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Ethical Aspects of Data

Fairness, Bias, in Data Representation

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28/11/2023

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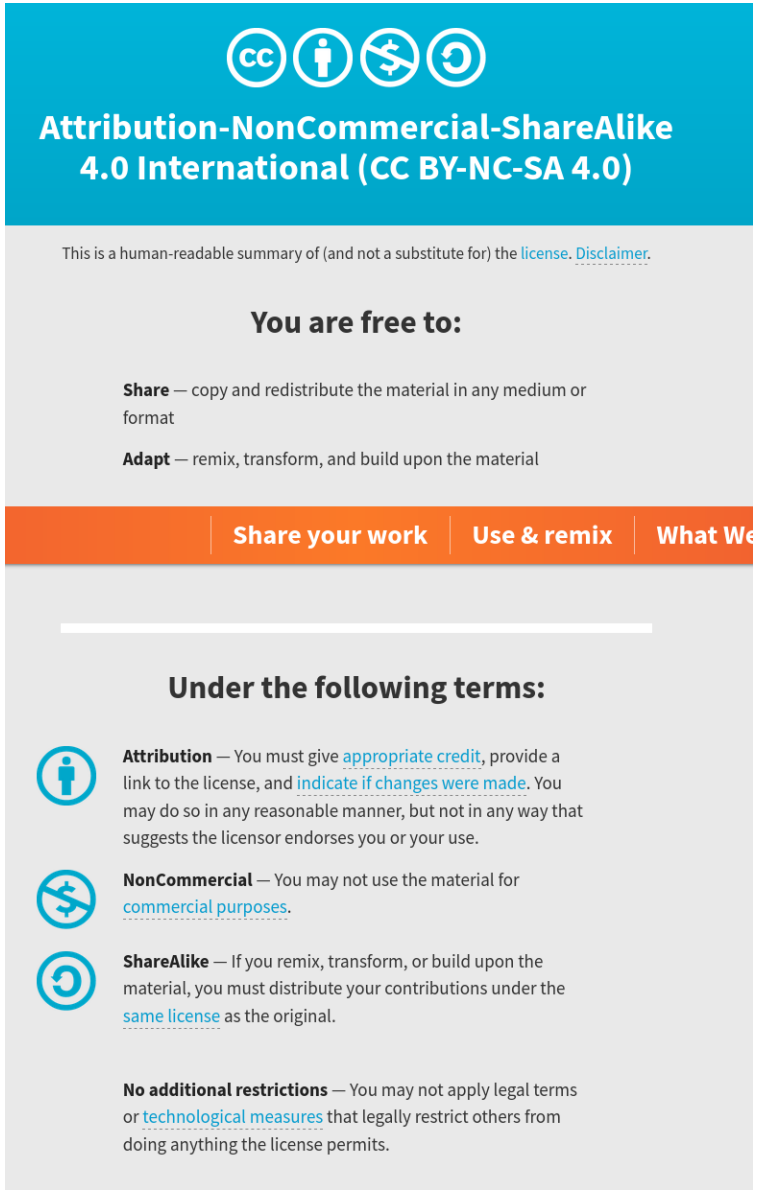

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Overview

- **Context**
- Text representation
- Bias in textual information

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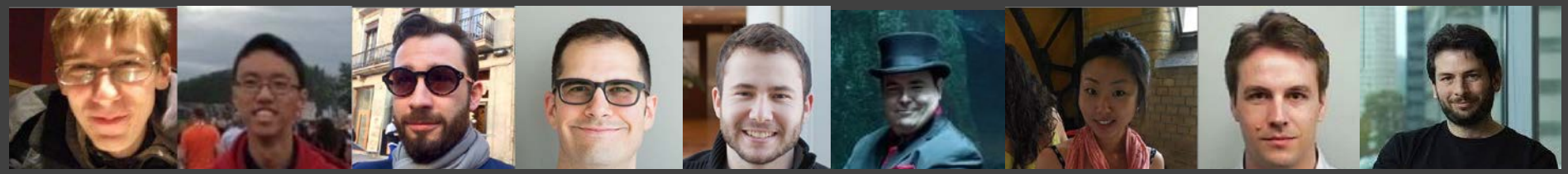
CONTEXT

Bias in the Vision and Language of Artificial Intelligence

Margaret Mitchell
Senior Research Scientist
Google AI

Conversation AI

Andrew Zaldivar | Me | Simone Wu | Parker Barnes | Lucy Vasserman | Ben Hutchinson | Elena Spitzer | Deb Raji | Timnit Gebru



Adrian Benton | Brian Zhang | Dirk Hovy | Josh Lovejoy | Alex Beutel | Blake Lemoine | Hee Jung Ryu | Hartwig Adam | Blaise Agüera y Arcas

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store
- Bananas on shelves
- Bunches of bananas
- Bananas with stickers on them
- Bunches of bananas with stickers on them on shelves in a store

...We don't tend to say
Yellow Bananas

Green ?

Margaret Mitchell

What do you see?

Green Bananas

Unripe Bananas

Margaret Mitchell

What do you see?

Ripe Bananas

Bananas with spots

Bananas good for banana bread

Margaret Mitchell

What do you see?

Yellow Bananas?

***Yellow* is prototypical for bananas**

Margaret Mitchell

Prototype theory is a cognitive theory of categorization that suggests that humans categorize objects, concepts, and experiences by comparing them to a mental representation of the "prototype" of that category. The prototype is an abstract idealized representation that encapsulates the typical or central features of a category.

Prototype Theory

One purpose of categorization is to **reduce the infinite differences** among stimuli **to** behaviourally and **cognitively usable proportions**

There may be some central, prototypical notions of items that arise from stored typical properties for an object category (Rosch, 1975)

May also store exemplars (Wu & Barsalou, 2009)

Fruit

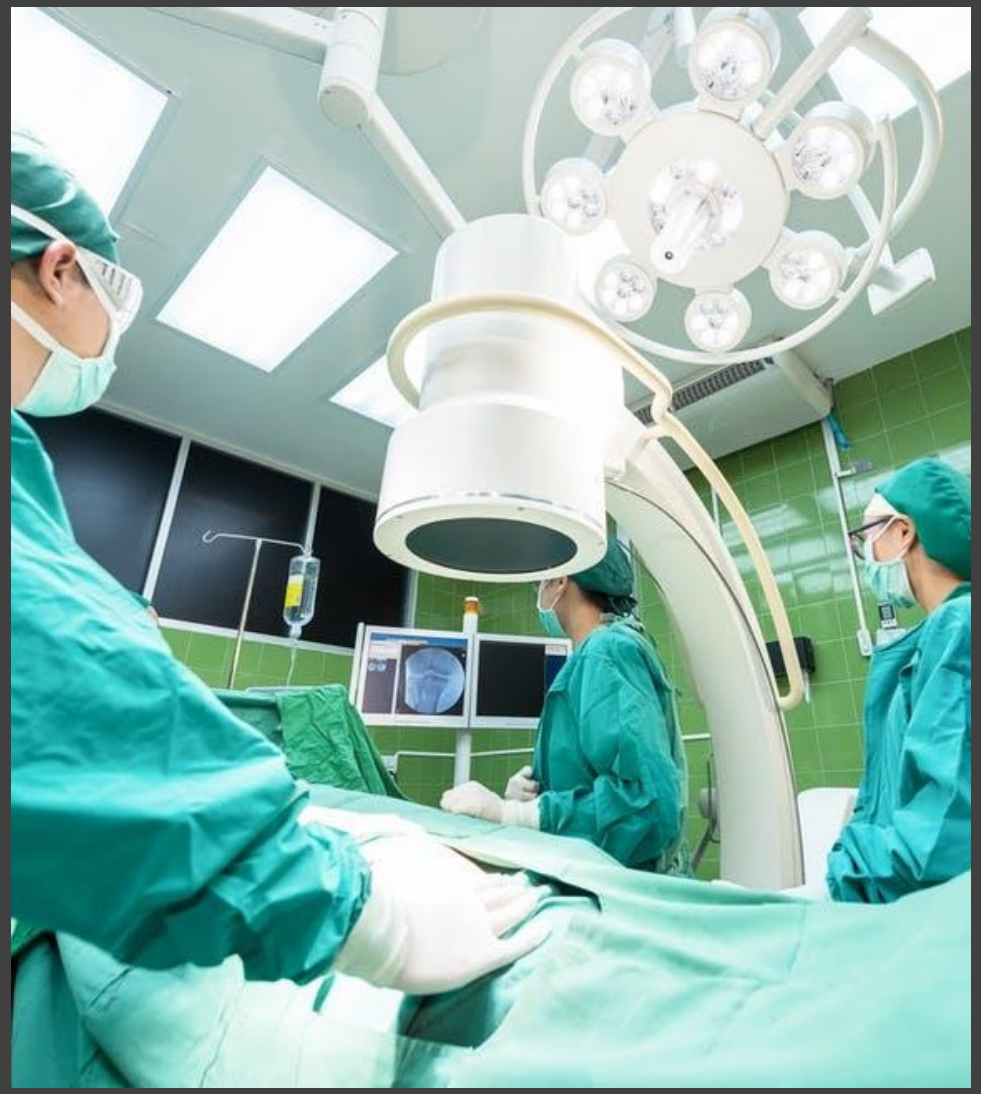
Bananas
“Basic Level”

Unripe Bananas,
Cavendish Bananas

A man and his son are in a terrible accident and are rushed to the hospital in critical care.

The doctor looks at the boy and exclaims "I can't operate on this boy, he's my son!"

How could this be?



Margaret Mitchell

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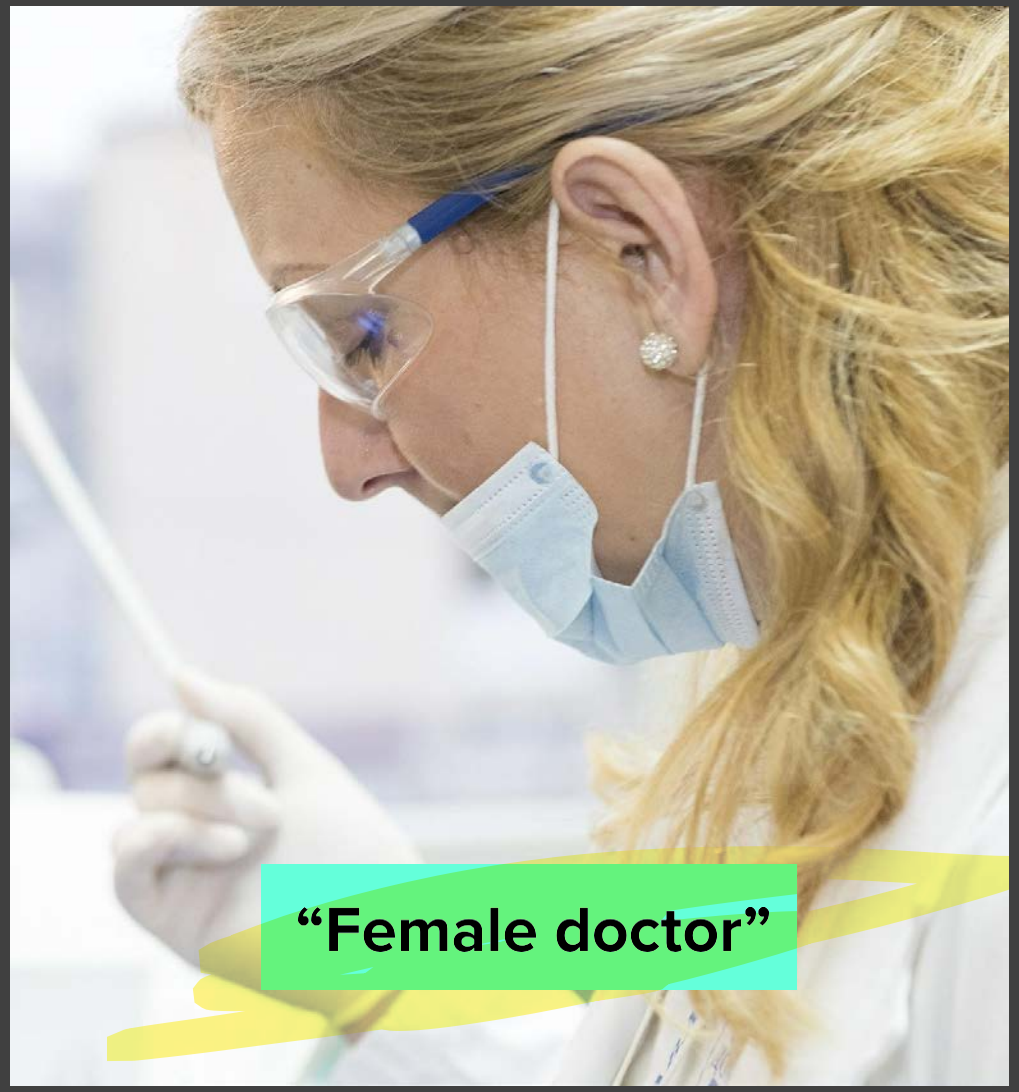

Margaret Mitchell

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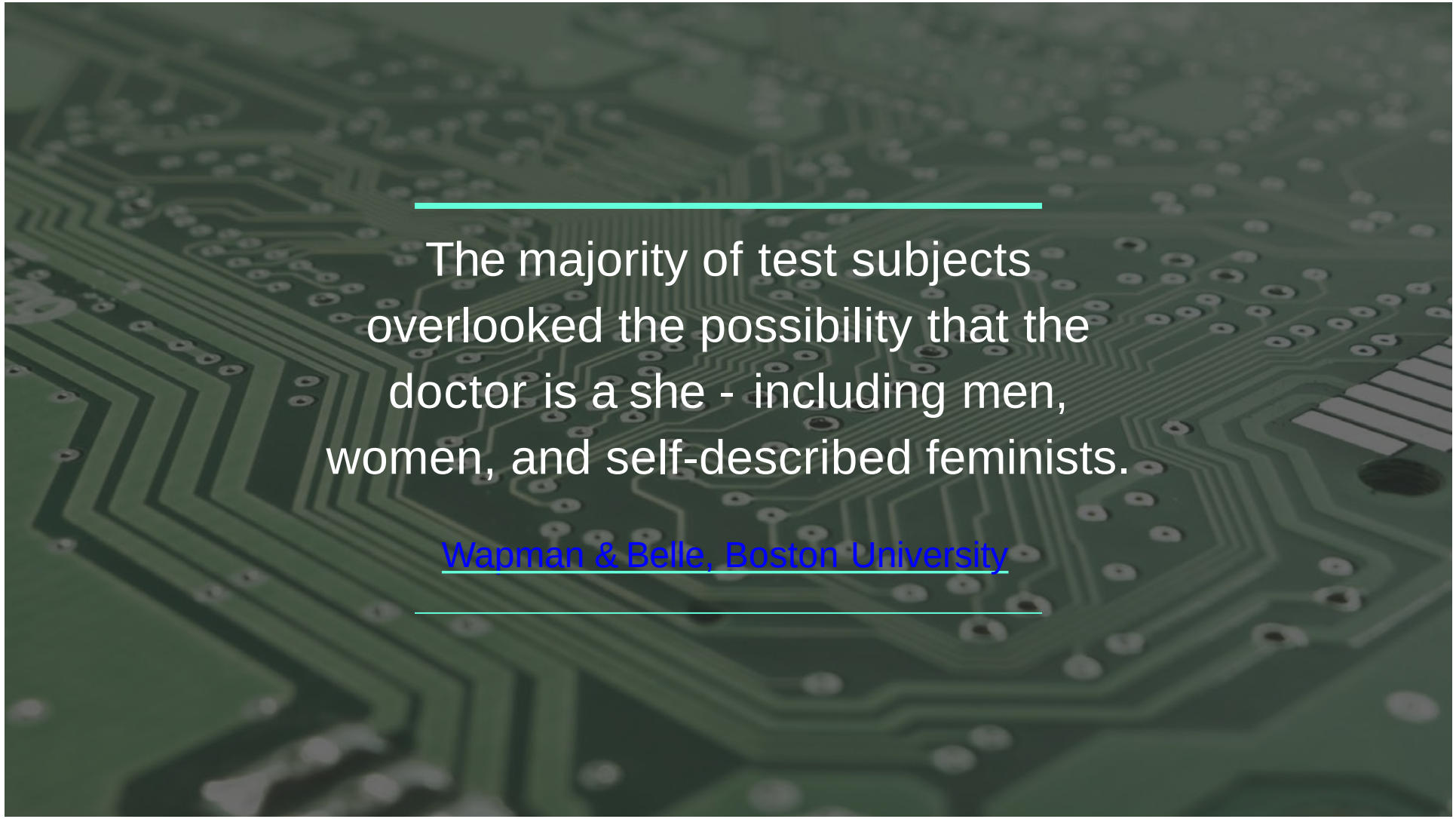

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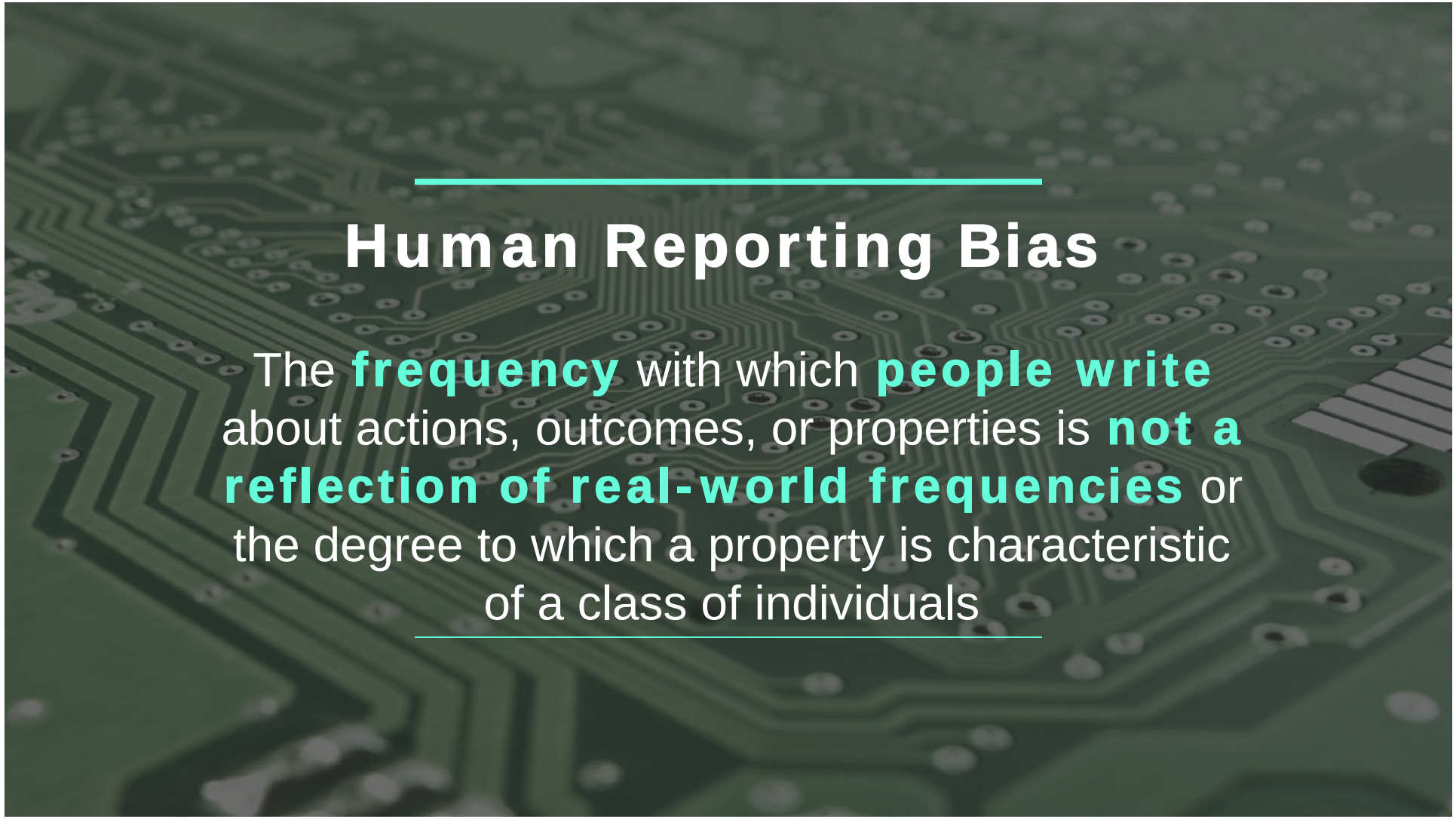

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Bias in Language

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

Figure 1: The most extreme occupations as projected on to the *she*−*he* gender direction on g2vNEWS. Occupations such as *businesswoman*, where gender is suggested by the orthography, were excluded.

Gender stereotype *she-he* analogies.

sewing-carpentry	register-nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	hairdresser-barber

Gender appropriate *she-he* analogies.

queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

Figure 2: **Analogy examples**. Examples of automatically generated analogies for the pair *she-he* using the procedure described in text. For example, the first analogy is interpreted as *she*:*sewing* :: *he*:*carpentry* in the original w2vNEWS embedding. Each automatically generated analogy is evaluated by 10 crowd-workers are to whether or not it reflects gender stereotype. Top: illustrative gender stereotypic analogies automatically generated from w2vNEWS, as rated by at least 5 of the 10 crowd-workers. Bottom: illustrative generated gender-appropriate analogies.

Bolukbasi et al., “Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings”, NIPS 2016

Bias in Language

Adjectives

Or type your own words...

doctor

he (158)

she (42)

he (47)

she (153)

http://wordbias.umiacs.umd.edu/

But…don't forget the biases in the initial data

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

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Bias in Vision

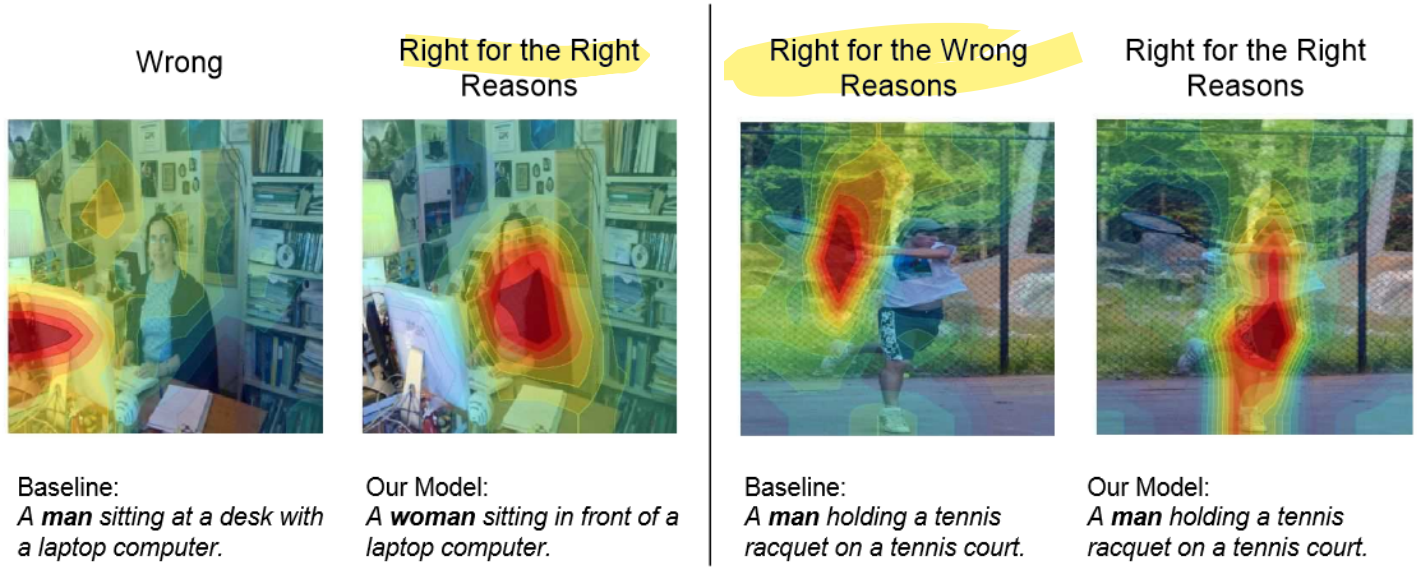


Fig. 1: Examples where our proposed model (Equalizer) corrects bias in image captions. The overlaid heatmap indicates which image regions are most important for predicting the gender word. On the left, the baseline predicts gender incorrectly, presumably because it looks at the laptop (not the person). On the right, the baseline predicts the gender correctly but it does not look at the person when predicting gender and is thus not acceptable. In contrast, our model predicts the correct gender word and correctly considers the person when predicting gender.

Burns et al., "Women also Snowboard: Overcoming Bias in Captioning Models", ECCV 2018

Bias in Vision

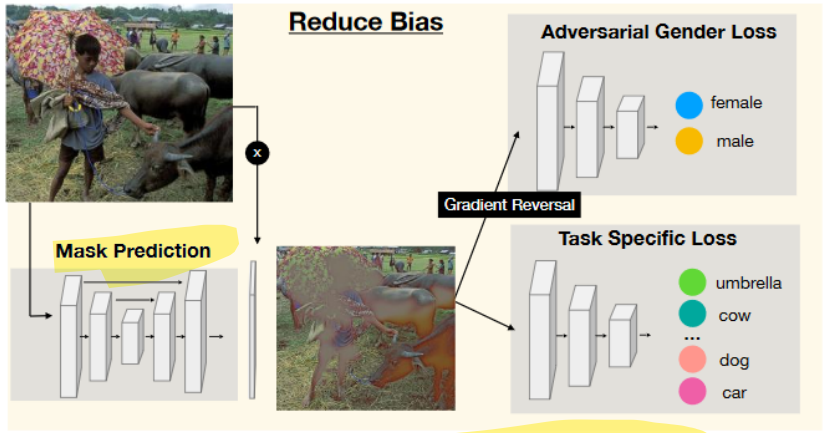


Figure 2. In our bias mitigation approach, we learn a task-specific model with an adversarial loss that removes features corresponding to a protected variable from an intermediate representation in the model – here we illustrate our pipeline to visualize the removal of features in image space through an auto-encoder network.

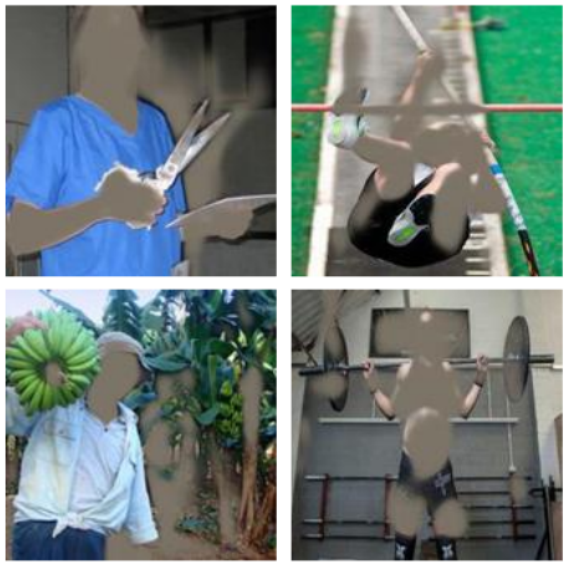
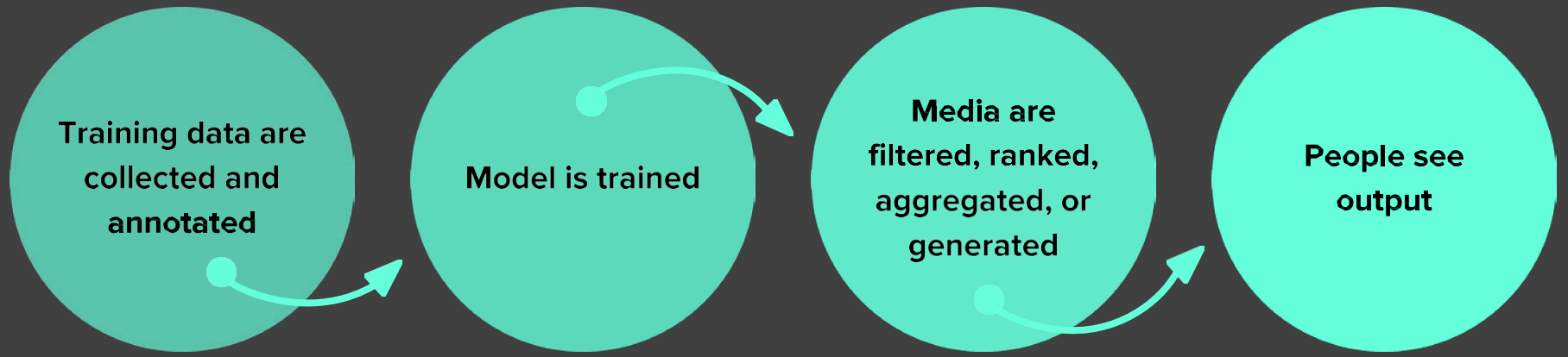


Figure 3. Images after adversarial removal of gender when applied to the image space. The objective was to preserve information about objects and verbs, e.g. scissors, banana (COCO) or vaulting, lifting (imSitu) while removing gender correlated features.

Wang et al., "Balanced Datasets Are Not Enough: Estimating and Mitigating Gender Bias in Deep Image Representations", ICCV 2019



Margaret Mitchell

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Overview

- Context
- **Text representation**
- Bias in textual information

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TEXT REPRESENTATION

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) ⇔ signified (idea or thing)

= denotational semantics

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How do we have usable meaning in a computer?

Common solution: Use e.g. WordNet, a thesaurus 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
```

e.g. hypernyms of "panda":

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

Problems with resources like WordNet

- Great as a resource but missing nuance
  - e.g. "proficient" is listed as a synonym for "good". This is only correct in some contexts.
- Missing new meanings of words
  - e.g., wicked, badass, nifty, wizard, genius, ninja, bombest
  - Impossible to keep up-to-date!
- Subjective
- Requires human labor to create and adapt
- Can't compute accurate word similarity

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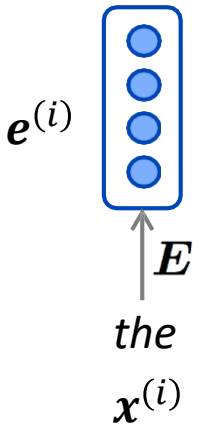
First let us now detail how to represent words as vectors: *word embedding*



Representing words as discrete symbols

In traditional NLP, we regard words as discrete symbols:
hotel, conference, motel – a localist representation

Means one 1, the rest 0s

Words can be represented by one-hot vectors:

motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]

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

Problem with words as discrete symbols

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

But:

motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
hotel = [0 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!

Solution:

- Could try to rely on WordNet's list of synonyms to get similarity?
  - But it is well-known to fail badly: incompleteness, etc.
- **Instead: learn to encode similarity in the vectors themselves**

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learn to encode similarity in the vectors themselves

1-of-N Encoding
(one-hot encoding)

apple = [1 0 0 0 0]

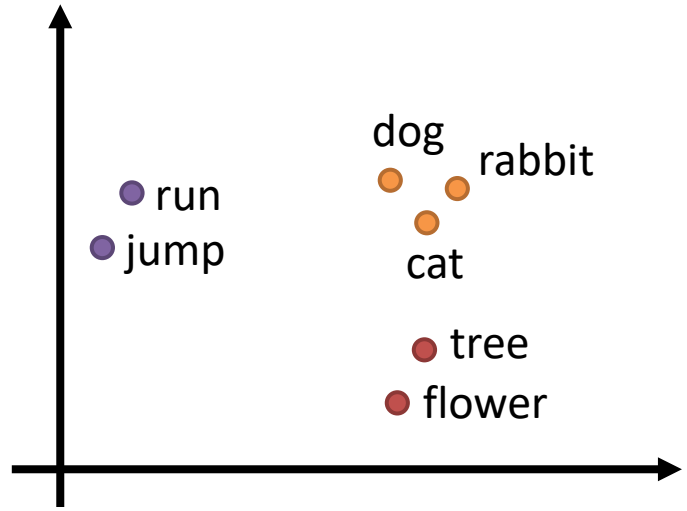
bag = [0 1 0 0 0]

cat = [0 0 1 0 0]

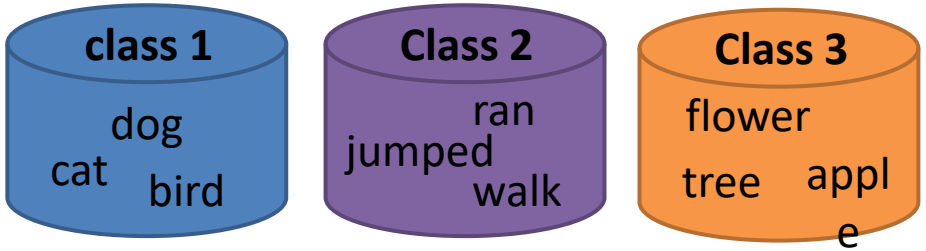
dog = [0 0 0 1 0]

elephant = [0 0 0 0 1]

Word Embedding



Word Class



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How to exploit the context?

- **Count based**
  - If two words w_i and w_j frequently co-occur, $V(w_i)$ and $V(w_j)$ would be close to each other
  - E.g. Glove Vector: http://nlp.stanford.edu/projects/glove/

$V(w_i) \cdot V(w_j)$ ⟷ $N_{i,j}$

Inner product

Number of times w_i and w_j in the same document

- **Prediction-based..**

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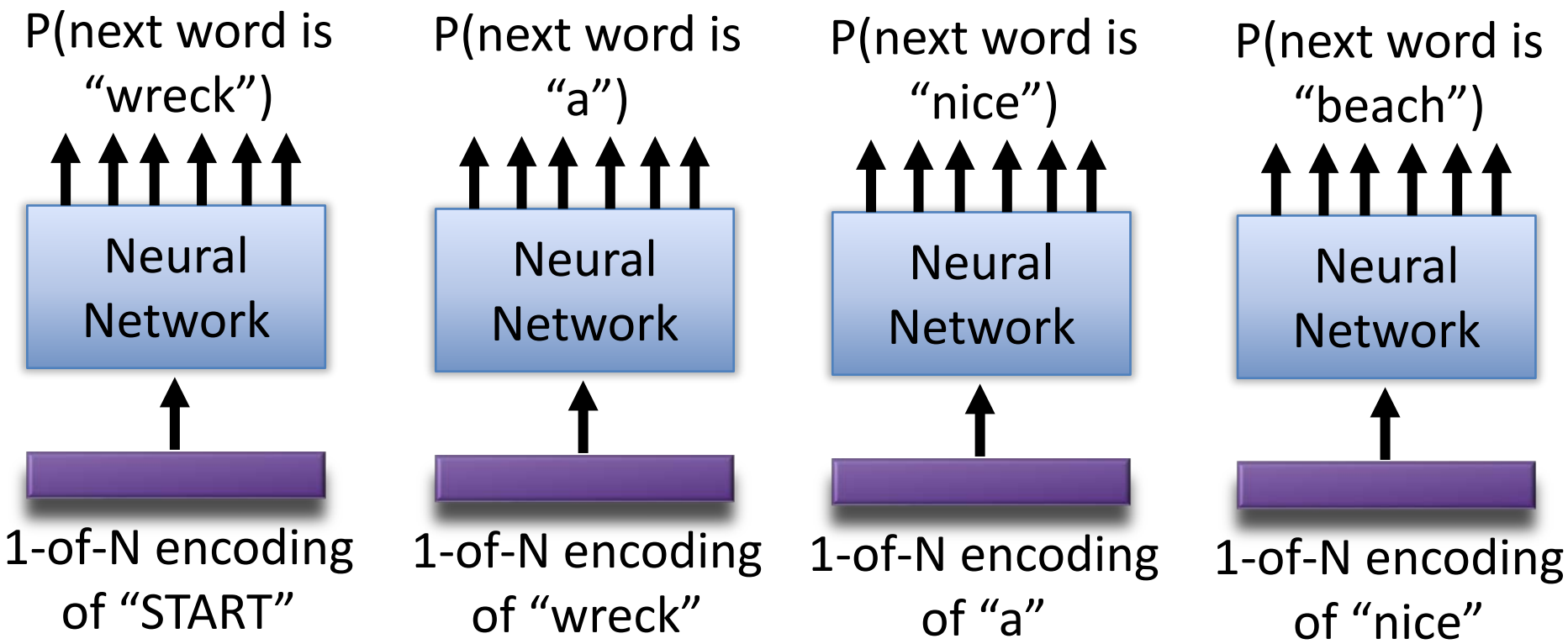
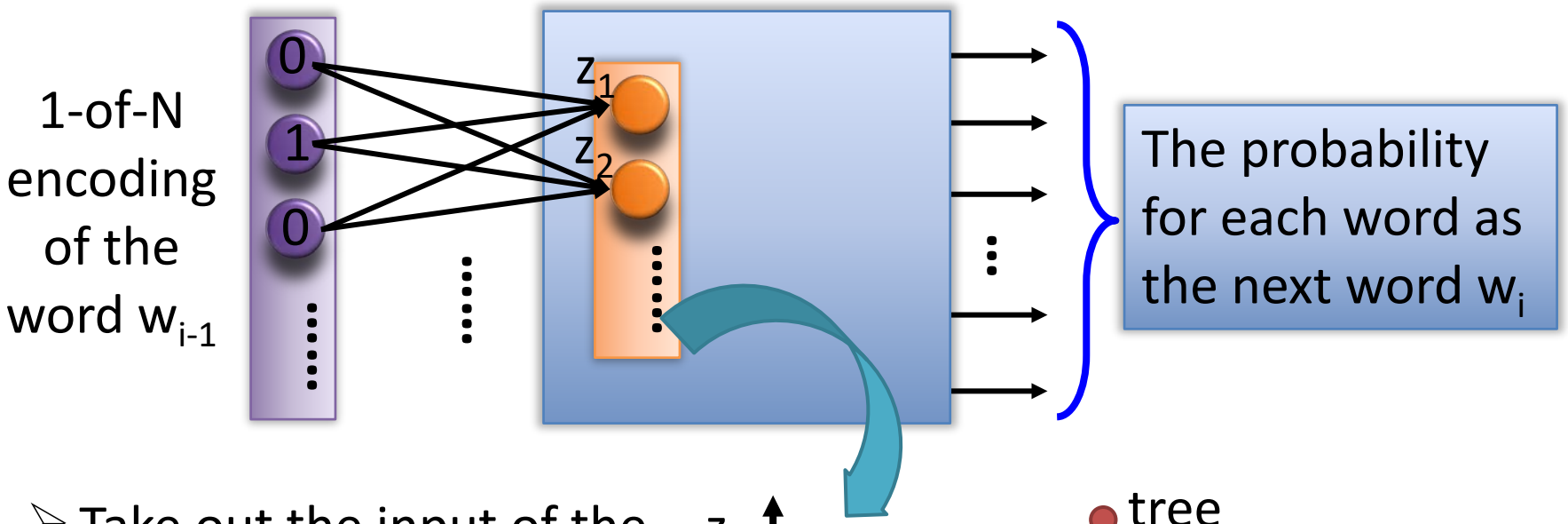
Prediction-based – Language Modeling

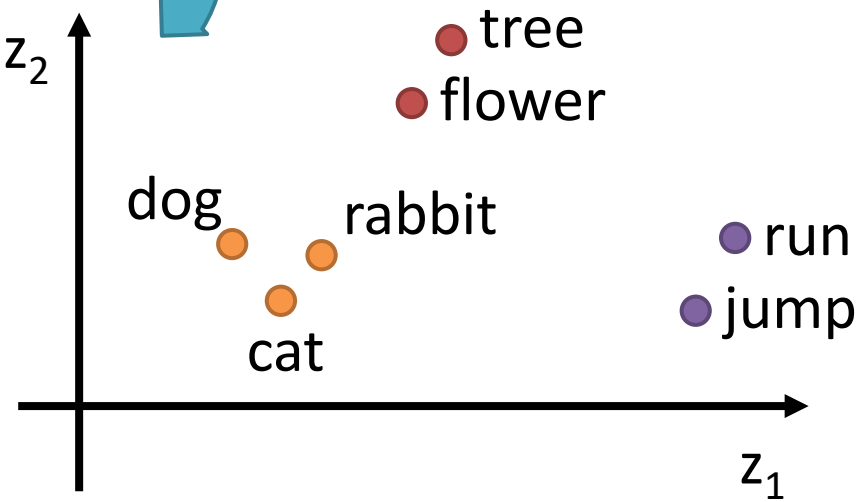
P("wreck a nice beach")
=P(wreck|START)P(a|wreck)P(nice|a)P(beach|nice)
P(b|a): the probability of NN predicting the next word.



Prediction-based



- Take out the input of the neurons in the first layer
- Use it to represent a word w
- Word vector, word embedding feature: V(w)



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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)
  - **One of the most successful ideas of modern statistical NLP!**
  - **However, this is a deliberate choice!!**
- When a word *w* appears in a text, its **context** is the set of words that appear nearby (within a fixed-size window).
- Use the many contexts of *w* to build up a representation of *w*

…government debt problems turning into	***banking***	*crises as happened in 2009…*
…saying that Europe needs unified	***banking***	*regulation to replace the hodgepodge…*
…India has just given its	***banking***	*system a shot in the arm…*

These context words will represent ***banking***

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What can we learn from reconstructing the input?

Stanford University is located in_____, California.

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What can we learn from reconstructing the input?

I put____fork down on the table.

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What can we learn from reconstructing the input?

The woman walked across the street,

checking for traffic over ____shoulder.

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

$$\textit{banking} = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{pmatrix}$$

Note: word vectors are sometimes called word embeddings or word representations. They are a distributed representation.

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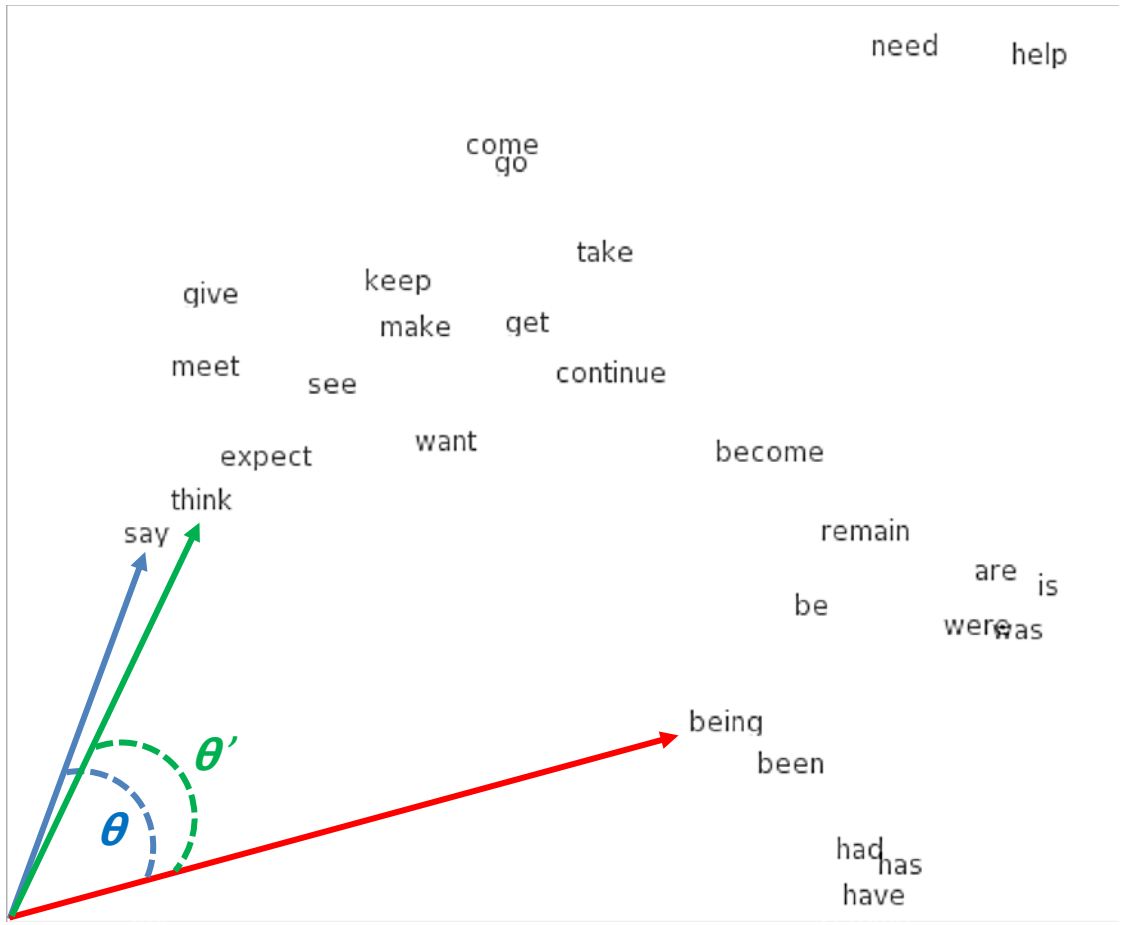
Word meaning as a neural word vector – visualization

$$expect = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \\ 0.487 \end{pmatrix}$$



$\theta' \cong \theta \Leftrightarrow$ think $\leftrightarrow$ say

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Word meaning as a neural word vector – visualization

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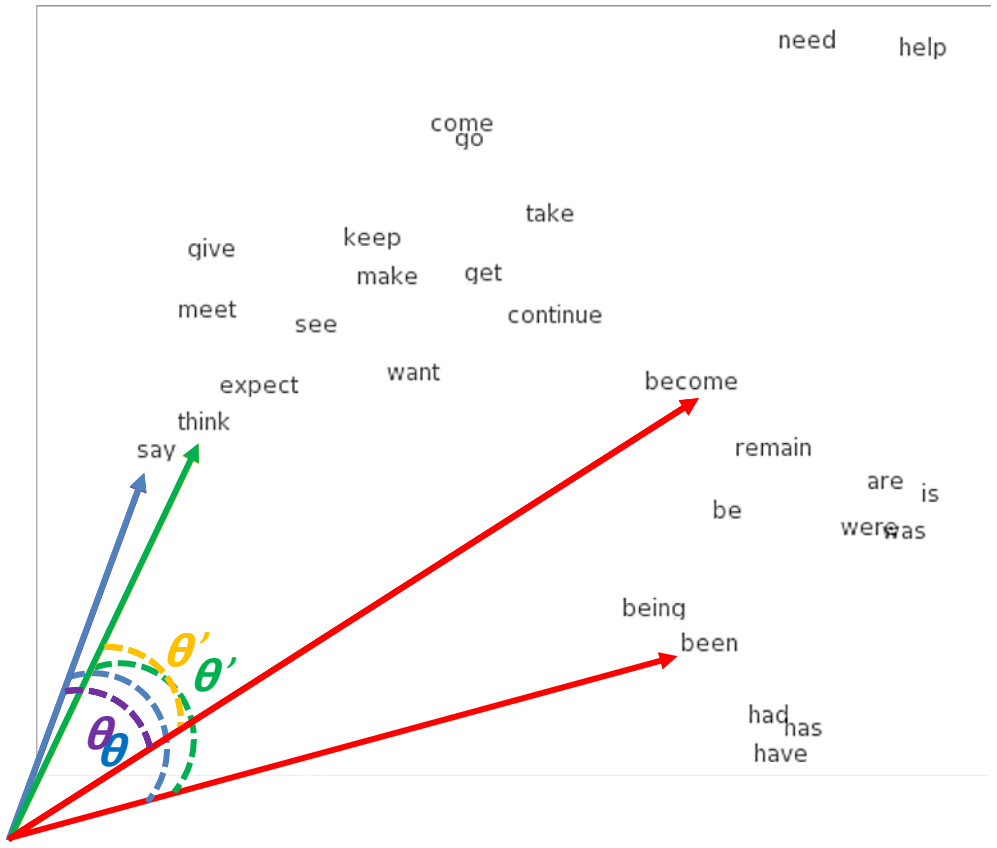

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Word2Vec Overview

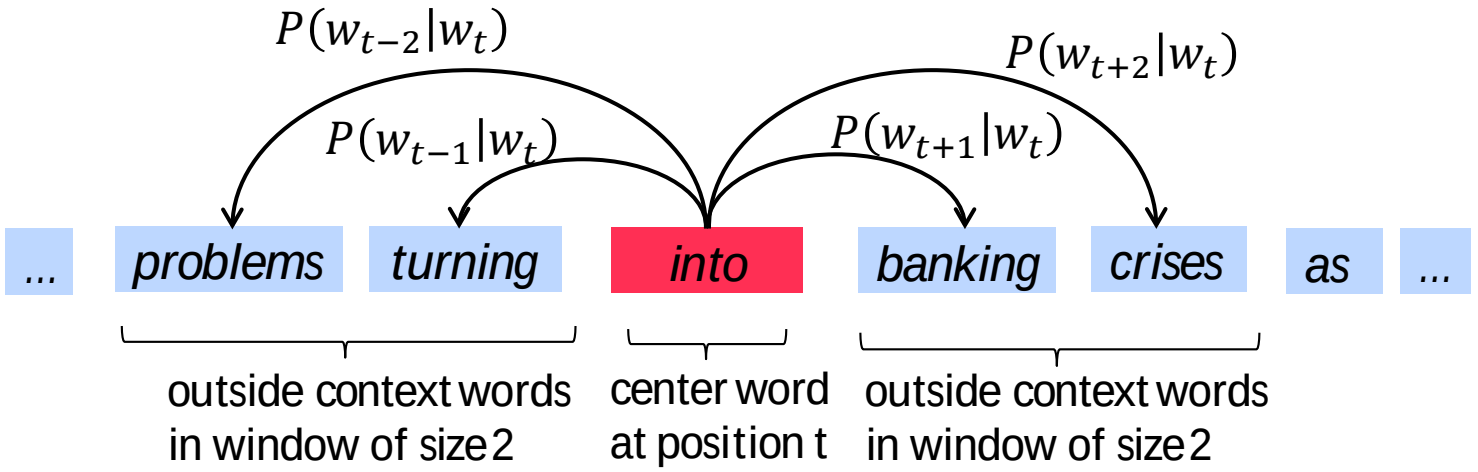
Word2vec (Mikolov et al. 2013) is a framework for learning word vectors

Idea:

- We have a large corpus of text
- Every word in a fixed vocabulary is represented by a vector
- **Go through each position** *t* in the text, **which has a center word** *c* and **context ("outside") words** *o*
- Use the similarity of the word vectors for *c* and *o* to calculate the probability of *o* given *c* (or vice versa)
- Keep adjusting the word vectors to maximize this probability

Word2Vec Overview

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



Word2Vec Overview

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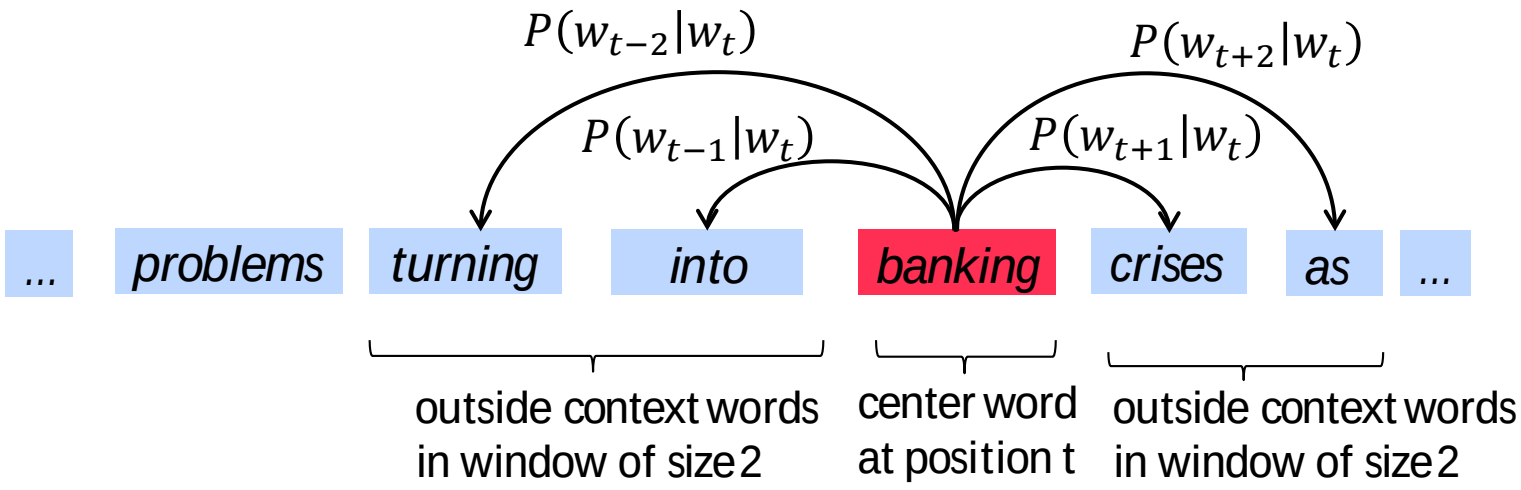

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Word2Vec: objective function

- We want to minimize the objective function, the (average) negative log likelihood :

$$J(\theta) = -\frac{1}{T}\log L(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\le j\le m \\ j\neq 0}} \log P\left(w_{t+j} \mid w_t; \theta\right)$$

Minimizing objective function ⟺ Maximizing predictive accuracy

- Question: How to calculate $P(w_{t+j}|w_t; \theta)$?
- Answer: We will *use two* vectors per word *w*:
  - V_w when *w* is a ***center*** word
  - u_w when *w* is a ***context*** word
- Then for a center word *c* and a context word *o*: $P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w\in V}\exp(u_w^T v_c)}$

Christopher Manning

Word2Vec: prediction function

Exponentiation makes anything positive

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

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

Normalize over entire vocabulary
to give probability distribution

- This is an example of the **softmax function** $\mathbb{R}^n \rightarrow \mathbb{R}^n$

$$\text{softmax}(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)} = p_i$$

- The softmax function maps arbitrary values to a probability distribution p_i
  - "max" because amplifies probability of largest x_i
  - "soft" because still assigns some probability to smaller x_i

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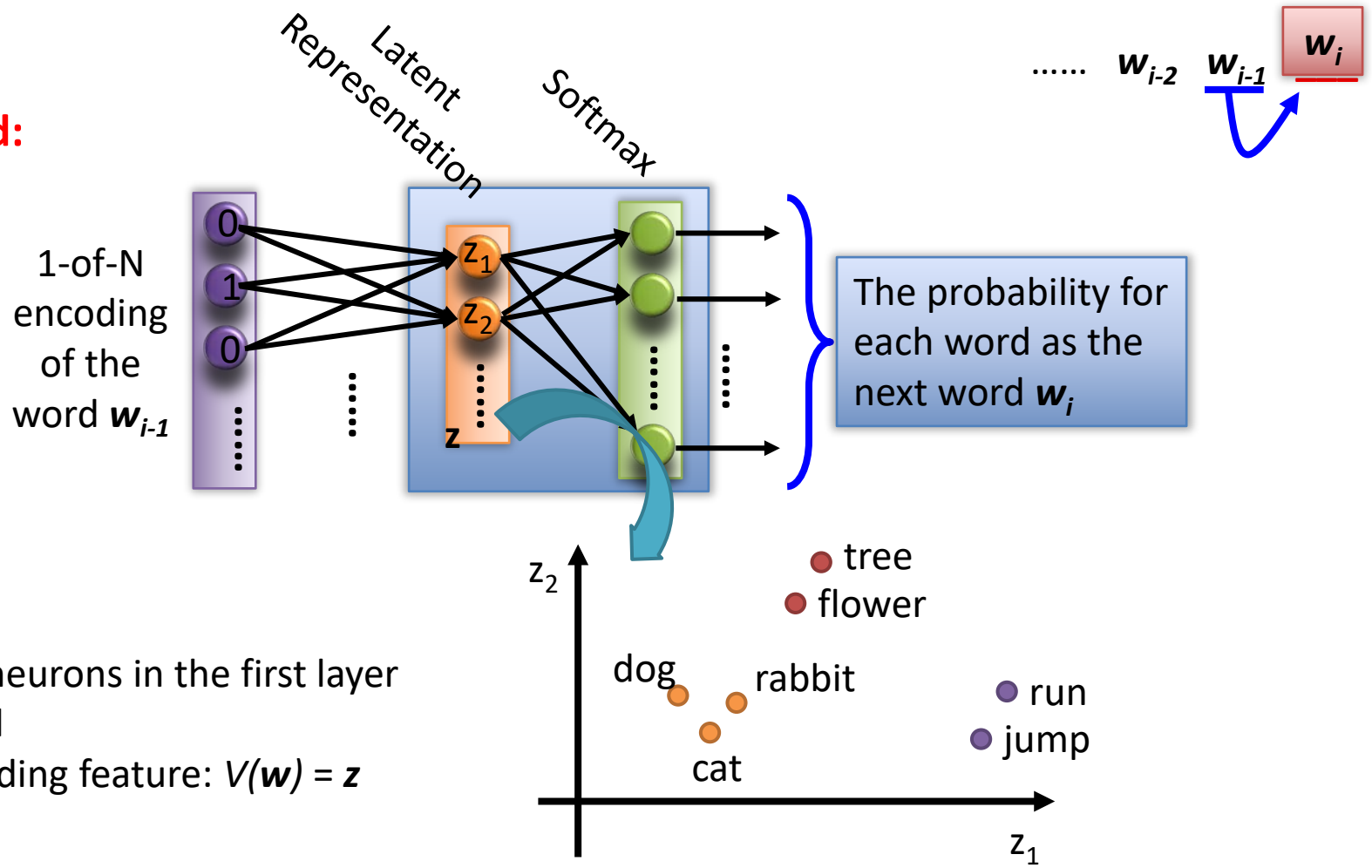
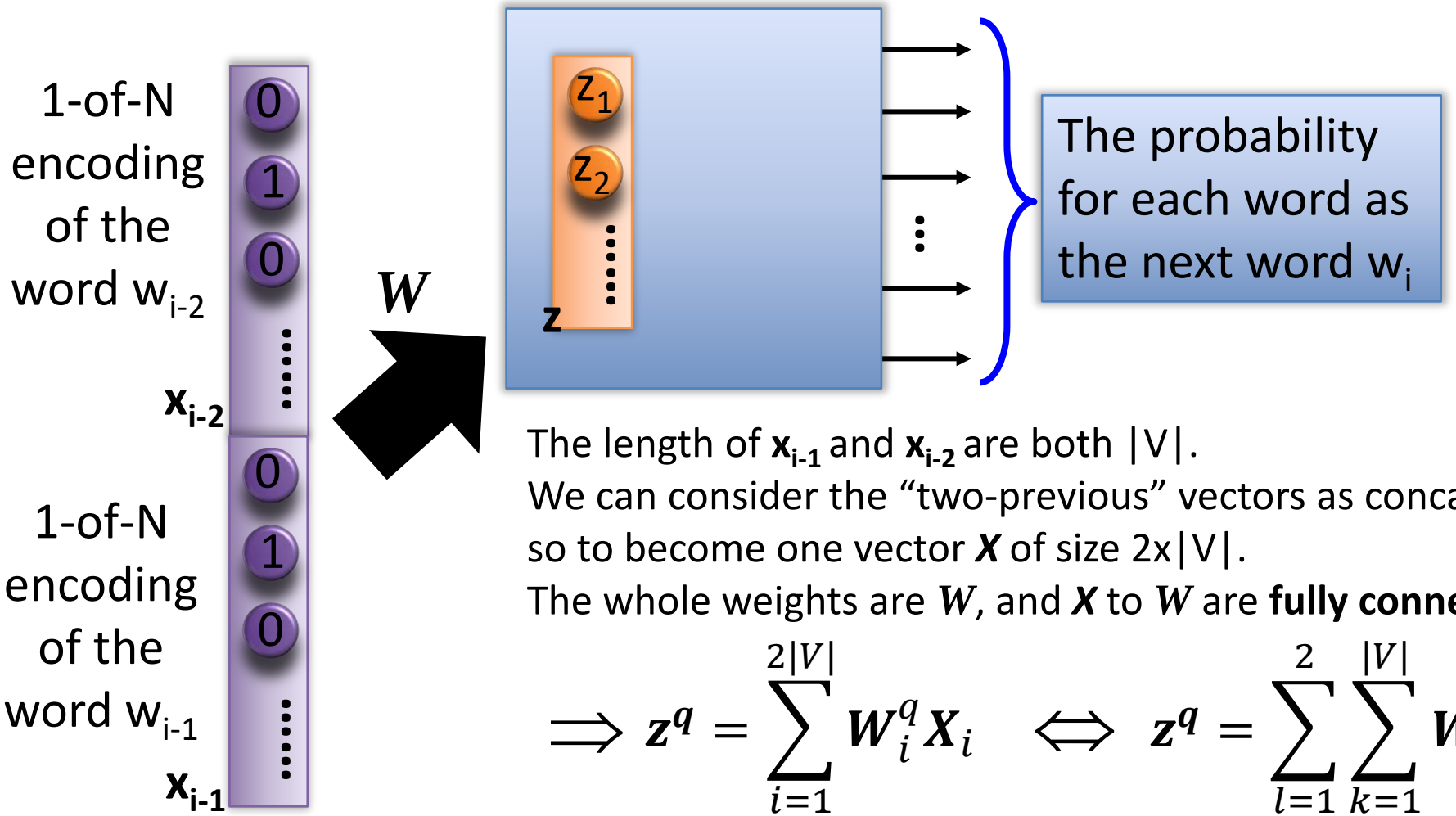
Reminder - Glove

Predicting the next word:



- Take out the **input** of the neurons in the first layer
- **Use it to represent a word**
- Word vector, word embedding feature: $V(\boldsymbol{w}) = \boldsymbol{z}$

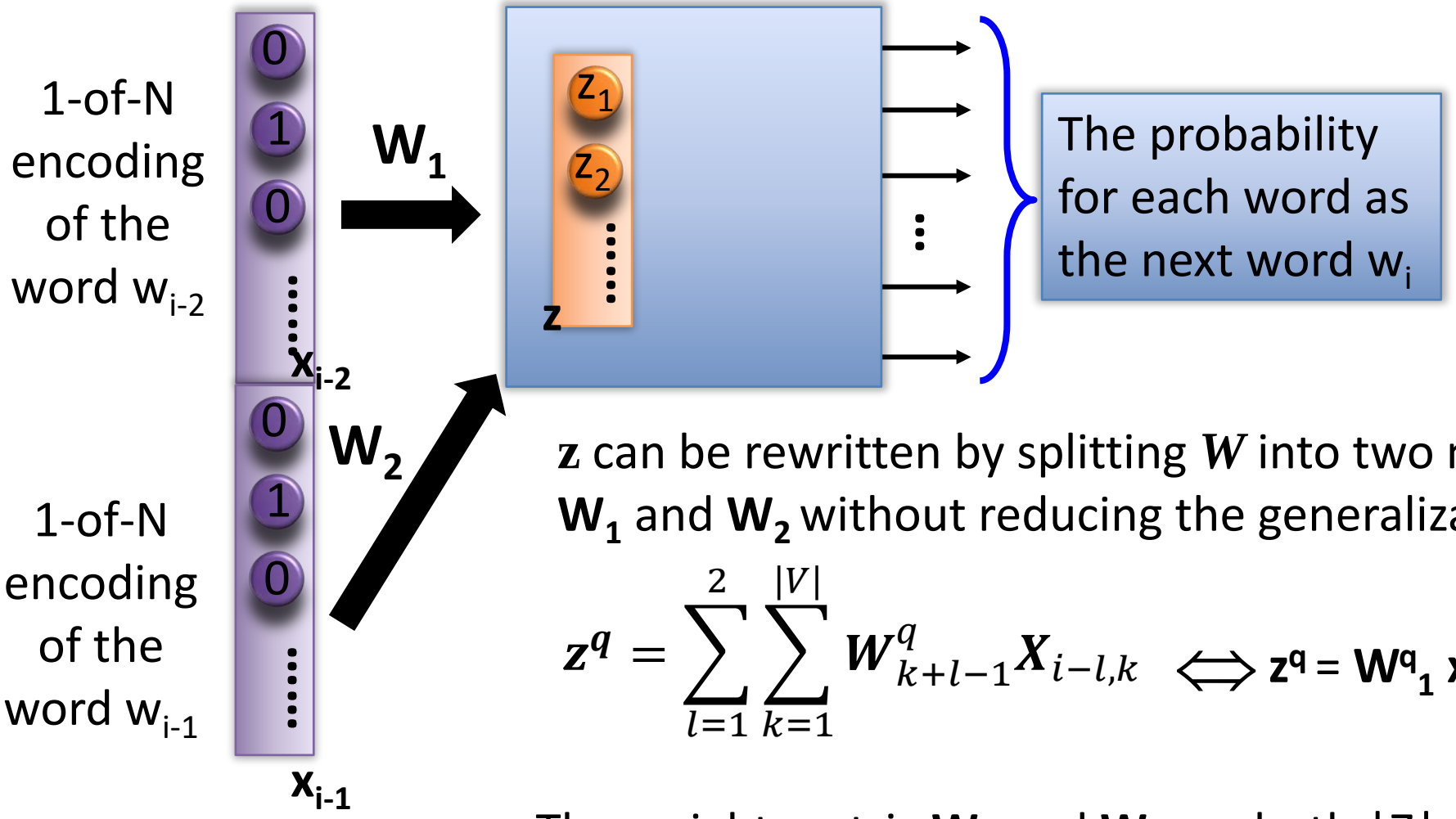
Prediction-based – Sharing Parameters



The length of $\mathbf{x}_{i-1}$ and $\mathbf{x}_{i-2}$ are both $|V|$.
We can consider the "two-previous" vectors as concatenated and so to become one vector $\boldsymbol{X}$ of size $2x|V|$.
The whole weights are $\boldsymbol{W}$, and $\boldsymbol{X}$ to $\boldsymbol{W}$ are **fully connected**.

$$\Rightarrow \boldsymbol{z^q} = \sum_{i=1}^{2|V|} \boldsymbol{W_i^q X_i} \quad \Leftrightarrow \quad \boldsymbol{z^q} = \sum_{l=1}^{2} \sum_{k=1}^{|V|} \boldsymbol{W_{k+l-1}^q X_{i-l,k}}$$

Prediction-based – Sharing Parameters

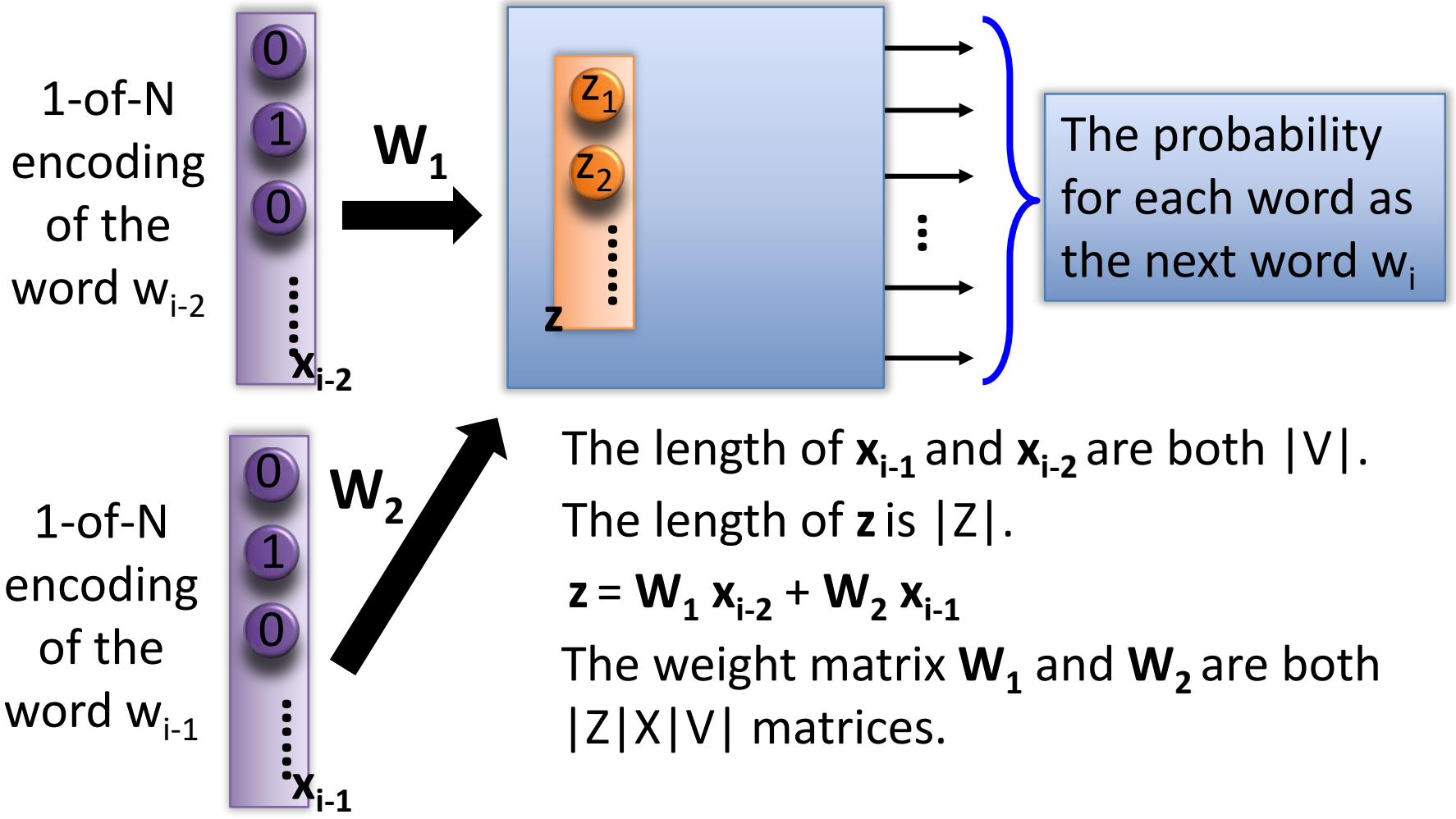


$\mathbf{z}$ can be rewritten by splitting W into two matrices $\mathbf{W_1}$ and $\mathbf{W_2}$ without reducing the generalizability:

$$z^q = \sum_{l=1}^{2} \sum_{k=1}^{|V|} W^q_{k+l-1} X_{i-l,k} \iff \mathbf{z^q = W^q_1\, x_{i-2} + W^q_2\, x_{i-1}}$$

The weight matrix $\mathbf{W_1}$ and $\mathbf{W_2}$ are both |Z|x|V|.

Prediction-based – Sharing Parameters



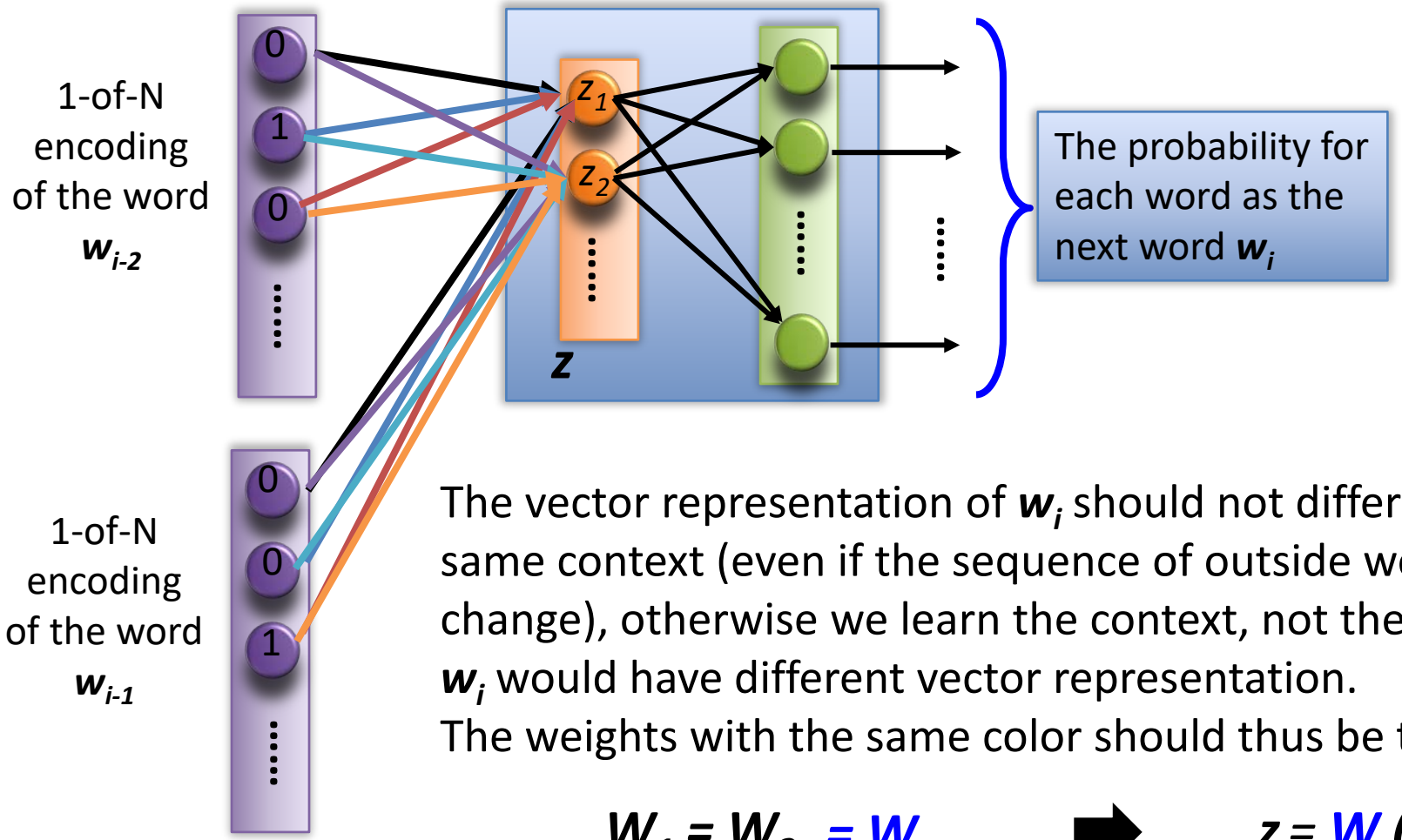
The length of $\mathbf{x}_{i-1}$ and $\mathbf{x}_{i-2}$ are both $|V|$.

The length of $\mathbf{z}$ is $|Z|$.

$\mathbf{z} = \mathbf{W}_1 \mathbf{x}_{i-2} + \mathbf{W}_2 \mathbf{x}_{i-1}$

The weight matrix $\mathbf{W}_1$ and $\mathbf{W}_2$ are both $|Z|X|V|$ matrices.

Prediction-based – Sharing Parameters

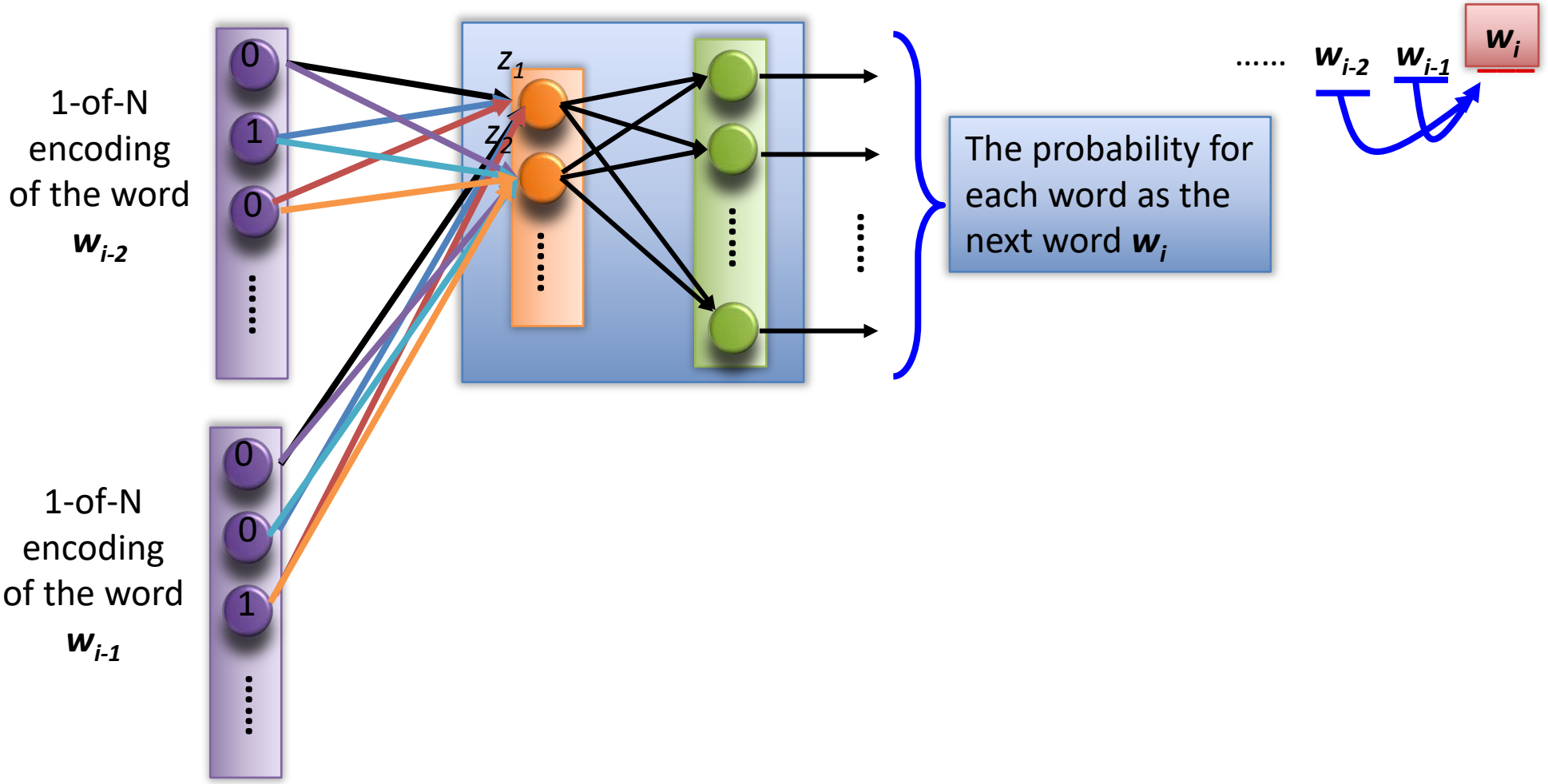


The vector representation of w_i should not differ from the same context (even if the sequence of outside words change), otherwise we learn the context, not the word w_i.
w_i would have different vector representation.
The weights with the same color should thus be the same.

$$W_1 = W_2 = W \quad \Rightarrow \quad z = W (x_{i-2} + x_{i-1})$$

It is the same idea as the shared connections in CNN, edge or corner extractors are actually defined by the weights

Prediction-based – Sharing Parameters



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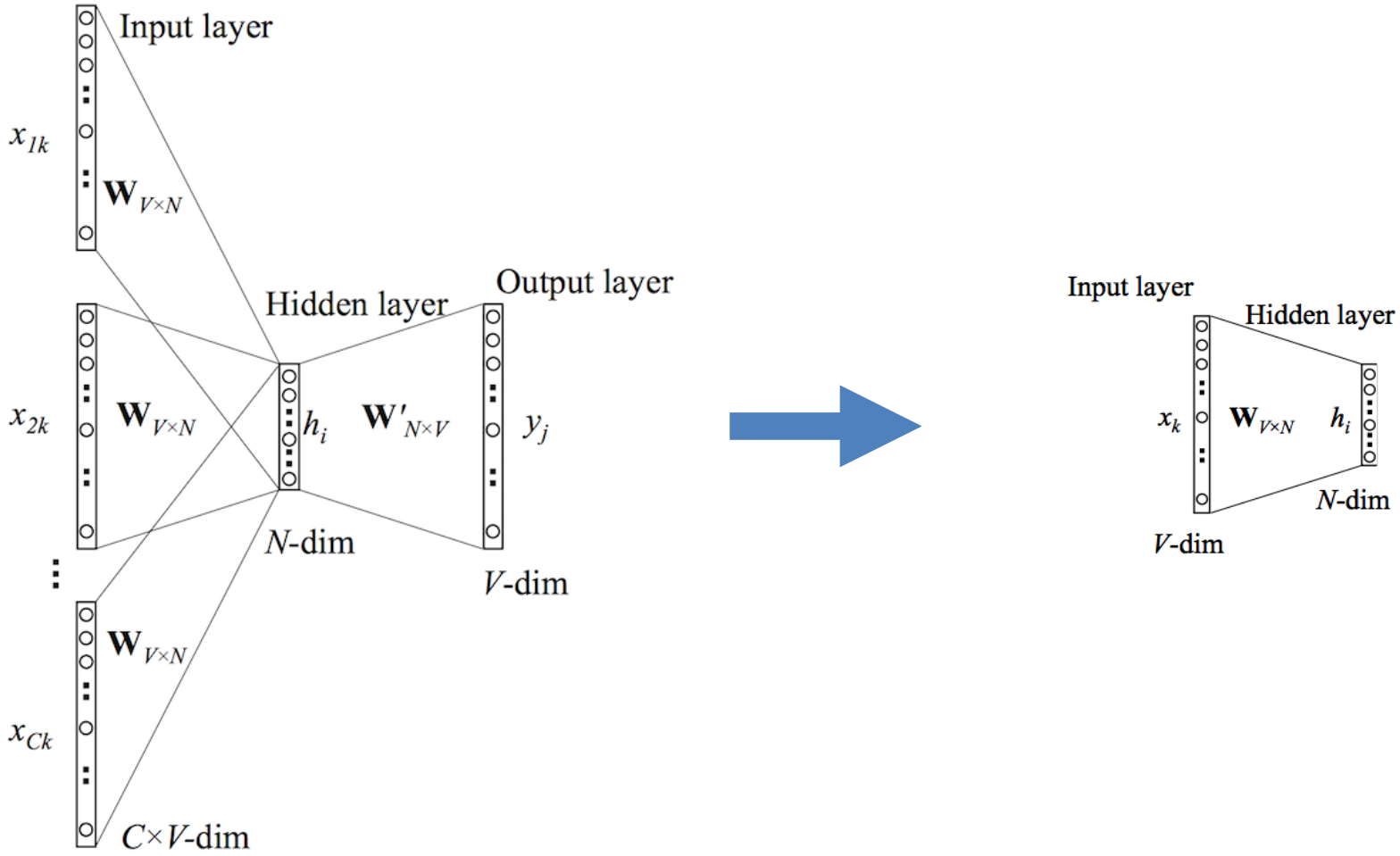
Word2Vec (CBOW) Overview



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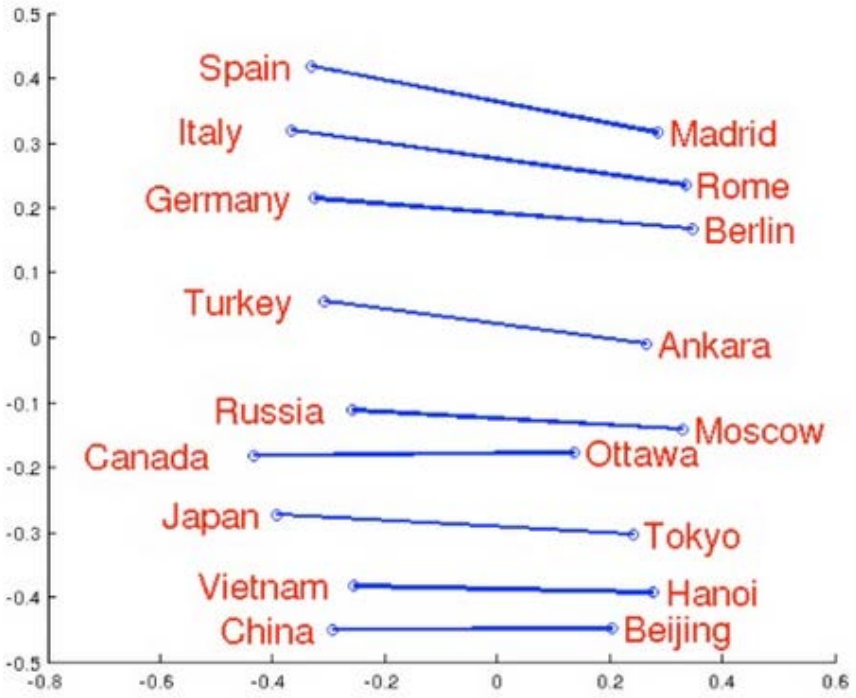
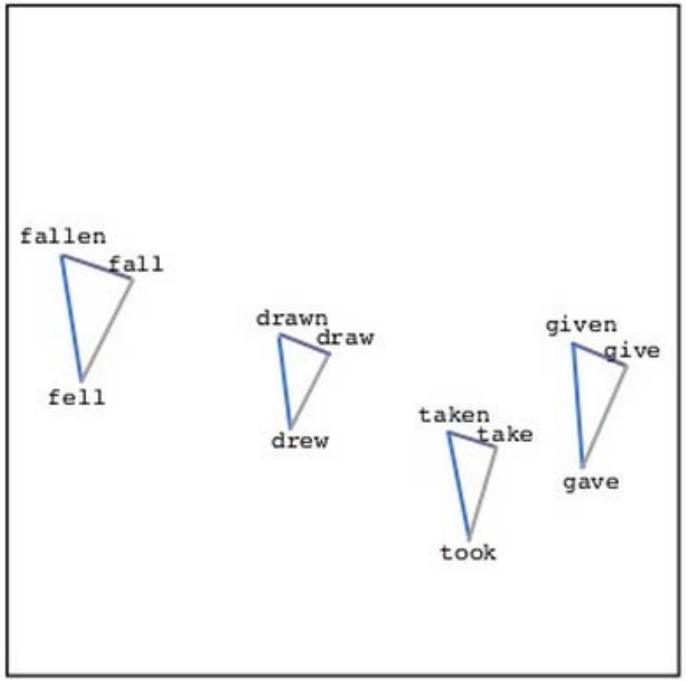
Word Embedding





Source: http://www.slideshare.net/hustwj/cikm-keynotenov2014

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Word Embedding

- Characteristics

$$V(Germany) \approx V(Berlin) - V(Rome) + V(Italy)$$

- Solving analogies

$$V(hotter) - V(hot) \approx V(bigger) - V(big)$$
$$V(Rome) - V(Italy) \approx V(Berlin) - V(Germany)$$
$$V(king) - V(queen) \approx V(uncle) - V(aunt)$$

Rome : Italy = Berlin : ?

Compute $V(Berlin) - V(Rome) + V(Italy)$

Find the word w with the closest V(w)

Word Embedding

- Word2vec is known to be good at certain kinds of analogies:

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Type of relationship	Word Pair 1		Word Pair 2	
Common capital city	Athens	Greece	Oslo	Norway
All capital cities	Astana	Kazakhstan	Harare	Zimbabwe
Currency	Angola	kwanza	Iran	rial
City-in-state	Chicago	Illinois	Stockton	California
Man-Woman	brother	sister	grandson	granddaughter
Adjective to adverb	apparent	apparently	rapid	rapidly
Opposite	possibly	impossibly	ethical	unethical
Comparative	great	greater	tough	tougher
Superlative	easy	easiest	lucky	luckiest
Present Participle	think	thinking	read	reading
Nationality adjective	Switzerland	Swiss	Cambodia	Cambodian
Past tense	walking	walked	swimming	swam
Plural nouns	mouse	mice	dollar	dollars
Plural verbs	work	works	speak	speaks

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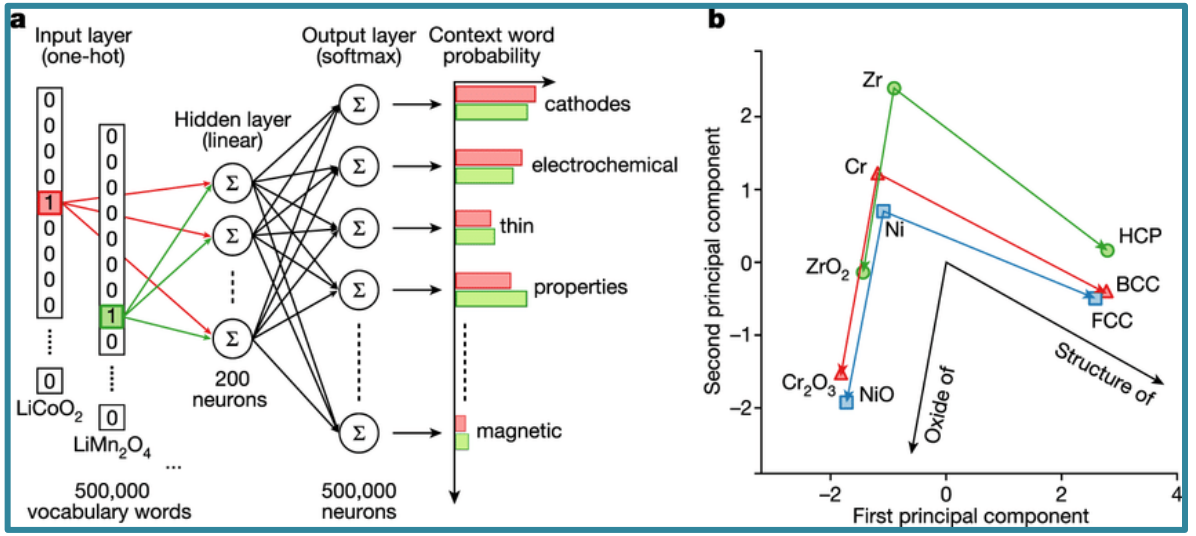
Word2Vec not for language (Nature 2019)

a) Target words 'LiCoO2' and 'LiMn2O4' are represented as vectors with ones at their corresponding vocabulary indices (for example, 5 and 8 in the schematic) and zeros everywhere else (one-hot encoding).

These one-hot encoded vectors are used as inputs for a neural network with a single linear hidden layer (for example, 200 neurons), which is trained to predict all words mentioned within a certain distance (context words) from the given target word.



- **For similar battery cathode materials such as LiCoO2 and LiMn2O4, the context words that occur in the text are mostly the same** (for example, 'cathodes', 'electrochemical', and so on), which leads to similar hidden layer weights after the training is complete.
- These hidden layer weights are the actual word embeddings.
- The softmax function is used at the output layer to normalize the probabilities.

- **b)** Word embeddings for Zr, Cr and Ni, their principal oxides and crystal symmetries (at standard conditions) projected onto two dimensions using principal component analysis and represented as points in space. The relative positioning of the words encodes materials science relationships, such that there exist consistent vector operations between words that represent concepts such as 'oxide of' and 'structure of'.

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Word2Vec not for language (Nature 2019)

Relationship	Example vector operation	Answer	Validation pairs	Accuracy (%)
Chemical element names	helium - He + Fe	= iron	8372	71.4
Crystal symmetries	cubic - GaAs + CdSe	= hexagonal	2034	35.4
Crystal structure names	zincblende - GaP + GaN	= wurtzite	556	18.7
Elemental crystal structures	dhcp - La + Cr	= bcc	1198	48.6
Principal oxides	Al_2O_3 - Al + Si	= SiO_2	650	48.8
Units	pressure - Pa + Hz	= frequency	452	35.4
Magnetic properties	ferromagnetic - NiCo + IrMn	= antiferromagnetic	622	41.0
Applications	thermoelectric - PbTe + LiFePO4	= cathode materials	-	-
Grammar	structures - structure + energy	= energies	15162	61.6
Total			29046	60.1

Materials science analogies

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Demos Word2Vec embeddings

- http://nlp.polytechnique.fr/word2vec
- Try:
  - France – paris + berlin
  - Paris – France + allemagne
  - Paris – France + brésil

→ What do you notice?

Word to Vec JS Demo (turbomaze.github.io)

Word2Vec Demo (remykarem.github.io)

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Overview

- Context
- Text representation
- **Bias in textual information**

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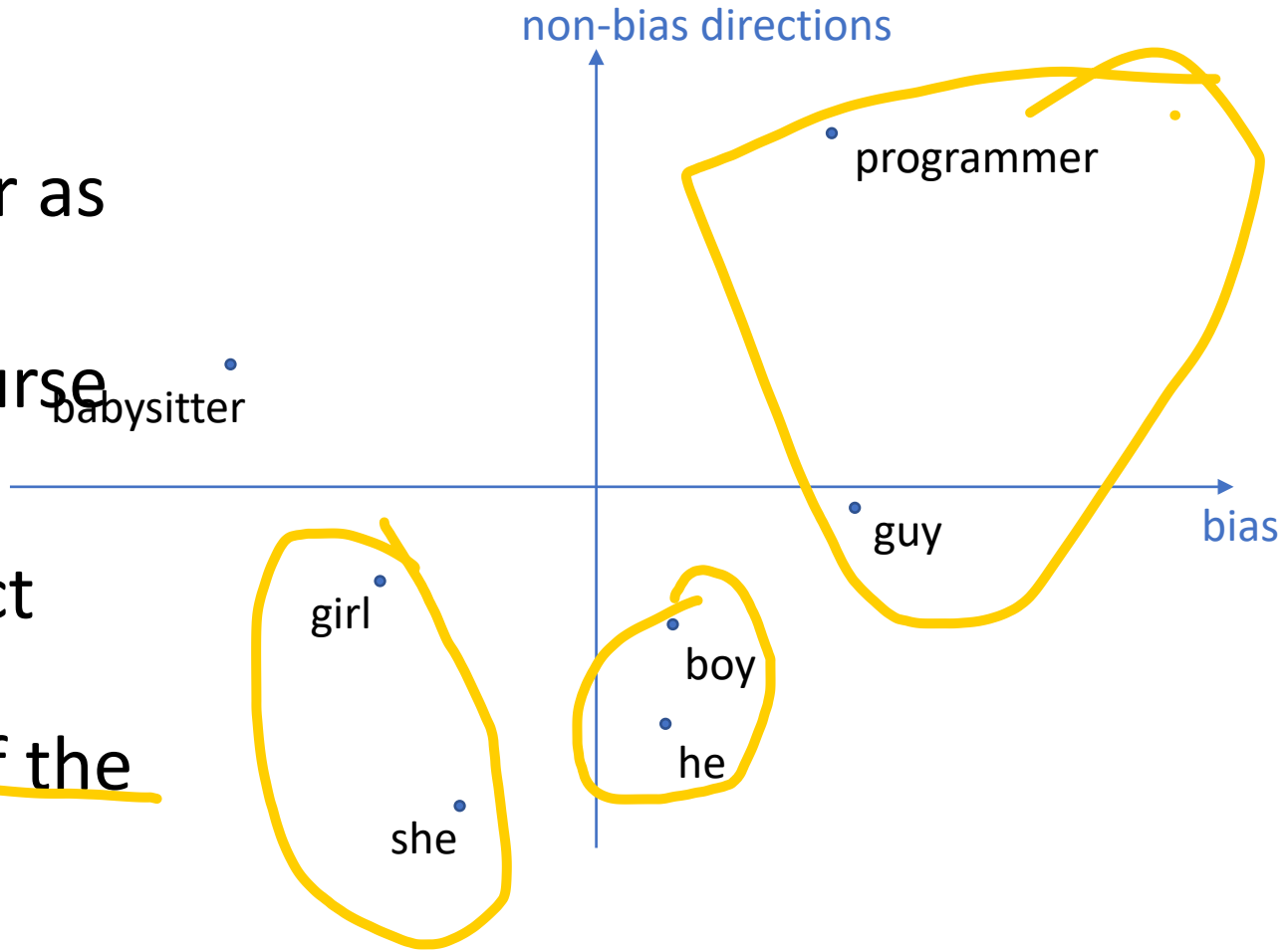
BIAS IN TEXTUAL INFORMATION

The problem of bias in word embeddings

- Man: Woman as King: Queen
- Man: Computer_Programmer as Woman: Homemaker
- Father: Doctor as Mother: Nurse

→ Word embeddings can reflect gender, ethnicity, age, sexual orientation, and other biases of the text used to train the model.



Bolukbasi et al., 2016, Man is to computer programmer as woman is to homemaker? Debiasing word embeddings. NeurIPS 2016.

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Definition of bias: human, in the data, learned by the AI system

- **A prior, arbitrary, non-technical choice: representing the meaning of a word by its context**
- Consequence: the numerical representation obtained (by the AI model) for each word reproduces associations of co-occurrences between concepts, including the problematics of…
- Biais (statistical): characteristic with different frequencies of occurrence between groups, in absolute terms, or with respect to other characteristics
- Biais (ethics for IA): statistical deviations from a model for groups of people based on protected attributes such as gender, race, age, etc.

[1] S. Fabbrizzi, S. Papadopoulos, E. Ntoutsi, and I. Kompatsiaris, "A survey on bias in visual datasets," Computer Vision and Image Understanding,2022.

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Human biases: measured by IAT scores

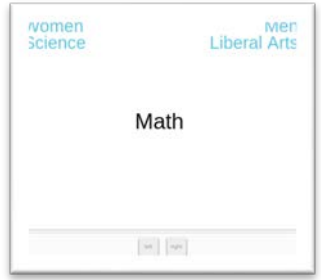
- Formulated in Cognitive and Social Psychology
- In our brains, the network of our semantic memory works through associations between concepts $\Rightarrow$ Bias when these associations are problematic:
  We think more of the savannah when we talk about lions, but also generally more quickly of men when we talk about science
- And we can measure the strength of these automatisms: **Implicit Association Test (IAT)**

- $$IAT\ \ Score = \frac{resp.time.for\ assoc.incomp.with.stereo - resp.time.for\ assoc.comp.with.stereo}{standard\ deviation\ over\ resp.times}$$

  - General Pop.: Fast Individuals on Stereotype-Compatible Trials
  - Statistically Significant Positive Score: Stereotype Is Well Established in the biological networks of the Semantic Memory

→ Testing Speed evaluates the Strength of Connections Between Concepts

→ Highly reliable IAT for testing implicit stereotypy



A. G. Greenwald, D. E. McGhee, and J. L. Schwartz, "Measuring individual differences in implicit cognition: the implicit association test.," Journal of personality and social psychology, June 1998.

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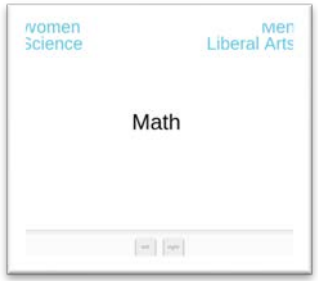
Human biases: measured by IAT scores



- Demo on IAT scores
  - Experiments | TELLab (https://lab.tellab.org/show/paradigm/iat)
  - The Implicit Association Test (IAT) | Outsmarting Implicit Bias: A Project at Harvard University (https://outsmartingimplicitbias.org/module/iat/)

A. G. Greenwald, D. E. McGhee, and J. L. Schwartz, "Measuring individual differences in implicit cognition: the implicit association test.," Journal of personality and social psychology, June 1998.

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Any Question?