Deep Generative Model for Joint Alignment and Word Representation

Embedalign

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Outline

Introduction

TL;DR

- Generative model that embeds words in their complete observed context
- Model learns from bilingual sentence-aligned corpora by marginalisation of latent lexical alignments
- Model embeds words as probability densities
- Model shows competitive results on context dependent Natural Language Processing applications

Introduction

Discriminative embedding models

word2vec

In the event of a chemical spill, most children know they should **evacuate** *as advised by people in charge.*

Place words in $\mathbb{R}^d$ as to answer questions like

"Have I seen this word in this context?"

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Fit a binary classifier

- positive examples
- negative examples

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  - Distributional hypothesis is strong but fails when context is not discriminative
  - Word senses are collapsed into one vector

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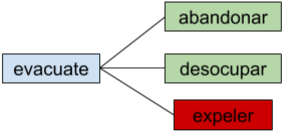
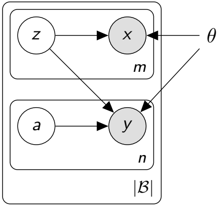
- Generative model to induce word representations
- Learn from positive examples
- Learn from richer (less ambiguous) context
  Foreign text is proxy to sense supervision (Diab and Resnik, 2002)

En caso de un derrame de productos químicos, la mayoría de los niños saben que deben **abandonar** *el lugar según lo aconsejado por las personas a cargo.*



Generative Model

quickly evacuate the area / deje el lugar rápidamente



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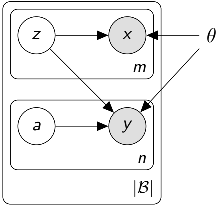

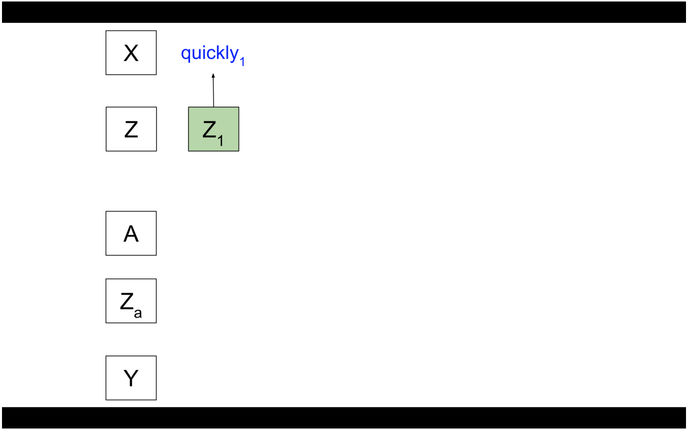

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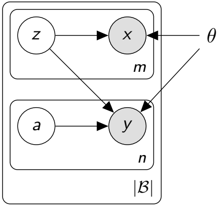

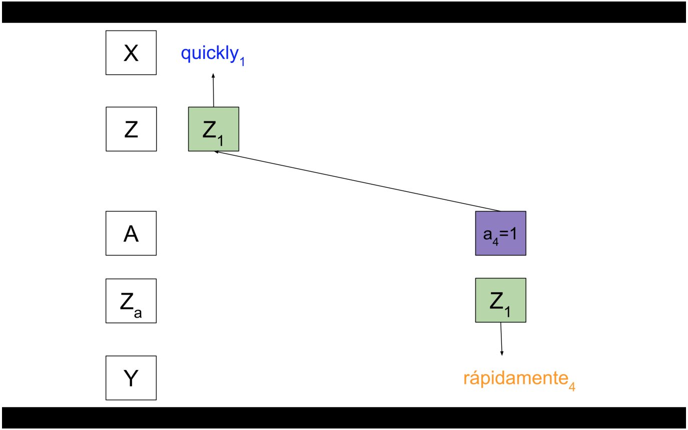

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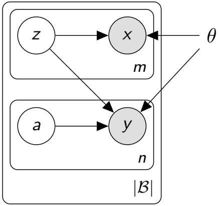

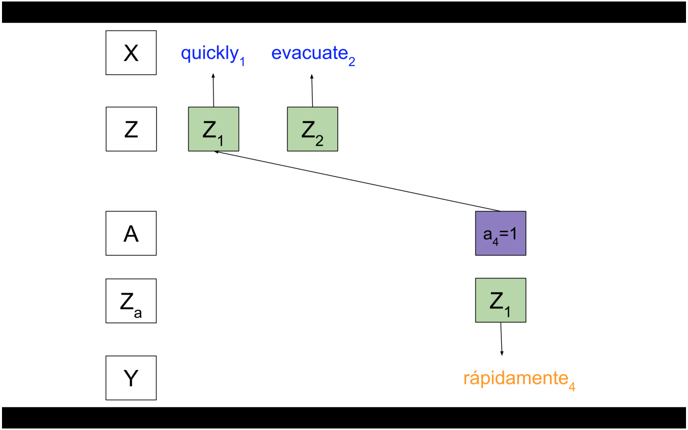

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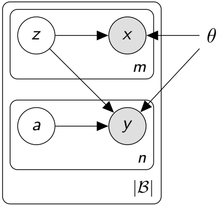

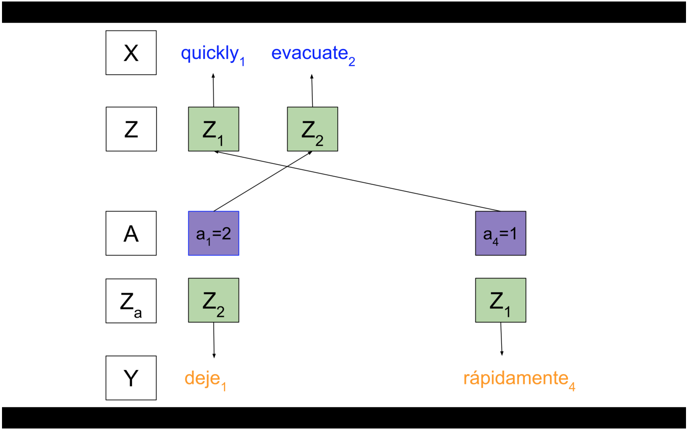

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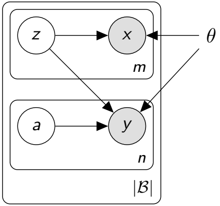

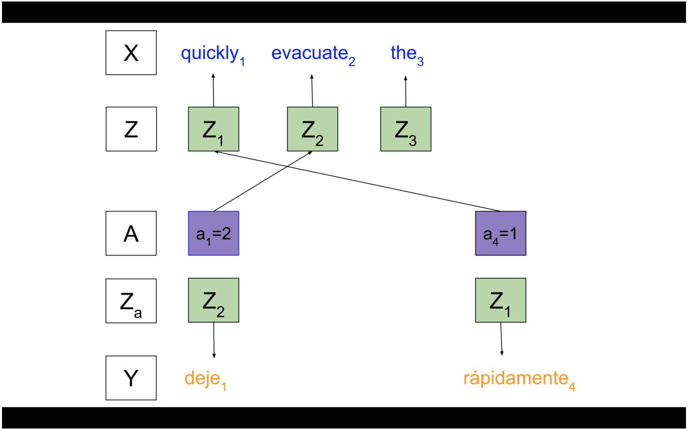

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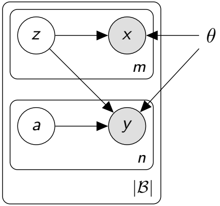

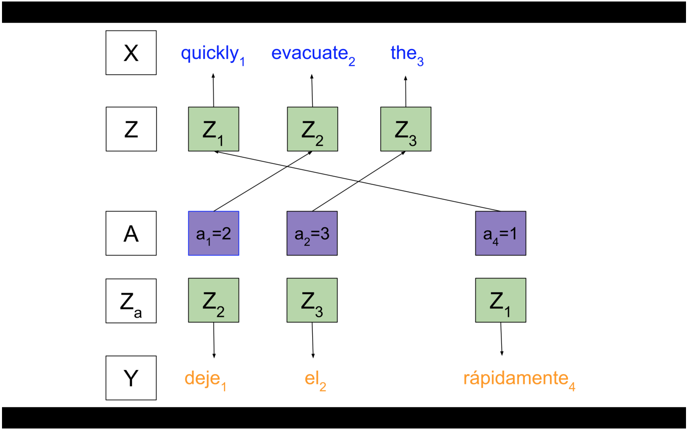

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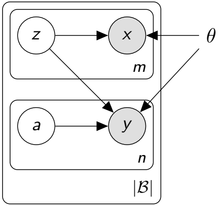

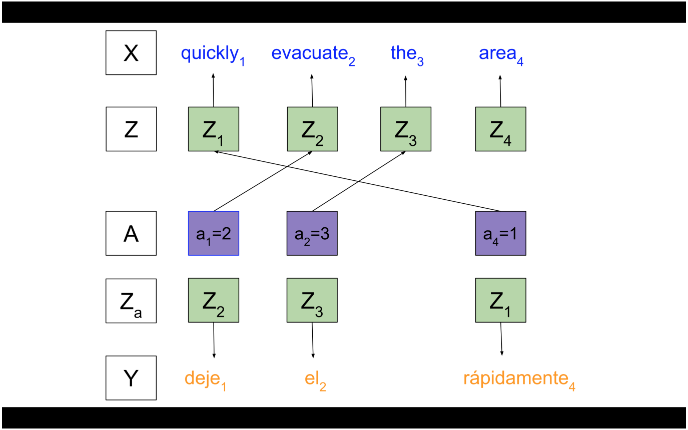

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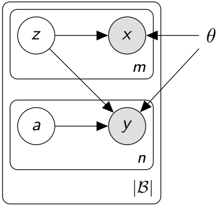

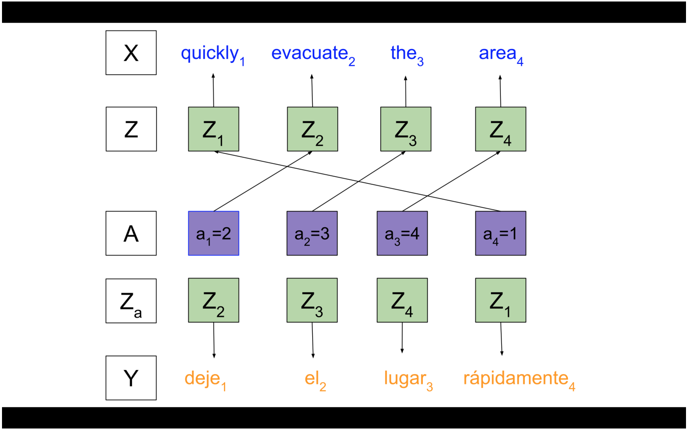

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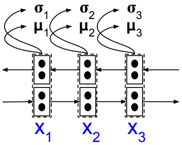

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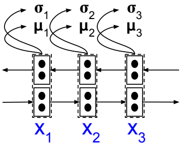

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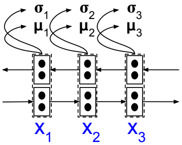

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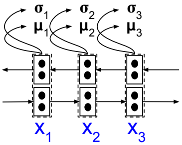

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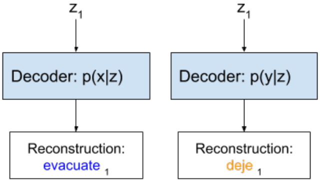

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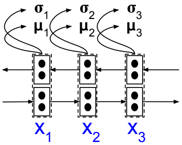

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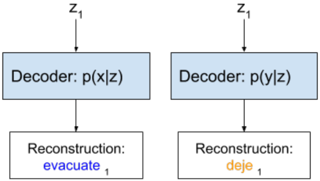
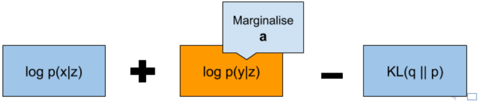


6. Maximise a lowerbound on likelihood
   (Kingma and Welling, 2014)

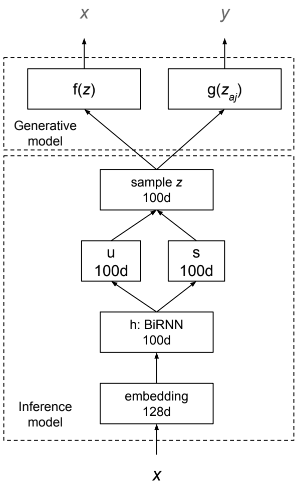


Outline

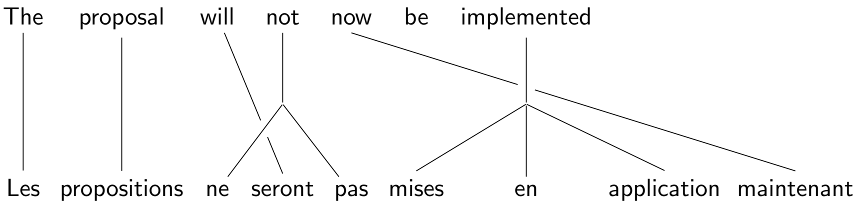
Data

Corpus	Sentence pairs (million)	Tokens (million)
Europarl EN-FR	1.7	42.5
Europarl EN-DE	1.7	43.5

Architecture



Word Alignment



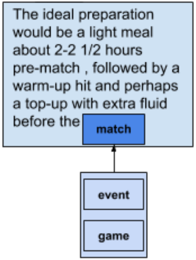
Word Alignment

- Model selection on Dev set

AER ↓

Model	En-Fr	En-De
IBM1	32.45	46.71
IBM2	22.61	40.11
EmbAlign	29.43 ± 1.84	48.09 ± 2.12

Lexical Substitution



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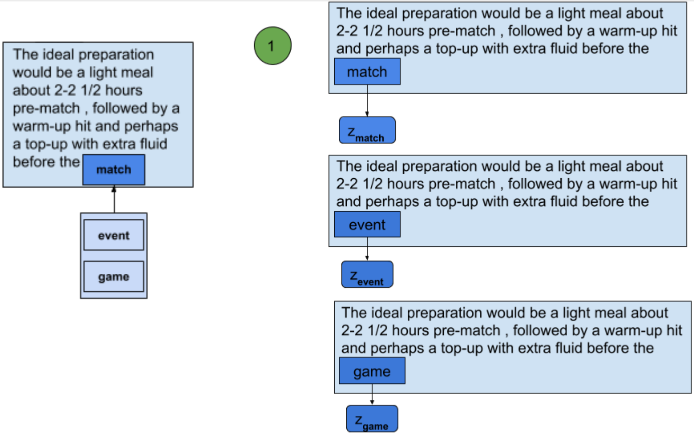

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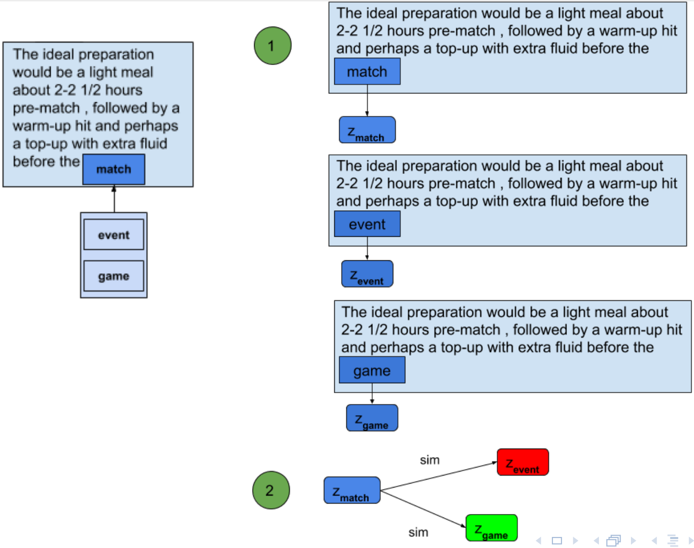
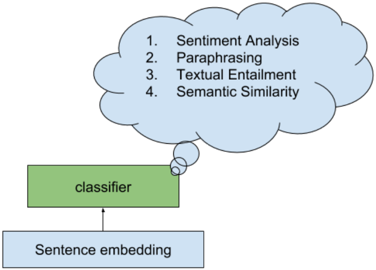


Lexical Substitution

Model	GAP ↑	Training size
Random	30.0	
SkipGram (Melamud et al., 2015)	44.9	ukWaC-2B
BSG (Bražinskas et al., 2017)	46.1	ukWaC-2B
En	21.31 ± 1.05	
En-Fr	42.19 ± 0.57	Euro-42M
En-De	42.07 ± 0.47	

Sentence Evaluation (SentEval)



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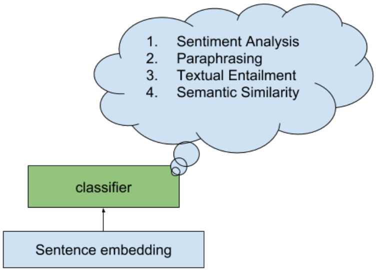

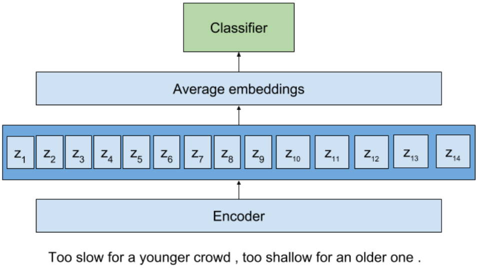

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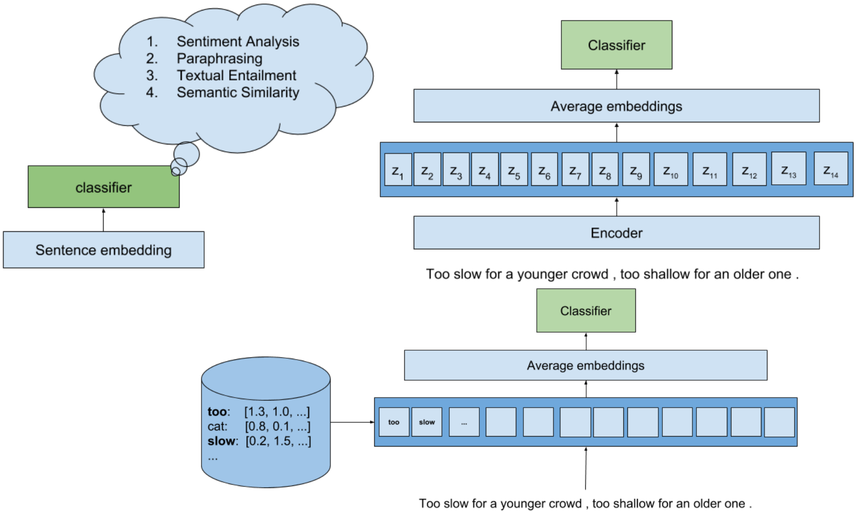

Sentence Evaluation (SentEval)

						ACC ↑	ACC/F1 ↑	CORR ↑		CORR ↑
Model	MR	CR	SUBJ	MPQA	SST	TREC	MRPC	SICK-R	SICK-E	STS14
SkipGram$_{\text{En}}$	**70.96**	**76.16**	**87.24**	**86.87**	**73.64**	65.20	70.7/80.1	0.710	76.2	0.45/0.49
En	57.5	67.1	72.0	70.8	57.0	58.0	70.6/80.3	0.648	74.4	0.59/0.59
En-Fr	64.0	71.8	79.1	81.5	64.7	58.4	72.1/81.2	0.682	74.6	0.60/0.59
En-De	62.6	68.0	77.3	82.0	65.0	66.8	70.4/79.8	0.681	75.5	0.58/0.58
Combo	66.1	72.4	82.4	84.4	69.8	**69.0**	**71.9**/**80.6**	**0.727**	**76.3**	**0.62**/**0.61**

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SkipGram (Conneau et al., 2017)	**77.7**	**79.8**	**90.9**	**88.3**	**79.7**	**83.6**	**72.5**/**81.4**	**0.803**	**78.7**	**0.65**/**0.64**
NMT$_{\text{En-Fr}}$ (Conneau et al., 2017)	64.7	70.1	84.8	81.5	-	82.8	-	-	-	0.42/0.43

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- Translation data
  - less ambiguous embeddings
  - model helps with semantic tasks e.g. paraphrasing

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- We **will** expand the distributional context to multiple foreign languages at once

DGM4NLP research at UvA-SLPL

- Try pre-trained Europarl model on SentEval: `https://github.com/uva-slpl/embedalign/blob/master/notebooks/senteval_embedalign.ipynb`

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- ACL-18 tutorial Variational Inference and Deep Generative Models: `http://acl2018.org/tutorials/`

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