Language Models

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Language model

- A language model is a probabilistic model for guessing the probabilities of words in a sequence
- Initially, models were designed to do only one task (e.g., word2vec)
- Most recent models generalize to different tasks and languages (e.g., BERT)
- **EXTREME benchmark**: Test considering 40 languages and 9 taskss

LINK

word2vec

- Proposed by Google in **2013**. Highly influential!
- These vectors are constructed following the principle*: "You shall know a word by the company it keeps"* Firth, 1957

- word2vec maps *words* in a high-dimensional continuous vector space
  - Each word is mapped to a vector of real number called **embedding**

- The vectors can be constructed using two models:
  - **Skip-gram**
  - **Continuous bag-of-words (CBOW)**

word2vec

- The vector embeddings can be used for a variety of reasons:
  - Word similarity
  - Analogies
  - …
- Example: Vector(France) + Vector(Paris) – Vector(Italy) = ?

DEMO

word2vec

Skip-gram model

- *Goal:* Given one word, predict the ones around it

- We can look at words that appear around *w* in an existing corpus and train a model that, given *w*, returns the best scores for words such as the ones we observed in our corpus

word2vec

Skip-gram model

- *Goal:* Given one word, predict the ones around it

- More formally, we want to maximize a function like

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0}\log p(w_{t+j}|w_t)$$

word2vec

Skip-gram model

- How can we implement the conditional probability *p*?
- We assign two vectors of real numbers ${v'}_{W_I}$ and v_{W_O} for each word in the vocabulary *W* and calculate *p* as:

$$p(w_O|w_I) = \frac{\exp\left({v'_{w_O}}^{\top} v_{w_I}\right)}{\sum_{w=1}^{W} \exp\left({v'_w}^{\top} v_{w_I}\right)}$$

Machine Learning digression

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- Remember: Our goal is to maximize

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0} \log p(w_{t+j}|w_t)$$

- How can we learn good values of v'_{W_I} and v_{W_O} to this end?
- Why is *p* so complex?

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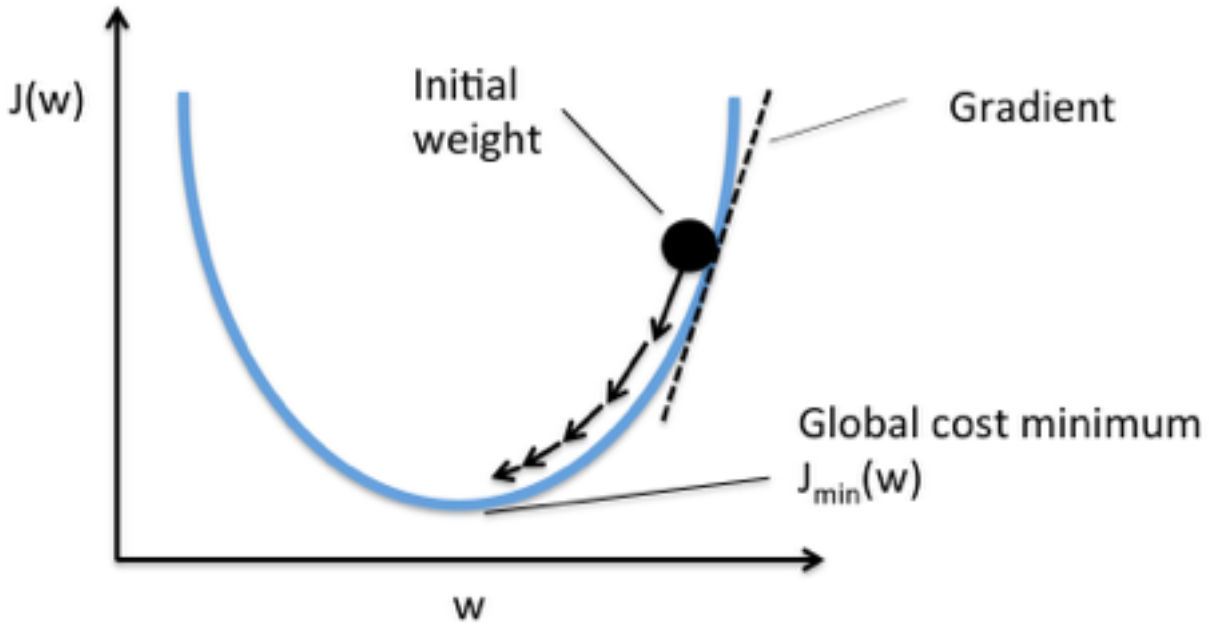
- Remember: The **gradient** of a function tells a direction of change



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- In machine learning, such function is called *softmax*
- Even though, at first sight it looks unnecessary complex, in practice it has very useful properties:
  - Sum is 1 (probabilities)
  - Calculating the gradient is very simple: $\frac{d(e^x)}{dx} = e^x$

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word2vec

Skip-gram model

- The original formulation of

$$p(w_O|w_I) = \frac{\exp\left({v'_{w_O}}^{\top} v_{w_I}\right)}{\sum_{w=1}^{W} \exp\left({v'_w}^{\top} v_{w_I}\right)}$$

  is expensive to calculate because it is proportional to the size of the dictionary (W)

- *Two* techniques improve the execution: *Hierarchical softmax* and *Negative Sampling*

word2vec

Continuous Bag-of-Words (CBOW)

- Alternative method to perform the same task

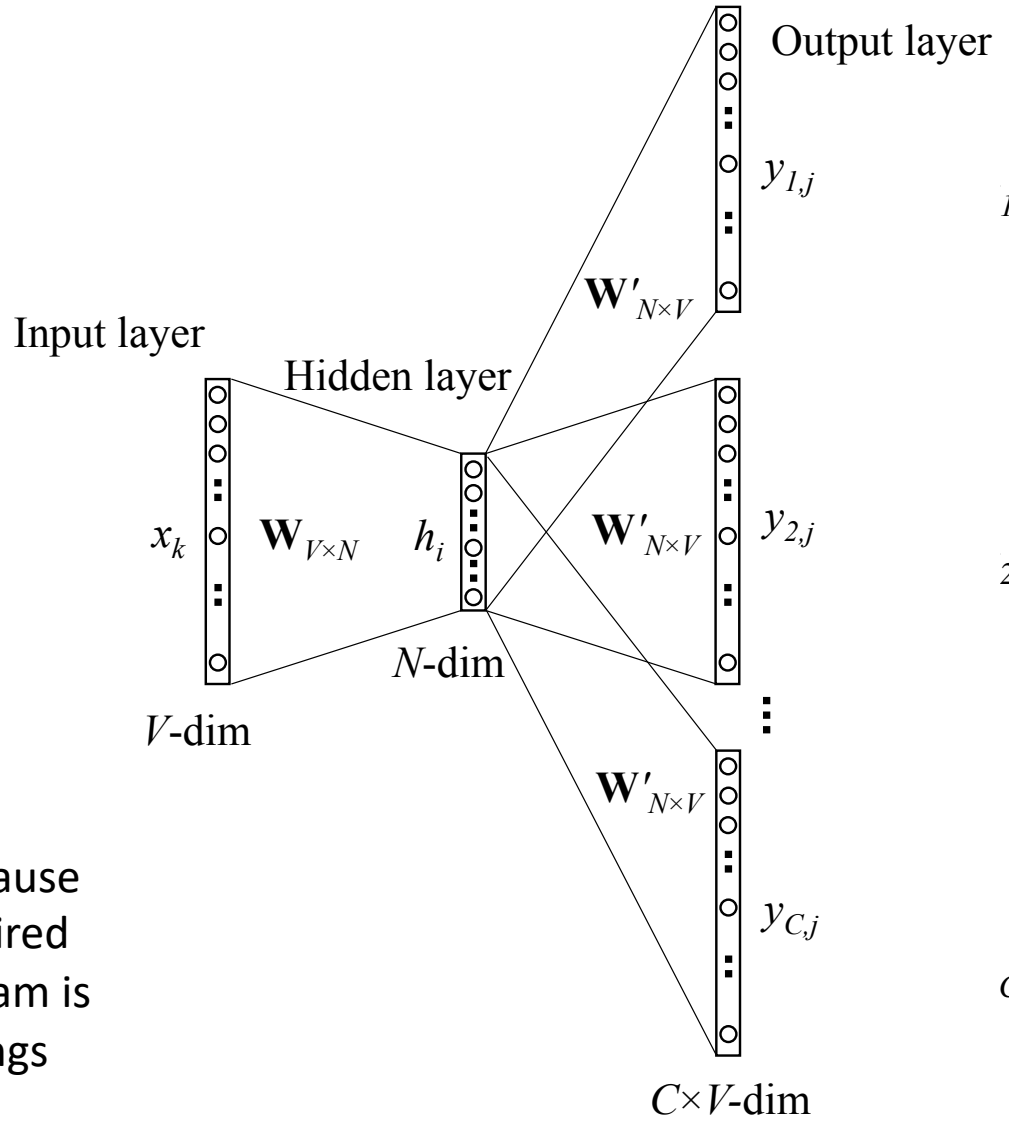
- In this case, the prediction is different: Given a context (w1, w2, w3,w4, w5), what's the probability that a new word appear?

word2vec

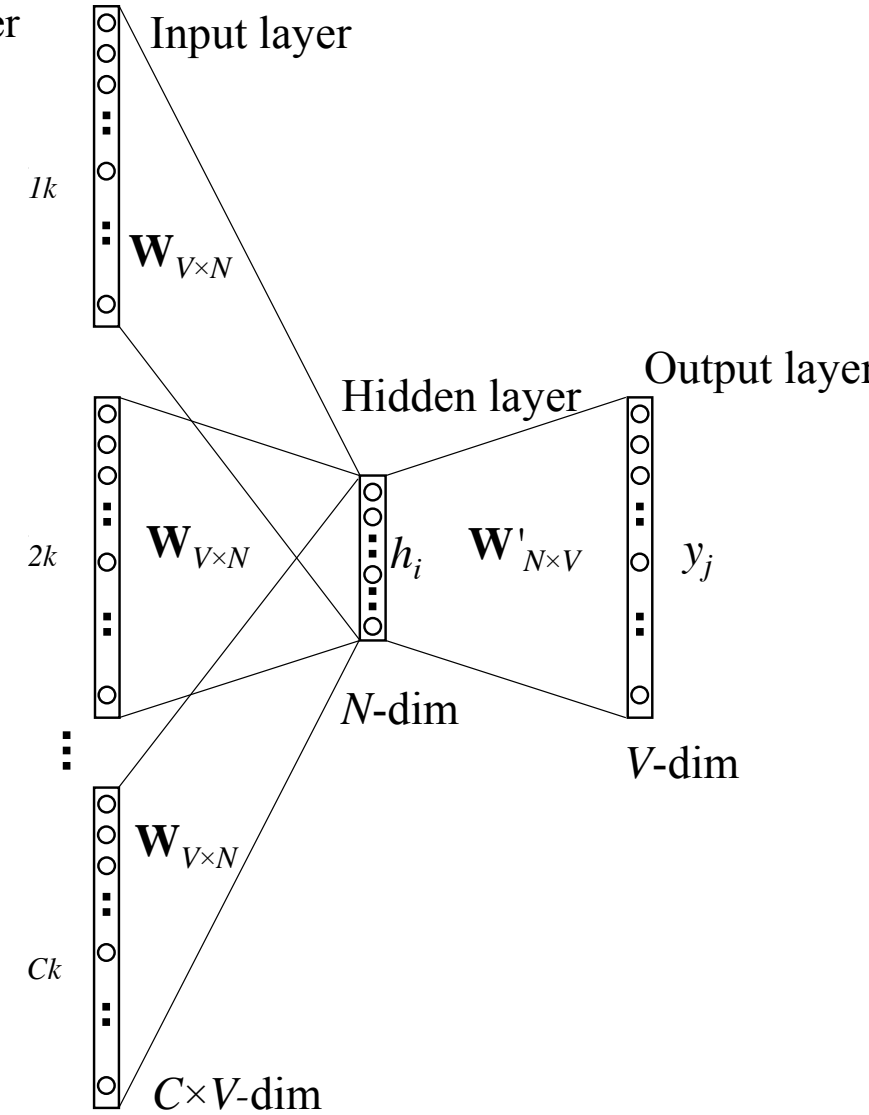
The products between the vectors can be calculated using a multi-layer neural network

In word2vec, the weights are trained using standard backpropagation

CBOW is significantly faster (because most of the computation is required in the second layer), but Skip-Gram is more accurate (CBOW embeddings are averaged)



Skip-Gram



CBOW

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BERT (Bidirectional Encoder Representations from Transformers)

BERT is a more recent language model designed by Google in 2018 to perform many NLP tasks [1]

- Significantly more complex than word2vec
- Designed for **pre-training;** some extra work is needed before it can be used for a specific task
- Changed the field: “in a little over a year, BERT has become a ubiquitous baseline in NLP experiments", counting over 150 research publications analyzing and improving the model” [2]

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[1] Devlin, Jacob; Chang, Ming-Wei; Lee, Kenton; Toutanova, Kristina. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding". arXiv:1810.04805v2
[2] Rogers, Anna; Kovaleva, Olga; Rumshisky, Anna (2020). "A Primer in BERTology: What We Know About How BERT Works"

BERT

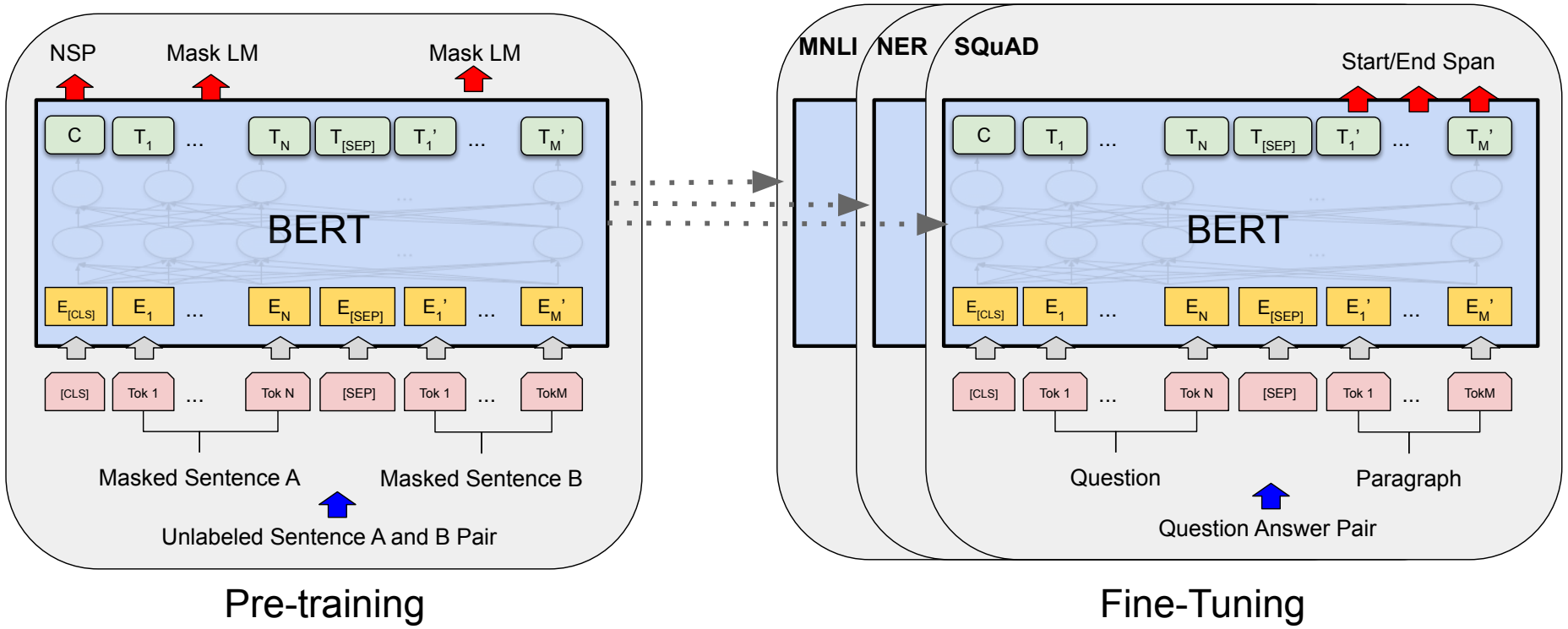
- BERT consists only of one encoder implemented with a transformer
- It has been pre-trained by Google consider all the content of Wikipedia and BooksCorpus
  - Task 1: Language Modeling
  - Task 2: Next Sentence Prediction

- BERT can be **fine-tuned** for some specific tasks
  - Single sentence classification
  - Question answering
  - Sentence tagging
  - Sentiment Analysis

BERT

Expensive, done by Google

Cheap, can be done by any of us



- Two variants:
  - BERT base – 12 layers, 12 attention heads and **110 million parameters**
  - BERT Large – 24 layers, 16 attention heads and **340 million parameters**

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BERT

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

BERT is a language model that is general enough to perform well on many different tasks. What kind of knowledge does it contain?

It is not entirely clear why BERT works so well

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https://github.com/google-research/bert

GPT

- Language model proposed by OpenAI in 2018
- Conceptually very similar to BERT (both use Transformers, but BERT uses an encoder while GPT uses a decoder)
- Like BERT, pre-training learns to predict the next word in a sequence
- Fine-tuning adapts the model for different tasks

Radford, Alec and Karthik Narasimhan. “Improving Language Understanding by Generative Pre-Training.” (2018).

GPT-2

- In 2019, OpenAI released GPT-2
- GPT-2 is significantly larger than BERT (1.5B parameters vs 340M parameters of BERT)
- Minimal (or no) fine-tuning
- **Translation:** Gives an "<*english*> = <*french*>" sentence as . Then provides "<english> = " and selects the most probable sequence
- **Summarization:** Provide "<article> TL;DR: <summary>". Then provides "<article>TL;DR: " and select the top sequence of 100 words
- Model outperforms BERT in many tasks

Radford, Alec et al. "Language Models are Unsupervised Multitask Learners." (2019).

GPT-3

- In 2020, OpenAI released the latest version of GPT
- Model contains **175 billion parameters**: (GPT-2 1.5 billions, BERT 340M)
- Source code, models are not available; Microsoft has exclusive rights to use the model
- Performance is truly impressive, GPT-3 can produce text that is indistinguisable from the one written by a human. For examples, see original paper (LINK)

Brown, Tom, et al. "Language models are few-shot learners." *Advances in neural information processing systems* 33 (2020): 1877-1901.

DALL-E and stable diffusion

- DALL-E 2 is a text-to-image model developed by OpenAI. Uses GPT-3 to interpret the input and generates the image. Open since September 2022 (https://openai.com/dall-e-2/)
- Stable Diffusion is another text-to-image model released in 2022 (https://stability.ai/blog/stable-diffusion-announcement). Source code is publicly available (demo)

Ramesh, Aditya, et al. "Hierarchical text-conditional image generation with clip latents." *arXiv preprint arXiv:2204.06125* (2022).

DALL-E 2 and stable diffusion

- “Portrait of a girl in a coffeeshop, reading a book, dramatic lighting”

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Example taken from https://medium.com/mlearning-ai/dall-e2-vs-stable-diffusion-same-prompt-different-results-e795c84adc56, photos by https://jimclydemonge.medium.com/