# Word Embeddings (I)

CS 485, Fall 2024
Applications of Natural Language Processing

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- Last week: Markov N-gram models
- Today: augment with word embeddings
  - 1. Markov model
  - 2. Skip-gram model

- Why?
  - Better LMs
  - Automatically learned word representations ("word embeddings") are interesting & can be used directly (continues Thursday)

# Word embeddings

- Today
  - 1. Question: how can we generally represent word meanings?
  - 2. Approach: train a language model with ***word embeddings*** to discover latent meanings of words!
    - ... which exploit the ***distributional hypothesis***

- Key idea: automatically discover aspects of language meaning, from raw textual corpora

# What is "asdfasdf"?

“ **asdfasdf**, Most Neglected American Fruit.” — NYTimes 1922

“ **asdfasdf** Recommended by U.S. Food Experts, Along With Persimmon, as War Nutrition” — NYTimes 1942

“ The **asdfasdf** is also pollinated by flies and other insects rather than by honeybees…”— NYTimes 2020

“Many people also cook with ripe **asdfasdf**, making bread, beer, ice cream, or this **asdfasdf** pudding…” — NYTimes 2020

## What is a *pawpaw* ?

## I. Look it up in a dictionary

https://www.merriam-webster.com/

https://www.oed.com/

https://en.wiktionary.org/

# pawpaw noun

Save Word

paw·paw

variants: *or less commonly* **papaw**

## Definition of *pawpaw*

**1** \ pə-ˈpȯ \ **:** PAPAYA

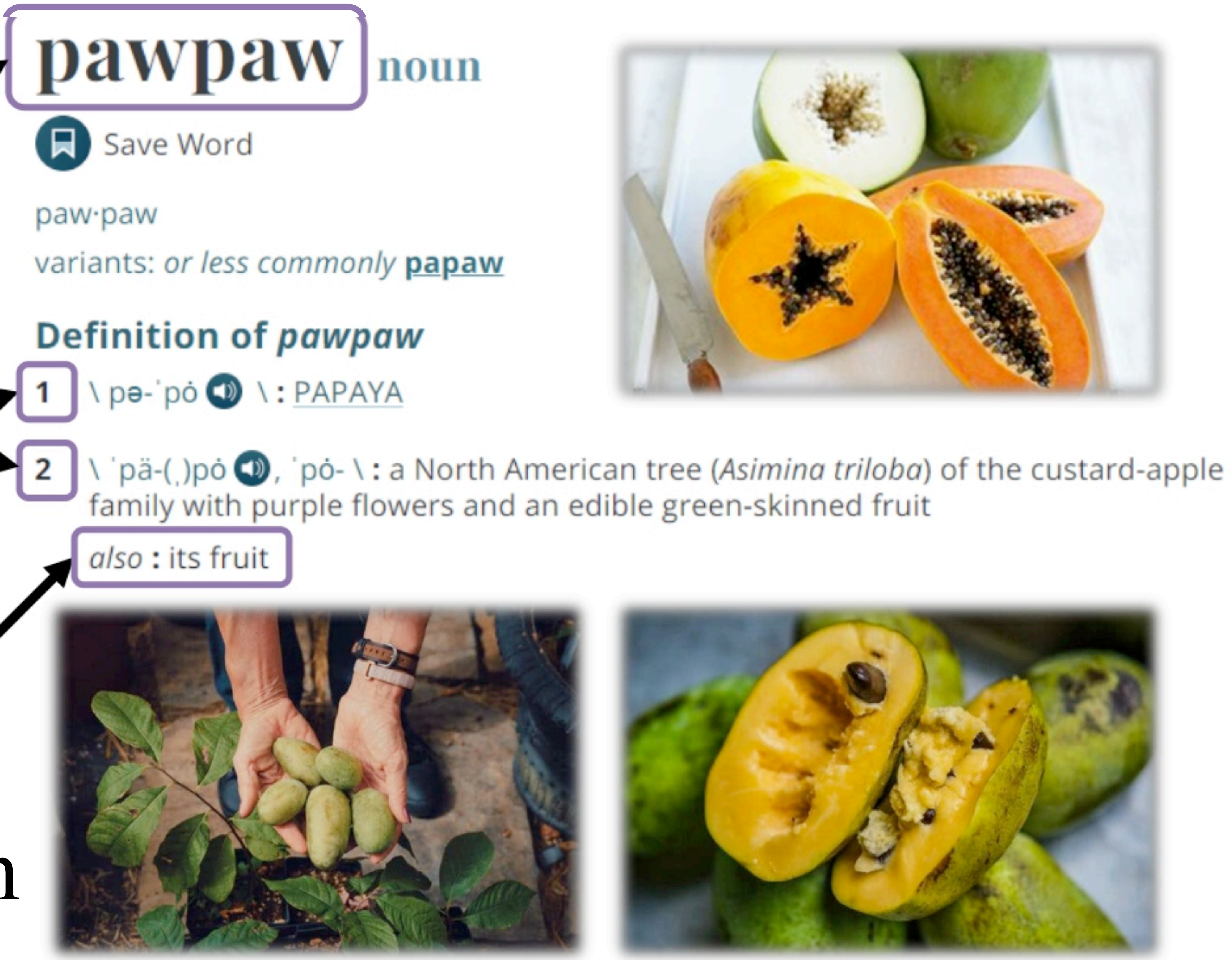
**2** \ ˈpä-(ˌ)pȯ, ˈpȯ- \ **:** a North American tree (*Asimina triloba*) of the custard-apple family with purple flowers and an edible green-skinned fruit

*also* **:** its fruit

Lemma

Word Senses

Definition



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## II. Look it at how its used

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“Many people also **cook** with **ripe** *pawpaws* , making **bread** , **beer**, **ice cream** , or this *pawpaw* **pudding** …” — NYTimes 2020

## Aspects of word meaning

**Synonyms**

- couch / sofa
- oculist / eye - doctor
- car / automobile
- water / $H_2O$
- draft / draught

**Antonyms**

- yes / no
- dark / light
- hot / cold
- up / down
- clip / clip

## Aspects of word meaning

**Similarity**

· cat / dog

· cardiologist / pulmonologist

· car / bus

· sheep / goat

· glass / mug

**Relatedness**

· coffee / cup

· waiter / menu

· farm / cow

· house / roof

· theater / actor

## Aspects of word meaning

- Connotation: the affective meaning of a word
- Osgood (1957)'s three-dimensional model:
  - Valence
    - unhappy, annoyed <---------------> happy, satisfied
  - Arousal
    - calm <---------------> excited
  - Dominance
    - awed, influences <---------------> controlling

| | Valence | Arousal | Dominance |
|---|---|---|---|
| courageous | 8.05 | 5.5 | 7.38 |
| music | 7.67 | 5.57 | 6.5 |
| heartbreak | 2.45 | 5.65 | 3.58 |
| cub | 6.71 | 3.95 | 4.24 |

# Word embeddings/vectors

- We need a representation of words capable of synonyms, rough similarity, or maybe even other aspects of meaning
- Give each word a k-dimensional **vector**
  - a vector is a list of numbers
  - a vector is a point/direction in k-dimensional space

# Learning word representations

- How to get word meanings?
  - Lexical resources like WordNet: dictionary-like databases of word synonyms & other word-to-word relationships, constructed manually
    - Can sometimes help, but typically don't cover all words or meanings any particular task needs

- OK, can we *learn* the word representations instead?

# Distributional Semantics

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

**Intuitions:** Harris (1954)

"If A and B have almost identical environments except chiefly sentences which contain both, we say they are synonyms: *oculist* and *eye- doctor* ."

# Learning word representations

- Could we automatically *learn* word meanings?
  - 1. We'd like to generalize word meanings beyond individual words, and
  - 2. Information from nearby words gives information about a word
- What model have we seen, that uses information from nearby words to make inferences about another word?

- Two word-embedding-based LMs
  - 1. Markovian left-to-right LM (Bengio et al. 2003)
  - 2. "Skip-gram" LM
    - Learns useful standalone embeddings

## Left-to-right LM as log. reg.

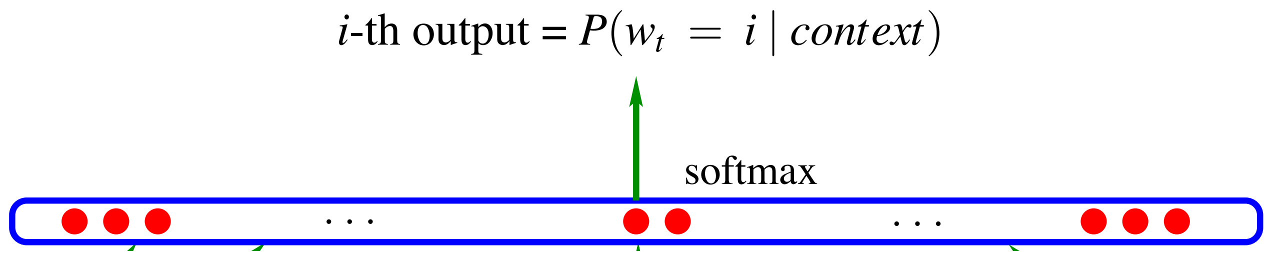
- Instead of only n-gram count ratios, model the next-word as softmax over the vocabulary.
- We can use anything to help predictions: features (Rosenfeld 1996) or neural networks (Bengio et al. 2003) to compose **$\mathbf{v_u}$**:

$$\mathrm{p}(w \mid u) = \frac{\exp(\boldsymbol{\beta}_w \cdot \boldsymbol{v}_u)}{\sum_{w' \in \mathcal{V}} \exp(\boldsymbol{\beta}_{w'} \cdot \boldsymbol{v}_u)} \qquad \begin{array}{r}\boldsymbol{\beta}_w \in \mathbb{R}^K \\ \boldsymbol{v}_u \in \mathbb{R}^K\end{array}$$

- Can use any information from the left context: long-distance topical information, or word vectors!

# Bengio et al. 2003: Markov word embedding LM

Key idea: represent words on left as **vectors.** Learn a vector for each word in the vocabulary. Better perplexity than an n-gram LM!



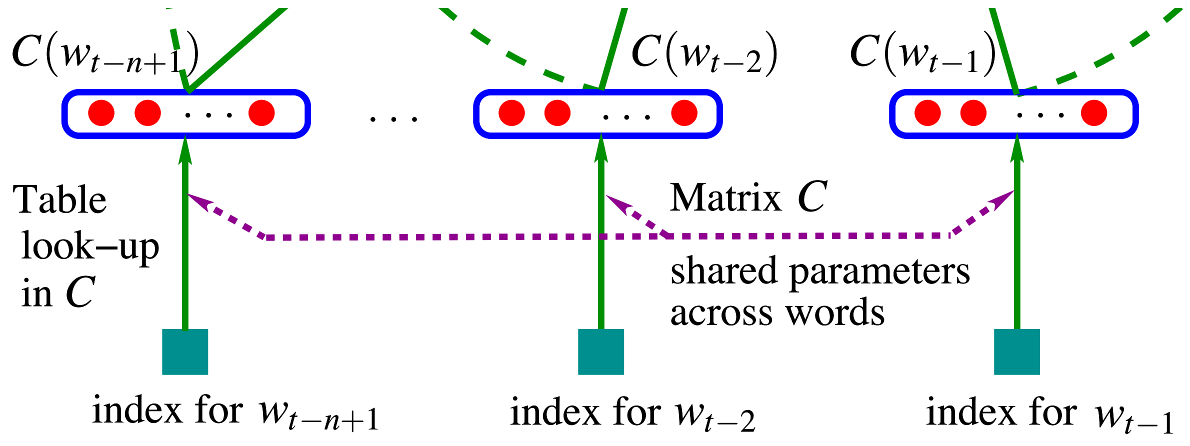
Output layer (softmax)

$$\hat{P}(w_t|w_{t-1},\cdots w_{t-n+1}) = \frac{e^{y_{w_t}}}{\sum_i e^{y_i}}.$$

*(ignore today)*
*hidden layer,*
*size h*

linear layer

$$y = \underbrace{b + Wx}_{} + \underbrace{U\,tanh(d+Hx)}_{}$$



$$x = (C(w_{t-1}), C(w_{t-2}), \cdots, C(w_{t-n+1}))$$

Word vector lookup layer
with concatenation

$C(i) \in \mathbb{R}^m$ Word embedding parameters

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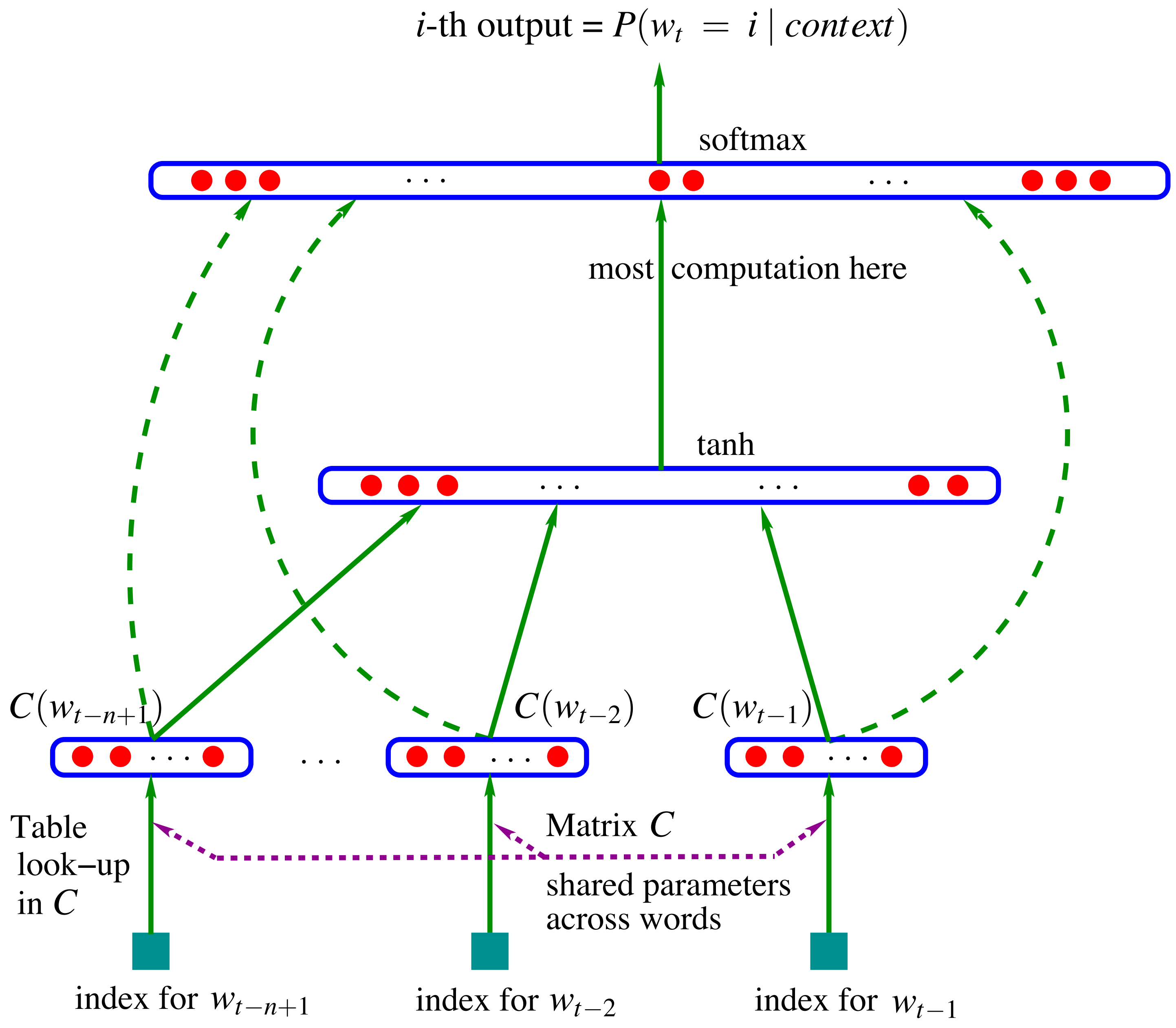

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linear layer

(ignore today) hidden layer, size $h$

$$y = \underbrace{b + Wx}_{\text{linear layer}} + \underbrace{U \tanh(d+Hx)}_{\text{hidden layer}}$$

$$x = (C(w_{t-1}), C(w_{t-2}), \cdots, C(w_{t-n+1}))$$

Word vector lookup layer with concatenation

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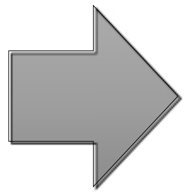
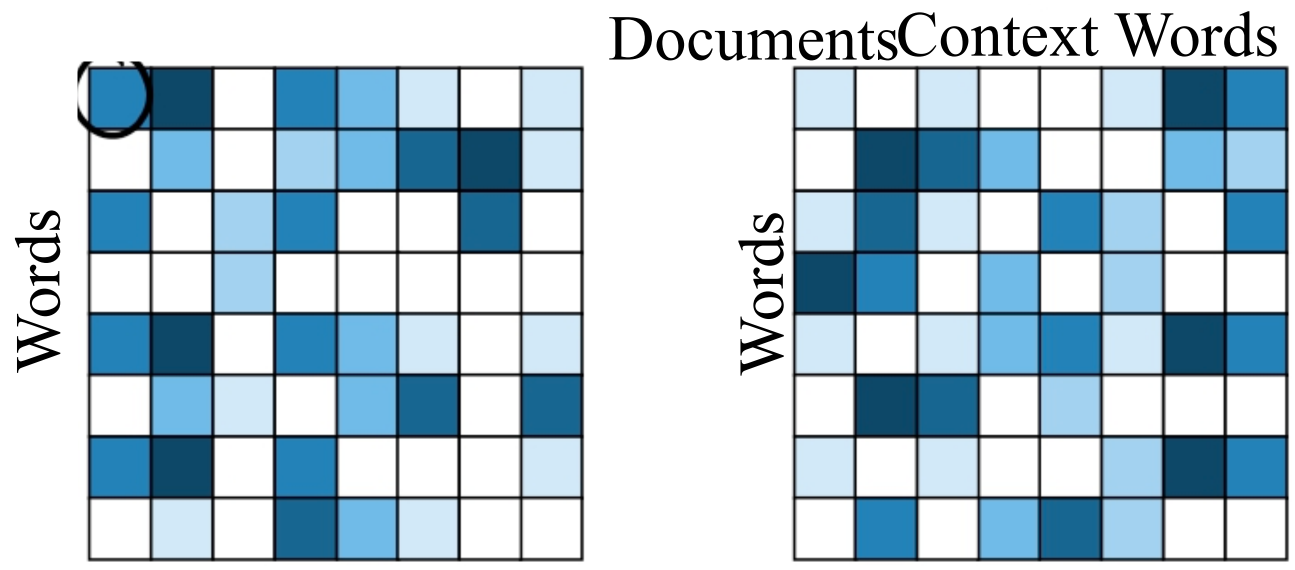
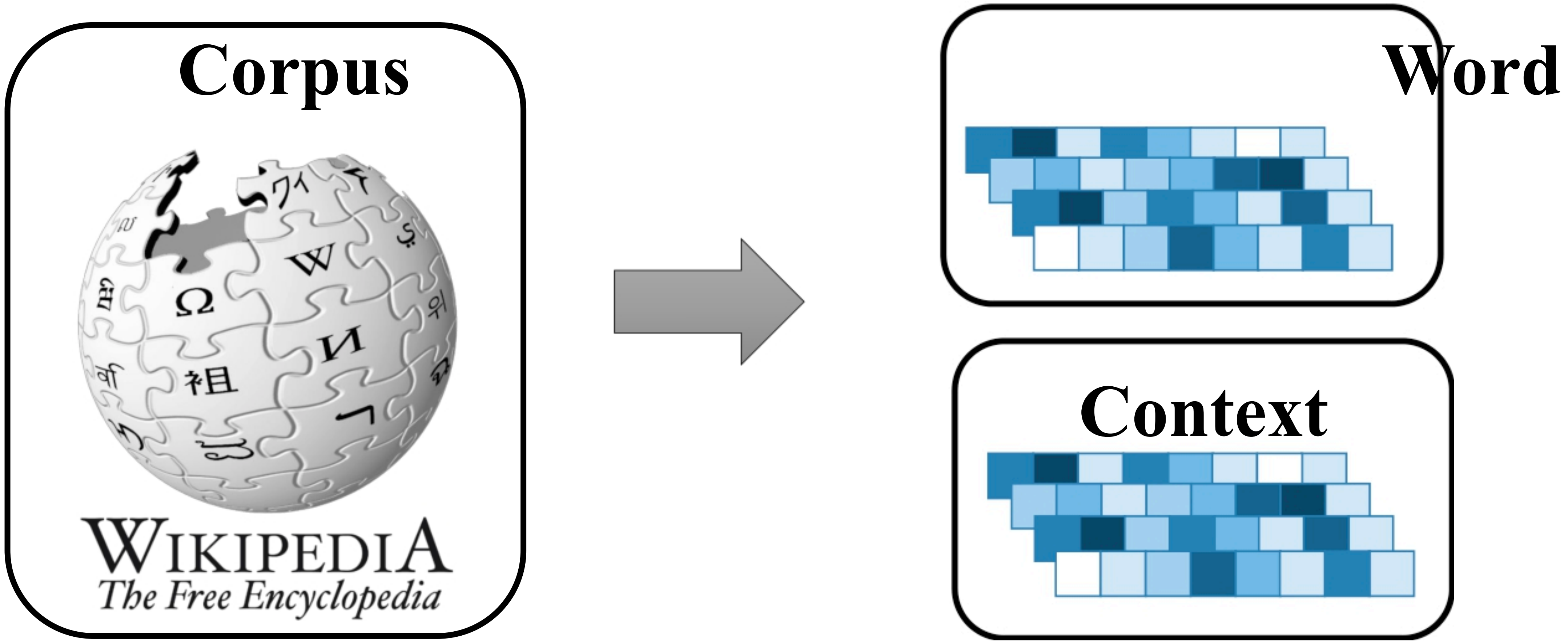
# Build vectors based on context



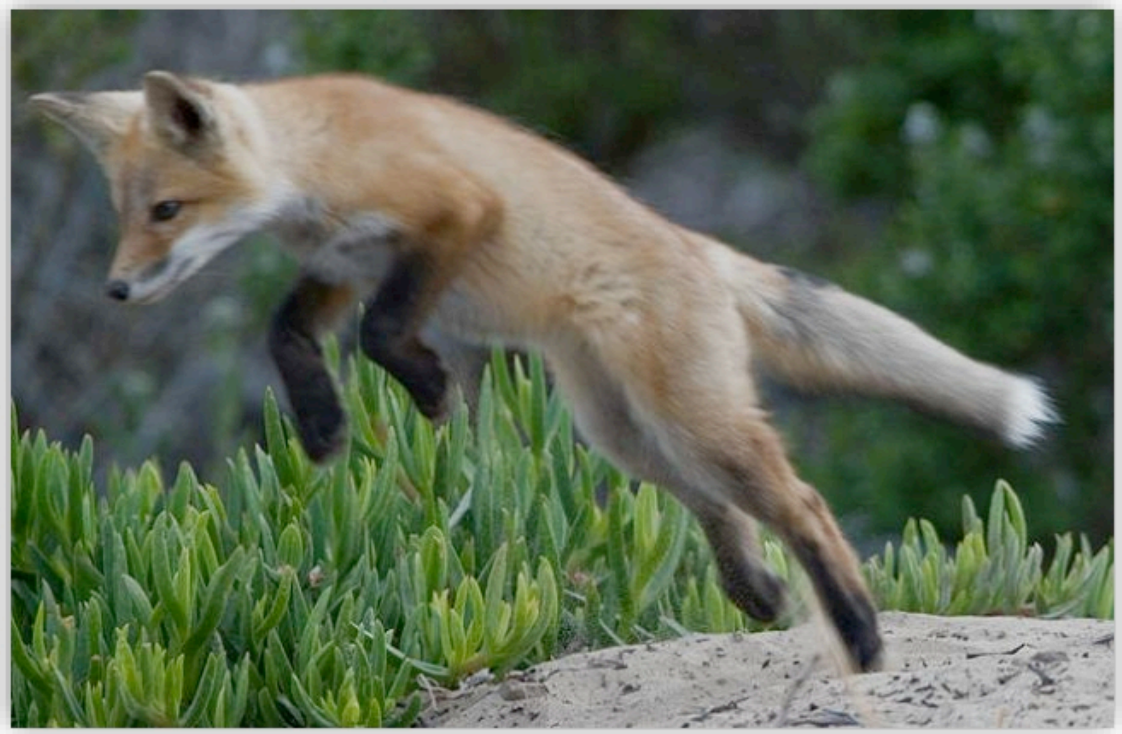


# Neural Word Embeddings



# Skip- Gram with Negative Sampling (SGNS)

The brown fox **jumps** over the lazy dog



## **SG** NS: Skip- Gram Model

The brown fox **jumps** over the lazy dog.

Context Window Size = 2

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The brown fox **jumps** over the lazy dog.

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Simple idea: from a word, predict its context words!
(A funny type of language model.)
Learn a vector that's good at that. Similar words should get similar vectors.

## Key idea: use unlabeled text as *implicitly supervised data*

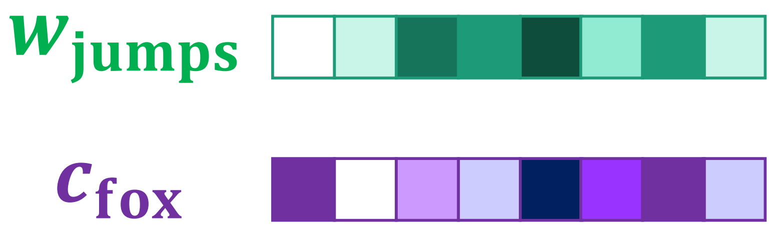
- A word *s* near *apricot*
  - Acts as gold 'correct answer' to the question
  - "Is word *w* likely to show up near *apricot*?"
- No need for hand-labeled supervision
- The idea comes from **neural language modeling**
  - Bengio et al. (2003)
  - Collobert et al. (2011)

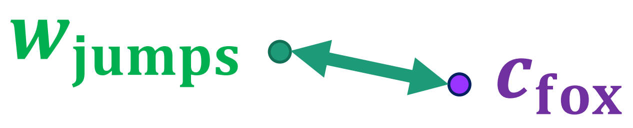
# Modeling goal

- Given a (word, context) tuple
    - [+] (apricot, jam) <- observed
    - [–] (apricot, aardvark) <- unseen
- Want binary probability
    - $P(c \mid w)$ for a real context [+])
    - $1-P(c \mid w)$ for a "fake", unseen context [–])
- Let $u_t$ and $v_c$ be their vectors.
- $P(c \mid w) = \sigma(u_w' v_c)$: logistic in their *affinity/similarity*
- Maximize $P(c \mid w)$ for all (w, c) pairs

# SGNS : Negative Sampling

Co-occurrence **jumps** , **fox**:





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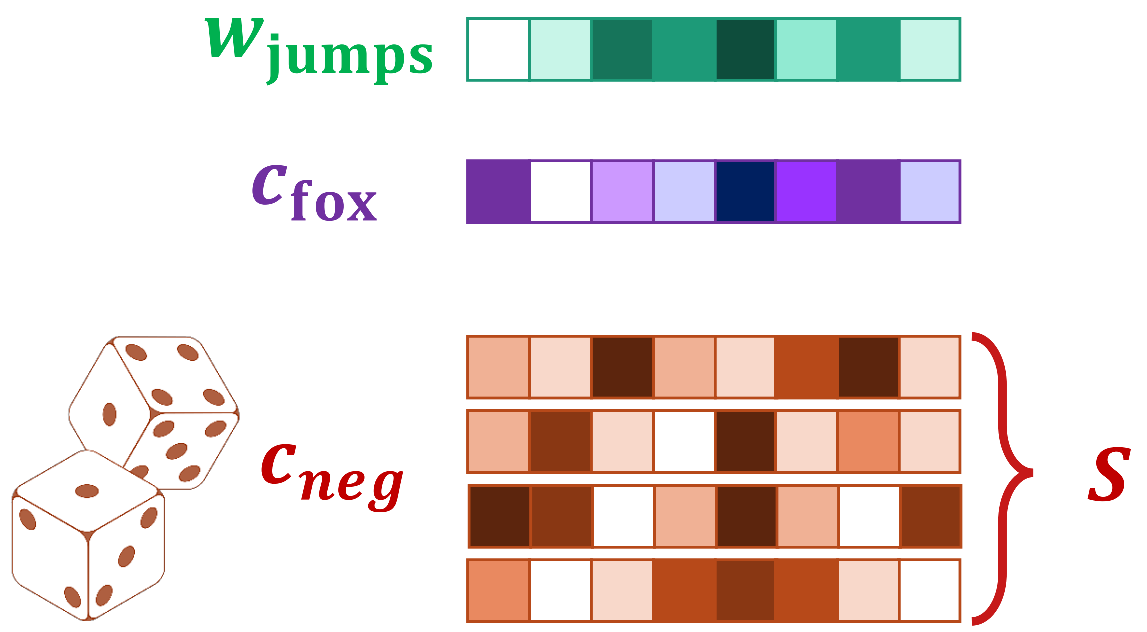
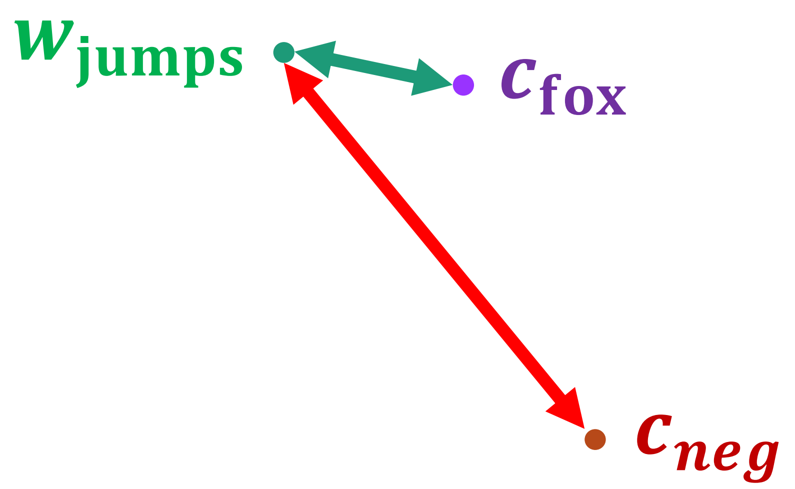


$w_{\text{jumps}}$
$c_{\text{fox}}$
$c_{neg}$
$S$



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