Leveraging Subword Embeddings for Multinational Address Parsing [1]

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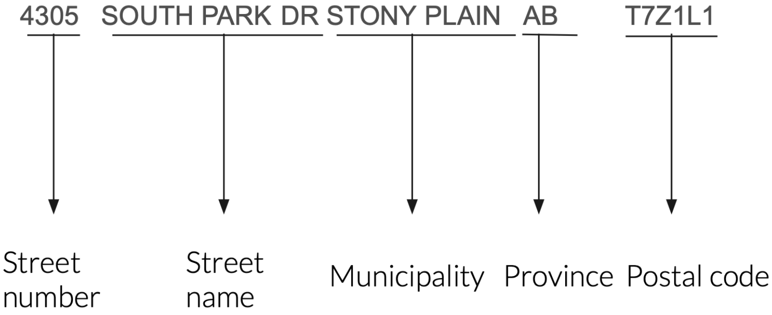
1. https://arxiv.org/abs/2006.16152

Agenda

Introduction

What's address parsing ?



Useful for tasks such as *Record Linkage* and *Geocoding*.

Agenda

Related Work - Address Parsing for One Country

- Rule based methods

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  - Conditional Random Fields (CRF) [Wang et al., 2016]
- Neural networks
  - Feed-forward Neural Network [Sharma et al., 2018]
  - Recurrent Neural Networks [Mokhtari et al., 2019]

Related work - Multinational address parsing

Libpostal [1]

- CRF based model

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No previous neural network approaches for multinational address parsing

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Word embedding : vector representation of a word

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Subword embedding : vector representation of a unit

- Character level
- Character *n-grams* (e.g : *fastText*)
- Byte pair embeddings (*BPEmb*) [Heinzerling and Strube, 2017]

Why subword embeddings ?

Multilingual setting

- Need of alignement vectors (*Muse* [Conneau et al., 2017])
- *fasText* support for OOV
- *MultiBPEmb* pre-trained on 275 languages

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- A encoding of words using MultiBPEmb and merge the obtained embeddings for each word into one word embedding using a Bidirectional LSTM (Bi-LSTM) (hidden state dimension of 300). We refer to this embeddings model technique as **BPEmb**.

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We run a comparison of the two methods (**fastText** and **BPEmb**) to evaluate which one gives better results in our setting.

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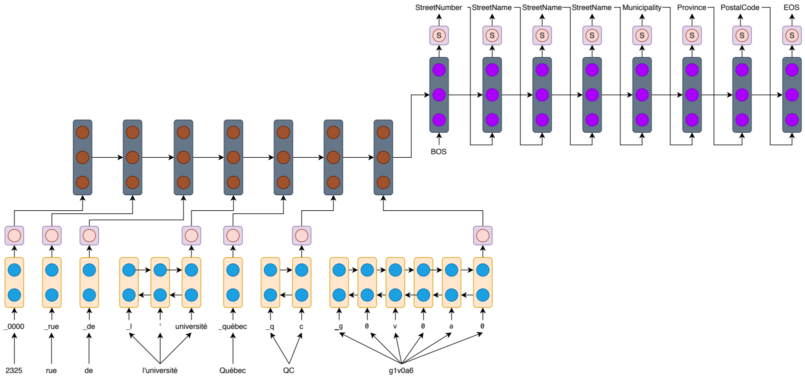
Both the encoder's and decoder's hidden states are of dimension 1024.

Architecture



About the Data

- Built using the open-source data on which Libpostal's models were trained.

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- Built using the open-source data on which Libpostal's models were trained.
- Contain 61 countries.
- We used eight tags : StreetNumber, StreetName, Unit, Municipality, Province, PostalCode, Orientation, and GeneralDelivery [1].

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Examples of Address and Their Patterns

We use five different address patterns (one for each color) and another for some countries' using more than a pattern (no color).

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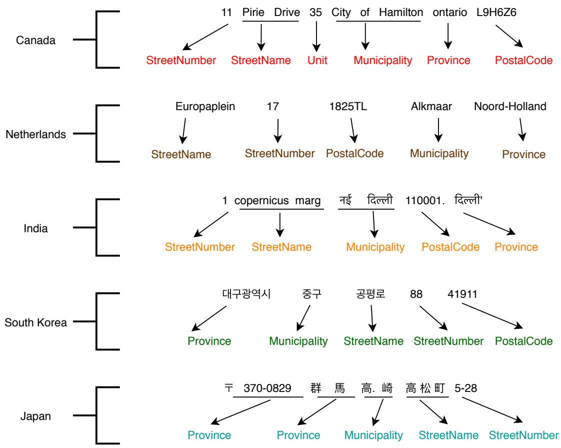

Training Data and Holdout Test Set

20 countries are used for multinational training with a sample size of $100,000$ per country. The rest is used as a holdout (table below).

Country	Number of samples	Country	Number of samples	Country	Number of samples	Country	Number of samples
United States	8,000,000	Germany	1,576,059	Poland	459,522	Czechia	195,269
Brazil	8,000,000	Spain	1,395,758	Norway	405,649	Italy	178,848
South Korea	6,048,106	Netherlands	1,202,173	Austria	335,800	France	20,050
Australia	5,428,043	Canada	910,891	Finland	280,219	United Kingdom	14,338
Mexico	4,853,349	Switzerland	474,240	Denmark	199,694	Russia	8115

Zero-Shot Test Set

41 countries are used for zero-shot transfer evaluation (never seen in training) (table below).

Country	Number of samples	Country	Number of samples	Country	Number of samples	Country	Number of samples
Belgium	66,182	Slovenia	9773	Réunion	2514	Singapore	968
Sweden	32,291	Ukraine	9554	Moldova	2376	Bangladesh	888
Argentina	27,692	Belarus	7590	Indonesia	2259	Paraguay	839
India	26,084	Serbia	6792	Bermuda	2065	Cyprus	836
Romania	19,420	Croatia	5671	Malaysia	2043	Bosnia	681
Slovakia	18,975	Greece	4974	South Africa	1388	Ireland	638
Hungary	17,460	New Zealand	4678	Latvia	1325	Algeria	601
Japan	14,089	Portugal	4637	Kazakhstan	1087	Colombia	569
Venezuela	10,696	Lithuania	3126	New Caledonia	1036	Uzbekistan	505
Philippines	10,471	Faroe Islands	2982	Estonia	1024		

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- Teacher forcing [Williams and Zipser, 1989].
- Trained using Poutyne [Paradis, 2018].

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Multinational Evaluation

Country	**FastText**	**BPEmb**	Country	**FastText**	**BPEmb**
United States	$\mathbf{99.61 \pm 0.09}$	98.55 ± 2.19	Poland	$\mathbf{99.69 \pm 0.07}$	99.19 ± 1.39
Brazil	$\mathbf{99.40 \pm 0.10}$	98.54 ± 1.68	Norway	$\mathbf{99.46 \pm 0.06}$	97.98 ± 1.31
South Korea	99.96 ± 0.01	$\mathbf{99.99 \pm 0.02}$	Austria	$\mathbf{99.28 \pm 0.03}$	98.28 ± 1.56
Australia	$\mathbf{99.68 \pm 0.05}$	99.21 ± 1.17	Finland	$\mathbf{99.77 \pm 0.03}$	99.72 ± 0.30
Mexico	$\mathbf{99.60 \pm 0.06}$	98.55 ± 2.22	Denmark	$\mathbf{99.71 \pm 0.07}$	99.20 ± 1.38
Germany	$\mathbf{99.77 \pm 0.04}$	99.23 ± 1.30	Czechia	$\mathbf{99.57 \pm 0.09}$	98.77 ± 2.22
Spain	$\mathbf{99.75 \pm 0.05}$	98.65 ± 2.36	Italy	$\mathbf{99.73 \pm 0.05}$	98.91 ± 1.76
Netherlands	$\mathbf{99.61 \pm 0.07}$	99.26 ± 1.23	France	$\mathbf{99.66 \pm 0.08}$	98.65 ± 2.00
Canada	$\mathbf{99.79 \pm 0.05}$	99.19 ± 1.33	United Kingdom	$\mathbf{99.61 \pm 0.10}$	98.66 ± 2.11
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- South Korean results are excellent despite the completely different alphabet.

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- We find that South Korea is the only country where a perfect accuracy (100 %) was achieved using **BPEmb** (3 out of 5).
- Randomly reordering 6000 South Korean address as either the first (red) or the second (brown) address pattern (equally divided between the two), the mean accuracy drops to 28.04% (the mean accuracy is of 12.29 % using a random tags procedure).

Zero-shot Evaluation

Country	FastText	BPEmb	Country	FastText	BPEmb
Belgium	**88.14 ± 1.04**	87.45 ± 1.37	Faroe Islands	74.14 ± 1.83	**86.59 ± 2.21**
Sweden	81.59 ± 4.53	**88.30 ± 2.92**	Réunion	**96.80 ± 0.45**	92.42 ± 2.38
Argentina	**86.26 ± 0.47**	86.00 ± 4.40	Moldova	**90.18 ± 0.79**	78.11 ± 16.79
India	69.09 ± 1.74	**76.33 ± 7.77**	Indonesia	64.31 ± 0.84	**69.25 ± 2.81**
Romania	**94.49 ± 1.52**	90.52 ± 2.35	Bermuda	92.31 ± 0.60	**92.65 ± 1.84**
Slovakia	82.10 ± 0.98	**89.40 ± 5.09**	Malaysia	78.93 ± 3.78	**92.76 ± 2.55**
Hungary	**48.92 ± 3.59**	24.61 ± 3.35	South Africa	**95.31 ± 1.68**	92.75 ± 7.43
Japan	**41.41 ± 3.21**	33.34 ± 3.83	Latvia	**93.66 ± 0.64**	72.46 ± 5.77
Iceland	96.55 ± 1.20	**97.61 ± 0.98**	Kazakhstan	86.33 ± 3.06	**88.28 ± 11.32**
Venezuala	**94.87 ± 0.53**	89.82 ± 5.74	New Caledonia	**99.48 ± 0.15**	96.44 ± 5.64
Philippines	77.76 ± 3.97	**78.00 ± 11.75**	Estonia	**87.08 ± 1.89**	76.18 ± 1.62
Slovenia	95.37 ± 0.23	**96.47 ± 2.05**	Singapore	**86.42 ± 2.36**	83.23 ± 6.38
Ukraine	**92.99 ± 0.70**	90.86 ± 2.90	Bangladesh	78.61 ± 0.43	**79.77 ± 3.65**
Belarus	**91.08 ± 3.08**	90.16 ± 11.89	Paraguay	96.01 ± 1.23	**96.22 ± 1.78**
Serbia	**95.31 ± 0.48**	88.49 ± 7.05	Cyprus	**97.67 ± 0.34**	92.92 ± 6.94
Croatia	**94.59 ± 2.21**	88.17 ± 4.58	Bosnia	**84.04 ± 1.47**	80.53 ± 6.56
Greece	**81.98 ± 0.60**	35.30 ± 13.51	Ireland	**87.44 ± 0.69**	84.93 ± 2.85
New Zealand	94.27 ± 1.50	**97.77 ± 3.23**	Algeria	**85.37 ± 2.05**	79.66 ± 11.68
Portugal	**93.65 ± 0.46**	90.13 ± 4.47	Colombia	**87.81 ± 0.92**	87.60 ± 3.61
Bulgaria	**91.03 ± 2.07**	87.44 ± 11.94	Uzbekistan	**86.76 ± 1.13**	73.75 ± 3.42
Lithuania	**87.67 ± 3.05**	75.67 ± 2.19			

Zero-shot Evaluation

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Zero-shot Evaluation

- 50 % (19 out of 41) near state-of-the-art performance (> 90 %) for **fastText**. Or 35 % for **BPEmb**.
- 80 % (34 out of 41) good performance (> 80 %) for **fastText**. Or 65 % for **BPEmb**.
- The lowest results (below 70%) occur for countries where the address pattern and the country official language were not seen in the training data such as India, Hungary, and Japan.

Zero-shot Evaluation

For Hungary and Japan, the poorest results of all are mostly due to the address structure (blue), which is the near inverse of the two most present ones (red and brown) (never seen structure and language).

But, Kazakhstan, which uses the same address pattern as Japan, achieves better results. The main difference being the presence of one of the official language (Kazakh and **Russian**) in the training dataset.

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Future Work

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For more, read the full article `https://arxiv.org/abs/2006.16152`

Acknowledgment

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