

Deep Co-attention Networks for Reading Comprehension

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Reading Comprehension

Problem: Locate the answer to a question within a corresponding context paragraph

► **Training**: Using the Stanford Question Answering Dataset (SQuAD) dataset

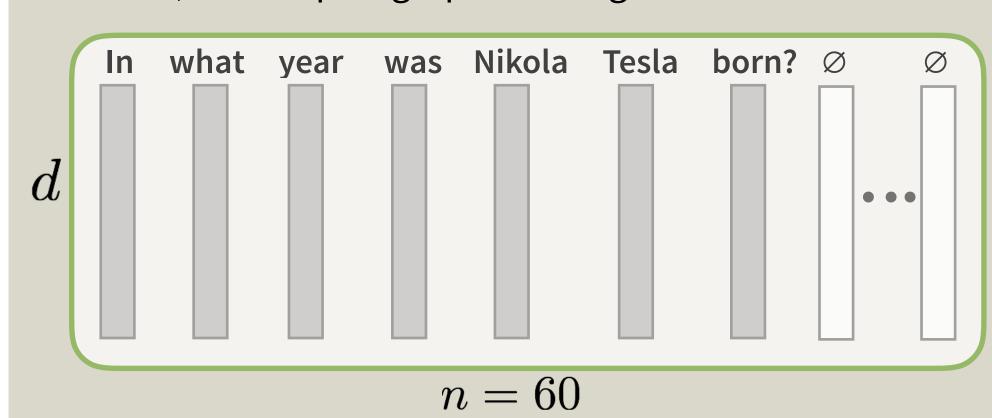
In what year was Nikola Tesla born?

Nikola Tesla (10 July 1856 - 7 January 1943) was a Serbian American inventor, electrical engineer, mechanical engineer, physicist, and futurist best known for his contributions to the design of the modern alternating current (AC) electricity supply system.

- ► **Output**: Predict the start and end index of the answer "span" in the paragraph: a_s and a_e
- ► **Challenges**: The need for multi-sentence reasoning; maintaining long-range context, accounting for variable answer length

Data Preprocessing

- ► **Tokenize** all questions, documents, and answers
- ► Obtain **GloVe word embeddings** for every word in the ~100K vocabulary, trimmed to dimension d = 100
- ► **Zero-pad** or truncate all questions to length n = 60 words, and all paragraphs to length m = 300



Method

Paragraph and Question Encoder

▶ Question Encodings: Encode the question word vectors using an LSTM, and stack the outputs horizontally.

$$q_t = \text{LSTM}_{enc}(q_{t-1}, x_t^Q)$$

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 $Q' = [q_1, q_2, \dots, q_n] \in \mathbb{R}^{\ell \times n}$

Add a nonlinear projection layer to the question encodings.

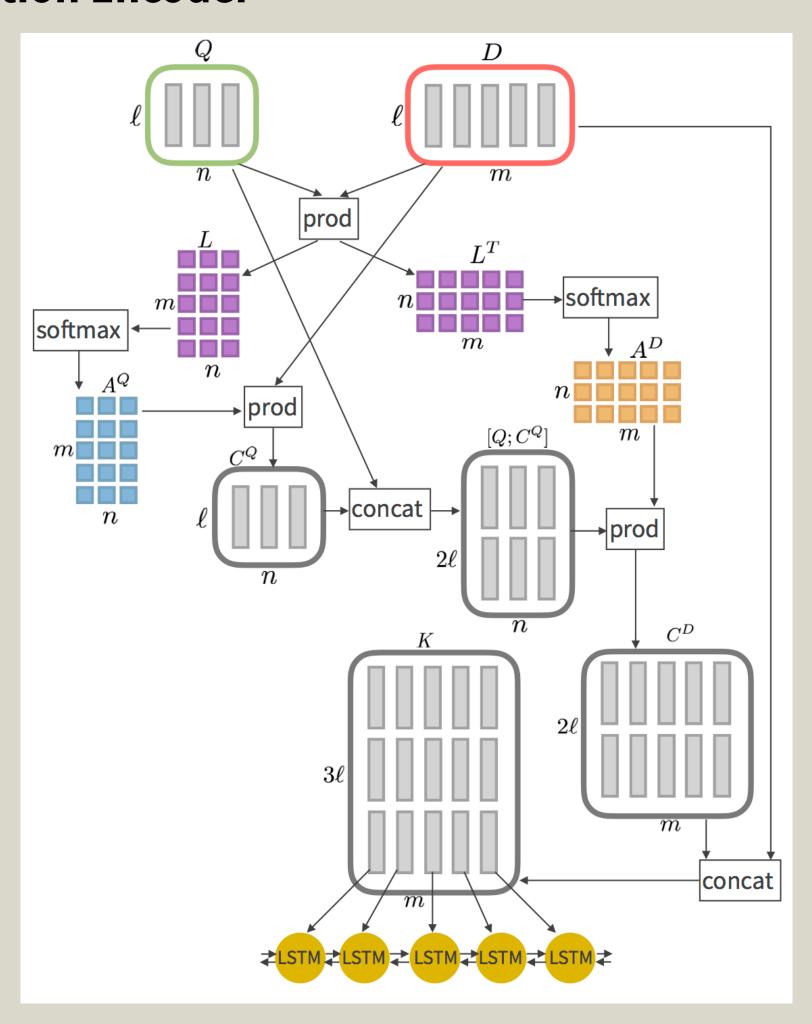
$$Q = \tanh(W^Q Q' + b^Q) \in \mathbb{R}^{\ell \times n}$$

► Paragraph Encodings: Encode the paragraph word vectors using the same LSTM, and stack the outputs horizontally.

$$d_t = \text{LSTM}_{enc}(d_{t-1}, x_t^D)$$

$$d_t = \text{LSTM}_{enc}(d_{t-1}, x_t^D)$$
 $D = [d_1, d_2, \dots, d_m] \in \mathbb{R}^{\ell \times m}$

Coattention Encoder



Decoder

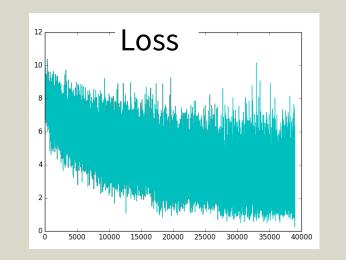
lacktriangle Train two m-way classifiers: one to output a_s and one for a_e

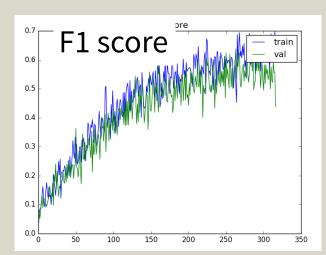
Experimental Setup

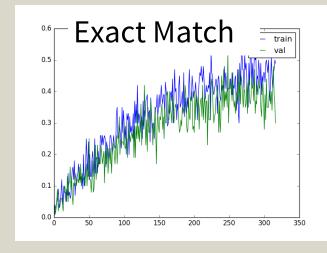
- ► Optimize with Adam SGD for 10 epochs, with batch size = 20
- ► Hidden size = 200 for all LSTMs, and dropout rate = 0.1
- ► Initial learning rate of 1e-3, which is annealed over time
- ► Clip gradient norms at 10

Results

► **Metrics**: ExactMatch (% predictions that match GT exactly) and <u>F1 Score</u> (avg overlap between prediction and GT)



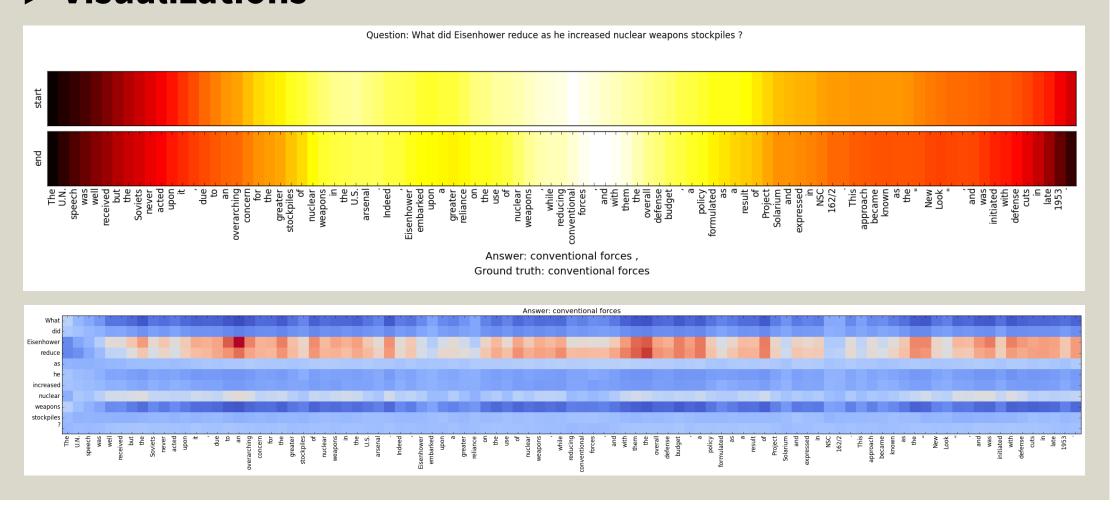




▶ Quantitative Results

Model	Train F1	Train EM	Dev F1	Dev EM
Coattention, no dropout	71.93	54.50	50.41	33.89
Coattention, w/ dropout			59.37	42.4

▶ Visualizations



Future Work

- ► Add a more complicated decoder, so that the start and end answer are not in the same encoding space
- lacktriangle Add a simple constraint to ensure that $\,a_s \leq a_e\,$