

# Lecture 9: Introduction to Language

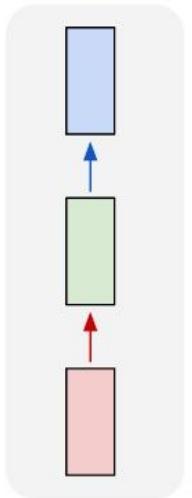
(new Gen Z friendly lecture)

# Administrative

- Assignment 2 was due on Tuesday
- Assignment 1 grades will be released this week
- Assignment 3 will be released this week
- Quiz 2 this Friday

# “Vanilla” Neural Network

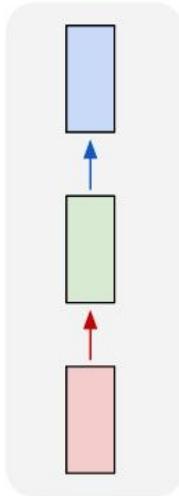
one to one



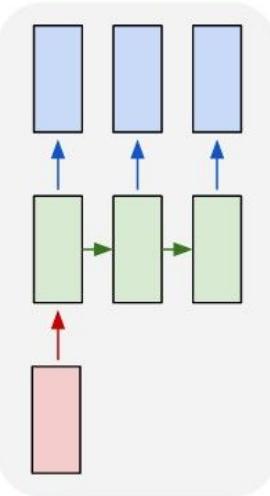
**Vanilla Neural Networks**

# Recurrent Neural Networks: Process Sequences

one to one



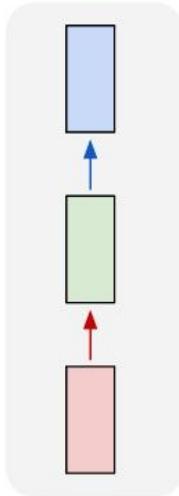
one to many



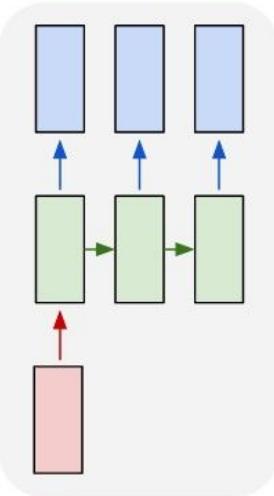
e.g. **Image Captioning**  
image -> sequence of words

# Recurrent Neural Networks: Process Sequences

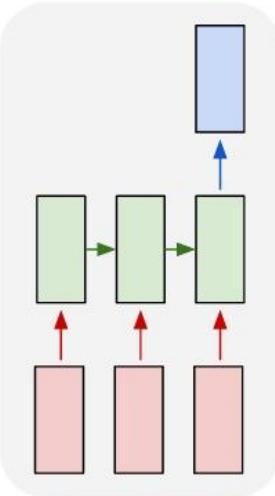
one to one



one to many



many to one

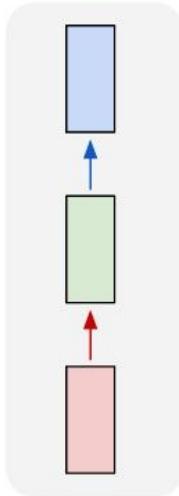


e.g. **action prediction, sentiment classification**

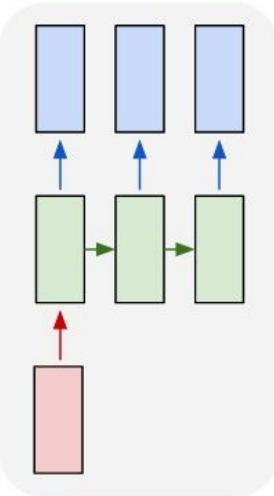
sequence of video frames -> action class

# Recurrent Neural Networks: Process Sequences

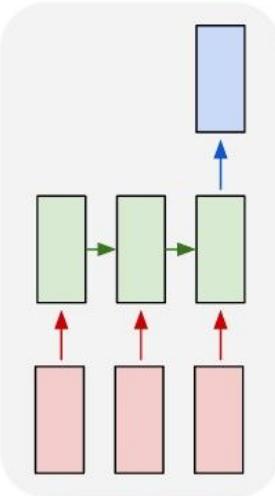
one to one



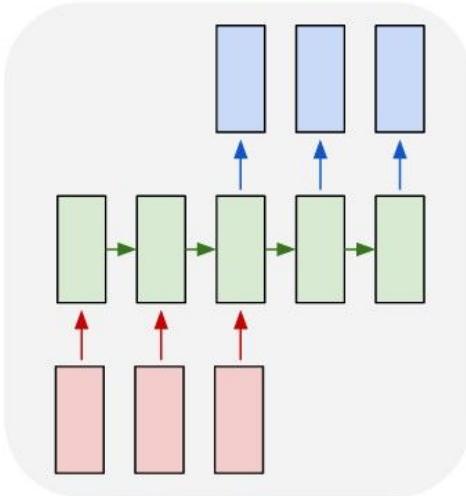
one to many



many to one



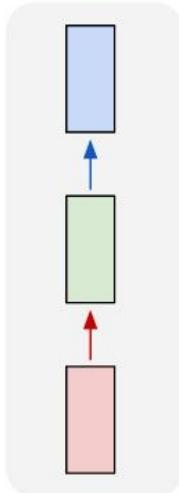
many to many



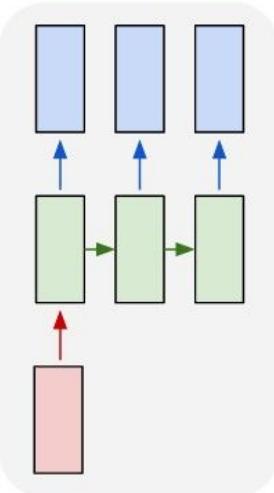
E.g. **Video Captioning**  
Sequence of video frames -> caption

# Recurrent Neural Networks: Process Sequences

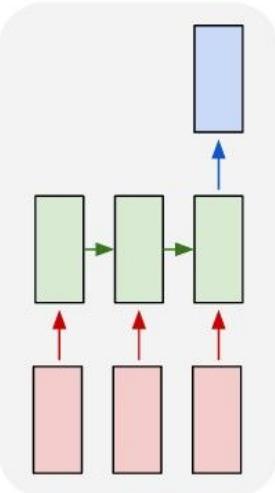
one to one



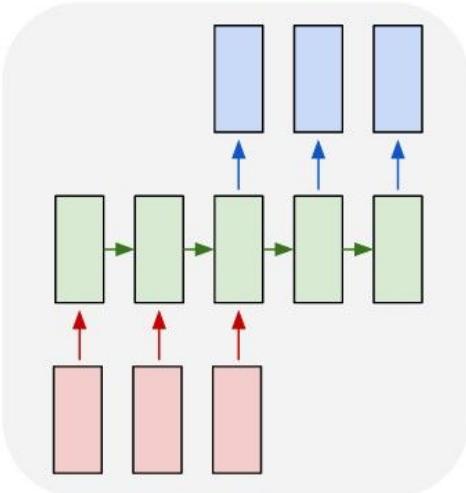
one to many



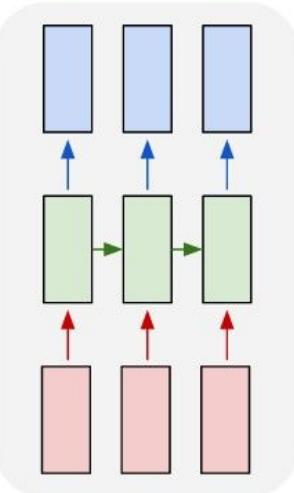
many to one



many to many



many to many



e.g. Video classification on frame level  
Fill in the blanks with words



# Sequential Processing of Non-Sequence Data

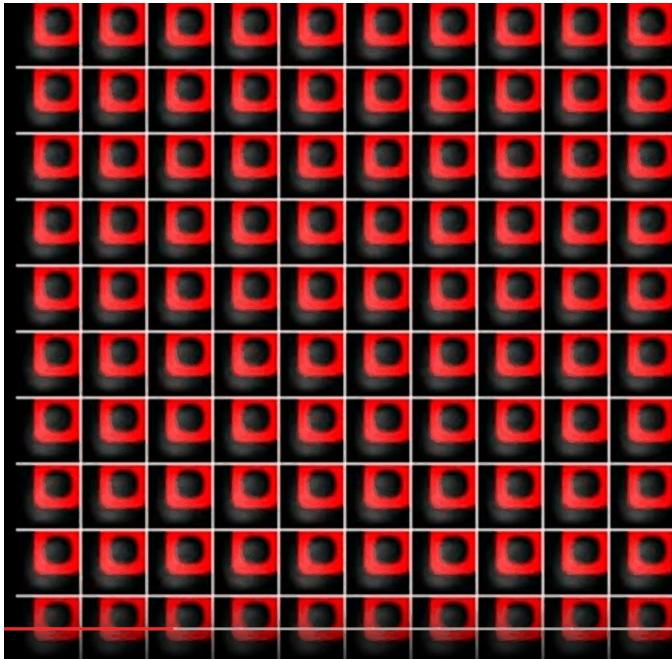
Classify images by taking a series of “glimpses”



Ba, Mnih, and Kavukcuoglu, “Multiple Object Recognition with Visual Attention”, ICLR 2015.  
Gregor et al, “DRAW: A Recurrent Neural Network For Image Generation”, ICML 2015  
Figure copyright Karol Gregor, Ivo Danihelka, Alex Graves, Danilo Jimenez Rezende, and Daan Wierstra, 2015. Reproduced with permission.

# Sequential Processing of Non-Sequence Data

Generate images one piece at a time!



Gregor et al, "DRAW: A Recurrent Neural Network For Image Generation , ICML 2015

Figure copyright Karol Gregor, Ivo Danihelka, Alex Graves, Danilo Jimenez Rezende, and Daan Wierstra, 2015. Reproduced with permission.

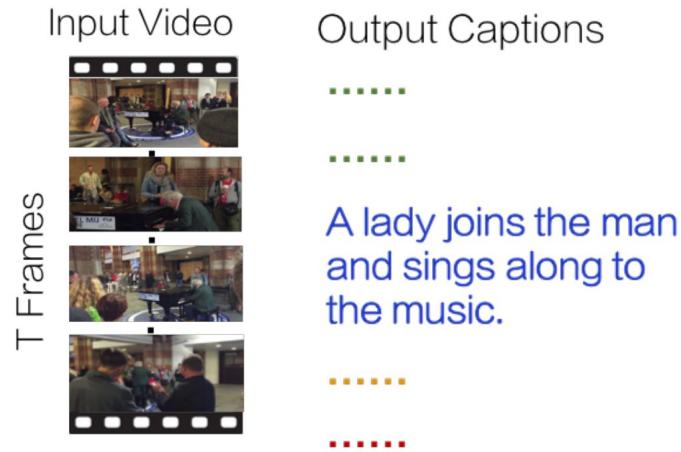
# Why existing neural networks are insufficient?

Variable sequence length inputs and outputs!

**Example task:** video captioning

**Input** video can have variable number of frames

**Output** captions can be variable length.



Krishna, et al. Dense captioning Events in Videos. ICCV 2019

Figure copyright Ranjay Krishna, Kenji Hata, Frederic Ren, Li Fei-Fei, and Juan Carlos Niebles, 2019. Reproduced with permission.

# Today: Introduction to language

# Language models are revolutionizing search

**User:** when did Kendrick lamar's first album come out?

**GPT:** July 2, 2011

when did Kendrick lamar's first album come out?



wikipedia.org  
[https://en.wikipedia.org/wiki/Kendrick\\_Lamar\\_discography](https://en.wikipedia.org/wiki/Kendrick_Lamar_discography) ::

## Kendrick Lamar discography - Wikipedia

Lamar's debut studio album **Section.80**, was released on **July 2, 2011**, and issued on independent record label Top Dawg Entertainment (TDE). It peaked at number ...

[Albums](#) · [Singles](#) · [Other charted and certified songs](#) · [Other guest appearances](#)

wikipedia.org  
[https://en.wikipedia.org/wiki/Kendrick\\_Lamar](https://en.wikipedia.org/wiki/Kendrick_Lamar) ::

## Kendrick Lamar - Wikipedia

Following the success of his alternative rap debut album **Section.80 (2011)**, Lamar secured a joint contract with Aftermath Entertainment and Interscope Records.

[Discography](#) · [Damn \(Kendrick Lamar album\)](#) · [Kendrick Lamar \(EP\)](#) · [Baby Keem](#)

genius.com  
<https://genius.com/artists/Kendrick-lamar/first-al...> ::

## When did Kendrick Lamar's first album release? - Genius

Kendrick Lamar's first album **Y.H.N.I.C. (Hub City Threat: Minor of the Year)** released in **2004**.

allmusic.com  
<https://www.allmusic.com/artist/kendrick-lamar-m...> ::

## Kendrick Lamar Songs, Albums, Reviews, Bio & More | AllMusic

Lamar's major-label debut, **good kid, m.A.A.d city**, was released in **October 2012** and entered the Billboard 200 at number two. Three of its singles -- "Swimming ...

# Language models can learn to follow examples

S: I broke the window.

Q: What did I break?

S: I gracefully saved the day.

Q: What did I gracefully save?

S: I gave John flowers.

**What will GPT generate?**

# Language models can learn to follow examples

S: I broke the window.

Q: What did I break?

S: I gracefully saved the day.

Q: What did I gracefully save?

S: I gave John flowers.

Q: Who did I give flowers to?

# Language models can learn to follow examples

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Q: What did I gracefully save?

S: I gave John flowers.

Q: Who did I give flowers to?

S: I gave her a rose and a guitar.

**What will GPT generate?**

# Language models can learn to follow examples

S: I broke the window.

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Q: What did I gracefully save?

S: I gave John flowers.

Q: Who did I give flowers to?

S: I gave her a rose and a guitar.

Q: Who did I give a rose and a guitar to?

# Language models can even write code / sql

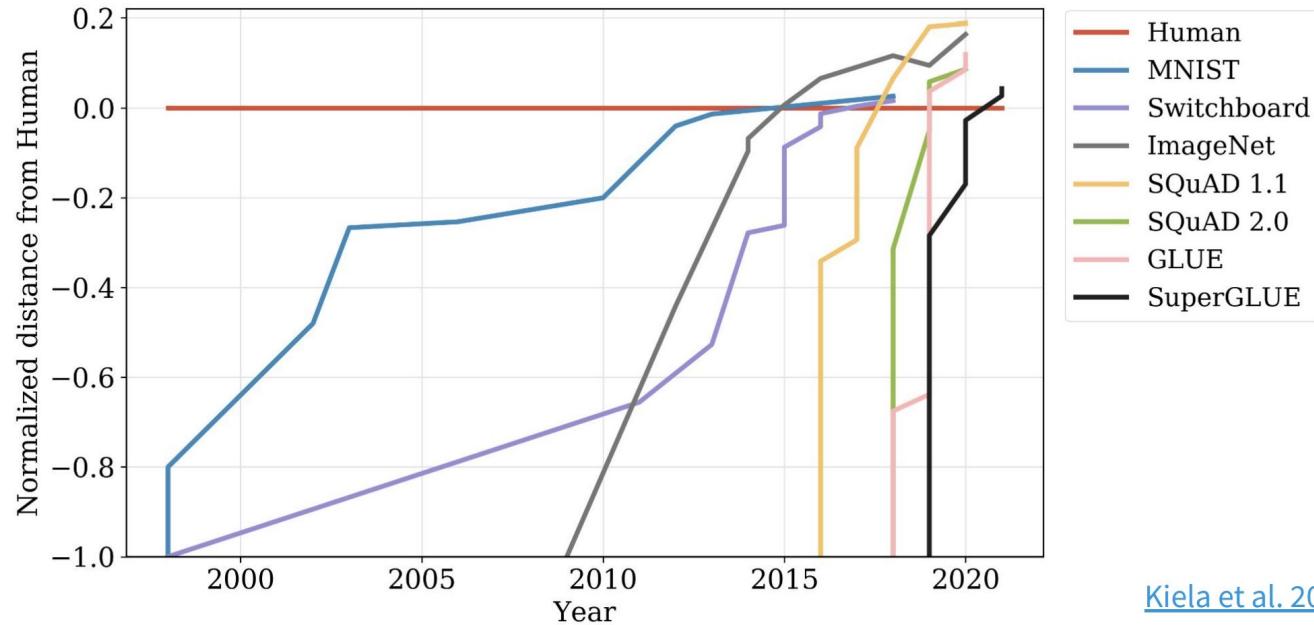
How many users have signed up since the start of 2020?

```
SELECT count(id) FROM users WHERE created_at >  
'2020-01-01'
```

What is the average number of influencers each user is subscribed to?

```
SELECT avg(count) FROM ( SELECT user_id, count(*)  
FROM subscribers GROUP BY user_id ) AS  
avg_subscriptions_per_user
```

# Compared to Vision (ImageNet, MNIST), language benchmarks reach super-human fast!



[Kiela et al. 2021](#)

Kiela et al. Dynabench: Rethinking Benchmarking in NLP NAACL 2021

# An example that you all will resonate with:

## GPT-4 capabilities today

RA

You

Please write up a polite letter to my professor, Ranjay Krishna, explaining why I need two more late days to submit my assignment 3. Make up a good excuse. I live in seattle.



ChatGPT

Subject: Request for Extension on Assignment 3 Submission

Dear Professor Ranjay Krishna,

I hope this message finds you well. I am writing to respectfully request an extension for the submission of Assignment 3.

Unfortunately, I have encountered an unforeseen and challenging situation that has significantly hindered my ability to complete the assignment on time. The recent severe weather conditions in Seattle, coupled with unexpected power outages in my area, have greatly impacted my ability to work effectively. The power outages have not only disrupted my internet access, which is crucial for research and accessing course materials, but have also made it challenging to maintain a conducive environment for studying.

I have been making every effort to keep up with the coursework and had planned my schedule to complete the assignment on time. However, these circumstances have been beyond my control and have unexpectedly set back my progress.

In light of this, I kindly request a two-day extension for the submission of Assignment 3. This additional time would be immensely helpful in allowing me to complete the assignment to the best of my ability, despite the challenges posed by the current situation.

# Make it more deferential!



ChatGPT

Subject: Respectful Request for Extension on Assignment 3 Submission

Dear Professor Ranjay Krishna,

I hope this message finds you in good health and spirits. I am writing to humbly request your consideration for an extension on the submission of Assignment 3. I deeply respect the high academic standards of your course and it is with great reluctance that I find myself in a position to ask for this concession.

# Make it MORE DEFERENTIAL!!



ChatGPT

Subject:



ChatGPT

Dear F

I hope  
your c  
respec  
I find r

Subject: Humble Request for Extension on Assignment 3 Submission Due to  
Unforeseen Circumstances

Dear Esteemed Professor Ranjay Krishna,

I hope this message reaches you in the best of health and spirits. I am writing to you with a deep sense of respect and humility, to request an extension for the submission of Assignment 3. It is with a heavy heart that I find myself in a position where I must seek your understanding and compassion due to unforeseen circumstances beyond my control.

Ranjay Krishna, Sarah Pratt

Lec

RA

You

Please write up a polite letter to my professor, Ranjay Krishna, explaining why I need two more late days to submit my assignment 3. Make up a good excuse. I live in seattle.



ChatGPT

Subject: Document for Extension on Assignment 3 Submission

respectfully request an extension for

challenging situation that has arisen. I am currently facing difficulties with my assignment on time. The recent days have been particularly challenging due to unexpected power outages in my residential area. The power outages have not only disrupted my ability to work on my research and accessing course materials, but also created a less than ideal environment for focused study.

I have been managing my coursework and had planned my assignments accordingly; however, these circumstances have significantly impacted my progress.

In light of this, I kindly request a two-day extension for the submission of Assignment 3. This additional time would be immensely helpful in allowing me to complete the assignment to the best of my ability, despite the challenges posed by the current situation.

# Make it MORE DEFERENTIAL!!!!



ChatGPT

Subject



ChatGPT

Dear F

I hope  
your c  
respec  
I find n

Subject: Hi



ChatGPT

Unforesee

Dear Estee

I hope this  
with a deep  
of Assignm  
seek your i  
my control

RA

You

Please write up a polite letter to my professor, Ranjay Krishna, explaining why I need two more late days to submit my assignment 3. Make up a good excuse. I live in seattle.



ChatGPT

Subject: Document for Extension on Assignment 3 Submission

Subject: Most Respectful Request for Extension on Assignment 3 Due to Extenuating Circumstances

Honorable Professor Ranjay Krishna,

I hope this message finds you in the best of health and circumstances. It is with the utmost respect and a deep sense of humility that I find myself compelled to write to you, seeking your compassionate understanding and consideration. I am fully aware of the gravity of my request and approach you with great reverence, hoping for your empathy in a matter that significantly affects my academic responsibilities.

# How do we represent the **meaning** of a word?

Definition: **meaning** (Webster dictionary)

- the idea that is represented by a word, phrase, etc.
- the idea that a person wants to express by using words, signs, etc.
- the idea that is expressed in a work of writing, art, etc.

Commonest **linguistic** way of thinking of meaning:

signifier (symbol)  $\Leftrightarrow$  signified (idea or thing)

tree  $\Leftrightarrow \{ \img[alt="bush icon"], \img[alt="pine tree icon"], \img[alt="palm tree icon"], \dots \}$

# How do we have usable meaning in a computer?

Previous solution by Linguists: Use a thesaurus (e.g., [WordNet](#)) containing lists of **synonym sets** and hypernyms (“is a” relationships).

*e.g., synonym sets containing “good”:*

```
from nltk.corpus import wordnet as wn
poses = { 'n':'noun', 'v':'verb', 's':'adj (s)', 'a':'adj', 'r':'adv'}
for synset in wn.synsets("good"):
    print("{}: {}".format(poses[synset.pos()],
                          ".join([l.name() for l in synset.lemmas()])))
```

```
noun: good
noun: good, goodness
noun: good, goodness
noun: commodity, trade_good, good
adj: good
adj (sat): full, good
adj: good
adj (sat): estimable, good, honorable, respectable
adj (sat): beneficial, good
adj (sat): good
adj (sat): good, just, upright
...
adverb: well, good
adverb: thoroughly, soundly, good
```

# How do we have usable meaning in a computer?

Previous solution by Linguists: Use a thesaurus (e.g., [WordNet](#)) containing lists of synonym sets and **hypernyms** (“is a” relationships).

*e.g., hypernyms of “panda”:*

```
from nltk.corpus import wordnet as wn
panda = wn.synset("panda.n.01")
hyper = lambda s: s.hypernyms()
list(pandaclosure(hyper))
```

```
[Synset('procyonid.n.01'),
Synset('carnivore.n.01'),
Synset('placental.n.01'),
Synset('mammal.n.01'),
Synset('vertebrate.n.01'),
Synset('chordate.n.01'),
Synset('animal.n.01'),
Synset('organism.n.01'),
Synset('living_thing.n.01'),
Synset('whole.n.02'),
Synset('object.n.01'),
Synset('physical_entity.n.01'),
Synset('entity.n.01')]
```



classes were derived from WordNet

**22K** categories and **14M** images

- Animals
  - Bird
  - Fish
  - Mammal
  - Invertebrate
- Plants
  - Tree
  - Flower
  - Food
  - Materials
- Structures
  - Artifact
  - Tools
  - Appliances
  - Structures
- Person
- Scenes
  - Indoor
  - Geological Formations
- Sport Activities

# Problems with resources like WordNet

A useful resource but missing nuance:

- e.g., “proficient” is listed as a synonym for “good”  
**This is only correct in some contexts**
- Also, WordNet lists offensive synonyms without any coverage of the connotations or appropriateness of words

Missing new meanings of words:

- e.g., sus, cap, glow up, fam, drip, vibe, G.O.A.T.
- **Impossible to keep up-to-date** with Gen Z!

Subjective

- Requires **human labor** to create and adapt
- Can’t capture similarity between words

# Representing words as discrete symbols

In traditional NLP, we regard words as discrete symbols:

*hotel, conference, motel* – each has its own symbol.

This is a **localist representation**

Such symbols for words can be represented by **one-hot vectors**:

$\text{motel} = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0]$

$\text{hotel} = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]$

Vector dimension = number of words in vocabulary (e.g., 500,000+)

# Problem with words as discrete symbols

Example: in web search, if a user searches for “Seattle motel”, we would like to match documents containing “Seattle hotel”

But:

$$\text{motel} = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0]$$

$$\text{hotel} = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]$$

These two vectors are orthogonal

There is no natural notion of similarity for one-hot vectors!

# Can we use WordNet-like taxonomies?

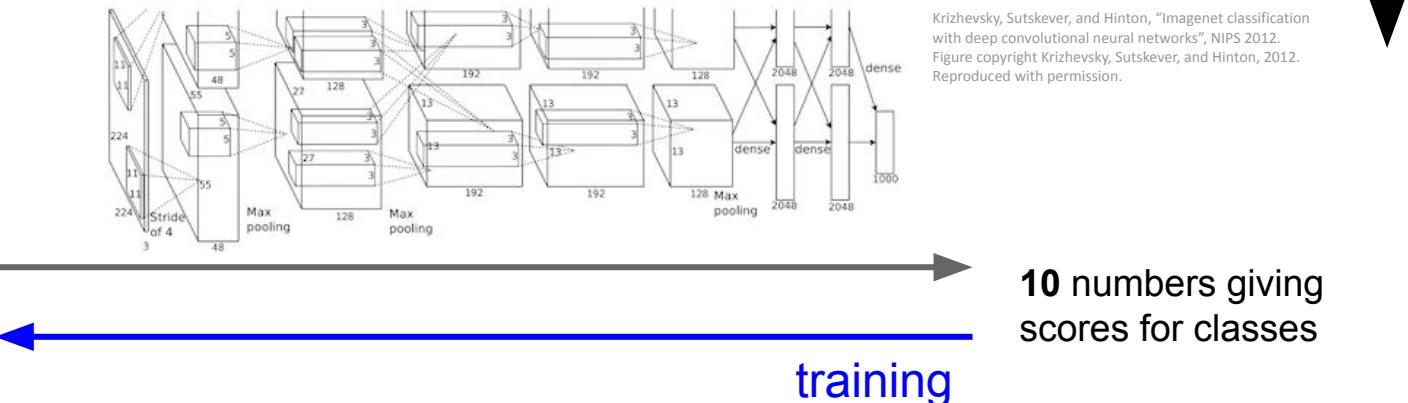
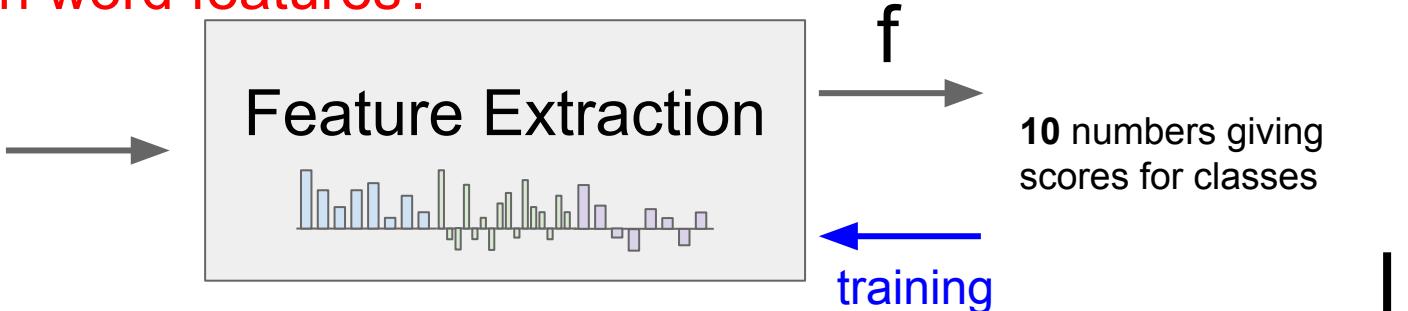
Could try to rely on WordNet's list of synonyms to get similarity?

- But it is well-known to fail badly: incompleteness, etc.

**New idea:** learn better word representations that encode similarity in the vectors themselves

- Similar to deep learning representations for images!
- Can we learn representations for words?

Just as Neural networks extract linearly separate image features,  
can we learn word features?



# Representing words by their context



**Distributional semantics:** A word's meaning is given by the words that frequently appear close-by

“You shall know a word by the company it keeps” (J. R. Firth 1957: 11)

One of the most successful ideas of modern statistical language modeling!

**High level idea:** a word  $w$  in text is a function of its contextual words.

# Let's try it: Fill in the blanks.

It's cold today! Don't forget to wear a \_\_\_\_\_.



The \_\_\_\_\_ is a popular tourist attraction in Seattle.

I missed \_\_\_\_ bus.

I had 3 pencils and lost one so now I have \_\_\_\_\_ pencils.

# Let's try it: Fill in the blanks.

It's cold today! Don't forget to wear a jacket / coat / sweater.



The \_\_\_\_\_ is a popular tourist attraction in Seattle.

I missed \_\_\_\_ bus.

I had 3 pencils and lost one so now I have \_\_\_\_\_ pencils.

# Let's try it: Fill in the blanks.

It's cold today! Don't forget to wear a jacket / coat / sweater.

→ The \_\_\_\_\_ is a popular tourist attraction in Seattle.

I missed \_\_\_\_ bus.

I had 3 pencils and lost one so now I have \_\_\_\_\_ pencils.

# Let's try it: Fill in the blanks.

It's cold today! Don't forget to wear a jacket / coat / sweater.

→ The Space Needle is a popular tourist attraction in Seattle.

I missed \_\_\_\_ bus.

I had 3 pencils and lost one so now I have \_\_\_\_\_ pencils.

# Let's try it: Fill in the blanks.

It's cold today! Don't forget to wear a jacket / coat / sweater.

The Space Needle is a popular tourist attraction in Seattle.

→ I missed \_\_\_\_ bus.

I had 3 pencils and lost one so now I have \_\_\_\_\_ pencils.

# Let's try it: Fill in the blanks.

It's cold today! Don't forget to wear a jacket / coat / sweater.

The Space Needle is a popular tourist attraction in Seattle.

→ I missed the bus.

I had 3 pencils and lost one so now I have \_\_\_\_\_ pencils.

# Let's try it: Fill in the blanks.

It's cold today! Don't forget to wear a jacket / coat / sweater.

The Space Needle is a popular tourist attraction in Seattle.

I missed the bus.

→ I had 3 pencils and lost one so now I have \_\_\_\_\_ pencils.

# Let's try it: Fill in the blanks.

It's cold today! Don't forget to wear a jacket / coat / sweater.

The Space Needle is a popular tourist attraction in Seattle.

I missed the bus.

→ I had 3 pencils and lost one so now I have 2 / two pencils.

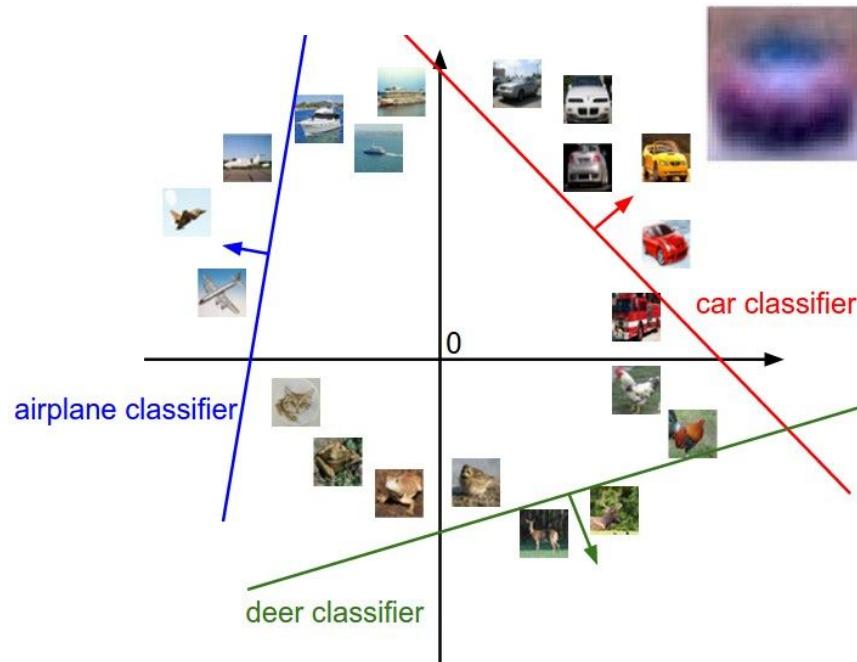
# What we want in the end: word vectors

We will build a **dense vector** for each word,

- chosen so that it is similar to vectors of words that appear in similar contexts: e.g. **jacket / coat / sweater**.
- measuring similarity as the vector dot (scalar) product.
- Word vectors are also called (word) **embeddings** or (neural) **word representations**

$$\begin{matrix} \text{Jacket} = \\ \left[ \begin{array}{c} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{array} \right] \end{matrix}$$

# Remember the Geometric Viewpoint



$$f(x, W) = Wx + b$$

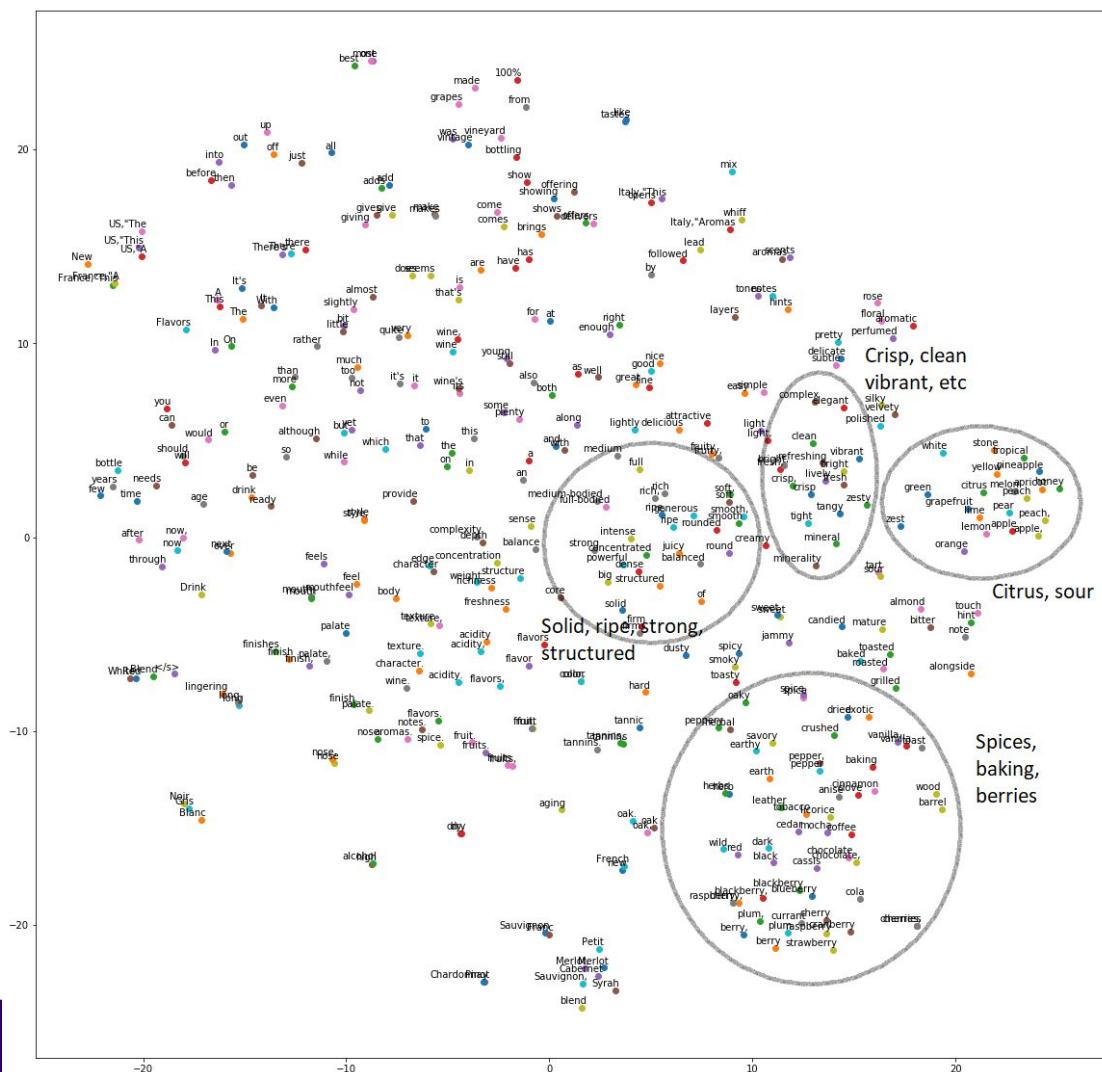


Array of **32x32x3** numbers  
(3072 numbers total)

[Cat image](#) by [Nikita](#) is licensed under [CC-BY 2.0](#)

Plot created using [Wolfram Cloud](#)

# Visualizing word vectors in 2D (trained on wine reviews)



# How do we train these word vectors: **Word2vec**



[Jeff Dean's tweet](#)

They won test of time award in December 2023!

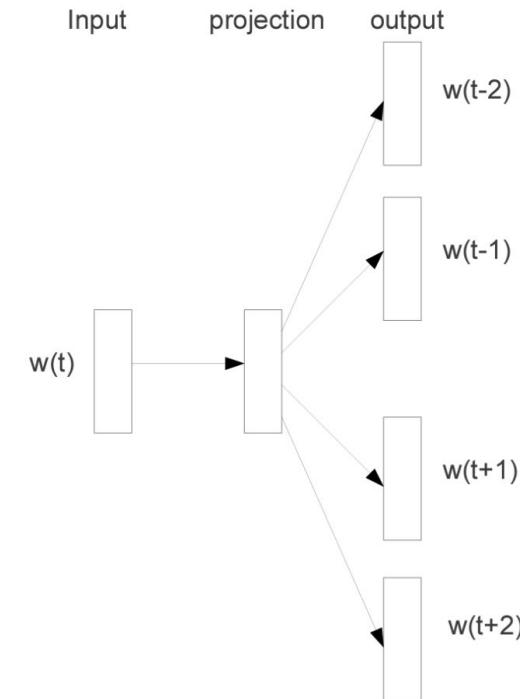
**Original paper** was **rejected** and never published (has 40K citations!)  
Mikolov et al. Efficient Estimation of Word Representations in Vector Space" 2013

**Next paper** by same authors is what won the award and was published in NeurIPS 2013 (also 40K citations!)  
Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." Advances in neural information processing systems 26 (2013).

# Word2vec is a framework for learning word vectors

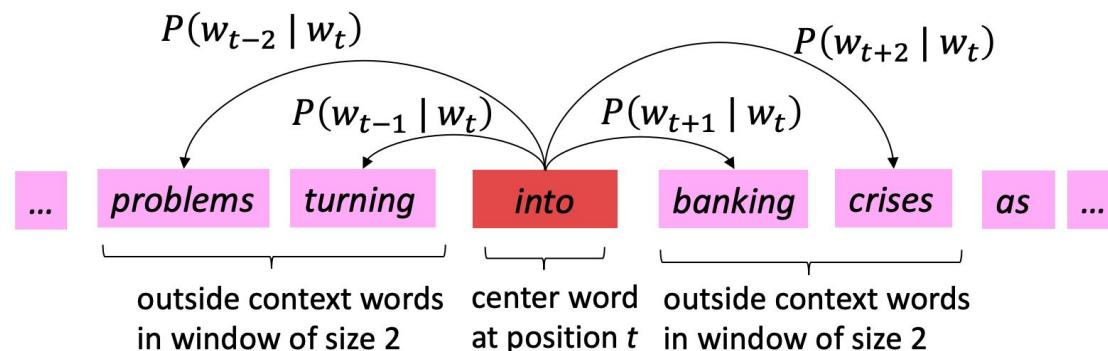
Idea:

1. Collect a large corpus (“body”) of text: a long list of words from the internet
2. Establish a fixed vocabulary of size  $V$ .
  - a. Usually most frequent  $V$  words are used.
  - b. All other words are mapped to an <unknown> or <unk> word.
3. Initialize every word by a random vector
4. Go through each position  $t$  in the text,
  - a. Let the word in that position be  $c$
  - b. Let all (“outside”) words  $o$  be within context
  - c. Calculate the probability of  $o$  given  $c$  (or vice versa)
  - d. Maximize this probability



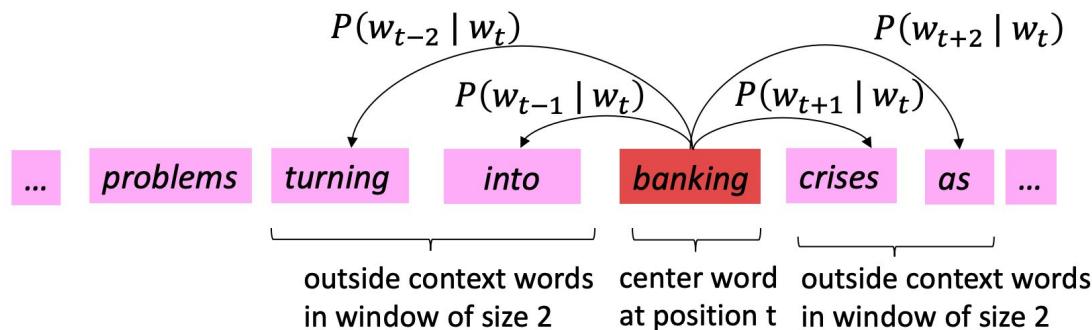
# Using a context size of 2!

Example windows and process for computing  $P(w_{t+j} | w_t)$



# Move to the next word

Example windows and process for computing  $P(w_{t+j} | w_t)$

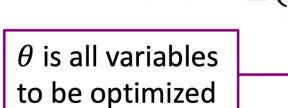


# The learning objective is to maximize the probabilities

For each position  $t = 1, \dots, T$ , predict context words within a window of fixed size  $m$ , given center word  $w_t$ . Data likelihood:

$$\text{Likelihood} = L(\theta) = \prod_{t=1}^T \prod_{\substack{-m \leq j \leq m \\ j \neq 0}} P(w_{t+j} | w_t; \theta)$$

$\theta$  is all variables  
to be optimized



# The loss function

For each position  $t = 1, \dots, T$ , predict context words within a window of fixed size  $m$ , given center word  $w_t$ . Data likelihood:

$$\text{Likelihood} = L(\theta) = \prod_{t=1}^T \prod_{\substack{-m \leq j \leq m \\ j \neq 0}} P(w_{t+j} | w_t; \theta)$$

$\theta$  is all variables to be optimized

The loss function  $L(\theta)$  is the (average) negative log likelihood:

$$L(\theta) = -\frac{1}{T} \log L(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \log P(w_{t+j} | w_t; \theta)$$

Minimizing loss function  $\Leftrightarrow$  Maximizing predictive accuracy

# How do we calculate this probability?

We want to minimize the objective function:

$$L(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \log P(w_{t+j} | w_t; \theta)$$

**Question:** How to calculate  $P(w_{t+j} | w_t; \theta)$

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**Question:** How to calculate  $P(w_{t+j} | w_t; \theta)$

The best idea #1: **Use a neural network** whenever you need to model a function



# How did Word2Vec design $f_j()$ ?

We will use two vectors per word  $w$ :

- $v_w$  when  $w$  is a center word
- $u_w$  when  $w$  is a context word

Let  $f_1(w_t, w_{t+1}) = w_t^T w_{t+1}$  be a simple dot product

- so now learnable parameters except the word vectors.

Then for a center word  $c$  and a context word  $o$ :

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

# Remember the Softmax (cross-entropy) Classifier



Want to interpret raw classifier scores as **probabilities**

$$s = f(x_i; W)$$

$$P(Y = k|X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

Softmax Function

cat  
car  
frog

3.2
5.1
-1.7

Unnormalized  
log-probabilities / logits

exp

24.5
164.0
0.18

unnormalized  
probabilities

normalize

0.13
0.87
0.00

probabilities

$$L_i = -\log P(Y = y_i|X = x_i)$$

Probabilities  
must be  $\geq 0$

Probabilities  
must sum to 1

compare

1.00

Cross Entropy

$$H(P, Q) =$$

$$H(p) + D_{KL}(P||Q)$$

0.00

0.00

Correct  
probs

# Understanding the calculation

② Exponentiation makes anything positive

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

① Dot product compares similarity of  $o$  and  $c$ .  
 $u^T v = u \cdot v = \sum_{i=1}^n u_i v_i$   
Larger dot product = larger probability

③ Normalize over entire vocabulary  
to give probability distribution

# To train the model: Optimize word vectors of all words to minimize loss using backprop

**Recall:**  $\theta$  represents all the model parameters, in one long vector

- $d$ -dimensional vectors
- $V$  - many words,
- every word has two vectors

$$\theta = \begin{bmatrix} v_{aardvark} \\ v_a \\ \vdots \\ v_{zebra} \\ u_{aardvark} \\ u_a \\ \vdots \\ u_{zebra} \end{bmatrix} \in \mathbb{R}^{2dV}$$

Use stochastic gradient descent with batches of  $N$  center words

# Why did this algorithm use two vectors?

We will use two vectors per word  $w$ :

- $v_w$  when  $w$  is a center word
- $u_w$  when  $w$  is a context word

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

**Hint:** this paper came out in 2013, 1 year after AlexNet.

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**Hint:** this paper came out in 2013, 1 year after AlexNet.

Do you think the results would be better if they used 1 instead of 2 vectors?

# What are the final word vectors?

It is the average of the two vectors:

$$\frac{1}{2} (v_w + u_w)$$

# Variant of algorithm: The skip-gram model

Predict all context (“outside”) words (position independent) given center word

Instead of  $f_j()$



Learn one function  $f()$  for all positions



# What's another issue with this calculation?

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

# Solution: negative sampling

$$\log P(o|c) = -\log \sigma(\mathbf{u}_o^T \mathbf{v}_c) - \sum_{k \in \{K \text{ sampled indices}\}} \log \sigma(-\mathbf{u}_k^T \mathbf{v}_c)$$

Replace denominator with randomly sampled k vocabulary instances.

New hyperparameter: k

How should we sample?

- Rare words (aardvark) are unlikely to be helpful.
- You can sample a word  $w$  based on its probability of occurrence:
  - $p(w) = U(w) / Z$
  - where  $Z$  is total number of words
  - $U(w)$  is number of times word  $U$  appears.

# Solution: negative sampling

$$\log P(o|c) = -\log \sigma(\mathbf{u}_o^T \mathbf{v}_c) - \sum_{k \in \{K \text{ sampled indices}\}} \log \sigma(-\mathbf{u}_k^T \mathbf{v}_c)$$

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- where  $Z$  is total number of words

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In practice,  $p(w) = U(w)^{3/4} / Z$

# Problem of sparse gradients

We iteratively take gradients at each  $m$  window for SGD

- In each window, we only have at most  $2m + 1$  words
- plus  $2km$  negative words with negative sampling
- so the gradient for each update is sparse for  $V$  of size 500K

$$\nabla_{\theta} J_t(\theta) = \begin{bmatrix} 0 \\ \vdots \\ \nabla_{v_{like}} \\ \vdots \\ 0 \\ \nabla_{u_I} \\ \vdots \\ \nabla_{u_{learning}} \\ \vdots \end{bmatrix} \in \mathbb{R}^{2dV}$$

# Implementation detail

Most DL packages represent word vectors using a special **embedding layer**

$$|V| \begin{bmatrix} \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}^d$$

Rows represent words

- even though we usually talk about words as column vectors
- In implementations, they are row vectors.
- It is a hash table with look up and write functions to avoid writing to the entire  $V \times d$  matrix.

# Indirectly, skim-gram is trying to calculate co-occurrence of words

It does this using backprop and by iterating through the entire corpus of text data multiple times.

Can we do better?

Can we building a co-occurrence matrix directly?

- Calculate co-occurrence of words within a window.
- captures some syntactic and semantic information (“word space”)
- If window is too large (size of entire articles or documents):
  - Co-occurrence matrix will represent general topics
  - Example, all sports words will have similar entries

# Example co-occurrence matrix

- Let's try an example with window length 1 (it is more common to use 5–10)
- Symmetric (irrelevant whether left or right context)

Example corpus:

- I like deep learning
- I like UW
- I enjoy class

counts	I	like	enjoy	deep	learning	UW	class	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
UW	0	1	0	0	0	0	0	1
class	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

# Co-occurrence vectors

Problem with simple count co-occurrence vectors

- Vectors increase in size with vocabulary
- Very high dimensional: require a lot of storage (though sparse)

**Idea:** Low-dimensional vectors

- Idea: store “most” of the important information in a fixed, small number of dimensions: **a dense vector**
- Usually 25–1000 dimensions, similar to word2vec
- **But how should we reduce the dimensionality from 500K to <1000?**

# Classic Method: Dimensionality Reduction

From linear algebra: **Singular Value Decomposition** of co-occurrence matrix X

$$\underbrace{\begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}}_X = \underbrace{\begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix}}_U \underbrace{\begin{bmatrix} \bullet & & \\ & \bullet & \\ & & \bullet \end{bmatrix}}_{\Sigma} \underbrace{\begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}}_{V^T}$$

U and V are orthogonal matrices

$\Sigma$  is a diagonal matrix of singular values.

# Classic Method: Dimensionality Reduction

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$$\begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix} = \underbrace{\begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix}}_U \underbrace{\begin{bmatrix} \cdot & & \\ & \cdot & \\ & & \cdot \end{bmatrix}}_{\Sigma} \underbrace{\begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}}_{V^T}$$

We can discard **all except the largest d** singular values and their corresponding multiplicative values in U and V

New d-dimensional word vector representations are: **top-d(U) \* top-d( $\Sigma$ )**

# Making co-occurrence counts work

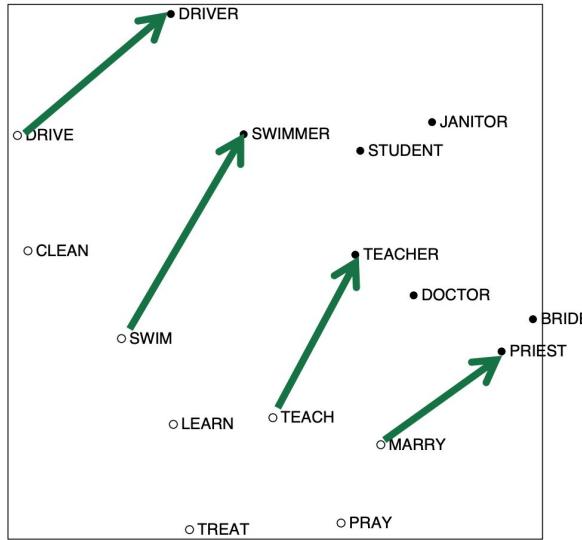
Running an SVD on raw counts doesn't work well.

**Problem:** function words (the, he, has) are too frequent à syntax has too much impact.

Some fixes:

- Use log the frequencies instead
- Limit the maximum values:  $\min(X, t)$ , with  $t \approx 100$
- Ignore the function words
- Ramped windows that count closer words more than further away words

# Interesting semantic patterns emerge



COALS model from Rohde et al. ms., 2005. An Improved Model of Semantic Similarity Based on Lexical Co-Occurrence

# Comparing the two methods:

## Co-occurrence vectors

- Fast training
  - Single iteration over data
  - SVD is fast as long as vocabulary is reasonable.
- Good for capturing word similarities
- Needs hacks to work
- Not good for anything beyond similarities
- SVD is very slow for large vocabularies

## Skip-gram algorithm

- Scales well with increasing vocabulary size
- Good for many other tasks
- Now as good for word similarities
- Needs multiple iterations across the dataset as backprop is slow

# Can we combine the strengths of both methods?

Log bilinear model:

- Let every word be a d-dimensional vector
- Remember from skip-gram that dot product is the probability of one word given its context

$$w_i \cdot w_j = \log P(i|j)$$

GloVe [Pennington, Socher, and Manning, EMNLP 2014]: Encoding meaning components in vector differences

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$$w_i \cdot w_j = \log P(i|j)$$

**Main idea:** Similarity between two words should be proportional to their co-occurrence count.

- Log of count used as a hack

$$L(\theta) = \sum_{i,j=1}^V f(X_{ij}) \left( w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij} \right)^2$$

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**Main idea:** Similarity between two words should be proportional to their co-occurrence count.

- Log of count used as a hack
- $f()$  is a threshold for large values

$$L(\theta) = \sum_{i,j=1}^V f(X_{ij}) [w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}]^2$$

GloVe [Pennington, Socher, and Manning, EMNLP 2014]: Encoding meaning components in vector differences

# Glove vectors are very good at analogies

a:b :: c:?

man:woman :: king:?

# Glove vectors are very good at analogies

$$\boxed{a:b :: c: ?} \quad \longrightarrow \quad \boxed{d = \arg \max_i \frac{(x_b - x_a + x_c)^T x_i}{\|x_b - x_a + x_c\|}}$$

man:woman :: king:?

$$(\text{man} - \text{woman} + \text{king})^* w_i$$

# Glove vectors are very good at analogies

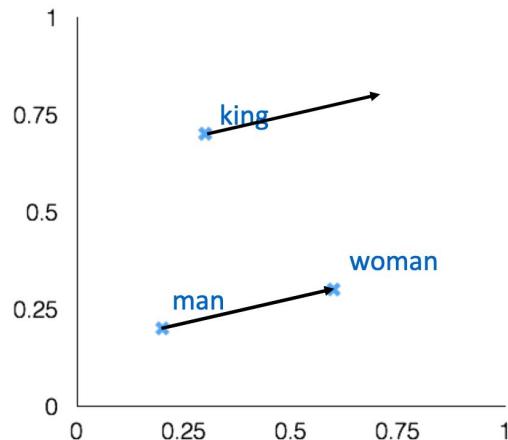
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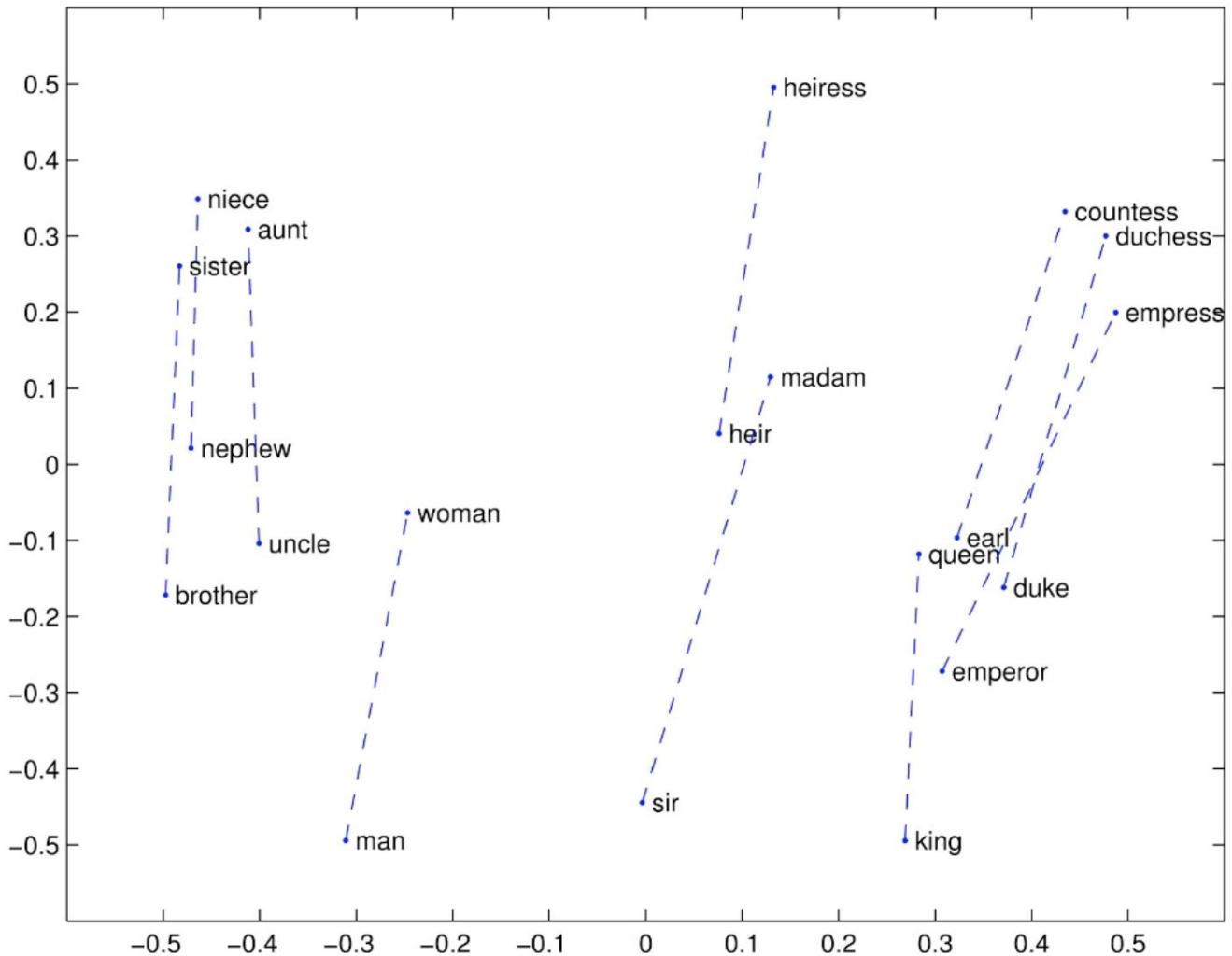
$$d = \arg \max_i \frac{(x_b - x_a + x_c)^T x_i}{\|x_b - x_a + x_c\|}$$

man:woman :: king:?

$$(\text{man} - \text{woman} + \text{king})^* w_i$$



# More visualizations



# Glove vectors correlate with human judgement

Linguists have created a dataset of word similarity judgements

- Word vector distances and their correlation with human judgments
- Example dataset: [WordSim353](#)

Word 1	Word 2	Human (mean)
tiger	cat	7.35
tiger	tiger	10
book	paper	7.46
computer	internet	7.58
plane	car	5.77
professor	doctor	6.62
stock	phone	1.62
stock	CD	1.31
stock	jaguar	0.92

# Problem of polysemy

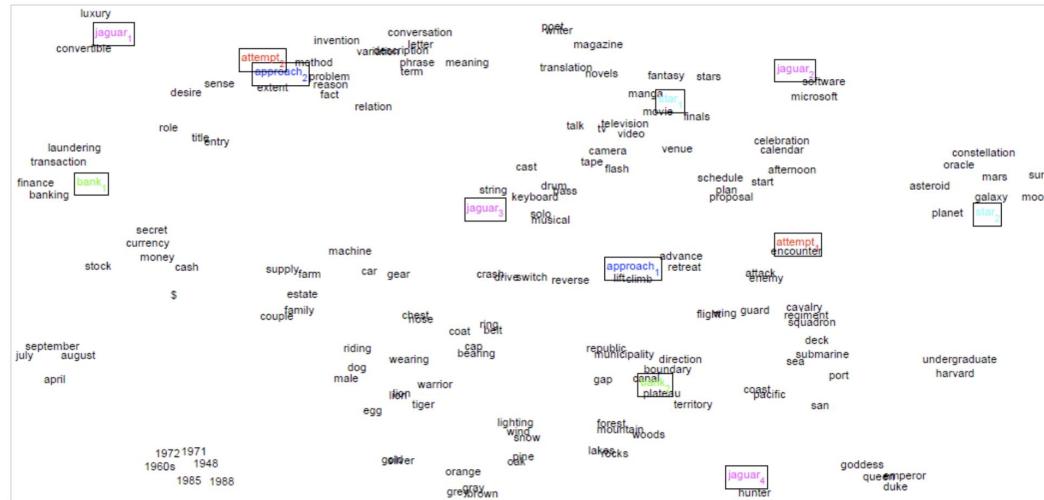
Word senses and word sense ambiguity

Cap

- Using to only be similar to Hat
- But now, thanks to gen z, should also be closer to Lying

Can one vector capture all these meanings? Probably not!

Researchers have tried to segregate words into multiple vectors, each with its own meaning



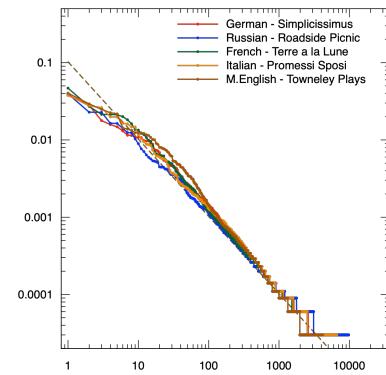
But it doesn't work well. A word's usage in a sentence defines its meaning.  
**Words should be a function of not just its context but its position in the sentence**  
-> **Next lecture**

# So far: vectors are associated with words

Our vocabulary was comprised of all of the **words in a language**

## Problems:

- **500,000** words Webster's English Dictionary (3rd edition)
- Language is **changing** all of the time
  - 690 words were added to Merriam Webster's in September 2023 ("rizz", "goated", "mid")
- **Long tail** of infrequent words.
  - Zipf's law: word frequency is inversely proportional to word rank
- Some words **may not appear** in a training set of documents
- No modeled **relationship between words** - e.g., "run", "ran", "runs", "runner" are all separate entries despite being linked in meaning



Zipf's Law: Word Rank  
vs. Word  
Frequency for Several  
Languages

# Character level vectors instead?

What about assigning a vector to every character instead?

**(Maybe add capital letters, punctuation, spaces, ...)**

**Pros:**

- Small vocabulary size ( for English)
- Complete coverage (unseen words are represented by letters)

**Cons:**

- Encoding a single sentence becomes very long!
  - # chars instead of # words
- Characters mean very different things in different words!
  - Even worse for representing multiple meanings

# Subword tokenization!

How can we combine

1. the **high coverage** of character-level representations
2. with the efficiency of word-level representation?

Subword tokenization! (e.g., **Byte-Pair Encoding**)

- Start with character-level representations
- Build up representations from there

[Original BPE Paper](#) (Sennrich et al., 2016)

# Example of how Byte-pair encoding works

Let's say our entire dataset contains only these 3 sentences:

$$\mathcal{D} = \{ \text{"i hug pugs"}, \text{"hugging pugs is fun"}, \text{"i make puns"} \}$$

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Let's say our entire dataset contains only these 3 sentences:

$$\mathcal{D} = \{ \text{"i hug pugs"}, \text{"hugging pugs is fun"}, \text{"i make puns"} \}$$

Initialize the vocabulary as all the individual characters. Current Vocab:

$$\mathcal{V} = \{ \text{' '}, \text{'a'}, \text{'e'}, \text{'f'}, \text{'g'}, \text{'h'}, \text{'i'}, \text{'k'}, \text{'m'}, \\ \text{'n'}, \text{'p'}, \text{'s'}, \text{'u'} \}, |\mathcal{V}| = 13$$

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Let's say our entire dataset contains only these 3 sentences:

$$\mathcal{D} = \{ \text{"i hug pugs"}, \text{"hugging pugs is fun"}, \text{"i make puns"} \}$$

Let's split it up into words by splitting right **before the whitespace**:

$$\mathcal{D} = \{ \text{"i"}, \text{" hug"}, \text{" pugs"}, \text{"hugging"}, \text{" pugs"}, \\ \text{" is"}, \text{" fun"}, \text{"i"}, \text{" make"}, \text{" puns"} \}$$

# Example of how Byte-pair encoding works

The vocabulary for reference:

$$\mathcal{V} = \{‘ ’, ‘a’, ‘e’, ‘f’, ‘g’, ‘h’, ‘i’, ‘k’, ‘m’, ‘n’, ‘p’, ‘s’, ‘u’\}, |\mathcal{V}| = 13$$

Let's split it up into words by splitting right **before the whitespace**:

$$\mathcal{D} = \{“i”, “hug”, “pugs”, “hugging”, “pugs”, “is”, “fun”, “i”, “make”, “puns”\}$$

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$$\mathcal{V} = \{‘ ’, ‘a’, ‘e’, ‘f’, ‘g’, ‘h’, ‘i’, ‘k’, ‘m’, ‘n’, ‘p’, ‘s’, ‘u’\}, |\mathcal{V}| = 13$$

Let's represent the dataset

with only vocabulary  
elements:

$$\mathcal{D} = \{ [‘i’], [‘ ’, ‘h’, ‘u’, ‘g’], [‘ ’, ‘p’, ‘u’, ‘g’, ‘s’], [‘h’, ‘u’, ‘g’, ‘g’, ‘i’, ‘n’, ‘g’], [‘ ’, ‘p’, ‘u’, ‘g’, ‘s’], [‘ ’, ‘i’, ‘s’], [‘ ’, ‘f’, ‘u’, ‘n’], [‘i’], [‘ ’, ‘m’, ‘a’, ‘k’, ‘e’], [‘ ’, ‘p’, ‘u’, ‘n’, ‘s’] \}$$

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$$\mathcal{V} = \{‘ ’, ‘a’, ‘e’, ‘f’, ‘g’, ‘h’, ‘i’, ‘k’, ‘m’, ‘n’, ‘p’, ‘s’, ‘u’\}, |\mathcal{V}| = 13$$

Now, let's find the most common bi-gram

$$\mathcal{D} = \{ [‘i’], [‘ ’, ‘h’], [‘u’, ‘g’], [‘ ’, ‘p’], [‘u’, ‘g’], [‘s’], [‘h’], [‘u’, ‘g’], [‘g’], [‘i’], [‘n’], [‘g’], [‘ ’, ‘p’], [‘u’, ‘g’], [‘s’], [‘ ’, ‘i’], [‘s’], [‘ ’, ‘f’], [‘u’], [‘n’], [‘i’], [‘ ’, ‘m’], [‘a’], [‘k’], [‘e’], [‘ ’, ‘p’], [‘u’], [‘n’], [‘s’] \}$$

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Create new vocab:

$$v_{14} := \text{concat}(‘u’, ‘g’) = ‘ug’$$

# Example of how Byte-pair encoding works

Update vocabulary with new vocab  $v_{14}$ :

$$\mathcal{V} = \{ ' ', 'a', 'e', 'f', 'g', 'h', 'i', 'k', 'm', 'n', 'p', 's', 'u', \text{ug}' \}, |\mathcal{V}| = 14$$

Update dataset by replace bigram with new vocab  $v_{14}$ :

$$\mathcal{D} = \{ ['i'], [' ', 'h', \text{ug}'], [' ', 'p', \text{ug}', 's'], ['h', \text{ug}', 'g', 'i', 'n', 'g'], [' ', 'p', \text{ug}', 's'], [' ', 'i', 's'], [' ', 'f', 'u', 'n'], ['i'], [' ', 'm', 'a', 'k', 'e'], [' ', 'p', 'u', 'n', 's'] \}$$

Create new vocab:

$$v_{14} := \text{concat}('u', 'g') = \text{ug}'$$

# Example of how Byte-pair encoding works

Current vocabulary:

$$\mathcal{V} = \{ ' ', 'a', 'e', 'f', 'g', 'h', 'i', 'k', 'm', \\ 'n', 'p', 's', 'u', 'ug' \}, |\mathcal{V}| = 14$$

Find the next common bigram:

$$\mathcal{D} = \{ ['i'], [' ', 'h', 'ug'], [' ', 'p', 'ug', 's'], \\ ['h', 'ug', 'g', 'i', 'n', 'g'], [' ', 'p', 'ug', 's'], \\ [' ', 'i', 's'], [' ', 'f', 'u', 'n'], ['i'], \\ [' ', 'm', 'a', 'k', 'e'], [' ', 'p', 'u', 'n', 's'] \}$$

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Current vocabulary:

$$\mathcal{V} = \{ ' ', 'a', 'e', 'f', 'g', 'h', 'i', 'k', 'm', \\ 'n', 'p', 's', 'u', 'ug' \}, |\mathcal{V}| = 14$$

Find the next common bigram:

Create new vocab:

$$\mathcal{D} = \{ [i], [ ' ', h, 'ug' ], [ ' ', p, 'ug', s ], \\ [h, ug, g, i, n, g ], [ ' ', p, ug, s ], \\ [ ' ', i, s ], [ ' ', f, u, n ], [i], \\ [ ' ', m, a, k, e ], [ ' ', p, u, n, s ] \}$$

$v_{15} := \text{concat}(' ', p) = ' p'$

# Example of how Byte-pair encoding works

Update vocabulary with new vocab  $v_{15}$ :

$$\mathcal{V} = \{ ' ', 'a', 'e', 'f', 'g', 'h', 'i', 'k', 'm', 'n', 'p', 's', 'u', \textcolor{green}{'ug'}, \textcolor{pink}{' p'} \}, |\mathcal{V}| = 15$$

Update dataset by replace bigram with new vocab  $v_{15}$ :

$$\mathcal{D} = \{ [\textcolor{brown}{'i'}], [', 'h', \textcolor{green}{'ug'}], [\textcolor{pink}{' p'}, \textcolor{green}{'ug'}, 's'], [', 'h', \textcolor{green}{'ug'}, 'g', 'i', 'n', 'g'], [\textcolor{pink}{' p'}, \textcolor{green}{'ug'}, 's'], [', 'i', 's'], [', 'f', 'u', 'n'], [i], [', 'm', 'a', 'k', 'e], [\textcolor{pink}{' p'}, 'u', 'n', 's'] \}$$

Create new vocab:  
 $v_{15} := \text{concat}(' ', 'p') = ' p'$

# Repeat until vocab size reaches the amount you want (20 for example)

Final vocabulary:

$$\mathcal{V} = \{ ' ', 'a', 'e', 'f', 'g', 'h', 'i', 'k', 'm', 'n', 'p', 's', 'u', \\ 'ug', 'p', 'hug', 'pug', 'pugs', 'un', 'hug' \},$$

Final dataset:

$$\mathcal{D} = \{ ['i'], ['hug'], ['pugs'], \\ ['hug'], ['g'], ['i'], ['n'], ['g'], ['pugs'], \\ [''], ['i'], ['s'], [''], ['f'], ['un'], ['i'], \\ [''], ['m'], ['a'], ['k'], ['e'], ['p'], ['un'], ['s'] \}$$

# With this vocabulary, can you represent (or, tokenize/encode):

Q: Can you encode “apple”?

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# Benefits of Byte-pair encoding

1. Efficient to run (greedy vs. global optimization)
2. Lossless compression
3. Potentially some shared representations
  - a. e.g., the token “hug” could be used both in “hug” and “hugging”

# Byte-pair encoding - ChatGPT Example

Call me Ishmael. Some years ago—never mind how long precisely—having  
little or no money in my purse, and nothing particular to interest me on  
shore, I thought I would sail about a little and see the watery part of  
the world. It is a way I have of driving off the spleen and regulating  
the circulation. Whenever I find myself growing grim about the mouth;  
whenever it is a damp, drizzling November in my soul; whenever I find  
myself involuntarily pausing before coffin warehouses, and bringing up  
the rear of every funeral I meet; and especially whenever my hypos get  
such an upper hand of me, that it requires a strong moral principle to  
prevent me from deliberately stepping into the street, and methodically  
knocking people's hats off—then, I account it high time to go to sea  
as soon as I can. This is my substitute for pistol and ball. With a  
philosophical flourish Cato throws himself upon his sword; I quietly  
take to the ship. There is nothing surprising in this. If they but knew  
it, almost all men in their degree, some time or other, cherish very  
nearly the same feelings towards the ocean with me.

TEXT TOKEN IDS

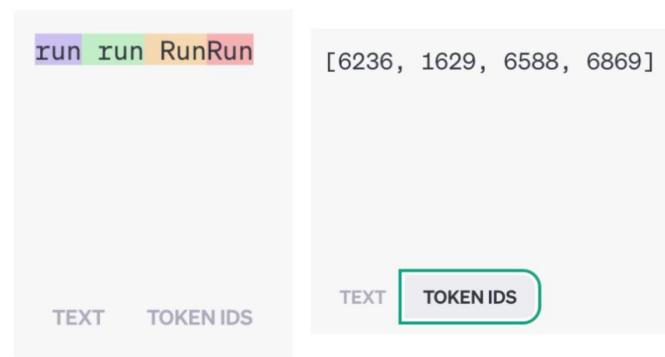
Tokens	Characters
239	1109

[7368, 757, 57704, 1764, 301, 13, 4427, 1667, 4227, 2345, 37593, 4059, 1268, 1317, 24559, 2345, 69666, 2697, 477, 912, 3300, 304, 856, 53101, 11, 323, 4400, 4040, 311, 2802, 757, 389, 31284, 11, 358, 3463, 358, 1053, 30503, 922, 264, 2697, 323, 1518, 279, 30125, 727, 961, 315, 279, 1917, 13, 1102, 374, 264, 1648, 358, 617, 315, 10043, 1022, 279, 87450, 268, 323, 58499, 279, 35855, 13, 43633, 358, 1505, 7182, 7982, 44517, 922, 279, 11013, 26, 15716, 433, 374, 264, 41369, 11, 1377, 73825, 6841, 304, 856, 13836, 26, 15716, 358, 1505, 7182, 4457, 3935, 6751, 7251, 985, 1603, 78766, 83273, 11, 323, 12967, 709, 279, 14981, 315, 1475, 32079, 358, 3449, 26, 323, 5423, 15716, 856, 6409, 981, 636, 1778, 459, 8582, 1450, 315, 757, 11, 430, 433, 7612, 264, 3831, 16033, 17966, 311, 5471, 757, 505, 36192, 36567, 1139, 279, 8761, 11, 323, 1749, 2740, 50244, 1274, 753, 45526, 1022, 2345, 3473, 11, 358, 2759, 433, 1579, 892, 311, 10616, 636, 311, 9581, 439, 5246, 439, 358, 649, 13, 1115, 374, 856, 28779, 369, 40536, 323, 5041, 13, 3161, 264, 41903, 67784, 356, 4428, 3872, 5678, 5304, 813, 20827, 26, 358, 30666, 1935, 311, 279, 8448, 13, 2684, 374, 4400, 15206, 304, 420, 13, 1442, 814, 719, 7020, 433, 11, 4661, 682, 3026, 304, 872, 8547, 11, 1063, 892, 477, 1023, 11, 87785, 1022, 7514, 279, 1890, 16024, 7119, 279, 18435, 449, 757, 13]

# Weird properties of tokenizers

Token != word

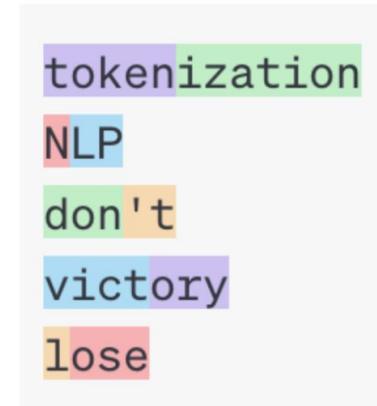
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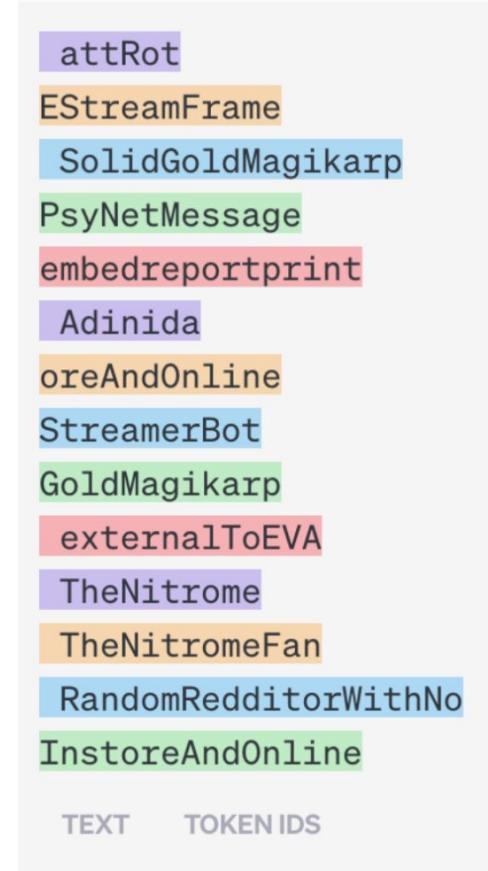
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These words are all 1 token in GPT-3’s tokenizer!

Does anyone know why?



Next time:  
RNNs & LSTMs