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Why ?

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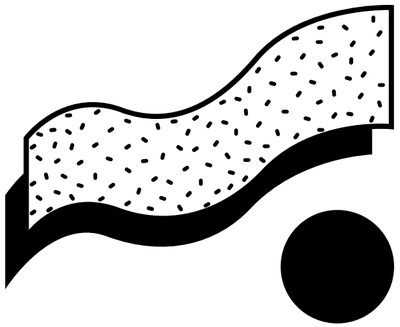
you could become an expert in any field.
Why is this not happening ?

- **Research papers are really though to read**
- **We make reading papers easier**

Plan



For one paper

Explain every keyword

For many papers

Connect all your papers

What’s Next ?

Explain every keyword

Demo Time !

https://adpt-lrn-phys.streamlit.app/

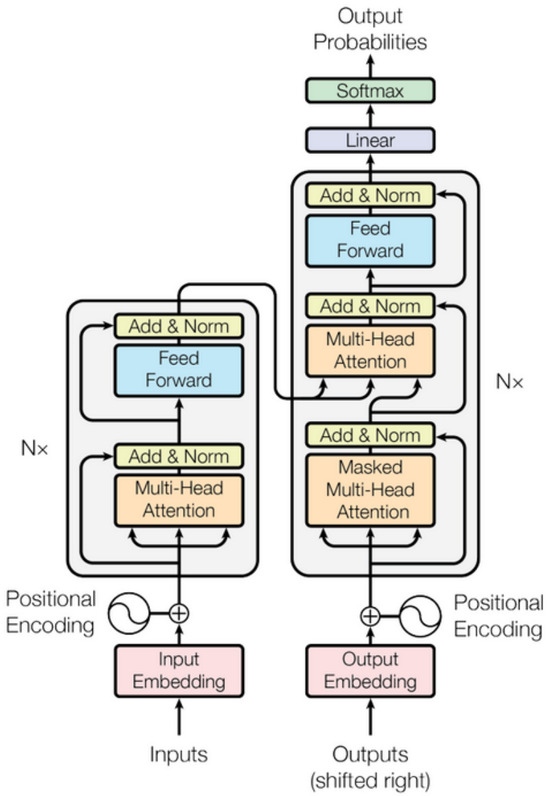


Figure 1: The Transformer - model architecture.

The Transformer follows this overall architecture using stacked self-attention and point-wise, fully connected layers for both the encoder and decoder, shown in the left and right halves of Figure 1, respectively.

3.1 Encoder and Decoder Stacks

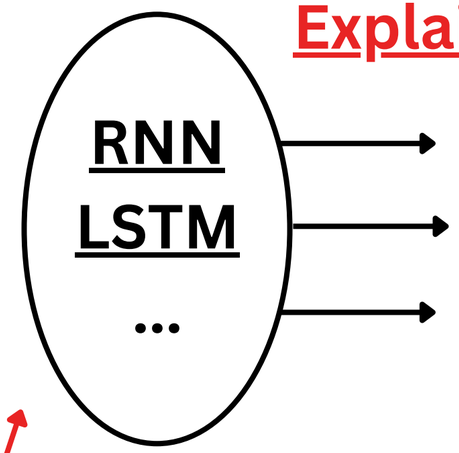
Encoder: The encoder is composed of a stack of $N = 6$ identical layers. Each layer has two sub-layers. The first is a multi-head self-attention mechanism, and the second is a simple, position-wise fully connected feed-forward network. We employ a residual connection [11] around each of the two sub-layers, followed by layer normalization [1]. That is, the output of each sub-layer is $\mathrm{LayerNorm}(x + \mathrm{Sublayer}(x))$, where $\mathrm{Sublayer}(x)$ is the function implemented by the sub-layer itself. To facilitate these residual connections, all sub-layers in the model, as well as the embedding layers, produce outputs of dimension $d_{\text{model}} = 512$.

Decoder: The decoder is also composed of a stack of $N = 6$ identical layers. In addition to the two sub-layers in each encoder layer, the decoder inserts a third sub-layer, which performs multi-head attention over the output of the encoder stack. Similar to the encoder, we employ residual connections around each of the sub-layers, followed by layer normalization. We also modify the self-attention sub-layer in the decoder stack to prevent positions from attending to subsequent positions. This masking, combined with fact that the output embeddings are offset by one position, ensures that the

ChatGPT explains it

The introduction provides an overview of recurrent neural networks (RNNs), memory (LSTM), and gated recurrent neural networks. These architectures h used in sequence modeling and transduction problems such as language mo machine translation. The introduction also mentions recent advancements i language models and encoder-decoder architectures.

Keywords extraction



Explain Keywords in parallel

RNNs, or recurrent neural networks, are a t

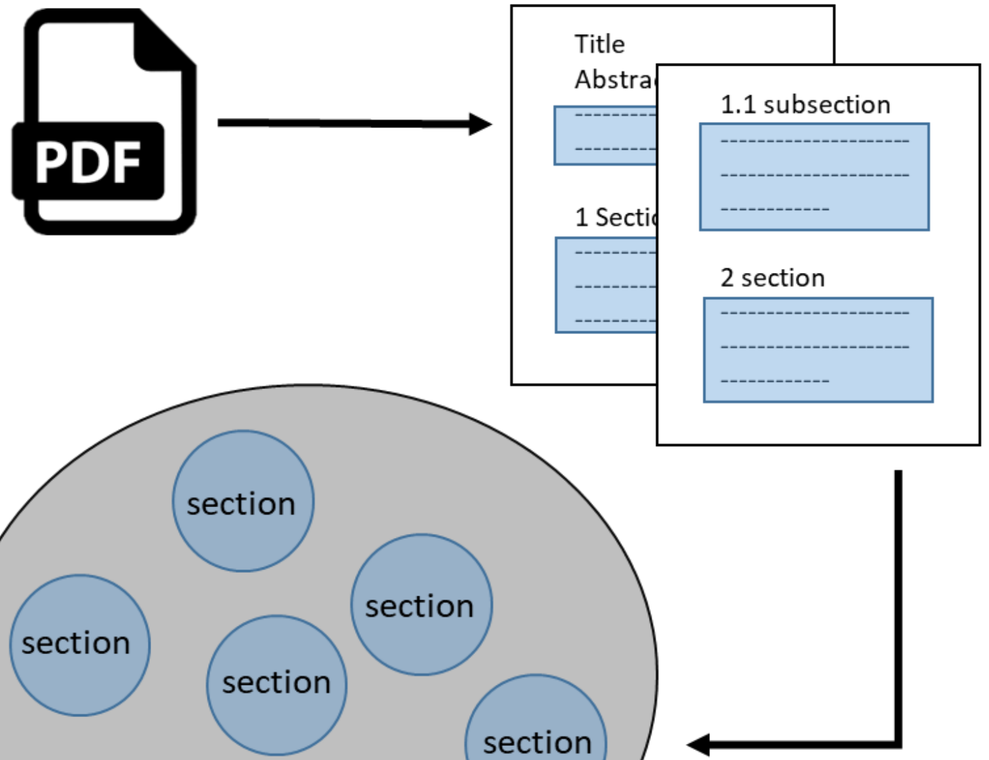
LSTM stands for Long Short-Term Memory, wh

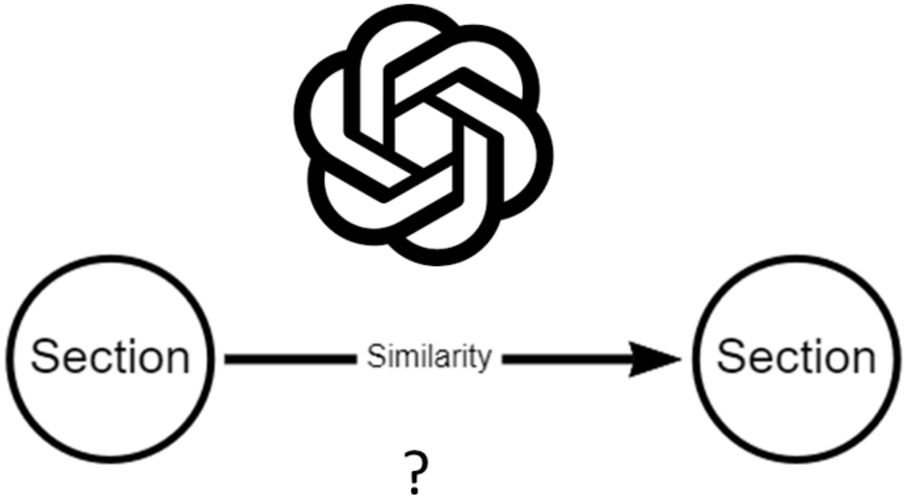
Inject it into the explanation

Generating Graph

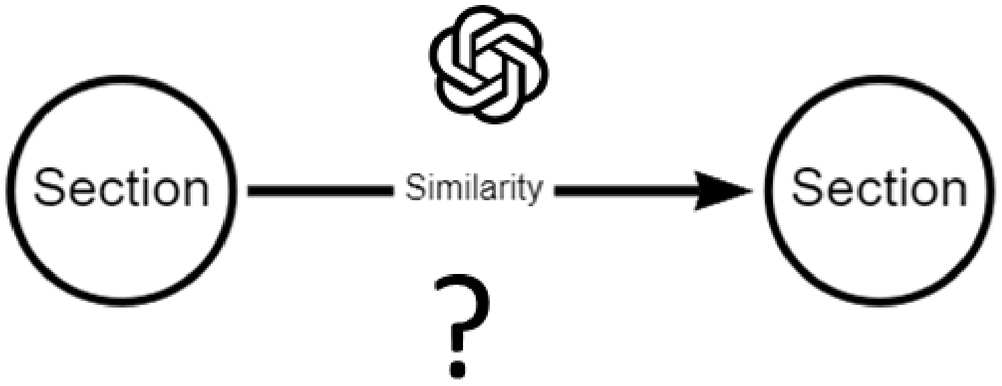
Doc to Nodes

Define Edges



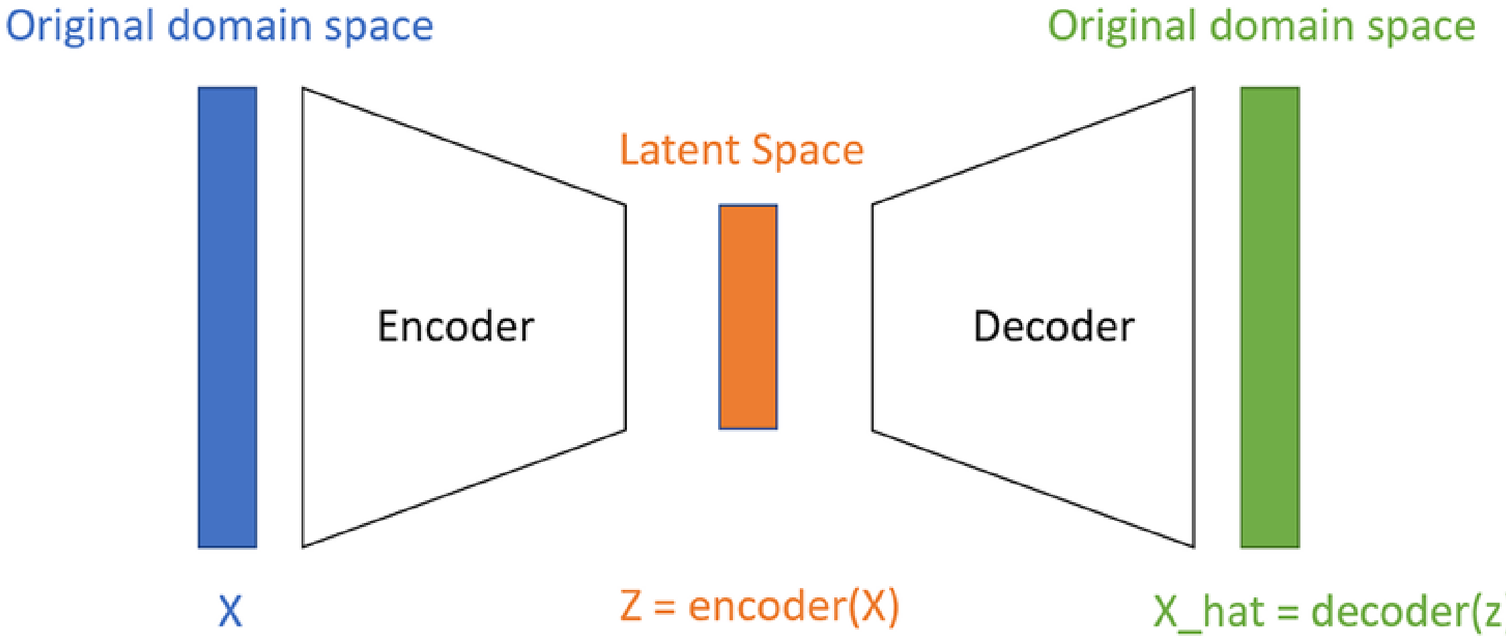


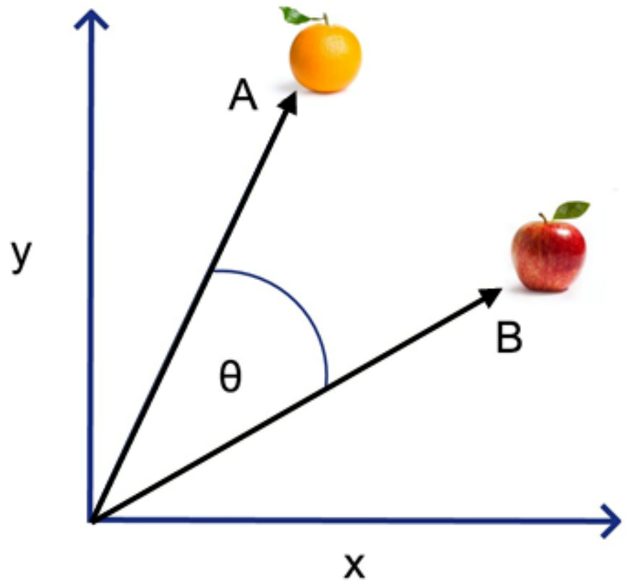
Similarity Measure



Cosine similarity

$$Sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$





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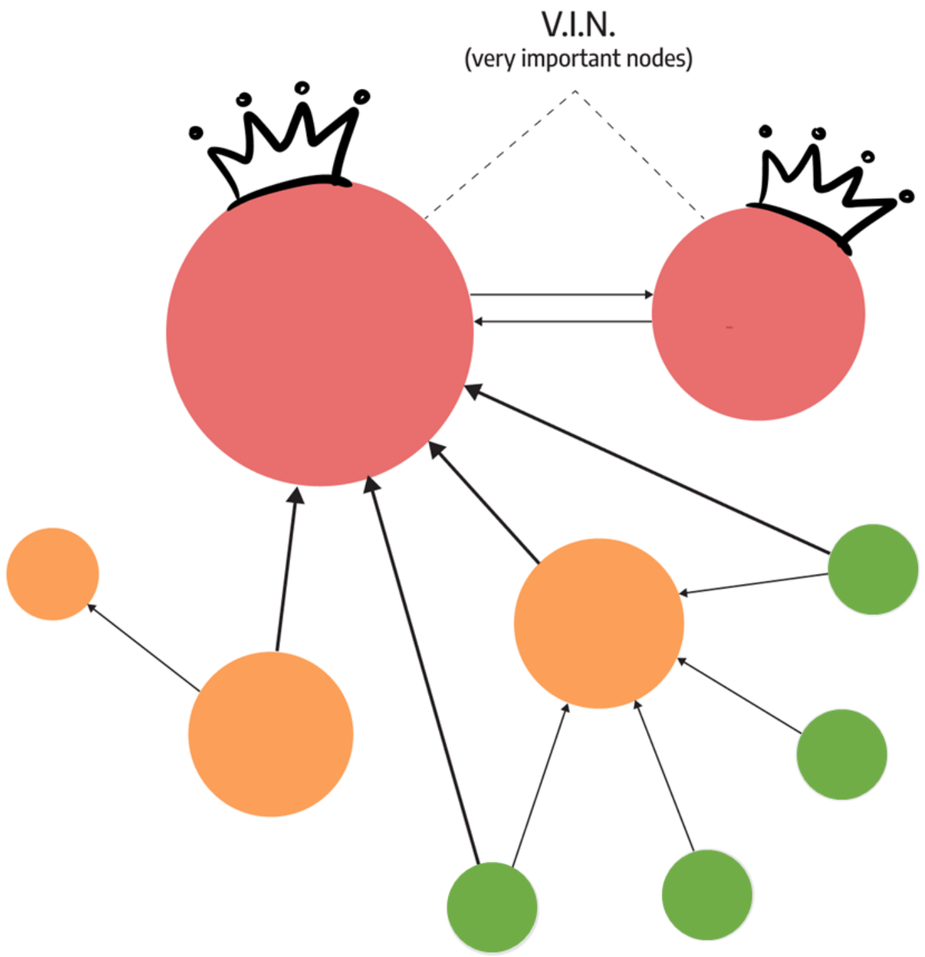
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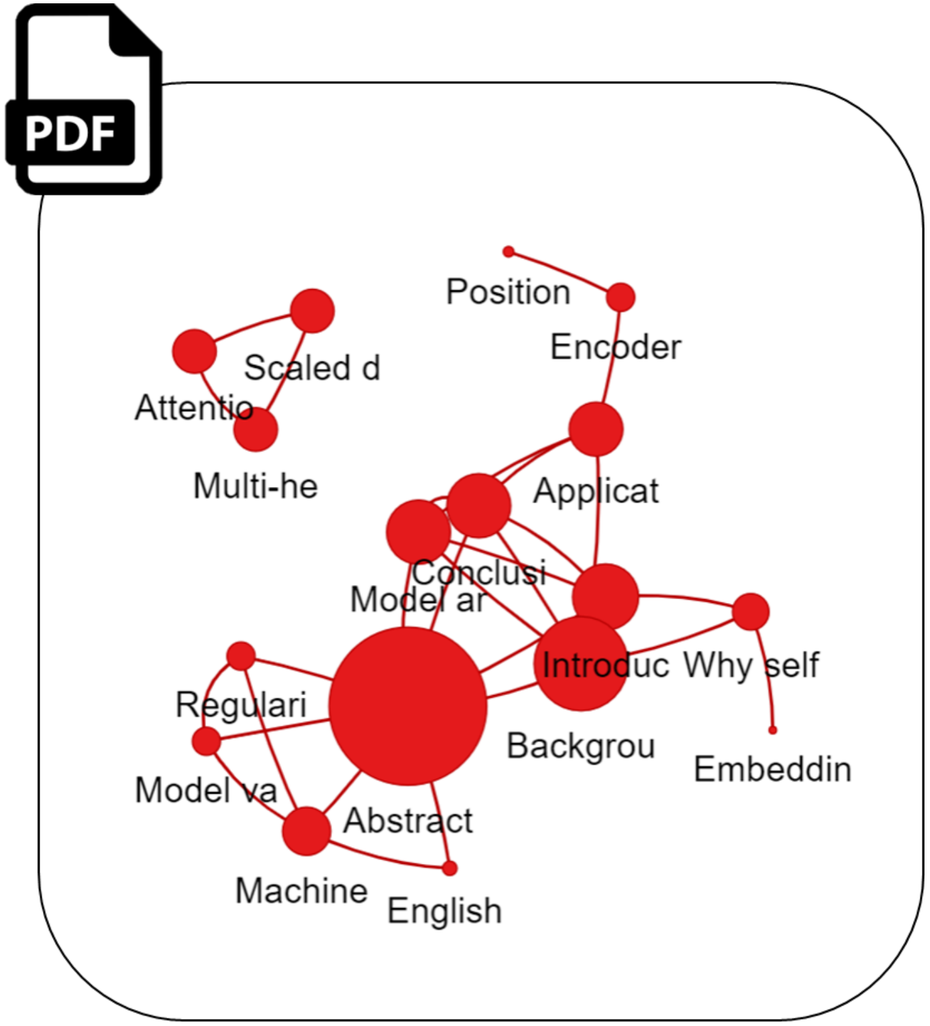
(very important nodes)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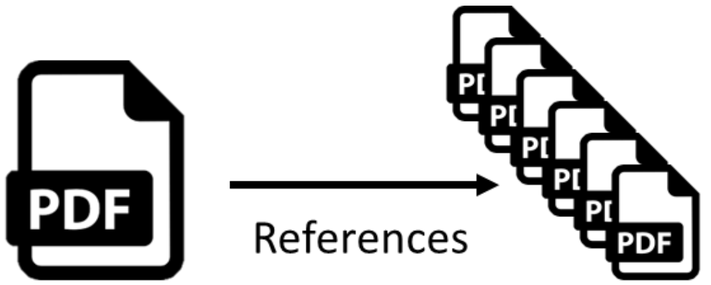
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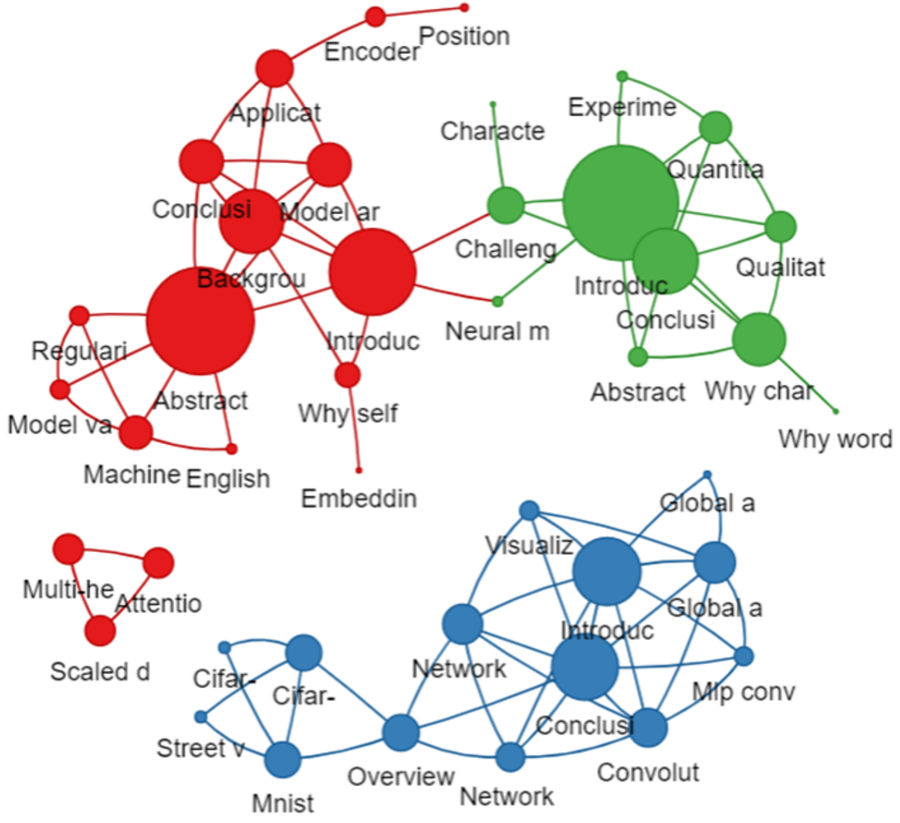
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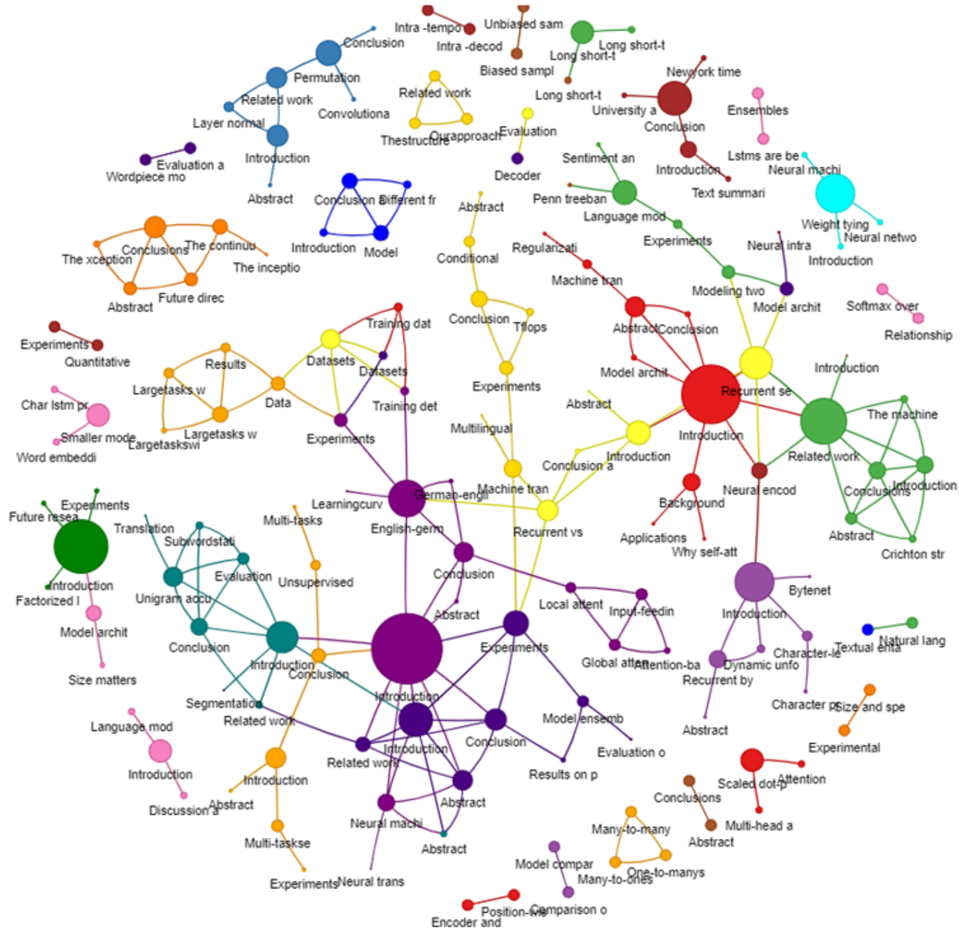
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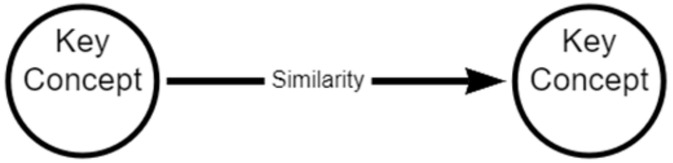

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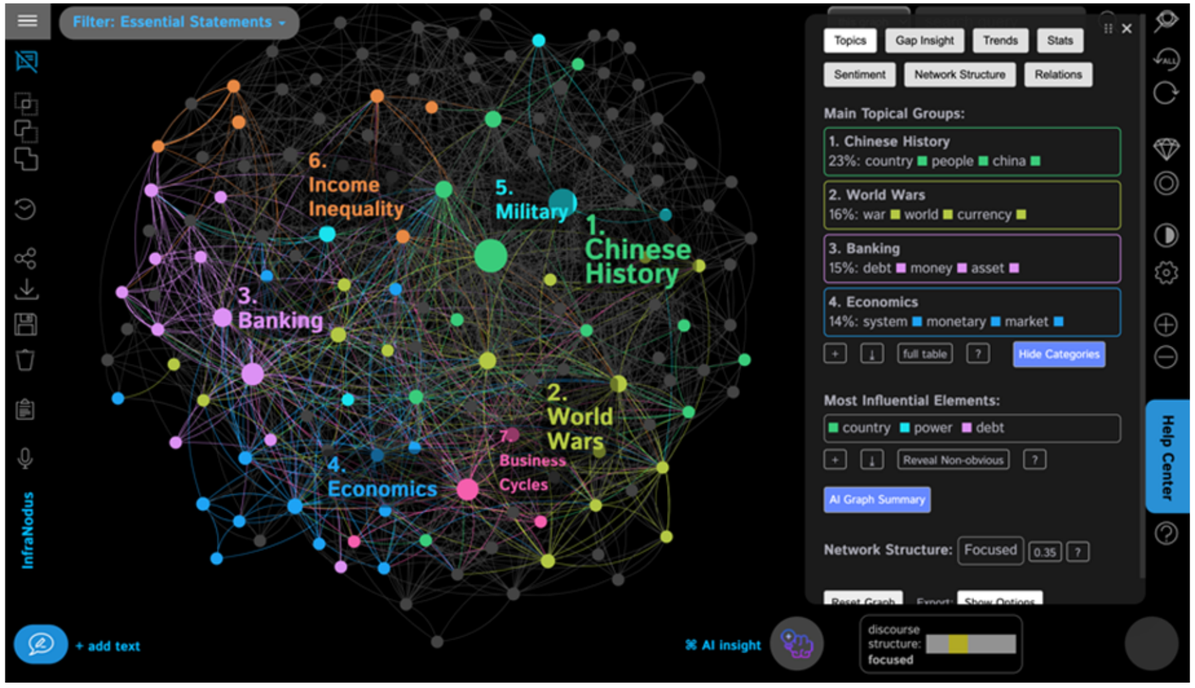

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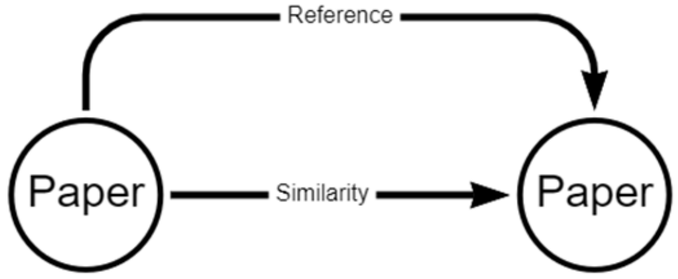
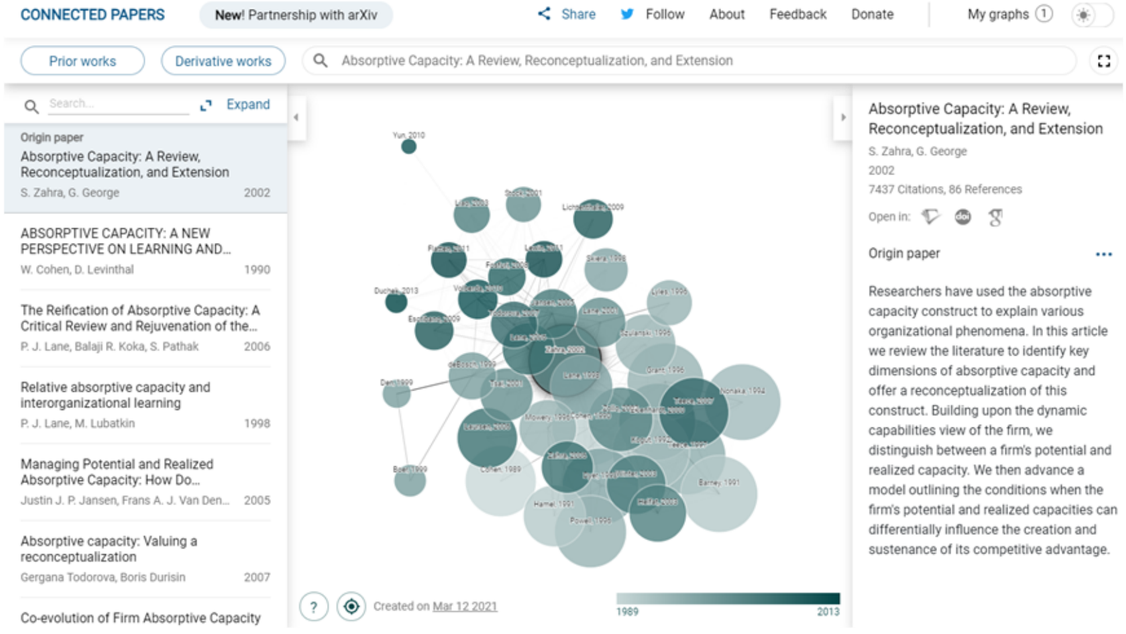


CONNECTED PAPERS



What’s next ?

- More features (UI)
  - Learned keyword
  - Study-path recommendation
  - Scientific-writing recommendation
- Improve keyword explanation
- Scalability
- Robustness
- Extend Pdf extraction
  - images
  - tables
- Extend to more than arXiv papers and include book

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