

DISTANTLY SUPERVISED RELATION EXTRACTION WITH SENTENCE RECONSTRUCTION AND KNOWLEDGE BASE PRIORS

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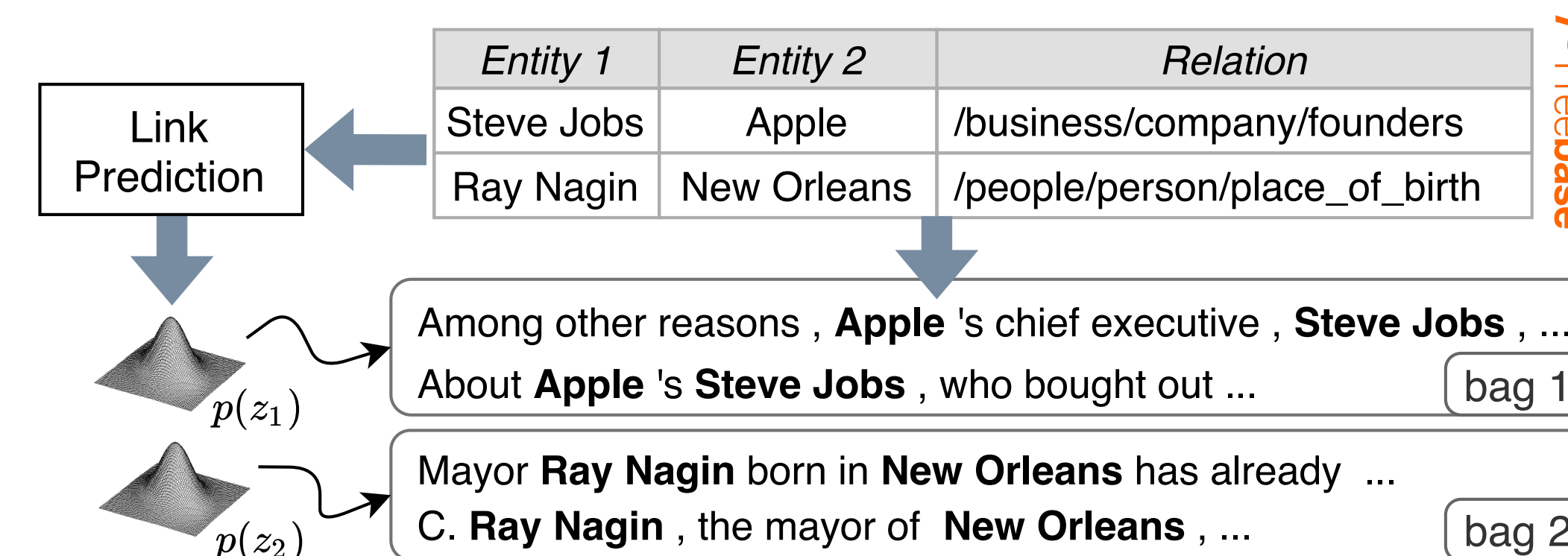
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INTRODUCTION

- Using KB information in DSRE is beneficial for identifying factual knowledge.
- Prior methods:
 - Require explicit usage of KB embeddings into the model.
 - Force same predictions between KB and sentence pairs.
- Inject signals from the KB to the target task via a probabilistic approach
- A few methods follow a rather flawed evaluation setting, where several test pairs are included in the training set → exaggerated generalisability.

BAG-LEVEL SETTING

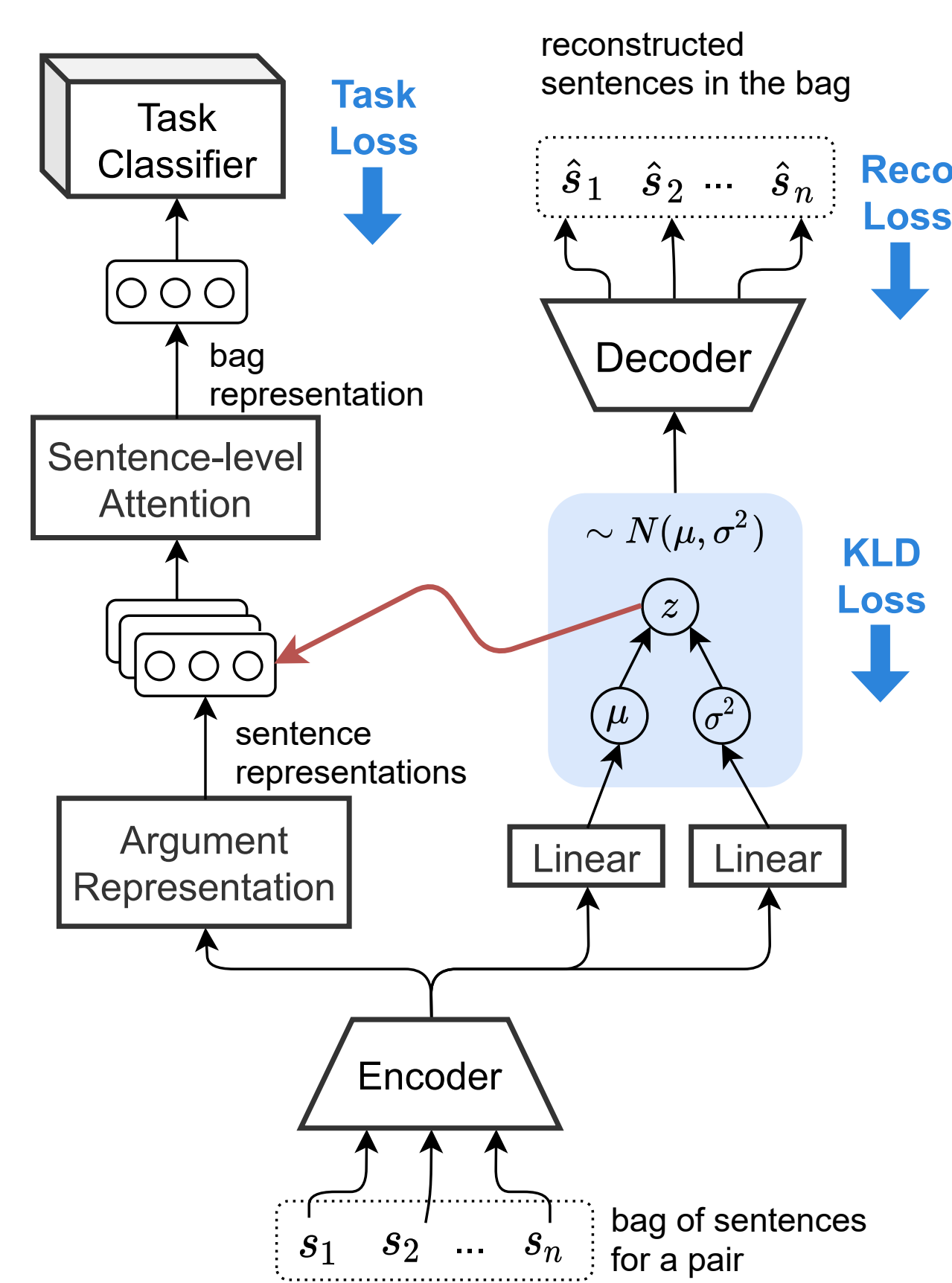


MAIN IDEA: VAE & KB PRIORS

- Take advantage of two properties:
 - Reconstruction via encoder-decoder networks helps sentence expressivity.
 - Signals from the KB can assist detection of factual relations.
- Combine these two using a VAE together with a bag-level relation classifier.
- Each sentence's latent code can be close to the Normal [2] or to a prior distribution obtained from TransE embeddings:

$$p_{\theta}(z) \sim \mathcal{N}(\mu_{KB}, \mathbf{I}), \text{ with } \mu_{KB} = \mathbf{e}_h - \mathbf{e}_t$$

METHODOLOGY



- The model consists of two branches:
 - Left branch: Bag classification
 - Right branch: Bag reconstruction
- Communication is achieved via the latent vector \mathbf{z} , constructed from the last hidden and cell state of the encoder:

$$\mu = \mathbf{W}_{\mu}[\mathbf{h}; \mathbf{c}] + \mathbf{b}_{\mu}, \quad \sigma^2 = \mathbf{W}_{\sigma}[\mathbf{h}; \mathbf{c}] + \mathbf{b}_{\sigma}$$

$$\mathbf{z} = \mu + \sigma \odot \epsilon, \text{ where } \epsilon \sim \mathcal{N}(0, \mathbf{I}) \text{ or } \epsilon \sim \mathcal{N}(\mu_{KB}, \mathbf{I})$$
- Decoder is responsible for reconstructing each sentence in the bag:

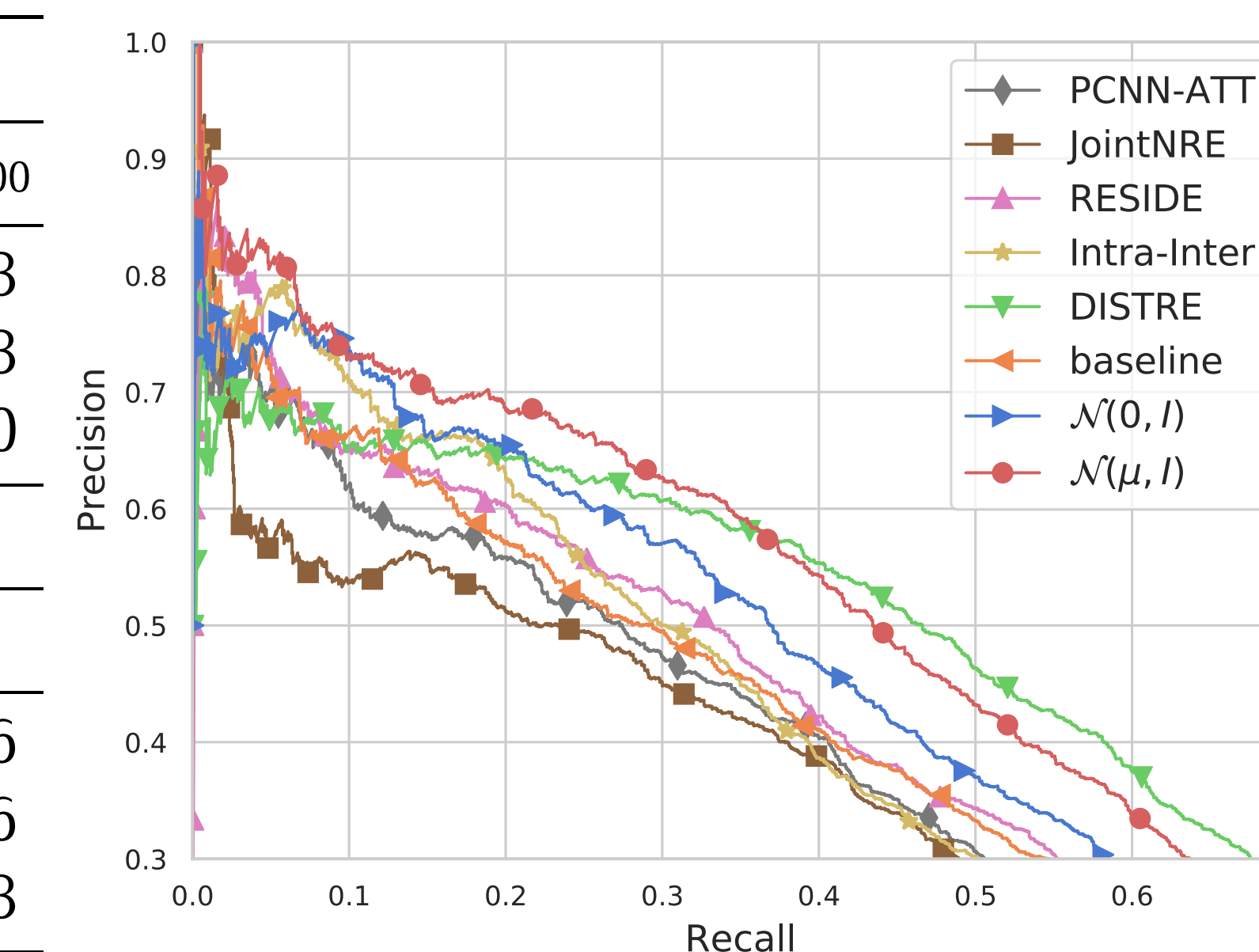
$$\mathbf{h}'_0 = \mathbf{W}\mathbf{z} + \mathbf{b}, \quad \mathbf{x}'_i = [\mathbf{w}_i; \mathbf{z}],$$
- Classifier uses sentence representations and attention to form bag representations:

$$\mathbf{e}_i = \frac{1}{|e_i|} \sum_{k \in e_i} \mathbf{o}_k, \quad \mathbf{s} = \mathbf{W}_v[\mathbf{z}; \mathbf{e}_1; \mathbf{e}_2], \quad \mathbf{B}_r = \sum_{i=1}^{|B|} a_r^{(s_i)} \mathbf{s}_i,$$
- Total Loss: $L = \lambda L_{BCE} + (1 - \lambda)L_{ELBO}$

RESULTS

NYT-10		
Method	520K AUC	570K AUC
Baseline	34.94	43.59
+ $p_{\theta}(z) \sim \mathcal{N}(0, \mathbf{I})$	38.59	44.64
+ $p_{\theta}(z) \sim \mathcal{N}(\mu_{KB}, \mathbf{I})$	42.89	45.52
PCNN-ATT [5]	32.66	36.25
JOINT NRE [3]	30.62	40.15
RESIDE [6]	35.80	41.60
INTRA-INTER BAG [7]	34.41	42.20
DISTRE [1]	42.20	-

WIKIDISTANT				
Method	AUC	P@100	P@200	P@300
Baseline	28.54	94.0	93.0	88.3
+ $p_{\theta}(z) \sim \mathcal{N}(0, \mathbf{I})$	30.59	96.0	93.5	89.3
+ $p_{\theta}(z) \sim \mathcal{N}(\mu_{KB}, \mathbf{I})$	29.54	92.0	89.0	90.0
PCNN-ATT [4]	22.20	-	-	-
w/o non KB-prior pairs (72% of pairs preserved)				
Baseline	26.16	88.0	85.0	82.6
+ $p_{\theta}(z) \sim \mathcal{N}(0, \mathbf{I})$	27.46	90.0	88.0	84.6
+ $p_{\theta}(z) \sim \mathcal{N}(\mu_{KB}, \mathbf{I})$	28.38	94.0	95.0	89.3



CONCLUSIONS/TAKEAWAYS

- The proposed approach brings close sentences that contain the same KB pairs.
- Our method does not require any external information during inference time.
- Jointly reconstructing sentences with relation classification is helpful for DSRE and KB priors further boost performance.
- We show that we can manipulate the space of sentences to match the space of KB triples, while reconstruction keeps topic-related terms.
- We are able to surpass a pre-trained GPT-2 model on the NYT10 dataset!

PRIOR/POSTERIOR ANALYSIS

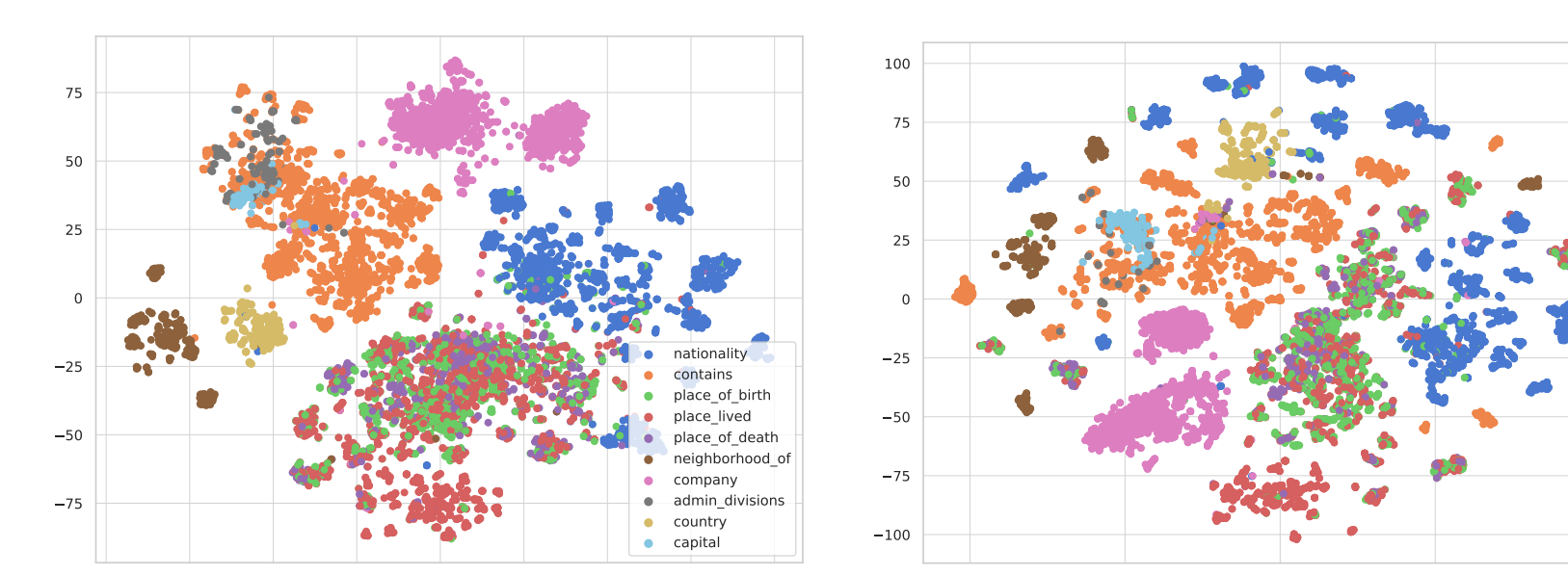


Figure 1: NYT-10 Priors and Posteriors

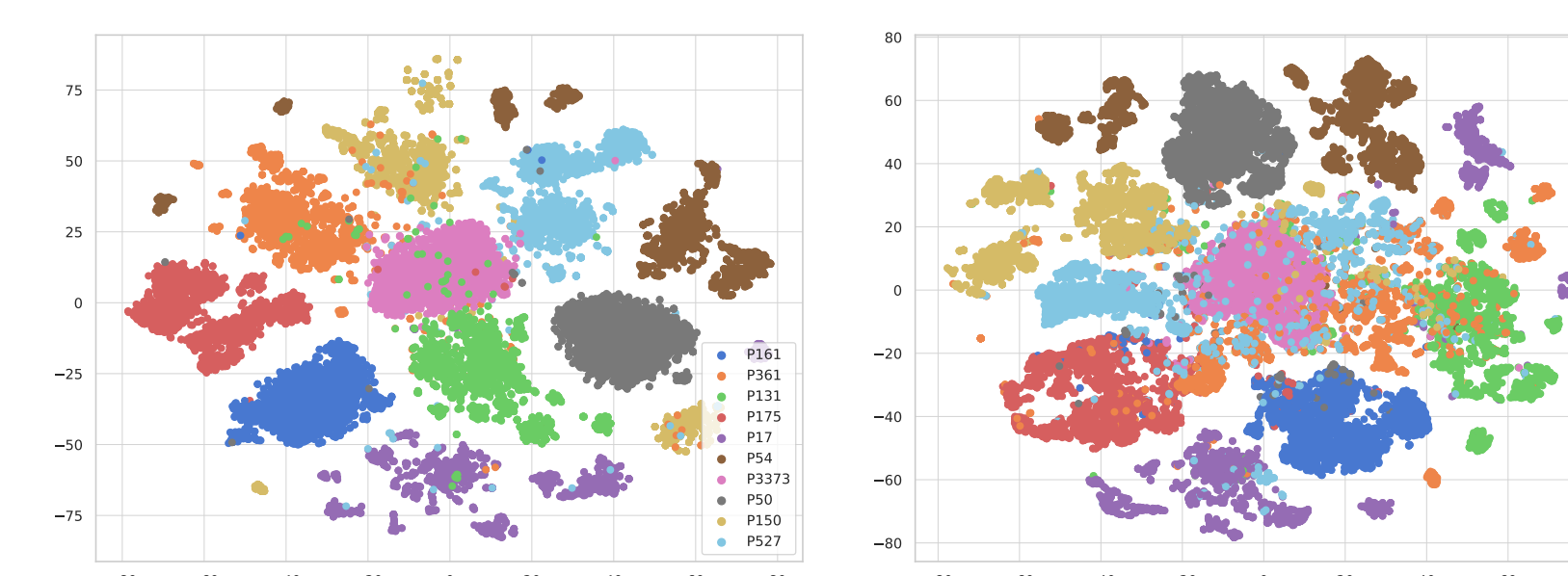


Figure 2: WIKIDISTANT Priors and Posteriors

SENTENCE RECONSTRUCTION

- Sentence reconstruction with KB priors produces quite plausible sentences
- Both the Normal and KB prior distributions preserve topic-related words

Examples from WIKIDISTANT:

	INPUT
	ng 's first role was in the # michael hui comedy film " the private eyes " .
$\mathcal{N}(0, \mathbf{I})$	MEAN the film was adapted into the # film ' the _ ' , directed by _ .
SAMPLE	in # , he appeared in ' the _ ' , a # film adaptation of the same name by _ .
$\mathcal{N}(\mu_{KB}, \mathbf{I})$	MEAN _ 's first film was ' the _ ' , starring _ and starring _ .
SAMPLE	_ , who was the first female actress to win the academy award for best actress .

References

- C. Alt, M. Hübner, and L. Hennig. Fine-tuning pre-trained transformer language models to distantly supervised relation extraction. In *Proceedings of ACL*, pages 1388–1398, 2019.
- S. R. Bowman, L. Vilnis, O. Vinyals, A. Dai, R. Jozefowicz, and S. Bengio. Generating sentences from a continuous space. In *Proceedings of SIGNLL*, pages 10–21, 2016.
- X. Han, Z. Liu, and M. Sun. Neural knowledge acquisition via mutual attention between knowledge graph and text. In *Proceedings of AAAI*, 2018.
- X. Han, T. Gao, and Y. e. a. Lin. More data, more relations, more context and more openness: A review and outlook for relation extraction. In *Proceedings of ACL*, pages 745–758, 2020.
- Y. Lin, S. Shen, Z. Liu, H. Luan, and M. Sun. Neural relation extraction with selective attention over instances. In *Proceedings of ACL*, pages 2124–2133, 2016.
- S. Vashishth, R. Joshi, and S. S. e. a. Prayaga. RESIDE: Improving distantly-supervised neural relation extraction using side information. In *Proceedings of EMNLP*, pages 1257–1266, 2018.
- Z.-X. Ye and Z.-H. Ling. Distant supervision relation extraction with intra-bag and inter-bag attentions. In *Proceedings of NAACL*, pages 2810–2819, 2019.