### **Organizational**

- Homework: You nearly did it!
  - Homework 7 released (you will have until Dec 6<sup>th</sup>)
  - → No more extensions
- Midterm Wednesday 11/29 4.30 to 5.45

### **Transformers**



(Image credit: Paramount Pictures)



#### **Transformers**

EN.601.482/682 Deep Learning

5) Concatenate the resulting Z matrices, 1) This is our 2) We embed 3) Split into 8 heads. 4) Calculate attention each word\* then multiply with weight matrix Wo to input sentence\* We multiply X or using the resulting R with weight matrices O/K/V matrices produce the output of the layer Output Probabilities Softmax Thinking Machines Linear WO Add & Norm Feed Forward Add & Norm Add & Norm Multi-Head Feed Attention N× Forward Add & Norm ... ... N× Add & Norm Masked Multi-Head Multi-Head Attention Attention Positional 6 Positional Encoding Encoding Input Output Embedding Embedding Inputs Outputs

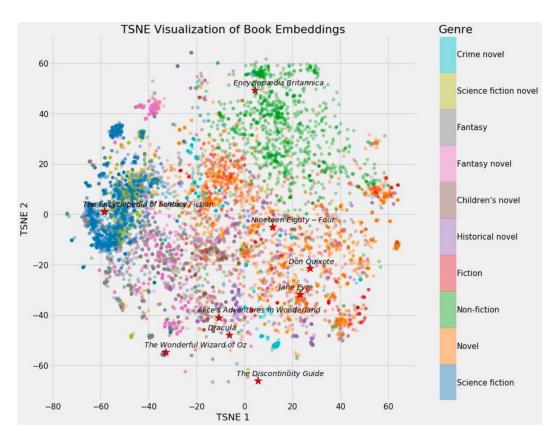


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Mathias Unberath

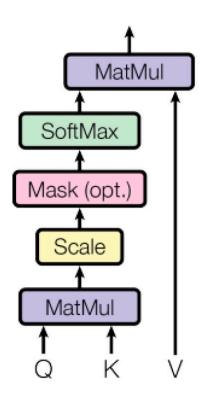
# **Embedding**

- From one-hot encoding (image patches) to a continues space.
- Dimensionality reduction.
- Semantic Clusters

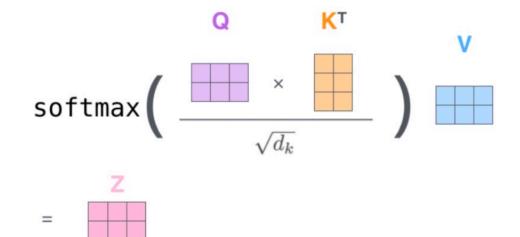




### **Attention**

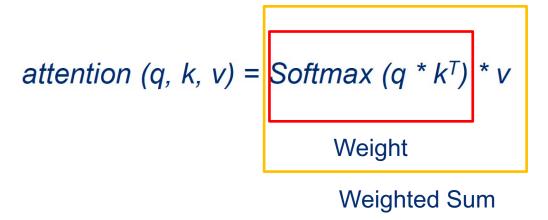


attention  $(q, k, v) = Softmax (q * k^T) * v$ 

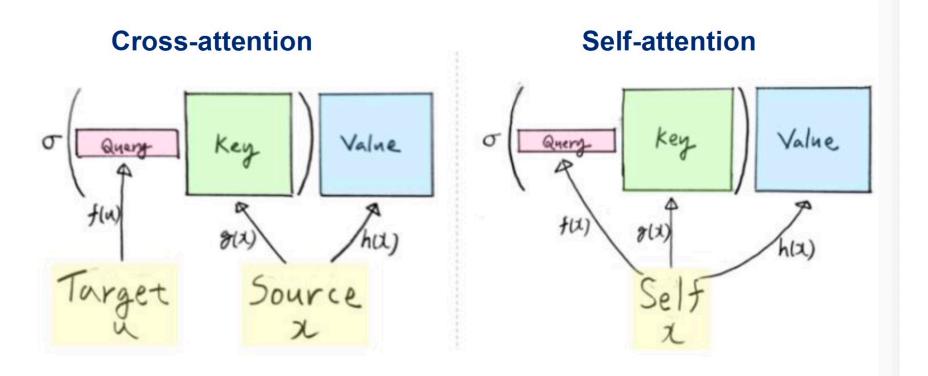


# What exactly is Attention?

- Feature aggregation for sequence.
- How do RNN do feature aggregation? -> sum them up.
- How do attention do feature aggregation? -> weighted sum.



### **Several Attentions**

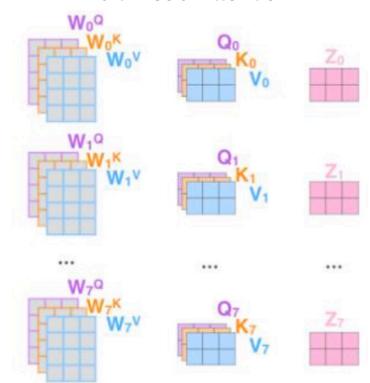


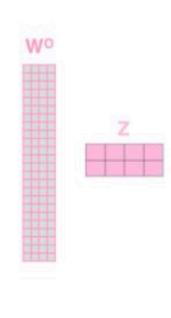
### **Several Attentions**

#### **Multi-head Attention**









#### **Transformers**

5) Concatenate the resulting Z matrices, 1) This is our 2) We embed 3) Split into 8 heads. 4) Calculate attention each word\* then multiply with weight matrix Wo to input sentence\* We multiply X or using the resulting R with weight matrices O/K/V matrices produce the output of the layer Output Probabilities Softmax Thinking Machines Linear WO Add & Norm Feed Forward Add & Norm Add & Norm Multi-Head Feed Attention N× Forward Add & Norm ... ... N× Add & Norm Masked Multi-Head Multi-Head Attention Attention Positional 6 Positional Encoding Encoding Input Output Embedding Embedding Inputs Outputs

Mathias Unberath

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(shifted right)

#### **Transformer vs RNN**

- Transformer can do parallel training.
- Transformer keeps the form of the whole sequence.

# Challenges that the Transformers are facing

- Broken Cybertron
- O(n<sup>2</sup>) complexity for attention.
- O(n<sup>2</sup>) complexity during inference-time.
- Take look at Retentive Network if you are interested in this.

### HW7

Three bonus problems: +1% towards hw per problem

Released, check Piazza

Due: Wednesday, Dec 6<sup>th</sup> by 11:59 pm

Submit: a zip to Gradescope (Entry Code BBVDNN)

### **Q1. Generative Adversarial Networks**

#### Training a GAN to generate MNIST image

- 1. Define a generator
- 2. Define a discriminator
- 3. Minimax optimization
- 4. Goal: generate reasonable image of inception score >= 1.5

### **Q2. Adversarial Attacks**

- 1. Implement a gradient-based attack method
- 2. Generate adversarial example for MNIST
- 3. Generate adversarial example for CIFAR-10
- 4. Generate adversarial example for a CIFAR-alike real world photo

More fun (optional):

Play with a physical attack method on an object detection algorithm!

### Q3. Word Embedding

- 1. Implement two word embedding methods:
  - a. CBOW (Continuous Bag of Words)
  - b. Skip-gram
- 2. Train the model to generate good embeddings
- 3. Use the embeddings to evaluate words similarity

# **Balancing your efforts on**

bonus problems (<=3% of 50%) vs.
the final project (25%)

