

Word Alignment Without NULL Words

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Problems with NULL Words

Several kinds of problems arise when using NULL words for word alignment:

- **Conceptual:** Untranslatable source words are aligned to NULL. Intuitively, they should depend on source side features as their presence is ultimately triggered by source side fluency requirements.
- **Distortion:** The NULL word has a position and thus induces implausibly long distortions that confuse the distortion model.
- **Sparsity:** There is one unique NULL word that occurs in every target sentence. Its distribution over source words tends to be extremely flat. This causes the “garbage collection problem”.

Idea

- Use source side language model to generate untranslatable words
- Introduce latent indicator variable Z that models choice between alignment and language model component
- Also capture tendency of individual words to collocate with their neighbours

Generative Story

- For each source position j
 - Choose an alignment link a_j according to $P(a_j)$
 - Dependent on the previous source word f_{j-1} decide whether to use the language model ($z_j = 1$) or the alignment model ($z_j = 0$) component
 - If $z_j = 1$, generate the source word f_j from its predecessor f_{j-1}
 - If $z_j = 0$, generate the source word f_j from its aligned target word e_{a_j}

We turn this into a Bayesian model by imposing Dirichlet/Beta priors on the Categorical/Bernoulli model parameters.

$$\begin{aligned} F_j | e, a_j, z_j = 0 &\sim \text{Cat}(\theta_{e_{a_j}}) & \Theta_{e_{a_j}} &\sim \text{Dir}(\alpha) \\ F_j | f_{j-1}, z_j = 1 &\sim \text{Cat}(\theta_{f_{j-1}}) & \Theta_{f_{j-1}} &\sim \text{Dir}(\beta) \\ Z_j | f_{j-1} &\sim \text{Bernoulli}(q_{f_{j-1}}) & Q_{f_{j-1}} &\sim \text{Beta}(s, r) \\ A &\sim \text{Cat}(\theta_a) & \Theta_a &\sim \text{Dir}(\gamma) \end{aligned}$$

Inference is done using a collapsed Gibbs sampler.

Experiments

Experiments were performed on WMT 2014 news data.

Model	En-De	En-Fr	En-Cs	En-Ja	De-En	Fr-En	Cs-En	Ja-En
Brown et al. (model 1)	15.14	26.86	14.88	28.36	19.36	27.41	20.07	25.26
Brown et al. (model 2)	+0.84	+0.77	+1.14	+3.02	+1.80	+1.77	+1.15	+2.95
Mermer et al. (model 1)	+0.52	+0.80	+1.30	+3.19	+1.51	+1.60	+1.77	+2.44
Mermer et al. (model 2)	+0.63	+0.33	+1.94	+3.00	+2.02	+1.22	+2.34	+2.48
This work (model 1)	+0.39	+0.23	+1.31	+3.33	+1.61	+0.98	+1.87	+2.56
This work (model 2)	+1.07	+1.47	+2.08	+2.65	+2.30	+2.19	+2.13	+3.21
Giza	+1.59	+0.87	+1.70	+4.24	+2.54	+2.08	+2.36	+3.94
fastAlign	+1.39	+1.23	+1.87	+2.47	+2.44	+2.06	+2.21	+3.58

Table : Symmetrised: alignments obtained in both directions independently and heuristically symmetrised (grow-diag-final-and).

Our Model

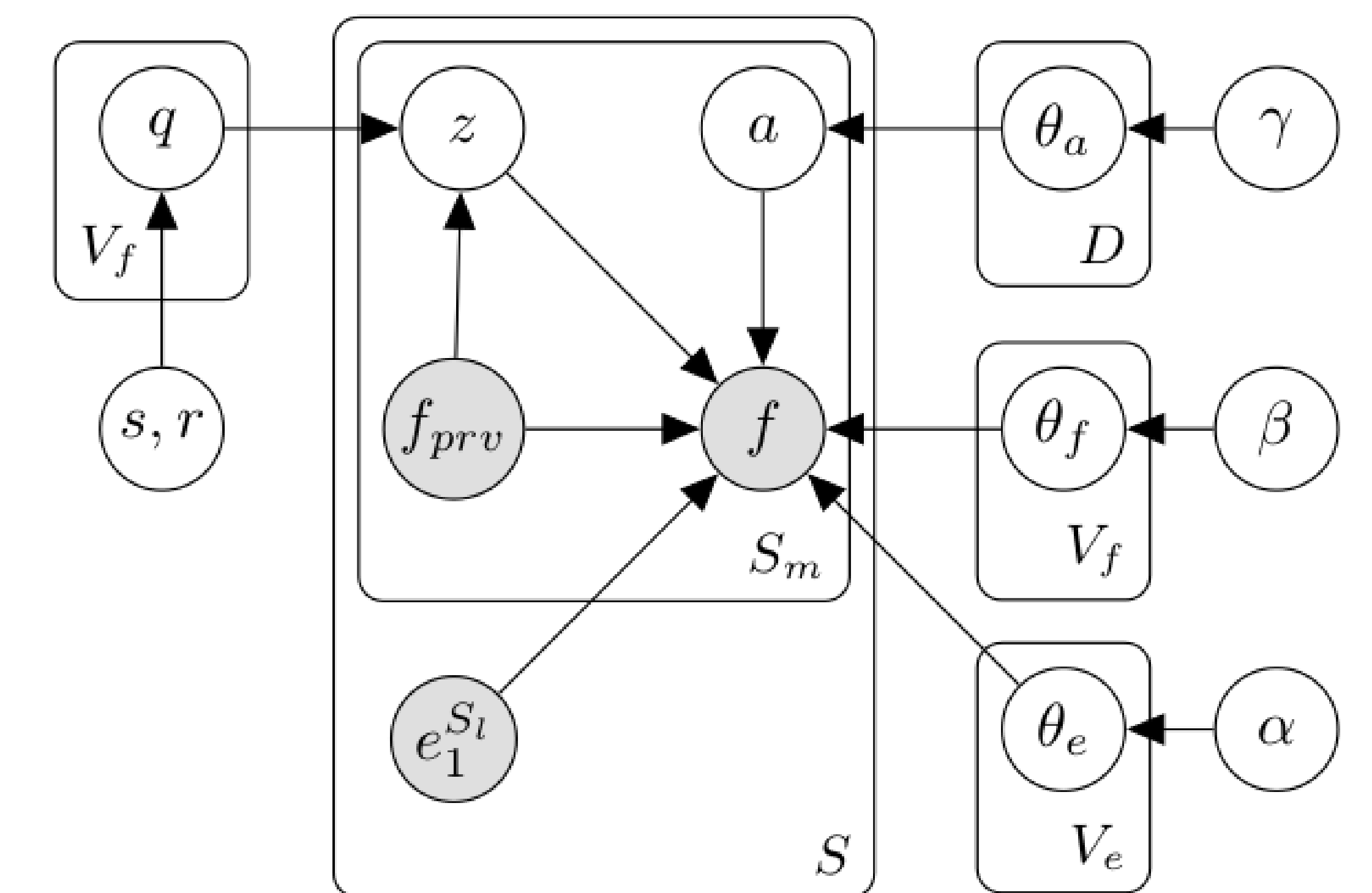


Figure : Graphical representation of our model.

Future Work

- Extend the alignment component to HMM
- Symmetric alignments
- Develop variational algorithm
- Use hierarchical language model
- Experiment with hierarchical SMT