**Transformers & BERT (Consider splitting up the notes)**

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**Basics:**

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Things to consider doing:

- <https://towardsdatascience.com/getting-started-with-google-colab-f2fff97f594c>

* HuggingFace: Library for transformers in NLP
  + -> Package is called ‘transformers’ (prvsly pytorch-transformers & pytorch-pretrained-bert)
    - Comes with 32+ pretrained models
* BERT uses two unsupervised training strategies:
  + Masked Language Model (MLM)
    - -> To avoid the word seeing itself; 15% of sentence randomly masked
    - Of these 15% Masked words:
      * 80% replaced w/ MASK token
      * 10% with random token
      * 10% unchanged
  + Next Sentence Prediction (NSP)
* BERT cased: true case & accent marks
* BERT Uncased: lower case & no accent marks
* When installing packages just look on anaconda website – line for most packages provided

**BERT Research 3 – Finetuning**

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<http://mccormickml.com/2019/07/22/BERT-fine-tuning/>

<https://www.youtube.com/watch?v=x66kkDnbzi4>

*Chris McCormick*

* Advantages of BERT:
  + Quick Development – Via Transfer Learning; Huge amount of data BERT trained on
  + Less training data – With finetuning we can train BERT w/ less data
  + Better results – All previous task-tailored solutions are outperformed by the general BERT model, hence you might waste your time task-tailoring
* Problems of BERT:
  + Very Large -> Slow finetuning & inferencing:
    - Embed Layer: 30K Tokens mapped to768 vals each ~23M
    - 12 Transformers w/ about 7M weights each ~85M
    - -> Params stored as 32bit float -> 4 Byte \* 109M = 400 Megabytes for state\_dict
  + Jargon (Domain Speicifc Knowledge)
    - Just like I’d have no clue, BERT might have no clue listening to liver doctors
  + Not all NLP applications
    - Yes:
      * Classification
      * Named Entity Recognition
      * Part of Speech Tagging (POS)
      * Question answering (if answer provided in some text)
    - No:
      * Language Modelling (Whats the next word in a sentence likely to be;
      * Text Generation
      * Translatio

**BERT Research 2 – The embedding**

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<https://www.youtube.com/watch?v=zJW57aCBCTk>

[*https://mccormickml.com/2019/05/14/BERT-word-embeddings-tutorial/*](https://mccormickml.com/2019/05/14/BERT-word-embeddings-tutorial/)

*Chris McCormick*

* ‘WordPiece’: BERT can encode ANY word as it uses substrings -> embedding becomes em, ##bed, ##ding; It wll obviously learn to pay a lot of attention to the substrings bed & ding when processing the ‘em’
  + ## indicates subword / char
* It knows all chars + ~30K most common words; worst case a word is broken down to chars
  + It might still know a word like bedroom and not break it down to bed & room, as it tries to keep the most of the word together as possible
* At the time of tokenizing river bank & (money) bank are still the same, BUT ONLY AFTER RUNNING THEM through the MODEL ONCE and then taking the vectors of banks from one of the LAST LAYERS (for the first it will still be the same, remember BERT has 12 LAYERS!), we see that it understood meanings
  + - In fact – first layer still slightly diff., due to positional encoding or perhaps randomness
    - BERT uses 768 Features & has 30K words
* Word Embeddings are really just about grouping words in a coordinate system -> Having only one word in a coord has absolutley no meaning, but once you have mutliple it gets meaning
  + -> This is done by simply looking if they appear in similar contexts (& in which contexts they do not appear at all together)
  + ## subwords have their OWN place in the dictionary i.e. in the 30K words there is one entry for bed and one entry for ##bed
  + There are also numbers etc in the vocabulary
  + -> JP/CN characters are similarly encoded into sub ‘signs’ (Radicals)
* According to Han Xiao (Bert-as-service), the embeddings start out in the first layer as having no contextual information (i.e., the meaning of the initial ‘bank’ embedding isn’t specific to river bank or financial bank) -> Hence this means they retrieve it from some pre-defined embedding dict (as before)
  + https://github.com/hanxiao/bert-as-service

**BERT Research 1 – Basic Idea**

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[*http://mccormickml.com/2019/11/11/bert-research-ep-1-key-concepts-and-sources/*](http://mccormickml.com/2019/11/11/bert-research-ep-1-key-concepts-and-sources/)

[*https://www.youtube.com/watch?v=FKlPCK1uFrc*](https://www.youtube.com/watch?v=FKlPCK1uFrc)

*Chris McCormick*

Links:

Bert Paper: https://arxiv.org/pdf/1810.04805.pdf

Bert Repo: [github.com/google-research/bert](https://github.com/google-research/bert)

Google Post: https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html

Attention is all you need: https://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf

From scratch Tranformer Impementation: https://nlp.seas.harvard.edu/2018/04/03/attention.html

Jai Posts:

1. **BERT** —— [The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning)](http://jalammar.github.io/illustrated-bert/)
   * Published: Dec 3, 2018
2. **Transformer** —— [The Illustrated Transformer](https://jalammar.github.io/illustrated-transformer/)
   * Published: Jun 27, 2018
3. **Attention** —— [Visualizing A Neural Machine Translation Model (Mechanics of Seq2seq Models With Attention)](https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/)
   * **A screenshot of a cell phone

     Description automatically generated**Published: May 9, 2018

NLP Course, Coursera (Already completed)

* RNNs
* Encoder-Decoder
* LSTMs
* Bidirectional RNN
* Attention

Fake Tasks:

- Do not matter in real life, but we have vasts amount of data on -> BERT was trained on two fake tasks

**LSTMs vs Transformers**

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[*https://www.youtube.com/watch?v=S27pHKBEp30*](https://www.youtube.com/watch?v=S27pHKBEp30)

*Leo Dirac*

* Vanishing & Exploding Gradient
  + W \* W \* W \* W \* W – No matter what values these are; it’ll most likely to yield a very high or very low value; esp. if you initialize e.g. from -1 to 1 -> tiny negative / positive value
    - Eigenvalue of a vector >1 / <1 says whether it’s going to explode / vanish
      * Eigenvalue says where the vector moves when a transformation (scaling the vector by some factor) is applied; If it is just 1 then the vector stays the same
* LSTM Problems:
  + A screenshot of a cell phone

    Description automatically generatedLoads of gradients
  + Transfer learning doesnt really work
* Transformer – 3 Parts:
  + FC
  + Multi Head Attention
    - All-to-all comparison (Each layer is O(N^2) for seq len of N) -> Thanks to GPUs these are still efficient – while in an LSTM you need to process them step by step (as the result matters for the next)
    - -> Output is Weighted Sum of all inputs (Great to visualize) (See very clearly that for European Economic Zone it suddenly pays attention to more words than just the equivalent as for The)
    - This works by generating a QUERY for every output your considering and a KEY for every input -> The relevance score is the dot product
    - A screenshot of a cell phone screen with text

      Description automatically generatedValues are the 3rd version of each token, which you dot product with Softmax (relevance) -> Final Out
    - Attention mechanism in pseudo-code; Input is one tensor per token in the input (list of tensors); Beginning is the calculation of the Q & K & V of each input -> self.Q etc are learned matrices
    - ‘Multi-headed part: You do that attention mechanism x times (e.g. 8) w/ different Q,K,V matrices; This lets the network learn 8 different semantic meanings (e.g. vocab, gender, tense) -> it looks at different parts of the sentence and do this at each layer
  + Input Embedding / Pos Encoding
    - Going away from bag of words (where work to live & live to work is the same)
    - They still use word2vec to calculate some vector for each input token
    - Then add sines & cosines ONTO the word embeddings (inspired by Fourier Theory) of different frequencies starting at just pi and then stretching out longer & longer
      * This lets the model reason about the relative position of the words
* Why ReLU works so much better than tanh & sigmoid:
  + tanh & sigmoid cannot tell the difference of 10 & 20 (due to the derivative being ~the same)
  + Hinton: ReLUs allow each Neuron to express a strong opinion
  + ReLUs Gradients do not saturate (i.e. stop changing)
  + ReLUs are less sensitive to initalization (For sigmoid you need to make values will be in that middle part)
  + Runs also in worse hardware 8BITFLOAT possible
  + Derivatives are ridiculously easy
  + Downsides:
    - Dead Neurons left of 0 (-> leakyRELU)
    - Grad Discontinous at 0 (-> GELU) (Used by BERT)
* DL Wisdom:
  + Do not bother w/ trying diff. activations, just go w/ ReLU
  + Different optimizers DO make a difference
    - Adam – fast X tends to overfit
    - SGD – slow (takes long to converge) X tends to generalize better
    - Sts RMSProp works best
    - SWA can easily improve quality
    - AdaTune – You do not need to pick a LR, dynamically calculated
  + There are no local minima only saddle points
    - You want to get to the middle of the global minima, but SGD has problems doing so – it converges in circles once it is close to the minima (due to the LR, i.e. it’s jumping from before the minima to after etc)
      * -> Stochastic Weight Averaging – Averages the results around the minimum to get into the middle
* MegatronLM by NVidia: Going to the limit of compute
  + 8.3B parameters; 512 GPUs for 9 days (450K$ on EC2)
  + Similar w/ XLM RoBERTa
* Key Advantages of TF’s:
  + Easier To Train, More Efficient
  + TRANSFER LEARNING WORKS!
  + Can be trained UNSUPERVISED -> All of the worlds text data becomes available
* LSTMs still good when:
  + Sequence length is long / infinite, such as real time control for robots
* word-CNNs
  + Similar to LSTMs only take a part of the text
  + Have the advantage of parallelization like Transformers
  + Do not need the positional encoding like Transformers
  + Cannot like transformers answer the question Does this concept exist anywhere in the document