CS769 Advanced NLP

Pre-trained Sentence and Contextualized Word Representations

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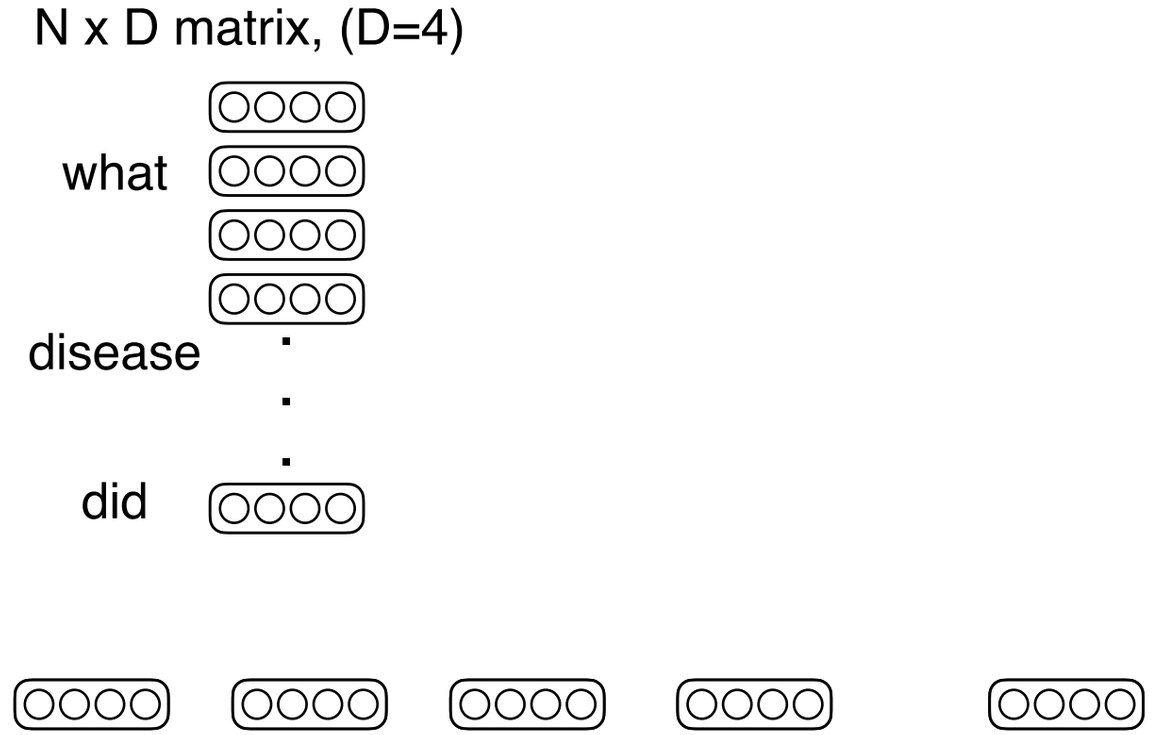
Slides adapted from Graham, Antonis
https://junjiehu.github.io/cs769-spring23/

Goals for Today

- Why **pre-training**?
- **Task** and **Pre-training** of contextualized **sentence** representations (GPT-2, Skip-thought, Paraphrase Contrastive Learning)
- **Task** and **Pre-training** of contextualized **word** representations (ELMO, BERT, XLNet, ELECTRA)

Words As Learnable Vectors



Word Vectors

"You shall know a word by the company it keeps!"
—John Firth (1957)

disease

antibiotics

What

eliminate

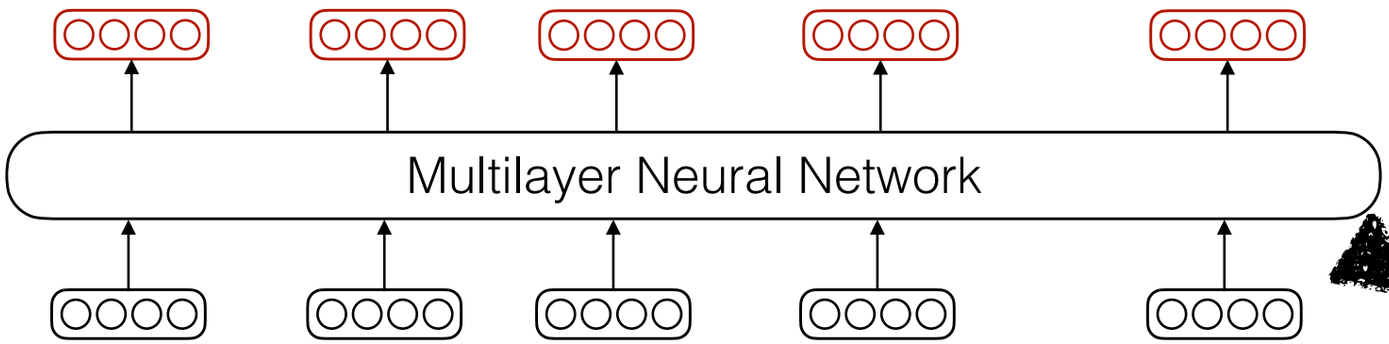
did

What disease did antibiotics eliminate

Static v.s.Contextualized Word Vectors

Contextualized Word Vectors

(McCann et al. 2017)
BERT, XLNet, etc

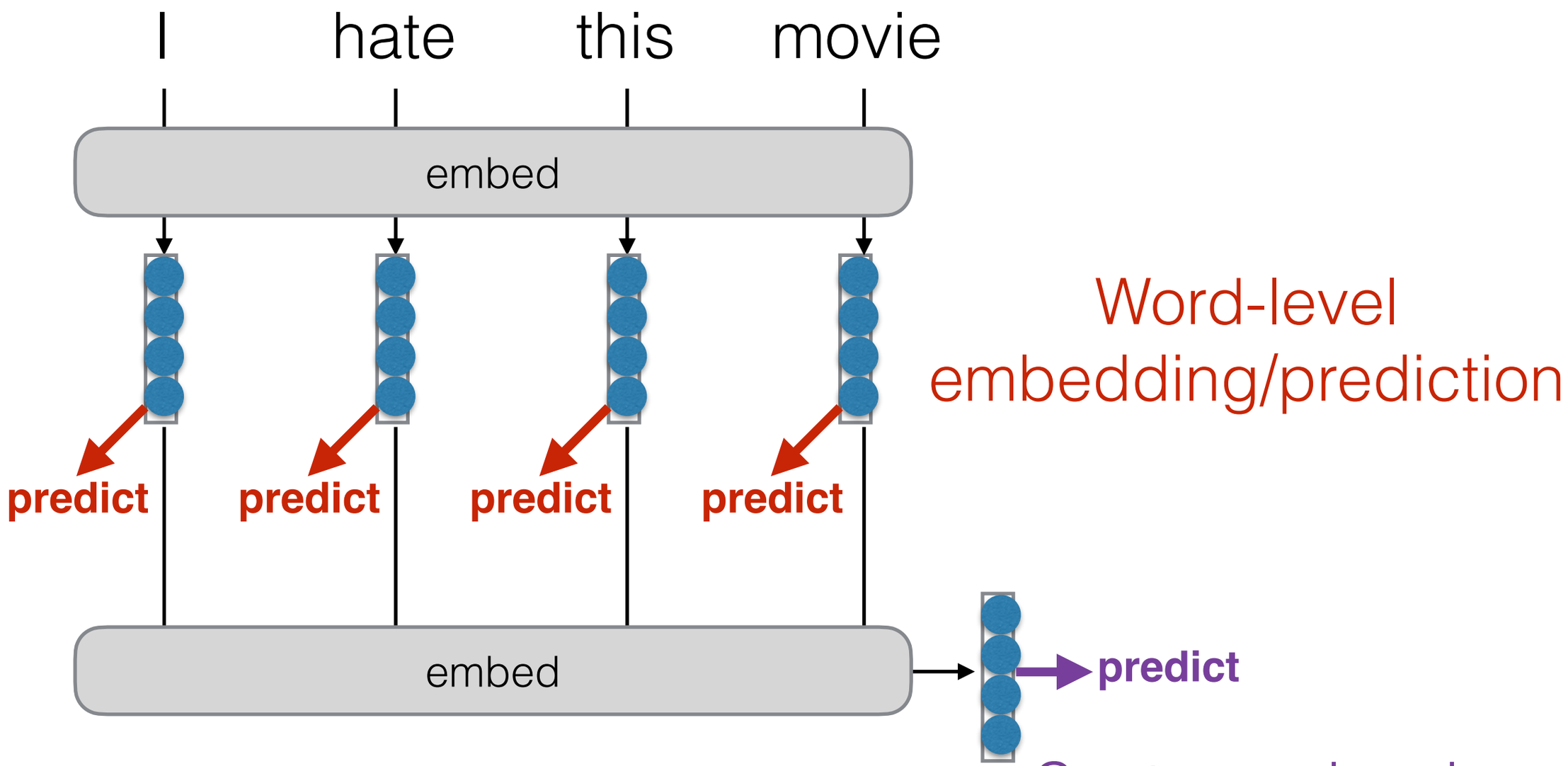


Non-contextualized Word Vectors

(Mikolov et al. 2013)

What disease did antibiotics eliminate

Remember: Neural Models



Review: Language Modeling Problem

- Input: training data a sequence $X = \langle x_1, x_2, \ldots, x_n \rangle \in \mathscr{V}^+$
    - Sometimes it's useful to consider a collection of training sentences, each in $\mathscr{V}^+$, but it complicates notation.
- Output: $P : \mathscr{V}^+ \rightarrow \mathbb{R}$

$$P(X) = \prod_{i=1}^{I} P(x_i \mid x_1, \ldots, x_{i-1})$$

Next Word Context

- Maximum Likelihood Estimation (MLE): Optimize the model

$$\theta^* = \arg\max \frac{1}{|\mathcal{D}|} \sum_{X \sim \mathcal{D}} \log P_\theta(X)$$

Why Pre-training?

Types of Learning

- **Multi-task learning** is a general term for training on multiple tasks

- **Transfer learning** is a type of multi-task learning where we only really care about one of the tasks

- **Pre-training** is a type of transfer learning where one pre-training objective is used first

Plethora of Tasks in NLP

- In NLP, there are a plethora of tasks, each requiring different varieties of data
  - **Only text:** e.g. language modeling
  - **Naturally occurring data:** e.g. machine translation
  - **Hand-labeled data:** e.g. most analysis tasks
- And each in many languages, many domains!

Rule of Thumb 1: Multitask to Increase Data

- Perform multi-tasking when one of your two tasks has many fewer data

- **General domain → specific domain**
  (e.g. web text → medical text)

- **High-resourced language → low-resourced language**
  (e.g. English → Telugu)

- **Plain text → labeled text**
  (e.g. LM → parser)

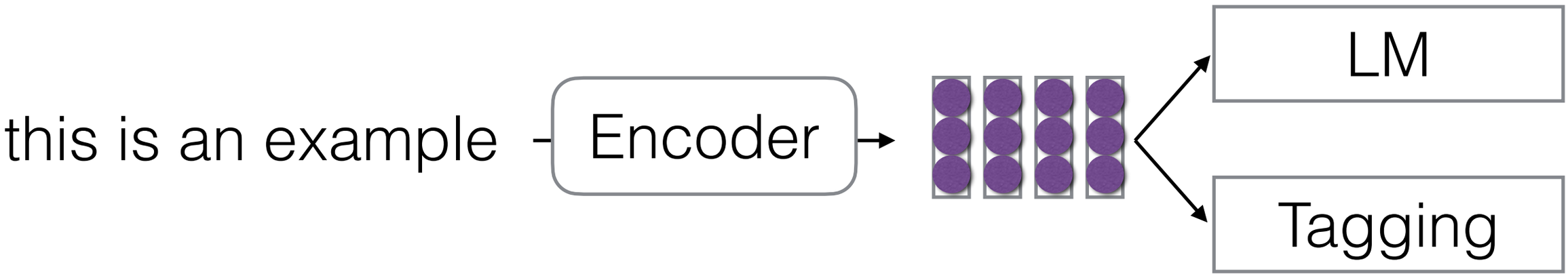
Rule of Thumb 2:

- Perform multi-tasking when your **tasks are related**

- e.g. predicting eye gaze and summarization (Klerke et al. 2016)

Standard Multi-task Learning

- Train representations to do well on multiple tasks at once

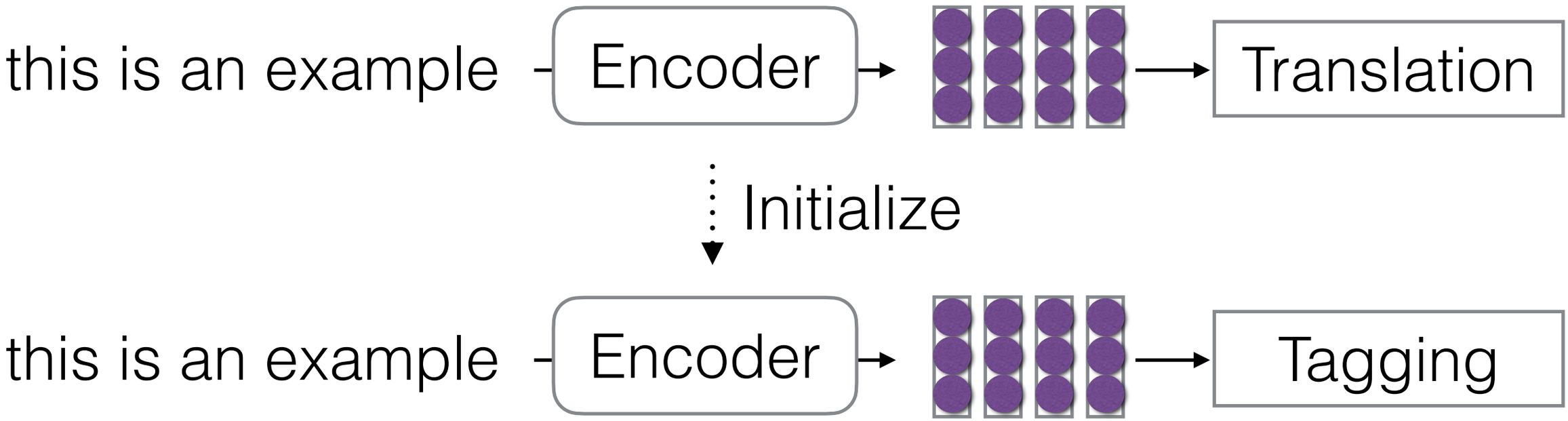


- In general, as simple as randomly choosing minibatch from one of multiple tasks

- Many many examples, starting with Collobert and Weston (2011)

Pre-training

- First train on one task, then train on another



- Widely used in word embeddings (Turian et al. 2010), sentence encoders (Dai et al. 2015) or contextualized word representations (Melamud et al. 2016)

Thinking about Multi-tasking, and Pre-trained Representations

- Many methods have names like ELMo, BERT, RoBERTa, XLNet along with pre-trained models
- These often refer to a combination of
  - **Model:** The underlying neural network architecture
  - **Training Objective:** What objective is used to pre-train
  - **Data:** What data the authors chose to use to train the model
- Remember that these are often conflated (and don't need to be)!

End-to-end vs. Pre-training

- For any model, we can always use an end-to-end training objective
  - **Problem:** paucity of training data
  - **Problem:** weak feedback from end of sentence only for text classification, etc.
- Often better to pre-train sentence embeddings on other task, then use or fine tune on target task

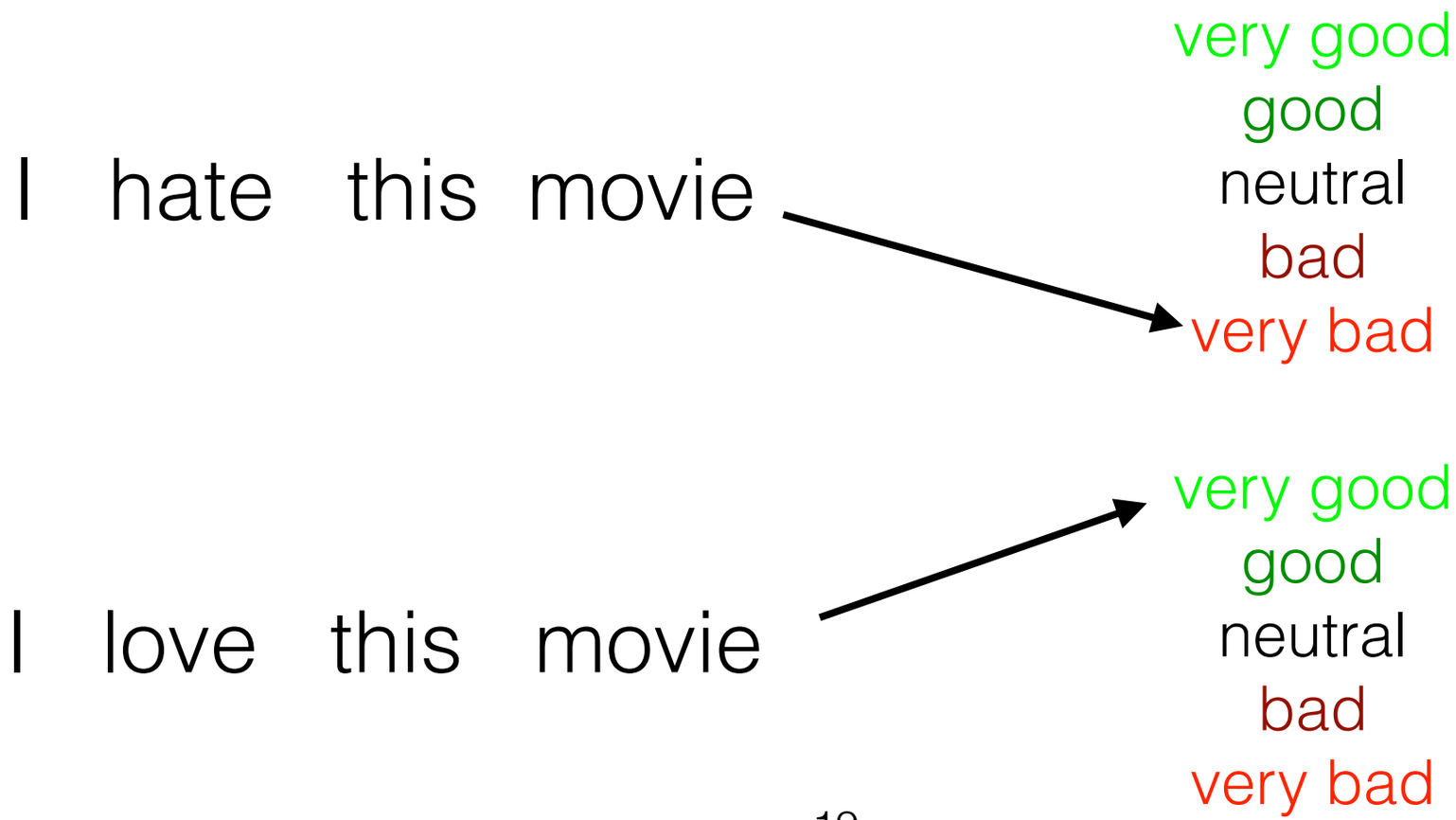
Tasks Using Sentence Representations

Where would we need/use Sentence Representations?

- Sentence Classification
- Paraphrase Identification
- Semantic Similarity
- Entailment
- Retrieval

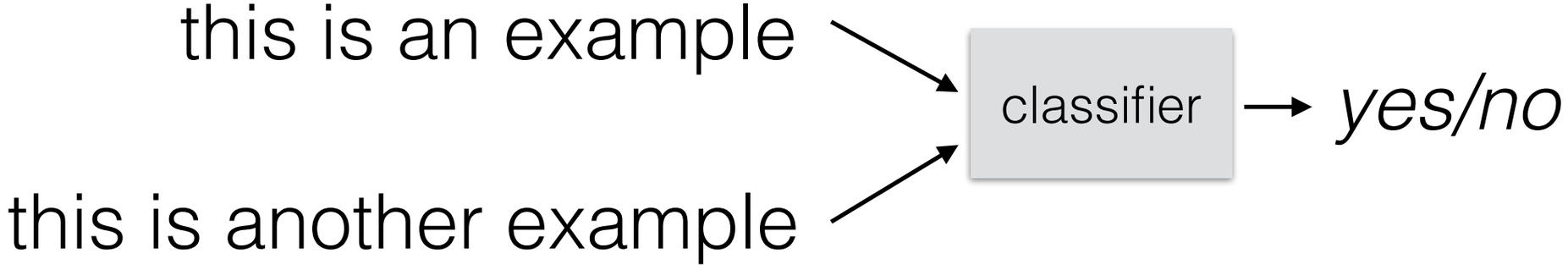
Sentence Classification

- Classify sentences according to various traits
- Topic, sentiment, subjectivity/objectivity, etc.



Sentence Pair Classification

- Classify over multiple sentences



Paraphrase Identification
(Dolan and Brockett 2005)

- Identify whether A and B mean the same thing

Charles O. Prince, 53, was named as Mr. Weill's successor.

Mr. Weill's longtime confidant, Charles O. Prince, 53, was named as his successor.

- **Note:** *exactly* the same thing is too restrictive, so use a loose sense of similarity

Semantic Similarity/Relatedness

(Marelli et al. 2014)

- Do two sentences mean something similar?

Relatedness score	Example
1.6	A: "*A man is jumping into an empty pool*" B: "*There is no biker jumping in the air*"
2.9	A: "*Two children are lying in the snow and are making snow angels*" B: "*Two angels are making snow on the lying children*"
3.6	A: "*The young boys are playing outdoors and the man is smiling nearby*" B: "*There is no boy playing outdoors and there is no man smiling*"
4.9	A: "*A person in a black jacket is doing tricks on a motorbike*" B: "*A man in a black jacket is doing tricks on a motorbike*"

- Like paraphrase identification, but with shades of gray.

Textual Entailment

(Dagan et al. 2006, Marelli et al. 2014)

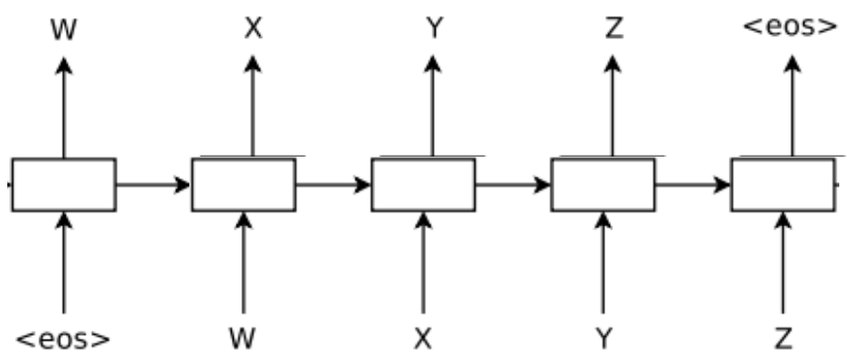
- **Entailment:** if A is true, then B is true (c.f. paraphrase, where opposite is also true)
  - The woman bought a sandwich for lunch
    → The woman bought lunch
- **Contradiction:** if A is true, then B is not true
  - The woman bought a sandwich for lunch
    → The woman did not buy a sandwich
- **Neutral:** cannot say either of the above
  - The woman bought a sandwich for lunch
    → The woman bought a sandwich for dinner

Pre-Training of Sentence Representations

Language Model+Transfer

(Dai and Le 2015)

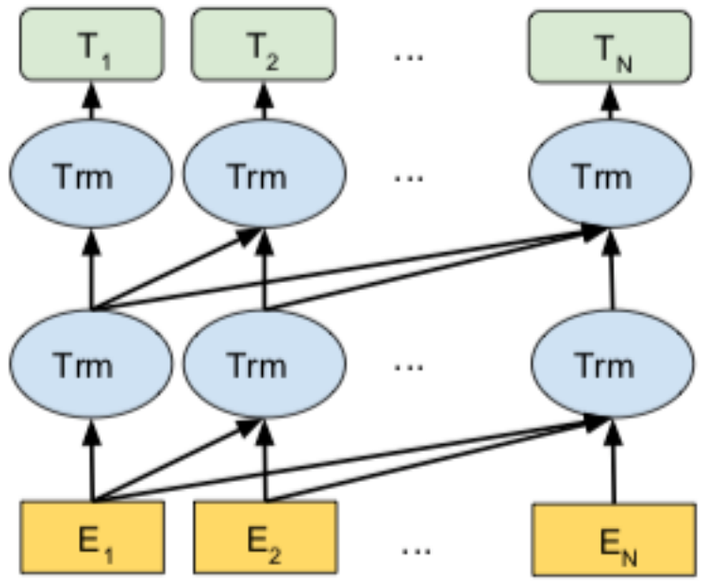
- **Model:** LSTM
- **Objective:** LM objective
- **Data:** Classification data itself, or Amazon reviews



- **Downstream:** On text classification, initialize weights and continue training

"GPT" (Radford et al. 2018)

- **Model:** Masked self-attention
- **Objective:** LM objective
- **Data:** BooksCorpus

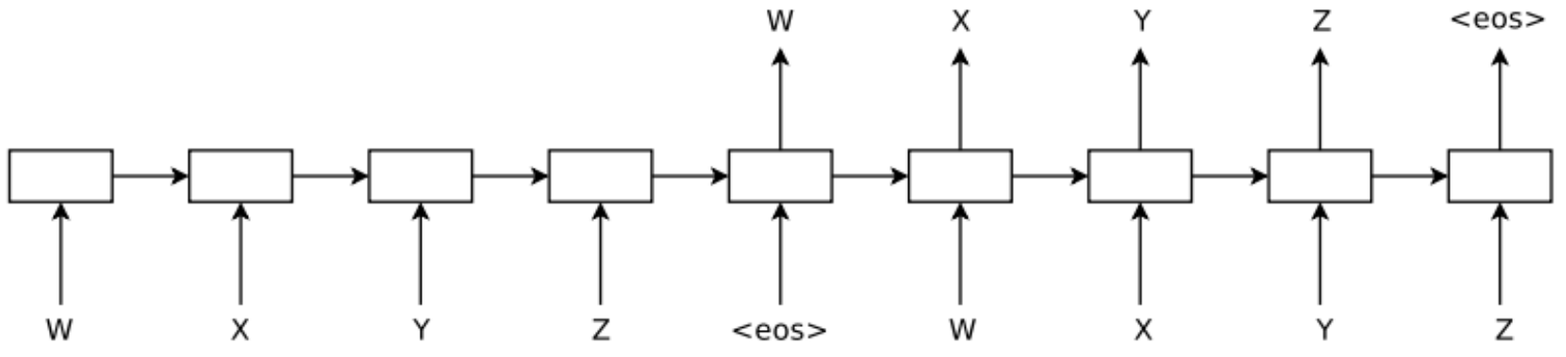


Downstream: Some task fine-tuning, other tasks additional multi-sentence training

Auto-encoder+Transfer

(Dai and Le 2015)

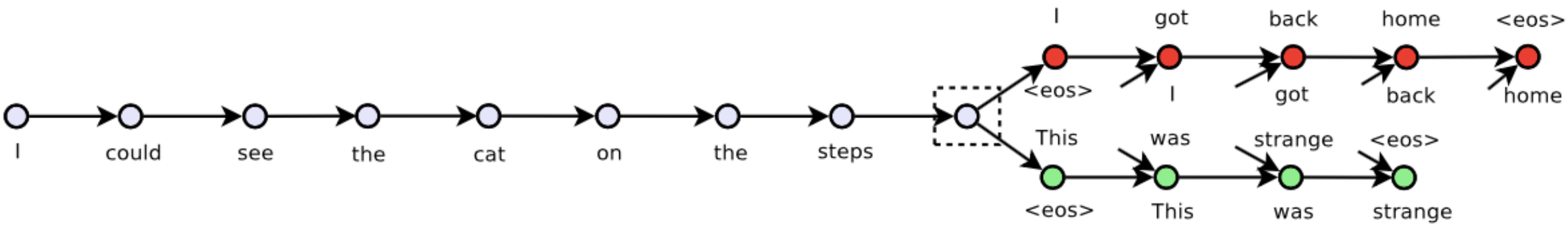
- **Model:** LSTM
- **Objective:** From single sentence vector, re-construct the sentence
- **Data:** Classification data itself, or Amazon reviews



- **Downstream:** On text classification, initialize weights and continue training

Sentence-level Context Prediction+Transfer: "Skip-thought Vectors" (Kiros et al. 2015)

- **Model:** LSTM
- **Objective:** Predict the surrounding sentences
- **Data:** Books, important because of context



- **Downstream Usage:** Train logistic regression on [|u-v|; u*v] (component-wise) for sentence pair classification (u, v are two sentence embeddings)
- Similar to Skip-gram that predict the surrounding words by the center words

Paraphrase-based Contrastive Learning

(Wieting et al. 2015)

- **Model:** Try many different ones
- **Objective:** Predict whether two phrases are paraphrases or not from
- **Data:** Paraphrase database (http://paraphrase.org), created from bilingual data
- **Downstream Usage:** Sentence similarity, classification, etc.
- **Result:** Interestingly, LSTMs work well on in-domain data, but word averaging generalizes better

Large Scale Paraphrase Data (ParaNMT-50MT)

(Wieting and Gimpel 2018)

- **Automatic construction of large paraphrase DB**
  - Get large parallel corpus (English-Czech)
  - Translate the Czech side using a SOTA NMT system
  - Get automated score and annotate a sample
- Corpus is **huge but includes noise**, 50M sentences (about 30M are high quality)
- Trained representations work quite well and generalize

Entailment+Transfer "InferSent"

(Conneau et al. 2017)

- Previous objectives use no human labels, but what if:
- **Objective:** supervised training for a task such as entailment learn generalizable embeddings?
  - Task is more difficult and requires capturing nuance → yes?, or data is much smaller → no?
- **Model:** Bi-LSTM + max pooling
- **Data:** Stanford NLI, MultiNLI
- Results: Tends to be better than unsupervised objectives such as SkipThought

Sentence Transformers

(Reimers and Gurevych 2019)

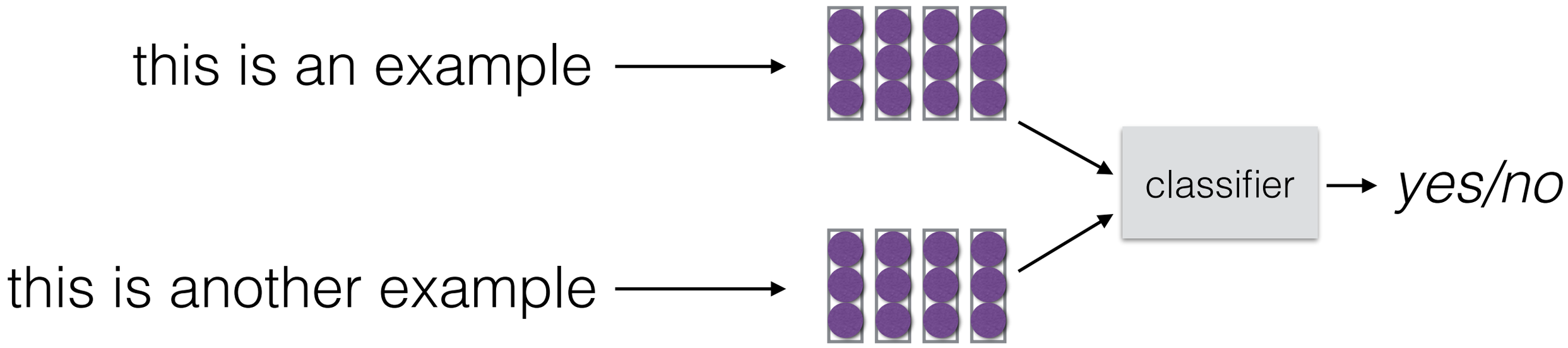
- A toolkit that implements a large number of sentence representations (e.g. BERT, paraphrase)

https://www.sbert.net/

Pre-training of Contextualized Word Representations

Contextualized Word Representations

- Instead of one vector per sentence, one vector per word!



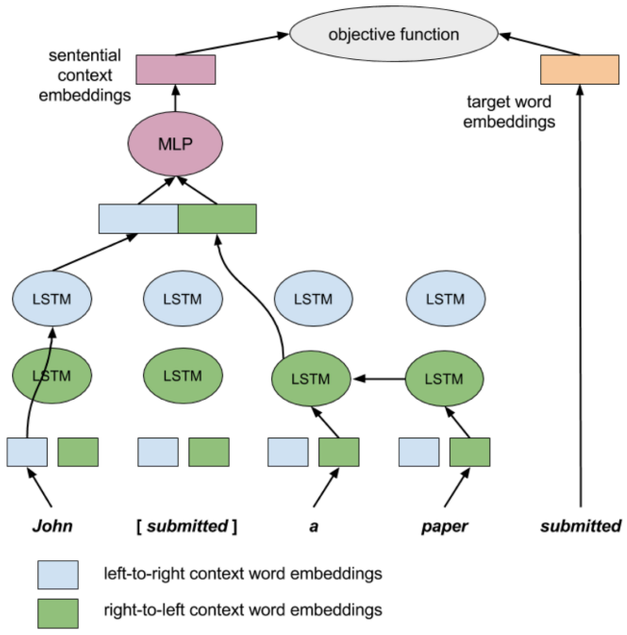
How to train this representation?

Central Word Prediction

context2vec

(Melamud et al. 2016)

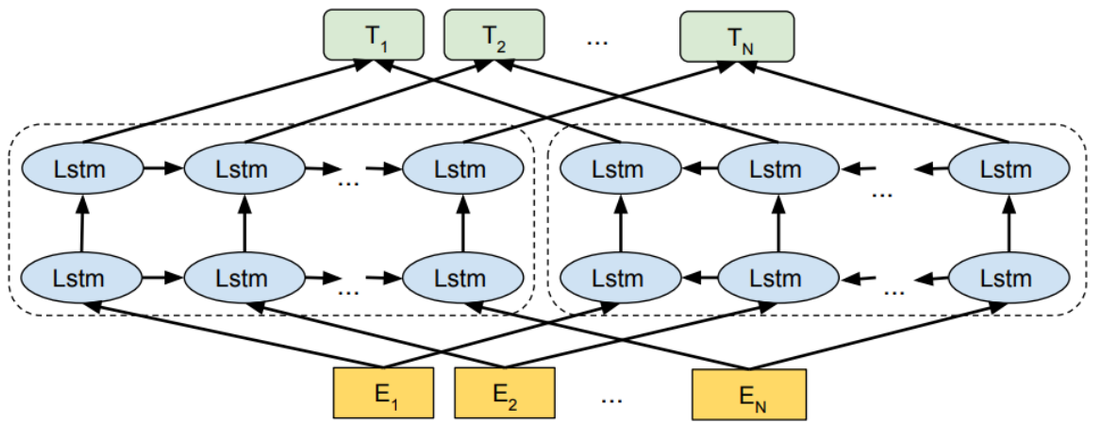
- **Model:** Bi-directional LSTM
- **Objective:** Predict the word given context
- **Data:** 2B word ukWaC corpus
- **Downstream:** use vectors for sentence completion, word sense disambiguation, etc.



ELMo

(Peters et al. 2018)

- **Model:** Multi-layer bi-directional LSTM
- **Objective:** Predict the next word left->right, next word right->left independently

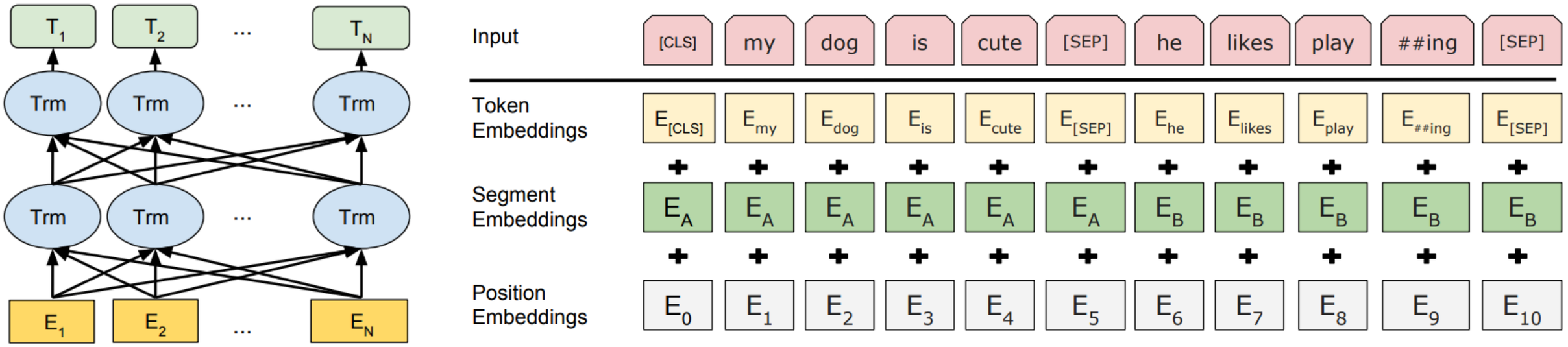


- **Data:** 1B word benchmark LM dataset
- **Downstream:** Finetune the weights of the linear combination of layers on the downstream task

Masked Word Prediction (BERT)

(Devlin et al. 2018)

- **Model:** Multi-layer self-attention. Input sentence or pair, w/ [CLS] token, subword representation



- **Objective:** Masked word prediction + next-sentence prediction
- **Data:** BooksCorpus + English Wikipedia (16GB)

Masked Word Prediction

(Devlin et al. 2018)

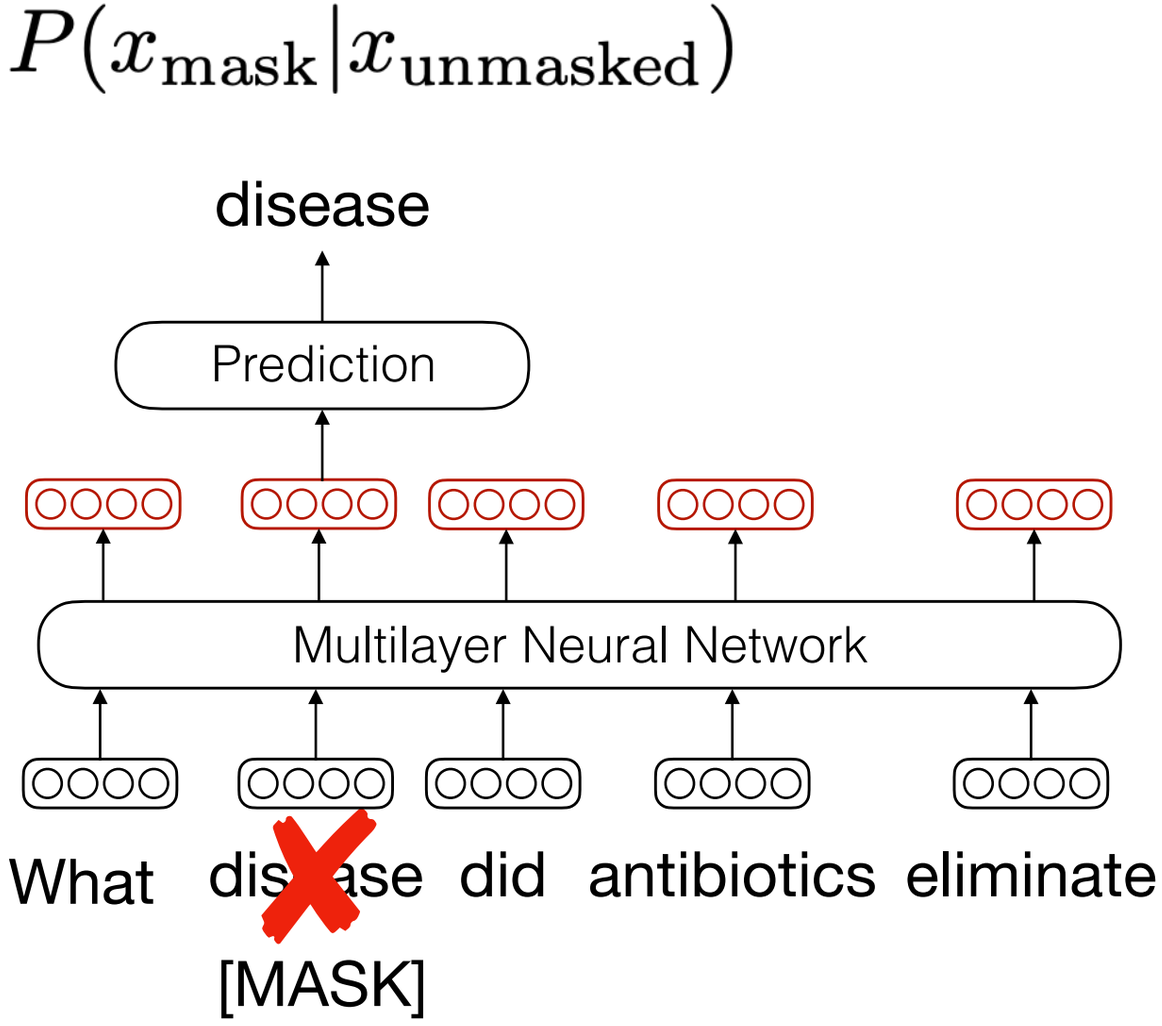
1. Select 15% of words at random in a sequence
2. For these selected words:
    - 80% of the time: substitute selected word with [MASK]
    - 10% of the time: substitute selected word with random word
    - 10% of the time: no change
3. Predict all the masked words

- Like context2vec, but **better suited for multi-layer self attention**

Masked Word Prediction

(Devlin et al. 2018)

$$P(x_{\text{mask}} | x_{\text{unmasked}})$$



Consecutive Sentence Prediction

(Devlin et al. 2018)

1. classify two sentences as consecutive or not:

   - 50% of training data (from OpenBooks) is "consecutive"

Input = `[CLS] the man [MASK] to the store [SEP]`
`penguin [MASK] are flight ##less birds [SEP]`
Label = `NotNext`

Input = `[CLS] the man went to [MASK] store [SEP]`
`he bought a gallon [MASK] milk [SEP]`
Label = `IsNext`

Hyperparameter Optimization/Data (RoBERTa)

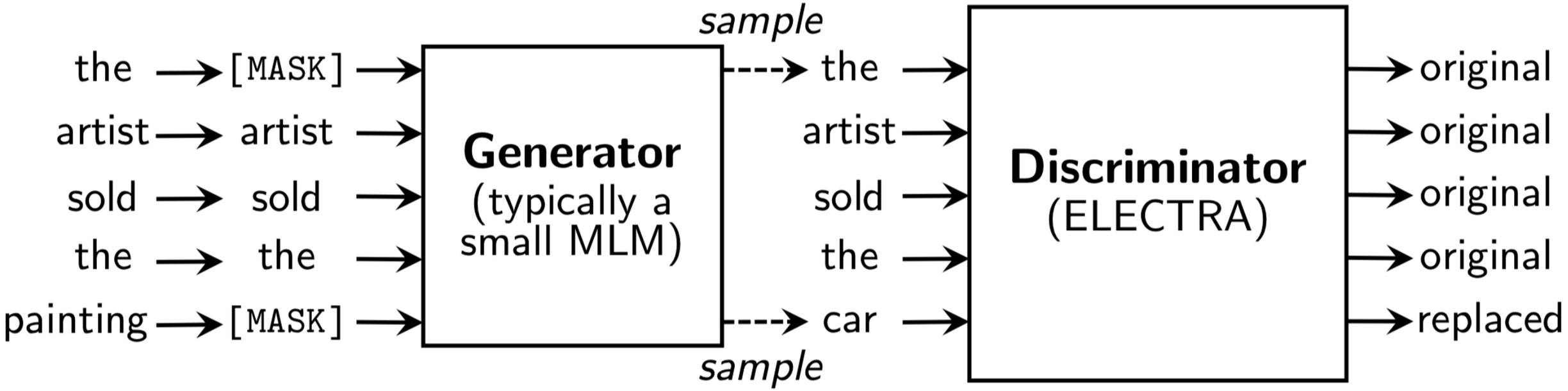
(Liu et al. 2019)

- **Model:** Same as BERT
- **Objective:** Same as BERT, but *train longer* and *drop sentence prediction* objective
- **Data:** BooksCorpus & English Wikipedia (16GB) + CC-News (76GB) + OpenWebText (38GB) + Stories (31GB)
- **Results:** are empirically much better

Distribution Discrimination (ELECTRA)

(Clark et al. 2020)

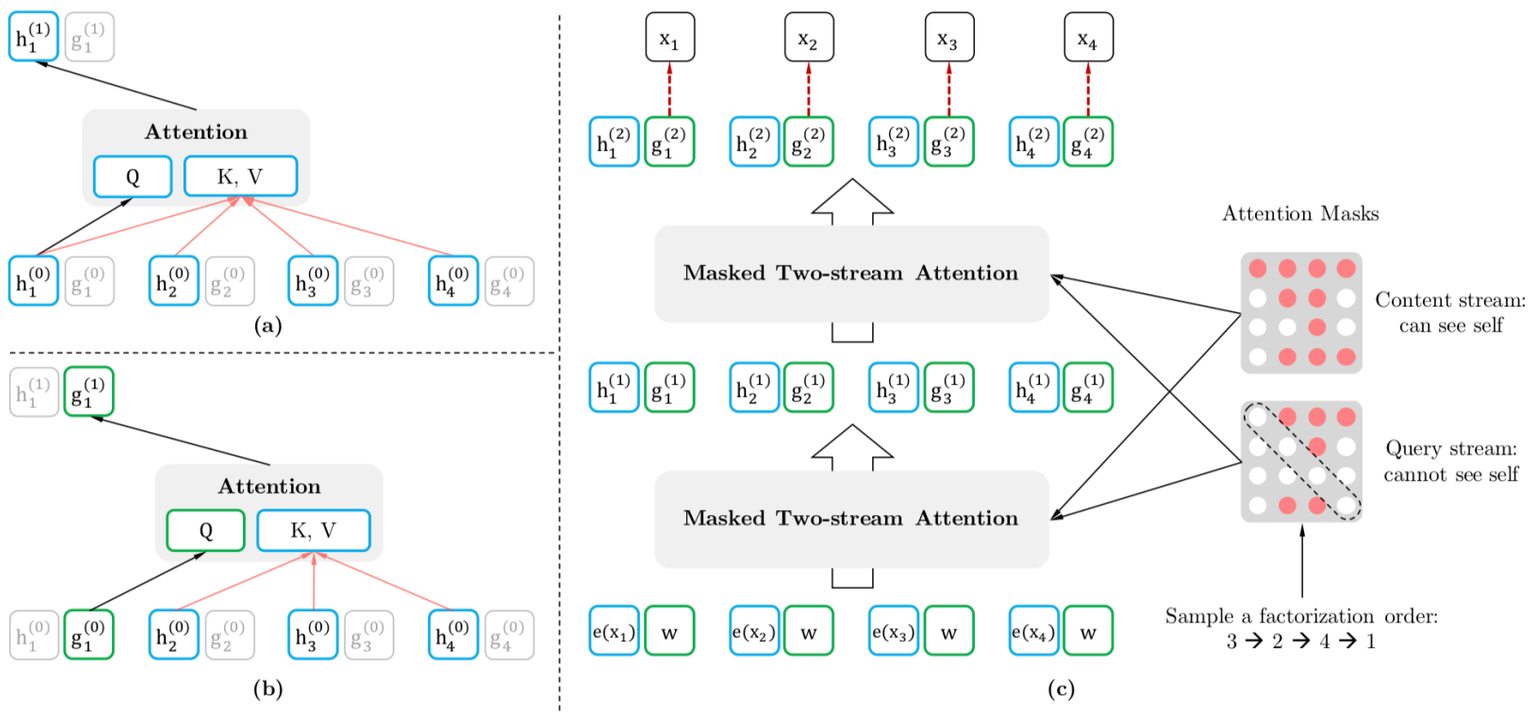
- **Model:** Same as BERT
- **Objective:** Sample words from language model, try to discriminate which words are sampled



- **Data:** Same as BERT, or XL-Net (next) for large models
- **Result:** Training much more efficient!

Permutation-based Auto-regressive Model + Long Context (XL-Net) (Yang et al. 2019)

- **Model:** Same as BERT, but include longer context
- **Objective:** Predict words in order, but different order every time



- **Data:** 39B tokens from Books, Wikipedia and Web

Compact Pre-trained Models

- Large models are expensive, can we make them smaller?

- **ALBERT (Lan et al. 2019):** Smaller embeddings, and parameter sharing across all layers, but the same inference time as the BERT counterpart.

- **DistilBERT (Sanh et al. 2019)**: Train a model to match the distribution of regular BERT

Which Method is Better?

Which Model?

- Wieting et al. (2015) find that simple word averaging is more robust out-of-domain

- Devlin et al. (2018) compare unidirectional and bi-directional transformer, but no comparison to LSTM like ELMo (for performance reasons?)

- Yang et al. (2019) have ablation where similar data to BERT is used and improvements are shown

Which Training Objective?

- Zhang and Bowman (2018) control for training data, and find that bi-directional LM seems better than MT encoder

- Devlin et al. (2018) find next-sentence prediction objective good compliment to LM objective, but Liu et al. (2019) find not

Which Data?

- Zhang and Bowman (2018) find that more data is probably better, but results preliminary.

- Yang et al. (2019) show some improvements by adding much more data from web, but not 100% consistent.

- Data with context is probably essential.

Pre-trained Large Language Models

- GPT-3: similar to GPT-2, but pre-trained on lot more data using autoregressive LM objective. Demonstrate good few-shot in-context prediction (Future lecture)

- ChatGPT: initialized from GPT-3 and fine-tuned by reinforcement learning with human feedback (RLHF)

Questions?