Question Answering

- Video: Week 3 Overview 6 min
- Reading: Week 3 Overview 10 min
- Video: Transfer Learning in 7 min
- Reading: Transfer Learning 10 min
- Video: ELMo, GPT, BERT, T5
- Reading: ELMo, GPT, BERT, T5 10 min
- Video: Bidirectional Encoder Representations from Transformers (BERT) 4 min
- Reading: Bidirectional **Encoder Representations** from Transformers (BERT) 10 min
- Video: BERT Objective
- Reading: BERT Objective 10 min
- Video: Fine tuning BERT
- (m) Reading: Fine tuning BERT 10 min
- Video: Transformer: T5 3 min
- Reading: Transformer T5 10 min
- Video: Multi-Task Training Strategy 5 min
- Reading: Multi-Task Training Strategy 10 min
- Video: GLUE Benchmark
- (m) Reading: GLUE Benchmark 10 min
- Video: Question Answering 2 min
- Reading: Question Answering 10 min
- Lab: SentencePiece and BPE
- Reading: Content Resource 10 min

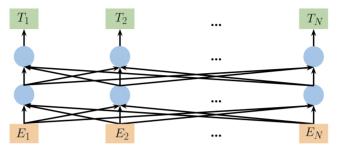
Assignment

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Bidirectional Encoder Representations from Transformers (BERT)

You will now learn about the BERT architecture and understand how the pre-training works.

• Makes use of transfer learning/pre-training:



There are two steps in the BERT framework: pre-training and fine-tuning. During pre-training, the model is trained on unlabeled data over different pre-training tasks. For fine tuning, the BERT model is first initialized with the pre-trained parameters, and all of the parameters are fine-tuned using labeled data from the downstream tasks. For example, in the figure above, you get the corresponding embeddings for the input words, you run it through a few transformer blocks, and then you make the prediction at each time point T_i .

- Choose 15% of the tokens at random: mask them 80% of the time, replace them with a random token 10% of the time, or keep as is 10% of the time.
- There could be multiple masked spans in a sentence
- Next sentence prediction is also used when pre-training.

The next video will talk about the BERT objective.







