Deep Sequence Models for Search Ranking - Session II

Tutorial Link: https://dlranking.github.io/dlrr/

Data source: https://huggingface.co/datasets/xglue

XGLUE: A New Benchmark Dataset for Cross-lingual Pre-training, Understanding and Generation)

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Agenda

- Brief History of Deep Learning Models For Search Ranking
- Sequence Models
  - RNN, LSTM
  - Attention, Self Attention
- Transformer Architecture
- Deep Classifier
- Deep Siamese Network
- Hands-on Session

Brief History of Deep Neural Network For Search Ranking

Key responsibilities of a search engine

Indexing — Ingesting and storing data efficiently so that it can be retrieved quickly

Querying — Providing retrieval functionality so that search can be performed by an end user

Ranking — Presenting and ranking the results according to certain metrics to best satisfy users' information needs

Brief History of Neural IR

- Neural IR resort to deep learning for tackling the feature engineering problem of learning to rank, by directly using only automatically learned features from raw text of query and document. □

- There have been some pioneer work, including DSSM [ref], and CDSSM [ref].

- Both DSSM and CDSSM directly apply deep neural networks to obtain the semantic representations of query and document, and the ranking score is produced by computing their cosine similarity.

- Studies such as DRMM [ref] and DeepRank [ref] argued that DSSM and CDSSM only consider the semantic matching between query and document, but ignored relevance matching as well as modeling the relevance generation process.

Learning Deep Structured Semantic Models for Web Search using Clickthrough Data (DSMM: 2013)

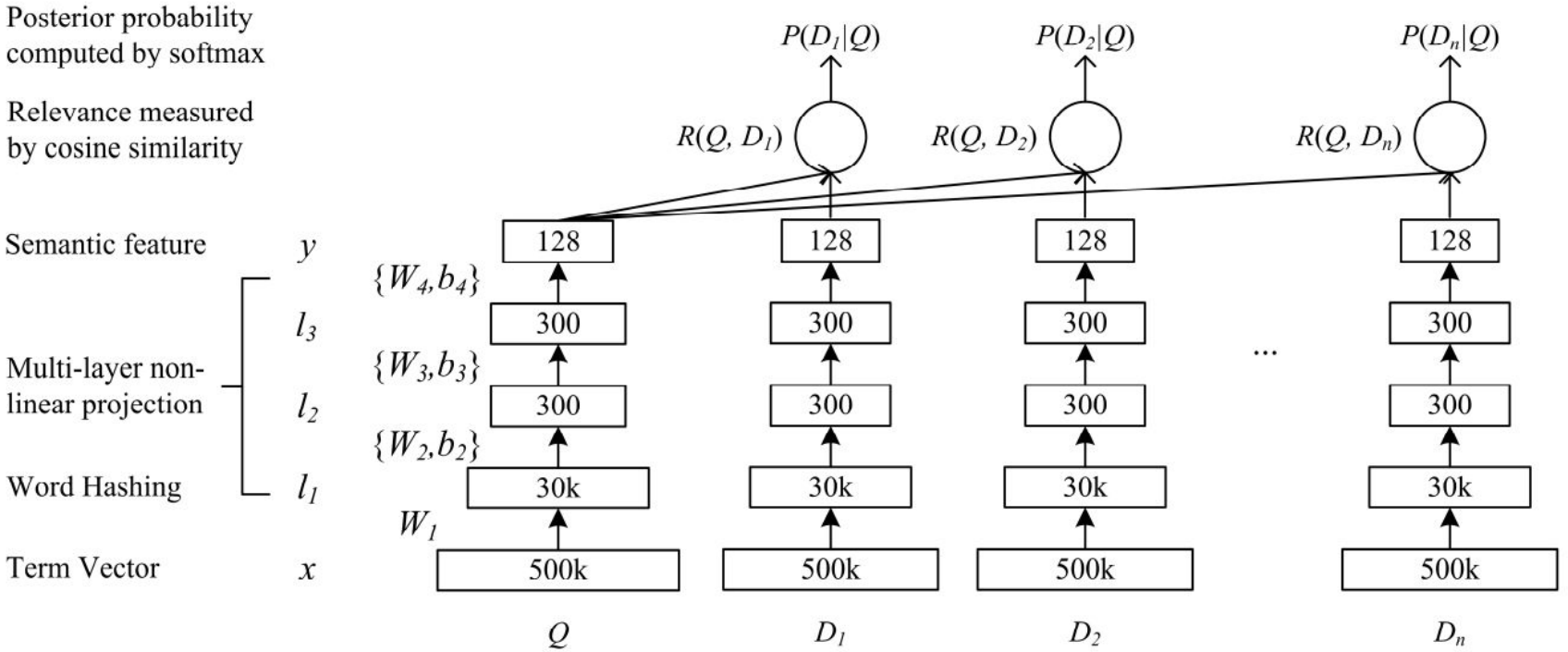


Figure 1: Illustration of the DSSM. It uses a DNN to map high-dimensional sparse text features into low-dimensional dense features in a semantic space. The first hidden layer, with 30k units, accomplishes word hashing. The word-hashed features are then projected through multiple layers of non-linear projections. The final layer's neural activities in this DNN form the feature in the semantic space.

A Deep Relevance Matching Model for Ad-hoc Retrieval (DRMM: 2017)

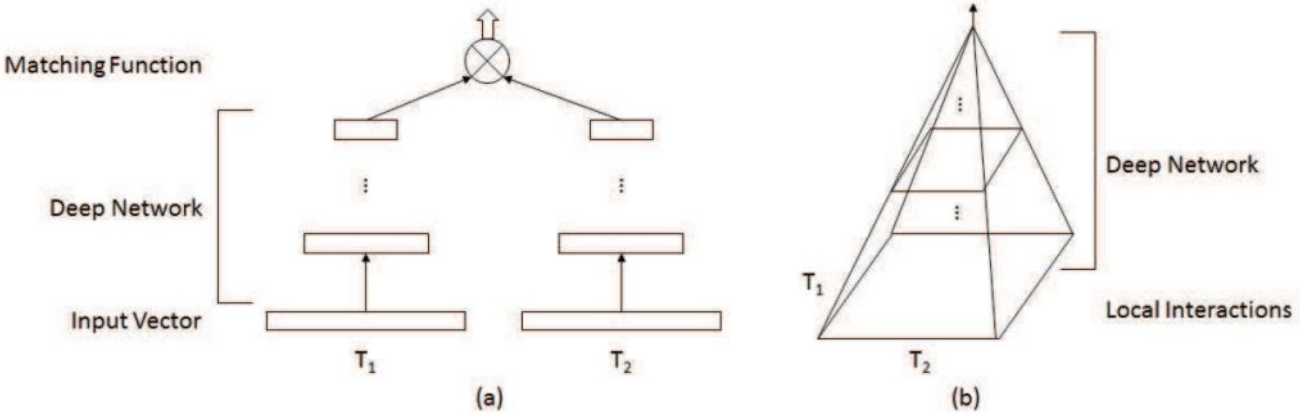


Figure 1: Two types of deep matching models: (a) Representation-focused models employ a Siamese (symmetric) architecture over the text inputs; (b) Interaction-focused models employ a hierarchical deep architecture over the local interaction matrix.

(Ref: link)

DRMM

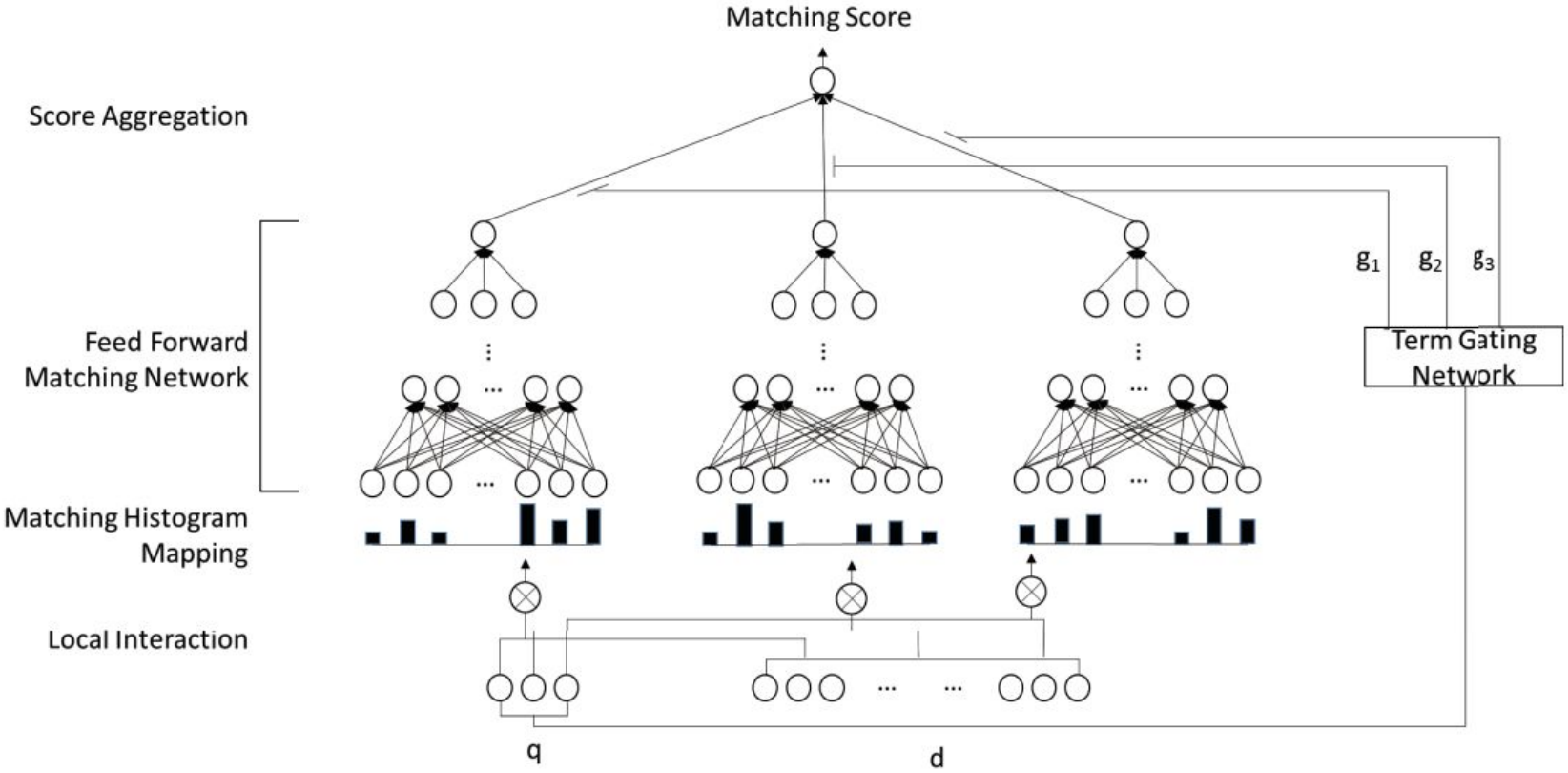


Figure 2: Architecture of the Deep Relevance Matching Model.

DeepRank: A New Deep Architecture for Relevance Ranking in Information Retrieval (2019)

Ref: (link)

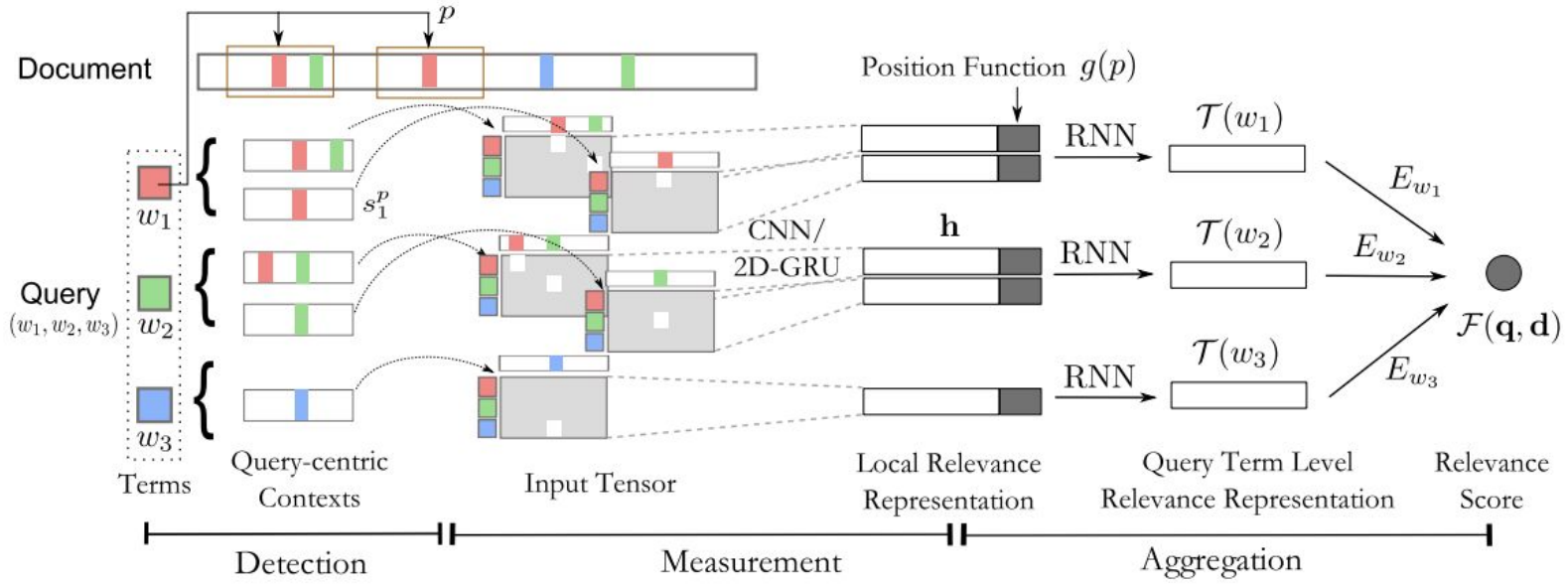
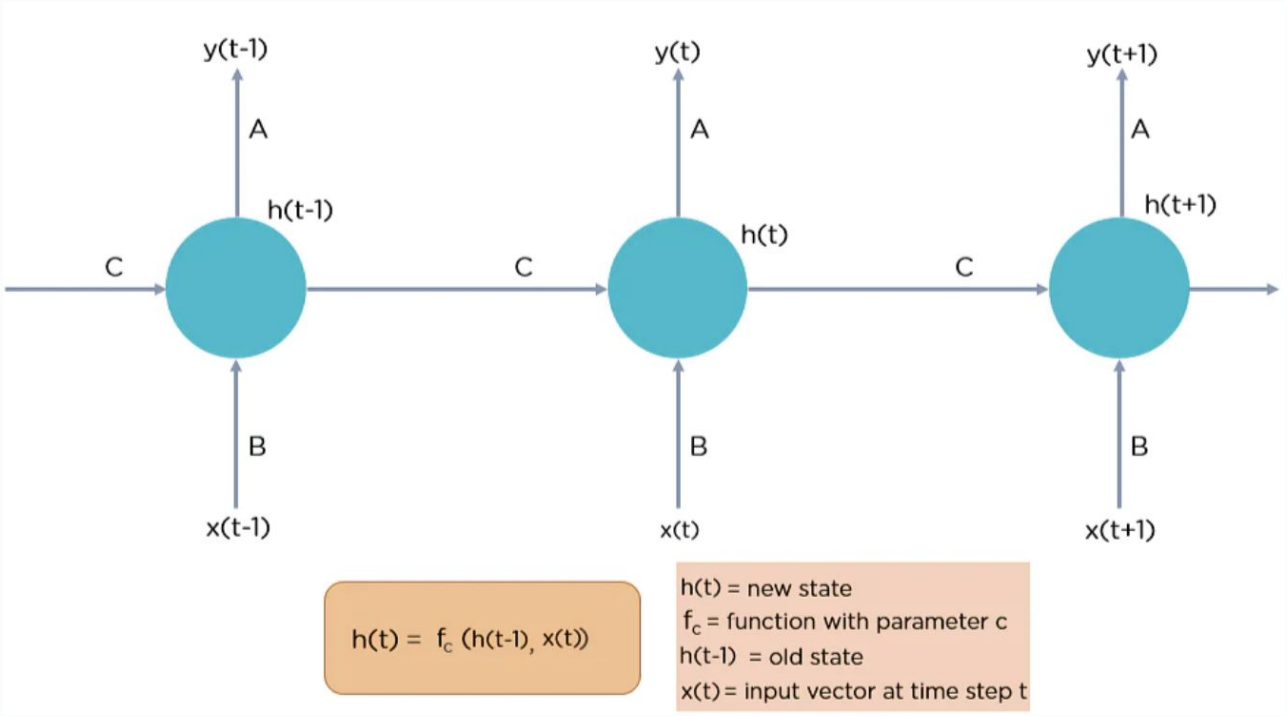


Figure 1: An illustration of DeepRank.

Sequence Models

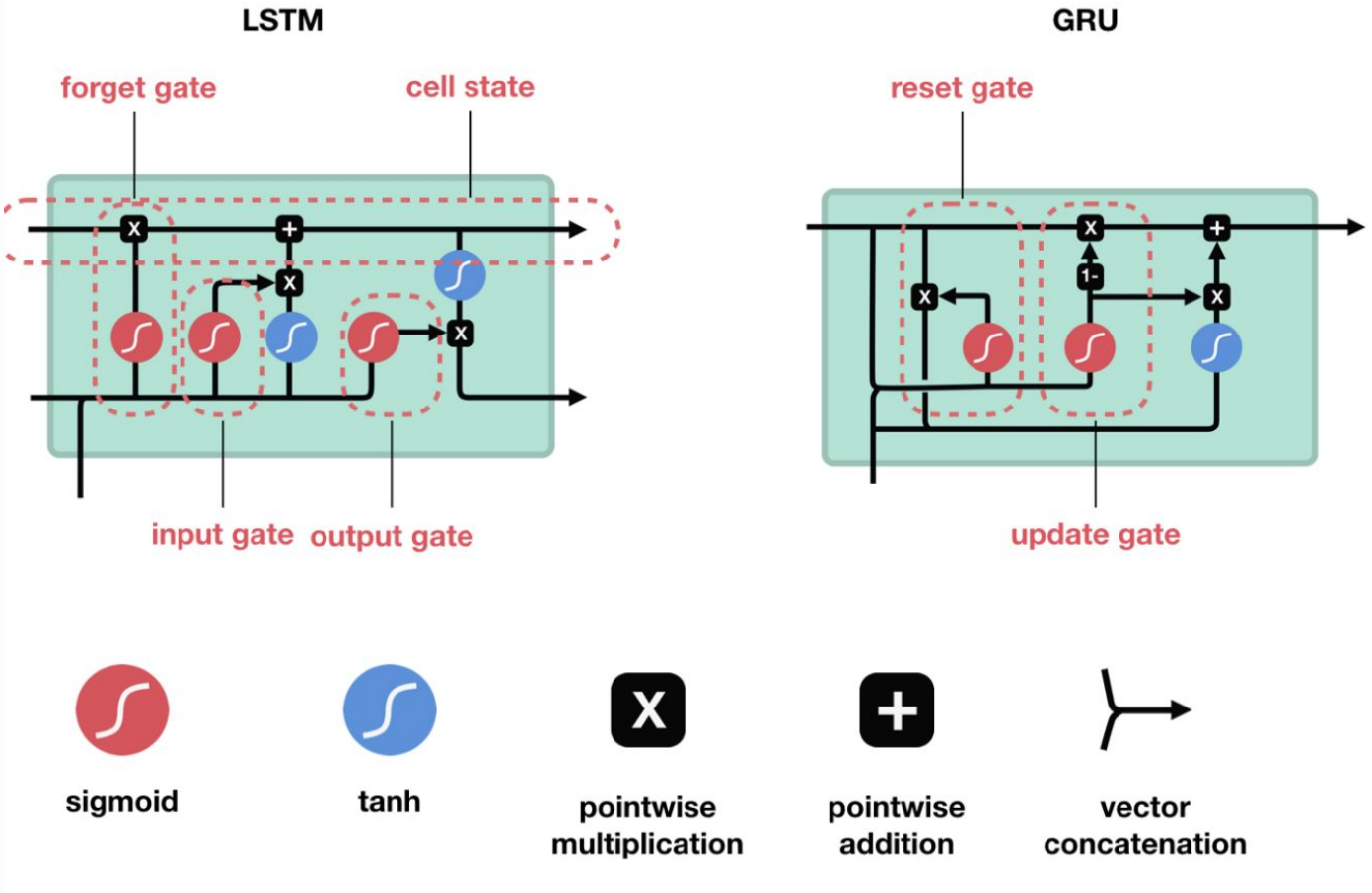
- RNN, GRU, LSTM
- Attention and Multi-attention
- Transformer

Recurrent Neural Network



torch.nn.RNN(input_size, hidden_layer, num_layer, bias=True, batch_first=False, dropout = 0, bidirectional = False)

GRU and LSTM



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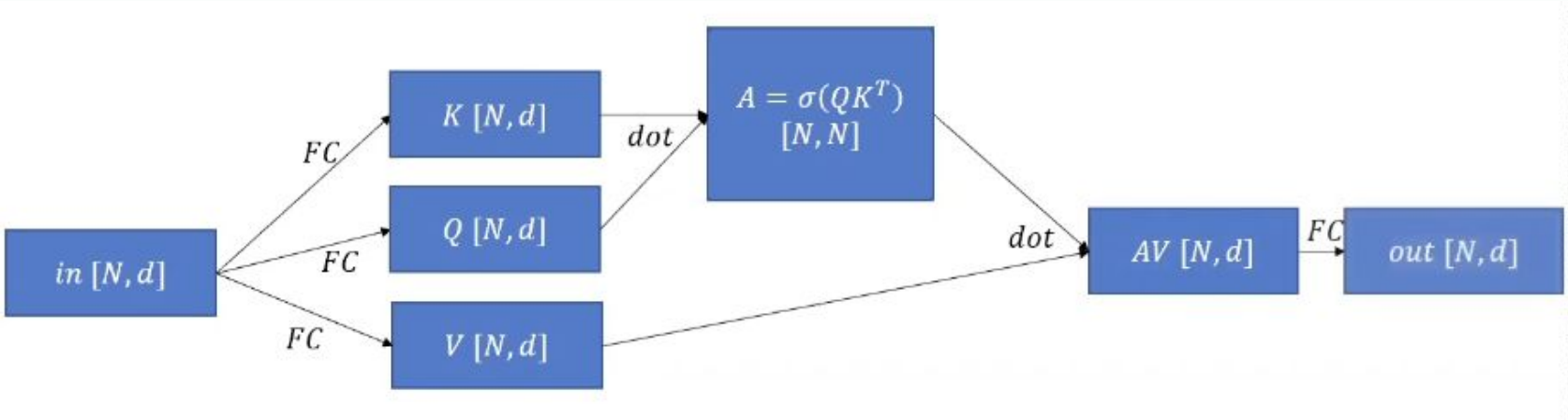
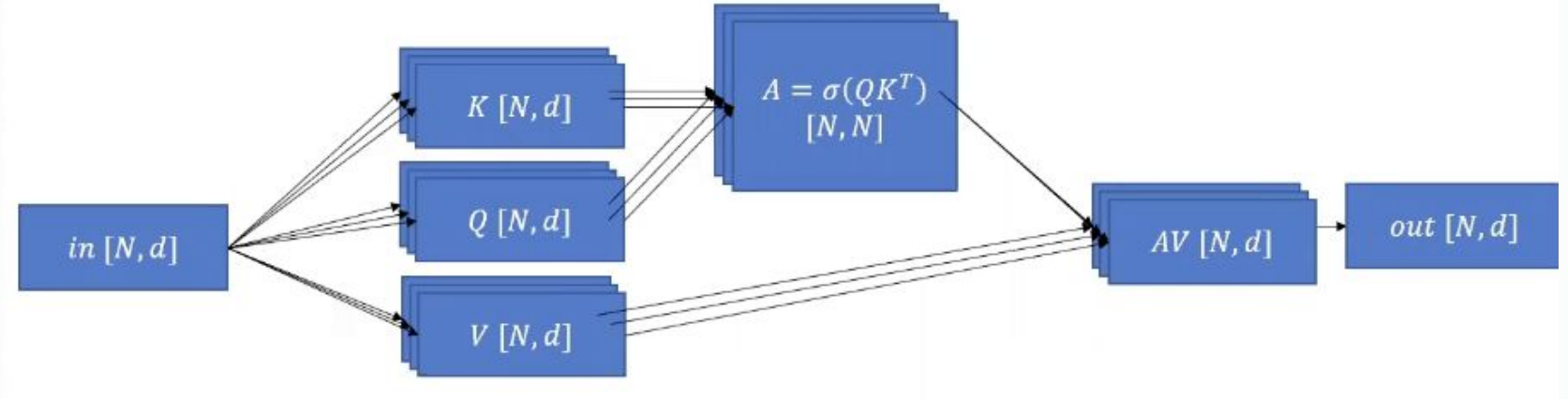
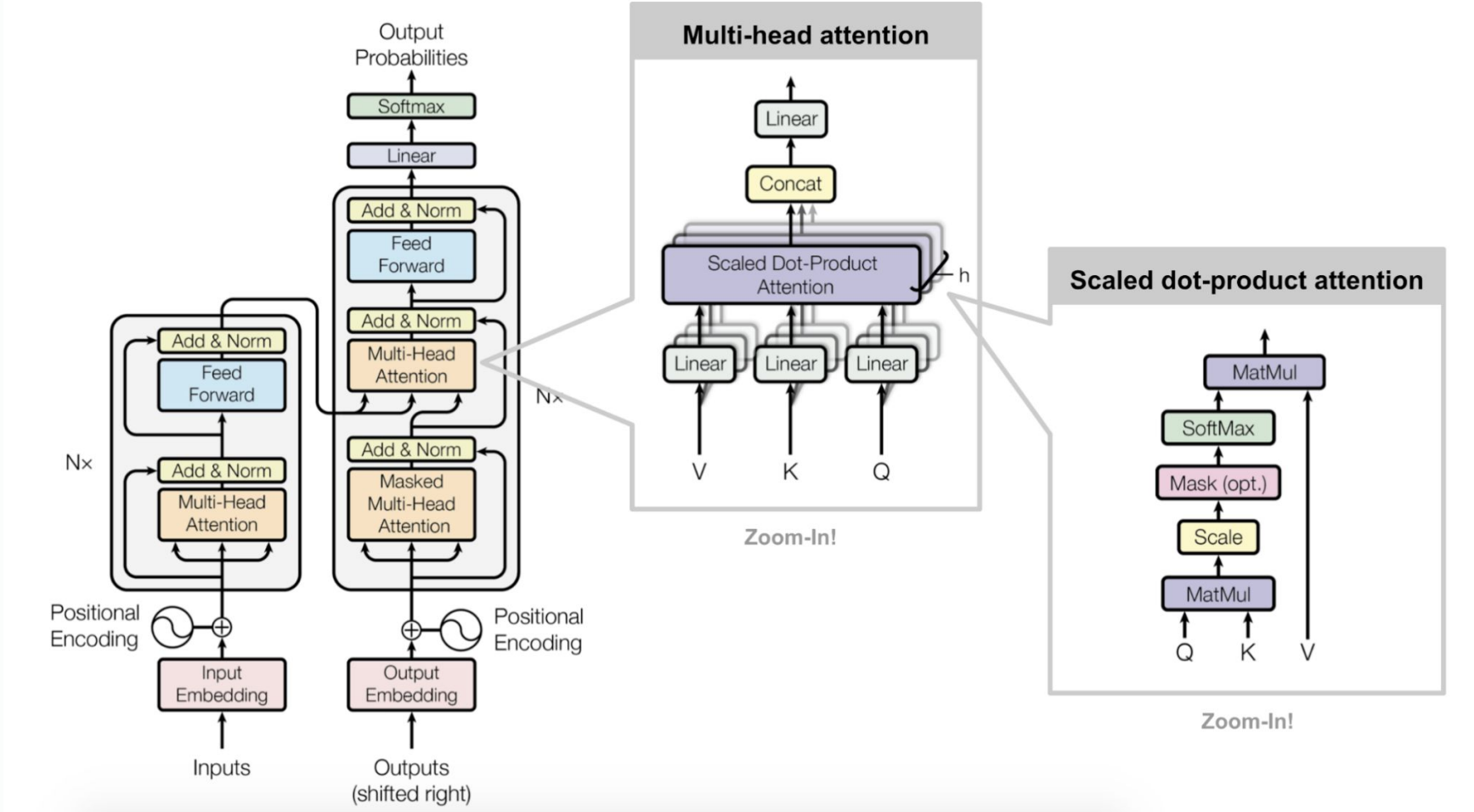
Single and Multi-Head Attention





Transformer

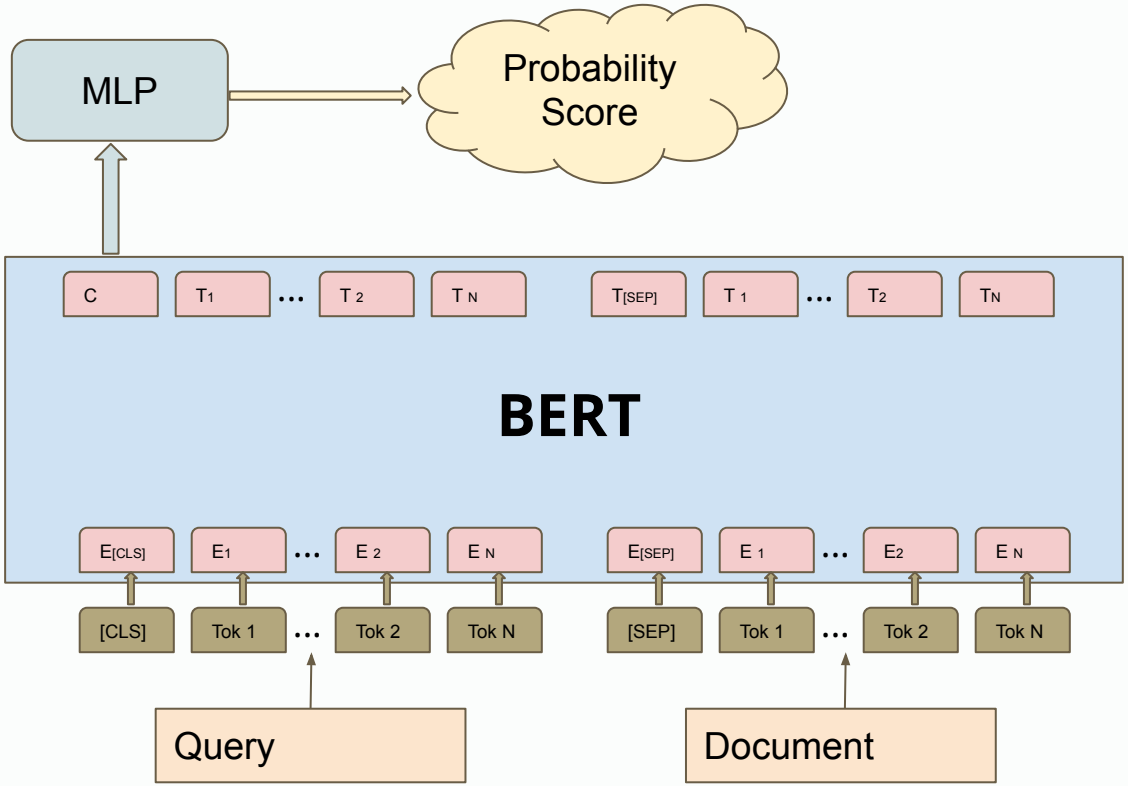


Deep Classifier Network

Deep Classifier Network

- The goal is to rank the documents based on the query document similarity.
- Use the BERT model to generate the embeddings of the queries and embeddings of the documents that capture the semantic meanings of them from the text.
- Concatenate the query and document embeddings, and feed into a classification network to calculate the probability of the document related to the query
- Rank the documents based on their probability score to the query

Deep Classifier Network



Deep Classifier Network

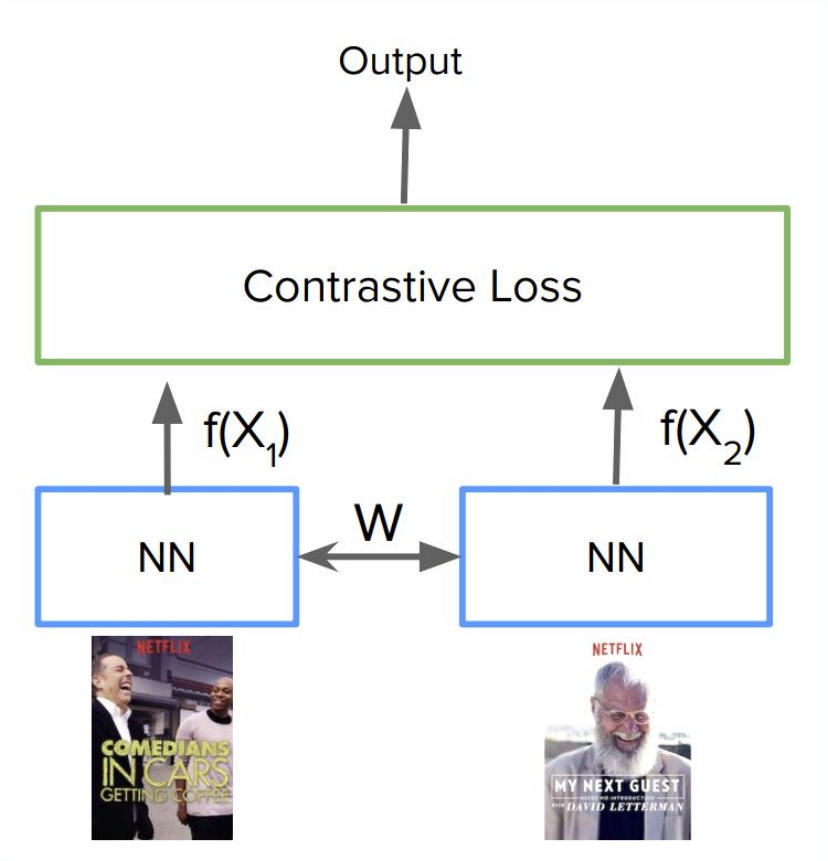
Colab Demo

Deep Siamese Network

Deep Metric Learning

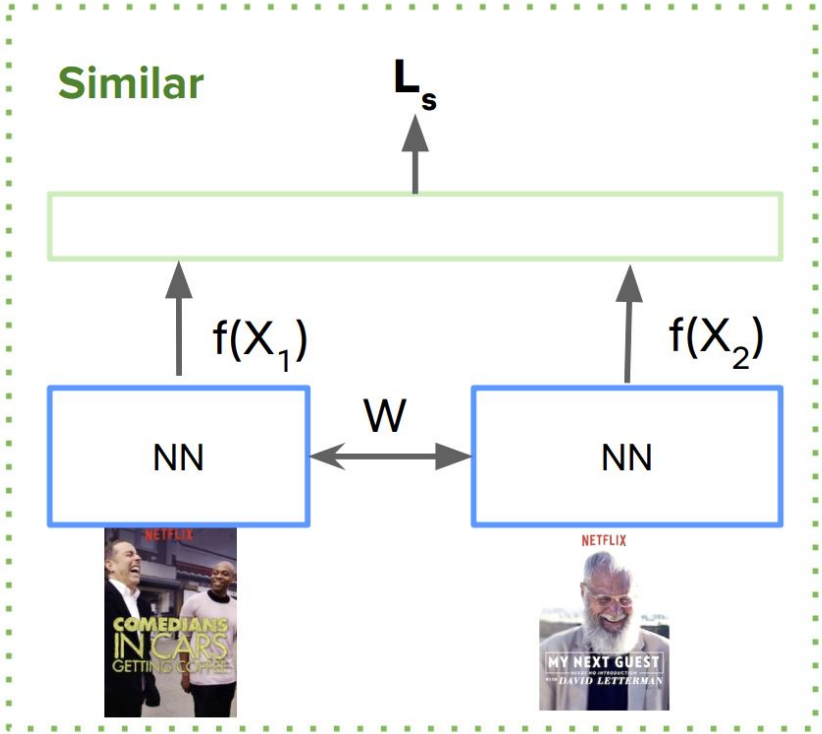
- The goal is to capture similarity between embeddings, such that the projected distance of similar items in the embedding space is smaller than the dissimilar items.
- Compared to the standard distance metric learning, it uses deep neural networks to learn a nonlinear mapping to the embedding space
- Helps with extreme classification settings with huge number classes, not many examples per class

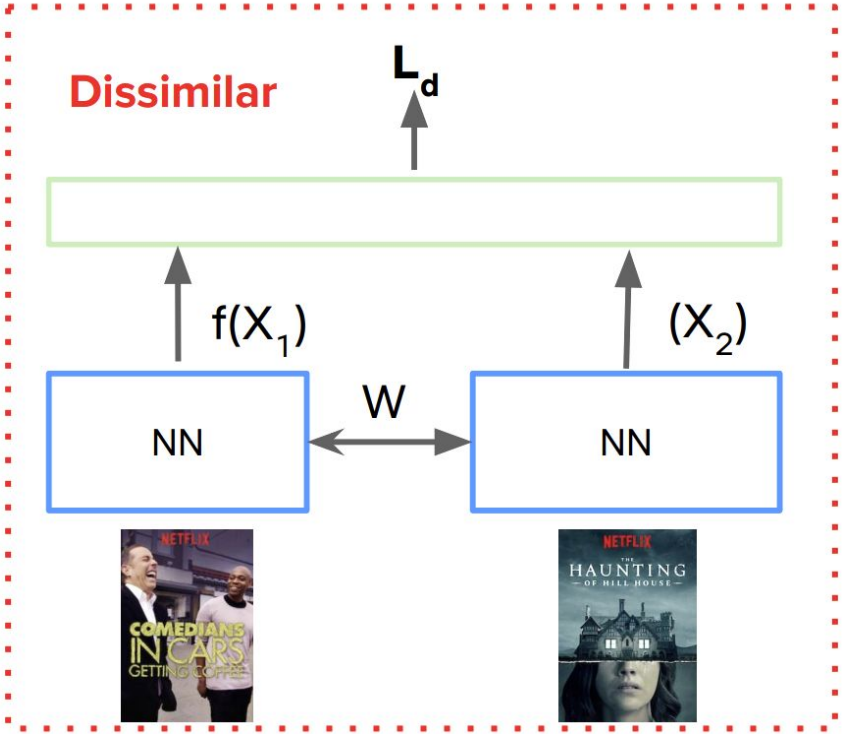
Siamese Networks



- Left and right legs of the network have identical structures (siamese)
- Weights are shared between the siamese networks during training
- Networks are optimized with a loss function, such as contrastive loss

Siamese Networks





$$L = \sum_{s} L_s + \sum_{d} L_d$$

Total loss is the sum of losses on similar pairs and dissimilar pairs

Contrastive Loss

The goal is to minimize L with respect to W, such that D_W is small for similar pairs, and large for dissimilar pairs

$$L^i = (1 - Y)L_s(D_W^i) + YL_d(D_W^i)$$

Y is set to 0 if pairs are similar otherwise 1

Exact loss is defined as:

$$L = (1 - Y)\frac{1}{2}(D_W)^2 + Y\frac{1}{2}\{\max(0, m - D_W)\}^2$$

m > 0 is the margin

Triplet Loss

The goal is the same, the distance between similar items must be low, and dissimilar items must be high.

$$L = \max(D(a,p) - D(a,n) + \alpha, 0)$$

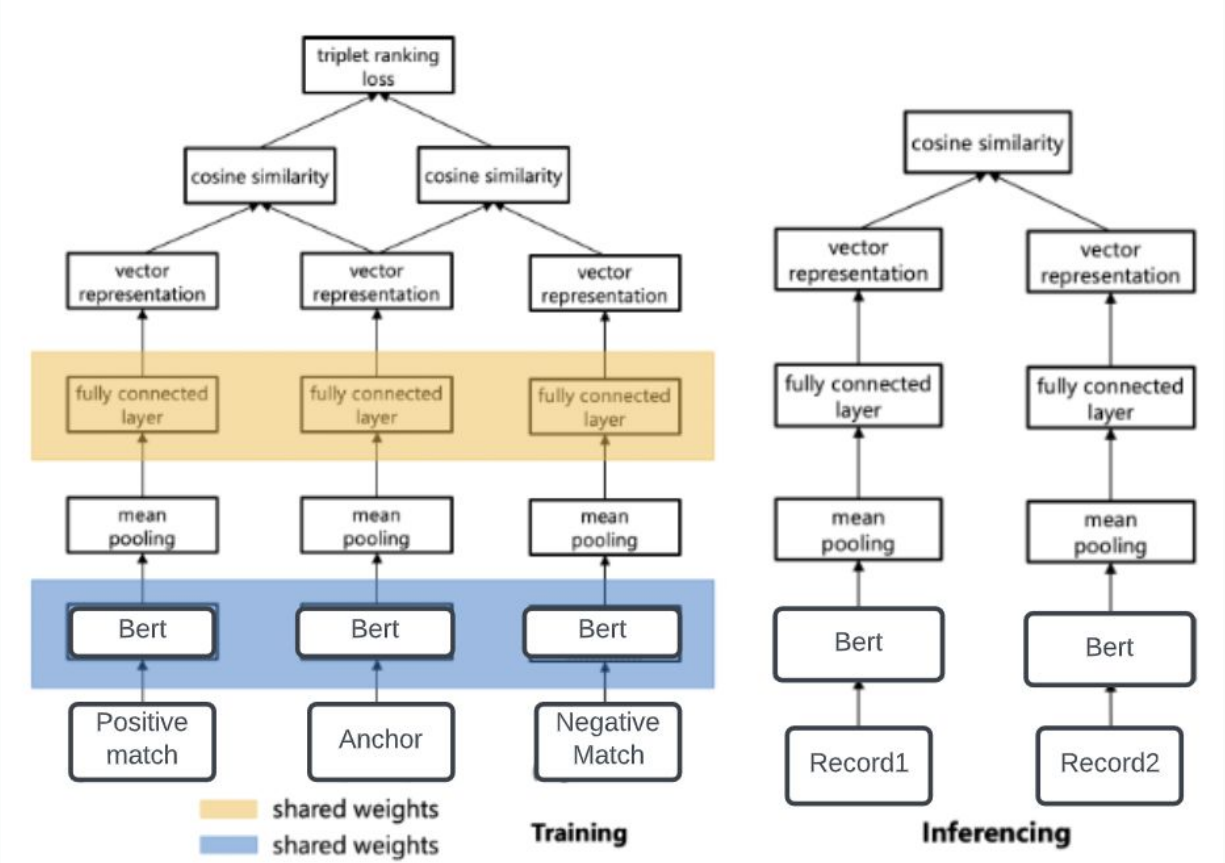
Loss of a triplet (a, p, n)

When using an Euclidean distance:

$$L = \frac{1}{Z} \sum_{i}^{N} \left[||f(x_i^a) - f(x_i^p)||_2^2 - ||f(x_i^a) - f(x_i^n)||_2^2 + \alpha \right]_+$$

$[.]_+ = \max(0, .)$
Hinge loss function

Deep Siamese Network



Triplet Loss Architecture

Deep Siamese Network

Similarity function:

$$s(x, y) = \frac{e(x) \cdot e(y)}{\|e(x)\|\|e(y)\|}$$

where $e()$ is the function that projects the raw input to an embedding vector (the sub-network in the Siamese network) and $\|e(x)\|$ denotes the norm of the vector $e(x)$.

Cost function:

$$L_{triplet} = \frac{1}{|X|} \sum_{(a,p,n) \in X} max(|s(a, p) - s(a, n) + \alpha|, 0)$$

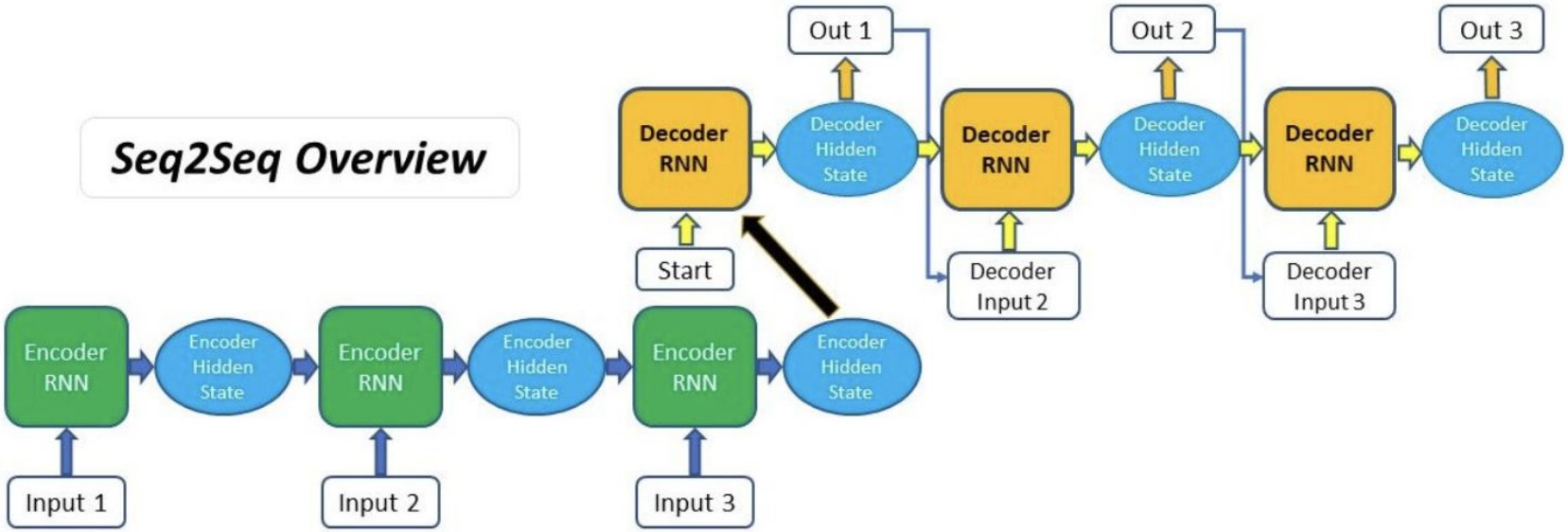
where X is the set of (a, n, p) triplets and α is a margin between positive and negative pairs. The triplet loss pushes $s(a, p)$ towards 1 and pushes $s(a, n)$ below than $s(a, p)$ by at least α. We set $\alpha = 0.3$ for the output shown in this work.

Deep Siamese Network

Demo

Let’s work on the hands on examples now!!

Encoder and Decoder for Seq2Seq



Types of Attentions (Bahdanau vs Luong)