Big Data Small Data, In Domain Out-of Domain, Known Word Unknown Word: The Impact of Word Representations on Sequence Labelling Tasks

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Introduction

The Impact of Word Representations for Sequence Labellings Tasks

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Distributed word representations, pre-trained from unlabelled data have become a mainstay of NLP, but. . . their quality depends on factors including:

- parameter optimisation
- the size of the training data
- the fit with the target application

Extrinsic evaluation on 4 labelling tasks under **FIX** experiment conditions:

- ✓ POS tagging
- ✓ Chunking
- ✓ NER
- ✓ MWE (multi-word expressions identification)

What we want to know about word embeddings

RQ1: Are word embeddings better than baseline approaches of one-hot unigram features and Brown clusters?

RQ2: To what degree can word embeddings reduce the amount of labelled data?

RQ3: What is the impact of updating word embeddings in sequence labelling tasks

RQ4: What is the impact of these word embeddings Out-of-Vocabulary items for *in-domain* and *out-of-domain* data?

RQ5: Are some word embeddings better than others in a sequence labelling context?

Experiments Setup

Fix the experiments conditions

- **Pre-trained word embeddings**
  - Corpora:
    - UMBC (Han et al.2013), 48.1GB
    - One Billion (Chelba et al.2013), 4.1GB
    - English Wikipedia, 49.6GB
  - Embedding dimensions:

    $d \in \{25, 50, 100, 200\}$
  - Context window size:

    $m \in \{1, 5, 10\}$

- **Selected Word Representations**
  - Brown clustering (Brown et al.1992)
  - CBOW (Mikolov et al.2013a),
  - Skipgram (Mikolov et al.2013b),
  - Global vectors (Pennington et al.2014)

Training, development and test data

	Training	Development	*In-domain* Test	*Out-of-domain* Test
POS tagging	WSJ Sec. 0-18	WSJ Sec. 19–21	WSJ Sec. 22–24	EWT
Chunking	WSJ	WSJ (1K sentences)	WSJ (CoNLL-00 test)	Brown
NER	Reuters (CoNLL-03 train)	Reuters (CoNLL-03 dev)	Reuters (CoNLL-03 test)	MUC7
MWE	EWT (500 docs)	EWT (100 docs)	EWT (123 docs)	—

RQ1: Word embeddings vs. one-hot unigram features vs. Brown clusters?

RQ2: To what degree can word embeddings reduce the amount of labelled data?

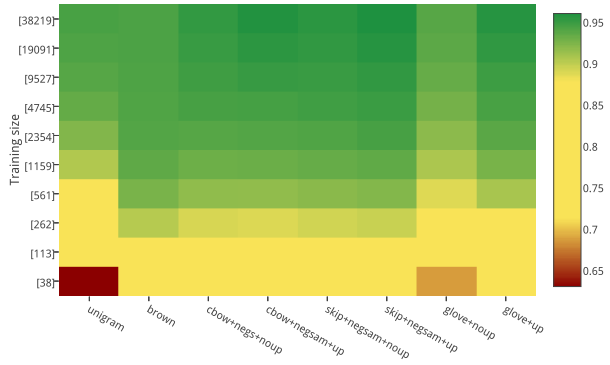


Figure : POS tagging (Acc)

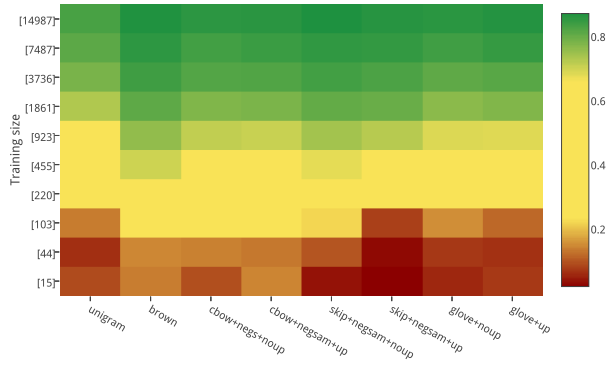


Figure : NER (F1)

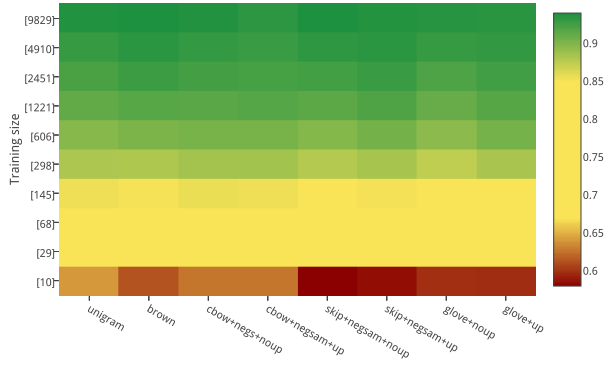


Figure : Chunking (F1)

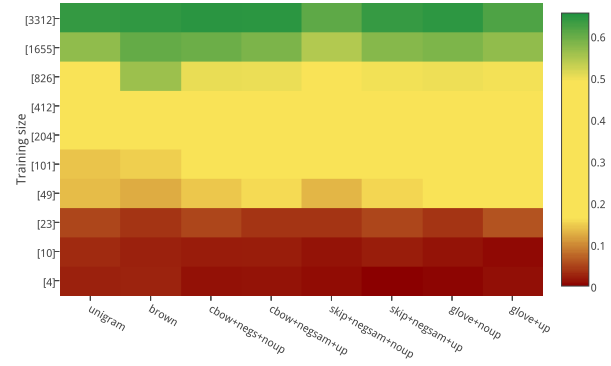


Figure : MWE (F1)

RQ3: : What is the impact of updating word embeddings geometrically over the vectors?

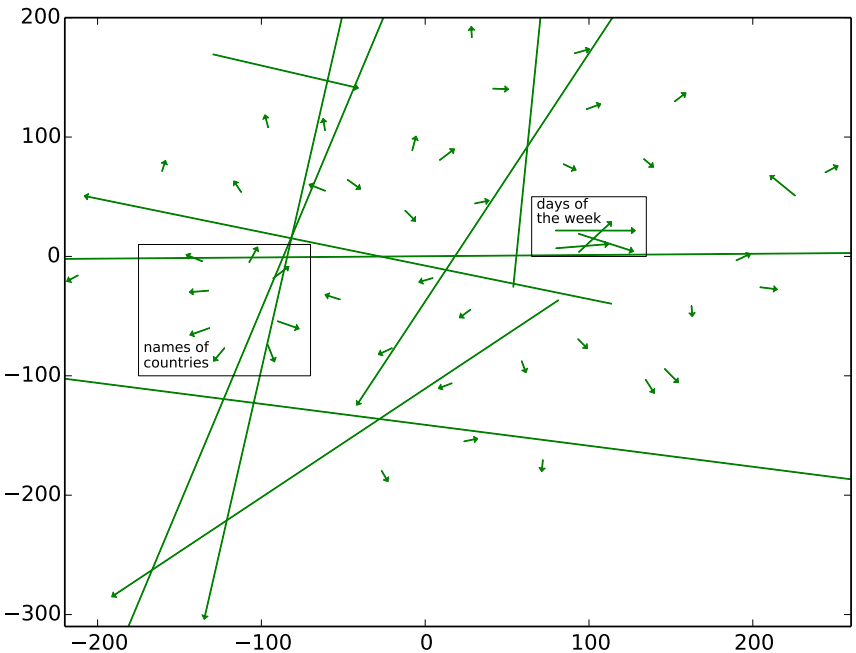


Figure : Chunking with SKIP-GRAM

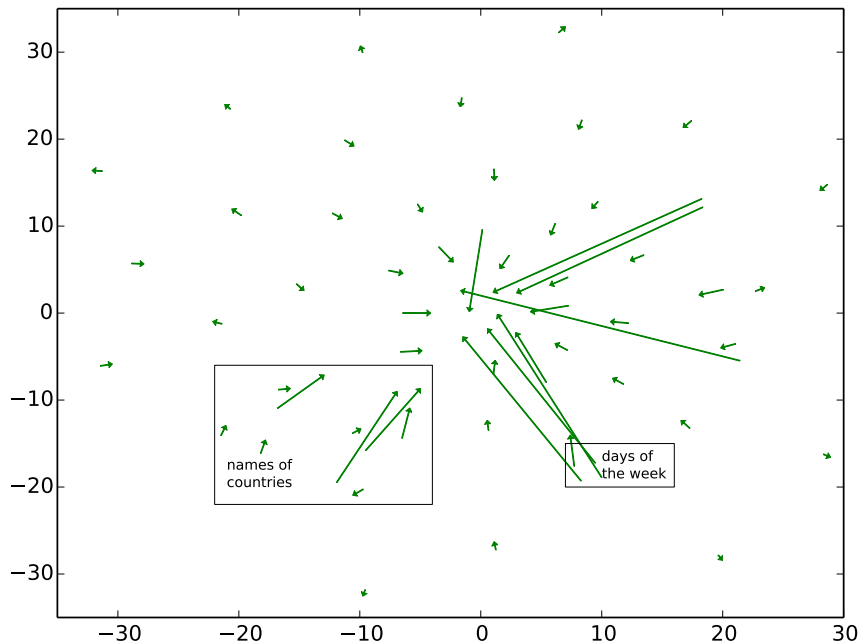
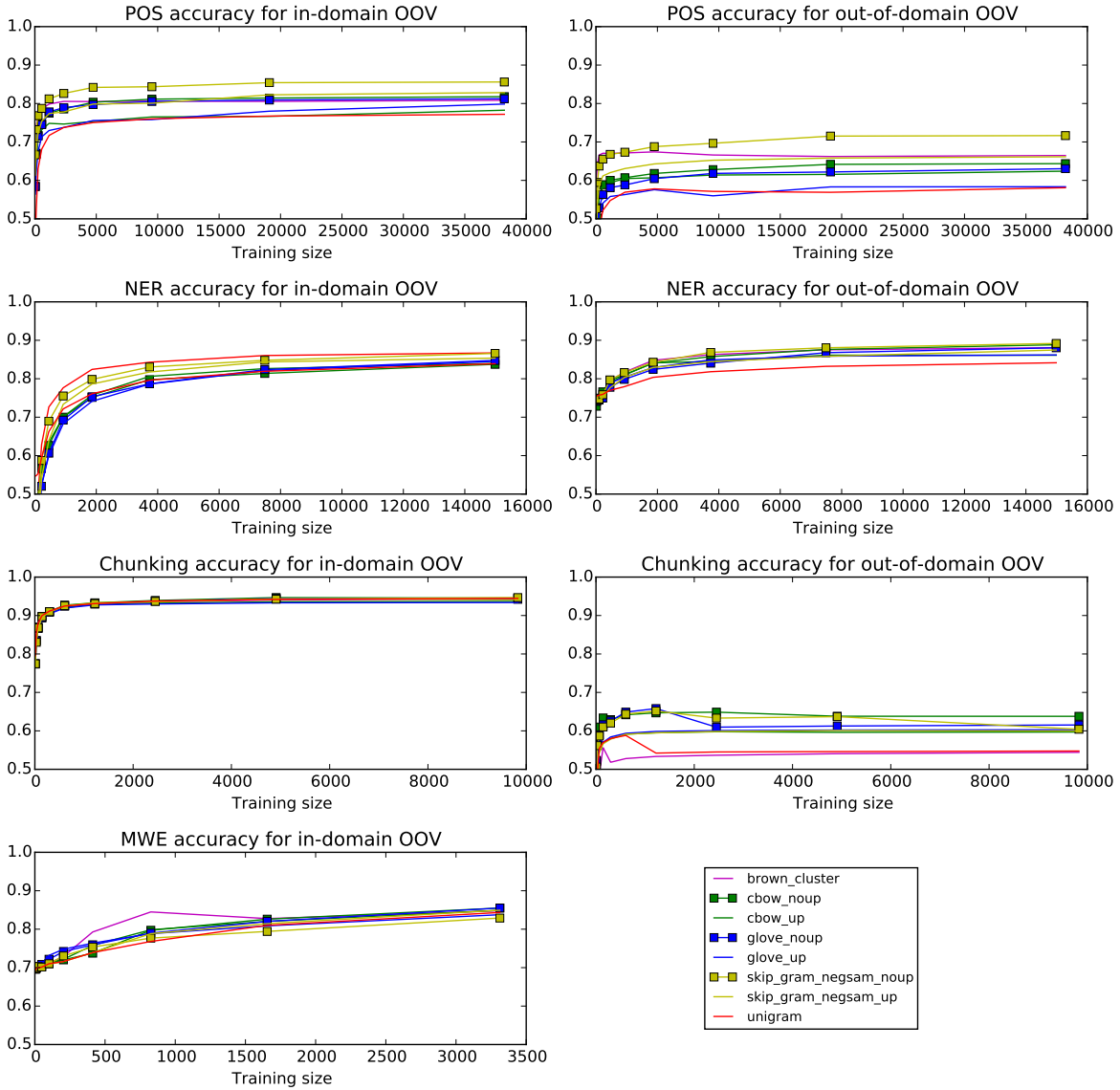


Figure : NER with SKIP-GRAM

RQ4: What is the impact of these word embeddings (with and without updating) on both OOV items (relative to the training data) and out-of-domain data?

RQ5: Are some word embeddings better than others in a sequence labelling context?



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