Neural language models

Statistical Methods in NLP 2
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Language models

- Language models assign probabilities to sequences
- The probability of sequence is estimated based on probability of each item (word) in the sequence
- Probability of each word in the sequence is predicted based on its context
- Language models can be trained with unlabeled text
- Language models have been traditionally an important part of some NLP applications (translation, ASR)
- Recently, they are used for (almost) any NLP task

N-gram language models

- We use probabilities of parts of the sentence (words) to calculate the probability of the whole sentence

$$P(w_1, w_2, \ldots, w_m) = P(w_2 \mid w_1) \times P(w_3 \mid w_1, w_2) \times \ldots \times P(w_m \mid w_1, w_2, \ldots w_{m-1})$$

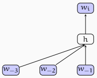
- Making a conditional independence assumption, we can simplify the model

$$P(w_1, w_2, \ldots, w_m) = P(w_2 \mid w_1) \times P(w_3 \mid w_1) \times \ldots \times P(w_m \mid w_{m-1})$$

Issues with n-gram language models

- Words are symbolic units. No notion of word similarity
- Morphologically complex languages: different inflections of the word
- Difficult to capture long-range dependencies
- No information from the following words

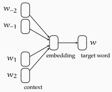
Feed-forward neural models



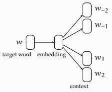
- Main idea is the same as n-gram models: predict the next word from a limited context
- The first layer is typically embeddings
- Continuous representations allow modeling similarities
- We can include right context, too

Short detour to word2vec

Is word2vec a language model?

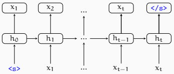


CBOW



Skip-gram

RNN language models



- RNNs can trivially be trained as language models
- Hidden representations provide contextual embeddings
- Can potentially handle long-range dependencies

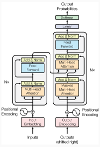
A real-world RNN language model: ELMo

- ELMo is the first popular pre-trained language model providing *contextualized* representations
- ELMo is simply a (stacked/deep) LSTM language model trained on a large corpus (30 million sentences)
- Each layer in ELMo builds contextual representations for words
- ELMo is bidirectional: forward and backward representations are concatenated
- Similar to static word embeddings, ELMo representations can be used for downstream NLP tasks
- Note that unlike the word embeddings, the whole model needs to be distributed

Shortcomings of RNN language models

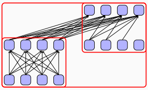
- RNNs solve many of the issues with n-gram (and feed-forward) language models
- Although RNN language models can model dependencies across arbitrary distances in theory, the memory is generally short even for gated RNNs
- RNN processing is inherently sequential to calculation of representations at each step require all earlier steps to be done

Back to Transformers: a recap



- The first layer is an *embedding* layer: no information from context information
- Subsequent layers use attention followed by a non-linear transformation (feed-forward layer)
- Feed-forward layer is a projection an up-projection followed by projection back to input/output dimensions
- Input and output dimensions to each Transformer block is the same
- Layer normalization is after (sometimes before) the attention and feed-forward calculations

Transformer language models



- The decoder of the original transformer is simply a language model: it predicts the next word based on earlier words
- Encoder–decoder models can be used as language models if trained using autoencoder (or similar) objectives
- Encoder side of the Transformer can also be used as a language model with *masked language model* (MLM) objective

Computational complexity of Transformers

- What is the computational complexity of Transformers in the sequence length n?
  - For each time step at each layer, we need to calculate attention over all previous time steps
  - This results in a $O(n^2)$ complexity at each layer

sequence length	operations
1	1
2	4
10	100
512	262144

- We want our sequences to be short
- Also remember: we also want to keep vocabulary size short (to avoid expensive softmax, among other problems)

Tokenization in language models

- Traditional tokenization (approximately words) produce very large vocabularies
- One option is working with characters
  - Not necessarily small Unicode has more than 150K, and growing
  - Results in long sequences
- Typical solution for this in current language models is *subword tokenization*

Subword tokenization: BPE

- Byte-pair encoding (BPE) is an algorithm to segment a set of words into sub-words
- The general idea is:
  - Start with a vocabulary with bytes (or characters)
  - Iteratively add most common pair to the vocabulary
  - Stop when vocabulary size increases to a pre-defined number
- Many current models use a version of BPE algorithm for tokenization with some alternations
- The vocabulary size differ. BERT: 30K, RoBERTa: 50K, XLM-R (large): 250K LLama 3: 128K

BPE demonstration

Corpus
```
r e a d e r
r e a d s
r e a d e r s
w r i t e r s
```
lexicon

a d e i r s t w

Best merge(s)

merge	freq
re	3
er	3
ea	3
ad	3

Corpus
```
re a d e r
re a d s
re a d e r s
w r i t e r s
```
lexicon

a d e i r s t w re

Best merge(s)

merge	freq
rea	3
er	3

Corpus
```
rea d e r
rea d s
rea d e r s
w r i t e r s
```
lexicon

a d e i r s t w re rea

Best merge(s)

merge	freq
rea	3
er	3

Corpus
```
rea d er
rea d s
rea d er s
w r i t er s
```
lexicon

a d e i r s t w re rea er

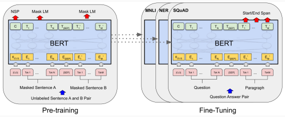
Best merge(s)

merge	freq
er	3

Encoder only transformers: masked language models

- Masked language models replace some of the words in the input with a special symbol `[MASK]`
- The task of the model is to predict the masked words
- The idea is similar to ‘fill in the blanks’ questions (cloze tests)
- It is also similar to ‘noisy’ autoencoding, but we do not reconstruct the full sentence, but only the masked tokens
- In the process, the model learns contextual representations that are useful for other NLP tasks

BERT: architecture



BERT: pretraining

- BERT uses two training objectives:
  - MLM masked language modeling
  - NSP next sentence prediction
- Input to BERT is pairs of sentences with `[SEP]` between them
- MLM typically predict the masked tokens, but some tokens are replaced with arbitrary words
- NSP is a binary classification taks trying to predict whether the second sentence follows the first one
- Later models (e.g., RoBERTa) typically drop the NSP objective

How to use encoder-only LMs in downstream applications?

- For downstream tasks, we typically *finetune* BERT with a supervised objective
- For sequence labeling task, we replace the NSP ‘head’ with a classification layer
- For sequence labeling we attach a classifier to every step in the sequence
- The new ‘heads’ are typically randomly initialized
- Finetuning procedure updates all the weights (including the language model weights trained during pretranining)

A note on representations from BERT

- Embeddings produced by BERT-like models are ‘contextualized’: they assign different representations for different senses of words
- Representations learned are more useful for downstream (classification) tasks than static embeddings (e.g., word2vec)
- It is also often claimed that representations from different layers learn different representations (with mixed results)
  - Earlier layers learning morphology and syntax
  - Later layers semantics, world knowledge
- BERT representations are *anisotropic*: distances and similarities are typically not very meaningful
- Subword tokenization may also complicate obtaining representations for words

Encoder-only models: a few examples

- BERT: the first encoder-only language model
- RoBERTa: the same architecture, trained longer with more data, some improvements to training procedure
- XLM-RoBERTa: multilingual version of RoBERTa supporting 100 languages
- ModernBERT: longer context, applying some of the lessons learned from other architectures
- Monolingual models for many languages exist
- There are also domain-specific architectures, e.g., for legal or medical texts

Encoder–decoder architectures

- The original transformer architecture without modification can also serve as pretrained language models
- It is particularly suitable for generation tasks (machine translation, summarization, questions answering)
- Encoder-decoder models can also be used for classification (and less commonly regression) tasks: model is finetuned to produce class label, given text input(s)
- This is a relatively less-common approach
- Well-known models include BART and T5

Decoder-only models

- It is relatively trivial to train the decoder side of the Transformer as a language model
- The attention mask is set up to attend only to preceding input: task becomes next token prediction
- Most well-known large language models are decoder-only models, e.g., GPT family, Llama, DeepSeek, …
- They are also known as *causal* LMs, or simply generative LMs
- These models are typically trained with much larger data, and tend to learn much more about language (and the world)
- Modern LLMs are not only trained with language modeling objective, they go through further training after LM pretraining

How to use generative models

- LLMs are next word predictors, using them do classification, or interact as chat agents require some additional work
- By default, one can construct special ‘prompts’ to use LLMs for certain tasks
  `The sentiment of the sentence "Not worth the time" is` ________
  - We can either let the model predict the next word
  - Or decide based on P(positive|context) and P(negative|context)
- Similar prompts can be built for other tasks
- More commonly, the LLMs go through additional training to interact with people the way we expect them to

Decoding from LLMs

- Decoding is the tasks of producing new tokens given the context:
  - Start with the context (or prompt)
  - Get the highest probability token given the context
  - Add the token to the context, and repeat until we sample end-of-sequence symbol
- Greedy decoding often leads to 'boring' text without much variation
- Instead we sample a random word, based on the softmax probabilities

Sampling with temperature

- One way to encourage further diversity is *temperature*.
- Instead of sampling based on $\text{softmax}(x)$, we use so $\text{softmax}(x/T)$
- $T = 1$ it is equal to normal sampling
- As T gets closer to 0, we approach greedy decoding: probability of most likely word tends to 1
- With high values for T, probabilities become smoother, allowing sampling less likely tokens

Post-training in LLMs

- Pretrained LLMs are useful, but for their typical use they generally go through a 'post-training'
  - Training on interactive prompts to adjust to typical human interaction, and increase their task performance: typically with supervised methods
  - Aligning with human preferences: typically through reinforcement learning

Finetuning LLMs

- The LLMs are typically very big, finetuning them require substantial resources
- They are typically used through zero-shot or few-shot prompting (so-called 'in-context learning')
- When needed, *parameter-efficient finetuning* is more common
  - Adapters: keep LM weights frozen, add new trainable parameters
  - Prefix-tuning: only update some input parameters
  - LoRA: Use low-rank approximation for parameter updates

Some issues with LLMs

- LLMs tend to be bad with factuality, they tend to 'hallucinate'
- LLM pretraining requires substantial amount of energy, raising environmental concerns
- All language models tend learn the biases in the training set
- They may produce toxic, or offensive language
- They may introduce privacy and copyright violations

Summary

- There are multiple neural architectures that can be used for language modeling
- The state-of-the are architectures are based on Transformer, and can be:
  - Encoder-only (e.g., BERT family)
  - Decoder-only (e.g., GPT family)
  - Encoder-decoder (e.g., T5)
- Reading: Jurafsky and Martin, 2025, Chapter 11

Next:

- More on Transformer language models
- Reading: Jurafsky and Martin, 2025, Chapter 10

Additional reading, references, credits

Jurafsky, Daniel and James H. Martin (2025). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models.* 3rd. Online manuscript released January 12, 2025. URL: https://web.stanford.edu/-jurafsky/slp3/.