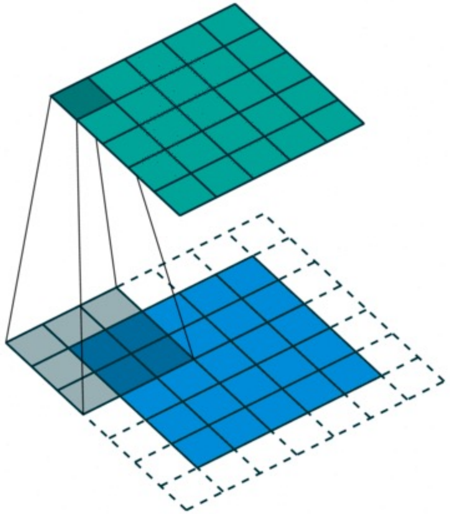
Announcements

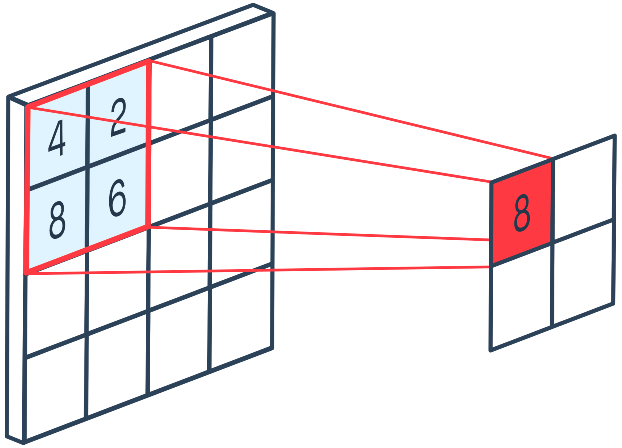
- HW 5 due **Wednesday, November 8at 8pm**
- Project Milestone 2 due **Wednesday, November 15 at 8pm**
- Recitation Friday, November 10th at 2:30pm
  - In Wu & Chen (Levine 101)

Recap: Pooling & Convolution

- Use layers that capture structure



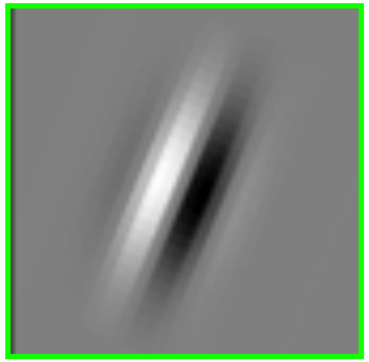
Convolution layers
(Capture equivariance)

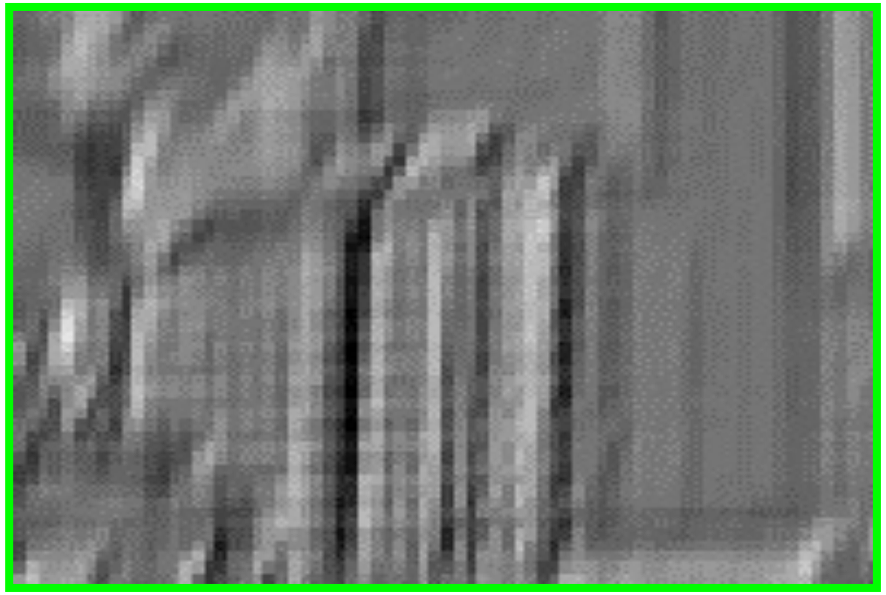


Pooling layers
(Capture invariance)

https://towardsdatascience.com/types-of-convolutions-in-deep-learning-717013397f4d
https://peltarion.com/static/2d_max_pooling_pa1.png

Recap: Convolution Layers

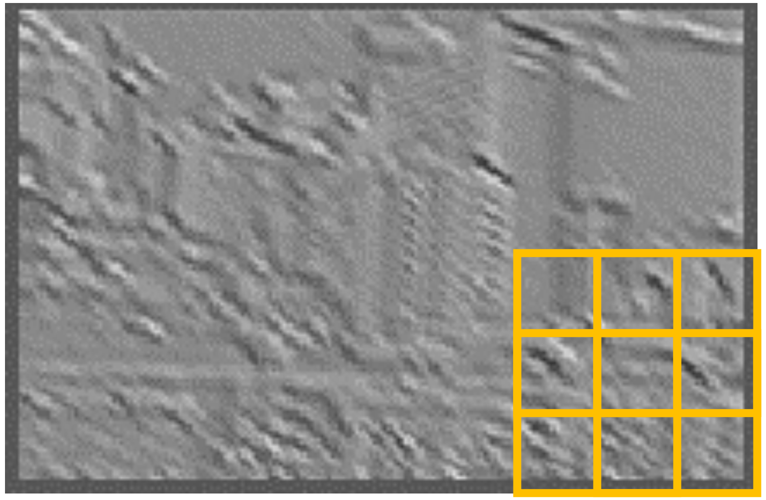


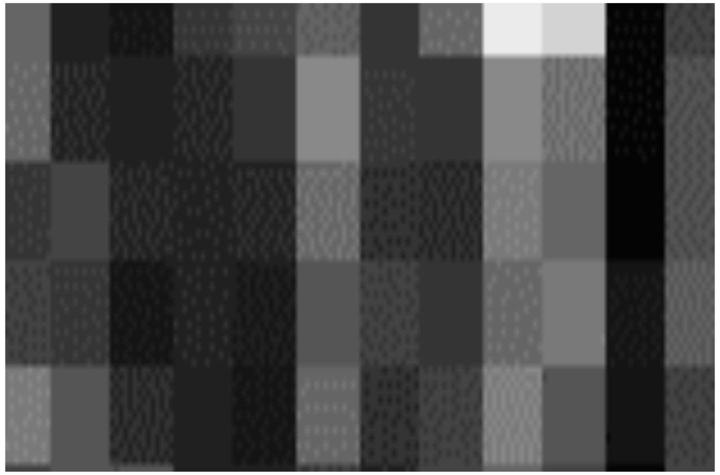


$$\text{output}[i,j] = \sum_{\tau=0}^{k-1}\sum_{\gamma=0}^{k-1} \text{filter}[\tau,\gamma] \cdot \text{image}[i+\tau, j+\gamma]$$

graphic credit: S. Lazebnik

Recap: Pooling Layers





$$\text{output}[i,j] = \max_{0 \le \tau < k} \max_{0 \le \gamma < k} \text{image}[i+\tau, j+\gamma]$$

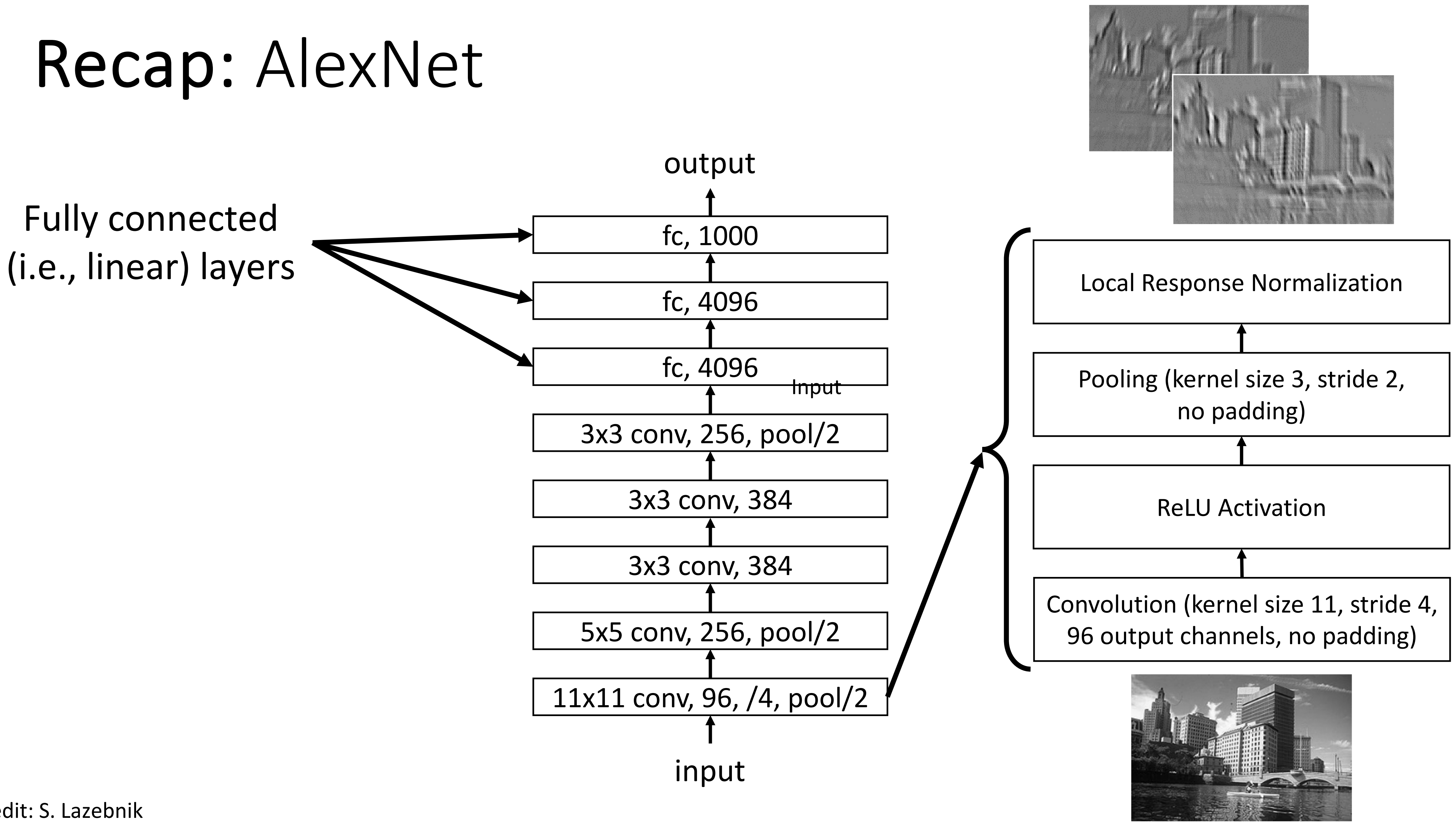
Recap: Convolution vs. Pooling

- **Convolution layers:** Translation equivariant
  - If object is translated, convolution output is translated by same amount
  - Produce "image-shaped" features that retain associations with input pixels

- **Pooling layers:** Translation invariant
  - Binning to make outputs insensitive to translation
  - Also reduces dimensionality

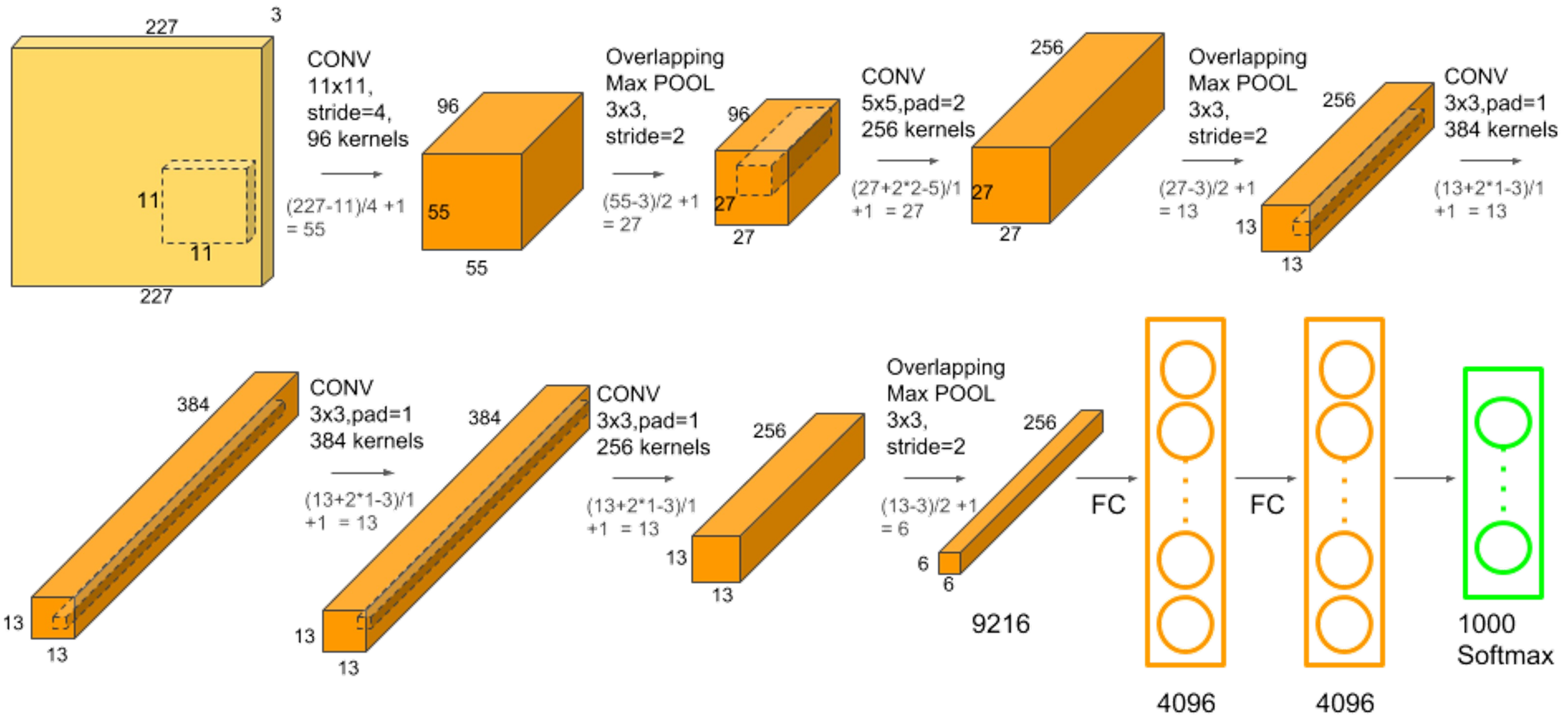
- Combined in modern architectures
  - Convolution to construct equivariant features
  - Pooling to enable invariance

Recap: AlexNet



slide credit: S. Lazebnik

Recap: AlexNet



Recap: Residual Connections

- **Challenges with deep networks**
  - Overfitting?
  - No, 56 layer network underfits!
- **Optimization/representation**
  - Difficulty representing the identity function!
- **Solution:** "Skip" connections
  - Facilitate direct feedback from loss
  - Easy to represent identity function

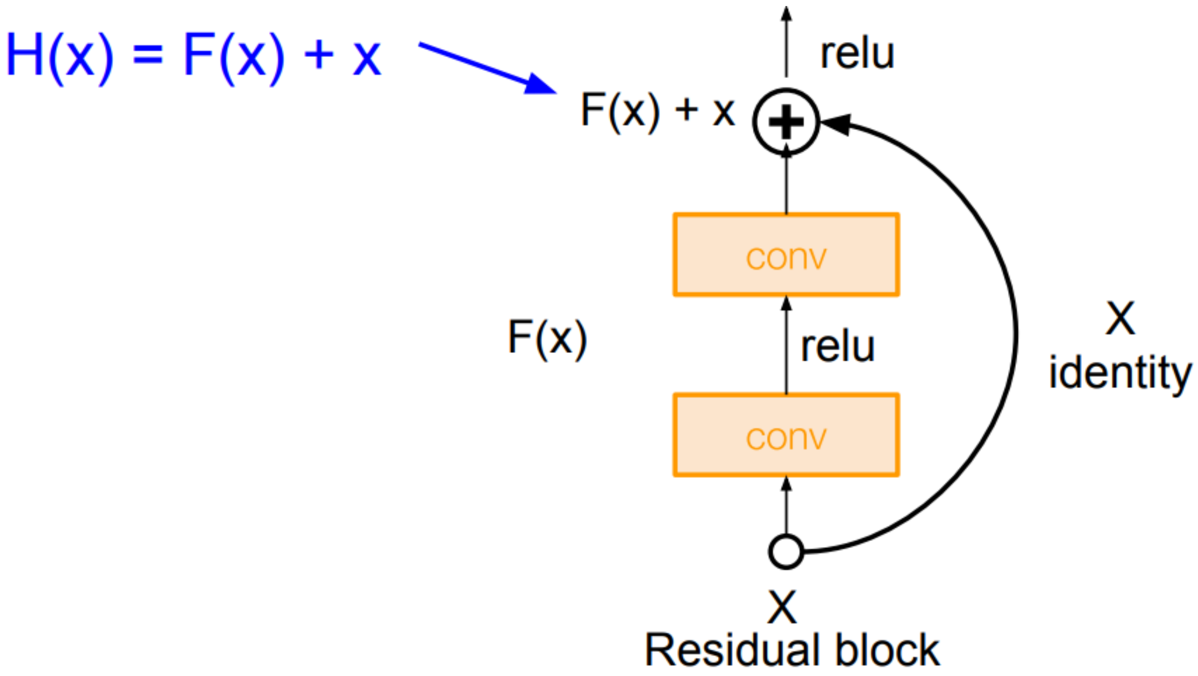


Image credit: Fei-Fei Li, Justin Johnson, Serena Yeung

Recap: Residual Networks

- Stack lots of residual blocks!
  - Kernel size 3, no padding, stride 1, no pooling
  - Reduce feature dimensions by using stride 2 once every K blocks
  - Maintains feature size to build very deep nets

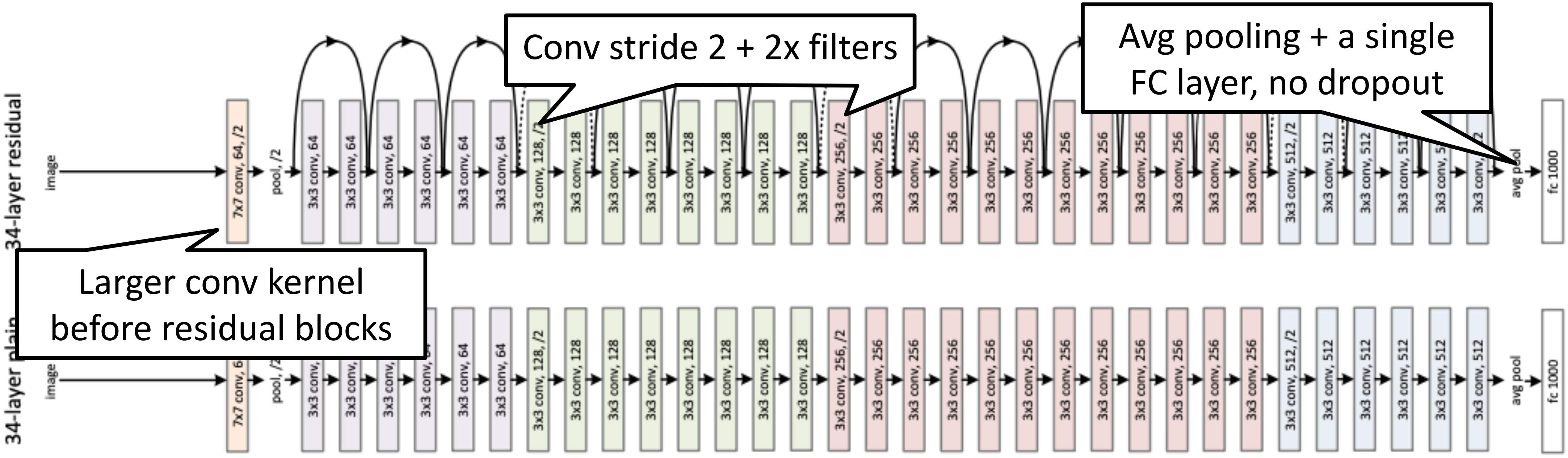


Image credit: He et al, Residual Nets, 2015

Recap: Transfer Learning/Finetuning

- **Transfer learning:** We can reuse trained concepts!
  - Since CNNs trained on ImageNet appear to learn general features
  - We can reuse these models in some way to perform new tasks
- **Strategy 1:** Feature extraction
  - Remove final (softmax) layer and replace with a new one
  - Train only the new layer
- **Strategy 2:** Finetuning
  - Do the same thing but train end-to-end

Lecture 18: NLP (Part 1)

CIS 4190/5190

Fall 2023

Goals of NLP

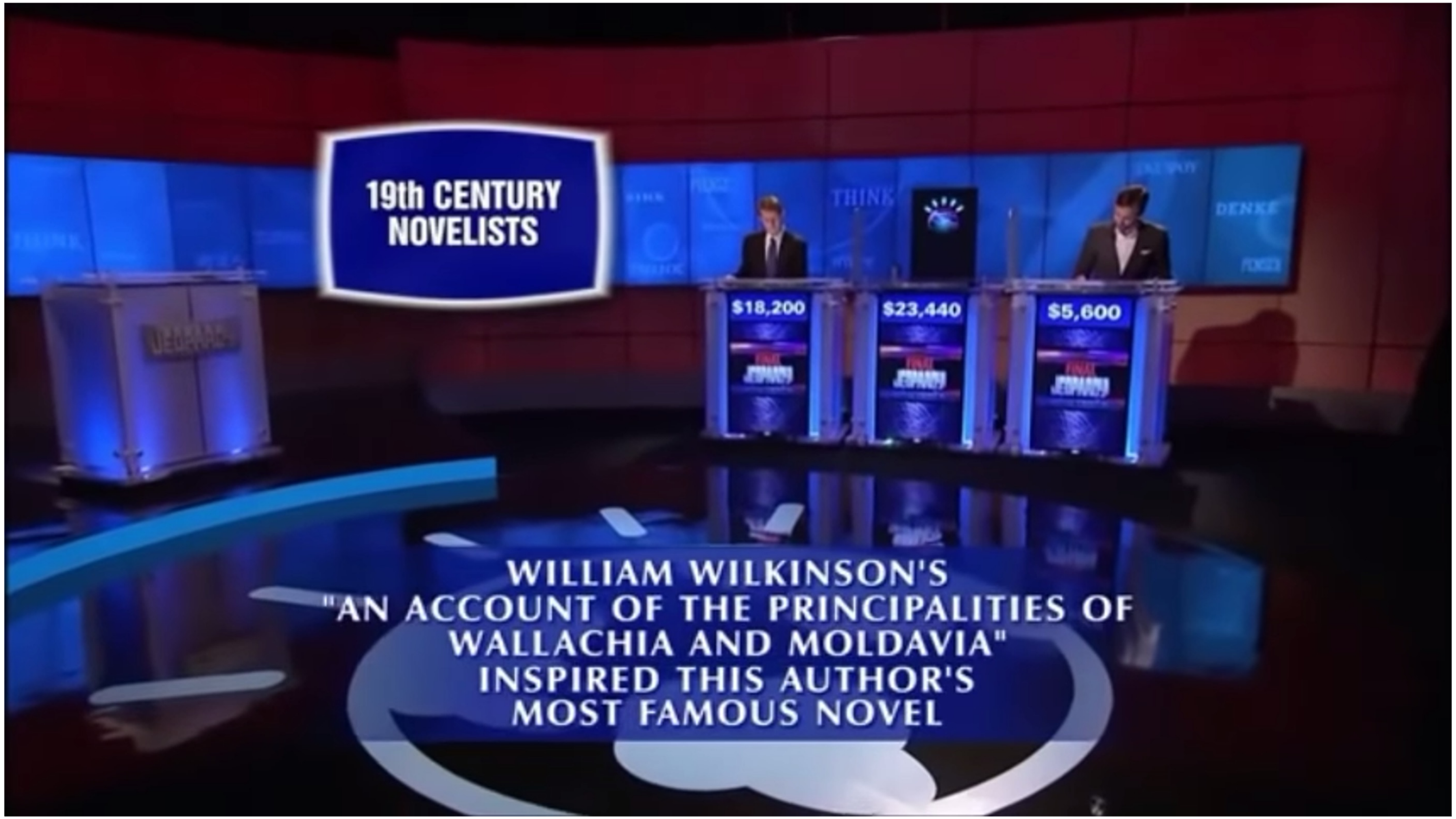
- Recognize spam email, fake news articles, etc.
- Read a textbook and solve an exam question
- Translate from English to French
- Search for webpages relevant to a search query
- Read tweets and understand public sentiment on a topic

- **Generally:** We would like to be able to understand text and extract all the same kinds of information in the same ways as humans might

Language Understanding is Hard!

- Did Abraham Lincoln have an iPhone?
  - No! (requires common sense)
- Mary fought with Kate because she was a bad person. Who was a bad person? Mary or Kate?
  - Ambiguous (requires long-term context)
- The guitar didn’t fit into the box because it was too small. What was too small? The guitar or the box?
  - The box (requires common sense)

IBM Watson Jeopardy! Challenge



https://www.youtube.com/watch?v=Sp4q60BsHoY

Smart Assistant Advancements

Google Assistant

Machine Translation

Question Answering

The first recorded travels by Europeans to China and back date from this time. The most famous traveler of the period was the Venetian Marco Polo, whose account of his trip to "Cambaluc," the capital of the Great Khan, and of life there astounded the people of Europe. The account of his travels, Il milione (or, The Million, known in English as the Travels of Marco Polo), appeared about the year 1299. Some argue over the accuracy of Marco Polo's accounts due to the lack of mentioning the Great Wall of China, tea houses, which would have been a prominent sight since Europeans had yet to adopt a tea culture, as well the practice of foot binding by the women in capital of the Great Khan. Some suggest that Marco Polo acquired much of his knowledge through contact with Persian traders since many of the places he named were in Persian.

How did some suspect that Polo learned about China instead of by actually visiting it?

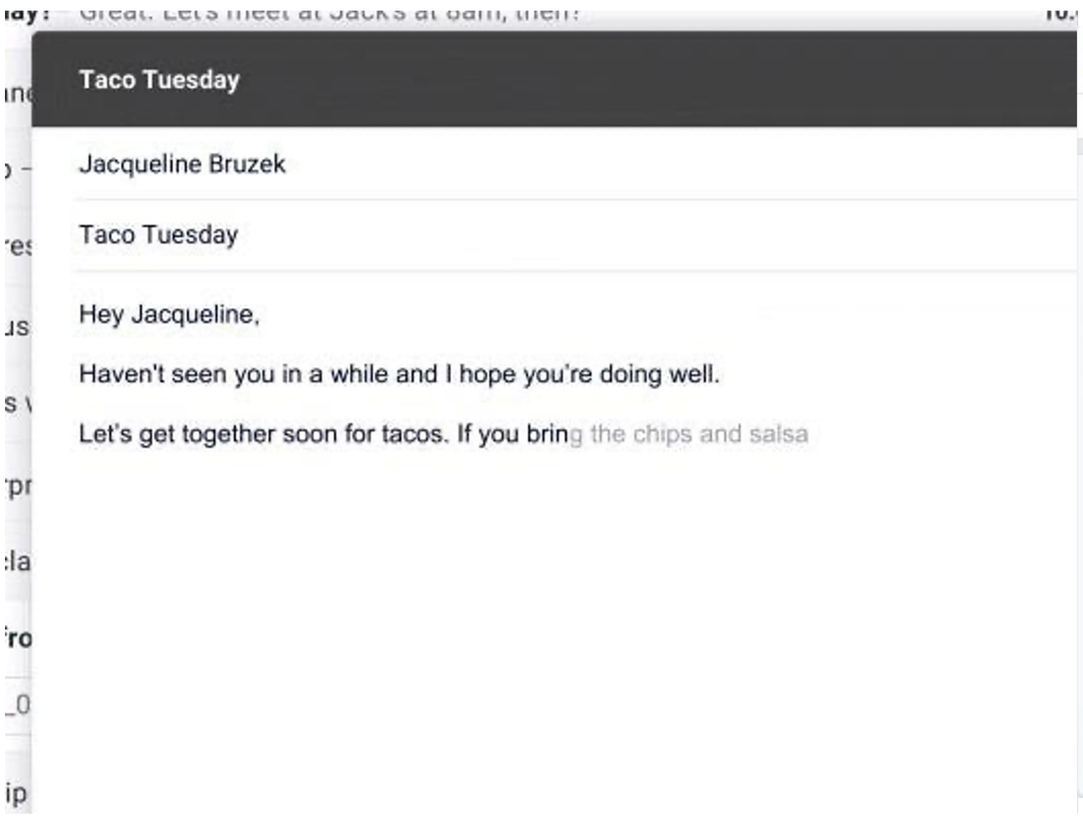
Answer: through contact with Persian traders

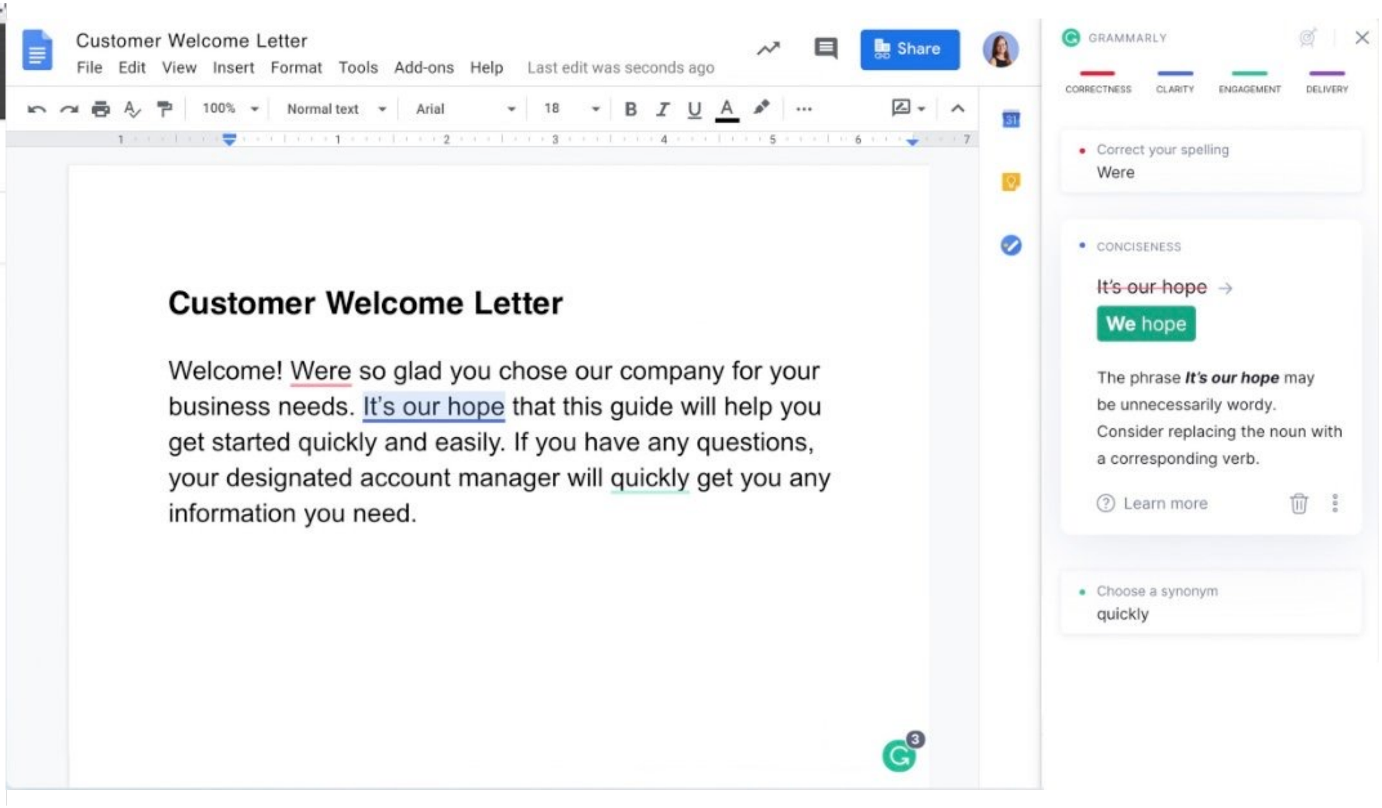
Leaderboard

SQuAD2.0 tests the ability of a system to not only answer reading comprehension questions, but also abstain when presented with a question that cannot be answered based on the provided paragraph.

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Apr 06, 2020	SA-Net on Albert (ensemble) *QIANXIN*	**90.724**	**93.011**
2 May 05, 2020	SA-Net-V2 (ensemble) *QIANXIN*	90.679	92.948
2 Apr 05, 2020	Retro-Reader (ensemble) *Shanghai Jiao Tong University* http://arxiv.org/abs/2001.09694	90.578	92.978

Text Completion





Text Generation

Prompt

Write a creative ad for the following product to run on Facebook aimed at parents:

Product: Learning Room is a virtual environment to help students from kindergarten to high school excel in school.

Sample response

Are you looking for a way to help your child excel in school? Look no further than Learning Room! Our virtual environment is designed to help students from kindergarten to high school learn and grow. With our help, your child will be able to get ahead in school and achieve their academic goals.

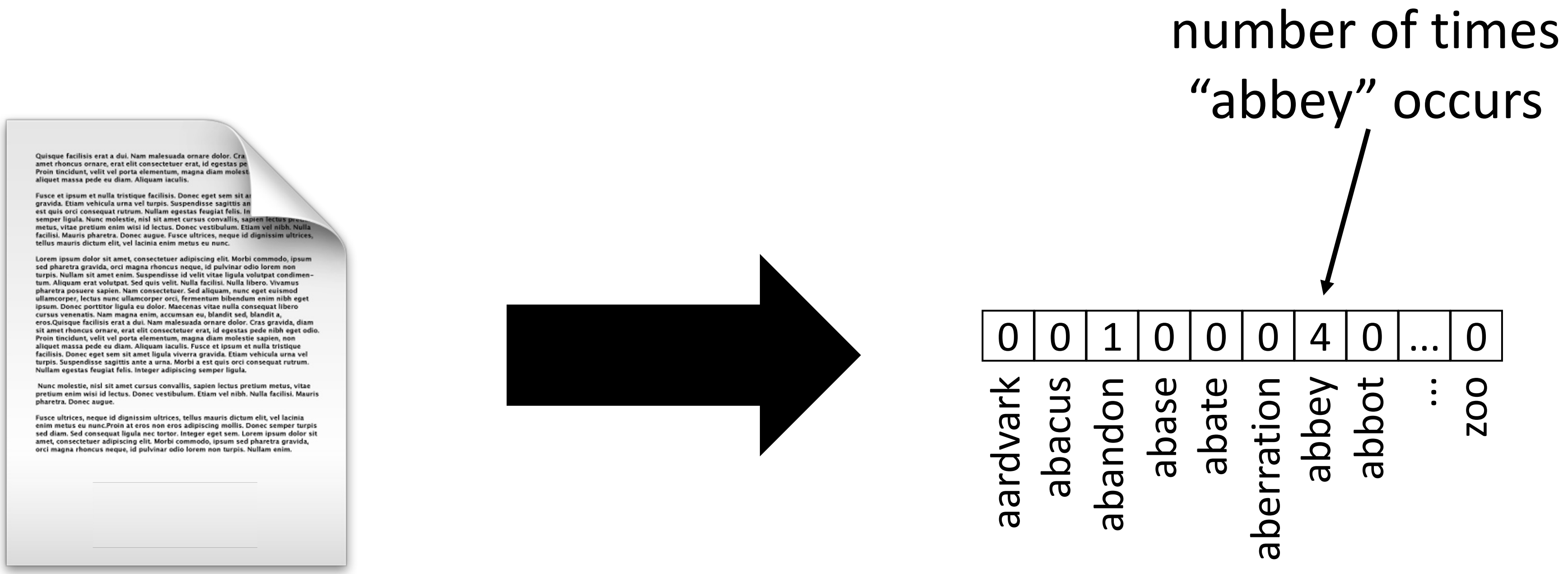
Basic NLP Pipeline

- **Classical approach**
  - **Step 1:** Manually construct feature mapping from text to $\mathbb{R}^d$
  - **Step 2:** Run supervised learning algorithm in conjunction with feature map
- **Deep learning approach**
  - **Step 1:** Design neural network architecture that can take text as input
  - **Step 2:** Train neural network end-to-end

Bag of Words Feature Map

- **Idea:** Treat each document as an **unordered** set of words
  - Simple but can be effective choice in practice
- **Lexicon:** Set of "all possible words"
  - Union of words from all documents in the dataset
  - Use a dictionary
  - Include "unknown" word
- Then, represent document as a vector $x \in \mathbb{R}^d$, where d is number of words in the lexicon
  - x_j is the number of occurrences of word j in the document

Bag of Words Feature Map



document x

$\phi(x)$

Shortcomings of Bag of Words

- Cannot distinguish word senses (which come from **context**)
  - “Took money out of the **bank**”
  - “Got stuck on the river **bank**”
  - “The pilot tried to **bank** the plane”

- Significance of some words vs. others
  - Articles (“a”, “an”, “the”) vs. unusual terms (“hagiography”)

Shortcomings of Bag of Words

- Ignores the fact that some words are more similar than others
  - “I have a dog”
  - “I have a cat”
  - “I have a tomato”

- Ignores ordering of words
  - “Mary runs faster than Jack”
  - “Jack runs faster than Mary”

Improvements to Bag of Words

- $\boldsymbol{n}$**-grams:** Each feature counts the number of times a sequence of n words occurs in the document
  - "I have a cat" → ["I have": 1, "have a": 1, "a cat": 1]
  - **Shortcoming:** Quickly becomes high dimensional!

- **TF-IDF:** Downweight words that occur across many documents
  - "a" counts for a lot less than "hagiography"
  - Can be used for feature selection

Practical Pipeline

- Basic preprocessing (filter stop words, lemmatize, etc.)
  - **Stop words:** “and”, “the”, etc. (lists are available)
  - **Lemmatize:** Remove conjugation (e.g., implemented in NLTK)
- Construct bigrams (i.e., 2-grams)
- Use TF-IDF to rank bigrams, and select top K (e.g., $K = 500$)
  - Also, manually process list
- Train machine learning model

Alternatives?

- Can we automatically learn representations of words?

- We can use deep learning to do so, but classical unsupervised learning approaches can also work well
  - Specialized to NLP

Word Embeddings

- **Embed words as vectors**
  - Automatically learn feature map $\phi(x) \in \mathbb{R}^d$
- **Bag-of-words:** $\phi(x) = \sum_{\text{word } i \in \text{document } x} \text{OneHot}(i)$
  - $\text{OneHot}(i)$ is the vector with all zeros except it equals one at position corresponding to word i
  - $\text{OneHot}(\text{“dog”}) = [0, 0, 0, 1, 0, 0, 0]$
  - $\text{OneHot}(\text{“cat”}) = [1, 0, 0, 0, 0, 0, 0]$
- We want to learn embeddings where the structure captures semantics, e.g., nearby vectors correspond to similar words

Document-Term Matrix

- Counts the number of times each word occurs in each document

Wikipedia Article / Words	**Cat**	**Dog**	Apple Inc.	Apple (fruit)	Microsoft Inc.	…
a	377	370	842	231	286	…
the	929	787	1690	503	872	…
apple	0	0	1091	166	14	…
computer	0	0	88	0	36	…
fur	15	2	0	0	0	…
hair	6	6	0	0	0	…
…	…	…	…	…	…	…

Document-Term Matrix

- **Key observation:** Similar words tend to co-occur

Wikipedia Article / Words	**Cat**	**Dog**	Apple Inc.	Apple (fruit)	Microsoft Inc.	…
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…	…	…	…	…	…	…

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hair	6	6	0	0	0	…
…	…	…	…	…	…	…

Document-Term Matrix

- **Key observation:** Similar words tend to co-occur
- **Potential idea:** Represent word by its row!

Wikipedia Article / Words	**Cat**	**Dog**	Apple Inc.	Apple (fruit)	Microsoft Inc.	…
a	377	370	842	231	286	…
the	929	787	1690	503	872	…
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fur	15	2	0	0	0	…
hair	6	6	0	0	0	…
…	…	…	…	…	…	…

Term-Term Matrix

- **Shortcoming:** Document-term matrix depends heavily on structure of documents in the training data
- **Alternative:** Term-term matrix counts co-occurrences of pairs of words across all documents

Term-Term Matrix

- Count how many times a word appears within the neighborhood "context" of another word (e.g., 4 words to the left/right)

Words Words	**pet**	**play**	tire	engine	run	…
dog	872	649	1	7	378	…
cat	789	831	5	0	285	…
tomato	12	4	290	927	562	…
…	…	…	…	…	…	…

Term-Term Matrix

- Count how many times a word appears within the neighborhood "context" of another word (e.g., 4 words to the left/right)
  - **Idea:** Represent each word by its row

Words / Words	**pet**	**play**	tire	engine	run	…
dog	872	649	1	7	378	…
cat	789	831	5	0	285	…
tomato	12	4	290	927	562	…
…	…	…	…	…	…	…

Term-Term Matrix

- **Intuition:** Each words is represented by words in its neighborhood

- "The **distributional hypothesis** in linguistics is derived from the semantic theory of language usage, i.e. words that are used and occur in the same contexts tend to purport similar meanings."
  - *"A word is characterized by the company it keeps"* – John Firth

Term-Term Matrix

- For example, the words that frequently co-occur with “dog” in a sentence might be words like “play”, “pet”, “sleep”, “fur”, “feed”, etc.
  - Would these words tend to co-occur with “cat”?
  - How about with “tomato”?
  - “I have a pet cat”
  - “I have a pet dog”
  - “I have a pet tomato”

- Similar words have similar embeddings

Shortcomings of Classical Approaches

- **Word embedding vector dimensions:**
  - Document-term = # of documents
  - Term-Term = # of words
- These are huge vectors!
  - Can we get a more compact representation?
- **Idea:** Train a neural network classifier to predict whether one word will co-occur in the context of another word
  - The **classifier weights** can be interpreted as word embeddings!

Word2Vec

- **Idea:** Train a neural network classifier to predict whether one word will co-occur in the context of another word

- Then, the **classifier weights** can be interpreted as word embeddings!

Word2Vec Training Data

- “The quick brown fox jumped over the lazy dog.”

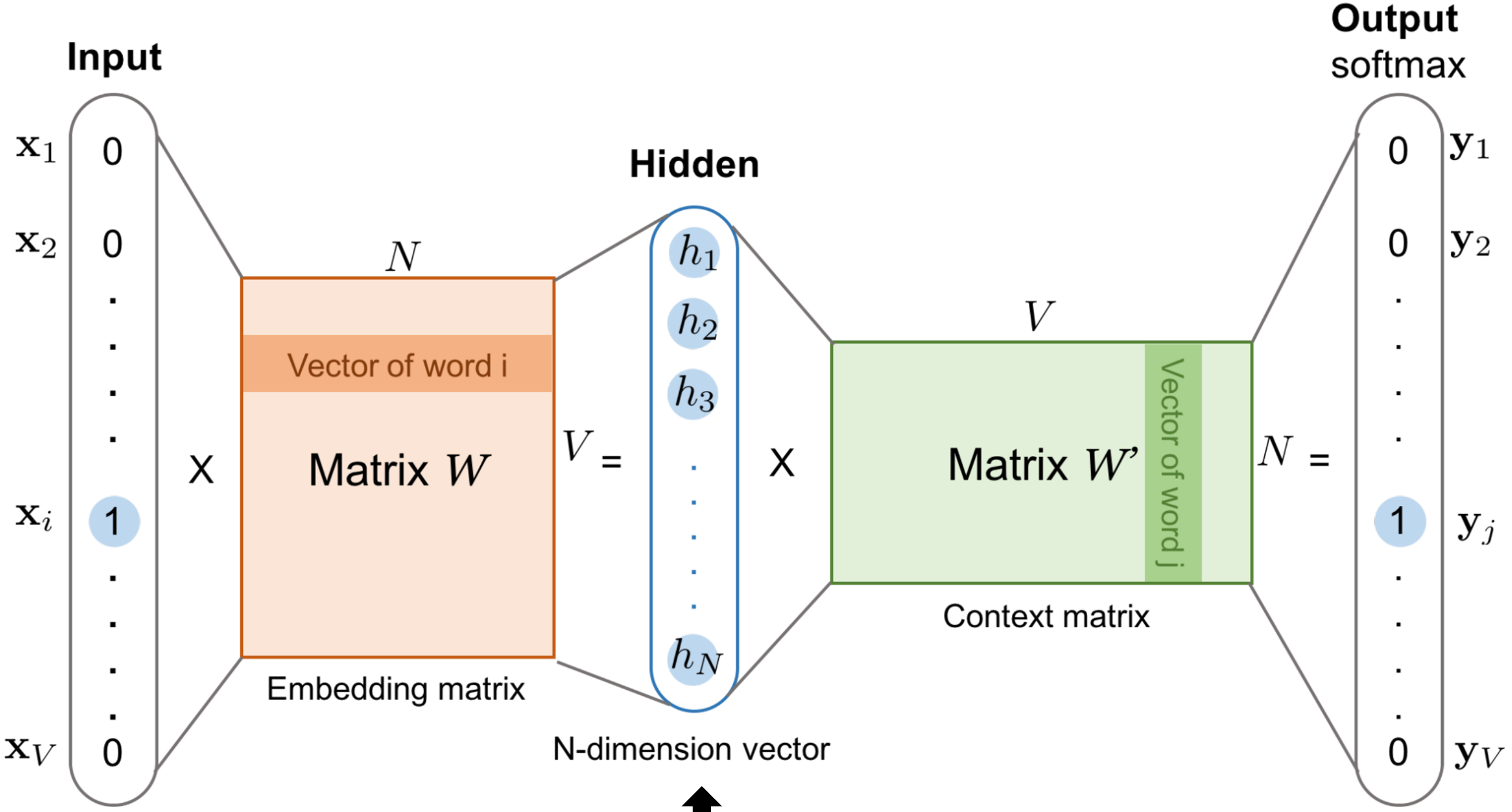
Word	**Context**
the	[quick]
quick	[the, brown]
brown	[quick, fox]
…	…

Word2Vec Training Data

- “The quick brown fox jumped over the lazy dog.”

Word	**Context**
the	quick
quick	the
quick	brown
brown	quick
brown	fox
…	…

Word2Vec Model



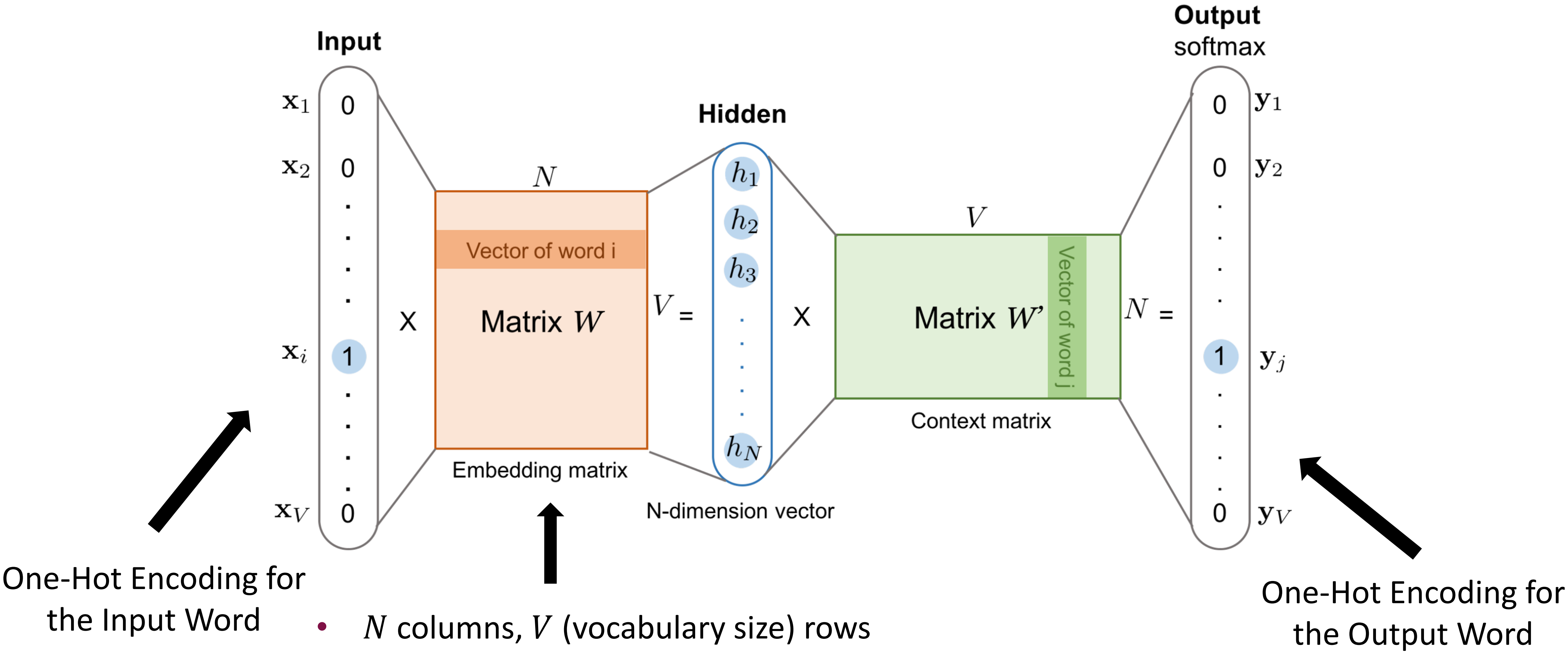
One-Hot Encoding for the Input Word

N hidden units, for $N \ll V$

One-Hot Encoding for the Output Word

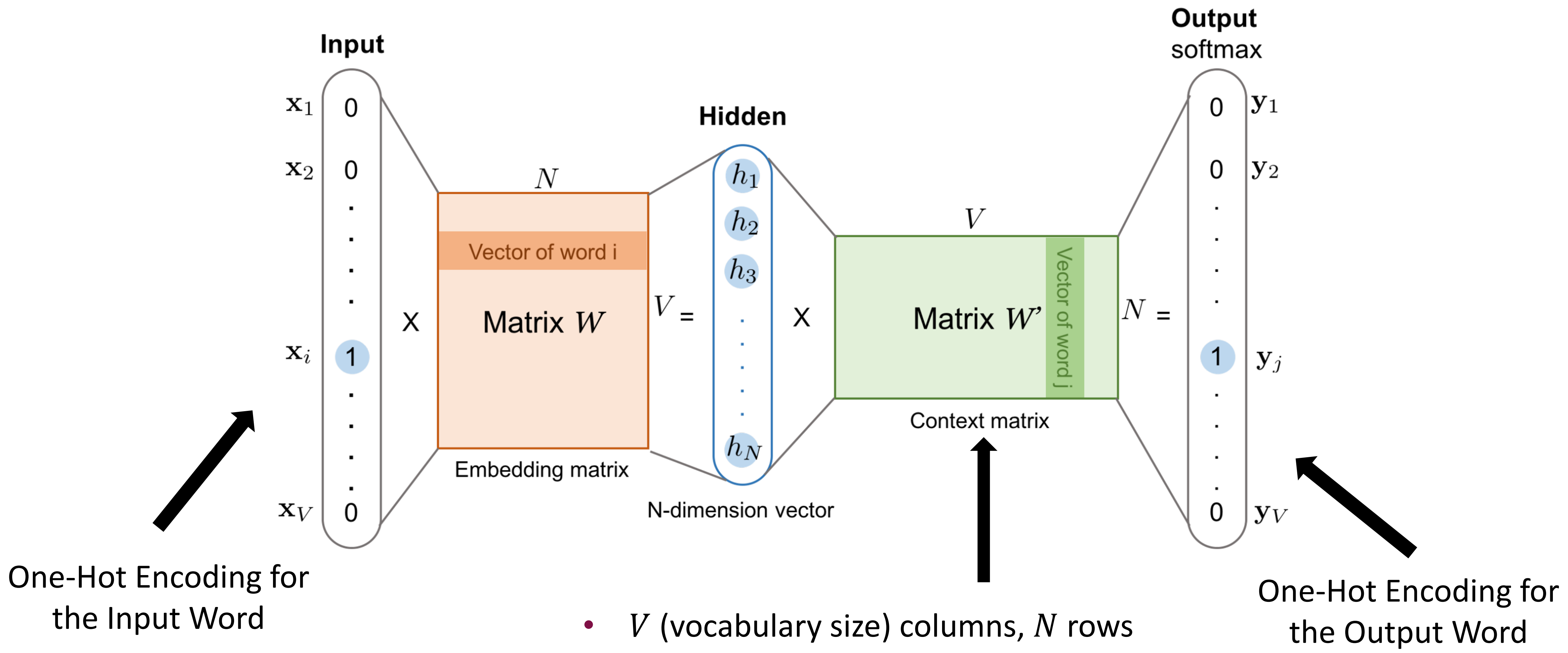
Source: https://lilianweng.github.io/lil-log/2017/10/15/learning-word-embedding.html

Word2Vec Model



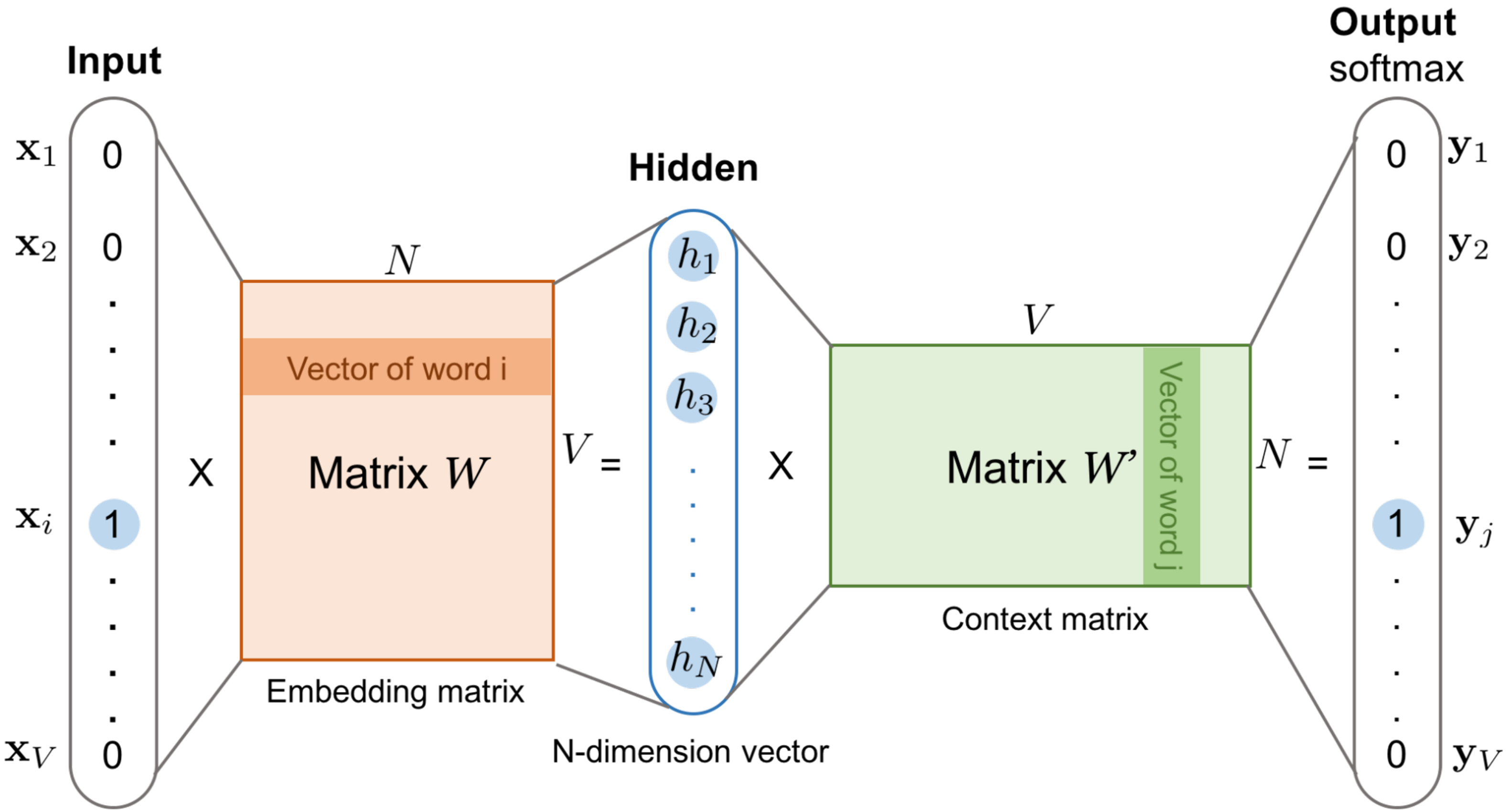
- N columns, V (vocabulary size) rows
- Each row corresponds to a word
- Row i = embedding for word i, called "target embedding"

Word2Vec Model



- V (vocabulary size) columns, N rows
- Each column corresponds to a word
- Column i = embedding for word i, called "context embedding"

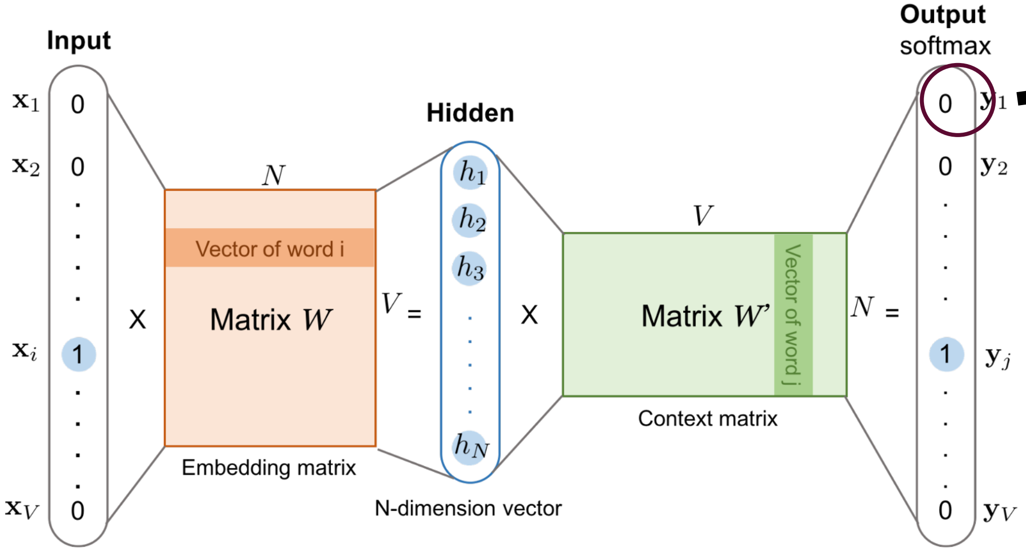
Word2Vec Model



We can concatenate the target and context embeddings to form our final word embedding

Word2Vec Training

- Standard softmax loss, then train the neural network

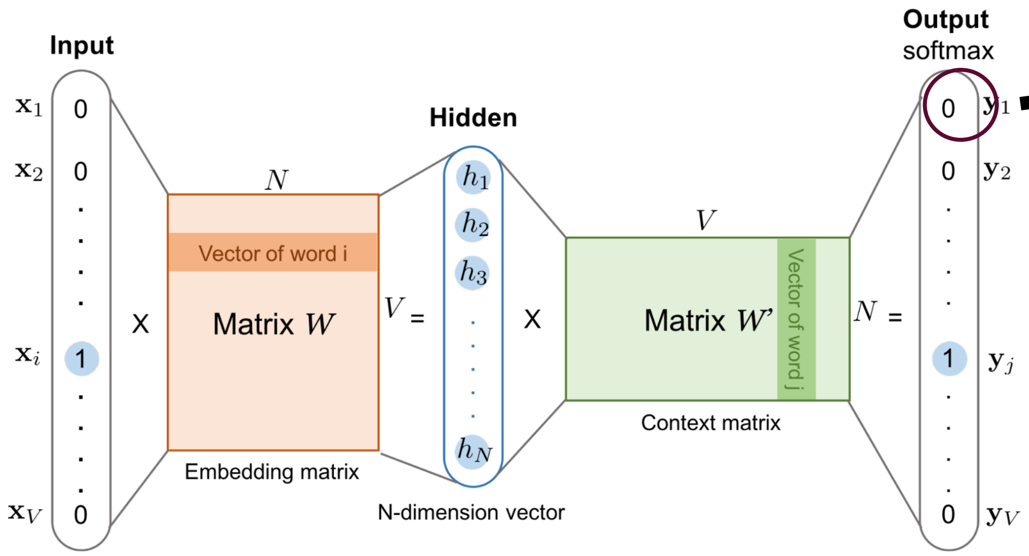


$$p(w_o|w_{in}) = \frac{\exp(v'_{w_o} . v_{w_{in}})}{\sum_{k=1}^{V} \exp(v'_{w_k} . v_{w_{in}})}$$

- Computing this denominator will be expensive.
- Remember that the vocabulary size V is of the order of millions of words!

Word2Vec Training

- Standard softmax loss, then train the neural network



$$p(w_o|w_{in}) = \frac{\exp(v'_{w_o} \cdot v_{w_{in}})}{\sum_{k=1}^{K} \exp(v'_{w_k} \cdot v_{w_{in}})}$$

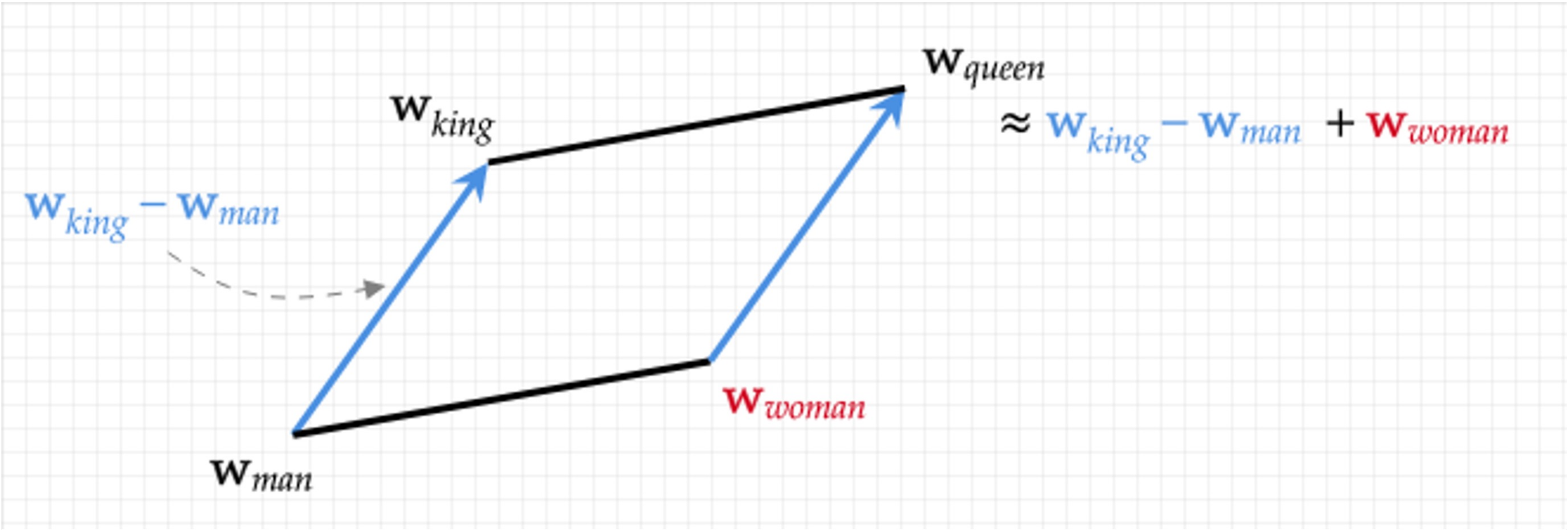
- **Simple Trick:** Sample some random $K - 1 \ll V$ negative example words for each sample. e.g. $K = 2, 5, 20$ etc.
- Also means we need to update many fewer weights during each iteration of gradient descent.

Properties of Word2Vec

- Words that co-occur have vector representations that are close together (in Euclidean distance)
  - “sofa” and “couch” (synonyms) will be close together
  - But also things like “hot” and “cold” (antonyms)
  - People say “It’s ____ outside today” for both

Properties of Word2Vec

- Vector operations (vector addition and vector subtraction) on word vectors often capture the semantic relationships of their words.

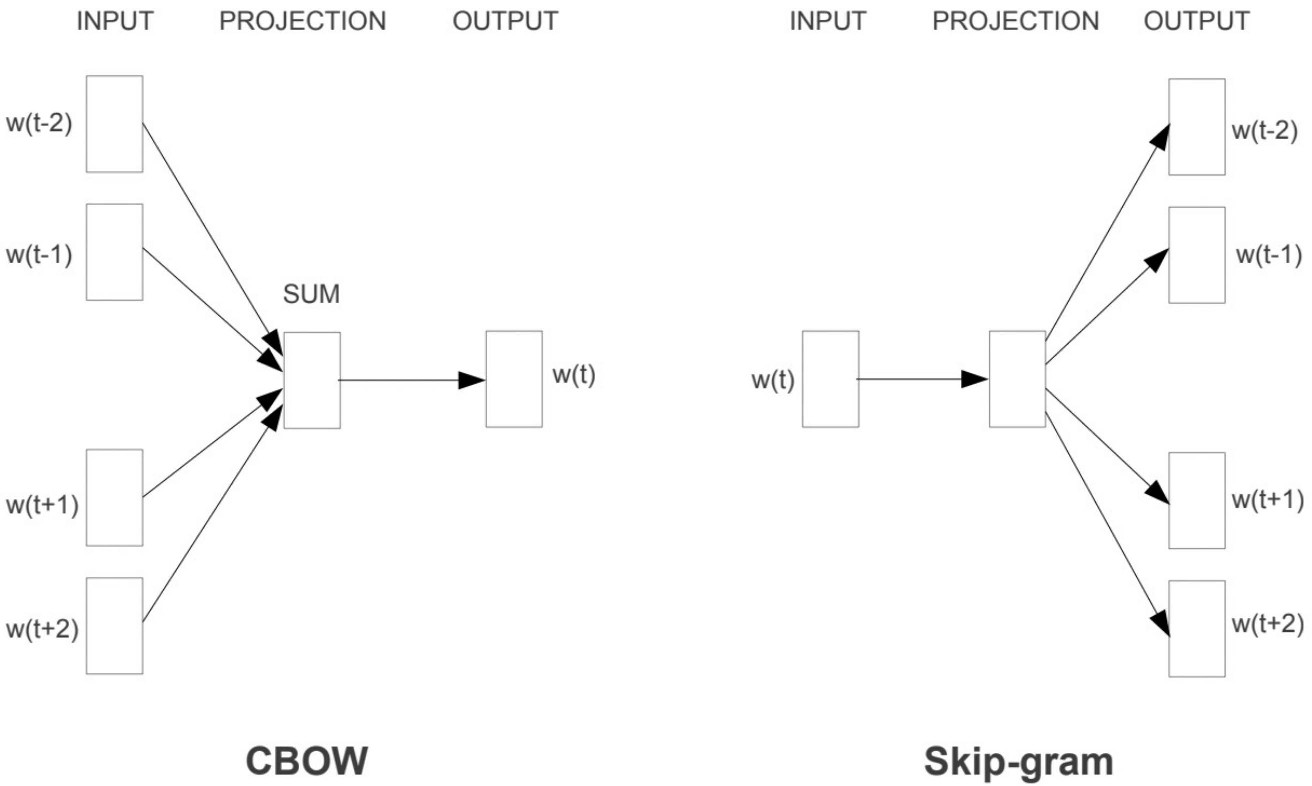


Source: https://www.ed.ac.uk/informatics/news-events/stories/2019/king-man-woman-queen-the-hidden-algebraic-struct

Use in Practice

- GLoVe is an alternative word vector embedding similar to word2vec
- Available freely, and often used off-the-shelf:
  - English word2vec weights trained on Google News data
  - GloVe vectors trained on the Common Crawl dataset and a Twitter dataset
- If you have a lot of training data or a different/niche domain (e.g., medical), you may want to train your own word vectors!

Other Variations



Predict word from bag-of-words context

Predict context from word

From Words to Documents

- Sentence2Vec, Paragraph2Vec scale these Word2Vec ideas to learn direct embeddings for sentences / paragraphs

- However, much more common to treat as a sequence of words, and represent each word by its word2vec-style representation

- Sequence models have produced huge advances in NLP

Words in Context

- While word2vec is trained based on context, after training, it is applied independently to each word
  - E.g., train linear regression of sum of word vectors, or n-grams
- **Why is this problematic?**
  - “He ate a tasty apple”
  - “He wrote his essay on his Apple computer”
- Both use the same embedding!