NLP for Supervised Learning - A Brief Survey

[llm deeplearning survey] · *23 min read*

It's hard to keep up with the rapid progress of natural language processing (NLP). To organize my thoughts better, I took some time to review my notes, compare the various papers, and sort them chronologically. This helped in my understanding of how NLP (and its building blocks) has evolved over time.

To reinforce my learning, I'm writing this summary of the broad strokes, including brief explanations of how models work and some details (e.g., corpora, ablation studies). Here, we'll see how NLP has progressed from 1985 till now:

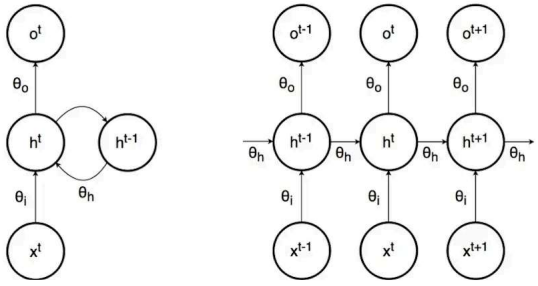
- Sequential models: RNN (1985), LSTM (1997), GRU (2014)
- Word embeddings: Word2vec (2013), GloVe (2014), FastText (2016)
- Word embeddings with context: ELMo (2018)
- Attention: Transformer (2017)
- Pre-training: ULMFiT (2017), GPT (2017)
- Combining the above: BERT (2018)
- Improving BERT: DistilBERT, ALBERT, RoBERTa, XLNet (2019); Big Bird, Multilingual embeddings (2020)
- Everything is text-to-text: T5 (2019)

(Did I miss anything important or oversimplify? Any errors? Please reach out with suggestions and I'll update. Thank you!)

Sequential models to process a sentences (1985)

Recurrent neural networks (RNNs) were first introduced around 1985 - 1986 (based on this thread). They differ from regular feedforward neural networks in that their hidden layers have connections to themselves. This allows them to operate over **sequences** (e.g., sentences of word tokens).

The state of the hidden layer at one time-step is used as input to the (same) hidden layer at the next time-step; thus the name "recurrent". This allows the hidden layers to learn information about the temporal relationships between tokens in the sequence. For more details, check out Andrej Karpathy's excellent post.



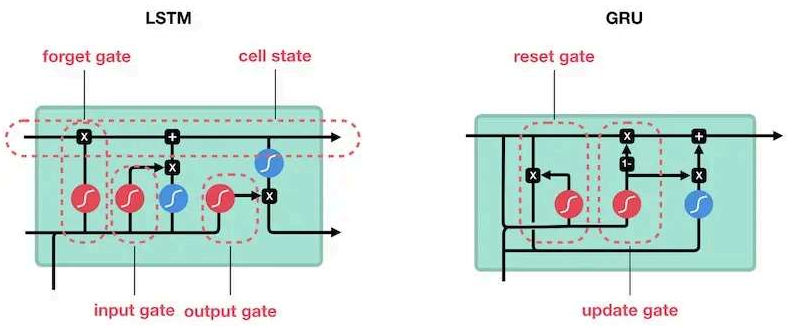
RNN (left) and its unrolled view (right) (source)

However, RNNs had difficulty with modelling long-range dependencies (e.g., words that are far apart in a long sentence) due to vanishing/exploding gradients. With long sequences, the product of partial derivatives (through backpropagation) becomes very small (i.e., vanish). This happens when the partial derivatives are < 1. The reverse occurs when the partial derivatives are > 1 and the product explodes.

The **Long Short-Term Memory (LSTM)** architecture introduced in 1997 improves on this. LSTMs model long-range dependencies better through *gates*:

- Forget gate: Decides what information, from the current input and previous hidden state, to forget (i.e., discard) via a sigmoid
- Input gate: Decides what information to remember (i.e., stored) via a sigmoid
- Output gate: Decides what the next hidden state should be

Together, these gates improve how the LSTM learns—what should be forgotten and what should be remembered? More details in Chris Olah's explanation. Though the LSTM was introduced in 1997, it wasn't until 2015 that they saw commercial use: Google Voice, Apple's QuickType and Siri, Amazon's Alexa, and Facebook's automatic translations.



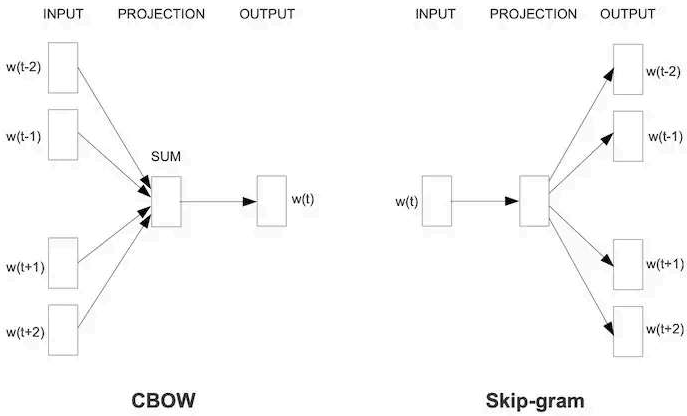
Comparison between the LSTM and GRU (source)

Gated Recurrent Units (GRUs) simplified the LSTM in 2014. It has only two gates, an update gate (similar to LSTM's forget and input gate) and a reset gate (which also decides how much to forget). Because it has fewer gates (and thus fewer math operations), it's faster to train. (In my work, I've found GRUs to converge faster with greater stability).

Word embeddings to learn from unlabelled data (2013)

In 2013, Word2vec (w2v) was introduced. Through **unsupervised learning**, it represents words as numbers, or more precisely, vectors of numbers. (Previously this was done via one-hot encoding). Being unsupervised, it's able to learn on large corpora of unlabelled data (e.g., Wikipedia). When used in a variety of downstream tasks (e.g., classification), these word embeddings greatly improve model performance.

There are two ways to train w2v models: **Continuous Bag of Words (CBOW)** and **Skip-gram**. In CBOW, we predict the *center* target word given the context words around it. In Skip-gram, we predict the *surrounding* context words given a center word (similar to CBOW, but in reverse). Skip-gram was found to work better with smaller amounts of data and to represent rare words better. CBOW trains faster and has better representations of more frequent words. (I've usually found Skip-gram to work better.)



Continuous Bag of Words vs. Skip-gram (source)

Why does Skip-gram work better for rare words?

Word2vec applied **subsampling**, where words that occurred relatively frequently were dropped out with a certain probability. This accelerated learning and improved word embeddings for rare words.

It also tweaked the problem slightly. Instead of predicting the most probable nearby words (out of all possible words), it tries to predict whether the word-pairs (from skip-gram) were actual pairs. This changes the final layer from a softmax with all the words (expensive) to a sigmoid that does binary classification (much cheaper) .

However, our dataset and word pairs only have positive samples. Thus, **negative sampling** is done to generate negative samples based on the distribution of the unigrams. (In the paper, they applied an interesting trick and raised the word counts to the 3/4 power.)

Global Vectors for Word Representation (GloVe) was introduced a year later (2014). While w2v learns word co-occurrence via a sliding window (i.e., local statistics), GloVe learns via a co-occurrence matrix (i.e., global statistics). GloVe then trains word vectors so their differences predict co-occurrence ratios. Surprisingly, though w2v and GloVe have different starting points, their word representations turn out to be similar.

There are also variants of w2v that learn subword or character embeddings. Subword embeddings learn the most frequent character segments (i.e., breaking a word into 2-3 character segments). One approach is **FastText** (where the original Word2vec author is a co-author). FastText open-sourced its code as well as the multiple-language word embeddings trained with it.

> **What did we do *before* embeddings?**

Improving word embeddings with context (2018)

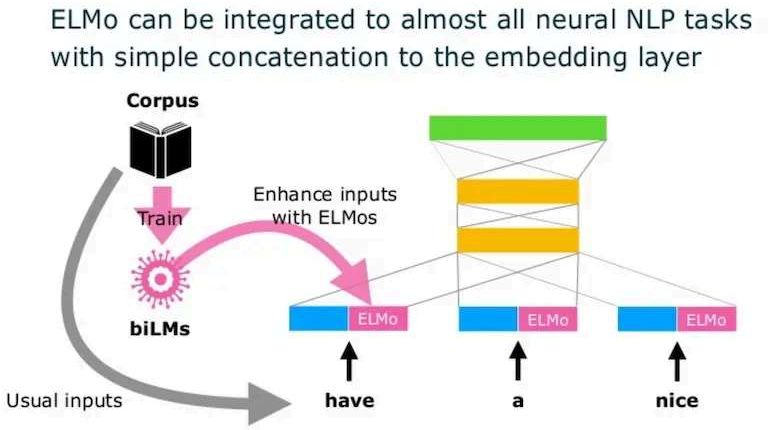
In traditional word embeddings (e.g., Word2vec, GloVe), each token has only one representation (i.e., embedding). This is regardless of how it's used in a sentence. For example, "date":

- They went out on a "date".
- What "date" is it today?
- She is eating her favourite fruit, a "date".
- That photo looks "dated".

Embeddings from Language Models (ELMo) improves on this (in 2018) by providing word representations *based on the entire sentence*. It does this via a bidirectional language model (biLM). ELMO's biLM comprises a two-layer bidirectional LSTM.

By going both left-to-right (LTR) and right-to-left (RTL), ELMo can learn more about a word's context. For example, in "Today is a *hellacious* day for writing", the LTR LM will encode "today is a" while the RTL LM will encode "writing for day". Together, they consider the entire sentence for the word "hellacious". These embeddings are learned via *separate* LMs and concatenated before being used downstream. (Why do these LMs have to be *separate*? See Why can't we use bidirectional context with multiple layers?)

Pre-trained ELMo can be used in a variety of supervised tasks. First, the biLM is trained and the word representation layers are frozen. Then, the ELMo word representation (i.e., vector) is concatenated with the token vector to enhance the word representation in the downstream task (e.g., classification).



ELMo embeddings concatenated with input tokens (the blue blocks) for downstream tasks (source)

Attention to remove the need for recurrence (2017)

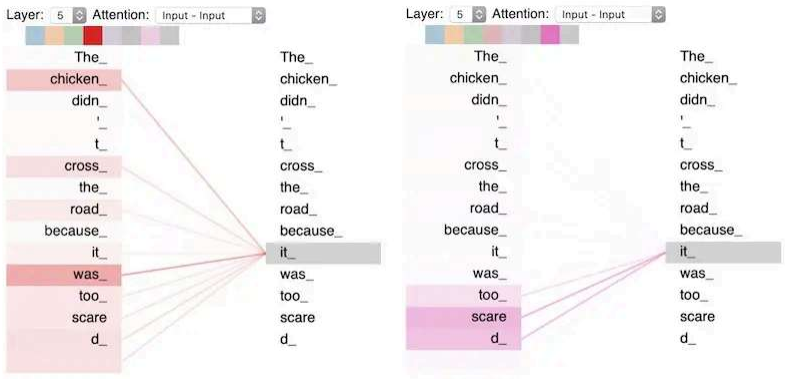
(We're done with word representations; back to model architectures.)

Recurrent models (e.g., RNN, LSTM, GRU) have a sequential nature—each hidden state requires the input of the previous hidden state. Thus, training cannot be parallelized. Furthermore, they can't learn long-range dependencies well; while LSTM and GRU improved on the RNN, they too had their limits.

The Transformer (2017) solved both problems with **attention**. At a high level, attention determines how other tokens (in the input sequence) should be weighted while encoding the current token (i.e., how the others words in "Today is a hellacious day for writing" should weigh on "hellacious"). Together with the **positional encodings** (more later), we can process the entire sentence at once (no recurrence!) and compute each word's representation based on the entire sequence.

The Transformer is made up of encoder and decoder stacks. In each encoder stack, there are six identical sub-layers, each having a self-attention mechanism followed by a fully connected feedforward neural network. The decoder stack is similar but includes an additional attention layer to learn attention over the encoder's output. (It seems the Transformer was intended for seq2seq problems such as translation.)

Multi-headed attention (eight heads) is used with each head randomly initialized. (Is it just me, or is this ensembling?) The outputs from these eight heads are concatenated and multiplied by an additional weight matrix. In the decoder stack, the attention mechanism is masked (to prevent looking ahead at future tokens).



*Why **didn't** the chicken cross the road? Attention from two different heads (source)*

To provide information about the relative and absolute position of tokens in a sequence, **positional encodings** were used at the bottom of the encoder and decoder stacks. This helps the model to learn from token positions as well as the distance between each token.

(Be sure to check out Jay Alammar's beautiful write-up on "The Illustrated Transformer".)

Fine-tuning learned embeddings (2017)

So far, we've mostly used word embeddings directly, or concatenated them with input tokens (i.e., ELMo). There was no fine-tuning of the word embeddings for specific tasks. This changed with ULMFiT and OpenAI GPT (**and transfer learning**).

ULMFiT (2017) uses AWD-LSTM (LSTM with dropout at the various gates) as its language model and introduced a fine-tuning phase as part of three steps. First, in **general-domain LM pre-training**, the LM is trained on unlabelled data. ULMFiT trained on Wikitext-103 (28.6k Wikipedia articles and 103 million words).

Then, in **target-task fine-tuning**, the LM is fine-tuned with the corpus of the target task (no labelled data introduced yet). *Discriminative fine-tuning* is applied, where each layer is fine-tuned with different learning rates—the last layer has the highest learning rate, with each subsequent layer having reduced learning rates. ULMFiT also adopted *slanted triangle learning rates* where the learning rate increases quickly before decaying at a slower rate.

Finally, in **target-task classifier fine-tuning**, two additional linear blocks are added on the LM (softmax for the last layer, ReLU for the intermediate layer). Gradual unfreezing is done, where we start with unfreezing the last LM layer and fine-tuning it. One by one, each subsequent layer is unfrozen and tuned.

GPT (2017; granddaddy of GPT-3) also applied **unsupervised pre-training**. It uses the Transformer's *decoder* stack. This is an improvement over LSTMs as the Transformer has better learning on long-ranged dependencies and is not recurrent in nature.

GPT is trained via two steps. First, **unsupervised pre-training** (similar to ULMFiT's first step) involves learning on a corpus to predict the next word. GPT used the BookCorpus dataset of 7,000 unique, unpublished books. (This differs from ELMo, which uses shuffled sentences, thus destroying the long-range structure).

Then, **supervised fine-tuning** tweaks the decoder block for the target task. Task-specific inputs and labels are passed through the pre-trained decoder block to obtain the input representation (i.e., embedding). This representation is then fed into an additional linear output layer. In this stage, an auxiliary objective is included. The auxiliary objective predicts the next word in the task-specific corpus (similar to ULMFiT's second step) and was found to improve generalisation and speed up convergence.

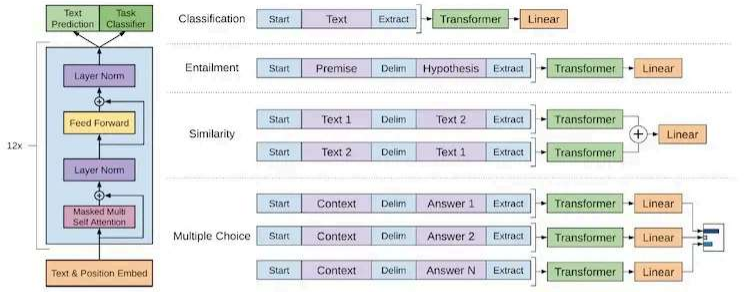


Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

Inputs are transformed into a single sequence based on the task (source)

To use GPT, **task-specific input transformations** were done for various tasks:

- Text classification: The model can be used directly.
- Textual entailment: The premise and hypothesis is concatenated with a `$` token.
- Similarity: We get both orders of the sentences (i.e., sentence1-sentence2, sentence2-sentence1) and concatenate them. The decoder output is added element-wise and fed into a linear layer.
- Multiple-choice Q&A: Concatenate the question with each possible answer and feed them through a linear layer. The outputs are normalised via softmax to get a probability distribution.

(Check out Modern NLP's Transfer Learning In NLP for comprehensive review on this.)

BERT: No recurrence, bidirectional, pre-trained (2018)

Towards the end of 2018, **Bidirectional Encoder Representations from Transformers (BERT)** was introduced. It obtained SOTA results on eleven NLP tasks. There were several elements from previous models that made BERT a pragmatic SOTA model:

- Transformer: BERT uses the Transformer *encoder* stack and does away with recurrence (parallelizable training).
- ELMo: Similar to ELMo, BERT has bidirectional context.
- ULMFiT and GPT: BERT *also* adopts pre-training and fine-tuning; thus, the LM (from pre-training) can be tuned for various downstream tasks.
- GPT: BERT also has a unified architecture and a single input representation.

BERT uses a multi-layer bidirectional Transformer encoder block as its language model. In contrast, GPT uses a unidirectional Transformer decoder block while ELMo uses twin, separate LSTMs.

Input to BERT is represented as a single sentence or a pair of sentences (e.g., question and answer). BERT uses WordPiece embeddings. It also introduces a special classification token (`CLS`) that is always the first token in a sequence—the final hidden state of this token is used for classification tasks. Sentence pairs are separated by a `SEP` token (similar to GPT).

Pre-training is done via two unsupervised tasks. First, a **masked language model (LM)** is trained via the cloze task. (The standard, predict-the-next-word task cannot be used with bidirectional context and multiple layers; more below). BERT masks 15% of tokens randomly (with the `MASK` token). However, this creates a mismatch between pre-training and fine-tuning. Thus, of the masked tokens, 80% are `MASK`, 10% are replaced by a random token, and 10% are unchanged. The LM predicts the original token with cross-entropy loss.

Why can't we use bidirectional context with multiple layers?

The second pre-training task involves **next sentence prediction (NSP)**. Assuming two consecutive sentences A and B, 50% of the time sentence B actually follows sentence A. The other 50% of the time sentence B is a random sentence.

For both pre-training tasks, BERT uses the BooksCorpus (that GPT also used) and English Wikipedia (2,500 million words, text passages only). A document-level corpus was specifically chosen to learn from long contiguous sentences.

Fine-tuning involves passing task-specific inputs and labels to tweak model parameters end-to-end. Then, BERT can be used in various ways:

- Single sentence and sentence-pair classification: Use the final hidden state of `CLS`
- Single sentence tagging: Use the final hidden state of each token
- Q&A: Predict two probabilities per token, whether it's the start or end of the text.

BERT is practical (read: lower cost and faster to train due to no recurrence) and high performing. As a result, it has been applied to Google Search.

> More examples of machine learning applied in the real-world: `applied-ml`

Ablation study: How does each BERT feature add to performance?

Improving on BERT (2019+)

Since BERT, several improvements have been made to make it lighter (DistilBERT, ALBERT), optimize it further (RoBERTa). BERT has also been applied to create sentence embeddings in 109 languages.

One problem BERT had was not being able to learn bidirectionally (which is why BERT used the *cloze* task for pre-training). XLNet (June 2019) addresses this via **permutation language modelling (LM)**; in contrast, BERT used masked language modelling.

Permutation LM is tricky but here's my attempt to explain it. Here's our example sentence and token indices: "Today(1) is(2) a(3) hellacious(4) day(5) for(6) writing (7)", with the sequence 1234567.

First, permutation LM creates multiple sequence permutations (e.g., 2347516). Then, it learns representations of each word based on *only* the preceding tokens: token 4 learns from tokens 2 & 3; token 7 leads from tokens 2, 3, 4. This ensures that the predicted word is never seen indirectly. (Note: This permutation is only used in the computation of attention; the order of tokens in the sequence is unchanged.)

BERT also had fixed-sized segments and thus could not handle sequences longer than the segment length (usually 512). XLNet uses previous work from Transformer-XL to get around this—it **transfers state across fixed-sized segments** (i.e., recurrence on segments) to handle sequences longer than the segment length. Nonetheless, with permutation LM and reintroducing recurrence, XLNet is much more computationally demanding to train.

Recently, Big Bird (28 July 2020) increased the segment length to 8x of what BERT could handle. BERT is limited by the *quadratic* dependency of its sequence length due to full attention, where each token has to attend to every other token. This leads to a memory limitation. On standard hardware (16gb RAM), this translates to input sequences (and segment length) of 512 tokens.

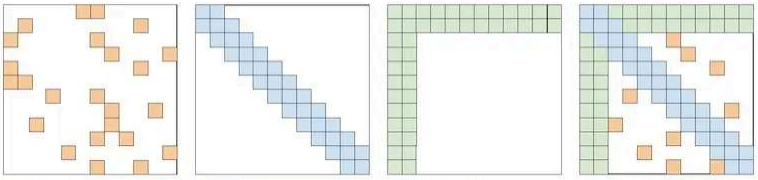


Figure 1: Building blocks of the attention mechanism used in BigBird. White color indicates absence of attention. (a) random attention with $r = 2$, (b) sliding window attention with $w = 3$ (c) global attention with $g = 2$. (d) the combined BigBird model.

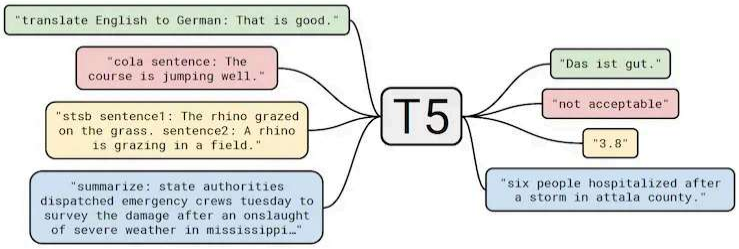
Big Bird has sparser attention that allows it to model on 8x the sequence length of BERT (source)

Big Bird proposed **generalized attention mechanism** which has linear complexity (as opposed to quadratic) on the sequence length. It has three aspects of attention:

- Random attention: Attends to `r` random tokens, leading to sparse attention (`r` = 2).
- Sliding window attention: Attends to a window of width `w` (`w` = 3). This is similar to Longformer which uses a localised sliding window-based mask to reduce computation and extend BERT to longer sequences.
- Global tokens: Global tokens are a subset of `g` tokens in a sequence (`g` = 2). Global tokens attend to all tokens in the sequence and vice versa. This includes additional tokens such as `CLS` ala BERT. (Using just random and sliding window attention were insufficient to compete with BERT).

Everything is text-to-text

Towards the end of 2019, the Text-To-Text-Transfer-Transformer (T5) introduced a **unified framework that converts all text-based problems into a text-to-text format**. Thus, the input and output are text-strings, making a single T5 fit for multiple tasks.



Translation, Q&A, classification are all text to text, with different prefixes to indicate the task (source)

The T5 uses the Transformer encoder-decoder based structure which the authors found to work best for text-to-text. Nonetheless, the authors introduced a few changes such as: removing the layer norm bias, placing the layer norm outside the residual path, and using a different position embedding scheme.

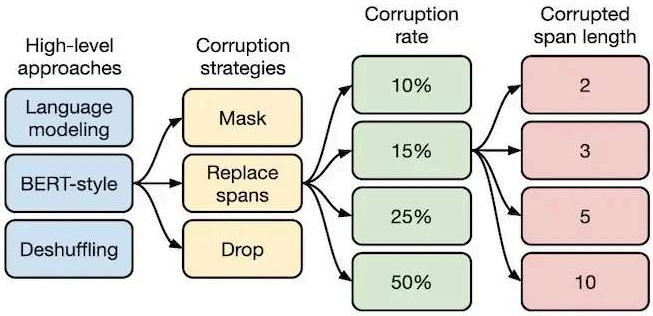
Pre-training was done on the Colossal Clean Crawled Corpus (C4), a high quality pre-processed English language corpus. It is approximately 750gb in size and is a cleaned version of the Common Crawl.

> **How did C4 come about?**

With the unified format, the authors thoroughly explored the **effectiveness of transfer learning in NLP**. I loved how a sizeable portion of the paper was devoted to experiments (and "What didn't work") on architectures, objectives, fine-tuning approaches, etc. Here's a high-level summary (reading the original paper is recommended):

- The encoder-decoder architecture with denoising objective worked best (vs. single Transformer stack, language modelling objective)
- Among the unsupervised objectives, masked language modelling (BERT-style) worked best (vs. prefix language modelling, deshuffling, etc.)
- There was limited difference between BERT-style objectives (e.g., replacing the entire corrupted span with a single `MASK`, dropping corrupted tokens entirely) and different corruption probabilities (e.g., 10%, 15%, 25%)

- Training on the full dataset for 1 epoch worked better than training on a smaller data set for multiple epochs (my view: **more data > more compute**)
- Fine-tuning all layers simultaneously performed best (vs. unfreezing each layer and tuning it, adding adapter layers of various sizes)
- Increasing model size had a bigger impact relative to increasing training time or batch size.



Hyperparameter tuning approach on unsupervised objectives for pre-training (source)

Downstream performance on a variety of benchmarks was evaluated (e.g., GLUE and SuperGLUE text classification, CNN/Daily Mail abstractive summarization, SQuAD question answering, and WMT translations.) With the insights from the experimental study, SOTA performance was achieved on 18 out of 24 tasks considered.

Summary

Whew, a lot has happened in NLP since 1985. To recap, here's what we covered so far:

- Sequential models: RNN (1985), LSTM (1997), GRU (2014)
- Word embeddings: Word2vec (2013), GloVe (2014), FastText (2016)
- Word embeddings with context: ELMo (2018)
- Attention: Transformer (2017)
- Pre-training: ULMFiT (2017), GPT (2017)
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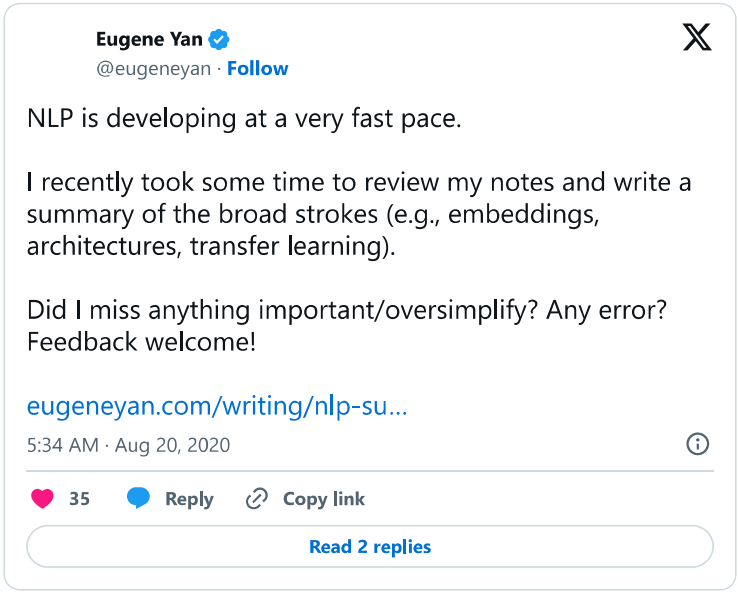
- Everything is text-to-text: T5 (2019)

And here's a table summary if that's what you prefer.

	Details
RNN (1985)	Learns on sequences; hidden state of one time-step used as input to next time-step
LSTM (1997)	Adds gates (e.g., forget, input) to RNN; models long-range dependencies better
GRU (2014)	Simplifies LSTM and has lesser gates (i.e., update, reset); faster to train
Word2Vec (2013)	Unsupervised learning of word representations via CBOW and Skip-gram with sampling and negative subsampling
GloVe (2014)	Unsupervised learning of word representations via co-occurrence matrix
FastText (2016)	Unsupervised learning of word representations via character segments
ELMo (2018)	Unsupervised learning of word representations via bidirectional language model (two-layer LSTM); considers context of entire sentence
Transformer (2017)	Removes need for recurrence via attention and positional encodings; faster and less compute heavy to train
ULMFiT (2017)	Pre-training and fine-tuning on AWD-LSTM with discriminative fine-tuning, slanted triangle learning rates, and gradual unfreezing
GPT (2017)	Pre-training and fine-tuning on Transformer decoder stack; single input representation for various tasks
BERT (2018)	Pre-training and fine-tuning on Transformer encoder stack, bidirectional context via masked language modelling, single input representation
XLNet (2019)	Permutation language modelling, recurrence across fixed sized segments to handle longer sequences
T5 (2019)	Unified text-to-text format on Transformer encoder-decoder architecture and denoising objective, trained on C4

	Details
Big Bird (2020)	Generalized attention mechanism to increase segment length to 8x of BERT

Did I miss any key milestones? Let me know by responding to this tweet or in the comments below!



References

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- GloVe: Global Vectors for Word Representation
- FastText: Enriching Word Vectors with Subword Information
- ELMo: Deep Contextualized Word Representations
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- XLNet: Generalized Autoregressive Pretraining for Language Understanding
- Longformer: The Long-Document Transformer
- Big Bird: Transformers for Longer Sequences
- T5: Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

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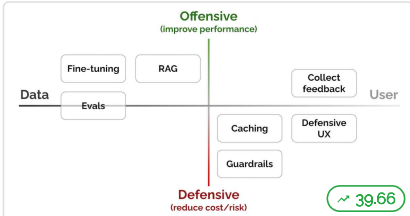

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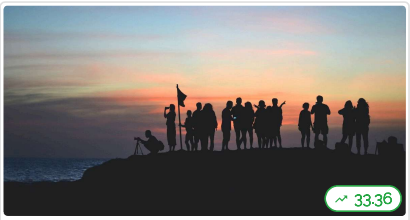

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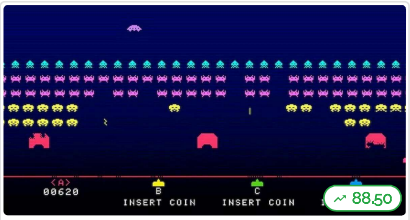

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Eugene Yan is a Principal Applied Scientist at Amazon building recommendation systems and AI-powered products that serve customers at scale. He's led ML/AI teams at Alibaba, Lazada, and a Healthtech Series A, and writes about RecSys, LLMs, and engineering at eugeneyan.com.