Edge Analysis

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- Labels
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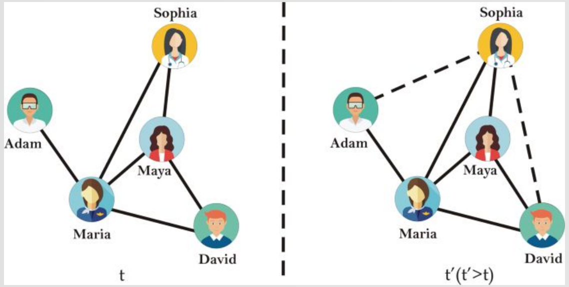

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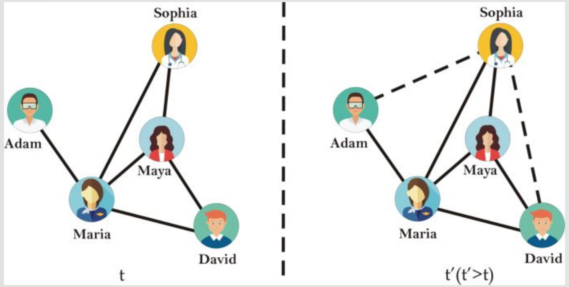

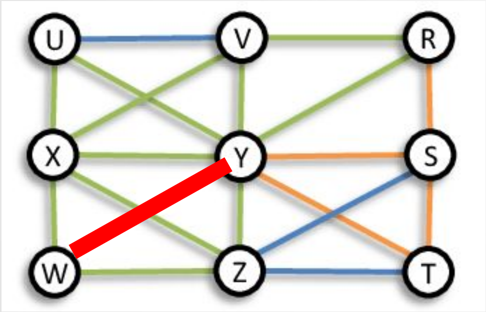

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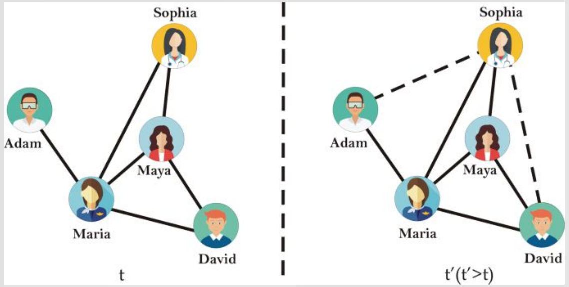

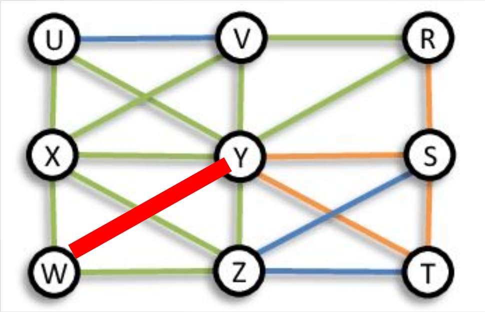

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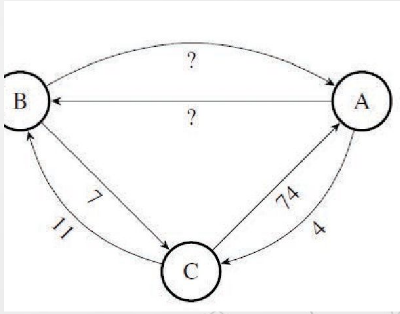

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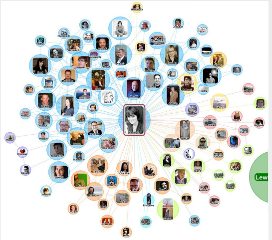

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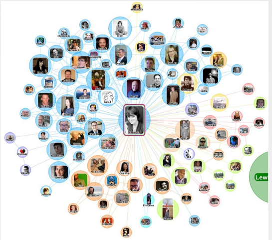

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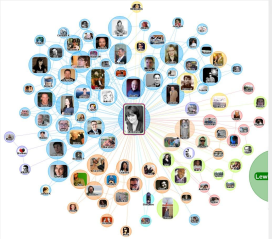

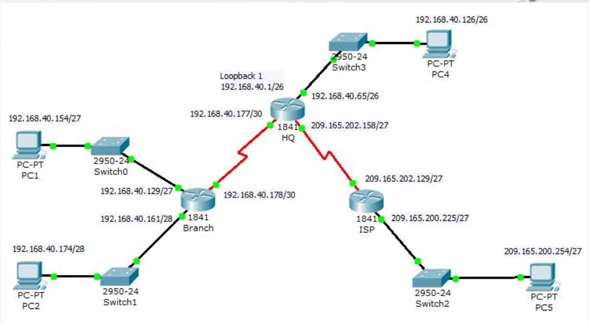

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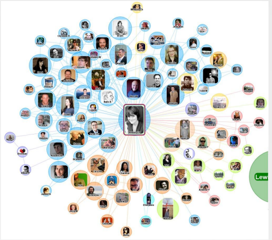
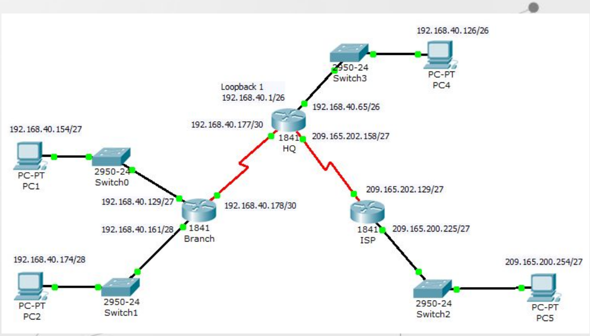


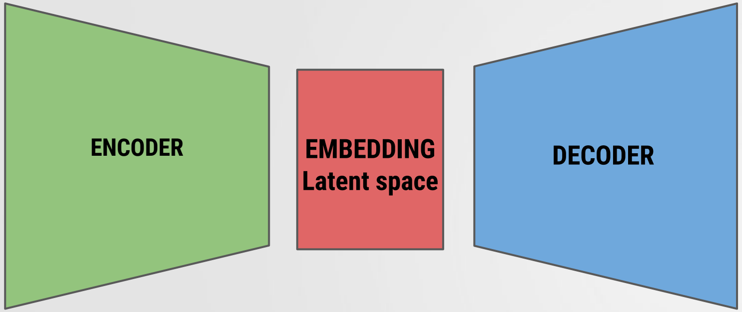
HOW TO SOLVE IT

- Topology based methods
- Node attribute based methods
- Based on embeddings
- Probabilistics relationship models
- Etc …



03 GAE for link prediction

Recap GAE



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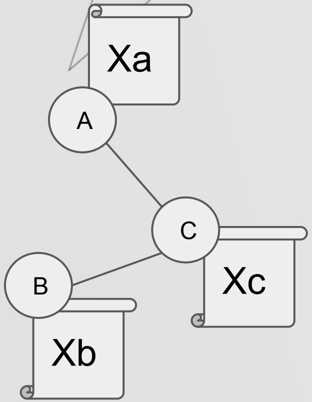

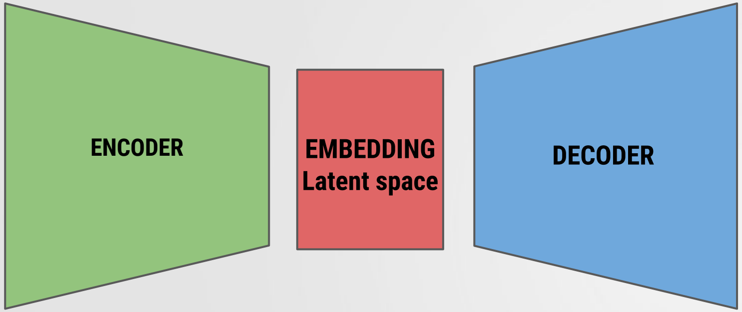

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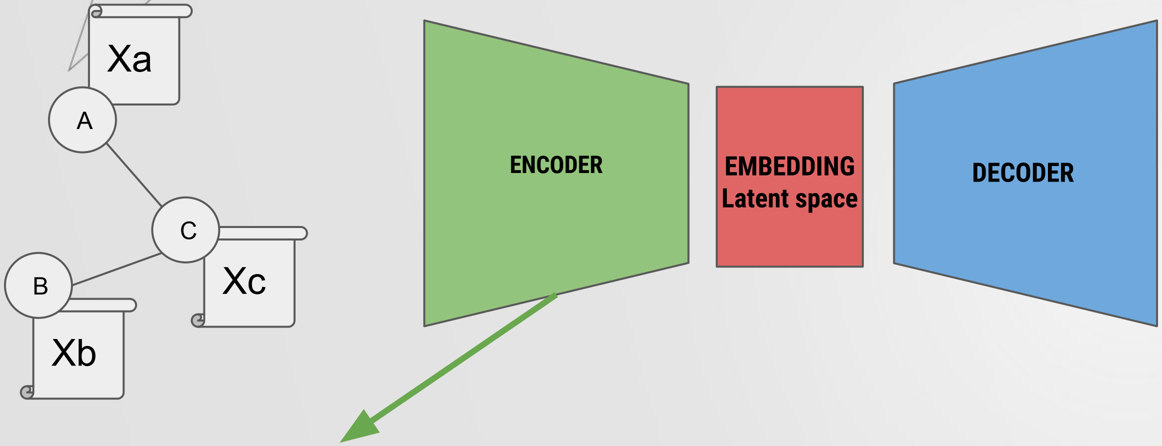

ONE convolutional
Graph neural network

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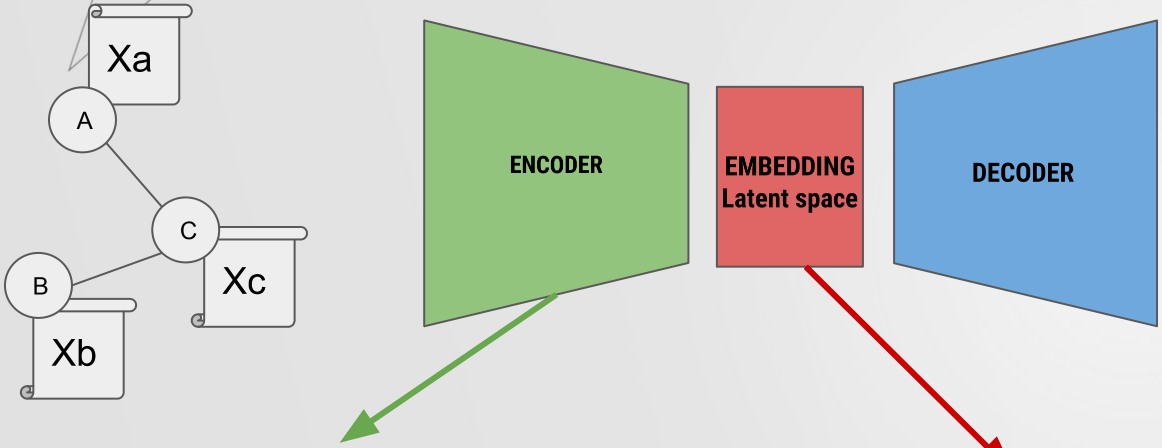

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$$Z = \bar{X}$$

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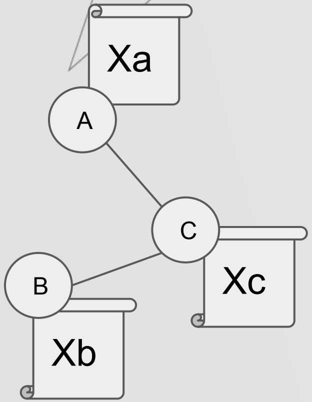

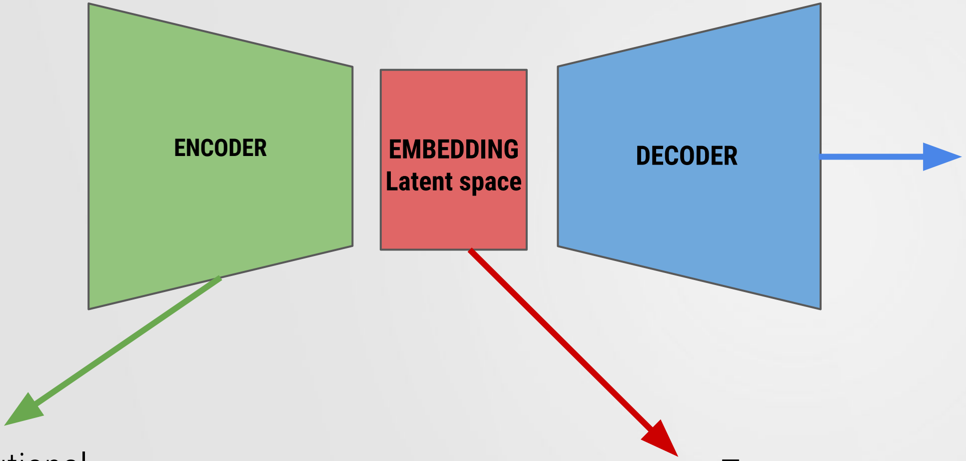

Inner product
Between latent variable Z

ONE convolutional
Graph neural network

$$Z = \bar{X}$$

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But..

What is the difference between the GAE for node embedding?

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The LOSS function

03 GAE for link prediction

GAE for node embedding

recon_loss (z, pos_edge_index, neg_edge_index=None) [source]

Given latent variables `z`, computes the binary cross entropy loss for positive edges `pos_edge_index` and negative sampled edges.

PARAMETERS:

- **z** (*Tensor*) – The latent space $\mathbf{Z}$.
- **pos_edge_index** (*LongTensor*) – The positive edges to train against.
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link_labels = get_link_labels(data.train_pos_edge_index, neg_edge_index)
loss = F.binary_cross_entropy_with_logits(link_logits, link_labels)
loss.backward()
optimizer.step()
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$$\ell(x, y) = L = \{l_1, \dots, l_N\}^\top$$

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$$\ell(x, y) = L = \{l_1, \dots, l_N\}^\top$$

$$l_n = -w_n \left[y_n \cdot \log x_n + (1 - y_n) \cdot \log(1 - x_n) \right]$$

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Binary cross entropy with logits loss

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03 GAE for link prediction

Jupyter - notebook

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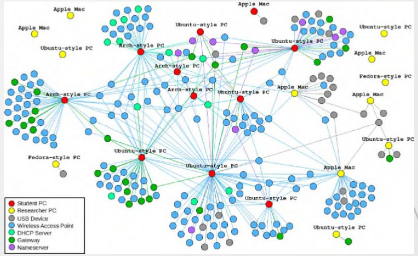

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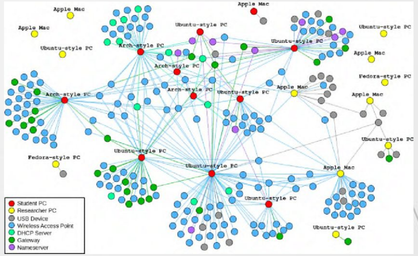

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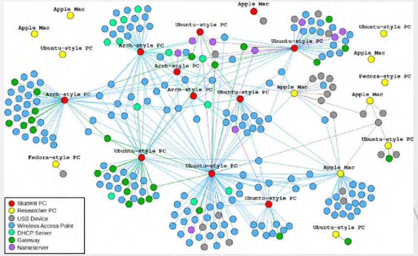

05 Node2Vec for Label Prediction

Jupyter - notebook