AMSI VACATIONRESEARCH SCHOLARSHIPS 2019–20

EXPLORE THE MATHEMATICAL SCIENCES THIS SUMMER

Study and Application of Concept-Extraction Algorithms in Natural Language Processing (NLP)

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Vacation Research Scholarships are funded jointly by the Department of Education and Training and the Australian Mathematical Sciences Institute.

About Me

- Name: Ana-Maria Vintila
- Age: 22
- International citizen, lived and studied in Canada for a majority of my life before returning to native Europe.
- Diligent, thrive in well-defined, scientific domains.
- Interests: Calculus, Scala / Haskell functional programming, Probability (with Wolfram-Mathematica in ProbOnto-style)
- Currently working towards doing Master By Research in NLP and / or Finance using applied maths and Bayesian statistics.
- Envisioning: NLP business to study text for global clients, and for financial analysis for currency exchange markets.

Introduction: Motivation for Text Processing

- Knowledge is trapped in media like html, pdfs, paper as opposed to being concept-mapped, interlinked, addressable and reusable at fine grained levels.
- Defeats exchanges between humans and AI.
- Fact: concept mapping enhances human cognition.
- Especially in domain-specific areas of knowledge, better interlinking would be achieved if concepts would be extracted using surrounding context, accounting for polysemy and key phrases.
- *"You shall know a word by the company it keeps"* (Firth, 1957).
- Previous models GloVe and Word2Vec motivated recent ones to move beyond simple co-occurrence counts to extract meaning.
- ERNIE 2.0 instead "broadens the vision to include more lexical, syntactic and semantic information from training corpora in form of **named entities** (like person names, location names, and organization names), **semantic closeness** (proximity of sentences), **sentence order or discourse relations**" (Sun et al., 2019).
- **Aim of This Project:** To understand how models make good language representations by inventorying Transformer, ELMo, BERT, Transformer-XL, XLNet, and ERNIE 1.0 in how they leverage entities, polysemy, context for concept extraction.

Word Embeddings

Definition: Word Embedding (Words as Vectors)

Word embeddings are unsupervised models that capture semantic and syntactic information about words in a compact low-dimensional vector representation ⇒ useful for reasoning about word usage and meaning (Melamud et al. 2016, p. 1).

- Sentence embeddings, phrase embeddings, character embeddings (for morphology)
- Can capture **vector space semantics**: can express word analogy “man is to woman as king is to queen” with arithmetic on learned word vectors: $vector(man) - vector(woman) = vector(king) - vector(queen)$

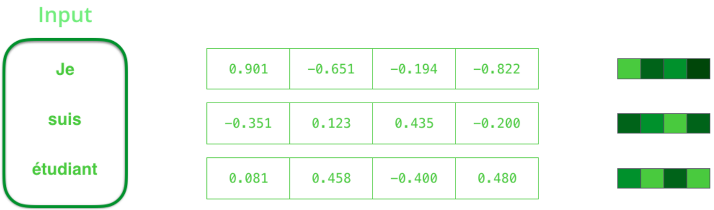

Figure 1: Example Word Embeddings. From *Visualizing Neural Machine Translation Mechanics of Seq2Seq Models with Attention*, by Jay Alammar, 2018.
http://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

What is Polysemy?

Definition: Polysemy

Polysemy means a word has multiple senses.

Definition: Distributional Hypothesis

Distributional hypothesis in NLP says meaning depends on context, and words in same contexts have similar meaning (Wiedemann et al., 2019).

Static Embeddings

- Classic word vectors are called **static embeddings**. They represent each word with a single vector, regardless of its context (Ethayarajh, 2019).

Example

Skip-Gram and Glove produce these "context-free" representations because they use co-occurrence counts, not the more dynamic **language modeling** approach (Batista, 2018).

Alert

All senses of a polysemic word are *collapsed* within a single vector representation (Ethayarajh, 2019).
Confusion!
"Plant"'s embedding would be the "average of its different contextual semantics relating to biology, placement, manufacturing, and power generation" (Neelakantan et al., 2015).

Better: Contextual Embeddings (CWE)

Definition: Contextual Word Embedding

A **contextual word embedding (CWE)** captures context using forward and backward history, using a bidirectional language model (biLM) (Antonio, 2019).
Static word embeddings are like "look-up tables" but contextual embeddings have word type information (Smith, 2019).

- Abandoning the idea of using a fixed word sense inventory (to model polysemy) allows CWE's to create create a vector representation for each **word type** in the vocabulary and each **word token** in a context.
- Experimentally superior to static embeddings.
- "sentence or context-level semantics together with word-level semantics proved to be a powerful innovation" in the NLP world (Wiedemann et al., 2019).

Language Models

Language Models

Definition

A **language model** takes a sequence of word vectors and outputs a sequence of predicted word vectors by learning a probability distribution over words in a vocabulary.
They predict words sequentially, unidirectionally, one token at a time, using some context words.

Formally, they compute the conditional probability of a word w_t given a context, such as its previous $n-1$ words, where the probability is: $P(w_t \mid w_{t-1}, \ldots, w_{t-n+1})$

- **n-gram language model:** an n-gram is a sequence of n words. The model finds a word's probability based on frequencies of its constituent n-grams, taking just preceding $n-1$ words as context instead of the entire corpus.
- **neural network model:** uses a linear $W \cdot x + b$ function called a neuron. By applying a nonlinear function $f(\cdot)$ to this equation and by incorporating many hidden layers and by stacking neurons together, a neural network can model any function.
  Has **embedding layer**, **intermediate layers** to transform embeddings, and **final layer**, which often uses softmax function to normalize word embedding matrix to create probability distribution over words.
- **bidirectional language model (biLM):** calculates probability of a token given its *forward* and *backward* tokens. Uses **forward** and **backward language model**s, respectively.

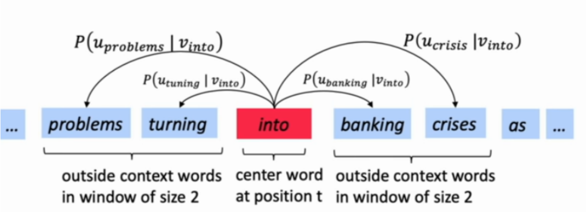

Figure 2: Example Bidirectional Language Model. From *Word2Vec Overview With Vectors*, by CS224n: Natural Language Processing with Deep Learning (Stanford), 2018. https://sangminwoo.github.io/2019-08-28-cs224n-lec1/. Copyright n.d. by n.d.

Word2Vec

Author(s):

- Mikolov et al. (2013a) in *Distributed Representations of Words and Phrases and their Compositionality*
- Mikolov et al. (2013b) in *Efficient Estimation of Word Representations in Vector Space*

Word2Vec: One-Hot Encodings

Definition: One-Hot Encoding

A **one-hot vector encoding** is the simplest type of word embedding where each cell in the vector corresponds to a distinct vocabulary word.

A 1 is placed in the cell marking the position of the word in the vocabulary, and a 0 is placed in all other cells.

Warning!

One-hot encodings cause ...

- high-dimensionality vector representations for large vocabularies, $\Rightarrow$ increased computational costs.
- similarity between (word) categories cannot be represented.

Word2Vec: Skip-Gram

- **Predicts context words given a single target word:** Uses a fixed sliding window c, or size of the training context, around a target word, to capture context (bidirectionally) along a sentence.
- Target center word (one-hot encoding) is input to a neural network which updates the vector with values near 1 in cells corresponding to predicted context words.

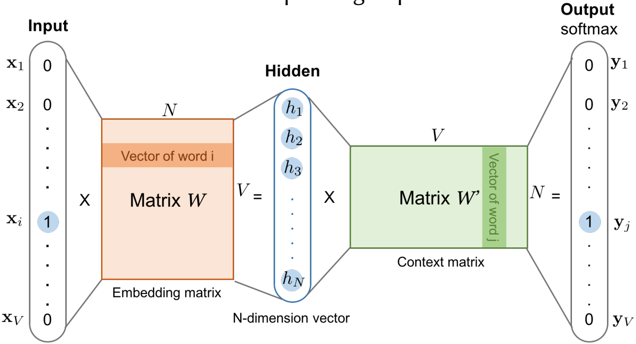

Figure 3: Skip-Gram Model; simplified version, with one input target word and one output context word. From *Learning Word Embeddings*, by Lilian Weng, 2017. https://lilianweng.github.io/lil-log/2017/10/15/learning-word-embedding.html. Copyright n.d. by n.d.

Word2Vec: Continuous-Bag-of-Words (CBOW)

- **Continuous bag of words model (CBOW)** is opposite of the Skip-Gram: predicts *target* word based on a *context* word.
- Averages n context words around target word w_t to predict target (in hidden layer calculation): $\vec{h} = \frac{1}{c} W \cdot \left(\vec{x_1} + \vec{x_2} + \ldots + \vec{x_c}\right) = \frac{1}{c} \cdot \left(\overrightarrow{v_{w_1}} + \overrightarrow{v_{w_2}} + \ldots + \overrightarrow{v_{w_c}}\right)$

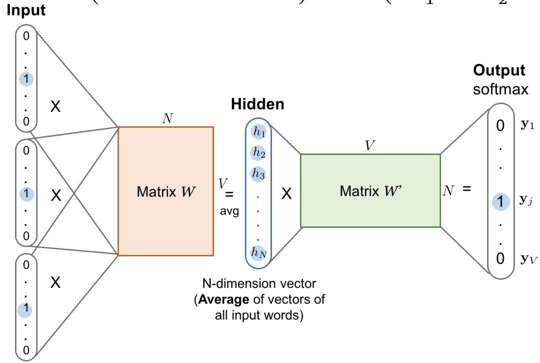

Figure 4: CBOW Model with several one-hot encoded context words at the input layer and one target word at the output layer. From *Learning Word Embeddings*, by Lilian Weng, 2017.
https://lilianweng.github.io/lil-log/2017/10/15/learning-word-embedding.html

Phrase-Learning in Skip-Gram

- **Problem with previous word vectors:** no *phrase representation*
  $\Rightarrow$ "Canada" and "Air" in a phrase could not be recognized as part of a larger concept and thus combined into "Air Canada" (Mikolov et al., 2013a).

- **Phrase-Skip-Gram Model**: uses *unigram and bigram counts* to make phrases.
  - $S_{phrase} = \frac{C(w_i w_j) - \delta}{C(w_i)C(w_j)}$ where $C(\cdot)$ = count of a unigram w_i or bigram $w_i w_j$ and δ is a discounting threshold to avoid making infrequent words and phrases.
  - Large S_{phrase} indicates the *phrase* is a phrase, less likely a bigram.
- **Result:** linear structure **additive compositionality** of word vectors
  - **Additive Compositionality:** lets some individual words be combined into a phrase and be viewed as a unique *entity*, while a bigram like "this is" should remain unchanged (Mikolov et al., 2013a, p. 5).
  - **How Does It Happen?** product of distributions in loss function acts like an "and" function

Example: Additive Compositionality

If the phrase "Volga River" appears numerously with "Russian" and "river" then:
$vector(\texttt{"Russian"}) + vector(\texttt{"river"}) \Rightarrow vector(\texttt{"Volga River"})$

GloVe (Global Vectors for Word Representation)

Author(s):

- Pennington et al. (2014) in *GloVe: Global Vectors for Word Representation*

GloVe: Problem With Word2Vec

- **Problem:** Word2Vec uses local not global counts.
  - **Example:** "the" and "cat" may occur frequently but Word2Vec does not know if this is because "the" is a common word or because "the" and "cat" are actually correlated (Kurita, 2018a).

- **Reason:**
  - Word2Vec implicitly optimizes over a co-occurrence matrix while streaming over input sentences ⇒ context words are processed equally.
  - Word2Vec's loss function $J = -\sum_i X_i \sum_j P_{ij} \log(Q_{ij})$ is the cross entropy between the *predicted* and *actual word distributions* in the context of word i. [1]
  - GloVe: cross entropy models long-tailed distributions poorly, and X_i means equal-weighting over words.
  - GloVe: no justification for equal-streaming: (1) use *unnormalized* probabilities, (2) get corpus-wide co-occurrence counts using sliding window.

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[1] $X_i = \sum_k X_{ik}$ is the total number of words appearing in the context of word i

$Q_{ij} = \text{softmax}\left(w_i \cdot w_j\right)$ is the probability that word j appears in context of word i

GloVe

How GloVe Uses Co-Occurrence Ratios [2]

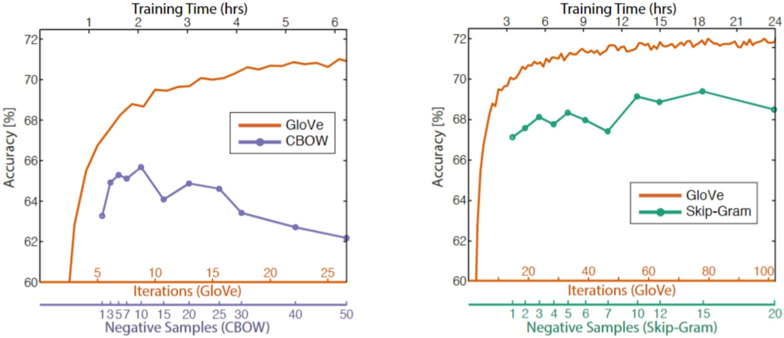
Consider two words `ice` and `steam`.

- **Case 1:** For context words related to `ice` but not "steam" (`solid`) ⇒ expect co-occurrence probability $p_{\text{co}}\left(\texttt{solid} \mid \texttt{ice}\right)$ is much larger than $p_{\text{co}}\left(\texttt{solid} \mid \texttt{steam}\right)$ ⇒ ratio $\dfrac{p_{\text{co}}\left(\texttt{solid} \mid \texttt{ice}\right)}{p_{\text{co}}\left(\texttt{solid} \mid \texttt{steam}\right)}$ gets very large.
- **Case 2:** Conversely, for words related to `steam` but not `ice` (like `gas`) ⇒ the co-occurrence ratio $\dfrac{p_{\text{co}}\left(\texttt{gas} \mid \texttt{ice}\right)}{p_{\text{co}}\left(\texttt{gas} \mid \texttt{steam}\right)}$ should be small.
- **Case 3:** For words w related to both `ice` and `steam` (like `water`) or related to neither (like `fashion`) ⇒ expect the ratio $\dfrac{p_{\text{co}}\left(w \mid \texttt{ice}\right)}{p_{\text{co}}\left(w \mid \texttt{steam}\right)}$ is near one.

[2] GloVe defines word co-occurrence probability as: $p_{\text{co}}\left(w_k \mid w_i\right) = \frac{C(w_i, w_k)}{C(w_i)}$ where $C(w_i, w_k)$ counts the co-occurrence between words w_i and w_k.

Performance: GloVe vs. Word2Vec

fig. 5 shows GloVe's learned embeddings have higher prediction accuracy over those of Skip-Gram and CBOW on **word analogy** and **named entity recognition (NER)**.



(a) GloVe vs CBOW (b) GloVe vs Skip-Gram

Figure 5: Overall accuracy on word analogy task as a function of training time, which is governed by the number of iterations for GloVe and by the number of negative samples for CBOW (a) and Skip-Gram (b). Pennington et al. (2014) train 300-dimensional vectors on the same 6B token corpus from Wikipedia and use a symmetric context window of size 10. From *GloVe: Global Vectors for Word Representation*, by Pennington et al., 2014. `https://nlp.stanford.edu/pubs/glove.pdf`. Copyright 2014 by Pennington et al.

Sequence to Sequence Model

Author(s):

- Sutskever et al. (2014) in *Sequence To Sequence Learning with Neural Networks*

Seq-To-Seq Model (Brief Overview)

- Used for machine translation task.
- **Encoder** takes in sequence of tokens (words, phrases), processes inputs into a *fixed-length* **context vector**, and sends it to **Decoder** that outputs another sequence of tokens.
- Encoder, Decoder are often RNNs [3] like LSTMs[4] and GRUs. [5]
- **Problem:** compressing inputs into **fixed-length vector** causes **long-term dependency problem** (memory loss) since only the *last hidden Encoder state is used.*
- **Solution:** to use **attention mechanism** for selectively focusing on parts of the inputs as required (creates a context vector for *each time step or word*, so all Encoder's output hidden states are used in Decoder)

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[3] RNN stands for **recurrent neural network**, which has a looping mechanism to share hidden states. Suffers from **long-term dependency problem**

[4] LSTM means **long-short term memory network**, and uses forget gates to regulate memory and information flow

[5] GRU means **gated-recurrent network**, and is a condensed version of LSTM.

Transformer

Author(s):

- Vaswani et al. (2017) in *Attention is All You Need*

Transformer: Self-Attention

- Kind of seq-to-seq model for machine translation. More parallelizable than seq-to-seq (no RNNs, just **self-attention**) to generate sequence of *contextual embeddings*.

Example: Motivation for Self-Attention

"The animal didn't cross the road because it was too tired."

What does "it" refer to? The road or animal?

- **Self-Attention:** *bake in* other word representations into "it" while processing input.
- Focus on important words; drown out irrelevant words.
- An **attention function** maps query and key-value pairs to output vector:
  - Query matrix $\boldsymbol{Q}$ ("it"); Key matrix $\boldsymbol{K}$ rows describe *each* word; Value matrix $\boldsymbol{V}$ rows for all other words (excluding "it").
  - Final output embedding of word is weighted sum:

$$\texttt{Attention}\left(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}\right) = \texttt{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^T}{\sqrt{\boldsymbol{d}_k}}\right)\boldsymbol{V}$$

Transformer: Multi-Head Attention

Definition: Multi-Head Attention

A **multi-head attention mechanism** comprises of several self-attention heads.

More attention heads means Transformer can focus on different words; while encoding "it", one attention head looks at "the animal" while another focuses on "tired" ⇒ representation of "it" includes some of all words.

A single attention head cannot do this because of averaging (Vaswani et al., 2017).

- Instead of calculating attention once, multi-head attention does (1) self attention many times in parallel on the projected dimensions, (2) concatenates the independent attention outputs, and (3) once again projects the result into the expected dimension to give a final value (Vaswani et al., 2017; Weng, 2018).

Transformer: Positional Encodings

Definition: Positional Encoding

A **positional encoding** injects relative / absolute token position info so Transformer can see *sentence order* when taking inputs.

Follows a specific, learned pattern to identify word position or the distance between words in the sequence (Alammar, 2018b).

$$PosEnc_{(pos,2i)} = \sin\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right)$$

$$PosEnc_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right)$$

where pos = a position, i = a dimension.

Otherwise ...

... “I like dogs more than cats” and “I like cats more than dogs” would encode the same meaning (Raviraja, 2019).

Transformer: More Layers

- **Positionwise feed-forward layer** is a kind of **feed-forward neural network (FFN)**, and is "position-wise" since the FFN is applied to each position separately and identically.
- **Residual Connection:** a sub-layer in Encoder and Decoder stacks for harmonizing gradient optimization procedure.
- **Masked Multi-Head Attention:** attention with masking tokens (while decoding word embedding $\overrightarrow{w_i}$, the Decoder is not allowed to see words $\overrightarrow{w_{>i}}$ past position i, only words before $\overrightarrow{w_{\leq i}}$, so no "cheating" occurs (Ta-Chun, 2018)).
- **Encoder:** is bidirectional RNN that concatenates *forward and backward* hidden states to get bidirectional context: $h_t = \left\{\overrightarrow{h}_t^T ; \overleftarrow{h}_t^T\right\}^T$, $t = 1, \ldots, T_x$. [6]
- **Decoder:** neural network generates hidden states $s_t = \text{Decoder}\left(s_{t-1}, y_{t-1}, c_t\right)$ for times $t = 1, \ldots, m$ [7]

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[8] Note: arrows here denote the direction of the network rather than vector notation.

[9] Context vector $c_t = \sum_{i=1}^{n} \alpha_{ti} \cdot h_i$ is a sum of the hidden states of the input sentence, weighted by alignment scores (same calculation as in the seq-to-seq model)

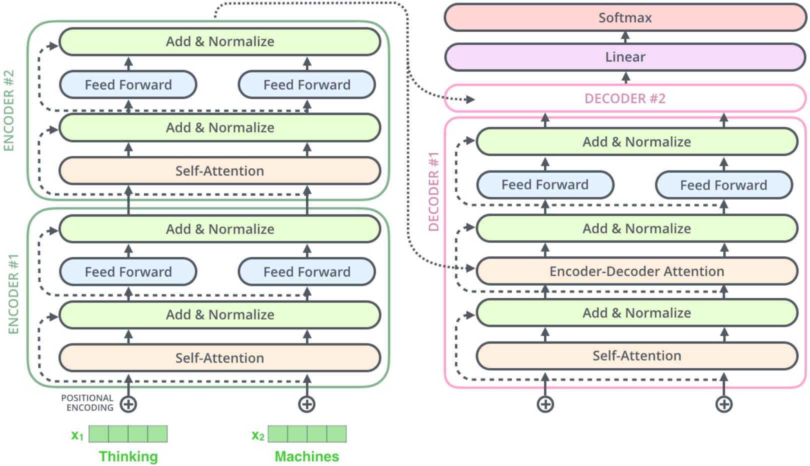

Figure 6: Transformer: Encoder and Decoder Stack in Detail. **Encoder layer** contains: (1) Multi-head attention, (2) Position-wise feed forward layer. **Decoder layer** contains: (1) Masked multi-head attention, (2) Encoder-Decoder attention, (3) Position-wise feed forward layer. From *The Illustrated Transformer*, by Alammar, 2018. https://jalammar.github.io/illustrated-transformer/. Copyright 2018 by Alammar.

ELMo: Embeddings from Language Models

Author(s):

- Peters et al. (2018) in *Deep Contextualized Word Representations*

ELMo: Motivation

Remember **polysemy**?

ELMo makes contextual embeddings of a word according to its senses, so that ...

Example

... homonyms “book” (text) and “book” (reservation) get different vectors, not different meanings collapsed in one vector...

Better than Word2Vec and GloVe!

ELMo: Structure

- **ELMo** uses bidirectional language model (biLM) to make *deep* word embeddings (derived from all its internal layers)
- Higher-level LSTM layers capture contextual meaning (useful for supervised word sense disambiguation (WSD)).
- Lower layers capture syntax information (useful for part of speech tagging (POS)).
- **Task-Specific:** ELMo mixes the layers' signals in task-specific way: [8]

$$\mathbf{ELMo}_k^{task} = E\left(R_k; \theta^{task}\right) = \gamma^{task} \sum_{j=0}^{L} s_j^{task}\, \mathbf{h}_{kj}^{LM}$$

- ELMo embeddings are thus richer than traditional word vectors.

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[8] the vector $\mathbf{s}^{task} = \left\{s_j^{task}\right\}$ of softmax-normalized weights and task-dependent scalar parameter γ^{task} allow the model for the specific $task$ to scale the entire $\mathbf{ELMo}_k^{task}$ vector. The index k corresponds to a k-th word, and index j corresponds to the j-th layer out of L layers. Here, h_{kj}^{LM} is the output of the j-th LSTM for word k, and s_j is the weight of h_{kj}^{LM} used to compute the representation for word k.

ELMo: Strengths in POS Tagging and Word Sense Disambiguation

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	Chico Ruiz made a spectacular play on Alusik 's grounder {...}	Kieffer , the only junior in the group , was commended for his ability to hit in the clutch , as well as his all-round excellent play .
	Olivia De Havilland signed to do a Broadway play for Garson {...}	{...} they were actors who had been handed fat roles in a successful play , and had talent enough to fill the roles competently , with nice understatement .

Table 1: Nearest neighbors to “play” found by GloVe and biLM context embeddings. From *Table 4 in Deep Contextualized Word Representations*, by Peters et al., 2018. https://arxiv.org/pdf/1802.05365.pdf. Copyright 2018 by Peters et al.

- GloVe’s neighbors have different parts of speech, like verbs (“played”, “playing”), and nouns (“player”, “game”) and only in the sport sense.
- biLM’s nearest neighbor sentences from “play” CWE show clear difference between *both* the parts of speech *and* word sense of “play”.
  - last row: input sentence has noun / acting sense of “play” and this is matched in the nearest neighbor sentence

BERT (Bidirectional Encoder Representations from Transformers)

Author(s):

- Devlin et al. (2019) in *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*
- Clark et al. (2019) in *What Does BERT Look At? An Analysis of BERT's Attention*
- Wiedemann et al. (2019) in *Does BERT Make Any Sense? Interpretable Word Sense Disambiguation with Contextualized Embeddings*
- Munikar et al. (2019) in *Fine-Grained Sentiment Classification Using BERT*

BERT: Motivation

- **Problem with ELMo:** shallowly combines “independently-trained” biLMs
- **Problem with OpenAI GPT:** unidirectional model ⇒ gets no bidirectional context ⇒ does poorly on *sentence-level* and *token-level* tasks (question answering (QA))
- **BERT’s Solution:** train “deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers” (Devlin et al., 2019).

BERT: Input Embeddings

- *WordPiece* **token embeddings:** *WordPiece* tokenization subdivides words to smaller units
  - to handle rare, unknown words (Weng, 2019) and reduce vocabulary size while increasing amount of data available per word.
  - **Example:** if `"play"` and `"**ing"` and `"**ed"` are present in the vocabulary but `"playing"` and `"played"` are not, then these can be recognized by their sub-units.
- **Segment embeddings:** are arbitrary spans of text (packing sentence parts). NOTE: Transformer-XL respects sentence boundaries.
- **Positional embeddings:** as in ordinary Transformer (to inject word order information).

BERT Framework: MLM and NSP

BERT does **pre-training** (trains on *unlabeled data* using MLM and NSP), and **fine-tuning** (to use pre-training parameters to train over *labeled data* for nlp tasks)

Masked language model (MLM):

- **Motivation:** bidirectional conditioning causes information leakage (a word can implicitly "see itself" letting the model trivially guess the target word in a multi-layered context (Devlin et al., 2019)).
- **Goal:** randomly masks some input tokens to predict original masked word using only its context.
- **Effect of MLM:** fuses left and right context to get *deep* bidirectional context (unlike ELMo's shallow left-to-right language model (Devlin et al., 2019)).

Next Sentence Prediction (NSP):

- **Motivation:** to capture *sentence-level* information $\Rightarrow$ to do well in question-answering (QA) and natural language inference (NLI) tasks
- **Goal:** task that finds if sentence is the next sentence of the other.

Probing BERT: BERT Learns Dependency Syntax

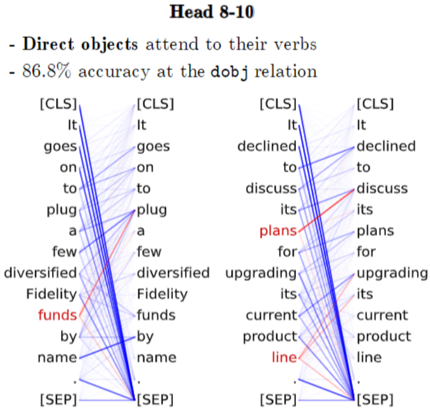

Figure 7: BERT attention heads capture syntax. In heads 8-10, direct objects are found to attend to their verbs. Line darkness indicates attention strength. Red indicates attention to/from red words, to highlight certain attentional behaviors. From *What Does BERT Look At? An Analysis of BERT's Attention*, by Clark et al., 2019. https://arxiv.org/abs/1906.04341.

Clark et al. (2019) found ...

- BERT's attention heads detect "direct objects of verbs, determiners of nouns, objects of prepositions, and objects of possessive pronouns with > 75% accuracy."
- Attention heads 8-10 in fig. 7 learn how direct objects attend to their verbs.
- BERT learns this using only *self-supervision*.

Probing BERT: BERT's Limitation in Segment Representation

- BERT does not use separator tokens ([SEP]) to gather segment-level information.
- BERT uses [SEP] as "no-op" or stub operations for attention heads when the head is not needed for a current task.
- How? Why? Authors investigated in two ways ...
  - If this were true, attention heads processing [SEP] should attend broadly over entire segment to make the segment vectors. But in fig. 7, heads 8-10 show direct objects attend to their verbs, and all other words attend to the [SEP] token.
  - Gradient measures: show much the attention to a token would change BERT's outputs. Attention to [SEP] increases in layers 5-10 (fig. 8), WHILE the gradients for attention to [SEP] decrease here (fig. 9) ⇒ attending to [SEP] does not significantly change BERT's outputs.

So, BERT's attention heads attend to [SEP] when they have no other job, not to gather segment-level information.

Transformer-XL by design improves this.

Probing BERT: BERT's Limitation in Segment Representation

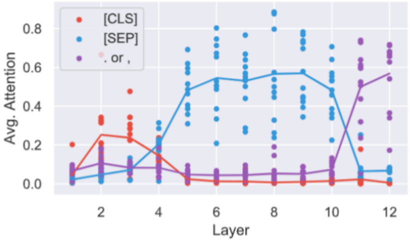

Figure 8: BERT's attention heads in layers 6-10 spend more than half the average attention to separator tokens; deep heads attend to punctuation, while middle heads attend to `[SEP]`, and early heads attend to `[CLS]`. From *What Does BERT Look At? An Analysis of BERT's Attention*, by Clark et al., 2019. https://arxiv.org/abs/1906.04341. Copyright 2019 by Clark et al.

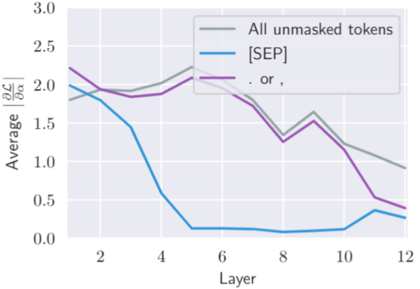

Figure 9: Gradient-based estimates for attention to separator and punctuation tokens. Authors "compute the magnitude of the gradient of the loss from the masked-language model (MLM) task with respect to each attention weight." From *What Does BERT Look At? An Analysis of BERT's Attention*, by Clark et al., 2019. https://arxiv.org/abs/1906.04341. Copyright 2019 by Clark et al.

BERT's Attempt at Polysemy

- ELMo and BERT were compared on **word sense disambiguation (WSD)** task ⇒ BERT more strongly separates polysemic word senses while ELMo cannot.

- BERT did well when the text had ...
  - *vocabulary overlap* "along the bank of the river" (input text) and "along the bank of the river Greta" (nearest neighbor found by BERT).
  - *semantic overlap* "little earthy bank" (input) and "huge bank [of snow]" (nearest neighbor found by BERT)

- BERT struggled when text had *vocabulary and semantic overlap at the same time*
  - False prediction 1: correct word sense of "balloon" is a verb while BERT predicted a noun sense, so it did not even get the word class correct.
  - False prediction 2: correct sense of "watch" was *to look attentively* while BERT predicted its sense as *to follow with the eyes or the mind; observe.*

Transformer-XL (extra-large)

Author(s):

- Dai et al. (2019) in *Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context*

Problem with Transformer

Warning: Fixed-Length Context

Transformers have **fixed-length context** (context dependency limited by input length)

Natural semantic boundaries formed by sentences are *not* respected.

- ⇒ Transformers lose context
- ⇒ Transformers forget words from a few sentences ago
- ⇒ **Context-Fragmentation Problem**

Problem with Transformer: Fixed-Length Context Illustrated

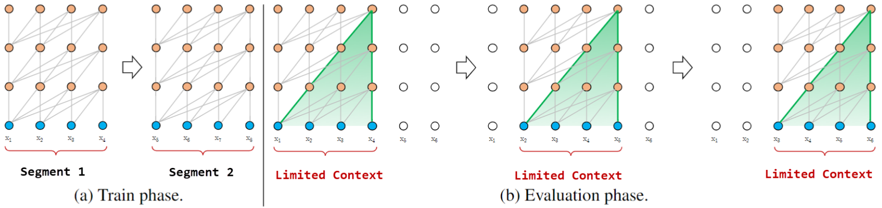

Figure 10: Vanilla Transformer with segment embedding length $= 4$. Training the model in fixed-length segments while disregarding natural sentence boundaries results in the *context fragmentation problem*: during each evaluation step, the Transformer consumes a segment embedding and makes a prediction at the last position. Then at the next step, the segment is shifted right by one position only, and the new segment must be processed from scratch, so there is no context dependency for first tokens of each segment and between segments. From *Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context*, by Dai et al., 2019. https://arxiv.org/pdf/1901.02860.pdf. Copyright 2019 by Dai et al.

Motivation for Transformer-XL

- **Transformer-XL** (extra long) learns longer dependencies without “disrupting temporal coherence” (Dai et al., 2019).
- Doesn’t chop sentences into arbitrary **fixed lengths**!
- Transformer-XL *respects natural language boundaries* like sentences and paragraphs, helping it gain richer context over sentences, paragraphs, and even longer texts like documents.
- Transformer-XL is composed of **segment-level recurrence mechanism** and **relative positional encoding** method (to fix **context fragmentation** and represent longer-spanning dependencies)

Transformer-XL: Segment-Level Recurrence Mechanism

When a segment is being processed, each hidden layer receives two inputs:

- the previous hidden layer outputs of the *current segment* (like vanilla transformer, visible as gray arrows in fig. 11)
- the previous hidden layer outputs of the *previous segment* (green arrows in fig. 11).

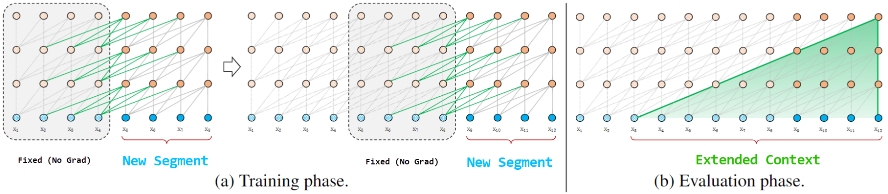

Figure 11: Segment level recurrence mechanism at work: the hidden state for previous segment is *fixed* and *stored* to later be reused as extended context while new segment is processed. Like in Transformer, gradient updates (training) still occurs within a segment, but extended context includes historical information. From *Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context*, by Dai et al., 2019. https://arxiv.org/pdf/1901.02860.pdf. Copyright 2019 by Dai et al.

Transformer-XL: Relative Positional Encoding

Problem when using Segment-Level Recurrence

How can positional word order be kept coherent when reusing hidden states?

Standard Transformer uses positional encodings (use absolute distance between tokens).

- ⇒ Applying to Transformer-XL caused consecutive word embedding sequences to be associated with the same positional encoding.
- ⇒ Tokens from different segments had SAME positional encodings
- ⇒ Transformer-XL couldn't distinguish positions of consecutive input tokens.
- ⇒ Ruined the point of positional encodings!

- **Solution: Relative Positional Encodings** to use *relative* distance between tokens

Transformer-XL: Experimental Results

Ablation study: Isolating effects of **segment-level recurrence mechanism** with different encoding schemes (Shaw (2018) uses relative, and Vaswani / Al-Rfou use absolute).

Remark	Recurrence	Encoding	Loss	PPL init	PPL best	Attn Len
Transformer-XL (128M)	✓	Ours	Full	**27.02**	**26.77**	**500**
-	✓	Shaw et al. (2018)	Full	27.94	27.94	256
-	✓	Ours	Half	28.69	28.33	460
-	✗	Ours	Full	29.59	29.02	260
-	✗	Ours	Half	30.10	30.10	120
-	✗	Shaw et al. (2018)	Full	29.75	29.75	120
-	✗	Shaw et al. (2018)	Half	30.50	30.50	120
-	✗	Vaswani et al. (2017)	Half	30.97	30.97	120
Transformer (128M)†	✗	Al-Rfou et al. (2018)	Half	31.16	31.16	120
					23.09	**640**
Transformer-XL (151M)	✓	Ours	Full	23.43	23.16	450
					23.35	300

Table 2: **PPL best** (model output) means perplexity score obtained using an optimal backpropagation training time length. **Attn Len** (model input) is the shortest possible attention length during evaluation to achieve the corresponding PPL best. From *Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context*, by Dai et al., 2019. https://arxiv.org/pdf/1901.02860.pdf. Copyright 2019 by Dai et al.

XLNet

Author(s):

- Yang et al. (2020) in *XLNet: Generalized Autoregressive Pretraining for Language Understanding*

XLNet: Problems with BERT

- An **autoregressive language model (AR)** estimates the probability distribution of a text sequence by factorizing a likelihood using tokens *before* a timestep, or tokens *after* a timestep ⇒ cannot model bidirectional context.

- An **autoencoding language model (AE)** like BERT is a masked language model ⇒ does not estimate densities like AR ⇒ can learn bidirectional contexts.

- **BERT's problems:**
  - **False Independence Assumption:** BERT factorizes its log likelihood probability assuming all masked tokens are rebuilt independently of each other (so BERT ignores long-term dependencies within texts)

  - **Data Corruption:** Masked tokens do not appear in real data during fine-tuning, so since BERT uses them in pre-training, a discrepancy arises between these two steps.

XLNet: Example of BERT's False Independence Assumption

Example: BERT predicting tokens independently

"I went to the [MASK] [MASK] and saw the [MASK] [MASK] [MASK]."

Two ways to fill this are:

"I went to New York and saw the Empire State building," or

"I went to San Francisco and saw the Golden Gate bridge."

But BERT might incorrectly predict something like: "I went to San Francisco and saw the Empire State building."

Independence assumption + predicting masked tokens simultaneously ⇒ BERT fails to learn their interlocking dependencies ⇒ weakens the "learning signal" (Kurita, 2019b).

XLNet: Motivation

To keep benefits of both autoencoding and autoregressive modeling while avoiding their issues...

1. XLNet adopts an AR model so that probability of a token can be factored via product rule, eliminating BERT's false independence assumption.
2. XLNet uses **permutation language model** to capture bidirectional context AND **two-stream attention** to adapt its Transformer to create target-aware predictions.

XLNet: Permutation Language Model

Created so that: a model can be trained to use **bidirectional context** while avoiding masking and its resulting problem of independent predictions.

Definition: Permutation Language Model

Like language models, a **permutation language model** predicts unidirectionally but in *random order.*

Forced to accumulate bidirectional context by finding dependencies between all *possible input combinations.*

(NOTE: only permutes factorization order, not order of word inputs)

XLNet: Target-Aware Predictions

- **Problem:** Trying to merge permutation language model and Transformer made XLNet's target predictions blind to the permutation positions generated by the permutation language model.

- Fault is due to Transformer: while predicting a token at a position, the model masks the token's embedding AND also its *positional* encoding ⇒ Transformer remains blind about the position of the target it should be predicting.

- **Solution: Target-awareness:** now, predictive distribution takes target position as argument ⇒ creates target-aware embeddings.

- **Two-Stream Attention:** uses two sets of hidden states (content stream and query stream) to create an overall hidden state.
  - **Content-Stream Attention:** takes *context* and *content* (prediction) token x_{z_t} (like ordinary Transformer)
  - **Query-Stream Attention:** takes *context* and target's *position* but NOT content (prediction) x_{z_t} (to evade the contradiction).

XLNet: Relative Segment Encodings

XLNet adopts Transformer-XL's idea of relative encodings ...

- BERT's segment embeddings distinguish words belonging to different segments.
- XLNet's segment embeddings encode if two words are *within the same segment* rather than *which specific segments the words are from* $\Rightarrow$ can apply XLNet to tasks that intake arbitrarily many sequences.

XLNet: Conceptual Difference with BERT

Example: Conceptual Difference between XLNet and BERT

Take the list of words $\left[\texttt{New}, \texttt{York}, \texttt{is}, \texttt{a}, \texttt{city}\right]$.

Prediction tokens: $\left[\texttt{New}, \texttt{York}\right]$

XLNet and BERT must maximize the log-likelihood: $\log \boldsymbol{P}(\texttt{New York} \mid \texttt{is a city})$.

Assumption: XLNet uses the factorization order $\left[\texttt{is}, \texttt{a}, \texttt{city}, \texttt{New}, \texttt{York}\right]$

Then each of their loss functions are:

$$\begin{aligned} \mathcal{J}_{\text{BERT}} &= \log \boldsymbol{P}\left(\texttt{New} \mid \texttt{is a city}\right) + \log \boldsymbol{P}\left(\texttt{York} \mid \texttt{is a city}\right) \\ \mathcal{J}_{\text{XLNet}} &= \log \boldsymbol{P}\left(\texttt{New} \mid \texttt{is a city}\right) + \log \boldsymbol{P}\left(\texttt{York} \mid \texttt{New}, \texttt{is a city}\right) \end{aligned} \tag{1}$$

Result: XLNet learns a stronger dependency than BERT between the pairs New and York (Dai et al., 2019).

ERNIE 1.0: Enhanced Representations through Knowledge Integration

Author(s):

- Sun et al. (2019) in *ERNIE: Enhanced Representations Through Knowledge Integration*

ERNIE: Motivations

- Previous models (Word2Vec, GloVe, BERT) make embeddings via context and co-occurrence ⇒ fail to use prior knowledge (tucked away in sentence ordering and proximity) to capture relationships between entities.

Example: ERNIE's Entity Capturing Skills

Consider the following training sentence:

"Harry Potter is a series of fantasy novels written by J. K. Rowling."

Using co-occurring words "J.", "K.", and "Rowling", BERT is limited to predicting the token "K." but utterly fails at recognizing the whole entity *J. K. Rowling*.

A model could use simple co-occurrence counts to predict the missing entity *Harry Potter* even without using long contexts ... but it would not be using the *relationship between the novel name and its writer*.

- **ERNIE to the rescue!** ERNIE can extrapolate the relationship between the *Harry Potter* entity and *J. K. Rowling* entity using implicit knowledge of words and entities ⇒ can predict Harry Potter is a series written by J. K. Rowling (Sun et al., 2019a).

ERNIE: Phrase and Entity-Level Masking

- ERNIE uses a Transformer Encoder coupled with **entity-level masking** and **phrase-level masking** (to encode prior knowledge in conceptual units like phrases and entities) ⇒ learns longer semantic dependencies, has better generalization, adaptability.
- **Phrase-level masking:** A phrase is a "small group of words or characters acting as a conceptual unit" (Sun et al., 2019a). ERNIE chunks sentences to find phrase boundaries, then masks and predicts them.
- **Entity-level masking:** name entities contain "persons, locations, organizations, products." Often include conceptual information. ERNIE parses the entities from a sentence, masks them, then predicts all slots within entities, as shown in fig. 12.

Sentence	Harry	Potter	is	a	series	of	fantasy	novels	written	by	British	author	J.	K.	Rowling
Basic-level Masking	[mask]	Potter	is	a	series	[mask]	fantasy	novels	[mask]	by	British	author	J.	[mask]	Rowling
Entity-level Masking	Harry	Potter	is	a	series	[mask]	fantasy	novels	[mask]	by	British	author	[mask]	[mask]	[mask]
Phrase-level Masking	Harry	Potter	is	[mask]	[mask]	[mask]	fantasy	novels	[mask]	by	British	author	[mask]	[mask]	[mask]

Figure 12: ERNIE uses basic masking to get word representations, followed by phrase-level and entity-level masking. From *ERNIE: Enhanced Representation Through Knowledge Integration*, by Sun et al., 2019. https://arxiv.org/pdf/1904.09223.pdf. Copyright 2019 by Sun et al.

ERNIE: Knowledge Learning To Fill-In-Blanks on Named Entities

Case	Text	ERNIE	BERT	Answer
1	"In September 2006, ___ married Cecilia Cheung. They had two sons, the older one is Zhenxuan Xie and the younger one is Zhennan Xie."	Tingfeng Xie	Zhenxuan Xie	Tingfeng Xie
4	"Australia is a highly developed capitalist country with ___ as its capital. As the most developed country in the Southern Hemisphere, the 12th largest economy in the world and the fourth largest exporter of agricultural products in the world, it is also the world's largest exporter of various minerals."	Melbourne	(Not a city name)	Canberra
6	"Relativity is a theory about space-time and gravity, which was founded by ___."	Einstein	(Not a word in Chinese)	Einstein

Table 3: Comparing ERNIE to BERT on Cloze Chinese Task. From *Figure 4 in ERNIE: Enhanced Representation Through Knowledge Integration*, by Sun et al., 2019. Copyright 2019 by Sun et al.

- Case 1: ERNIE predicts the correct father name entity based on prior knowledge in the article while BERT simply memorizes one of the sons' name, completely ignoring any relationship between mother and son.
- Case 4, 6: BERT fills the slots with characters related to the sentences but not with the semantic concept.
- Case 4: ERNIE predicts the wrong city name, though it still understands the semantic type.

Question and Answer Session

Questions?

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