Multilingual Distributional Semantics

Benno Kruit Sara Veldhoen

January 13, 2015

Outline

Multilingual DM

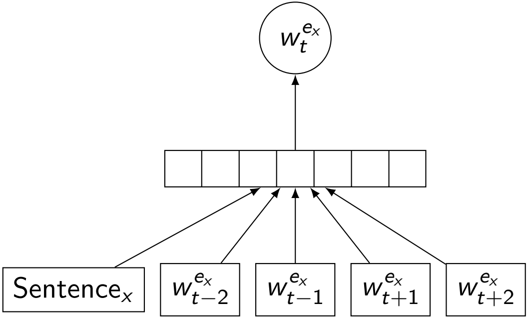


Figure : Bilingual distributed memory. The same architecture is trained with English context and word prediction replaced by the other language(s).

Multilingual Dbow

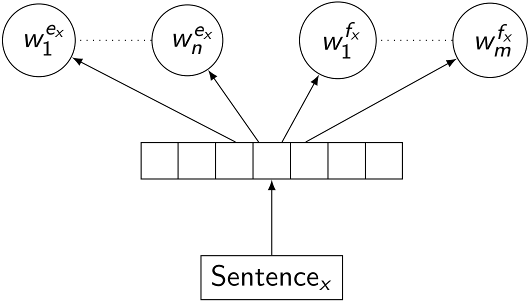


Figure : Bilingual dbow

Multilingual Dbow

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

Multilingual Dbow

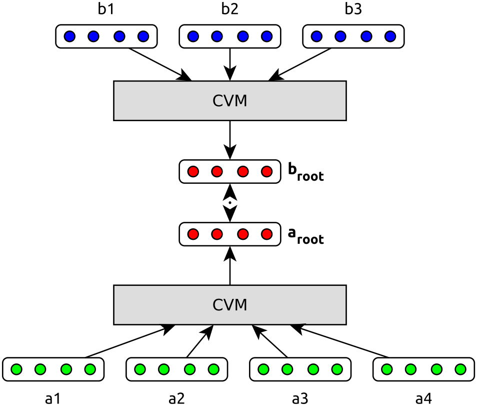
- Use the sentence embeddings to obtain word vector:

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

- Quite good performance (as we will see later)

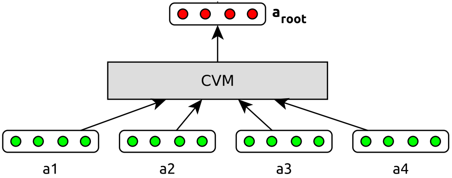
Multilingual Dbow

- Recall the model by Hermann and Blunsom:



Multilingual Dbow

- 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

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

Evaluation

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

RCV (Reuters) data:

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

Evaluation

TED data:

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

Results

Monolingual evaluation on English:

Setting	vector length	RCV (1000) accuracy	TED F1
Baseline		.468	.118
I-Matrix	40	.861	.154
Paragraph mono	256	-	.399
Paragraph bi	256	-	.438
Paraword mono	256	.866	.186
Paraword bi	256	.898	.216
Paraword multi	256	.903	.245
Google News	300	.951	.486

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:	sentence quality	Classification [train]-[test]			
		EN-EN	DE-DE	EN-DE	DE-EN
EN	.399	.186	.134	.084	.153
DE	.381	.132	.091	.076	.132
DE-EN	.622	.216	.189	.201	.220
multi		.404	.368	.387	.339

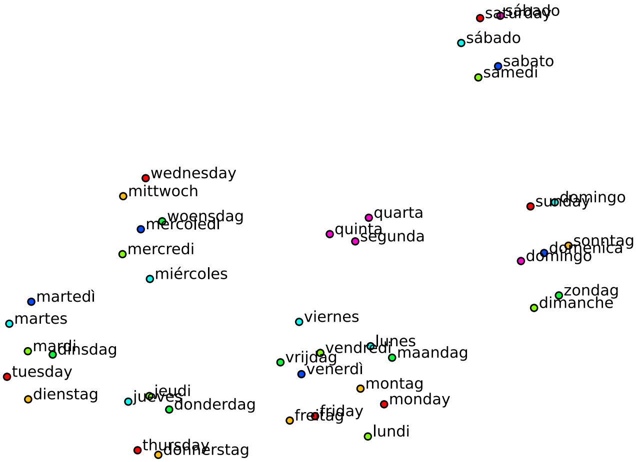
Results

- 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 Trained on	Tested 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

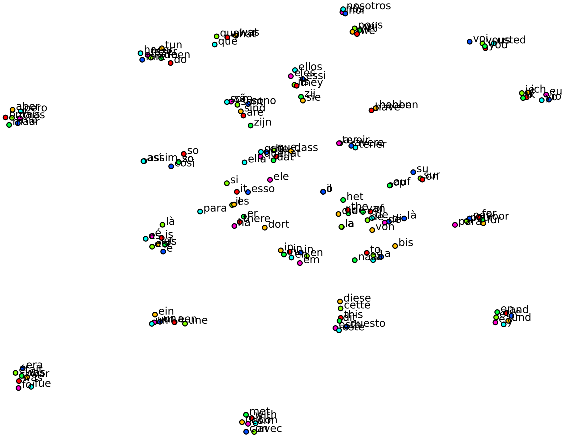
Graphics and concluding words

Words from *multilingual* dbow paragraphs (7 languages)



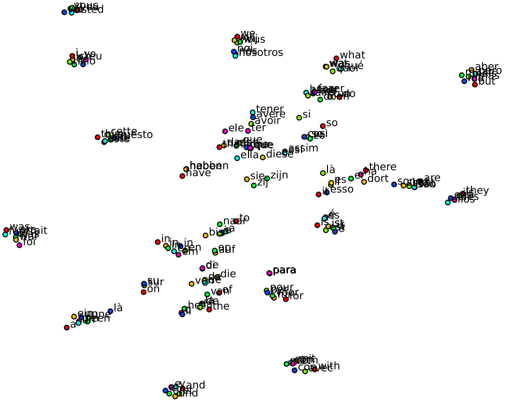
Graphics and concluding words

Words from *multilingual* dbow paragraphs (7 languages)



Graphics and concluding words

Words from *English transfer* dbow paragraphs (7 languages)



Discussion - F1 baseline

$$\begin{aligned} Prec &= \frac{TP}{TP + FP}, \\ Rec &= \frac{TP}{TP + FN}, \\ Acc &= \frac{TP + TN}{TP + FP + TN + FN} \end{aligned}$$

Majority class:

$$neg > pos \rightarrow \begin{cases} Acc = \frac{TP+TN}{TP+FP+TN+FN} = \frac{TN}{TN+FN} = \frac{neg}{total} \\ Prec = \frac{TP}{TP+FP} = 0 \rightarrow F1 = 0 \end{cases}$$

Discussion - F1 baseline

Now assume a stochastic classifier:

$P = P(pos) = \frac{pos}{total}$, $P(neg) = 1 - P$

$pos = P * |X|$, $neg = (1 - P) * |X|$

$$TP = P * pos = P^2 * |X|$$

$$FP = P * neg = P * (1 - P) * |X|$$

$$FN = (1 - P) * pos = (1 - P) * P * |X|$$

$$\begin{aligned} F1 &= \frac{2 * TP}{2 * TP + FN + FP} \\ &= \frac{2 * P2 * |X|}{2 * P * P * |X| + (1 - P) * P * |X| + (1 - P) * P * |X|} \\ &= \frac{2 * P^2}{2 * P^2 + (1 - P) * P + (1 - P) * P} \\ &= \frac{2 * P}{2 * P + (1 - P) + (1 - P)} = \frac{2P}{2} = P \end{aligned}$$