Evolution of NLP Models

8 August 2020

Jingli SHI

Content

Generation #1

• N-Gram

Generation #2

• Simple ML

Generation #3

• RNN / LSTM / GRU

Generation #4

• Seq2Seq (Encoder-Decoder)

Generation #5

• Transformer











Background

NLP began in the 1950s as machine translation (MT). These early MT efforts were intended to aid in code-breaking during World War II. Developers hoped MT would translate Russian into English, but results were unsuccessful. Although the translations were not successful, these early stages of MT were necessary stepping stones on the way to more sophisticated technologies.



Background (AI vs ML vs DL vs NLP)

Gen #1 (*N* - Gram)



P("This is a sentence")
= P("This")P("is" | "This")P("a" | "is", "This") ... P("sentence" | "is", "a")

Gen #1 (N-Gram)

- N-gram models almost does not know the complicated structure of human languages.
 - The ship {sailed, sank, anchored, ...}
- N-gram models only know some low-level syntax.
 - In study (noun) room
 - Study(verb) a language

Gen #2 (Simple ML)



Simple Neural Network

- Models like :
 - Linear Regression, Logistic Regression, Decision Tree, KNN, SVM, et, al.
- Works better on small data
- Financially and computationally cheap
- Easier to interpret



Evolution Accelerator



Word embedding models at early stage:

- Bag of words
- One-Hot
- TF-IDF
- Word2Vec
- GloVec (hypothesis: words that occur in same context tend to have similar meanings)

Gen #3 (RNN/LSTM/GRU)



RNN – Recurrent Neural Network



RNN - Unit



RNN – Hidden State



RNN - Tanh Activation



Activation function is used for regulating flow of information.

RNN – Vanishing Gradient



RNN – Vanishing Gradient Problem



Long Short-Term Memory (LSTM)



Ct: Cell state is an internal state that is not output; *Ht*: hidden state is an output

LSTM - Architecture



sigmoid

tanh

pointwise multiplication

pointwise addition vector concatenation

LSTM - Gates

- Input Gate
- Cell State ("memory" of network)
 - act as a transport highway that transfers relative information all the way down the sequence chain.
- Forget Gate
 - learn what information is relevant to keep or forget during training.
- Output Gate

LSTM – Sigmoid Activation



Forget / Update Information

GRU – Gated Recurrent Unit







tanh

pointwise pointwise multiplication addition

vector

vector concatenation

LSTM vs GRU

- GRU's has fewer tensor operations, a little speedier to train than LSTM's
- No clear winner which one is better.

Gen #4 (Encoder-Decoder/Seq2Seq)



Encoder-decoder sequence to sequence model

 Unlike sequence prediction with a single RNN, where every input corresponds to an output, the seq2seq model frees us from sequence length and order, which makes it ideal for translation between two languages.

Encoder-Decoder for MT



Encoder-Decoder for Chatbots



Generative Model Chatbots

Gen #5 (Transformer)

- Superior quality results on MT
- Parallelization benefits performance
- Learn long term dependency







Attention:

 Born to solve the incapability of seq2seq models to remember longer sequences

Transformer (Encoder – Decoder)





Transformer – Pre-Trained Models

ELMo, ULMfit Jan 2018 Training: 103M words 1 GPU day fast.ai

GPT June 2018 Training 800M words 240 GPU days Google Al OpenAI

BERT Oct 2018 Training 3.3B words 256 TPU days ~320-560 **GPU** days

GPT-2 Feb 2019 Training 40B words ~2048 TPU v3 days according to a reddit thread

OpenAI

XL-Net, ERNIE, Grover, AlBERT, Megatron-LM, T5, **RoBERTa**, GPT-3 July 2019-



Transformer – Pre-Training Model Progress

Rapid Progress from Pre-Training (GLUE benchmark)



Over 3x reduction in error in 2 years, "superhuman" performance

GPT-3 (latest monster)



GPT-3 (latest monster)

- 175 billion parameters
- Applied to **ANY** language task
- Code generator
 - <u>https://twitter.com/i/status/1282676454690451457</u>
- Text to SQL query
 - https://twitter.com/FaraazNishtar/status/1285934622891667457?s=20