# STOR566: Introduction to Deep Learning

## Lecture 11: NLP Pre-training

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Materials are from *Deep Learning (UCLA)*

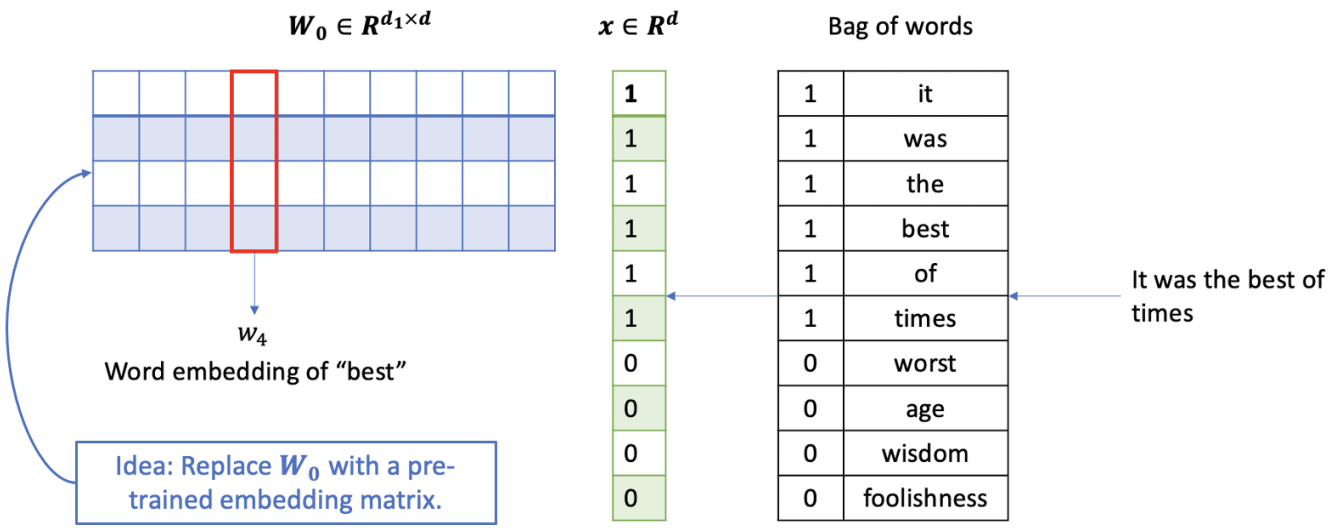
# Unsupervised pretraining for NLP

# Motivation

- Many unlabeled NLP data but very few labeled data
- Can we use large amount of unlabeled data to obtain meaningful representations of words/sentences?

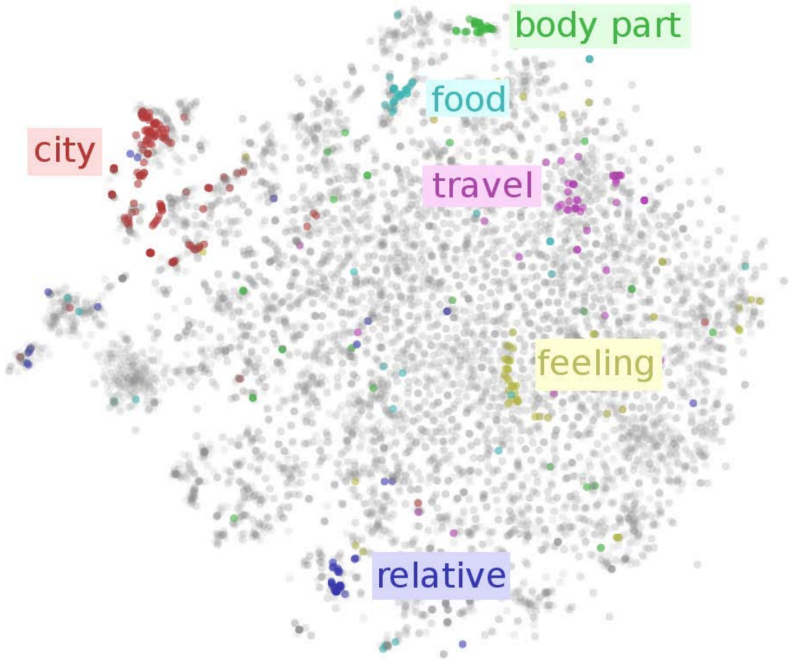
# Learning word embeddings

- Use large (unlabeled) corpus to learn a useful word representation
  - Learn a vector for each word based on the corpus
  - Hopefully the vector represents some semantic meaning
  - Can be used for many tasks
    - Replace the word embedding matrix for DNN models for classification/translation



# Methods for NLP Pre-training

- Two different perspectives but led to similar results:
  - Word2vec (Mikolov et al., 2013)
  - Glove (Pennington et al., 2014)
- Other Methods:
  - PPMI (Levy et al., 2014)
  - CoVe (McCann et al., 2017)
  - ELMo (Peter et al., 2018)
- New Trent:
  - BERT (Devlin et al., 2019)
  - CLIP (Radford et al., 2021)



# Context information

- Given a large text corpus, how to learn low-dimensional features to represent a word?
- For each word $w_i$, define the "contexts" of the word as the words surrounding it in an $L$-sized window:

$$w_{i-L-2}, w_{i-L-1}, \underbrace{w_{i-L}, \cdots, w_{i-1}}_{\text{contexts of } w_i}, w_i, \underbrace{w_{i+1}, \cdots, w_{i+L}}_{\text{contexts of } w_i}, w_{i+L+1}, \cdots$$

- Get a collection of (word, context) pairs, denoted by $D$.

# Word pair

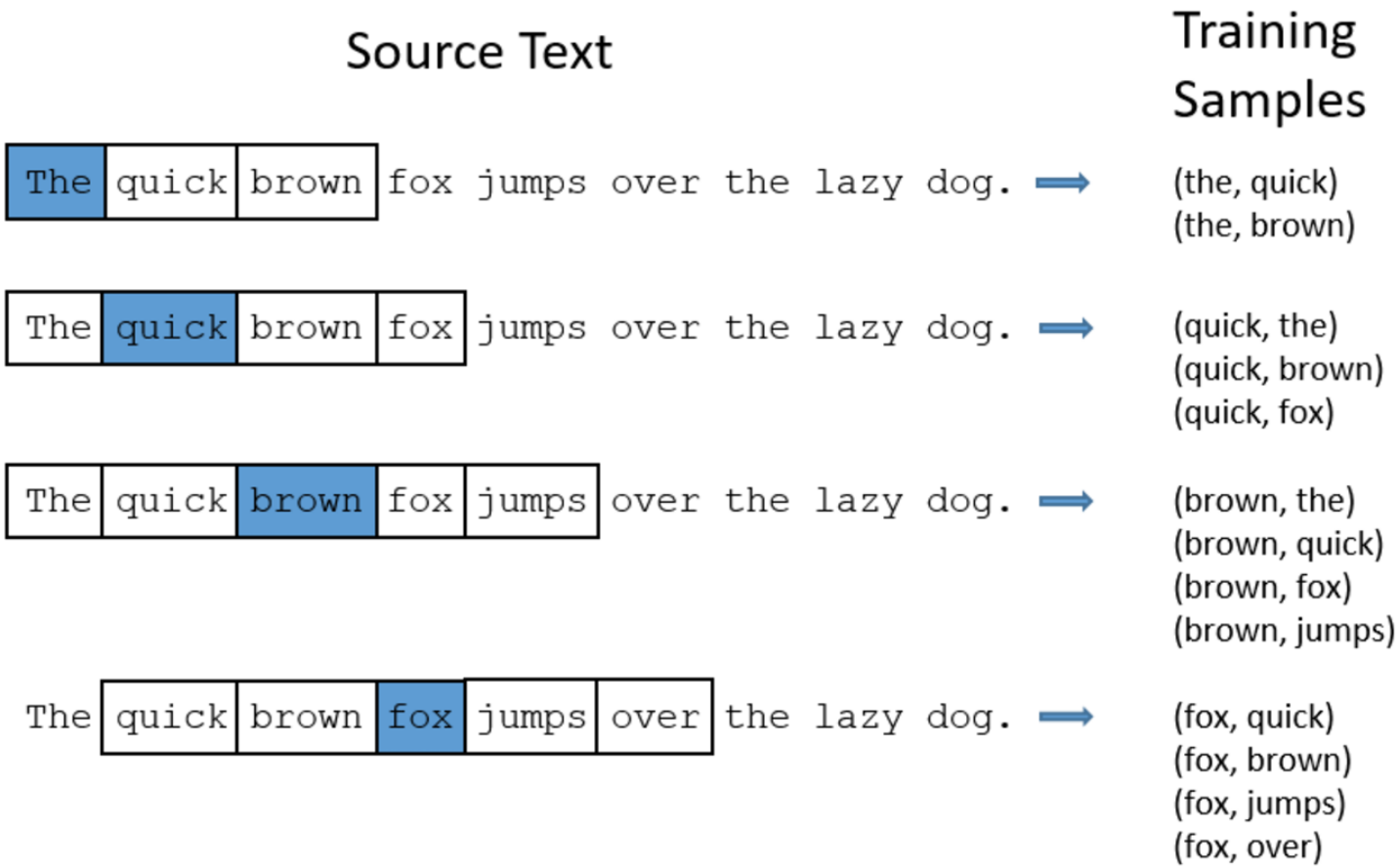



Figure from http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

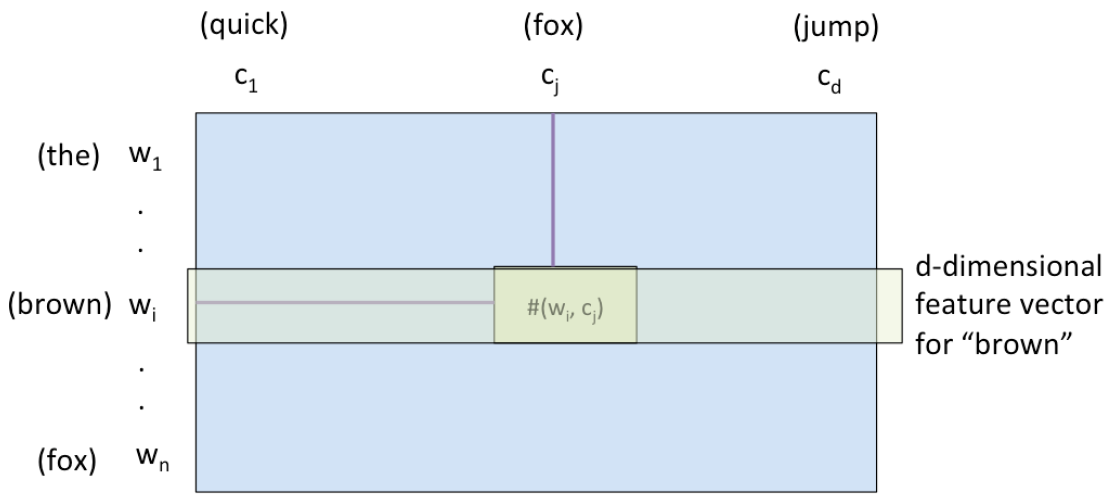
# Use bag-of-word model

- Idea 1: Use the bag-of-word model to "describe" each word
- Assume we have context words $c_1, \cdots, c_d$ in the corpus, compute

$$\#(w, c_i) := \text{ number of times the pair } (w, c_i) \text{ appears in } D$$

- For each word $w$, form a $d$-dimensional (sparse) vector to describe $w$

$$\#(w, c_1), \cdots, \#(w, c_d),$$



# PMI/PPMI Representation

- Similar to TF-IDF: Need to consider the frequency of each word and each context
- Instead of using co-ocurrent count $\#(w, c)$, we can define pointwise mutual information:

$$\text{PMI}(w, c) = \log\left(\frac{\hat{P}(w, c)}{\hat{P}(w)\hat{P}(c)}\right) = \log\frac{\#(w, c)|D|}{\#(w)\#(c)},$$

  - $\#(w) = \sum_c \#(w, c)$: number of pairs with word $w$
  - $\#(c) = \sum_w \#(w, c)$: number of pairs with word $c$
  - $|D|$: number of pairs in $D$

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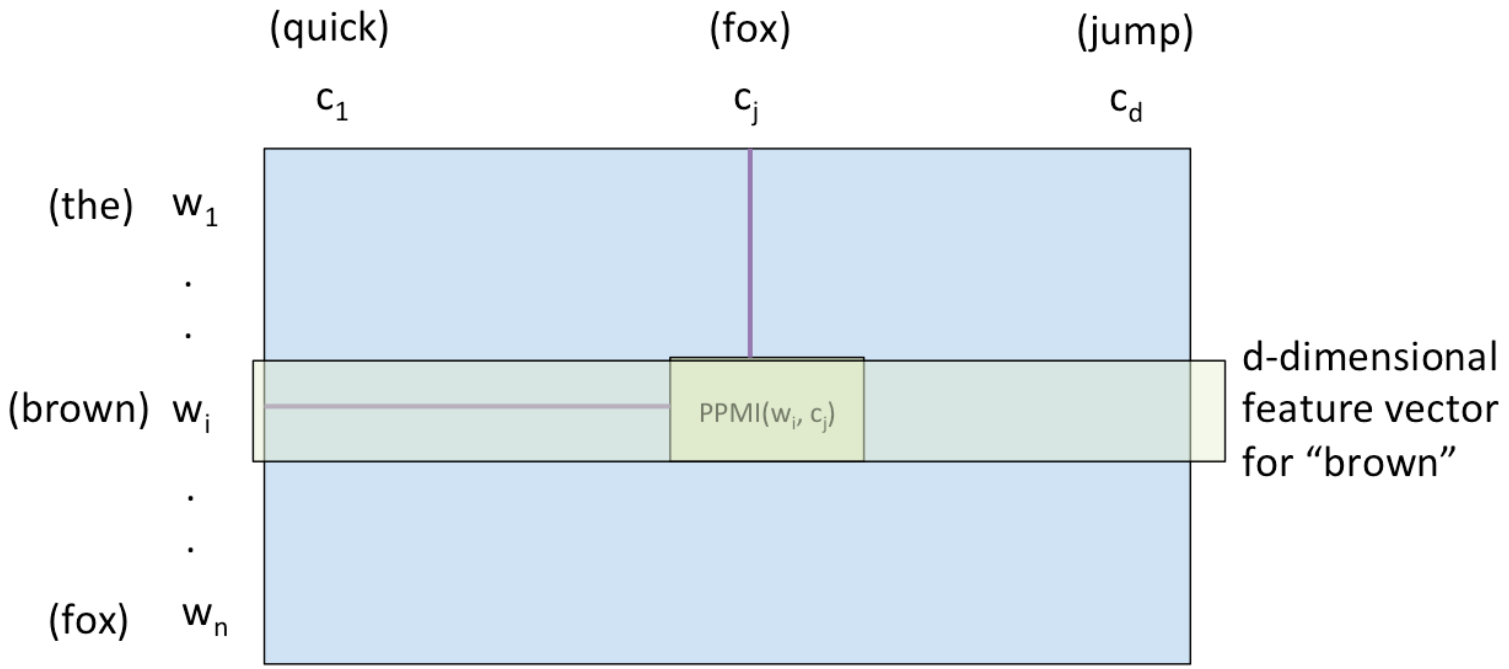
- Positive PMI (PPMI) usually achieves better performance:

$$\text{PPMI}(w, c) = \max(\text{PMI}(w, c), 0)$$

- $M^{\text{PPMI}}$: word feature matrix with $\text{PPMI}(w, c)$ as element

# PPMI Matrix


(quick)
(fox)
(jump)
$c_1$
$c_j$
$c_d$
(the) $w_1$
(brown) $w_i$
(fox) $w_n$
PPMI($w_i$, $c_j$)
d-dimensional feature vector for “brown”

# Low-dimensional embedding

- Perform PCA/SVD on the sparse feature matrix:

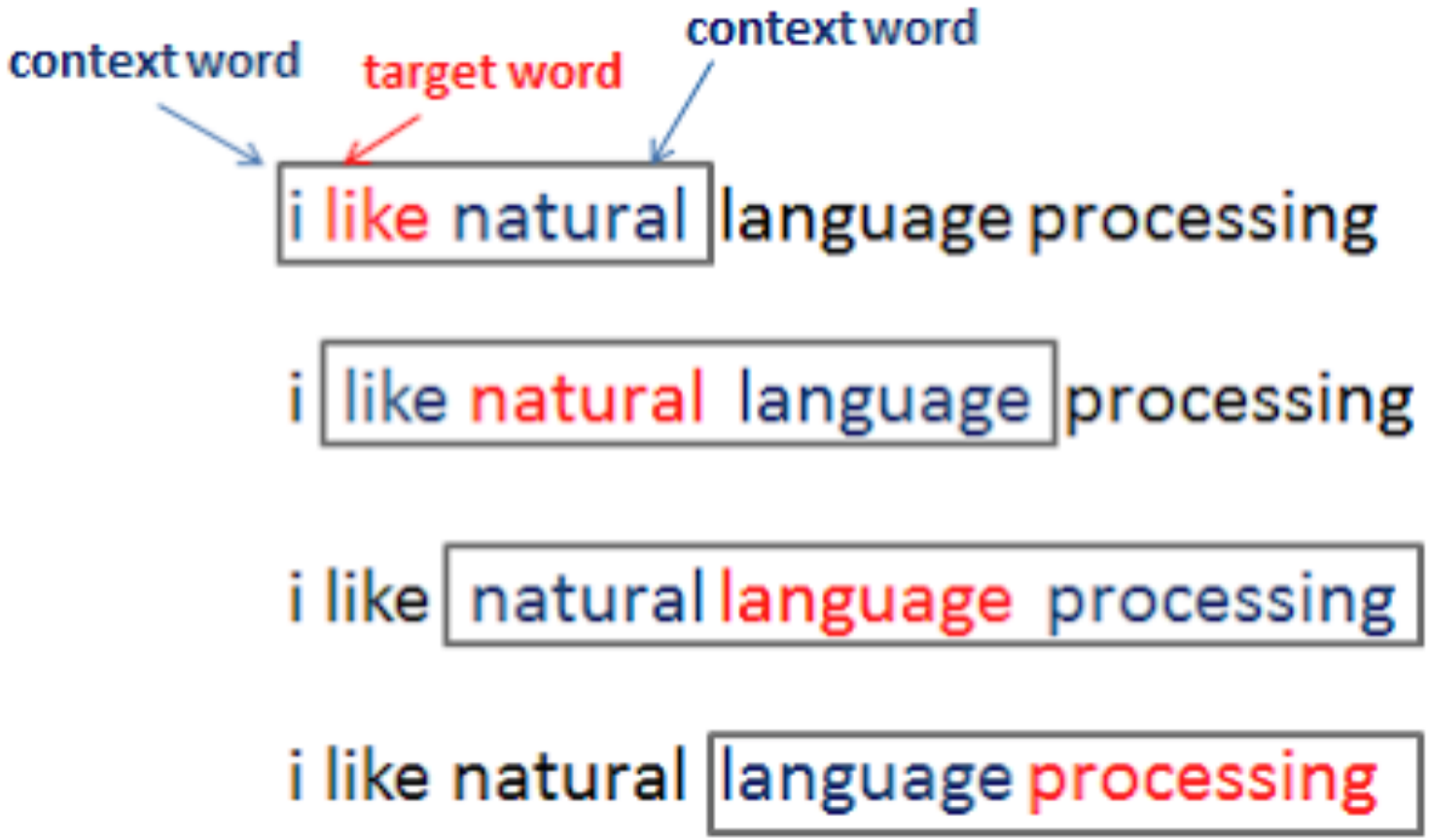
$$M^{\text{PPMI}} \approx U_k \Sigma_k V_k^T$$

  Then $W^{\text{SVD}} = U_k \Sigma_k$ is the context representation of each word (Each row is a $k$-dimensional feature for a word)

- $k << d$

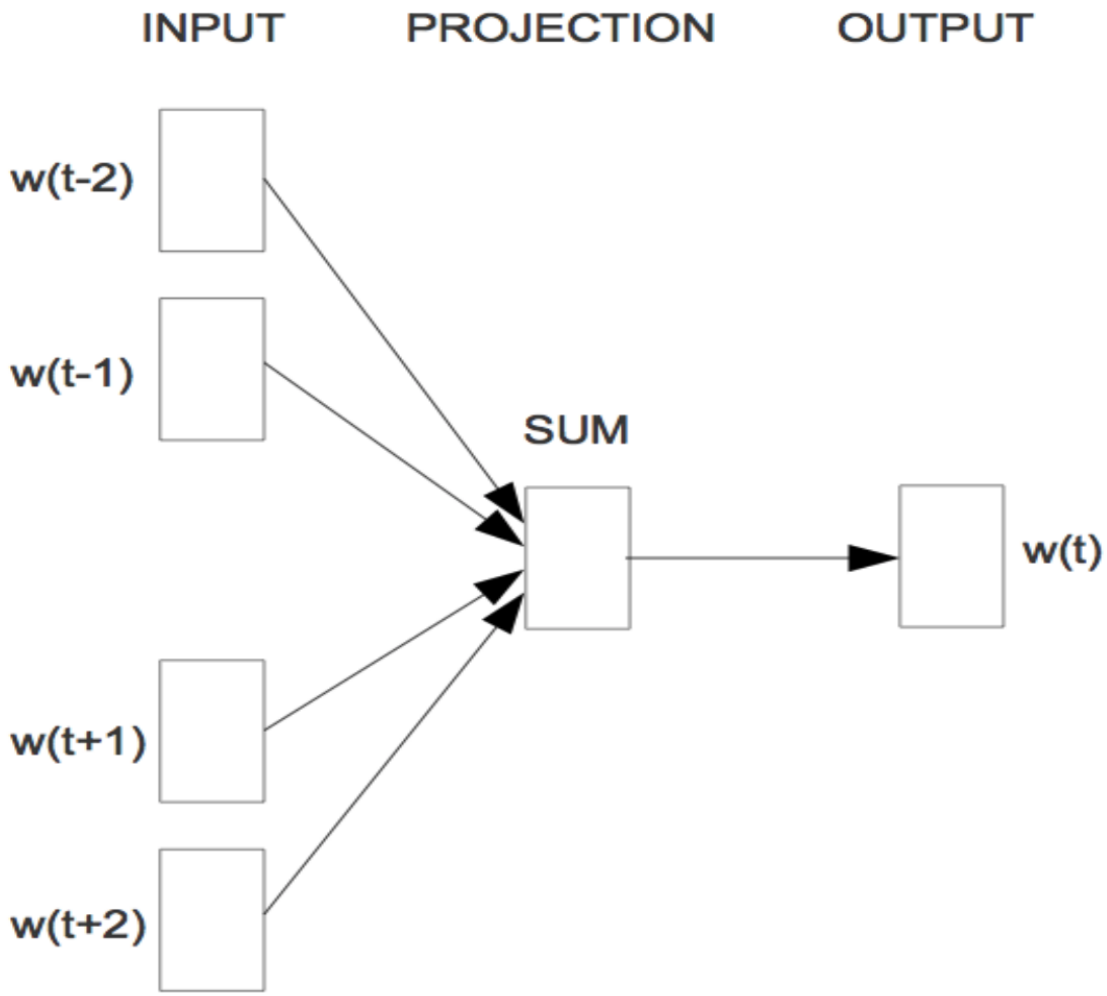
# Word2vec (Mikolov et al., 2013)

- A neural network model for learning word embeddings
- Main idea:
  - Predict the target words based on the neighbors (CBOW)
  - Predict neighbors given the target words (Skip-gram)



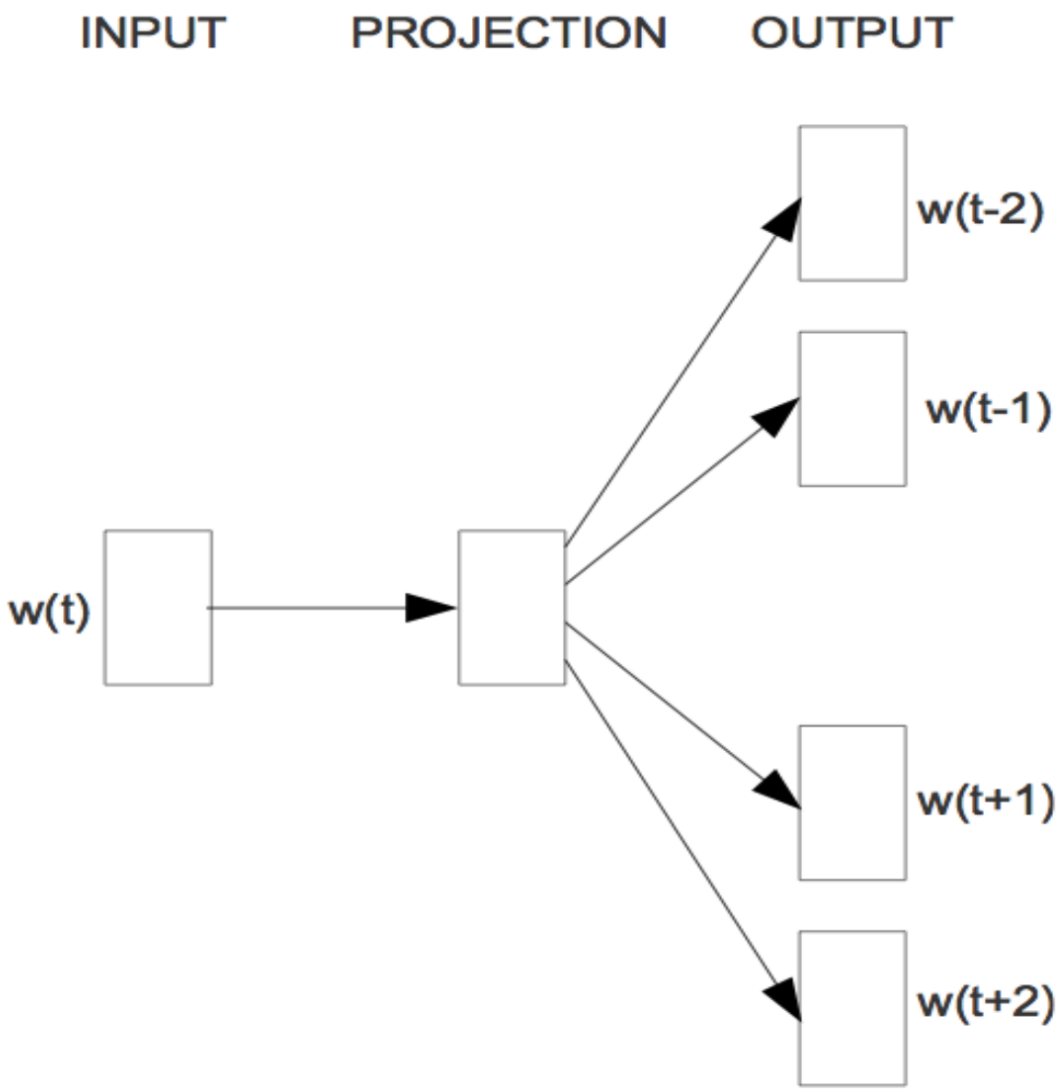
# CBOW

- Predict the target words based on the neighbors



# Skip-gram

- Predict neighbors using target word



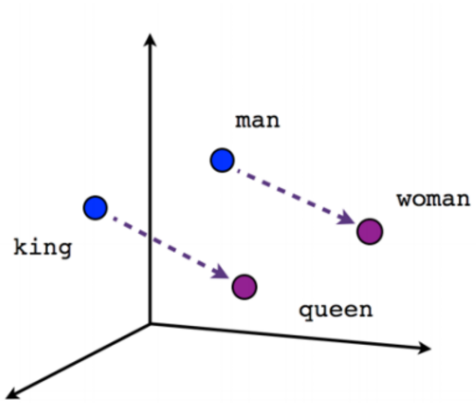
# More on skip-gram

- Learn the probability $P(w_{t+j}|w_t)$: the probability to see $w_{t+j}$ in target word $w_t$'s neighborhood
- Every word has two embeddings:
  - $v_i$ serves as the role of target
  - $u_i$ serves as the role of context
- Model probability as softmax:

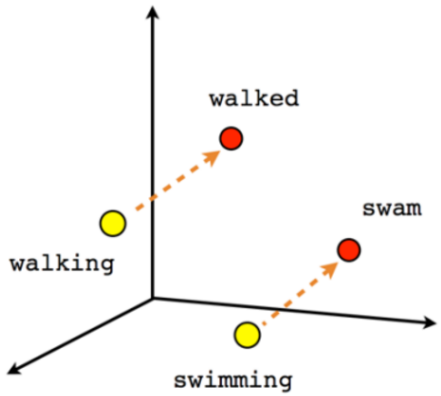
$$P(o|c) = \frac{e^{u_o^T v_c}}{\sum_{w=1}^{W} e^{u_w^T v_c}}$$

# Results

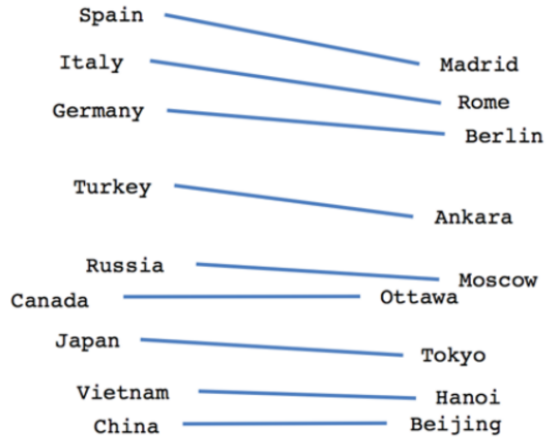
The low-dimensional embeddings are (often) meaningful:




Male-Female




Verb tense



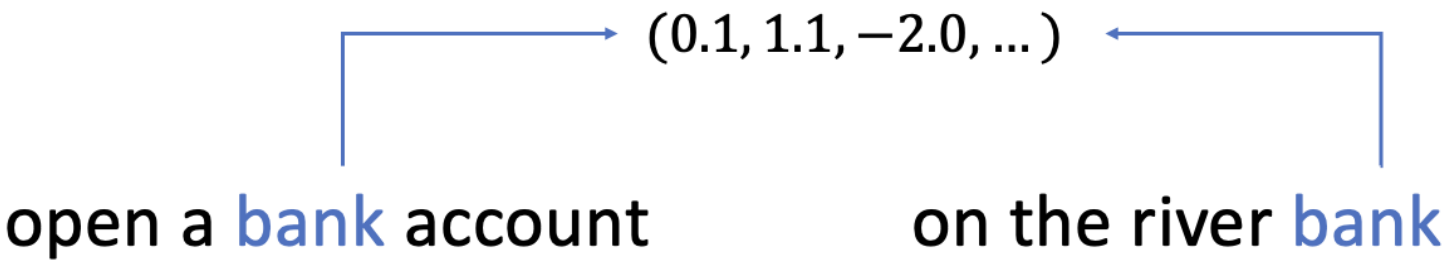

Country-Capital

Figure from https://www.tensorflow.org/tutorials/word2vec

# Contextual embedding

# Contextual word representation

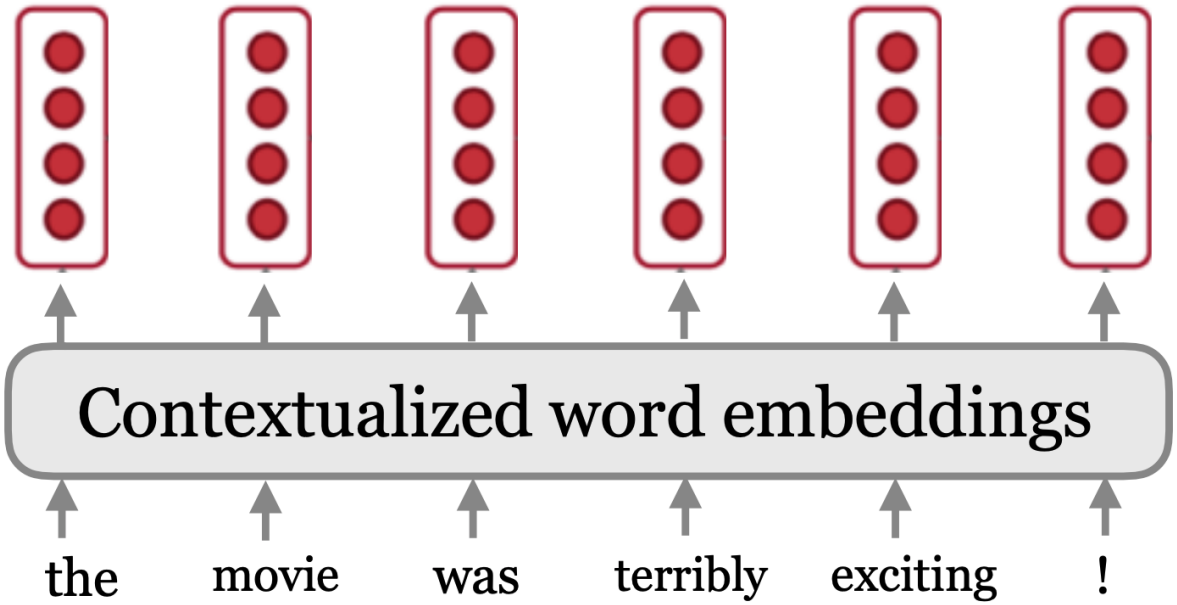
- Non-contextual word embedding:




- The semantic meaning of a word should depend on its context

# Contextual word representation

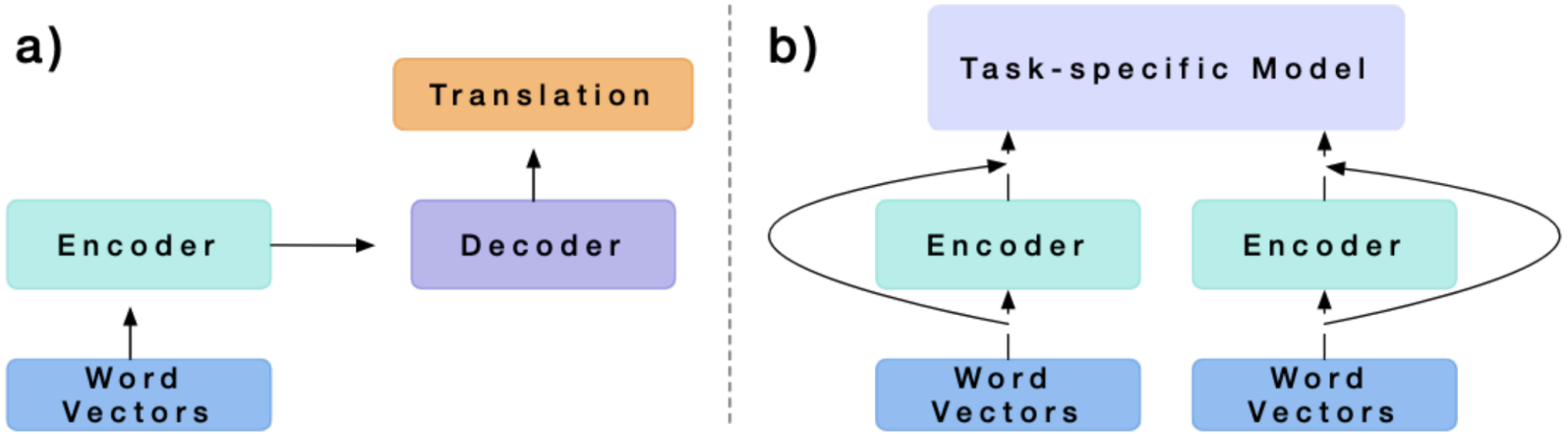
- Solution: Train a model to extract contextual representations on text corpus




- Share the model instead of the fixed embedding

# CoVe (McCann et al., 2017)

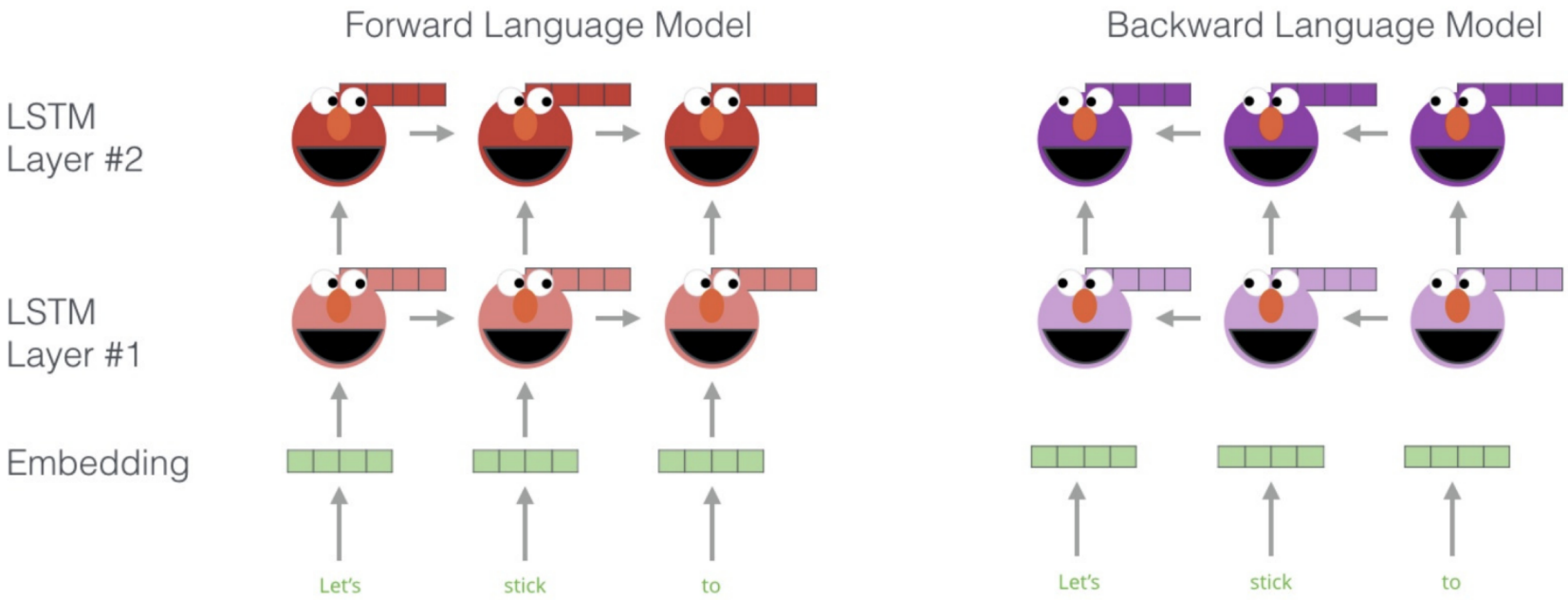
- Key idea: Train a standard neural machine translation model
- Take the encoder directly as contextualized word embeddings




- Bi-directional LSTM

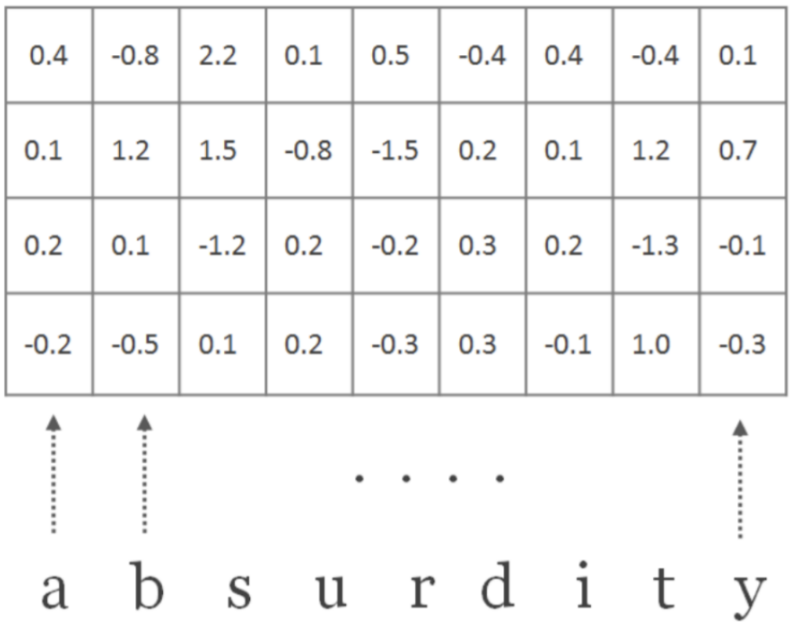
# ELMo (Peter et al., 2018)

- Key ideas:
  - Task: language model
  - Combine hidden states from multiple layers
  - Character level embedding



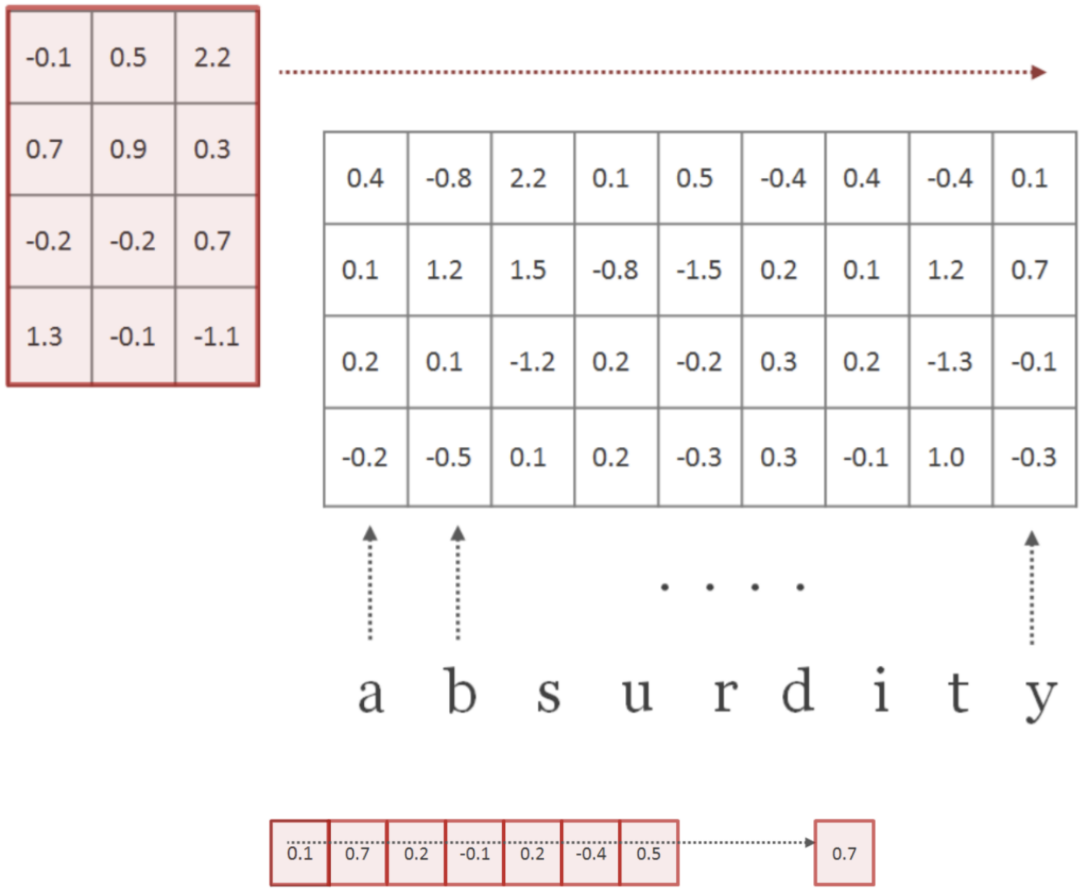
# Character Level Embedding

- Step 1: Break the word into a sequence of characters. Each character is mapped to an embedding vector.



# Character Level Embedding

- Step 2: Kernel convolve over the matrix and Max pooling




- Step 3: Multiple kernels ($d$) result in an $d$-dimensional vector

# ELMo results

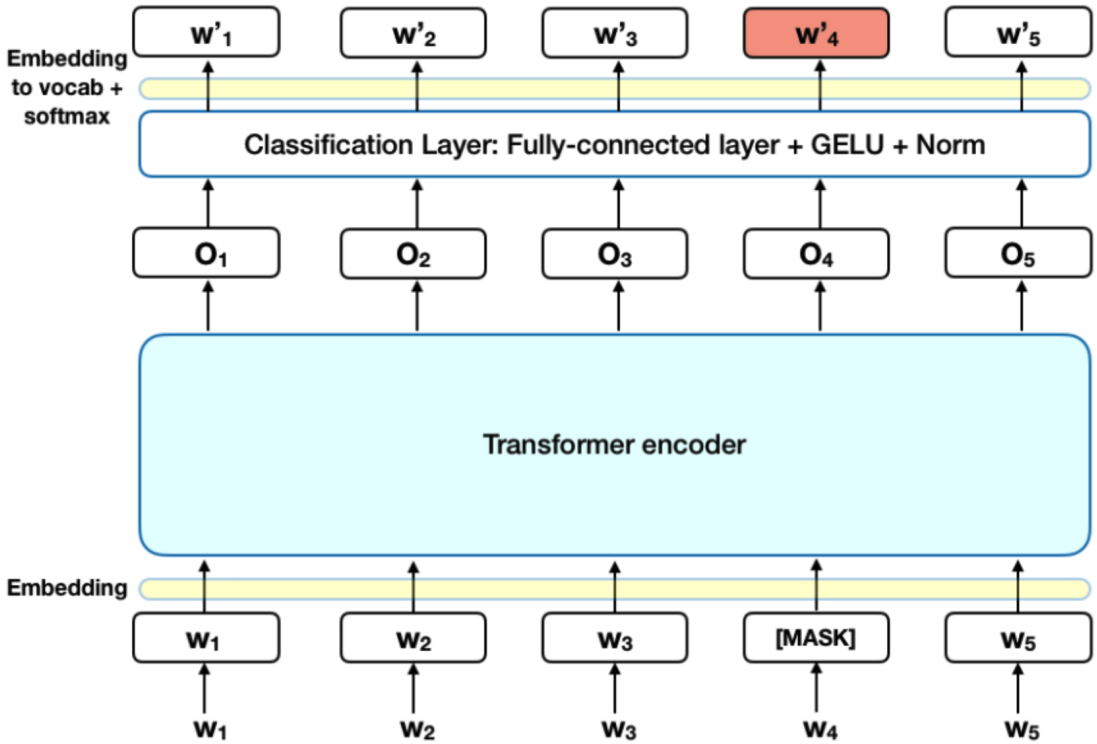
| Task | Previous SOTA | | Our baseline | ELMo + baseline | Increase (absolute/ relative) |
|---|---|---|---|---|---|
| SQuAD | Liu et al. (2017) | 84.4 | 81.1 | 85.8 | 4.7 / 24.9% |
| SNLI | Chen et al. (2017) | 88.6 | 88.0 | $88.7 \pm 0.17$ | 0.7 / 5.8% |
| SRL | He et al. (2017) | 81.7 | 81.4 | 84.6 | 3.2 / 17.2% |
| Coref | Lee et al. (2017) | 67.2 | 67.2 | 70.4 | 3.2 / 9.8% |
| NER | Peters et al. (2017) | $91.93 \pm 0.19$ | 90.15 | $92.22 \pm 0.10$ | 2.06 / 21% |
| SST-5 | McCann et al. (2017) | 53.7 | 51.4 | $54.7 \pm 0.5$ | 3.3 / 6.8% |

# BERT

- Key ideas: replace LSTM by Transformer
- Define the generated pretraining task by masked language model
- Two pretraining tasks
- Finetune both BERT weights and task-dependent model weights for each task

# BERT pretraining loss

- Masked language model: predicting each word by the rest of sentence
- Next sentence prediction: the model receives pairs of sentences as input and learns to predict if the second sentence is the subsequent sentence in the original document.

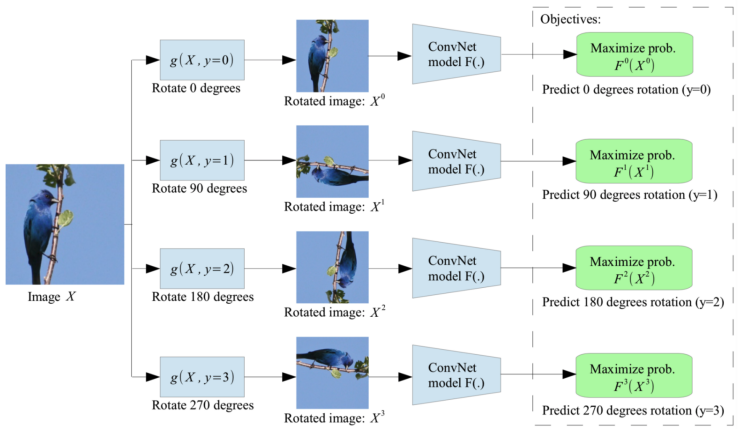


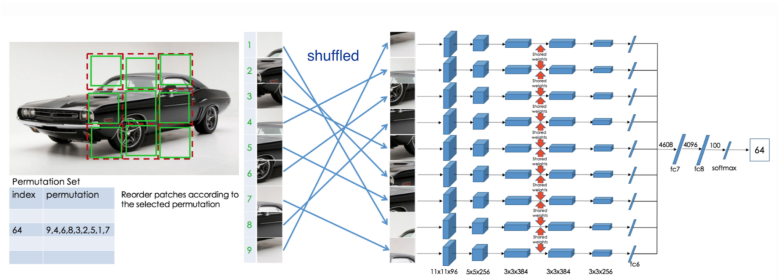
# BERT results

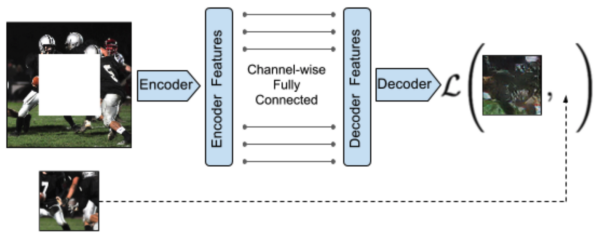
| System | MNLI-(m/mm) 392k | QQP 363k | QNLI 108k | SST-2 67k | CoLA 8.5k | STS-B 5.7k | MRPC 3.5k | RTE 2.5k | **Average** - |
|---|---|---|---|---|---|---|---|---|---|
| Pre-OpenAI SOTA | 80.6/80.1 | 66.1 | 82.3 | 93.2 | 35.0 | 81.0 | 86.0 | 61.7 | 74.0 |
| BiLSTM+ELMo+Attn | 76.4/76.1 | 64.8 | 79.8 | 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** |

# Unsupervised pretraining for Vision

- Pretrain image encoders without using labels
- Many "pretraining tasks" have been proposed
  - Rotation, coloring, jigsaw puzzle, generative modeling



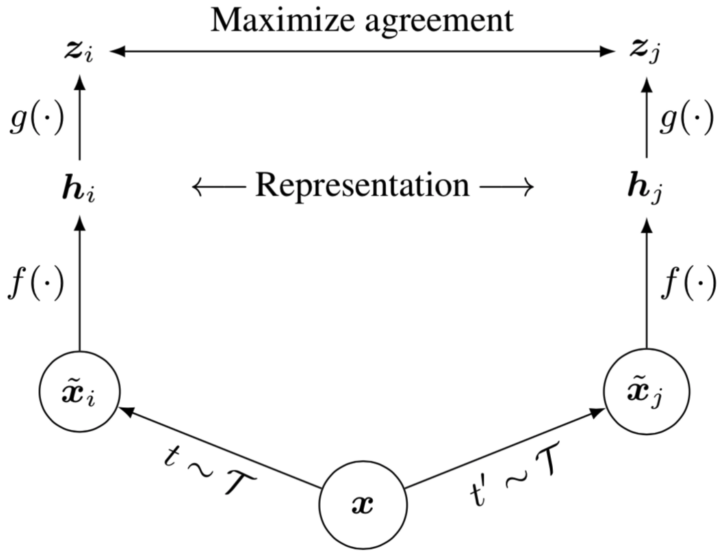



# Contrastive learning

- Learns representations of visual inputs by maximizing agreement between differently augmented views of the same sample (SimCLR, Chen et al., 2020)
  - Randomly sample a batch of images, for each $x$ generate $\tilde{x}_i, \tilde{x}_j$ based on different augmentations
  - Pass each image into encoder $z_i = g(f(\tilde{x}_i))$
  - Contrastive loss:

$$L_{i,j} = -\log \frac{e^{\text{sim}(z_i, z_j)/\tau}}{\sum_{k \neq i} e^{\text{sim}(z_i, z_k)/\tau}}$$



# Conclusions

- PPMI
- Word2vec
- Contextual embedding

Questions?