5     | WADV-P-1  | 1     |
| ADJR      | 56    | RDF       | 3     | WADV-2    | 1     |
| MD        | 56    | D-N       | 4     | WADV-MDF  | 1     |
| NS        | 52    | INTJ_S0   | 4     | WPRO_S0   | 1     |
| PRO-MDF   | 51    | INTJ_S1   | 4     | WPRO_S1   | 1     |
| ADJS      | 49    | P-PRO     | 4     | WPRO-PRO  | 1     |
| NEG~ADV   | 49    | RP-ADV-VBN| 4     | total     | 82,675|

Table 6: The complete tagset of 155 tags
Table 7: Parameters used for continued pre-training of XLM-roberta-base. These were the input parameters to the run_mlm.py script in the hugging face transformers package.

| parameter              | value             |
|------------------------|-------------------|
| model_name_or_path     | xlm-roberta-base  |
| fp16                   | True              |
| per_device_train_batch_size | 16              |
| gradient_accumulation_steps | 16              |
| per_device_eval_batch_size | 16              |

Table 8: Split of the YBC corpus for training embeddings

| section | # files | #tokens     |
|---------|---------|-------------|
| train   | 9714    | 647,885,718 |
| val     | 91      | 5,440,472   |
| total   | 9805    | 653,326,190 |

Table 9: Parameters used for training GloVe embeddings

| parameter | value |
|-----------|-------|
| memory    | 100.0 |
| min_count | 5     |
| vector_size | 300   |
| iter M    | 25    |
| window_size | 10    |
| binary    | 2     |
| x_max     | 10    |

Table 10a: Parameters used for training POS models with XLM-roberta-base embeddings

Table 10b: Parameters used for training POS models using GloVe embeddings

D.3 Alternate converted forms

The yiddish library converts the words to a SYO form. As discussed in Section 2, the words in the YBC corpus have a great deal of spelling variation and do not necessarily follow the SYO. In addition to the sort of spelling variations mentioned in that section, they differ on the use of diacritics.

We therefore created two alternate forms of the words from the conversion of the PPCHY files for use in training and evaluation of the POS tagger. The first alternate form results from replacing מ" (pasekh tsvey yudn) with מ" (tsvey yudn). The second alternate form results from also replacing ק" (paskeh alef) with ק" (shtumer alef) and ק" (khirek yud) with ק" (yud).

We do not discuss the results with these alternate forms in this paper, but they did not improve the current results. However, as discussed in Section 10.2 and the conclusion, our evaluation data is currently very limited, and we will revisit the use of these alternate forms when evaluating the tagger with material from the YBC and elsewhere. The software in ppchyprep contains the code for producing these alternate forms.

E Contextualized Embeddings Trained on the YBC

The training consisted of 10 epochs of continued pretraining on XLM-roberta-base. Since it was continued pretraining, it used the existing configuration for XLM-roberta-base, including the tokenization. The parameters used for the continued pretraining are in Table 7.

Of the 9805 files in the YBC corpus, 1% were randomly put into the validation section. The result of the 9805 files in the YBC corpus, 1% were randomly put into the validation section. The result

18A version of this material in Yiddish script has recently appeared (Olsvanger, 2022) - https://forward.com/yiddish/548219. The same procedure as with Hirshbein (1977) could therefore be carried out, but only with an electronic copy of the material.

F Non-contextualized Embeddings Trained on the YBC

The GloVe embeddings were trained using version 1.2 of GloVe, with the parameters shown in Table 9. The same train/val split of the YBC corpus was used as for the contextualized embeddings.

G POS Tagger Training

The POS models were trained with version 0.12.2 of Flair, with a slightly modified form of their supplied run_ner.py script. The parameters used for training the POS models with XLM-roberta-base embeddings are shown in Table 10a, and those used for training the models using GloVe embeddings are shown in Table 10b.

With use_final_model_for_eval set to False, the validation section was used to save the model with the best performance on that section. In both cases we omit parameters referring to the name or location of the embeddings, output directory, etc.
| parameter          | value       |
|-------------------|-------------|
| layers            | 1           |
| subtoken_pooling  | first       |
| fine_tune         | True        |

**SequenceTagger**

| hidden_size       | 256         |
| use_crf           | False       |
| use_rnn           | False       |
| reproject_embeddings | False   |

**ModelTrainer**

| learning_rate     | 5e-5        |
| mini_batch_size   | 32          |
| mini_batch_chunk_size | 1       |
| max_epochs        | 50          |
| weight_decay      | 0.0         |
| optimizer         | torch.optim.AdamW |
| scheduler         | LinearSchedulerWithWarmup |
| warmup_fraction   | 0.1         |
| use_final_model_for_eval | False |

(a) Using XLM-roberta-base embeddings

| parameter          | value       |
|-------------------|-------------|
| hidden_size       | 256         |
| tag_type          | pos         |
| use_crf           | True        |
| use_rnn           | default (True) |
| reproject_embeddings | default (True) |

**ModelTrainer**

| learning_rate     | 0.1         |
| mini_batch_size   | 32          |
| mini_batch_chunk_size | 1       |
| max_epochs        | 50          |
| use_final_model_for_eval | False |

(b) Using GloVe embeddings

| parameter          | value       |
|-------------------|-------------|
| WordEmbeddings    | (all default) |

Table 10: Parameters used for training POS tagger