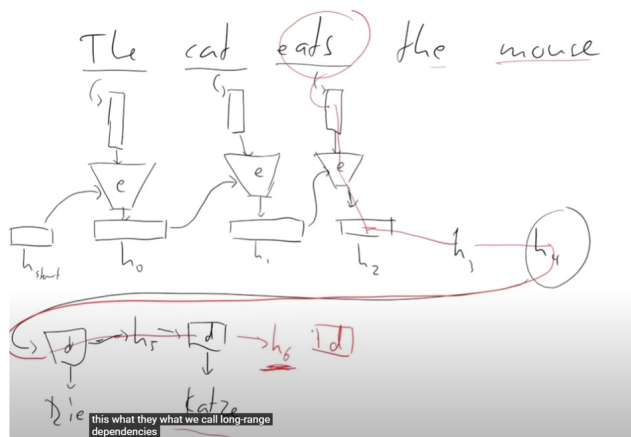


Transformer

The problem of RNN/LSTM: Long range dependency



To generate a translation of "eat", have to remember all the hidden states (red line)

How attention could solve this problem?

Attention serve as filter (similar as LSTM),

- source are embedded into two vectors - value (to store original value) & key (to help filter) (encoding)
- previous outputs are embedded into vector as query to help filter (encoding)
- calculate the dot product (similarity) for each query with all keys (decoding)
- softmax to select the most similar query-key pairs and filter out the others (decoding)

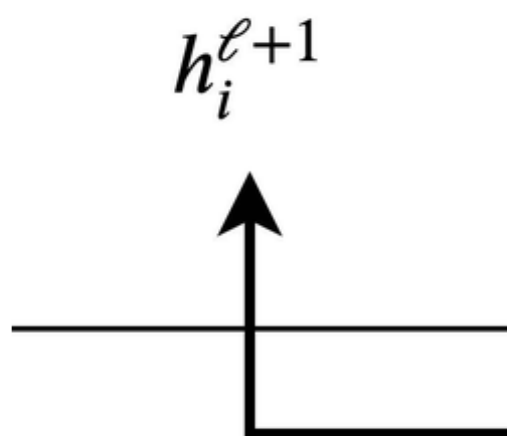
Note1. by filter out some hidden states, attention will help to solve long range dependency-- guess the result will be more accurate and the NN will be simpler.

Note2, use previous prediction to filter input by **dot products in decoder**, whereas LSTM filter by the **weights in the encoder of input and all previous hidden state**

🍎 Attention? Attention!

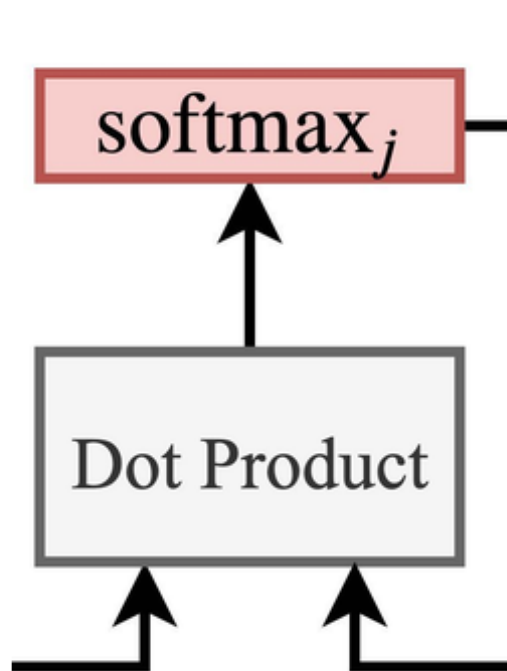
Why Transformers are Graph Neural Networks?

former



structure by translating words and vectors. We use layer $\ell + 1$ as

attention $(Q^\ell h_i^\ell, K^\ell h_j^\ell)$



$$h_i^{\ell+1} = \sum_{j \in \mathcal{S}} w_{ij} (V^\ell h_j^\ell)$$

$\text{softmax}_j (Q^\ell h_i^\ell, K^\ell h_j^\ell)$

in the sentence

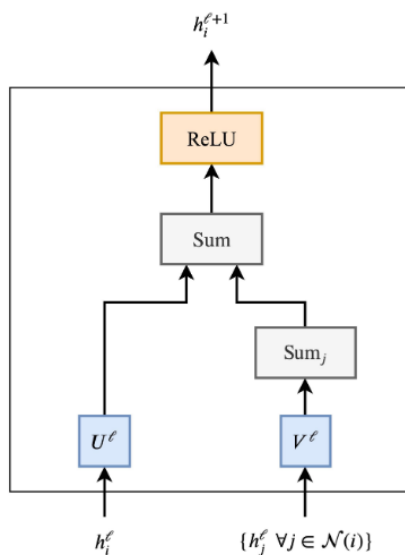


and Value for the
is performed on

— It is performed per
 — nodes in one shot—i
 — d-by-word.

Transformer:

update h_{i+1} : for current query i (the work you are going to translate/predict), calculate similarity of it with all input embedded as key_j as filter/(another cuz QKV are embedding vectors)weight, after selection/application, h_{i+1} = sum over all weighted input value j (including i itself input)



In their most basic form, GNNs update the hidden features h of node i (for example, 🍌) at layer ℓ via a non-linear transformation of the node's own features h_i^ℓ added to the aggregation of features h_j^ℓ from each neighbouring node $j \in \mathcal{N}(i)$:

$$h_i^{\ell+1} = \sigma \left(U^\ell h_i^\ell + \sum_{j \in \mathcal{N}(i)} (V^\ell h_j^\ell) \right),$$

where U^ℓ, V^ℓ are learnable weight matrices of the GNN layer and σ is a non-linearity such as ReLU. In the example, $\mathcal{N}(\text{🍌}) = \{\text{🍌}, \text{🍌}, \text{🍌}, \text{🍌}\}$.

— In the example, the node's own features are added to the aggregation of features from its neighbors.

GNN:

update h_{i+1} : for the target node i , embedding all its neighbors with weight, h_{i+1} = sum over weighted i and all its neighbors

Difference:

transformer softmax first (filter) then sumover

GNN sum first then Relu

▼ Click here to expand...

If we were to do multiple parallel heads of neighbourhood aggregation and replace summation over the neighbours \diamond with the attention mechanism, *i.e.*, a weighted sum, we'd get the **Graph Attention Network** (GAT). Add normalization and the feed-forward MLP, and voila, we have a **Graph Transformer**!