Generative models of word representation

DGM4NLP

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Outline

1. Word embeddings
2. EmbedAlign
   - Model
   - Evaluation
   - Conclusions and Future Work
3. EmbedAlign-2

Introduction

Discriminative embedding models

word2vec

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Fit a binary classifier

- positive examples
- negative examples

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- Trained on the English-German translation task.
- The encoder learns the embedding vectors of English words to translate them into German.

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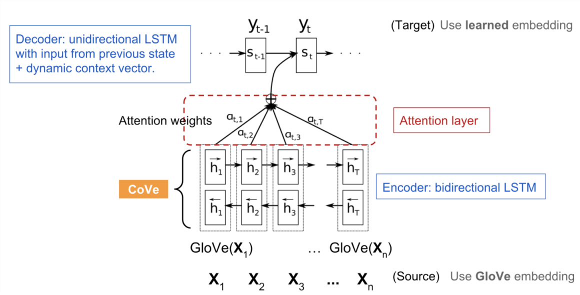
- Motivation: The encoder captures high-level semantic and syntactic meanings.
  The encoder output is used on various downstream NLP tasks.



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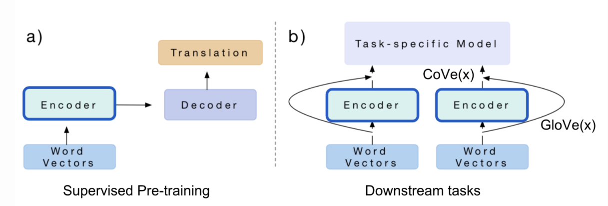

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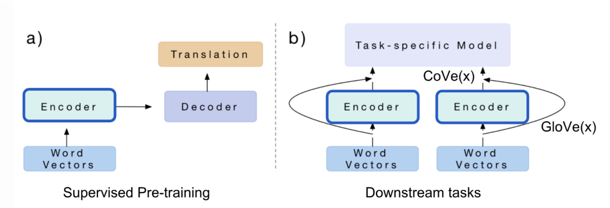

- Limitation use of parallel training data

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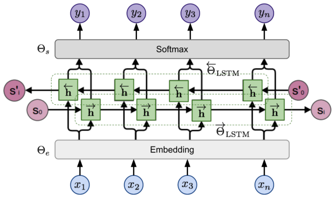

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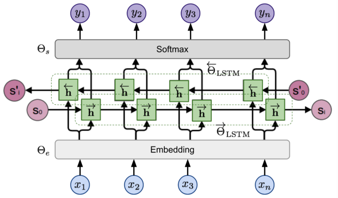

- Objective negative log likelihood in both directions:

$$\mathcal{L} = -\sum_{i=1}^{n} \left(\log p\left(x_i | x_1, \ldots, x_{i-1}; \Theta_e, \Theta_{\text{fwLSTM}}, \Theta_s\right) + \log p\left(x_i | x_{i+1}, \ldots, x_n; \Theta_e, \Theta_{\text{bwLSTM}}, \Theta_s\right)\right)$$

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- The weights, s^t task are learned for each end task The scaling factor γ^t is used to correct the misalignment between the distribution of biLM hidden states and the distribution of task specific representations.
  $v_i = f\left(R_i; \Theta^t\right) = \gamma^t \sum_{\ell=0}^{L} s_i^t \mathbf{h}_{i,\ell}$

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- Syntax task: The part-of-speech (POS) tagging task aims to infer the grammatical role of a word in one sentence.
  A higher accuracy can be achieved by using the biLM first layer than the top layer.

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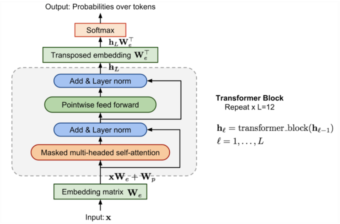
- Transformer Decoder:
  The model avoids the encoder part, only one single input sentence rather than source and target sequences.



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- Supervised Fine-Tuning use the pre-trained language model directly

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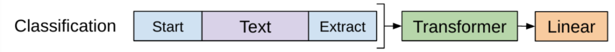

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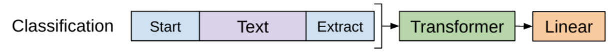

- $p(y|x_1, \ldots, x_n) = \mathrm{Cat}(\mathrm{softmax}\left(\mathbf{h}_L^{(n)}\mathbf{W}_y\right))$

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- $$\begin{aligned}\mathcal{L}_{\text{cls}} &= \sum_{(\mathrm{x},y)\in\mathcal{D}} \log p\left(y|x_1,\ldots,x_n\right)\\ \mathcal{L}_{\text{LM}} &= -\sum_i \log p\left(x_i|x_{i-k},\ldots,x_{i-1}\right)\\ \mathcal{L} &= \mathcal{L}_{\text{cls}} + \lambda\mathcal{L}_{\text{LM}}\end{aligned} \tag{1}$$

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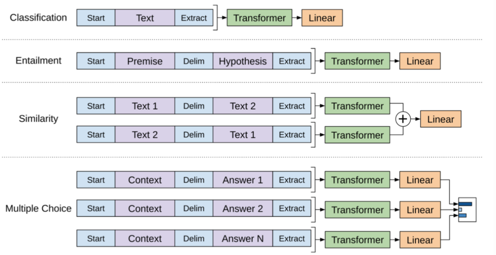
- 

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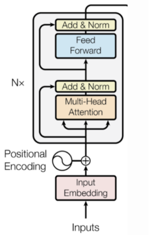
- BERT is trained with two auxiliary tasks instead of only the LM.



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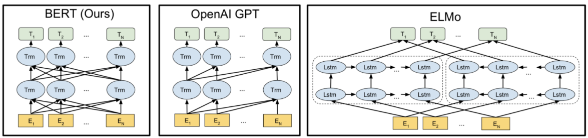

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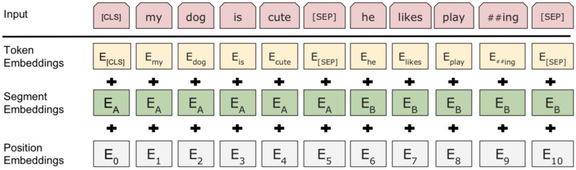
- Position embeddings: Positional embeddings are learned instead of hard-coded.



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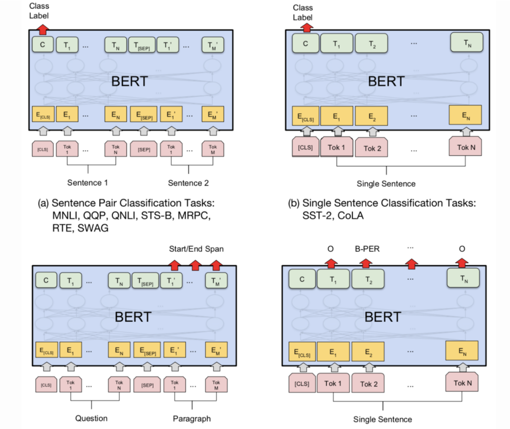
- BERT fine-tuning requires the final hidden state of the special first token [CLS], $h_L^{[CLS]}$.



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- Large improvements by GPT-2 are specially noticeable on small datasets and datasets used for measuring long-term dependency.
- Zero-Shot Transfer: All the downstream language tasks are framed as predicting conditional probabilities and there is no task-specific fine-tuning.

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  The decoder is denoted by $p_\theta(x \mid z)$.
- The loss is the negative log-likelihood with a regulariser.
  $\mathcal{L}(\theta, \phi|x) = \mathbb{E}_{q(z|x)}\left[\log p_\theta\left(x|z\right)\right] - \mathrm{KL}\left(q_\phi(z|x)\|p_\theta(z)\right)$

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- we can sample from it like this:
  $z = \mu + \sigma \odot \epsilon$
  where $\epsilon \sim Normal(0, I)$.

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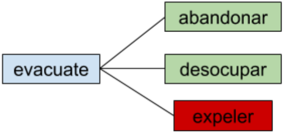
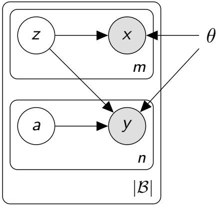
- Learn from richer (less ambiguous) context
  Foreign text is proxy to sense supervision (Diab and Resnik, 2002)

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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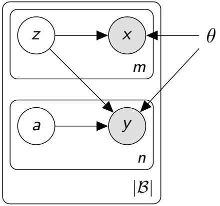

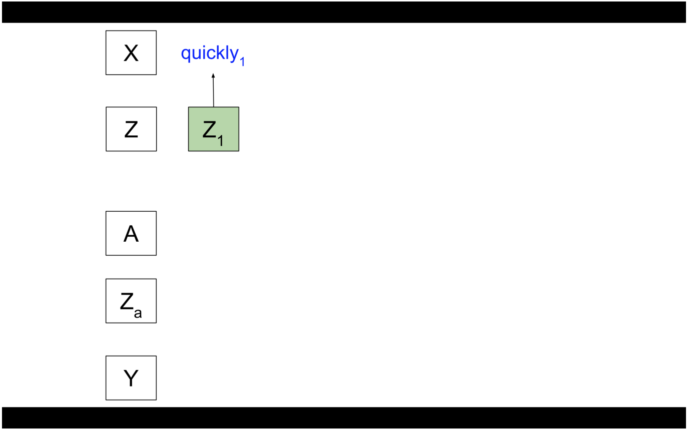

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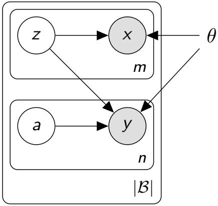

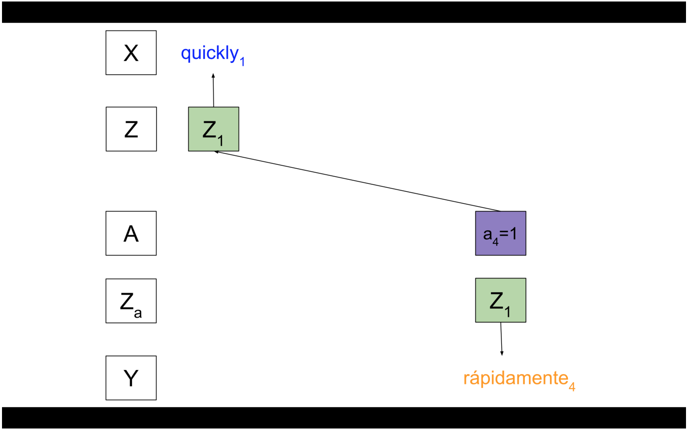

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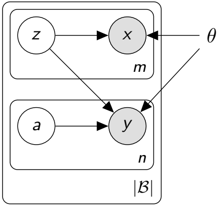

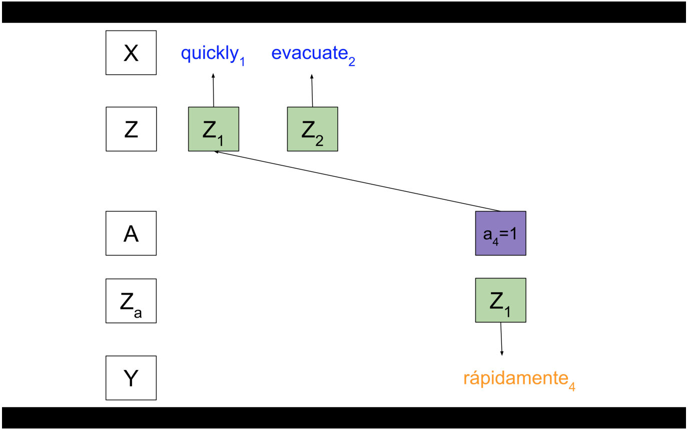

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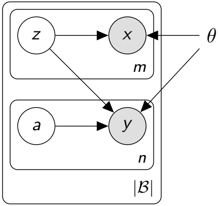

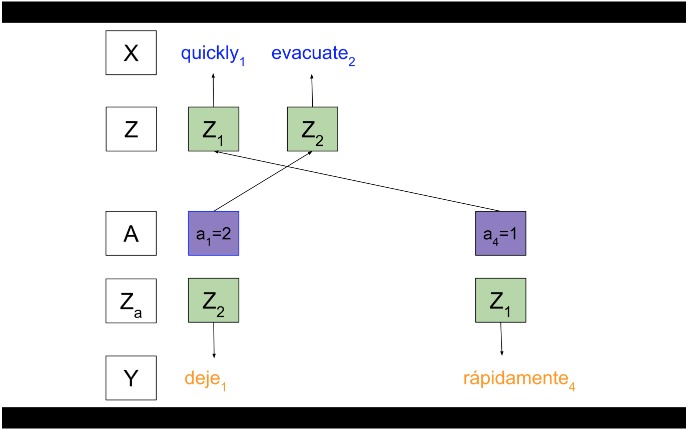

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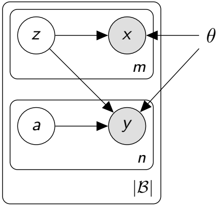

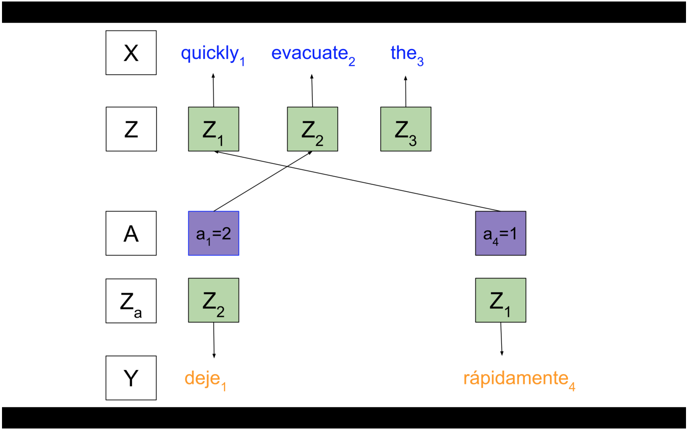

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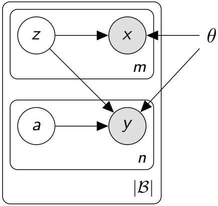

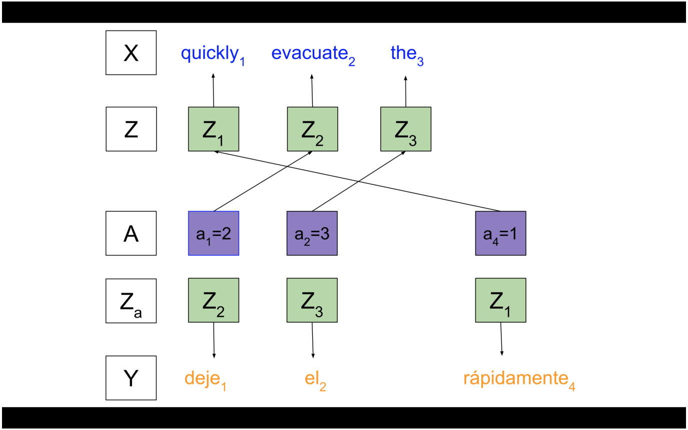

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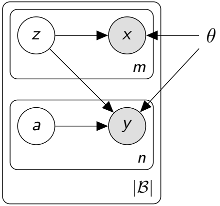

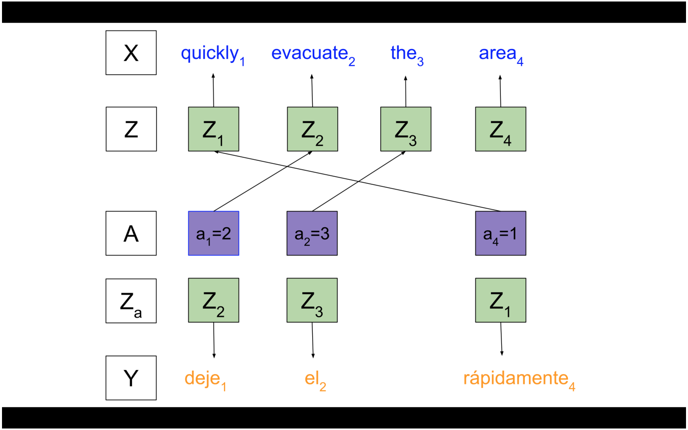

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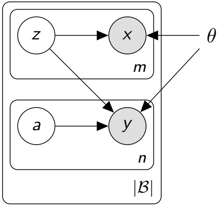
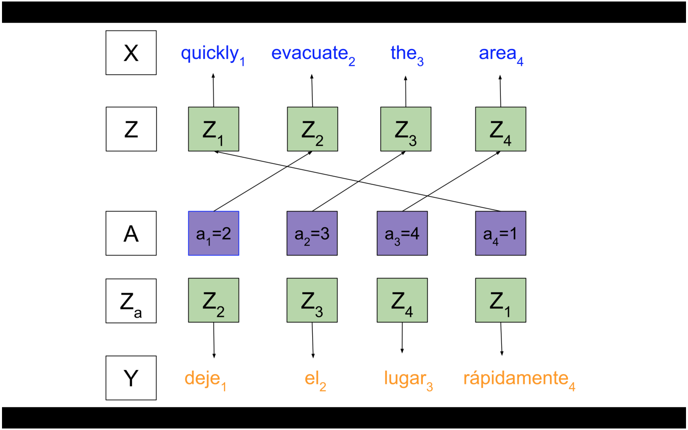


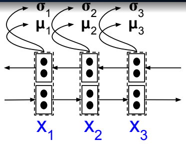


Learning

1. Read sentence

Learning

1. Read sentence
2. Predict posterior mean μ_i and std σ_i



evacuate$_1$ the$_2$ area$_3$

Learning

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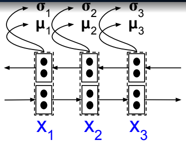

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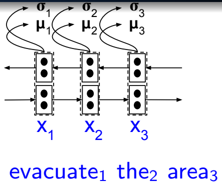

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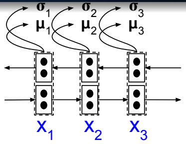

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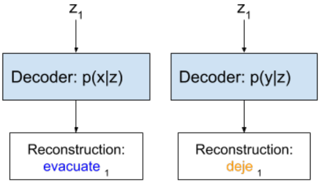

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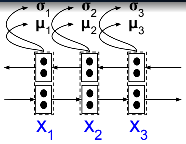

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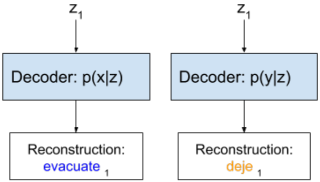


6. Maximise a lowerbound on likelihood (Kingma and Welling, 2014)

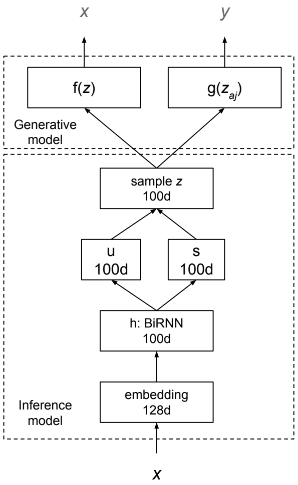
log p(x|z) + log p(y|z) − KL(q || p)

Marginalise **a**

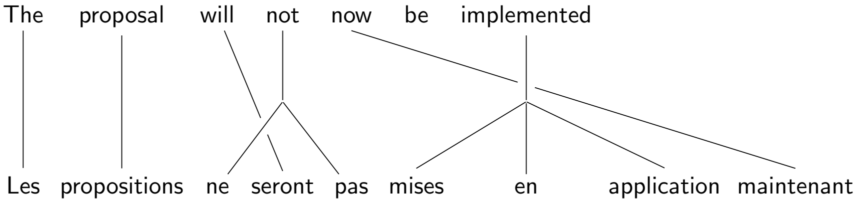
Data

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

Architecture



Word Alignment



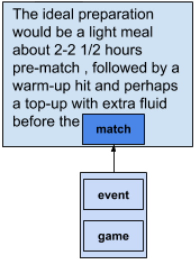
Word Alignment

- Model selection on Dev set

AER $\downarrow$

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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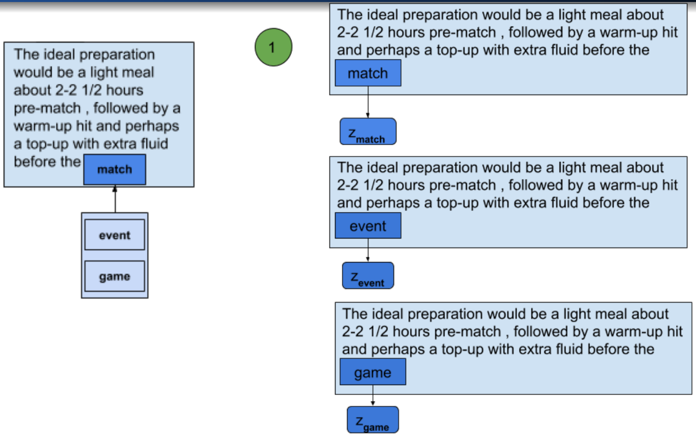

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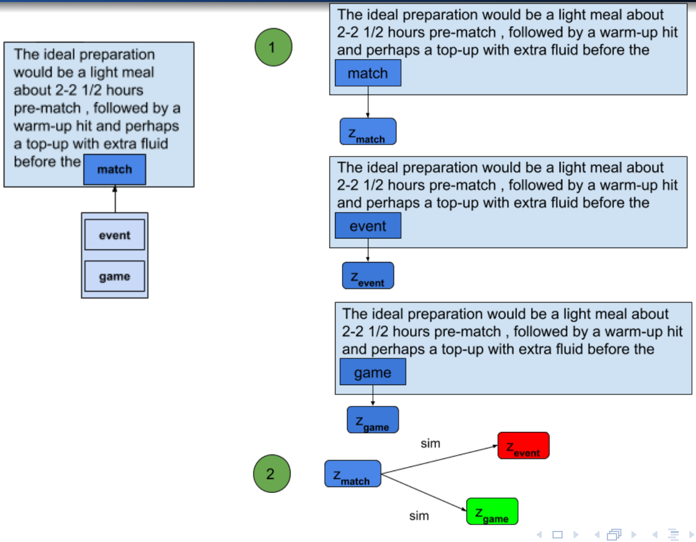
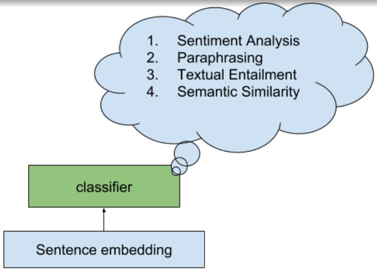


Lexical Substitution

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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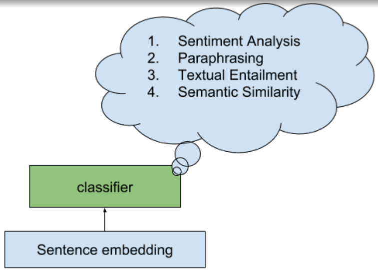

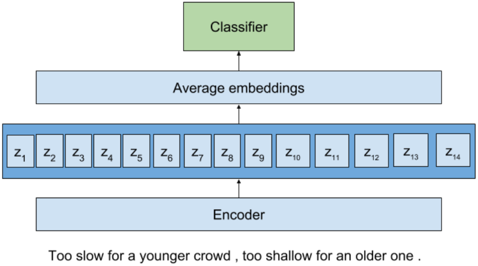

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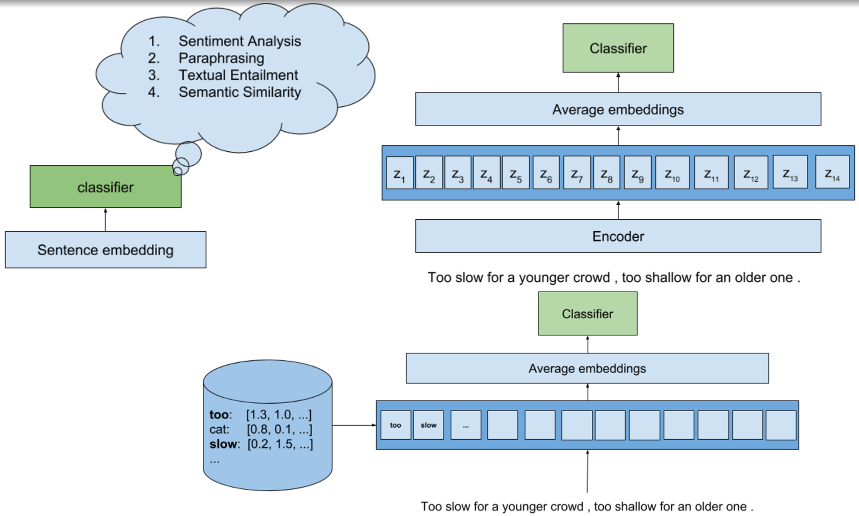

Sentence Evaluation (SentEval)

						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

Conclusions

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

Open Source Code

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

Outline

1. Word embeddings
2. EmbedAlign
   - Model
   - Evaluation
   - Conclusions and Future Work
3. EmbedAlign-2

EmbedAlign-2

- Hierarchical generative model of words and sentences by exploiting automatically generated paraphrasing data.

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- How to represent paraphrases that introduce **syntactic variations**.
- How to represent **noisy** automatically generated data.

Reference Translation	Machine Translation
so, what's half an hour?	half an hour won't kill you.
well, don't worry. i've taken out tons and tons of guys. lots of guys.	don't worry, i've done it to dozens of men.
it's gonna be ...... classic.	yeah, sure. it's gonna be great.
greetings, all!	hello everyone!
but she doesn't have much of a case.	but as far as the case goes, she doesn't have much.
it was good in spite of the taste.	despite the flavor, it felt good.

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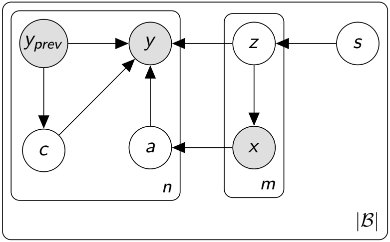
- Parallel data $\langle x_1^m, y_1^n \rangle$ where x_1^m is a sentence in original English and y_1^n is a sentence paraphrase English.
- Hierarchical generative model parameterised by neural networks.

$$
\begin{aligned}
S &\sim \mathcal{N}(0, I) \\
Z_i &\sim \mathcal{N}(\mu(s), \sigma^2(s))
\end{aligned}
\tag{2}
$$



Model I

- With a Gaussian distributed sentence embedding s and word embeddings z_1^m, we can marginalise collocation and alignment components.
  Latent decision is modelled with a Bernoulli trial:

$$p(y_j|x_1^m, z_1^m) = p(c_j = 0)p(y_j|y_{j-1}) + p(c_j = 1)\sum_{a_j=1}^{m} p(a_j|m, n)p(y_j|z_{a_j}) \quad (3)$$

Model II

- Inference:

$$q(s, z_1^m) = q_s(s) \prod_{i=1}^{m} q_{z_i}(z_i) \tag{4}$$

where $S \sim \mathcal{N}(\mathbf{u}_0, \mathbf{s}_0^2)$ and $Z_i \sim \mathcal{N}(\mathbf{u}_i, \mathbf{s}_i^2)$.

- Collocation is rudimentary language model condition on previously generated word.
- Alignment identifying relationships among words in the parallel data.

Model III

- Estimate parameters via maximisation of a lower-bound on marginal likelihood:

$$
\begin{aligned}
\log p(x_1^m, y_1^n) \geq \mathbb{E}[\log p(x_1^m|z_1^m)] \\
+\mathbb{E}[\log p(y_j|x_1^m, z_1^m)] \\
-\sum_{i=1}^{m} \mathbb{E}[\mathrm{KL}(q(z_i|x)\|p(z|s))] \\
-\mathrm{KL}(q(s|x)\|\mathcal{N}(0, I))
\end{aligned}
\tag{5}
$$

Evaluation

- Sentence-level paraphrases PARANMT-5M with 5 million sentences **EN1-EN2**.
- English-French **EN-FR** and English-German **EN-DE** from Europarl-v7.

Word Alignment

- Test alignment error rate (AER) on bilingual models.
- report on IBM models 1, 2 and FastAlign.

Model	En-Fr ↓	En-De ↓
IBM1	0.32	0.47
IBM2	0.23	0.40
EmbedAlign	0.29 ± 0.02	0.48 ± 0.02
FastAlign	0.19	0.36
This work	0.18 ± 0.01	0.40 ± 0.01

Evaluation

Model	MR	CR	MPQA	SUBJ	SST	TREC	MRPC	SICK-E	SICK-R	STS14
Baselines										
ELMO	79.87	84.85	89.21	94.19	85.67	92.80	72.93/80.90	81.21	0.82/0.75	0.61/0.58
SkipGram$_{\text{En1}}$	72.11	78.20	85.51	88.82	75.56	72.20	71.54/81.02	76.16	0.75/0.66	0.44/0.48
Ours										
En-Fr	66.76	71.18	85.40	82.32	67.52	70.45	71.90/80.77	75.18	0.67/0.62	0.49/0.50
En-De	66.00	72.21	85.71	81.63	67.64	70.45	71.83/80.85	75.73	0.66/0.62	0.49/0.59
En1-En2	66.88	71.59	81.80	82.97	69.14	67.30	71.33/80.36	75.62	0.72/0.66	0.53/0.52

EmbedAlign-2

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  - **S**ick **R** 0.727 $\rightarrow$ 0.770 CORR

EmbedAlign-2

- We modify alignment distribution
  - From IBM1 to IBM2
    En-Fr 29.43 → 18.20 AER
- We model word and sentence embeddings
  - **M**ovie **R**eviews 66.10 → 70.55 ACC
  - **M**icrosoft **P**araphrase 71.90/80.6 → 72.93/81.27 ACC/F1
  - **S**ick **R** 0.727 → 0.770 CORR
- We **will** expand the distributional context to multiple foreign languages at once

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