Multilingual Distributional Semantics

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Outline

Introduction - related work

Our first idea (and why it wouldn't work)

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Our first idea (and why it wouldn't work)

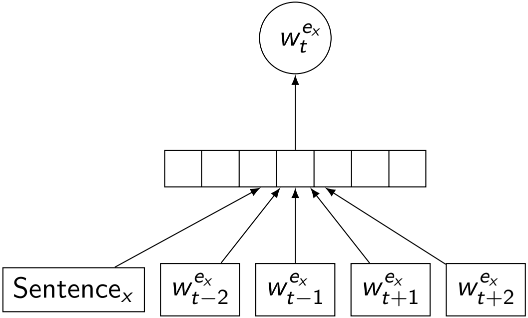


Figure : Bilingual distributed memory. The same architecture is trained with English context and word prediction replaced by the other language(s).

Our new idea

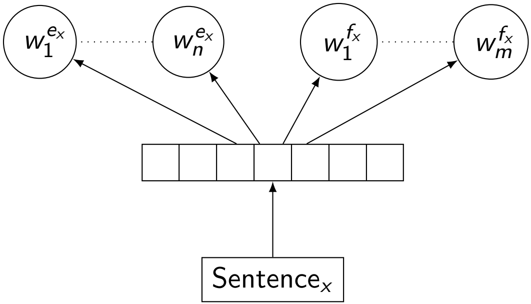


Figure : Bilingual dbow

Our new idea

- Training a single embedding for parallel sentences
- Word embeddings are not trained
- Can be extended to more than two languages

Our new idea

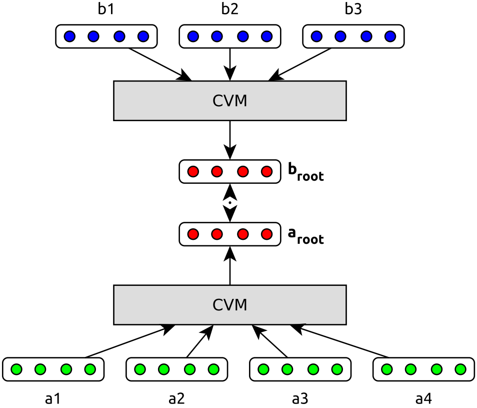
- Use the sentence embeddings to obtain word vector:

$$emb(w) = \frac{1}{freq(w, D)} \sum_{s \in D} freq(w, s) emb(s)$$

- Quite good performance (as we will see later)

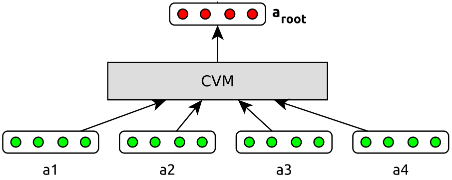
Our new idea

- Recall the model by Hermann and Blunsom:



Our new idea

- We could have a similar training procedure
- Only: we are not training the sentences, but assume fixed 'gold standard' sentence embeddings



- So, we could plug in any compositional model

Evaluation and results

- Training word embeddings: on Europarl data (50k or 500k sentences)
- Monolingual (English) evaluation: analogy task
- Crosslingual evaluation: document classification

Evaluation and results

Crosslingual Doccument classification:

- Given word embeddings, obtain document representation for train and test documents in all languages

$$emb(doc) = \sum_{w \in doc} idf(w) * emb(w)$$

- Train a classifier (averaged perceptron) on the training document representations for one language
- Test classifier performance on the test document representations for another language

Evaluation and results

RCV (Reuters) data:

- English-German
- Multiclass classification:
  each document is assigned a single class (topic)
- Performance measure: accuracy
- Baseline: majority class

Evaluation and results

TED data:

- Many languages
- Binary classification: each class (topic) has positive and negative examples
- Performance measure: F1 score
- Baseline: ??

Evaluation and results

Monolingual evaluation on English:

Setting	Length	RCV (1000) accuracy	TED F1
Baseline		.468	.118
I-Matrix	40	.861	.154
Paragraph mono	256		
Paragraph bi	256		
Paraword mono	256		
Paraword bi	256	.898	.216
Paraword multi	256	.903	.245
Google News	300	.951	.486

Evaluation and results

- Word vectors as average of the dbow-trained sentences they occur in.
- Sentences trained on 50k Europarl data in specified languages.
- Mono- and bilingual evaluation on TED data (F1 scores):

Sentences trained on:	Classification train-test EN-EN	DE-DE	EN-DE	DE-EN
EN				
DE				
DE-EN	.216	.189	.201	.220
multi	.404	.368	.387	.339

Evaluation and results

- Word vectors as average of the dbow-trained sentences they occur in.
- Sentences trained on 50k Europarl data in all languages.
- multilingual evaluation on TED data (F1 scores):

F1	Tested on						
Trained on	de	en	es	fr	it	nl	pb
de	0,36753	0,33879	0,4028	0,368	0,28221	0,37315	0,31928
en	0,38686	0,40439	0,38929	0,32149	0,35167	0,37379	0,35102
es	0,39853	0,30125	0,42759	0,38709	0,3536	0,36173	0,35515
fr	0,39842	0,41654	0,54487	0,40679	0,38499	0,33246	0,40565
it	0,40612	0,40535	0,37698	0,43608	0,37289	0,40004	0,35872
nl	0,4265	0,39681	0,41736	0,39255	0,41243	0,42775	0,32053
pb	0,40317	0,33343	0,36931	0,35449	0,37403	0,40549	0,31451