Quesion Answering

CS671: Course Project

April 14, 2018

Dataset

SQuAD Dataset

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- The training set consists of around 100,000+ question-answer pairs on 500+ wikipedia articles

SQuAD Dataset Example

- **Context :** "The Joan B. Kroc Institute for International Peace Studies at the University of Notre Dame is dedicated to research, education and outreach on the causes of violent conflict and the conditions for sustainable peace. It offers PhD, Master's, and undergraduate degrees in peace studies. It was founded in 1986 through the donations of Joan B. Kroc, the widow of McDonald's owner Ray Kroc. The institute was inspired by the vision of the Rev. Theodore M. Hesburgh CSC, President Emeritus of the University of Notre Dame. The institute has contributed to international policy discussions about peace building practices."

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- **Answer Start :** 4

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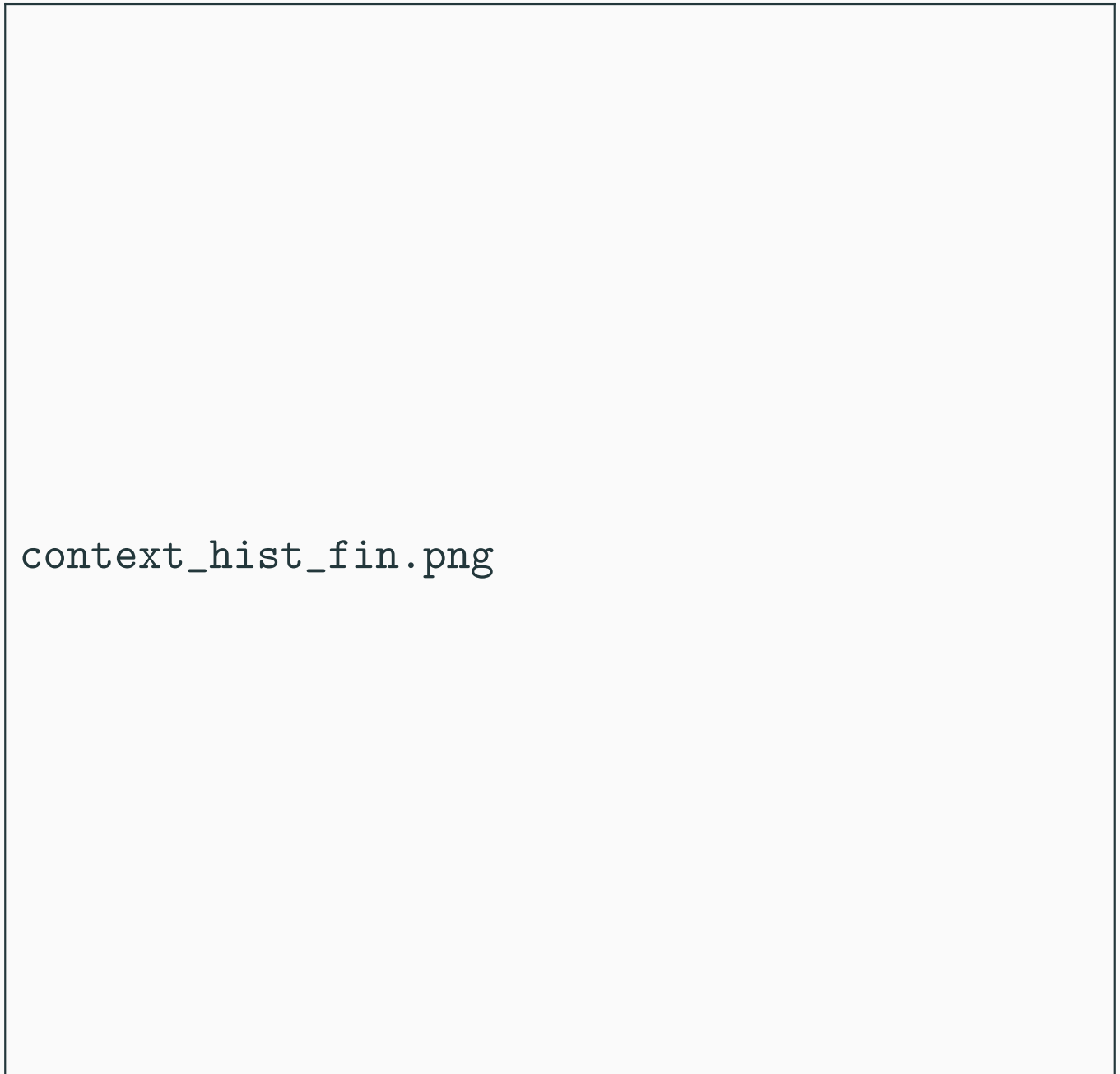
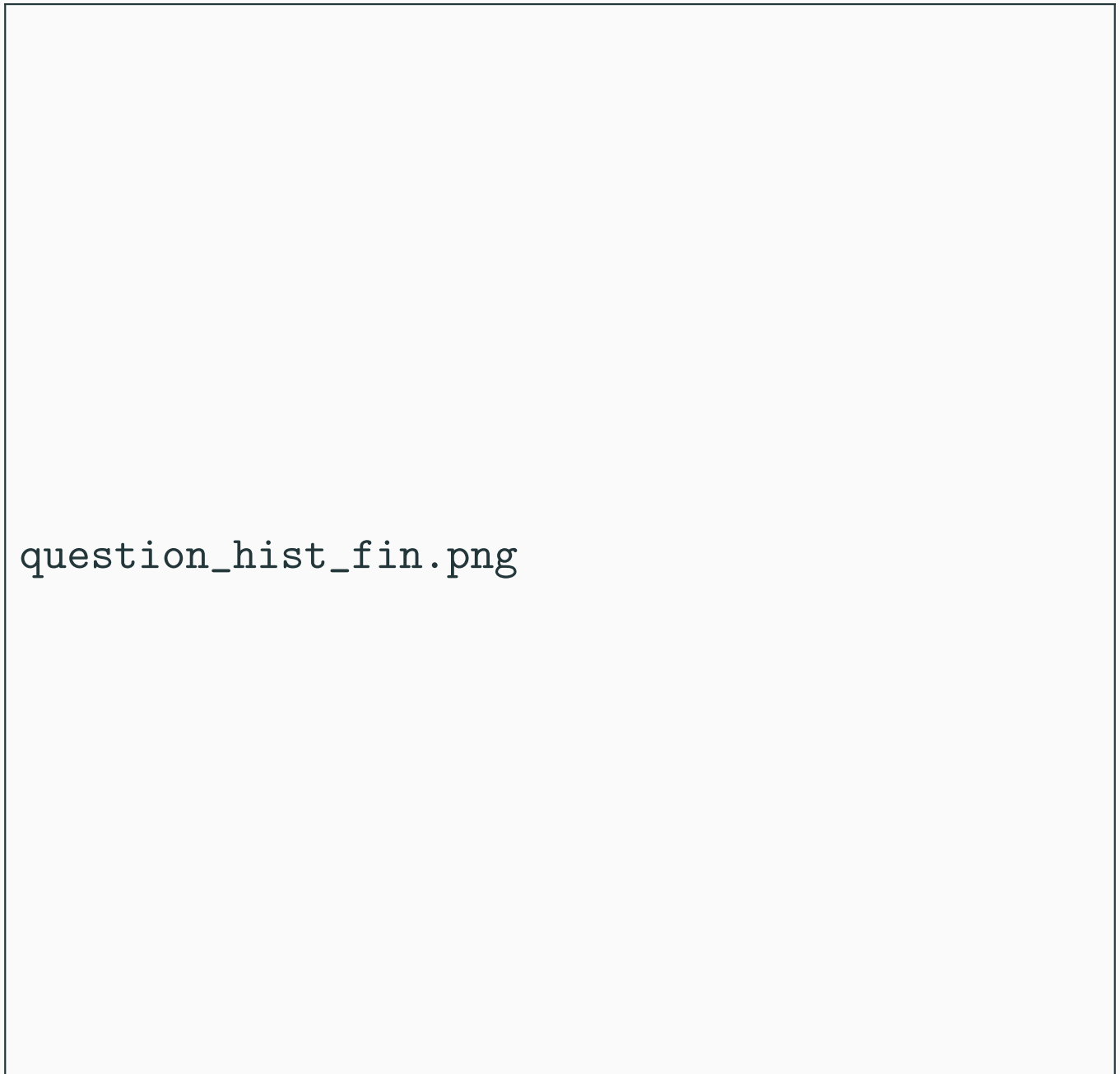
- We perform some basic analysis on the dataset in the form of histograms of the context paragraph lengths, question lengths, and answer lengths in the training set.

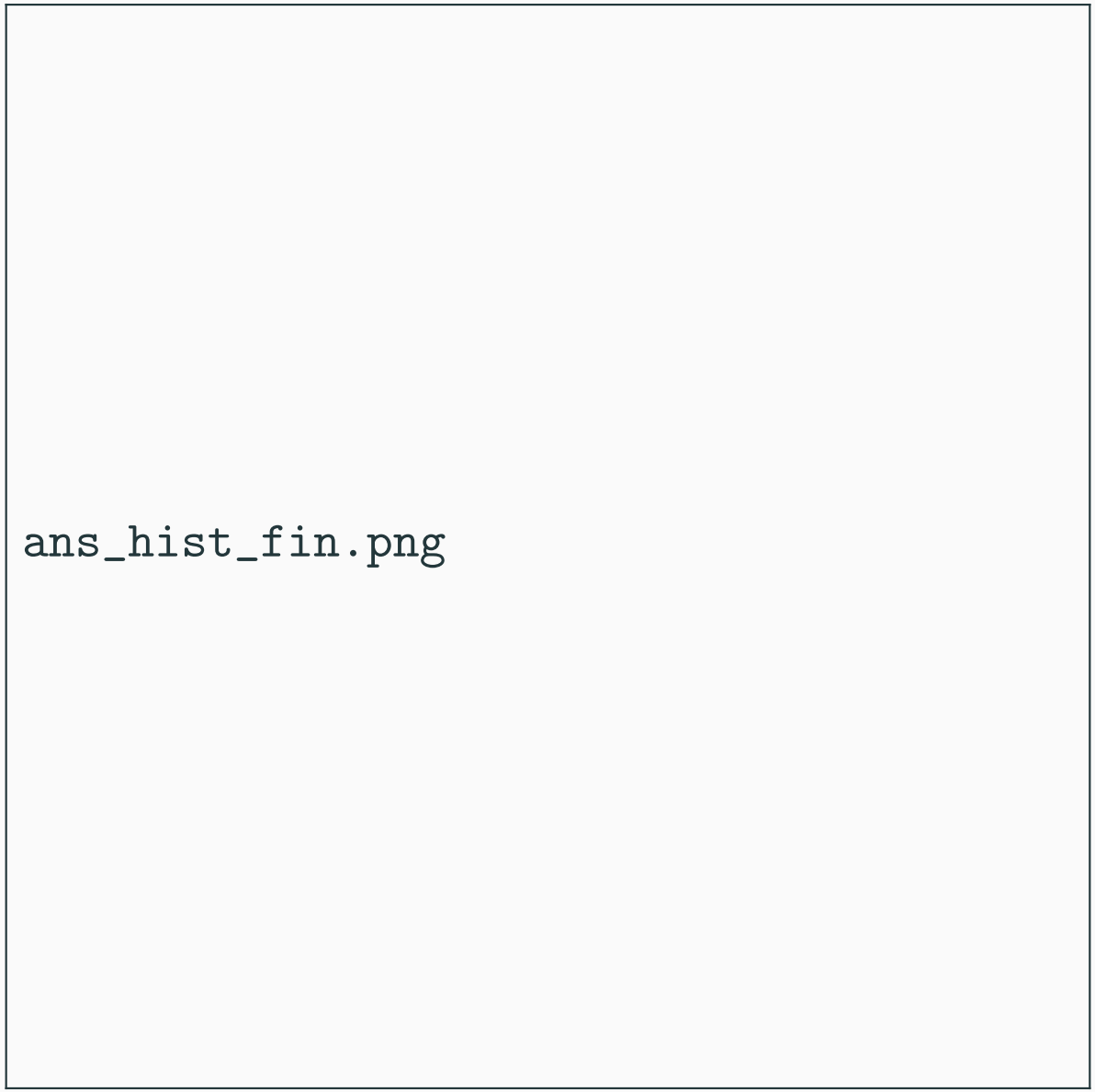
Analysing SQuAD Dataset - Graph(1/4)



Analysing SQuAD Dataset - Graph(2/4)

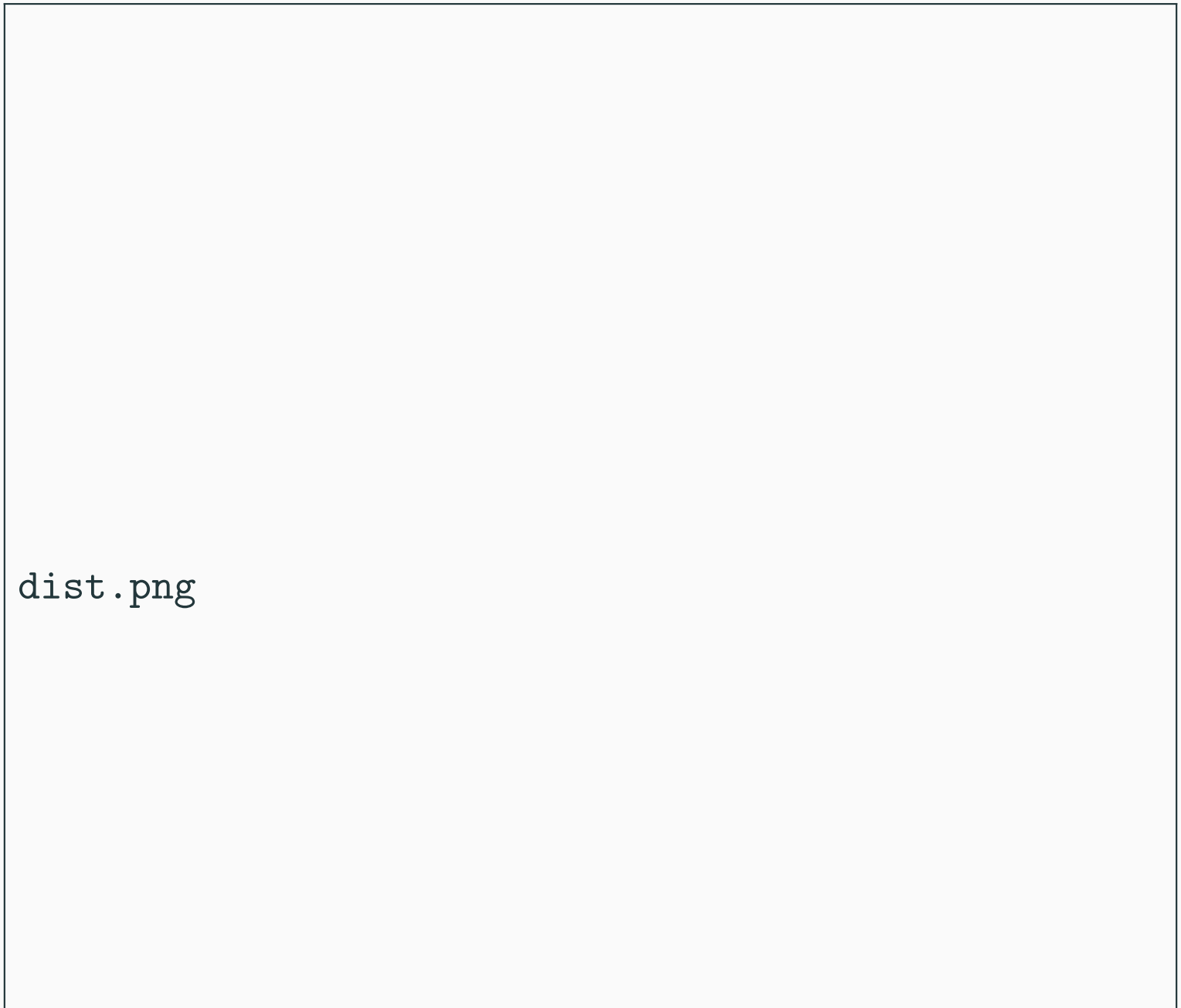


Analysing SQuAD Dataset - Graph(3/4)



- Most answers are shorter than 10 words

Analysing SQuAD Dataset - Graph(4/4)



Analysing SQuAD Dataset

- Based on the above analysis, we set an optimal choice for hyper parameters such as maxContextLength, maxQuestionLength, maxAnswerLength and use these to clip / pad the contexts, questions and answers

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$$\boldsymbol{H}^p = \overrightarrow{\text{LSTM}}(\boldsymbol{P}), \qquad \boldsymbol{H}^q = \overrightarrow{\text{LSTM}}(\boldsymbol{Q})$$

- The matrices $\boldsymbol{H}^p$ and $\boldsymbol{H}^q$ represent the hidden representations of the context and the question matrices, respectively.

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- where $\mathbf{W}^q$, $\mathbf{W}^p$, $\mathbf{W}^r$, $\in \mathbb{R}^{l \times l}$, $\mathbf{b}, \mathbf{w} \in \mathbb{R}^l$ and $\mathbf{b} \in \mathbb{R}$ are the parameters to be learned.

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- $\overrightarrow{\mathbf{h}_{i-1}^r} \in \mathbb{R}^l$ is the hidden vector at position i-1

Match-LSTM Layer

- Take the weighted version of the question and combine it with the current token of the context to form a vector $\overrightarrow{\mathbf{z}_i}$:

$$\overrightarrow{z_i} = \begin{bmatrix} \mathbf{h}_i^p \\ \mathbf{H}^q \overrightarrow{\alpha_i}^T \end{bmatrix}$$

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- This vector $\overrightarrow{\mathbf{z}_i}$ is fed into a standard one-directional LSTM to form our so-called match-LSTM:

$$\overrightarrow{\mathbf{h}_i^r} = \overrightarrow{\text{LSTM}}(\overrightarrow{\mathbf{z}_i}, \overrightarrow{\mathbf{h}_{i-1}^r}),$$

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  where the parameters are $(\mathbf{W}^q, \mathbf{W}^p, \mathbf{W}^r, \mathbf{b}^p, \mathbf{w}\ and\ b)$
- $\mathbf{z}_i$ and $\mathbf{h}_i$ are defined in similar manner.

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$$\mathbf{H}^r = \begin{bmatrix} \overrightarrow{\mathbf{H}^r} \\ \overleftarrow{H^r} \end{bmatrix}$$

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- This is used to compute a **attention vector** $\beta_k \in \mathbb{R}^{P+1}$, where $\beta_{j,k}$ is the probability of selecting the $j$context token as the $k$token in the answer.

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- Objective is to maximize $\mathbb{P}[\mathbf{a}|\mathbf{H}^r]$, and the answer corresponding to the maximum answer is reported as the answer to the query

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- This allows us to model each question type differently

Loss Function

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- The loss is given as

$$-\log p(a_s \mid \boldsymbol{P}_n, \boldsymbol{Q}_n) - \log p(a_e \mid \boldsymbol{P}_n, \boldsymbol{Q}_n)$$

Weighted Loss

Attention

Attention

- Model learns what to attend based on the input query.
- Mapping a query and a set of key-value pairs to an output.
- Output is a weighted sum of the values, weights are computed by a compatibility function of the query with the corresponding key.

Scaled Dot-Product Attention

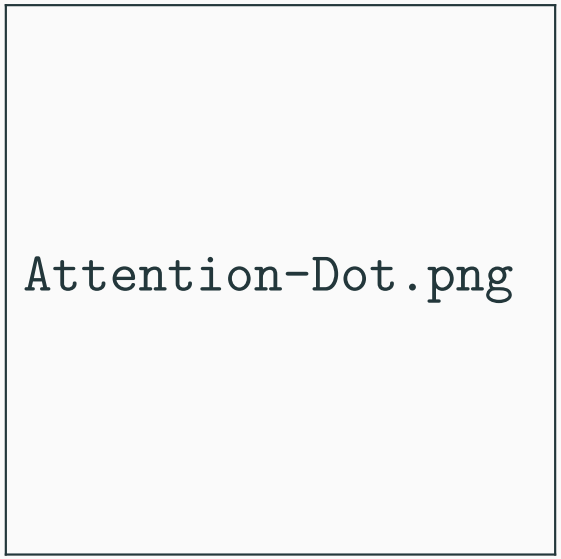

Figure 1: Scaled Dot-Product Attention [Source:][]–Attention is all you need

- We compute the dot products of the query(d_k) with all keys(d_k).
- Attention function is calculated on a set of queries simultaneously, packed together into a matrix Q.
- The keys and values are packed together into matrices K and V.

Scaled Dot-Product Attention

$$\text{Attention}(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

- For large values of d_k , the dot products grow large in magnitude. pushing the softmax function into regions where it has extremely small gradients. To counteract this effect, dot product is scaled by $\frac{1}{\sqrt{d}}$.
- Dot-Product Attention is much faster and more space-efficient in practice as compared to additive attention.

Multi-Head Attention

Figure 2: Multi-Head Attention [Source:][]–Attention is all you need

- Linearly projecting the queries, keys and values h times with different, learned linear projections to d_k , d_k and d_v dimensions, respectively.
- Now on each of these projected version perform the attention function in parallel.

Multi-Head Attention

$$\text{MultiHead}(Q, K, V) = Concat(head_1, ..., head_h)W^O$$

$$\text{where head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Projection are parameter matrices
$W_i^Q \in \mathbb{R}^{d_{model} \times d_k}, W_i^V \in \mathbb{R}^{d_{model} \times d_k}, W_i^Q \in \mathbb{R}^{d_{model} \times d_v}, W^O \in R^{hd^v \times d_m od}$
Due to the reduced dimension of each head, the total computational cost is similar to that of single-head attention with full dimensionality.

Pointer-Net

Pointer Net

- Used to predict the start(s) and end(e)
- Given the context representation $\{h_t^P\}_{t=1}^n$, the attention mechanism is utilized as a pointer to select the start position (p^1) and end position (p^2) from the context.
-

Dynamic Programming

Dynamic Programming

- After getting the logits for start and end positions, Dynamic Programming strategies are used.
- We select (s, e) where $s \leq e$ with the maximum value of $p_s^1 p_e^2$, which can be calculated in linear time using dynamic programming.
- Legal answer is selected with highest join probability of start and end. The F1 score was improved by 2 points.
- We then used a sentence-level DP to find the maximum $p_s^1 p_e^2$ where s and e are in same sentence. This improvement boosted the F1 score by another 0.5 point.