# Multilingual Distributional Semantics

Benno Kruit  Sara Veldhoen

January 13, 2015

# Outline

# Introduction - related work

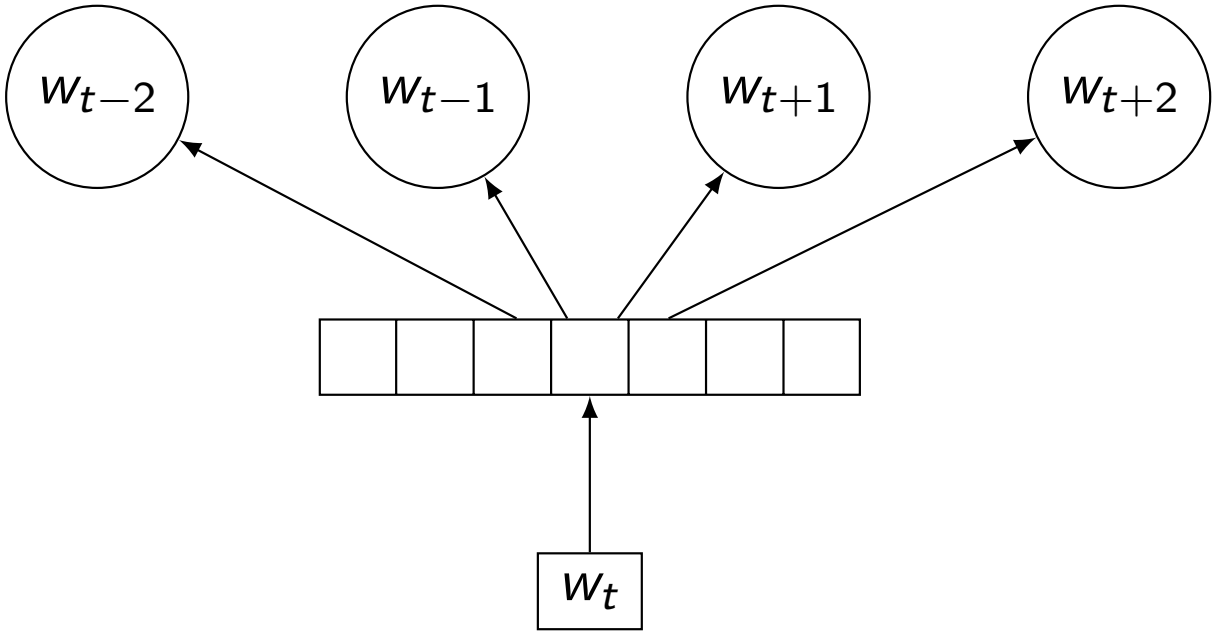



Figure : word2vec Skipgram

# Introduction - related work

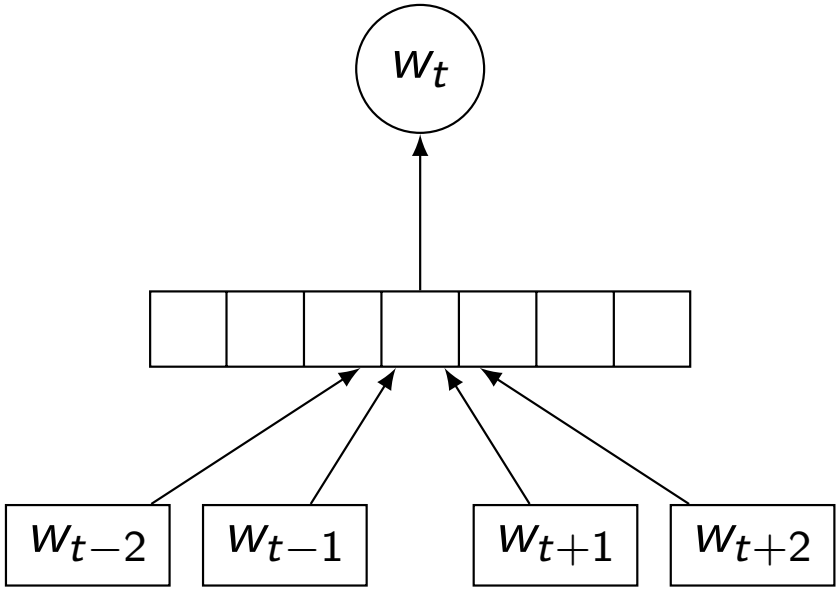



Figure : word2vec dbow

# Multilingual DM

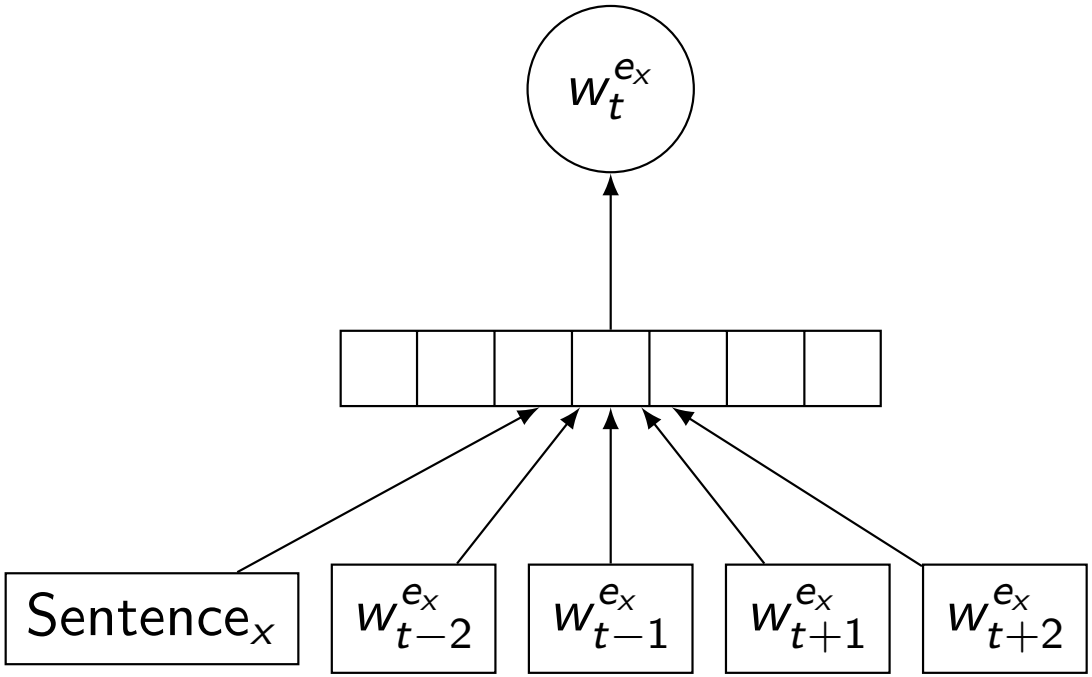



Figure : Bilingual distributed memory. The same architecture is trained with English context and word prediction replaced by the other language(s).

# Multilingual Dbow

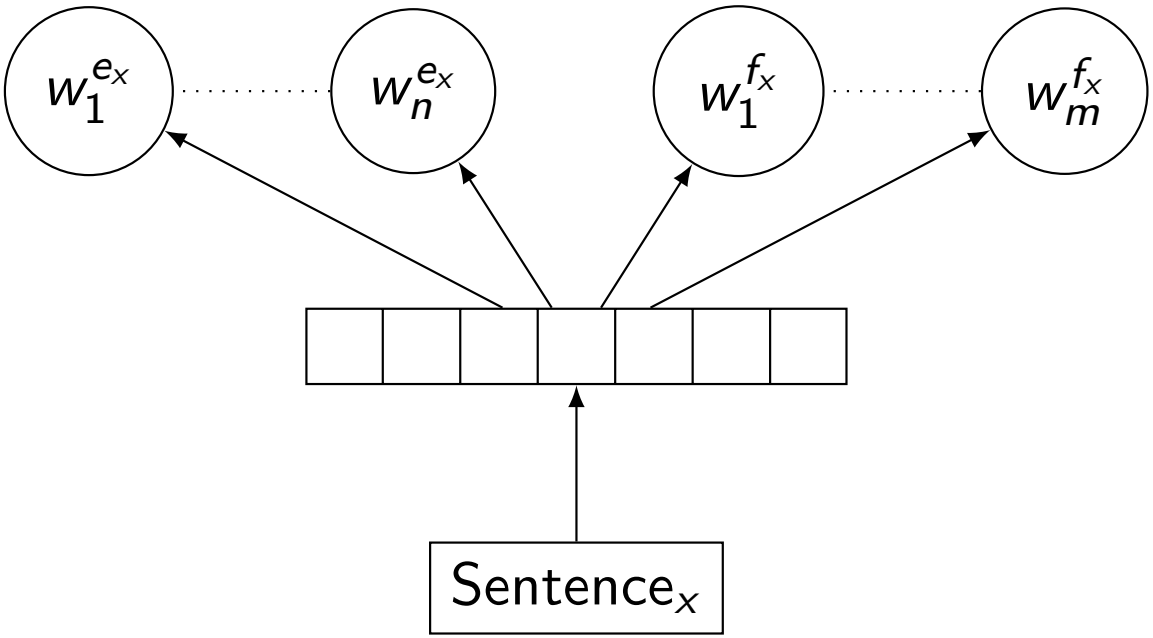



Figure : Bilingual dbow

# Multilingual Dbow

- Training a single embedding for parallel sentences
- Word embeddings are not trained
- Can be extended to more than two languages
- Results in 'good' sentence embeddings (without a compositional model)

# Multilingual Dbow

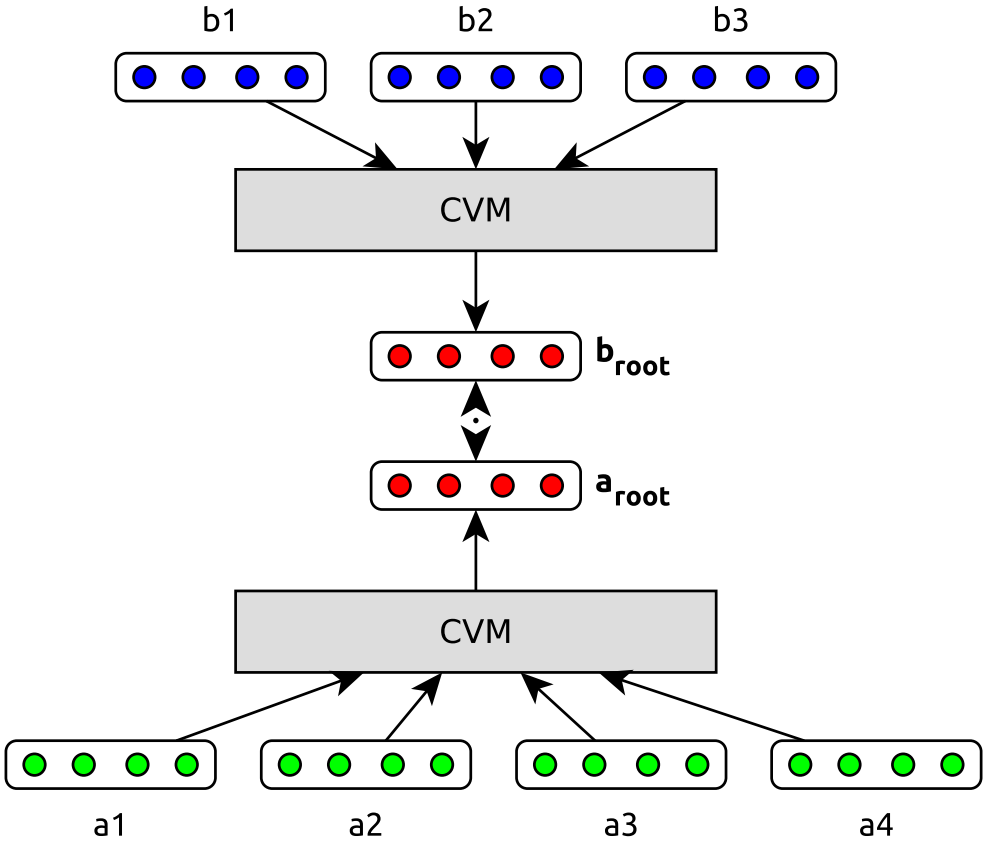
- Use the sentence embeddings to obtain word vector:

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

- Quite good performance (as we will see later)

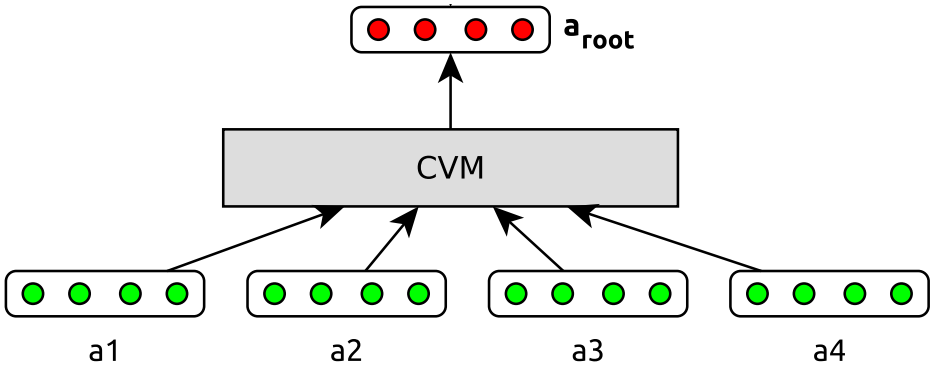
# Multilingual Dbow

- 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 |

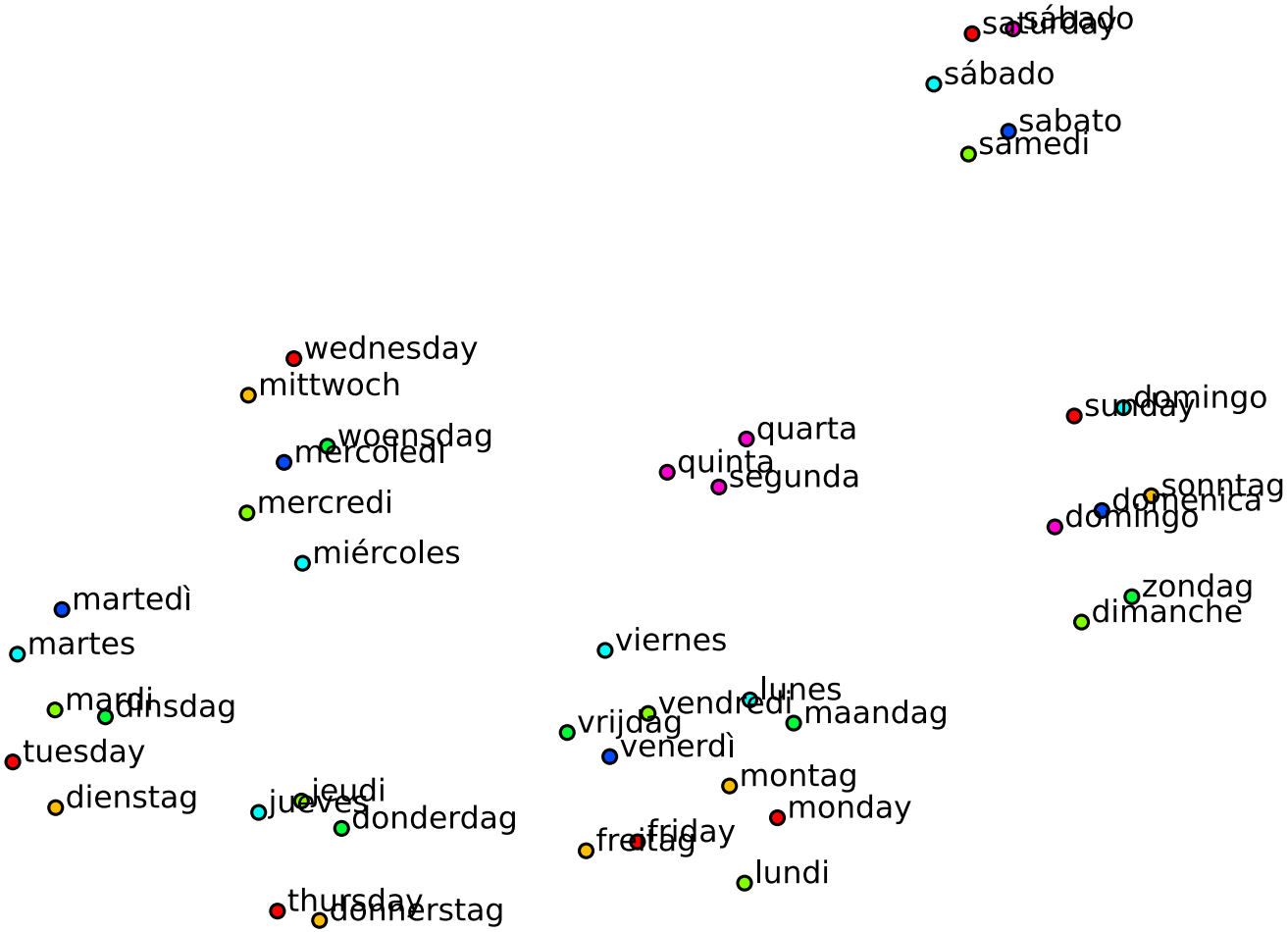
# Results

- 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 |

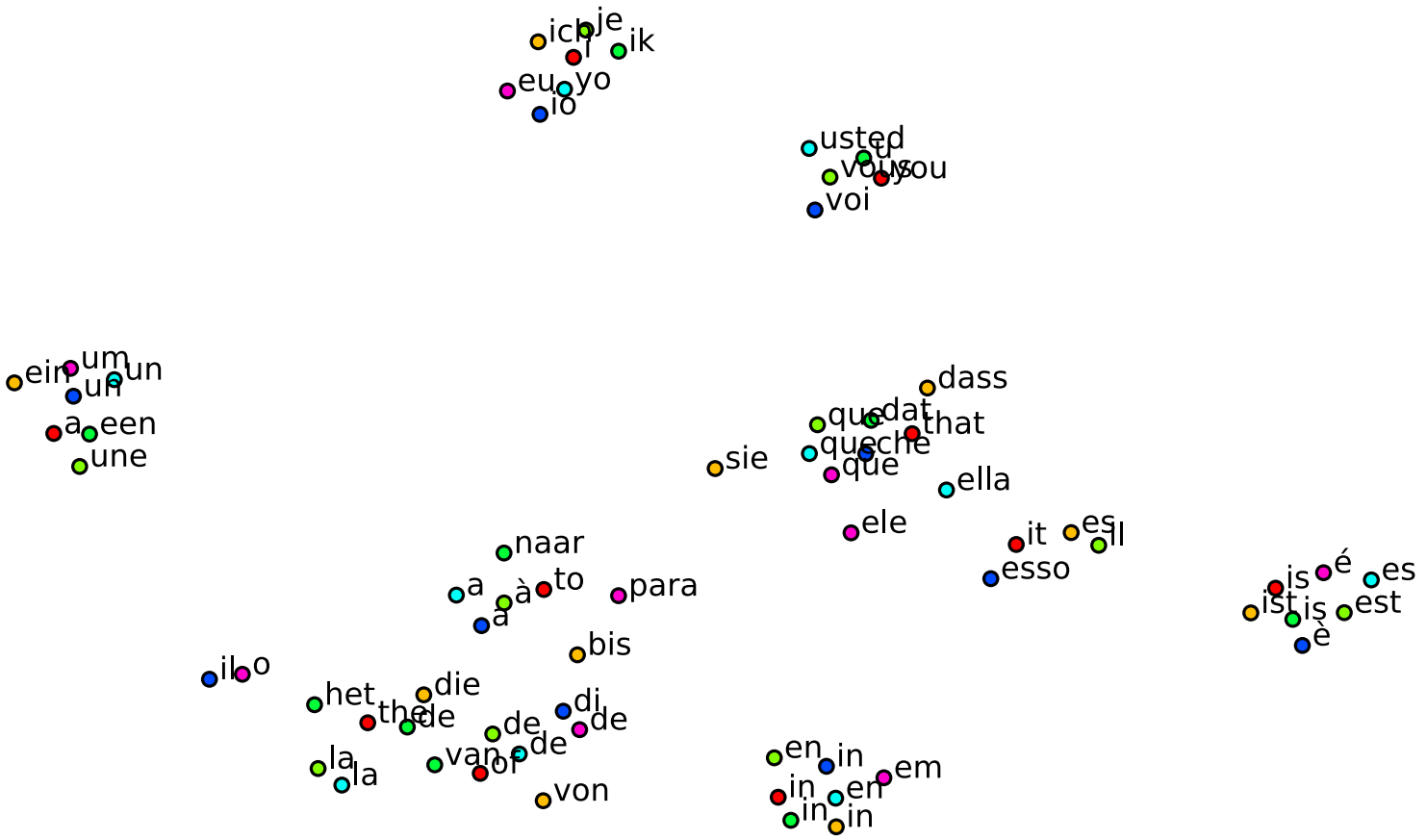
# Graphics and concluding words

## Words from *multilingual* dbow paragraphs (7 languages)



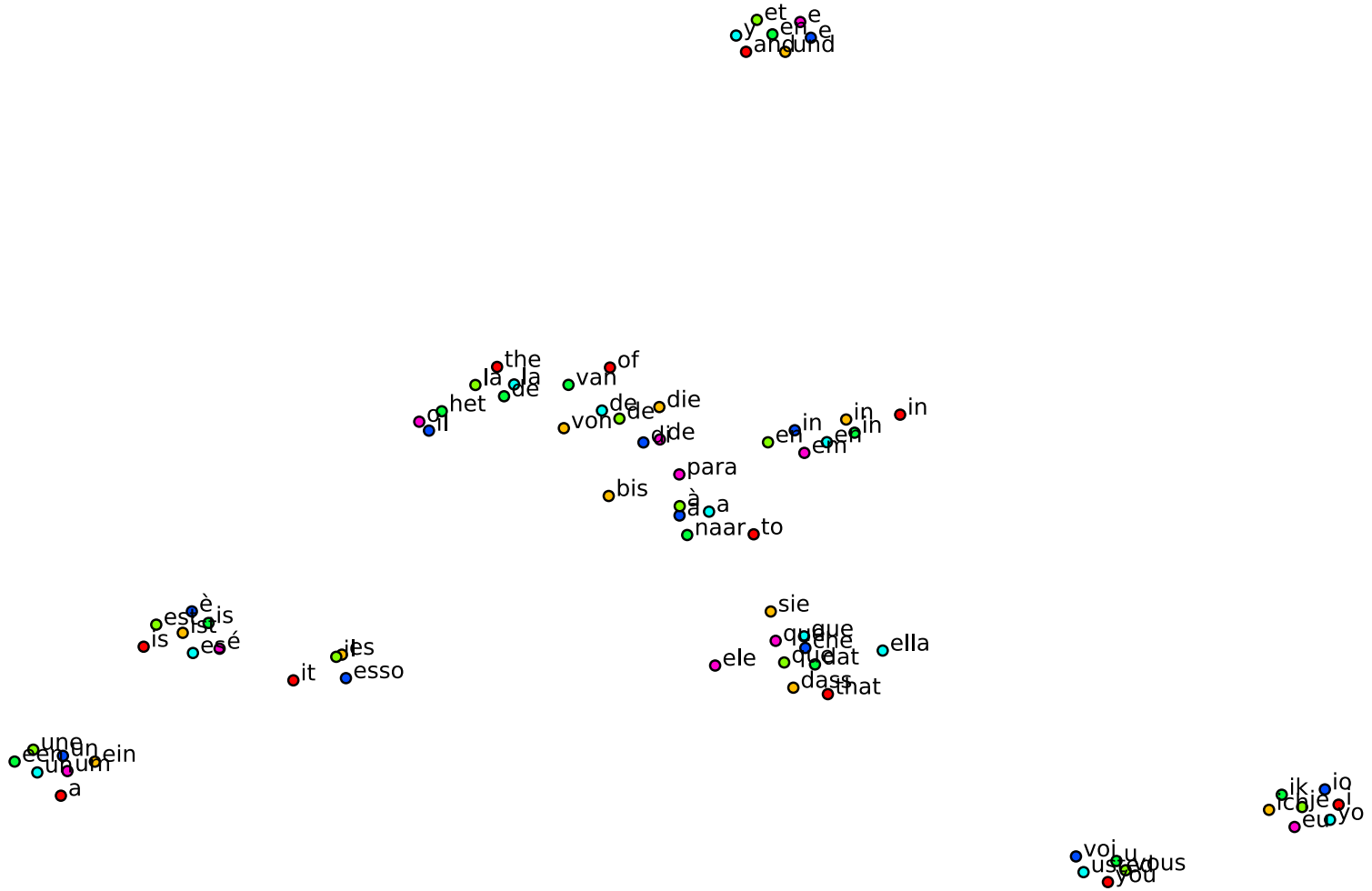
# Graphics and concluding words

## Words from *multilingual* dbow paragraphs (7 languages)



# Graphics and concluding words

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



# Discussion - F1 baseline

$$Prec = \frac{TP}{TP + FP},$$
$$Rec = \frac{TP}{TP + FN},$$
$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

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:

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

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

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

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

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

$$F1 = \frac{2 * TP}{2 * TP + FN + FP}$$

$$= \frac{2 * P2 * |X|}{2 * P * P * |X| + (1 - P) * P * |X| + (1 - P) * P * |X|}$$

$$= \frac{2 * P^2}{2 * P^2 + (1 - P) * P + (1 - P) * P}$$

$$= \frac{2 * P}{2 * P + (1 - P) + (1 - P)} = \frac{2P}{2} = P$$

Is $P$ a reasonable F1 baseline?