CS388: Natural Language Processing

Lecture 7: Word Embeddings

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Administrivia

- Mini 1 grades out tonight or tomorrow

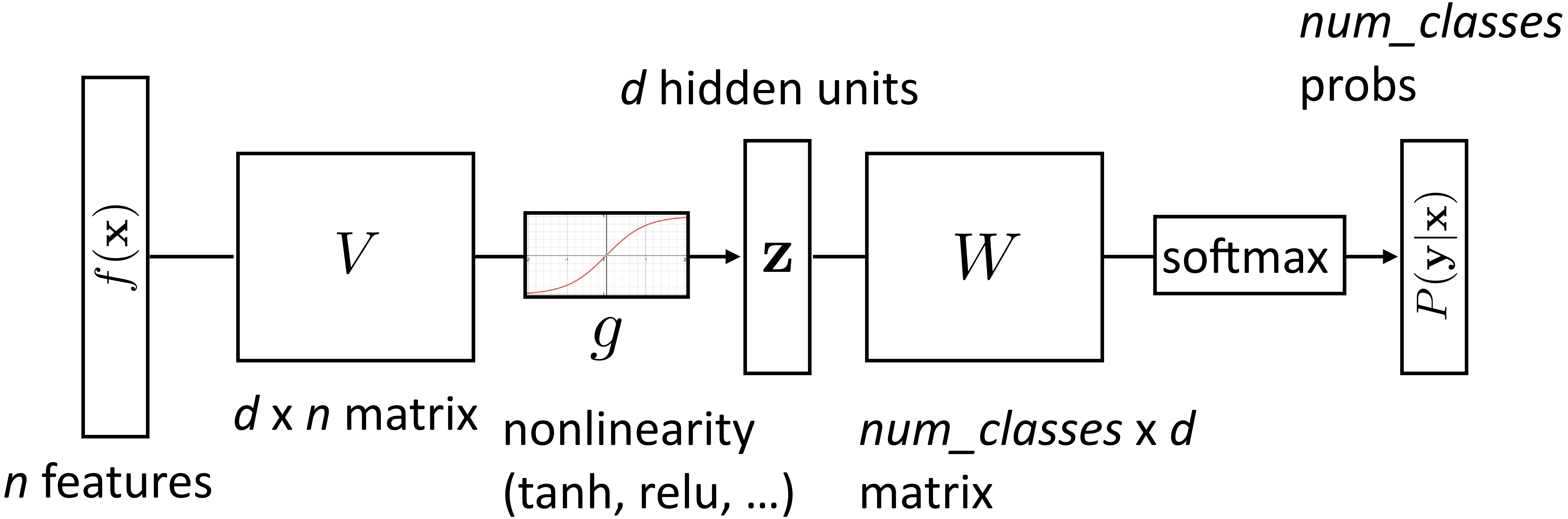
- Project 1 due Tuesday

Clarification: Forward-Backward

- Forward-backward slides showed forward-backward **in the HMM case** (emission scores were probabilities $P(x_i | y_i)$)
- For CRFs: use transition/emission potentials (computed from features + weights) instead of probabilities
- **Lecture 5 notes updated with F-B on CRFs**

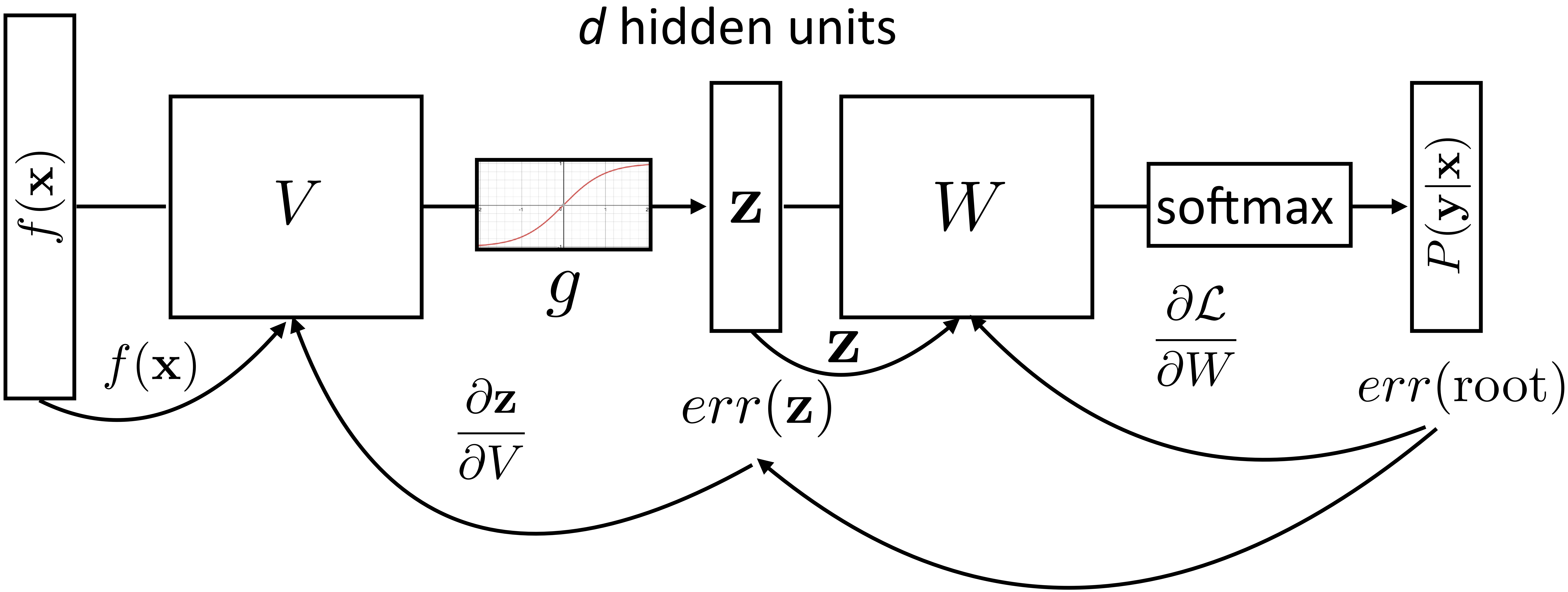
Recall: Feedforward NNs

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



Recall: Backpropagation

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



This Lecture

- Training tips
- Word representations
- word2vec/GloVe
- Evaluating word embeddings

Training Tips

Batching

- Batching data gives speedups due to more efficient matrix operations

- Need to make the computation graph process a batch at the same time

```
# input is [batch_size, num_feats]
# gold_label is [batch_size, num_classes]
def make_update(input, gold_label)
    ...
    probs = ffnn.forward(input) # [batch_size, num_classes]
    loss = torch.sum(torch.neg(torch.log(probs)).dot(gold_label))
    ...
```

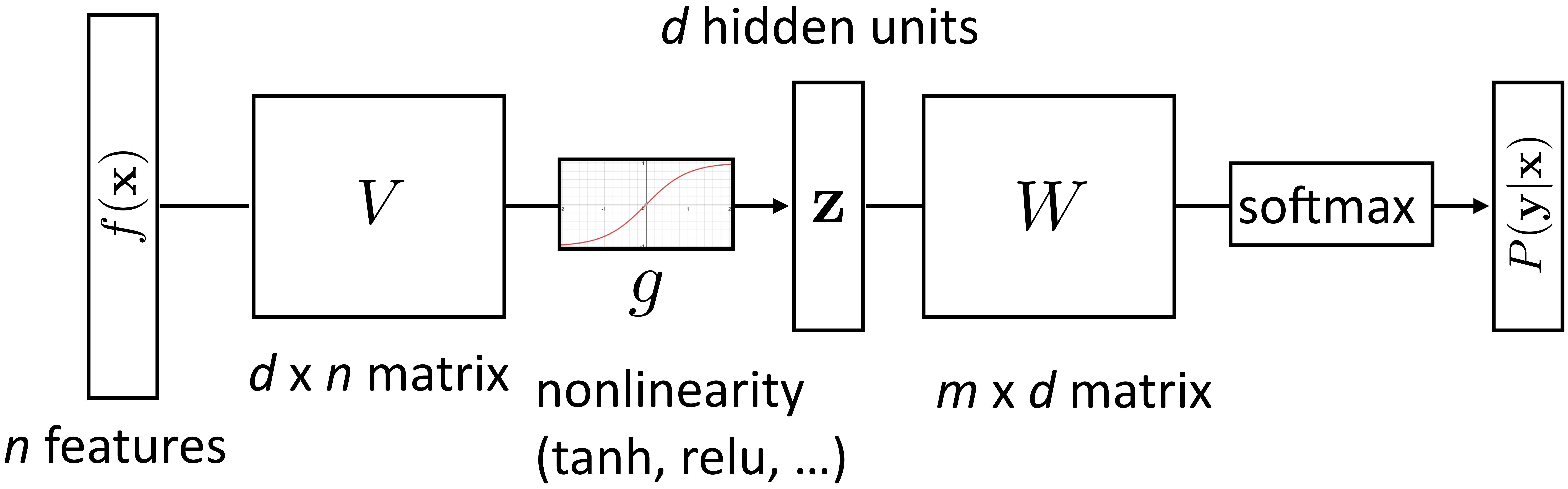
- Batch sizes from 1-100 often work well

Training Basics

- Basic formula: compute gradients on batch, use first-order optimization method (SGD, Adagrad, etc.)
- How to initialize? How to regularize? What optimizer to use?
- This lecture: some practical tricks. Take deep learning or optimization courses to understand this further

How does initialization affect learning?

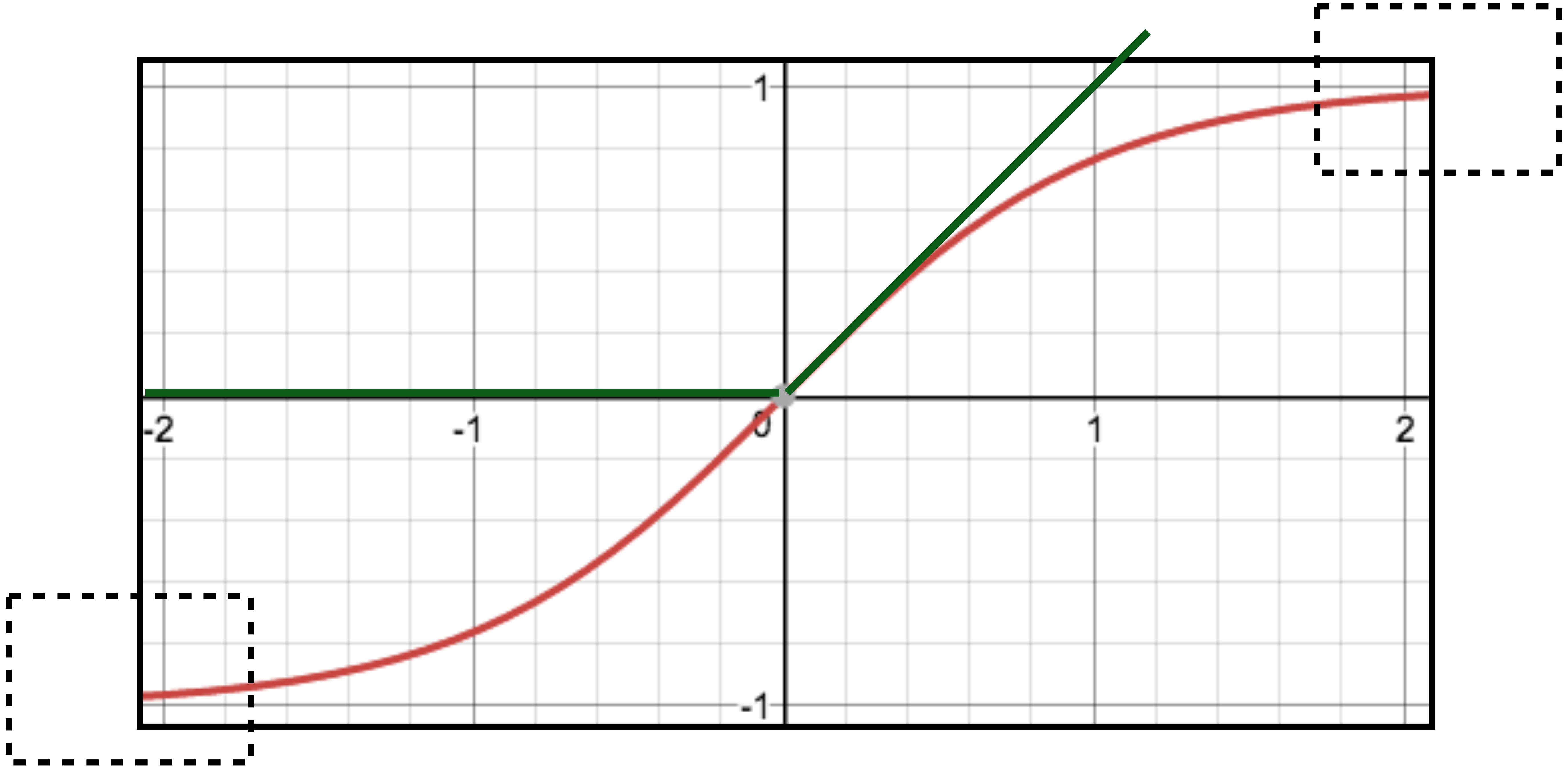
$$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(Wg(Vf(\mathbf{x})))$$



- How do we initialize V and W? What consequences does this have?
- *Nonconvex* problem, so initialization matters!

How does initialization affect learning?

- Nonlinear model…how does this affect things?



- If cell activations are too large in absolute value, gradients are small
- ReLU: larger dynamic range (all positive numbers), but can produce big values, can break down if everything is too negative

Initialization

1) Can't use zeroes for parameters to produce hidden layers: all values in that hidden layer are always 0 and have gradients of 0, never change

2) Initialize too large and cells are saturated

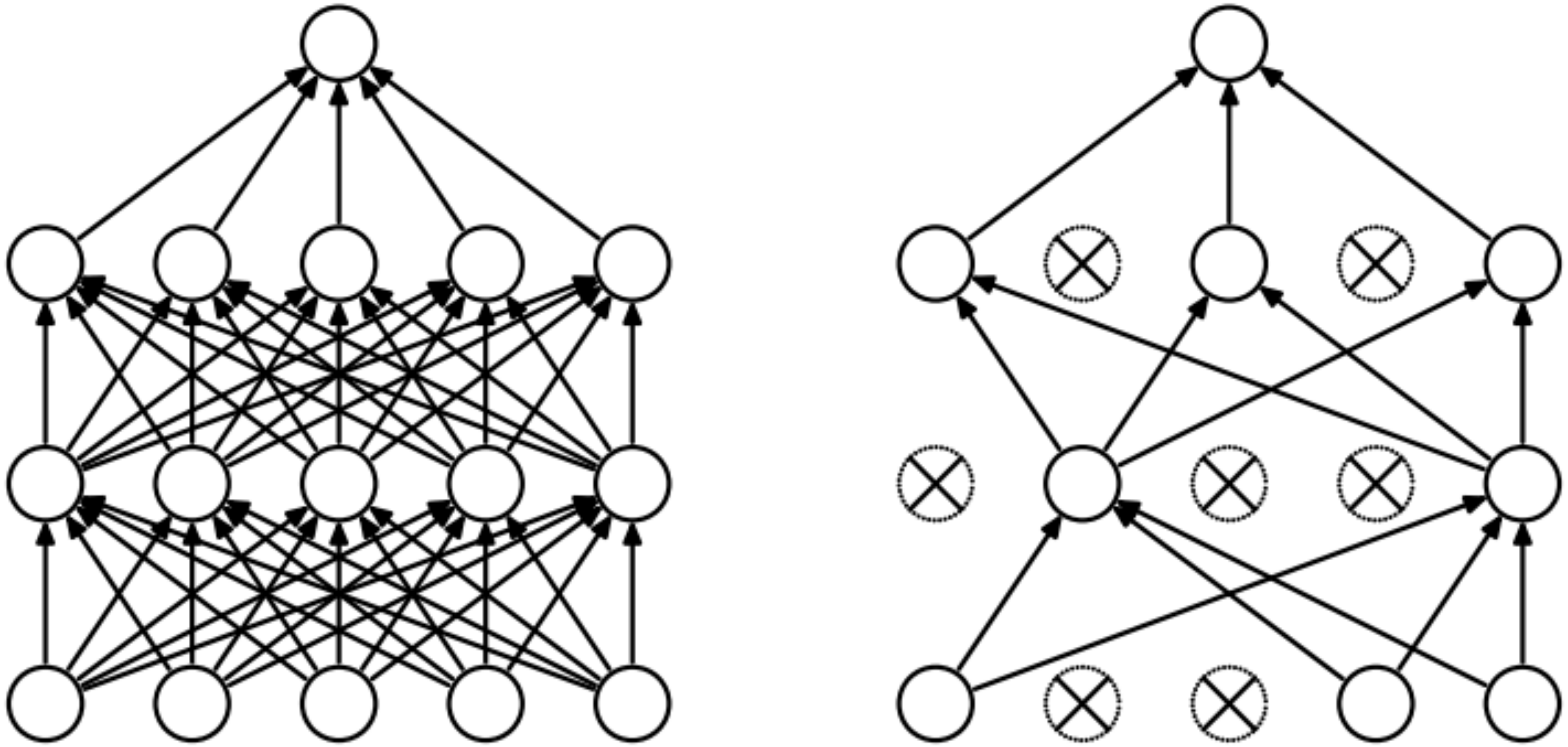
- Can do random uniform / normal initialization with appropriate scale
- Glorot initializer: $U\left[-\sqrt{\frac{6}{\text{fan-in} + \text{fan-out}}}, +\sqrt{\frac{6}{\text{fan-in} + \text{fan-out}}}\right]$
  - Want variance of inputs and gradients for each layer to be the same
- Batch normalization (Ioffe and Szegedy, 2015): periodically shift+rescale each layer to have mean 0 and variance 1 over a batch (useful if net is deep)

Dropout

- Probabilistically zero out parts of the network during training to prevent overfitting, use whole network at test time

- Form of stochastic regularization

- Similar to benefits of ensembling: network needs to be robust to missing signals, so it has redundancy



(a) Standard Neural Net

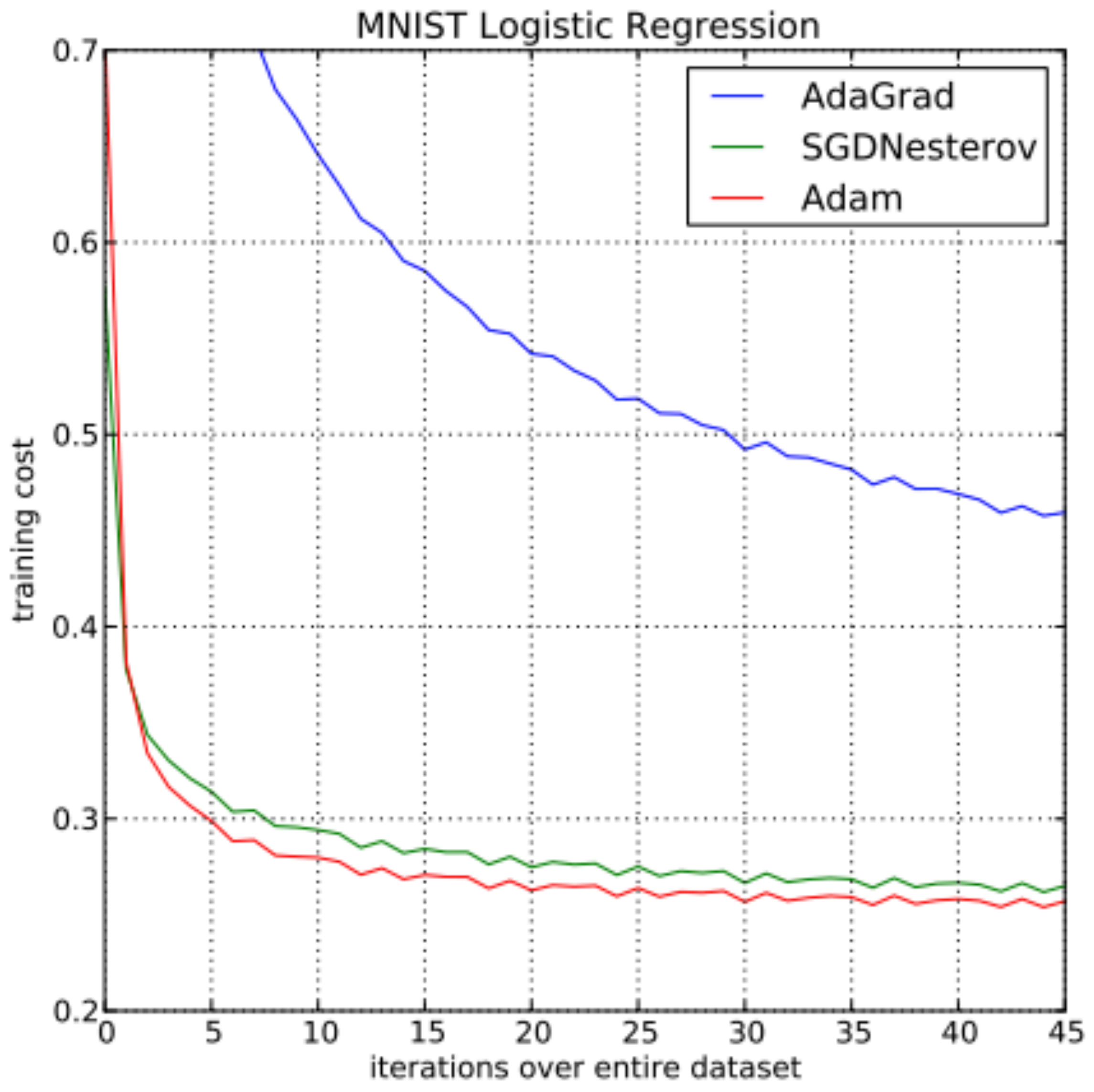
(b) After applying dropout.

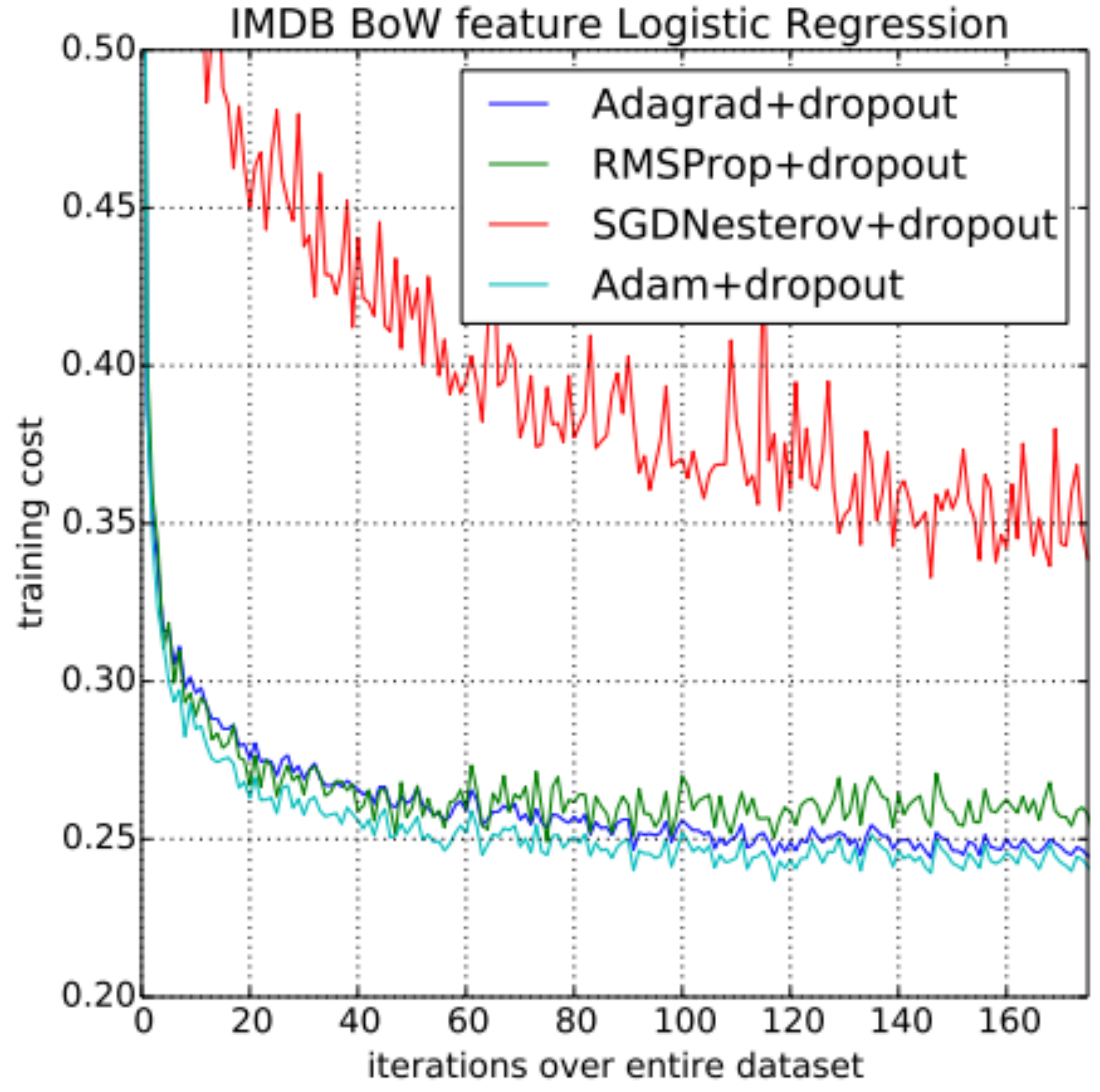
- One line in Pytorch/Tensorflow

Srivastava et al. (2014)

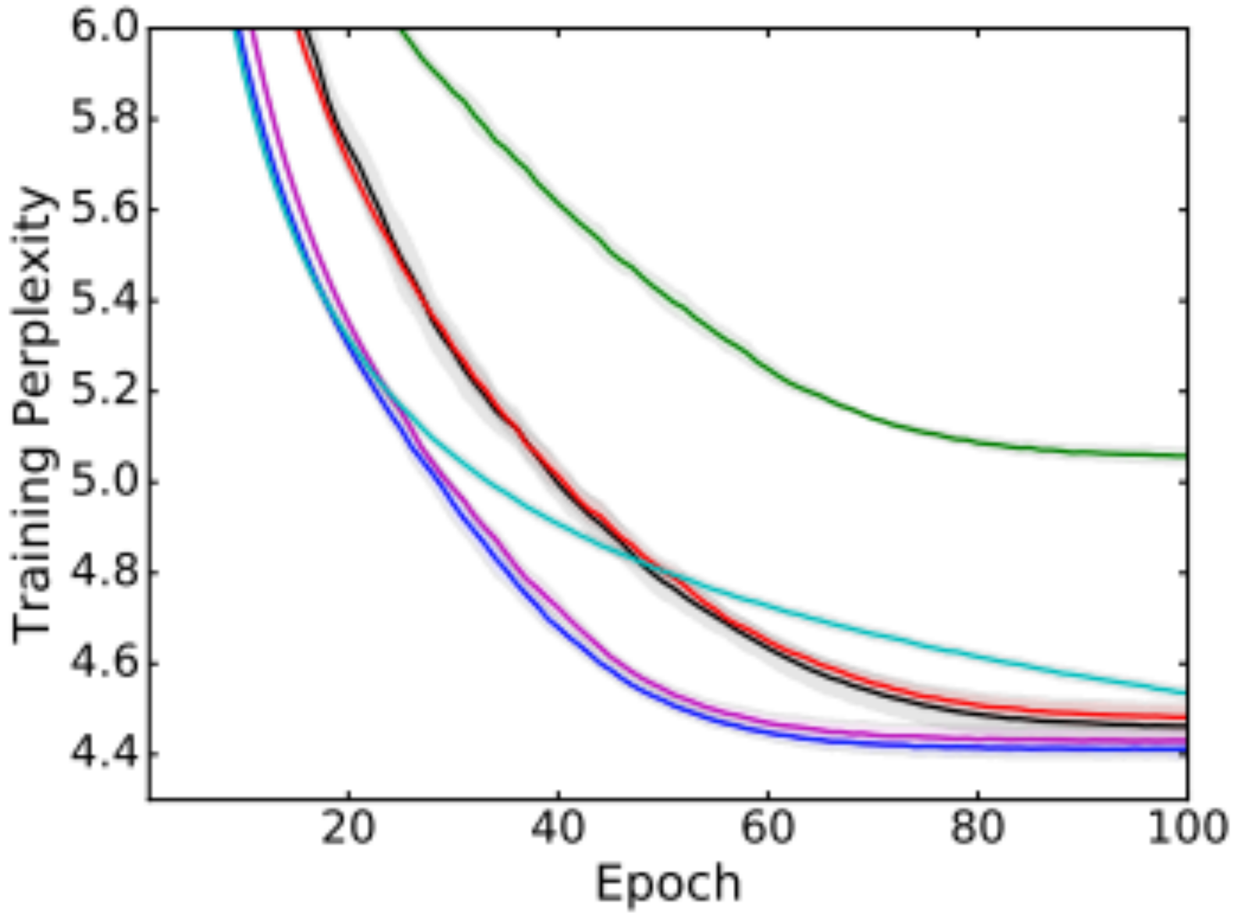
Optimizer

- Adam (Kingma and Ba, ICLR 2015): very widely used. Adaptive step size + momentum

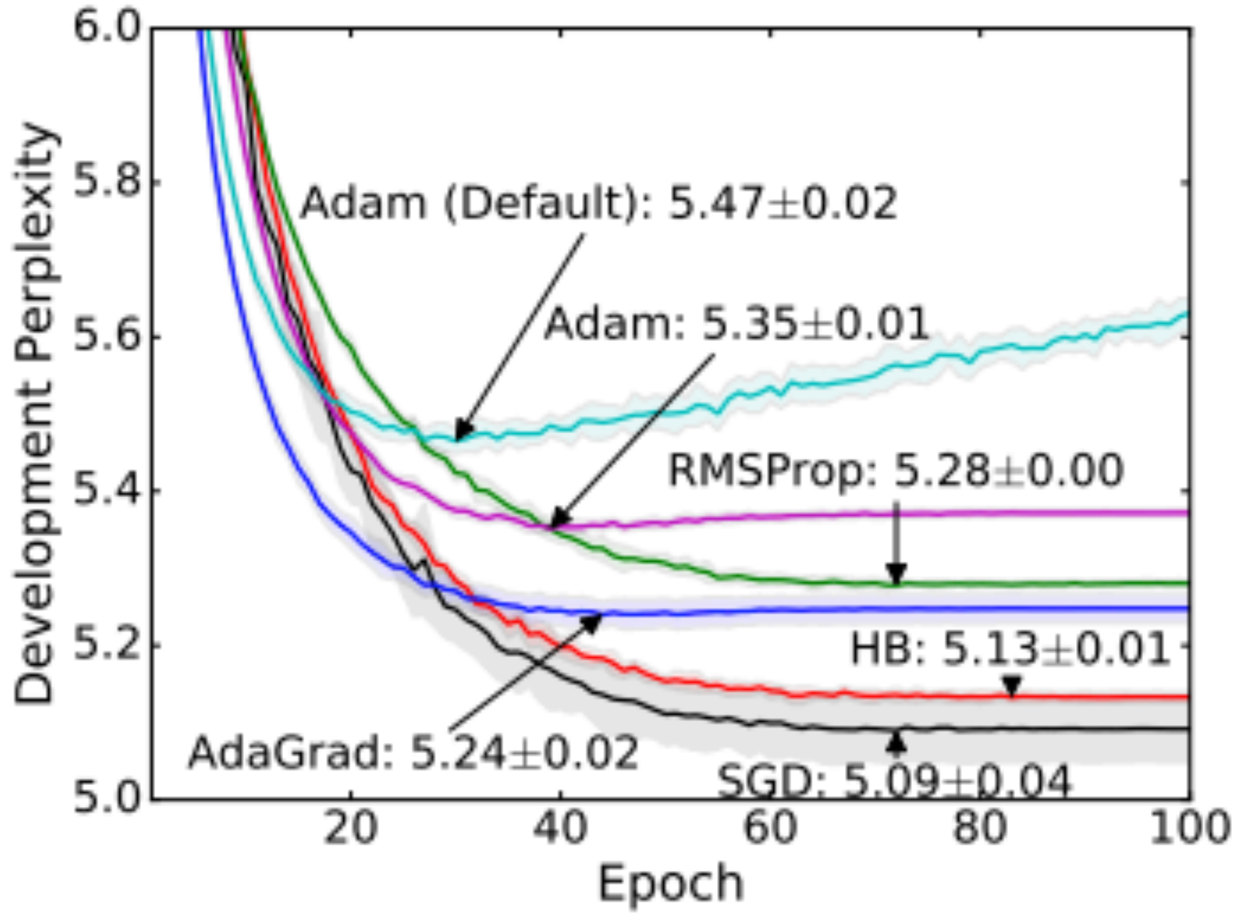




- Wilson et al. NIPS 2017: adaptive methods can actually perform badly at test time (Adam is in pink, SGD in black)



(e) Generative Parsing (Training Set)



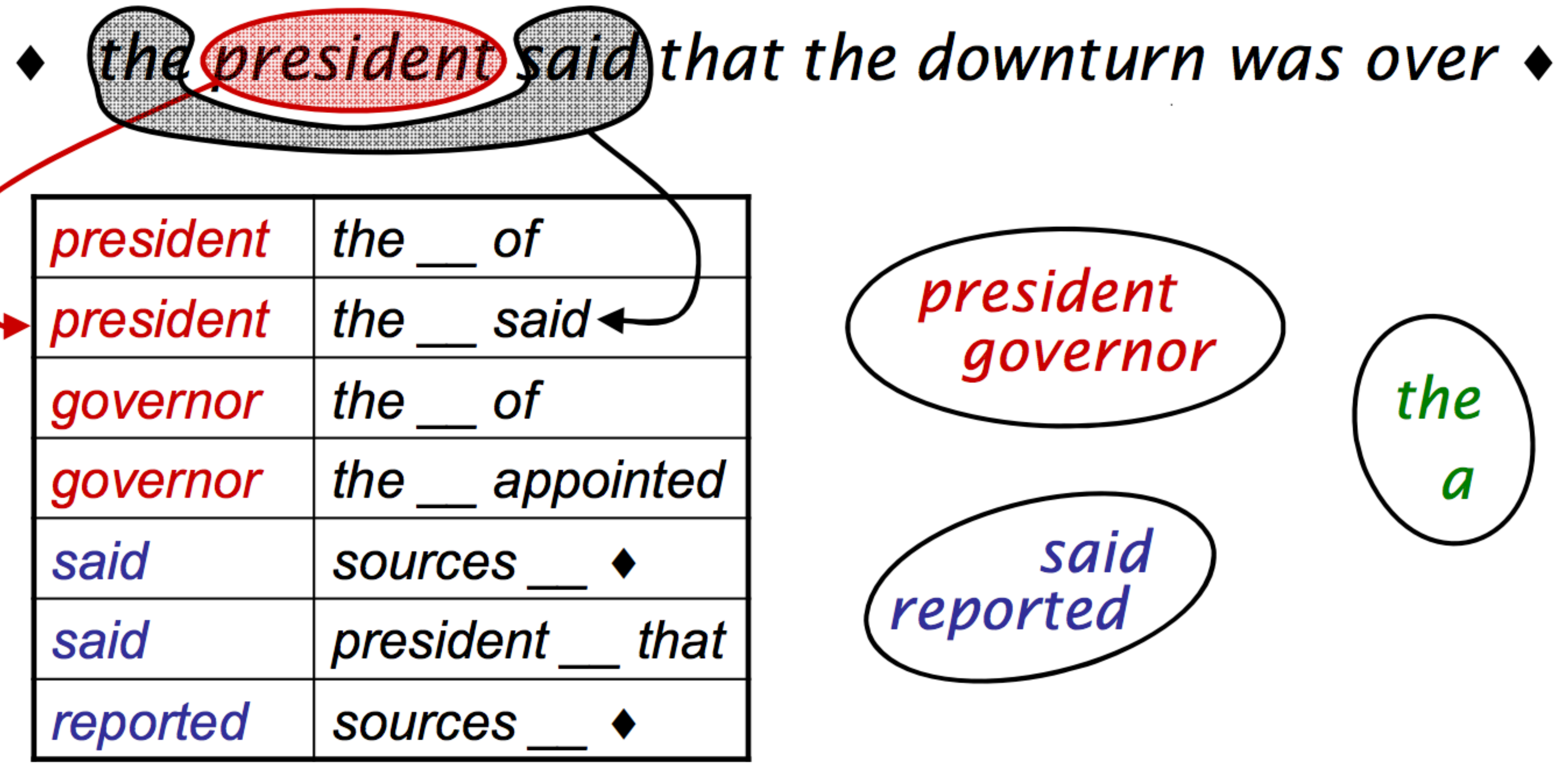
(f) Generative Parsing (Development Set)

- One more trick: **gradient clipping** (set a max value for your gradients)

Word Representations

Word Representations

- Neural networks work very well at continuous data, but words are discrete
- Continuous model <-> expects continuous semantics from input
- “You shall know a word by the company it keeps” Firth (1957)



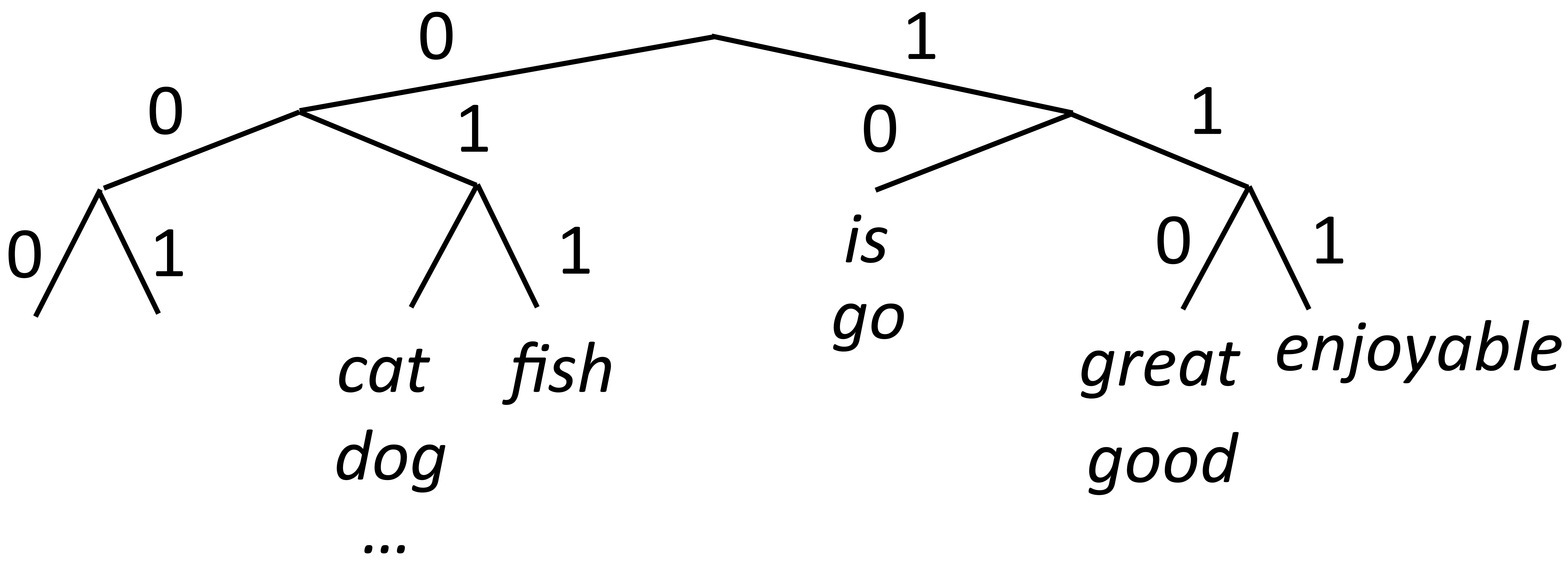
president	the __ of
president	the __ said
governor	the __ of
governor	the __ appointed
said	sources __ ♦
said	president __ that
reported	sources __ ♦

[Finch and Chater 92, Shuetze 93, many others]

slide credit: Dan Klein

Discrete Word Representations

- Brown clusters: hierarchical agglomerative *hard* clustering (each word has one cluster, not some posterior distribution like in mixture models)



- Maximize $P(w_i|w_{i-1}) = P(c_i|c_{i-1})P(w_i|c_i)$
- Useful features for tasks like NER, not suitable for NNs

Brown et al. (1992)

Word Embeddings

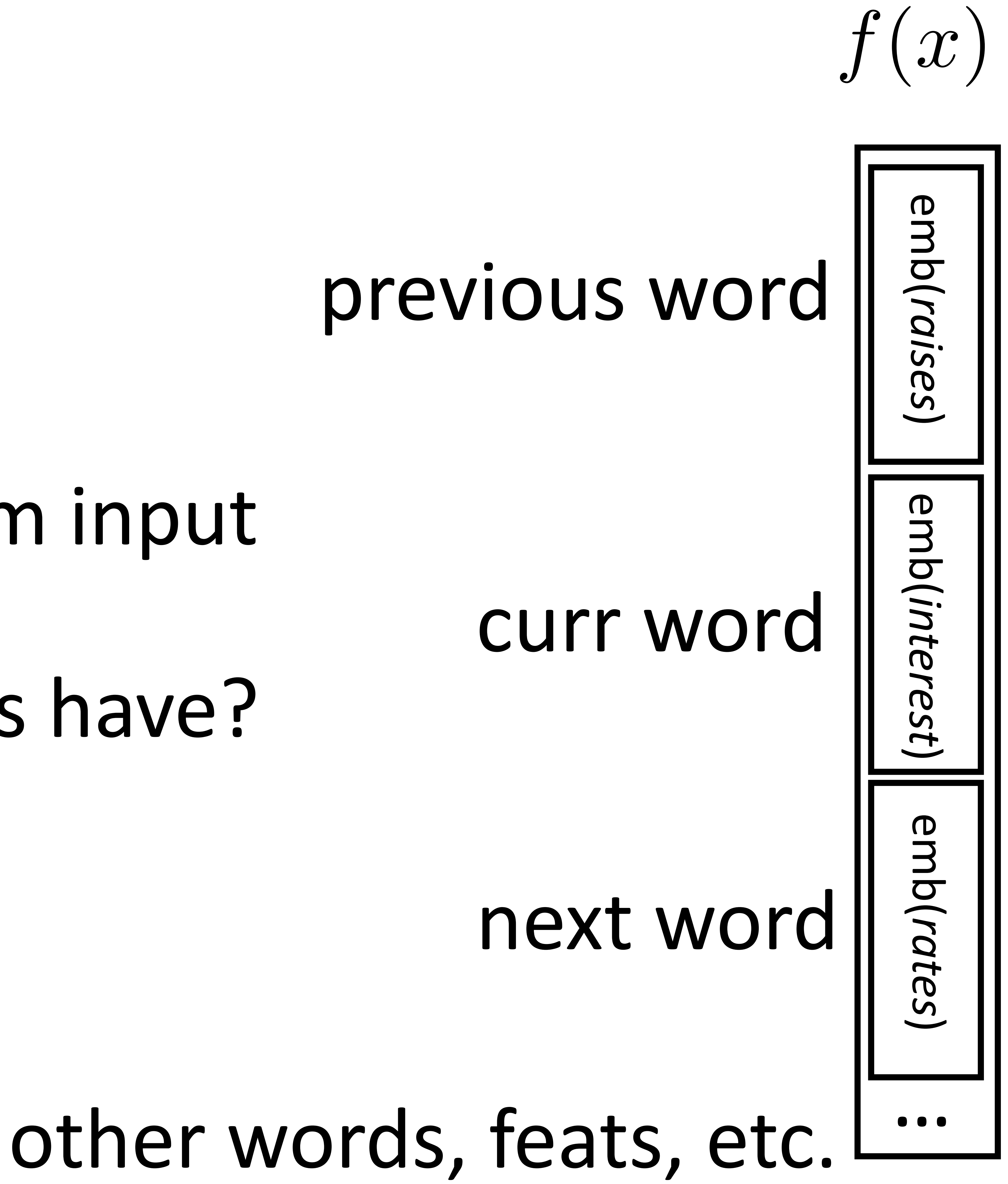
- Part-of-speech tagging with FFNNs

??

Fed raises ***interest*** *rates in order to …*

- Word embeddings for each word form input

- What properties should these vectors have?



Botha et al. (2017)

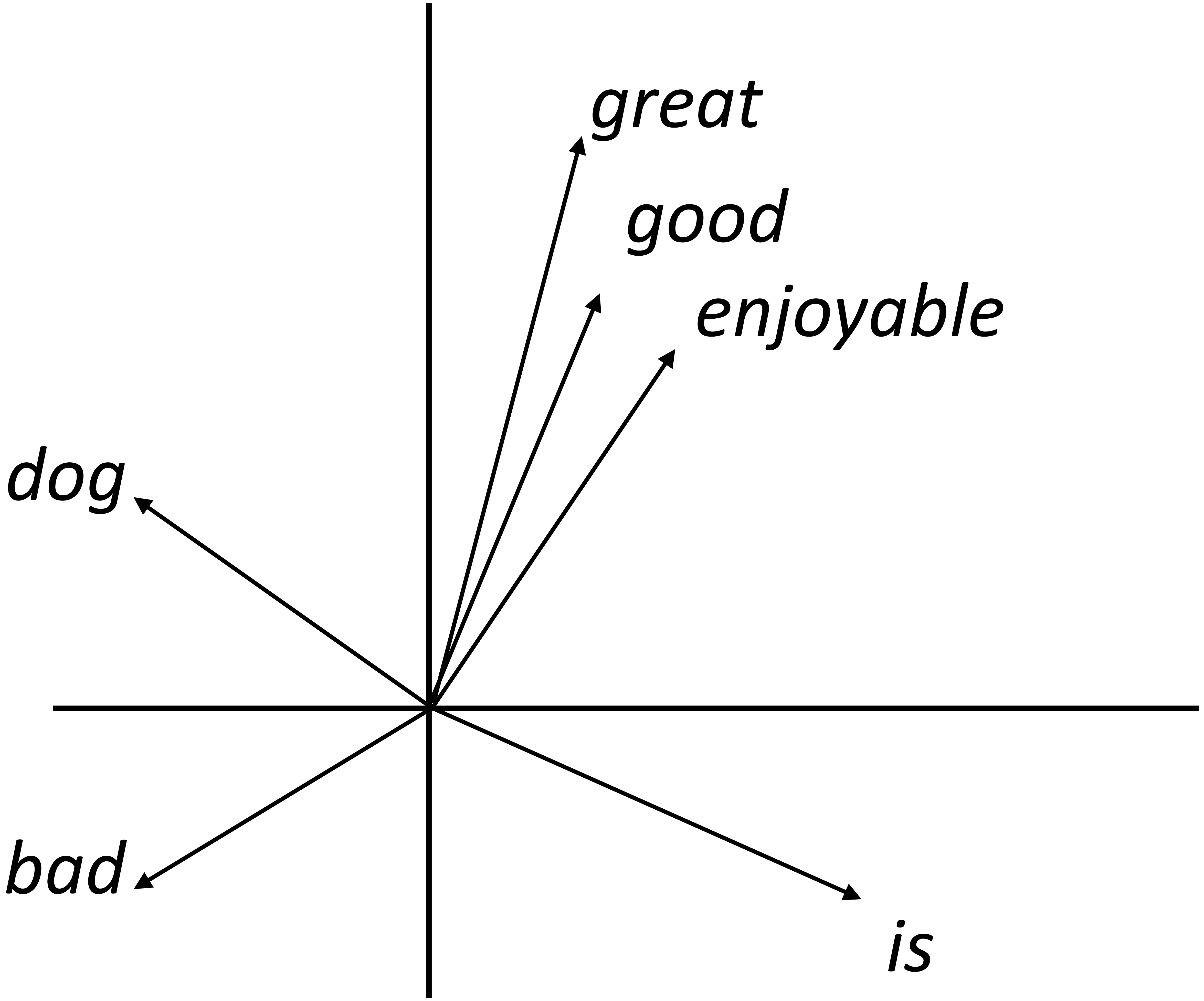
Word Embeddings

- Want a vector space where similar words have similar embeddings

the movie was great

≈

the movie was good

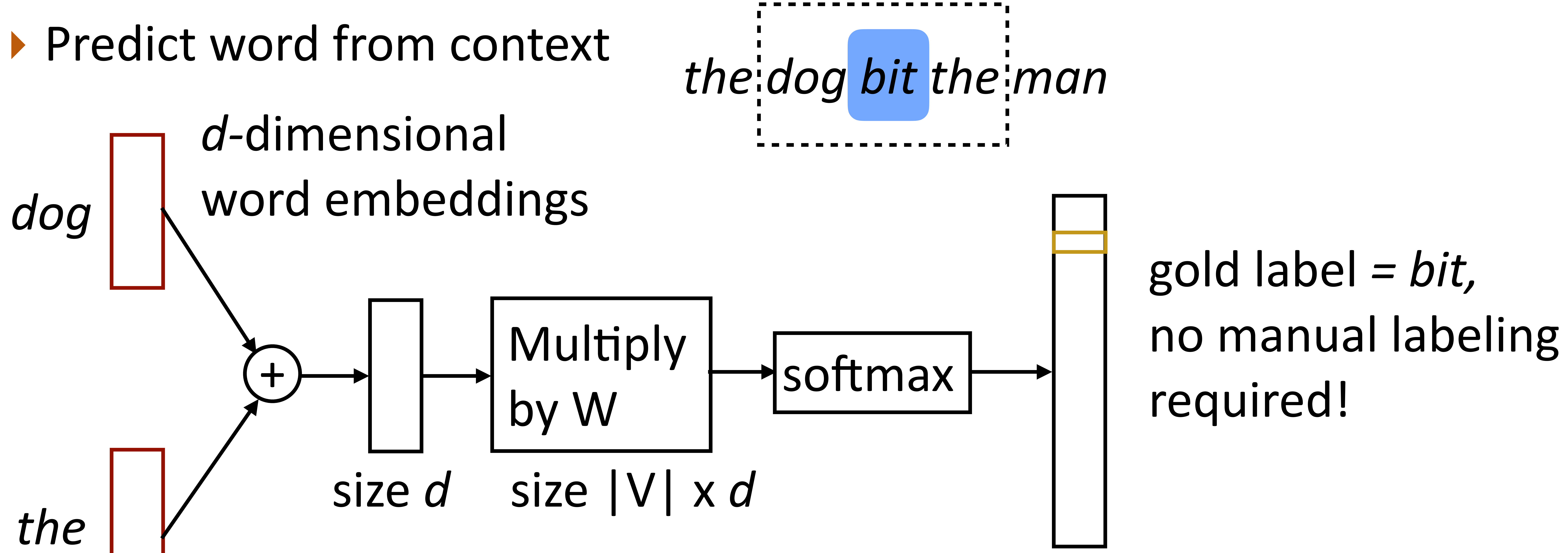


- Goal: come up with a way to produce these embeddings
- For each word, want "medium" dimensional vector (50-300 dims) representing it

word2vec/GloVe

Continuous Bag-of-Words

- Predict word from context



$$P(w|w_{-1}, w_{+1}) = \text{softmax}\left(W(c(w_{-1}) + c(w_{+1}))\right)$$

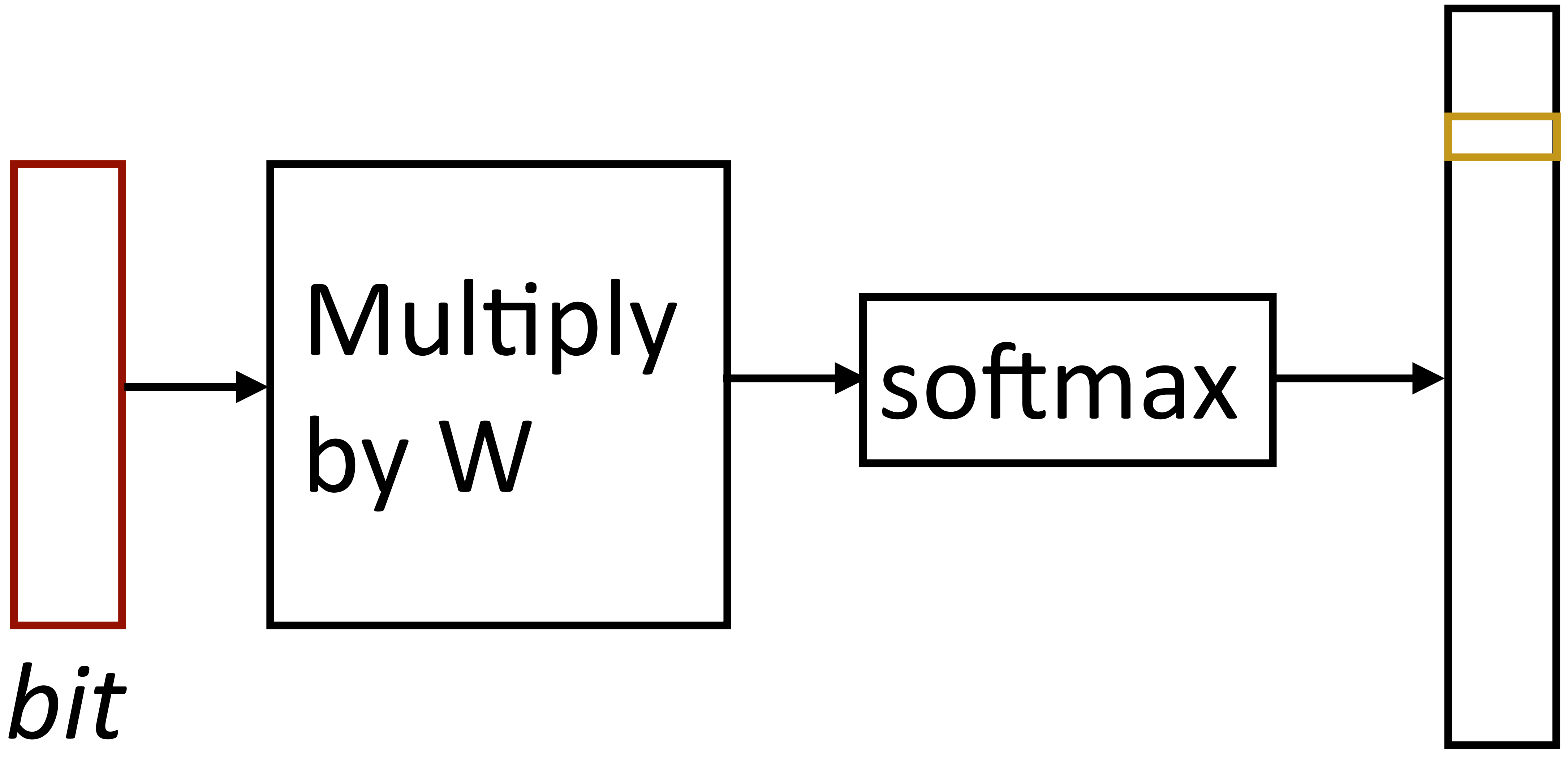
- Parameters: *d* x |V| (one *d*-length context vector per voc word),
  |V| x *d* output parameters (W)

Mikolov et al. (2013)

Skip-Gram

- Predict one word of context from word

the dog bit the man



gold = *dog*

$$P(w'|w) = \text{softmax}(We(w))$$

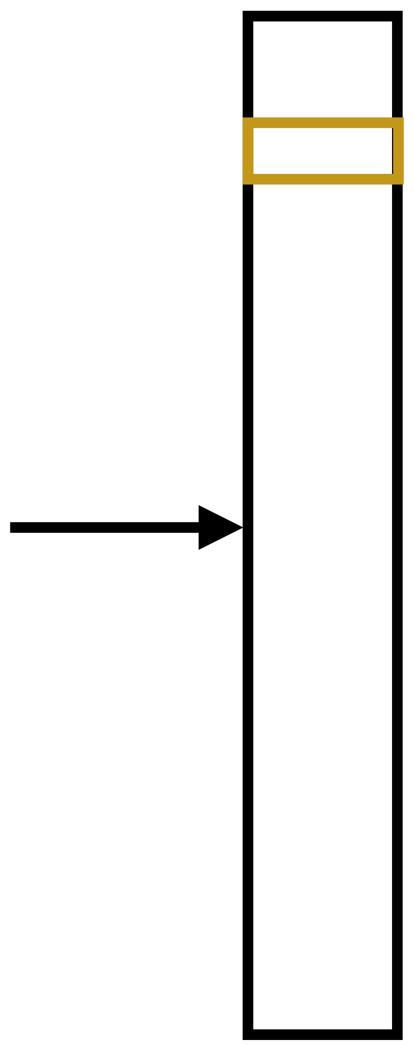
- Another training example: *bit* -> *the*
- Parameters: d x |V| vectors, |V| x d output parameters (W) (also usable as vectors!)

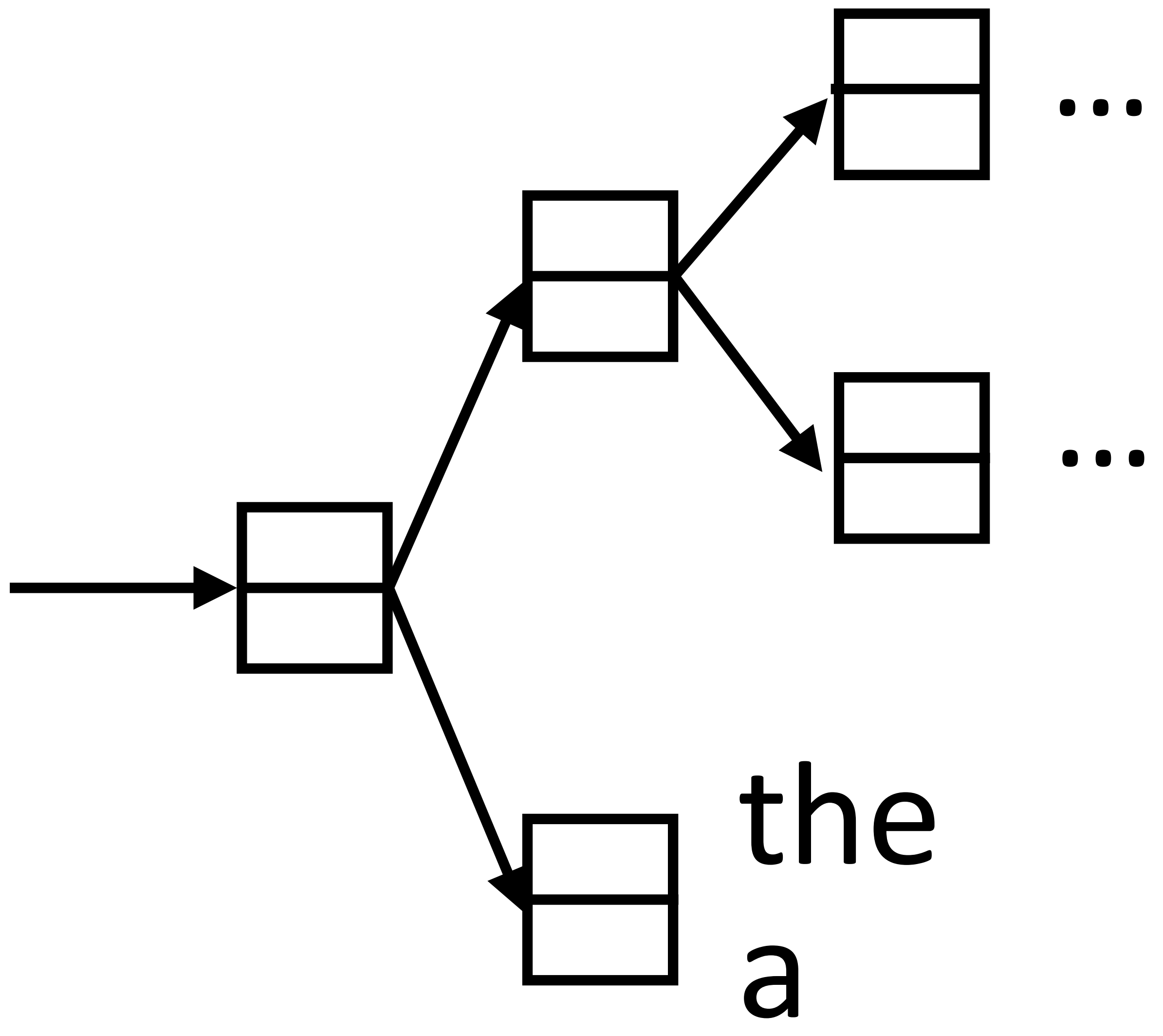
Mikolov et al. (2013)

Hierarchical Softmax

$$P(w|w_{-1}, w_{+1}) = \text{softmax}\left(W(c(w_{-1}) + c(w_{+1}))\right) \qquad P(w'|w) = \text{softmax}(We(w))$$

- Matmul + softmax over |V| is very slow to compute for CBOW and SG





- Huffman encode vocabulary, use binary classifiers to decide which branch to take
- log(|V|) binary decisions

- Standard softmax:
  [|V| x *d*] x *d*

- Hierarchical softmax:
  log(|V|) dot products of size *d*,
  |V| x *d* parameters

Mikolov et al. (2013)

Skip-Gram with Negative Sampling

- Take (word, context) pairs and classify them as "real" or not. Create random negative examples by sampling from unigram distribution

(*bit*, *the*) => +1

(*bit*, *cat*) => -1

(*bit*, *a*) => -1

(*bit*, *fish*) => -1

$$P(y = 1|w, c) = \frac{e^{w \cdot c}}{e^{w \cdot c} + 1}$$

words in similar contexts select for similar *c* vectors

- *d* x |V| vectors, *d* x |V| context vectors (same # of params as before)

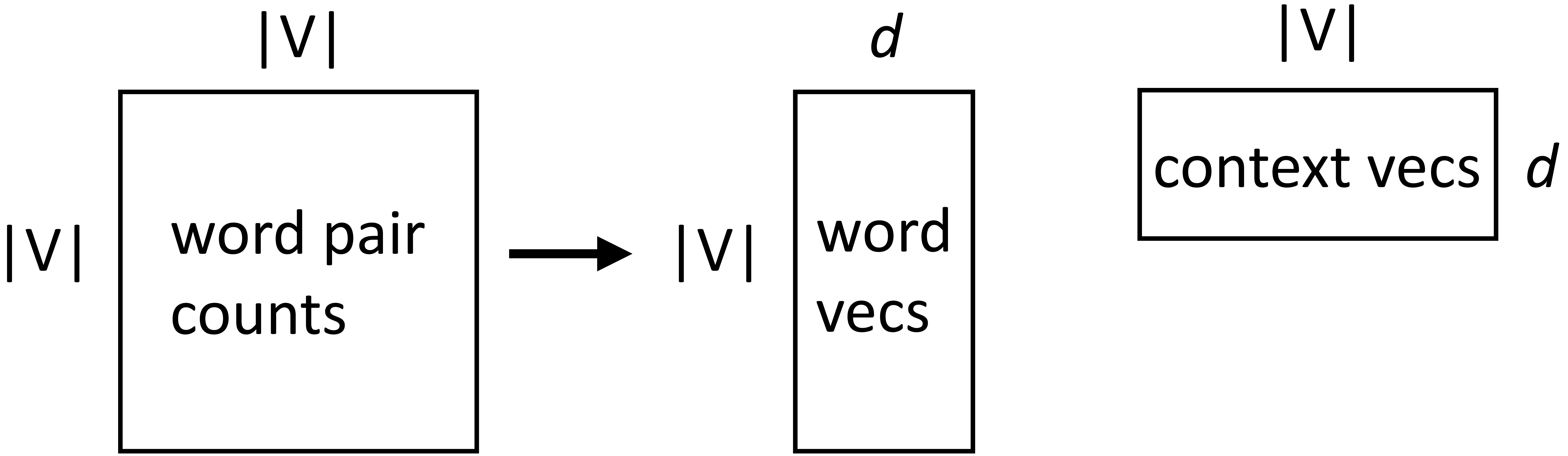
sampled

- Objective = $\log P(y = 1|w, c) + \frac{1}{k} \sum_{i=1}^{n} \log P(y = 0|w_i, c)$

Mikolov et al. (2013)

Connections with Matrix Factorization

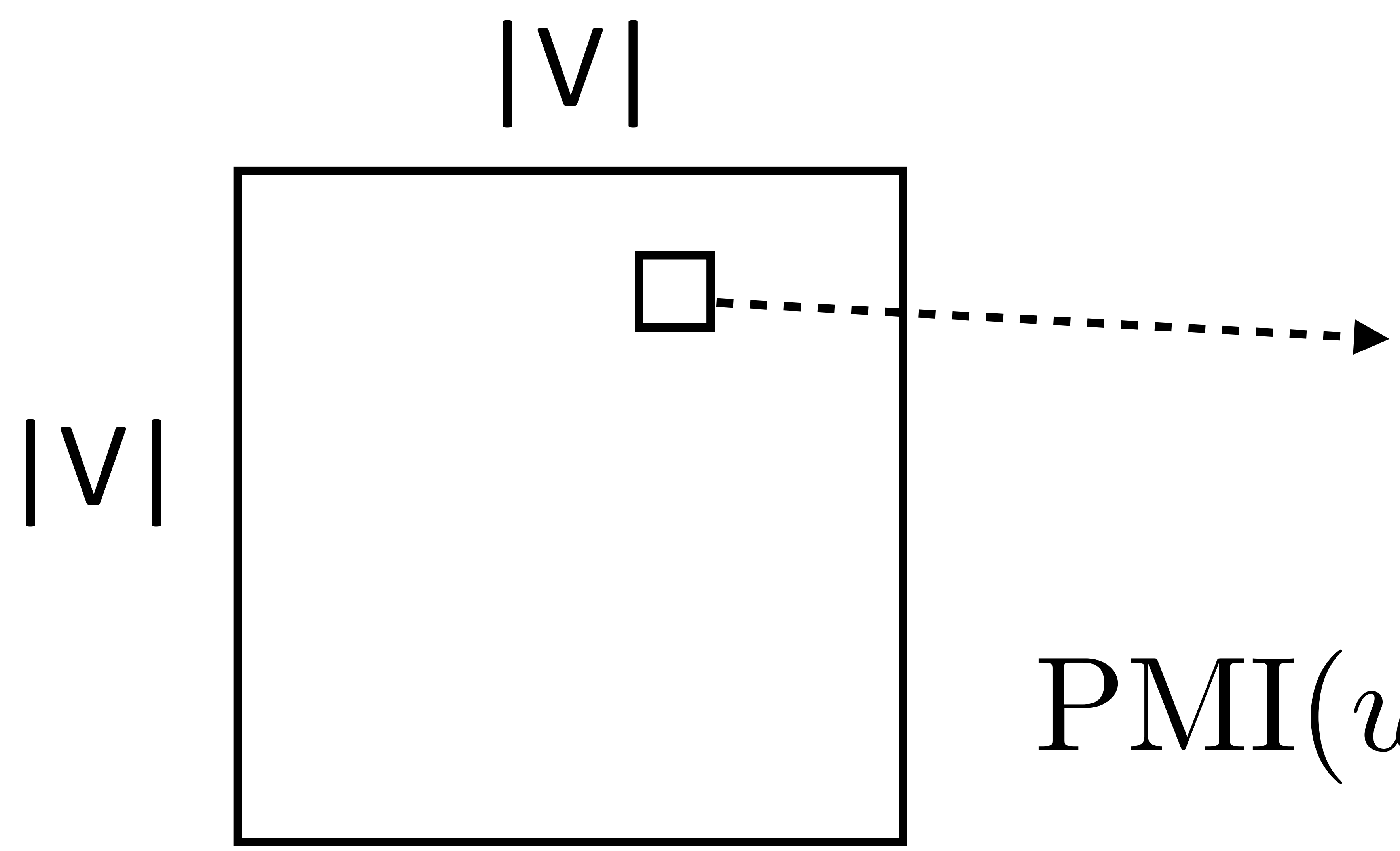
- Skip-gram model looks at word-word co-occurrences and produces two types of vectors



- Looks almost like a matrix factorization…can we interpret it this way?

Levy et al. (2014)

Skip-Gram as Matrix Factorization



num negative samples

$$M_{ij} = \mathrm{PMI}(w_i, c_j) - \log k$$

$$\mathrm{PMI}(w_i, c_j) = \frac{P(w_i, c_j)}{P(w_i)P(c_j)} = \frac{\frac{\mathrm{count}(w_i, c_j)}{D}}{\frac{\mathrm{count}(w_i)}{D}\frac{count(c_j)}{D}}$$

Skip-gram objective *exactly* corresponds to factoring this matrix:

- *If* we sample negative examples from the uniform distribution over words
- …and it's a *weighted* factorization problem (weighted by word freq)

Levy et al. (2014)

GloVe (**Glo**bal **Ve**ctors)

|V|

|V| word pair counts

- Also operates on counts matrix, weighted regression on the log co-occurrence matrix

- Objective = $\sum_{i,j} f(\mathrm{count}(w_i, c_j)) \left(w_i^\top c_j + a_i + b_j - \log \mathrm{count}(w_i, c_j) \right)^2$

- Constant in the dataset size (just need counts), quadratic in voc size

- By far the most common word vectors used today (5000+ citations)

Pennington et al. (2014)

fastText: Sub-word Embeddings

- Same as SGNS, but break words down into n-grams with n = 3 to 6

  where:
  3-grams: <wh, whe, her, ere, re>
  4-grams: <whe, wher, here, ere>,
  5-grams: <wher, where, here>,
  6-grams: <where, where>

- Replace $w \cdot c$ in skip-gram computation with $\left(\sum_{g \in \text{ngrams}} w_g \cdot c\right)$

- Advantages?

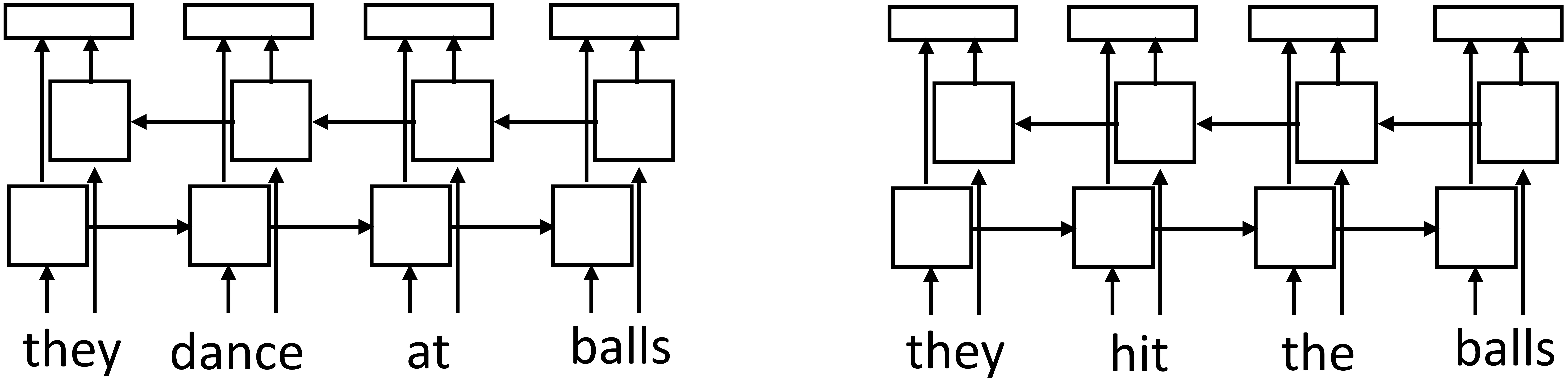
Bojanowski et al. (2017)

Using Word Embeddings

- Approach 1: learn embeddings as parameters from your data
  - Often works pretty well
- Approach 2: initialize using GloVe, keep fixed
  - Faster because no need to update these parameters
- Approach 3: initialize using GloVe, fine-tune
  - Works best for some tasks

Preview: Context-dependent Embeddings

- How to handle different word senses? One vector for *balls*



- Train a neural language model to predict the next word given previous words in the sentence, use its internal representations as word vectors
- *Context-sensitive* word embeddings: depend on rest of the sentence
- *Huge* improvements across nearly all NLP tasks over GloVe

Peters et al. (2018)

Compositional Semantics

- What if we want embedding representations for whole sentences?
- Skip-*thought* vectors (Kiros et al., 2015), similar to skip-gram generalized to a sentence level (more later)
- Is there a way we can compose vectors to make sentence representations? Summing?
- Will return to this in a few weeks as we move on to syntax and semantics

Evaluation

Evaluating Word Embeddings

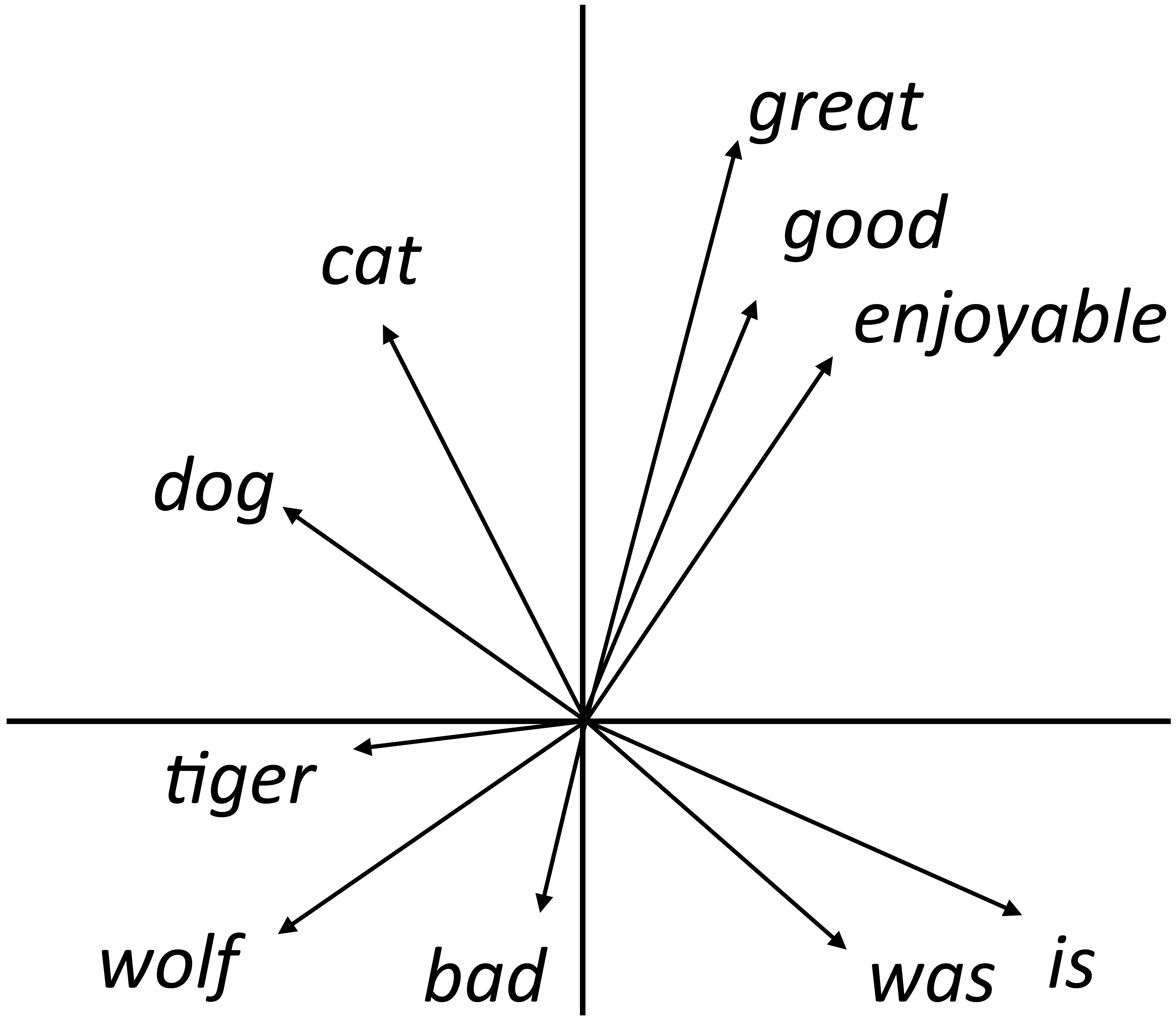
- What properties of language should word embeddings capture?

- Similarity: similar words are close to each other

- Analogy:

  good is to best as smart is to ???

  Paris is to France as Tokyo is to ???



Similarity

Method	WordSim Similarity	WordSim Relatedness	Bruni et al. MEN	Radinsky et al. M. Turk	Luong et al. Rare Words	Hill et al. SimLex
PPMI	.755	**.697**	.745	.686	.462	.393
SVD	**.793**	.691	**.778**	.666	**.514**	.432
SGNS	**.793**	.685	.774	**.693**	.470	**.438**
GloVe	.725	.604	.729	.632	.403	.398

- SVD = singular value decomposition on PMI matrix
- GloVe does not appear to be the best when experiments are carefully controlled, but it depends on hyperparameters + these distinctions don't matter in practice

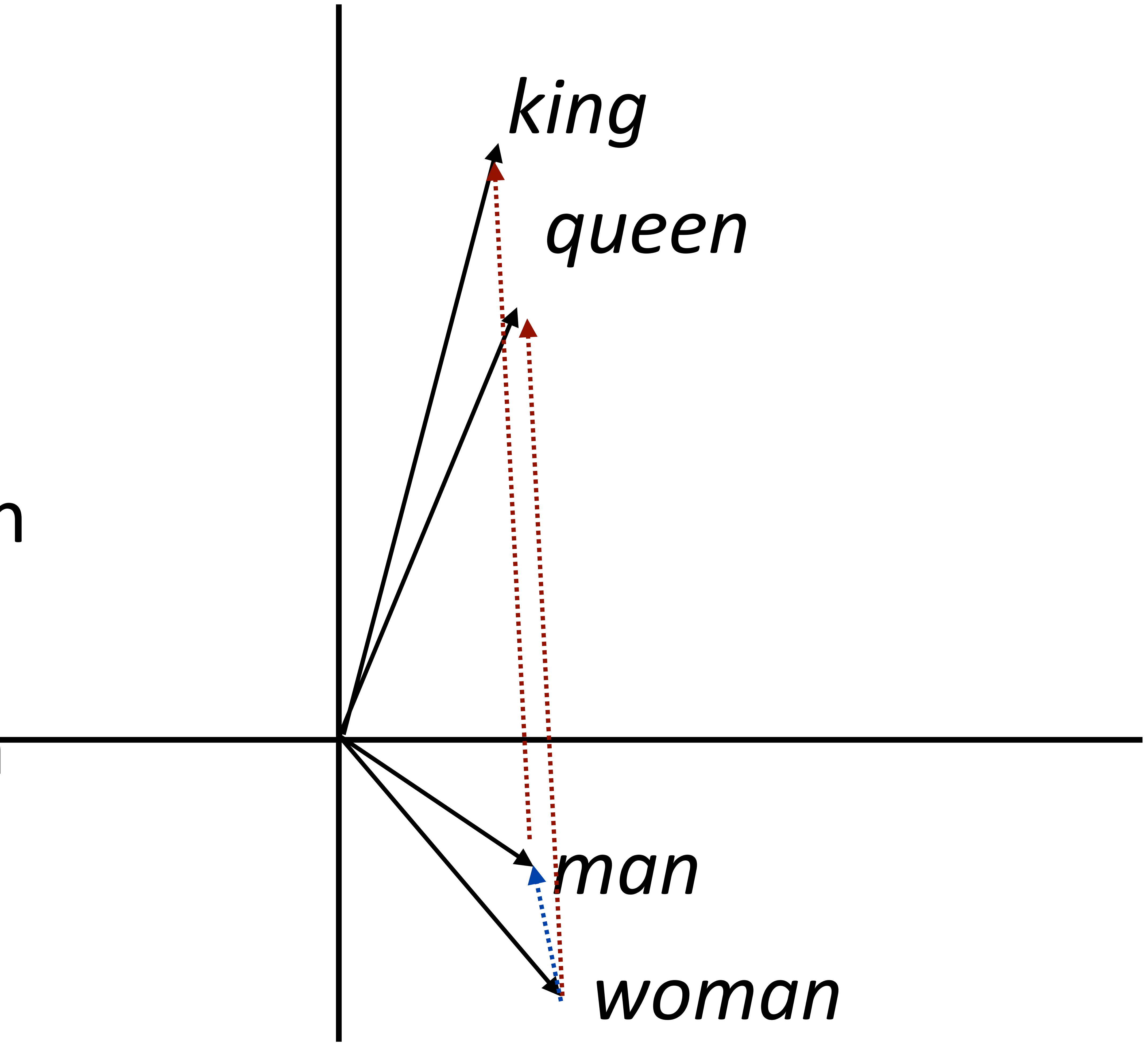
Levy et al. (2015)

Analogies

(king - man) + woman = queen

king + (woman - man) = queen

- Why would this be?
- woman - man captures the difference in the contexts that these occur in
- Dominant change: more “he” with man and “she” with woman — similar to difference between king and queen
- Can evaluate on this as well



What can go wrong with word embeddings?

- What’s wrong with learning a word’s “meaning” from its usage?
- What data are we learning from?
- What are we going to learn from this data?

What do we mean by bias?

- Identify *she* - *he* axis in word vector space, project words onto this axis

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

Bolukbasi et al. (2016)

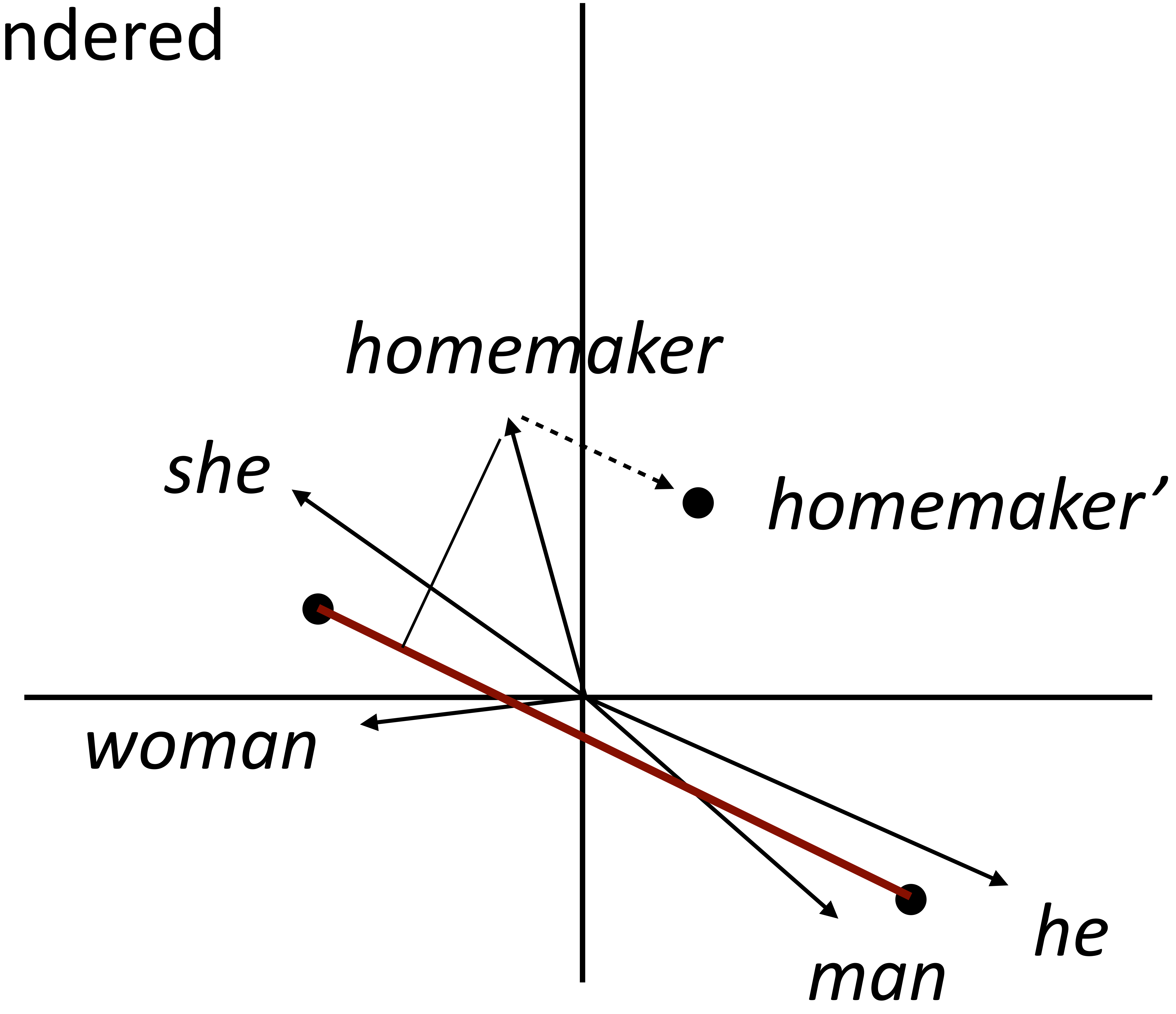
- Nearest neighbor of (b - a + c)

Racial Analogies	
black → homeless	caucasian → servicemen
caucasian → hillbilly	asian → suburban
asian → laborer	black → landowner
Religious Analogies	
jew → greedy	muslim → powerless
christian → familial	muslim → warzone
muslim → uneducated	christian → intellectually

Manzini et al. (2019)

Debiasing

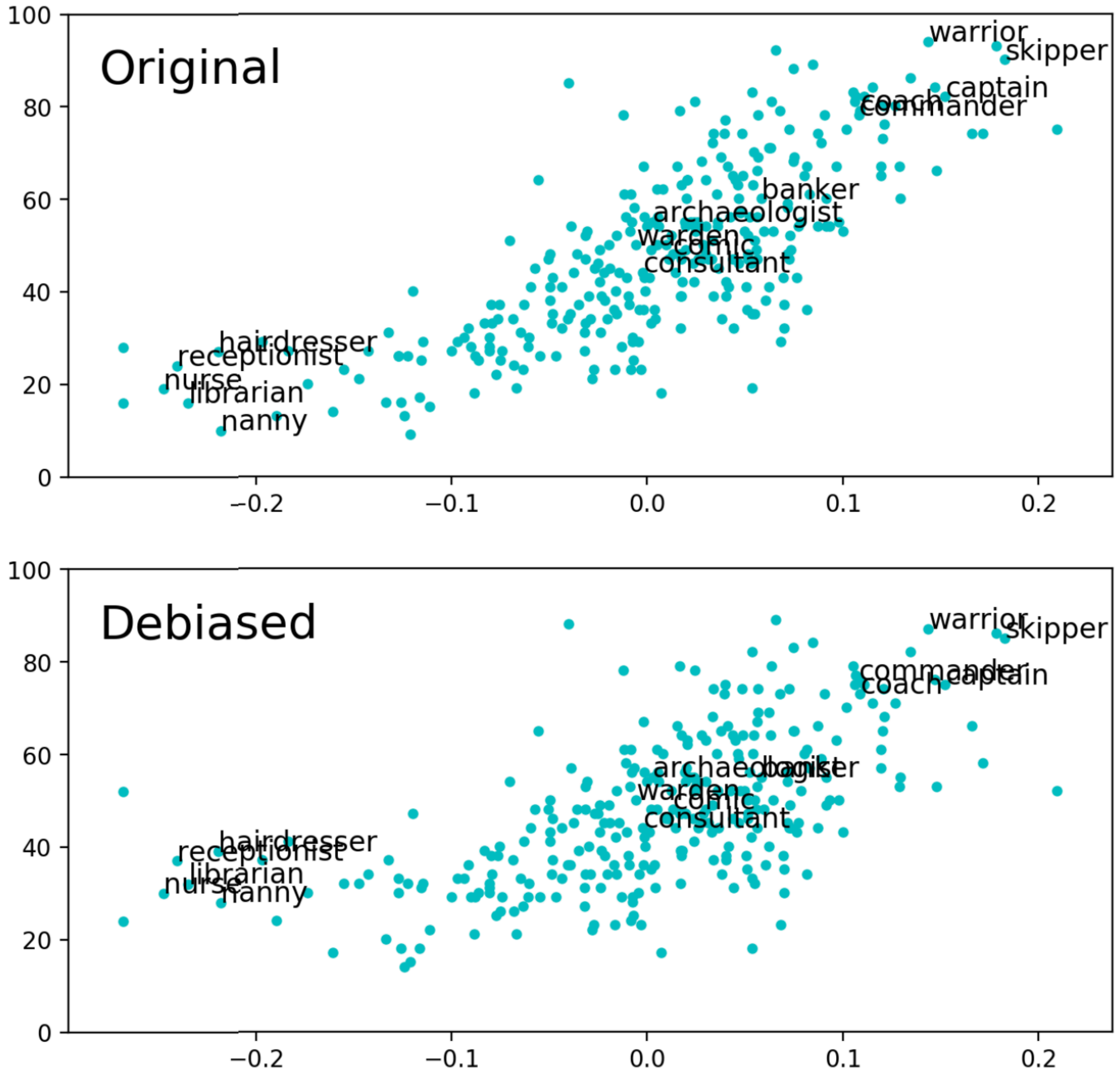
- Identify gender subspace with gendered words
- Project words onto this subspace
- Subtract those projections from the original word



Bolukbasi et al. (2016)

Hardness of Debiasing

- Not that effective…and the male and female words are still clustered together
- Bias pervades the word embedding space and isn't just a local property of a few words



(a) The plots for HARD-DEBIASED embedding, before (top) and after (bottom) debiasing.

Gonen and Goldberg (2019)

Takeaways

- Lots to tune with neural networks
  - Training: optimizer, initializer, regularization (dropout), …
  - Hyperparameters: dimensionality of word embeddings, layers, …
- Word vectors: learning word -> context mappings has given way to matrix factorization approaches (constant in dataset size)
- Lots of pretrained embeddings work well in practice, they capture some desirable properties
- Even better: context-sensitive word embeddings (ELMo)
- Next time: RNNs and CNNs