Contrastive Language-Entity Pre-training for Richer Knowledge Graph Embedding

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Multimodal Learning

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- Integration of multiple data modalities

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- Text and Images, or Text and Graph data for instance

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Paradisiac beach of a tropical South-Korean island

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- Can we learn a similar multimodal text-graph space
  for Knowledge Graphs?

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- Does it implicitely yield better KG representations?

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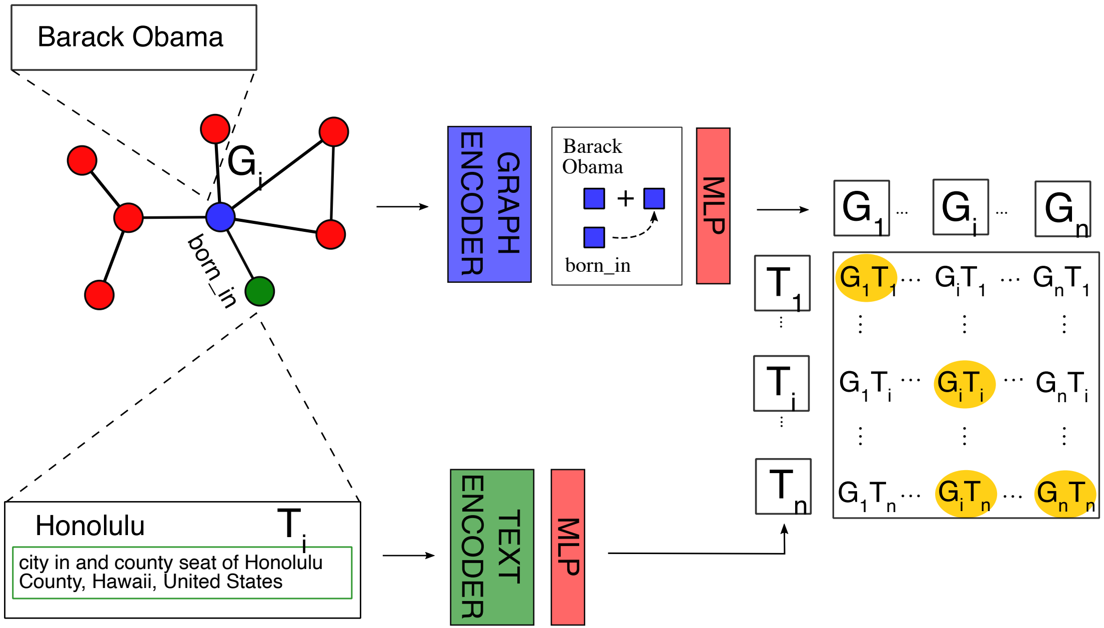
The CLEP Architecture

$(Barack\ Obama,\ born\_in,\ Honolulu)$



A Forward Pass

e^{head} : head node of the relational triplet

d^{tail} : description of the tail node

Batch of KG triplets

$$\{(e_1^{head}, r_1, d_1^{tail}),\ \ldots\ ,(e_n^{head}, r_n, d_n^{tail})\}$$

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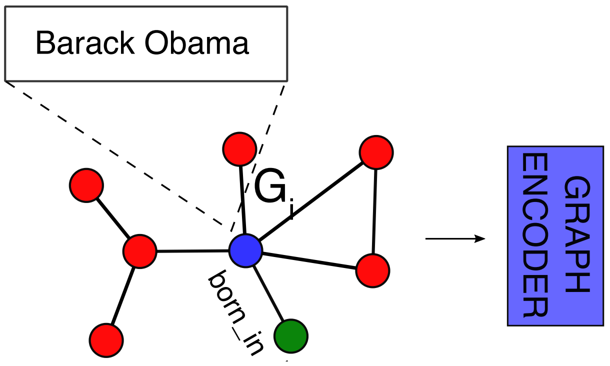

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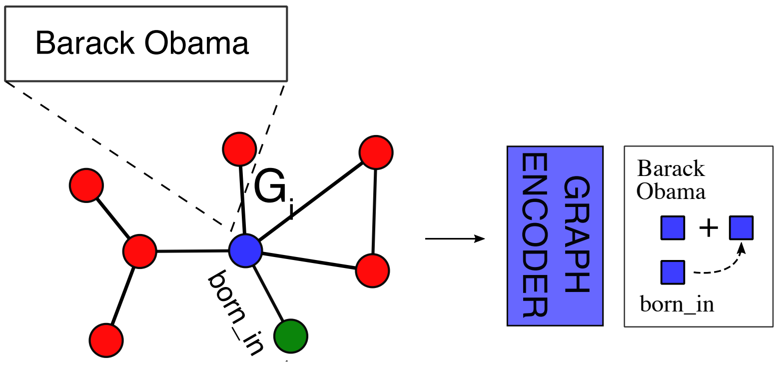

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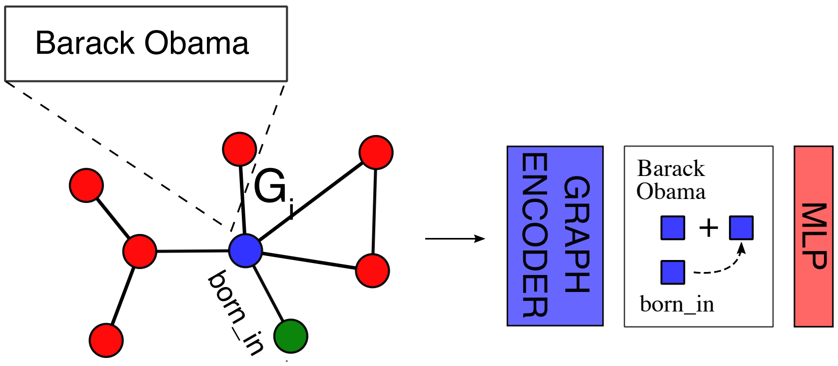

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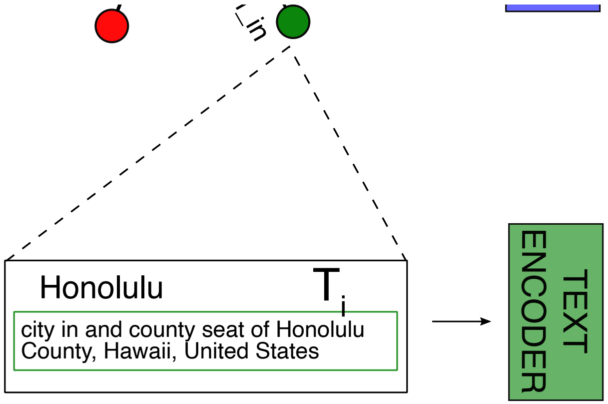

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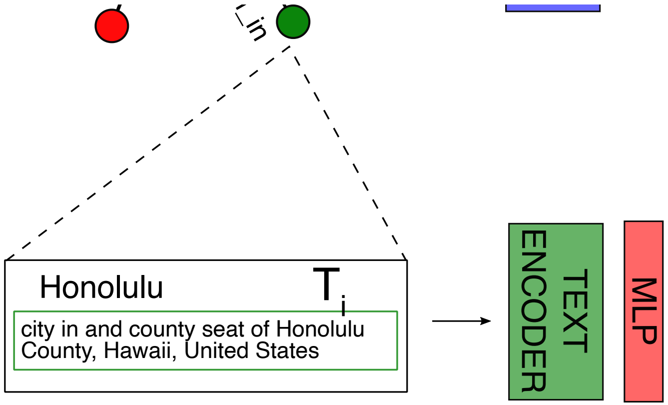

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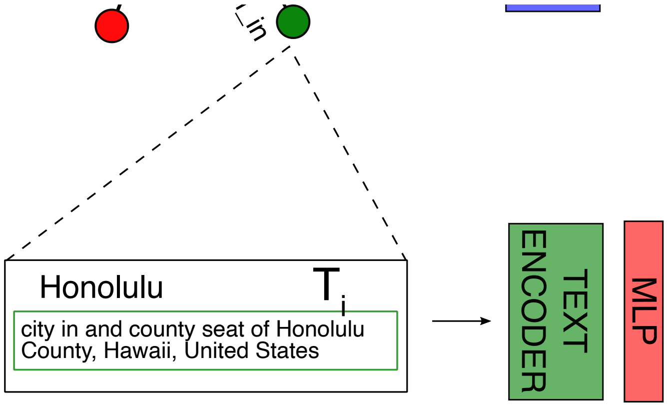

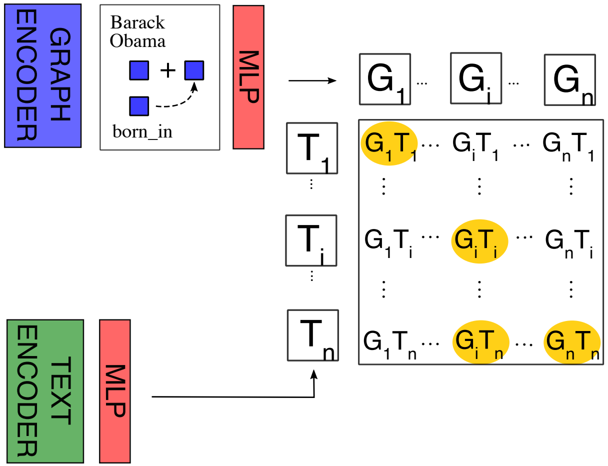

Cosine similarity matrix

$$m_{i,j} = \frac{\tilde{x}_i^{(g)} \cdot \tilde{x}_j^{(t)}}{\|\tilde{x}_i^{(g)}\| \|\tilde{x}_j^{(t)}\|} \cdot e^{\tau}$$

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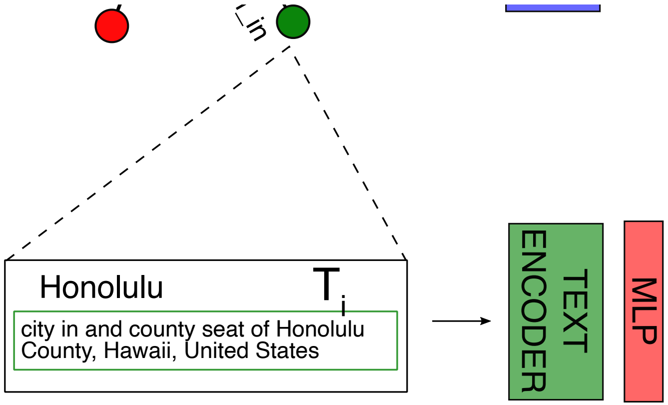

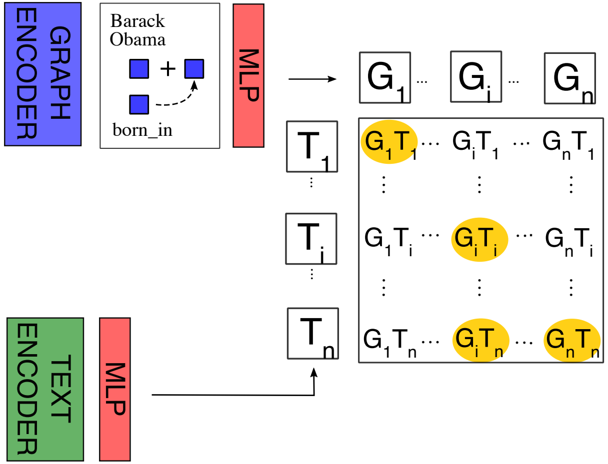

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τ : temperature scaling the logits

A Forward Pass

Row-wise Cross Entropy (CE)

$$\mathrm{CE}(M) = -\frac{1}{n}\sum_{i=1}^{n} \log \frac{e^{m_{i,i}}}{\sum_{j=1}^{n} e^{m_{i,j}}}$$

$$\begin{bmatrix} G_1T_1 & \cdots & G_iT_1 & \cdots & G_nT_1 \\ \vdots & & \vdots & & \vdots \\ G_1T_i & \cdots & G_iT_i & \cdots & G_nT_i \\ \vdots & & \vdots & & \vdots \\ G_1T_n & \cdots & G_iT_n & \cdots & G_nT_n \end{bmatrix}$$

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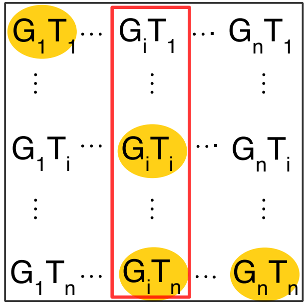

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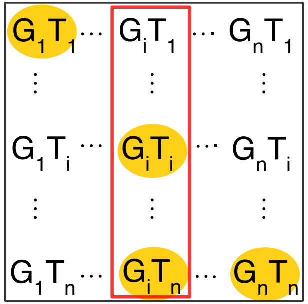

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$$\mathcal{L} = \frac{1}{2}\Big(\mathrm{CE}(M) + \mathrm{CE}(M^\top)\Big)$$

$\longrightarrow$ Enforces minimization of incorrect entity-description associations simultaneously in rows and columns!

The aligned Text-Graph space

Euclidean distance of the correct/incorrect entity-description associations

$$P\left(\|\tilde{x}_i^{(g)} - \tilde{x}_i^{(t)}\|\right) \qquad P\left(\|\tilde{x}_i^{(g)} - \tilde{x}_j^{(t)}\|_{i \neq j}\right)$$

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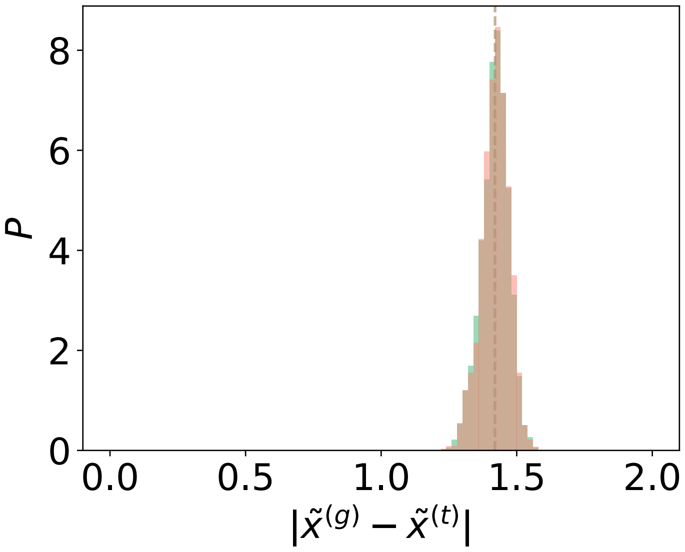

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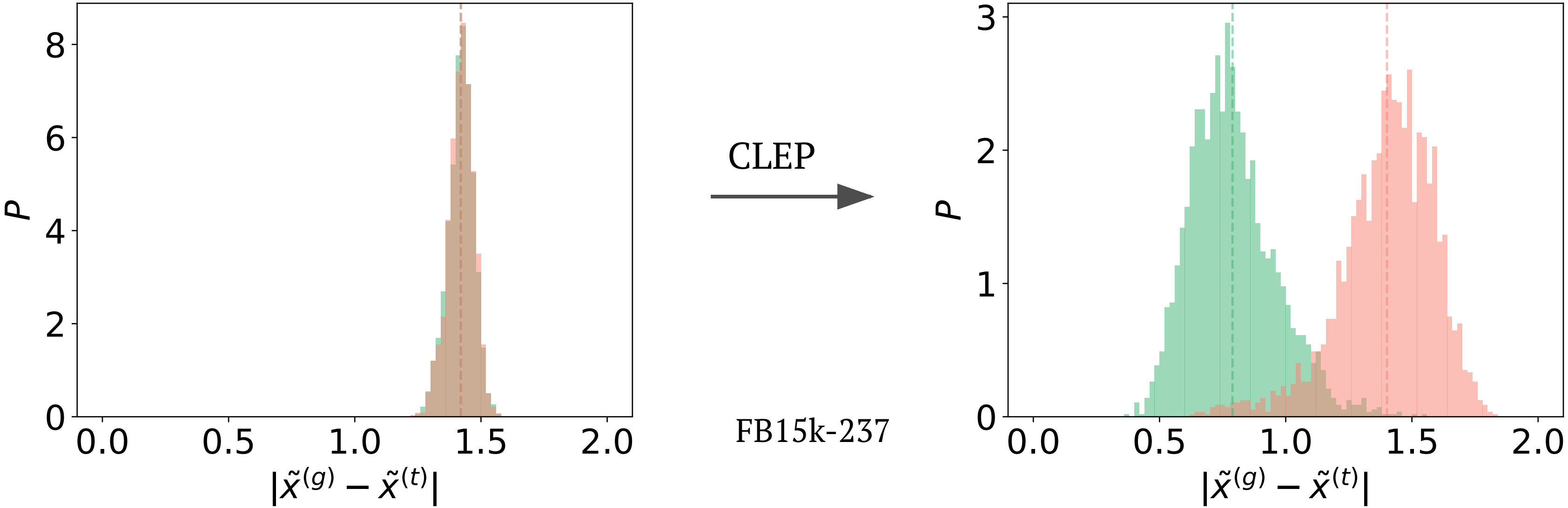

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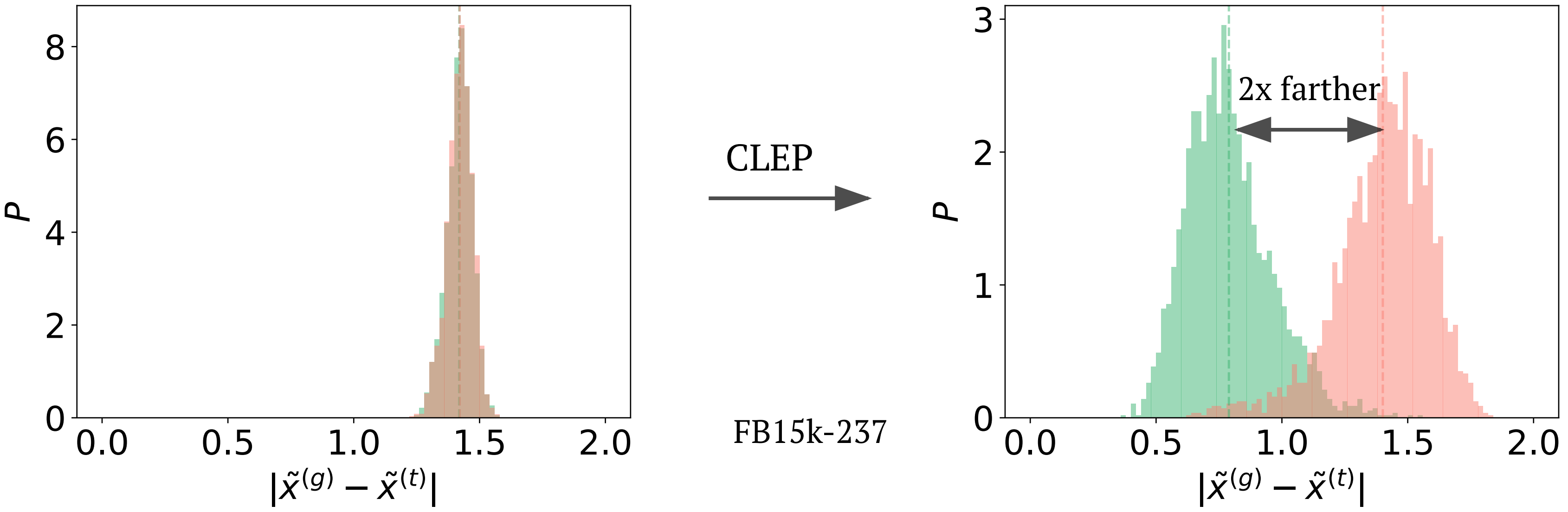

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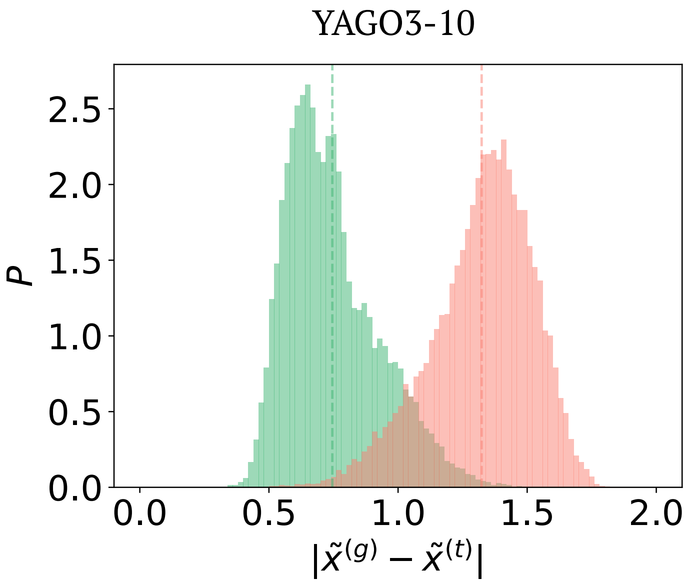

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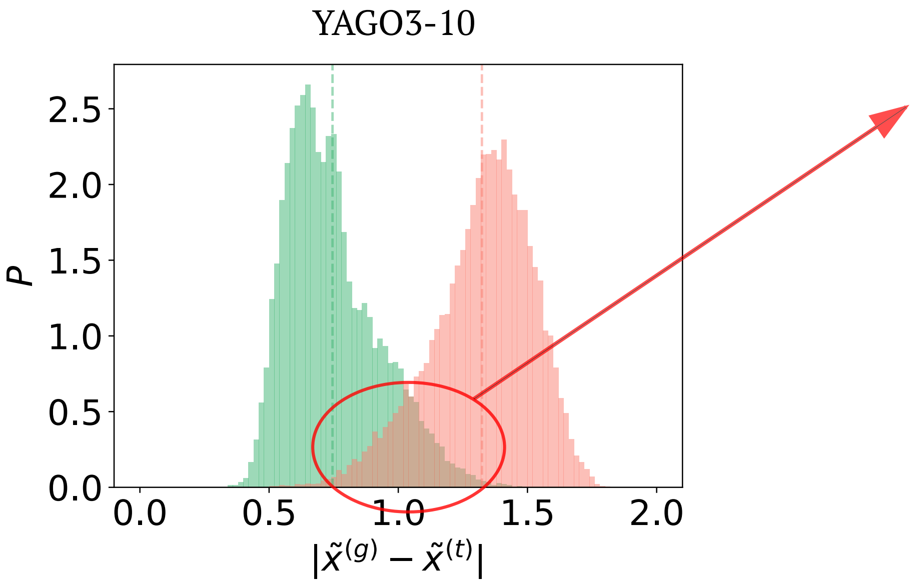

Incorrect pairs closer than correct ones

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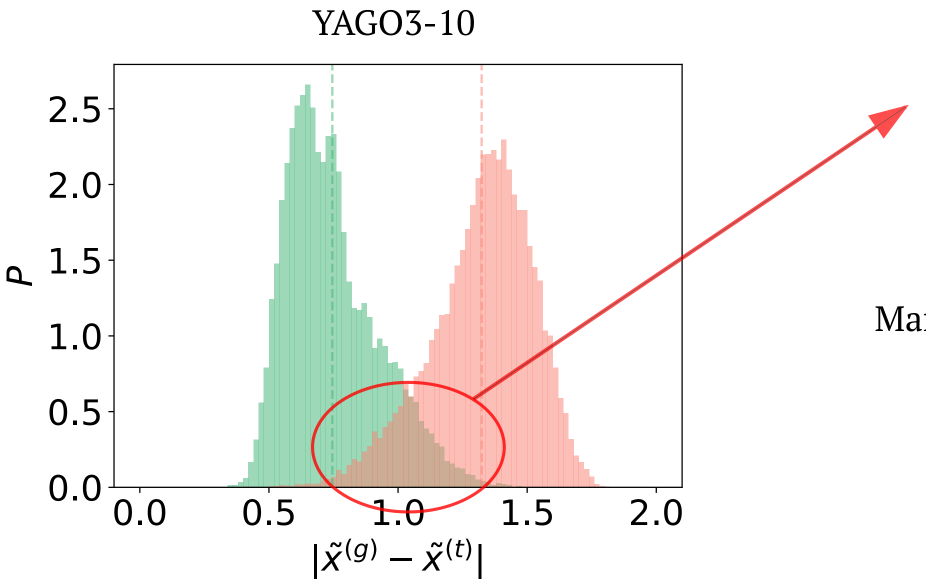

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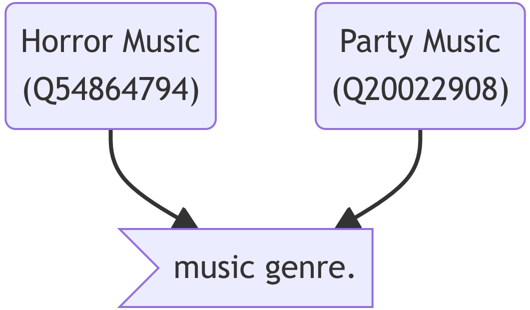
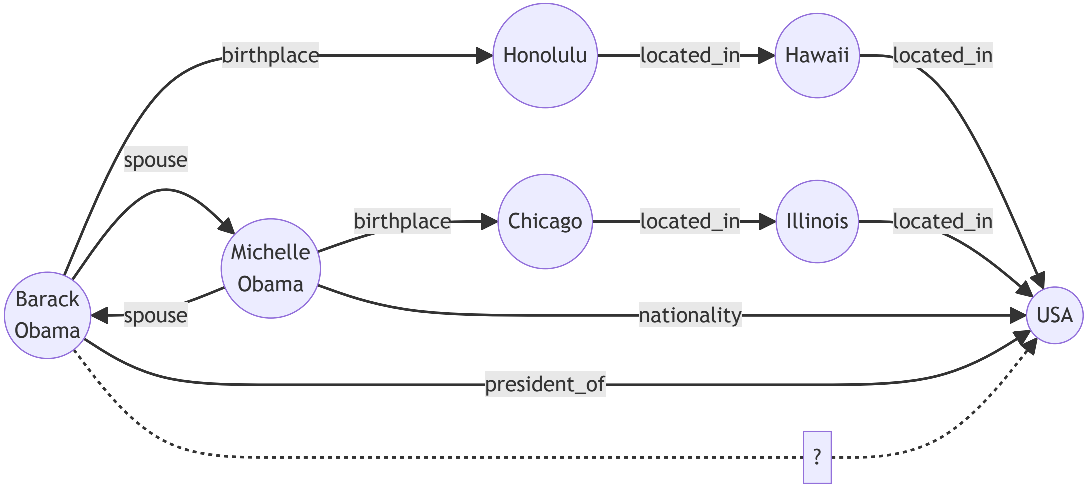
Many descriptions are shared over different entities



Link Prediction across spaces



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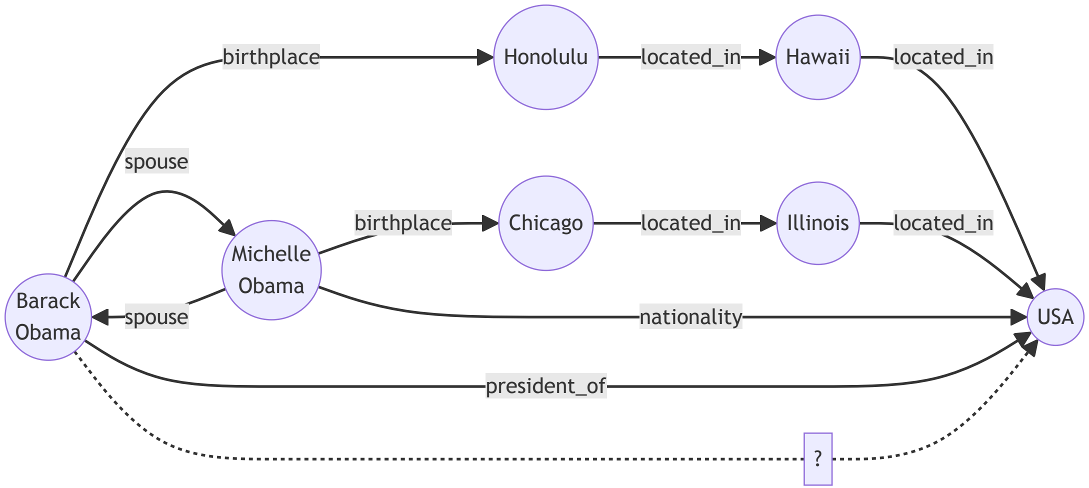

What's Barack Obama's Nationality?

$$f_s(\text{Barack Obama},\ \text{nationality},\ v) \quad \forall v \in \mathcal{G}$$

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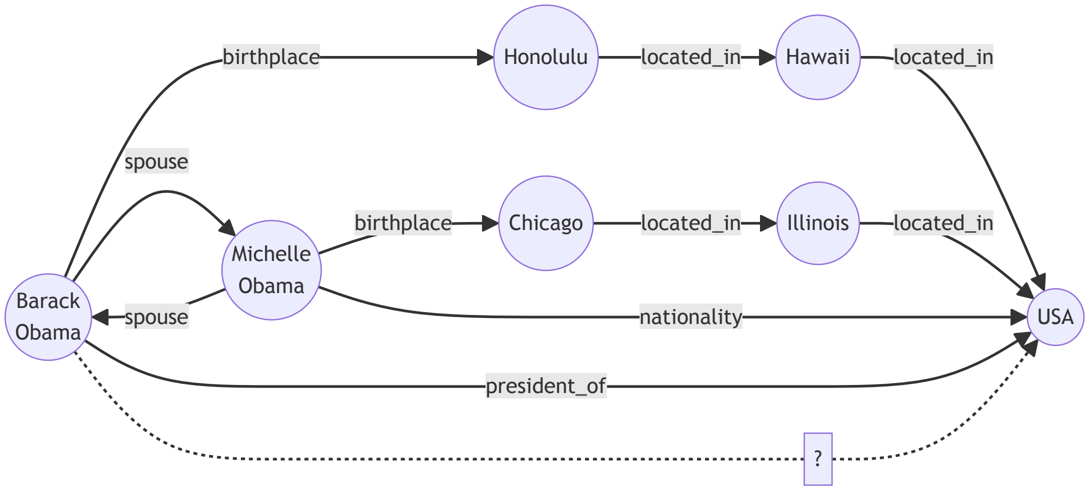

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Rank	f_s	Link
1	0.91	(Barack Obama, nationality, USA)
2	0.53	(Barack Obama, nationality, Hawaii)
3	0.44	(Barack Obama, nationality, Illinois)
.	.	.
.	.	.
.	.	.
n	0.11	(Barack Obama, nationality, Michelle Obama)

Link Prediction across spaces

- CLEP is trained to align head entities with tails descriptions $e^{head} + r \sim d^{tail}$

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Cosine Similarity score

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	MR	MRR	hits@1	hits@10
CLEP	**198**	0.222	0.137	0.396
RGCN + Distmult	315	**0.237**	**0.156**	**0.407**

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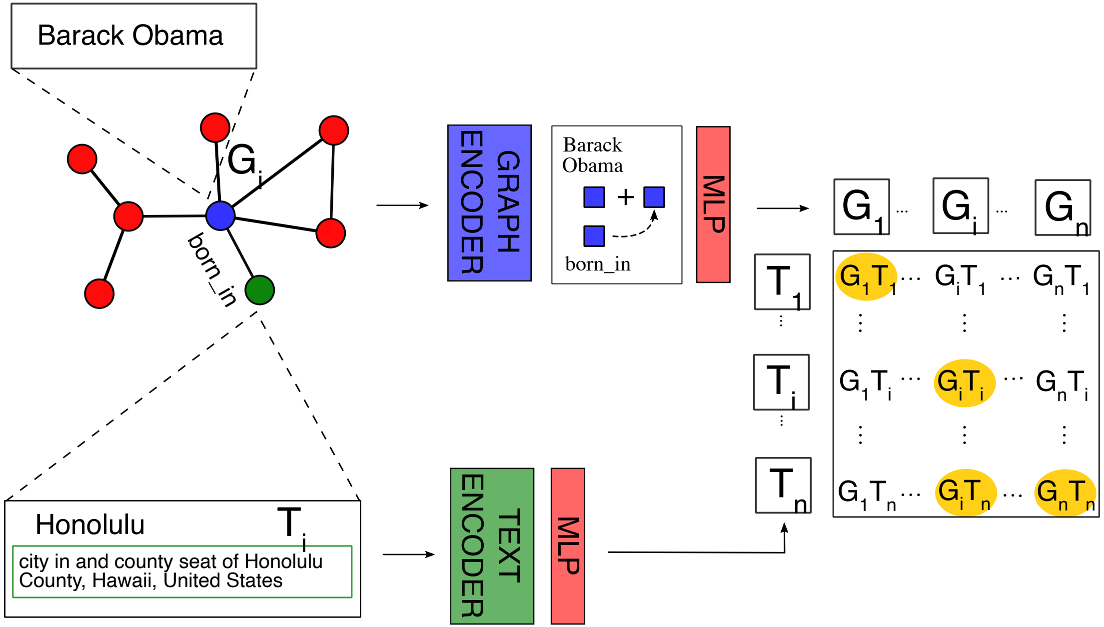
Link Prediction Finetuning

- Pretrain with CLEP



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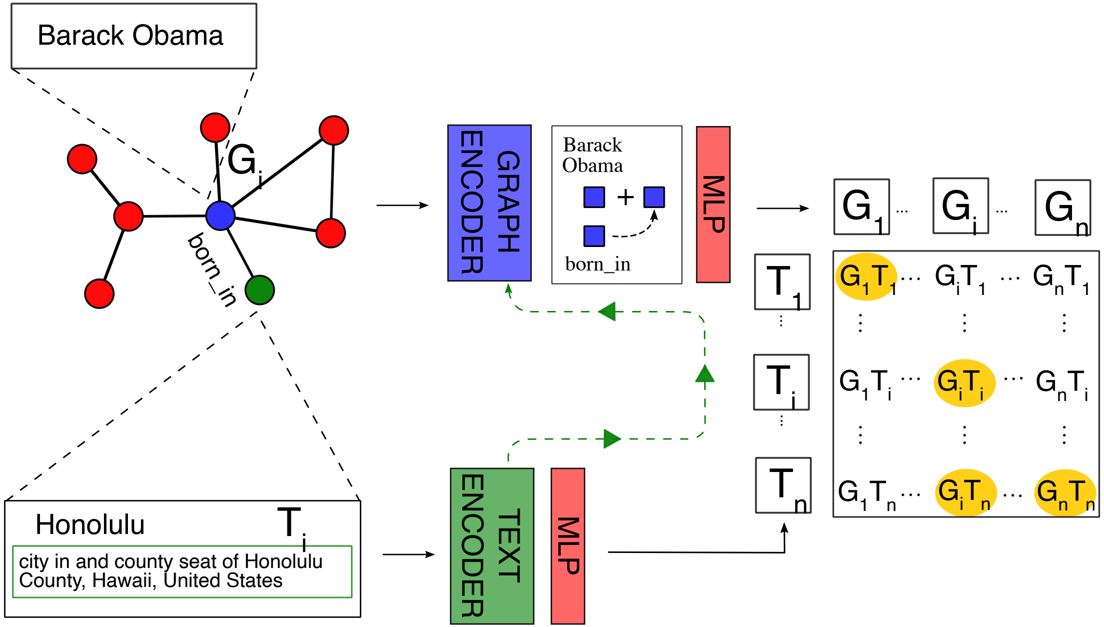

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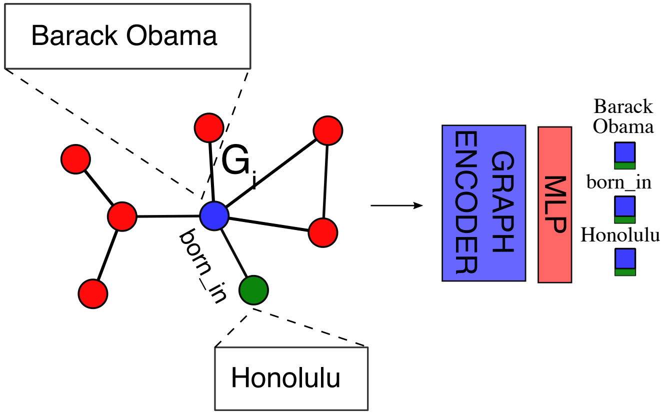

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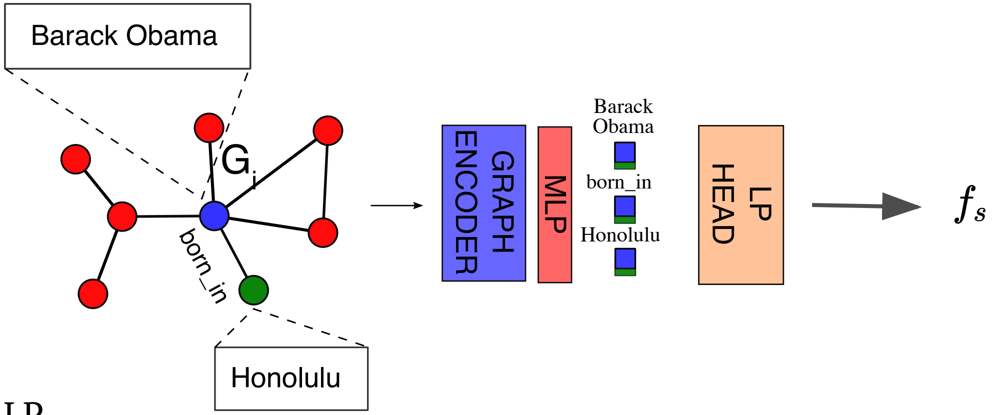

- Finetune on pure LP

RESCAL / DistMult

$$f_s(h, r, t) = h^T M_r t$$

TransE

$$f_s(h, r, t) = \|h + r - t\|$$

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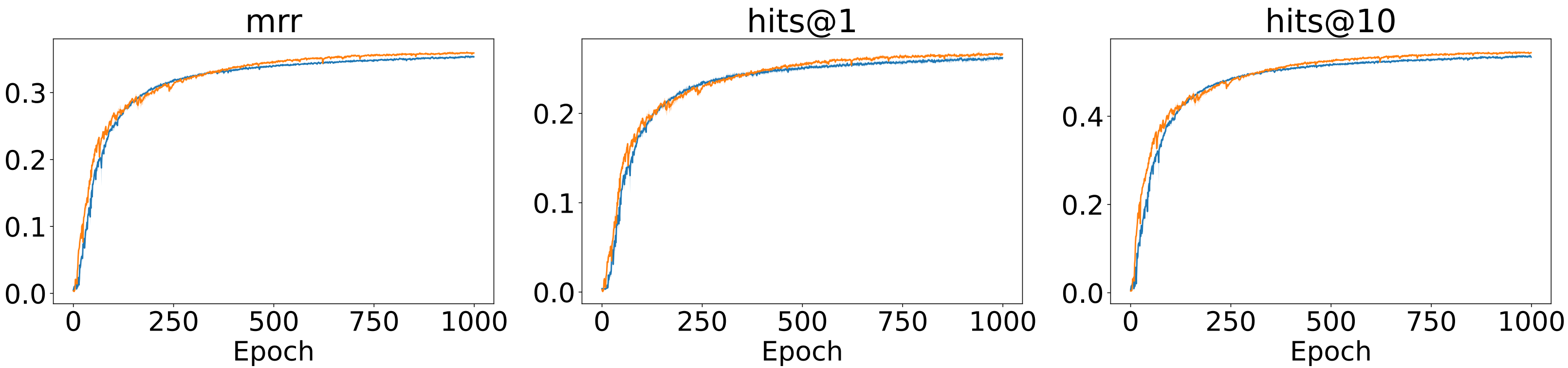

$\sim +1 \text{ - } 2\%$

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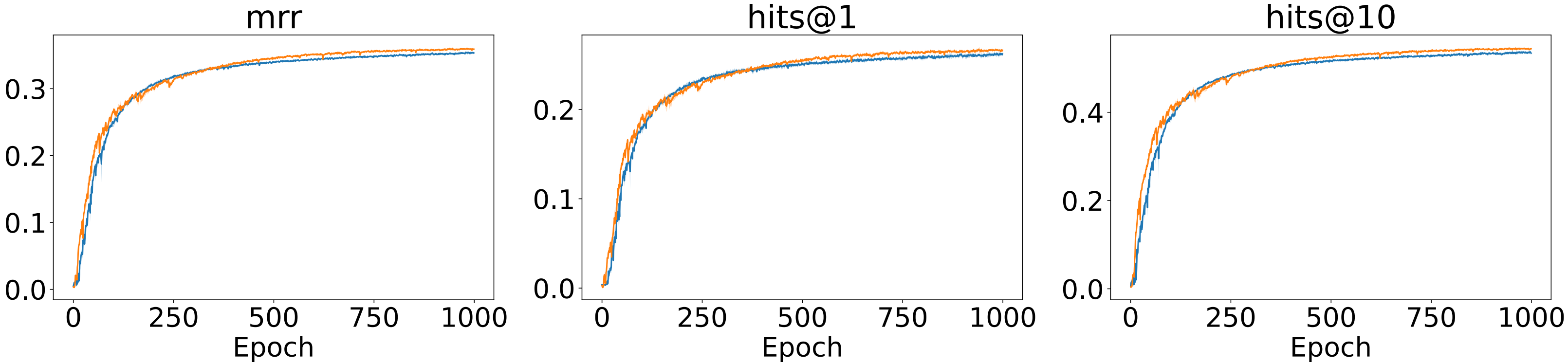

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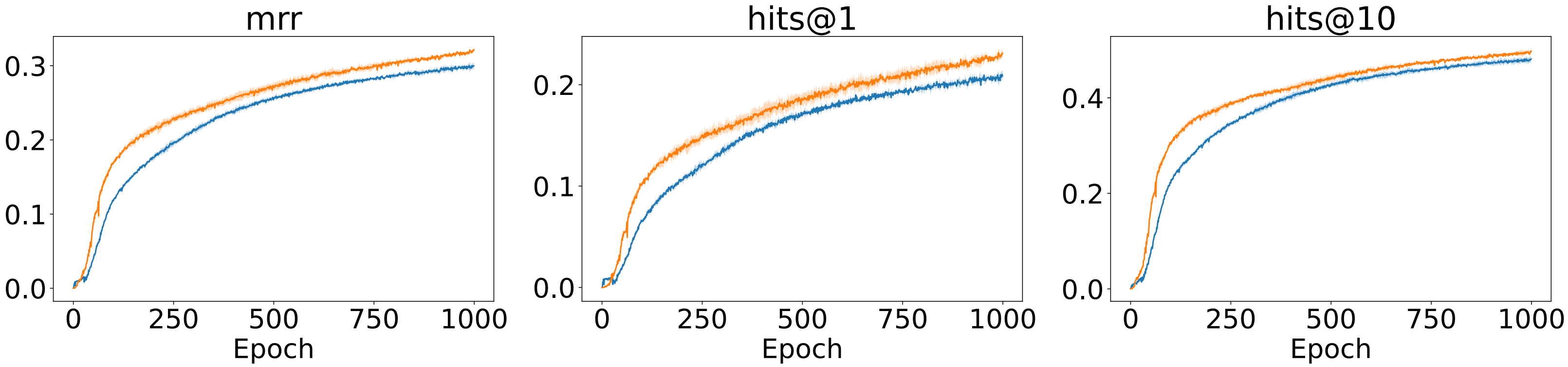
YAGO3-10



$\sim +4\text{-}10\%$

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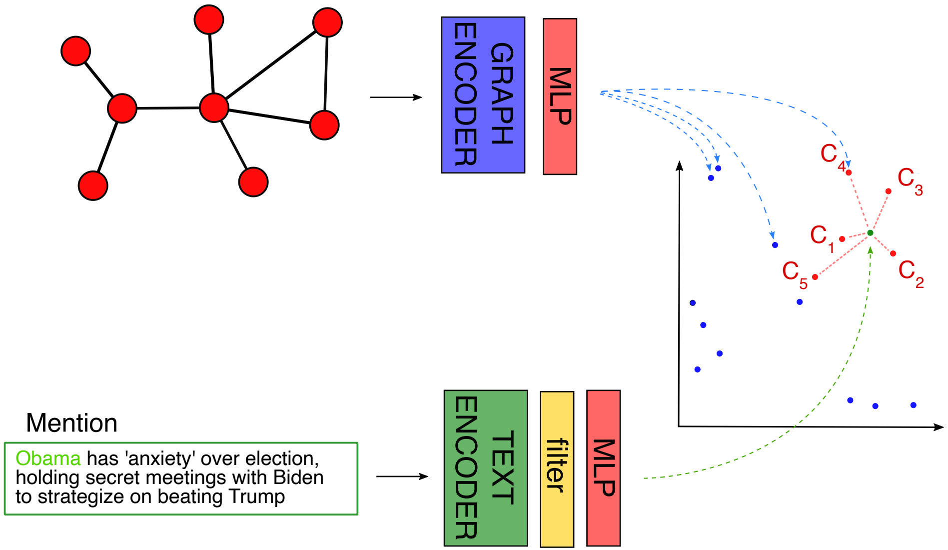
  → zero-shot Entity Linking: comparison of entity mentions and node embeddings
- Stable diffusion based Graph Generative Model for Information Extraction

Thank you for the Attention!

Zero-shot Entity Linking

- Candidates generation $(C_1, C_2, \ldots, C_n)$ through calculating the distance from the mention m



Stable Diffusion for Graph Generation