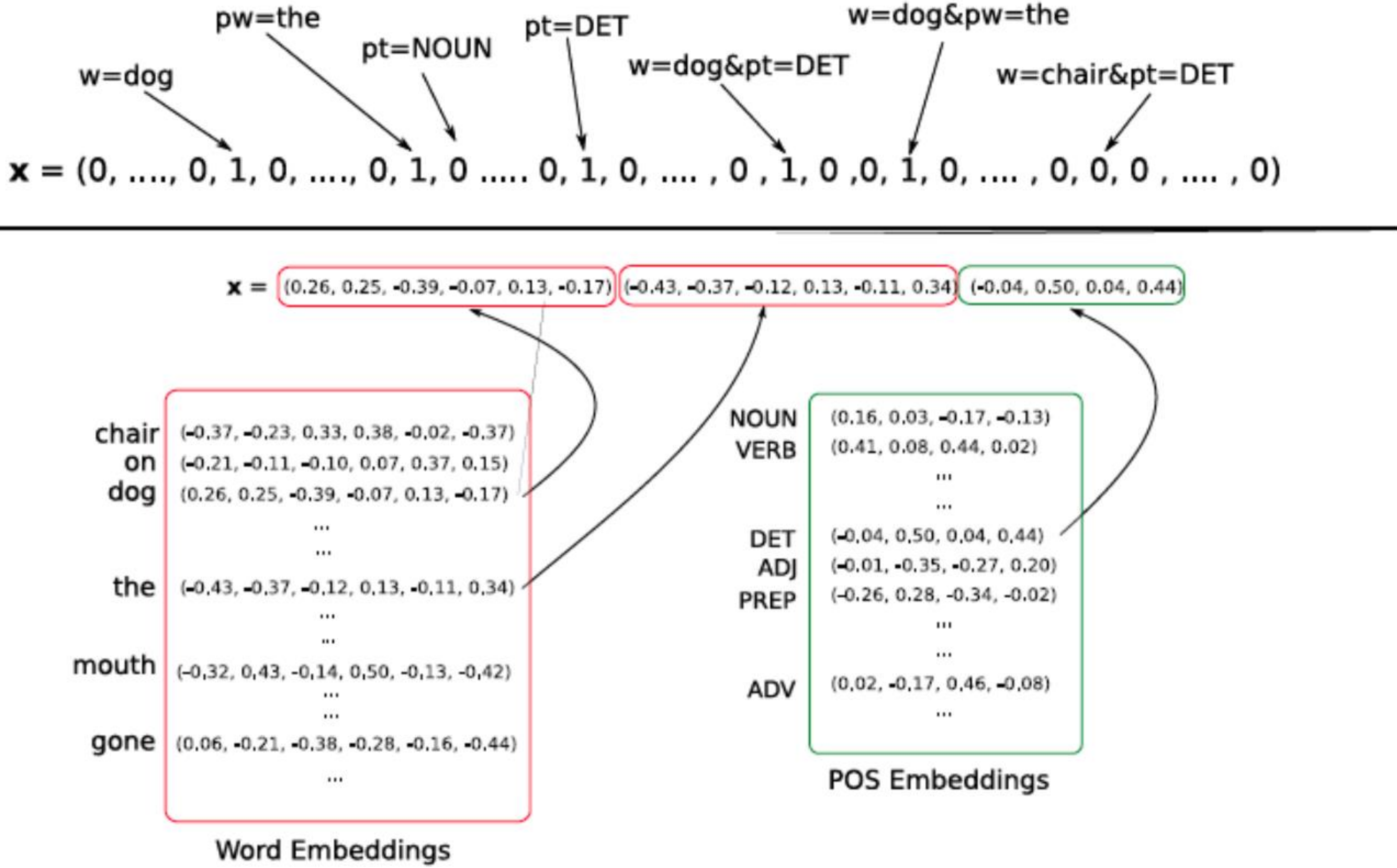
Variable Length Sequences
N-gram features
Convolutional Networks

Yoav Goldberg

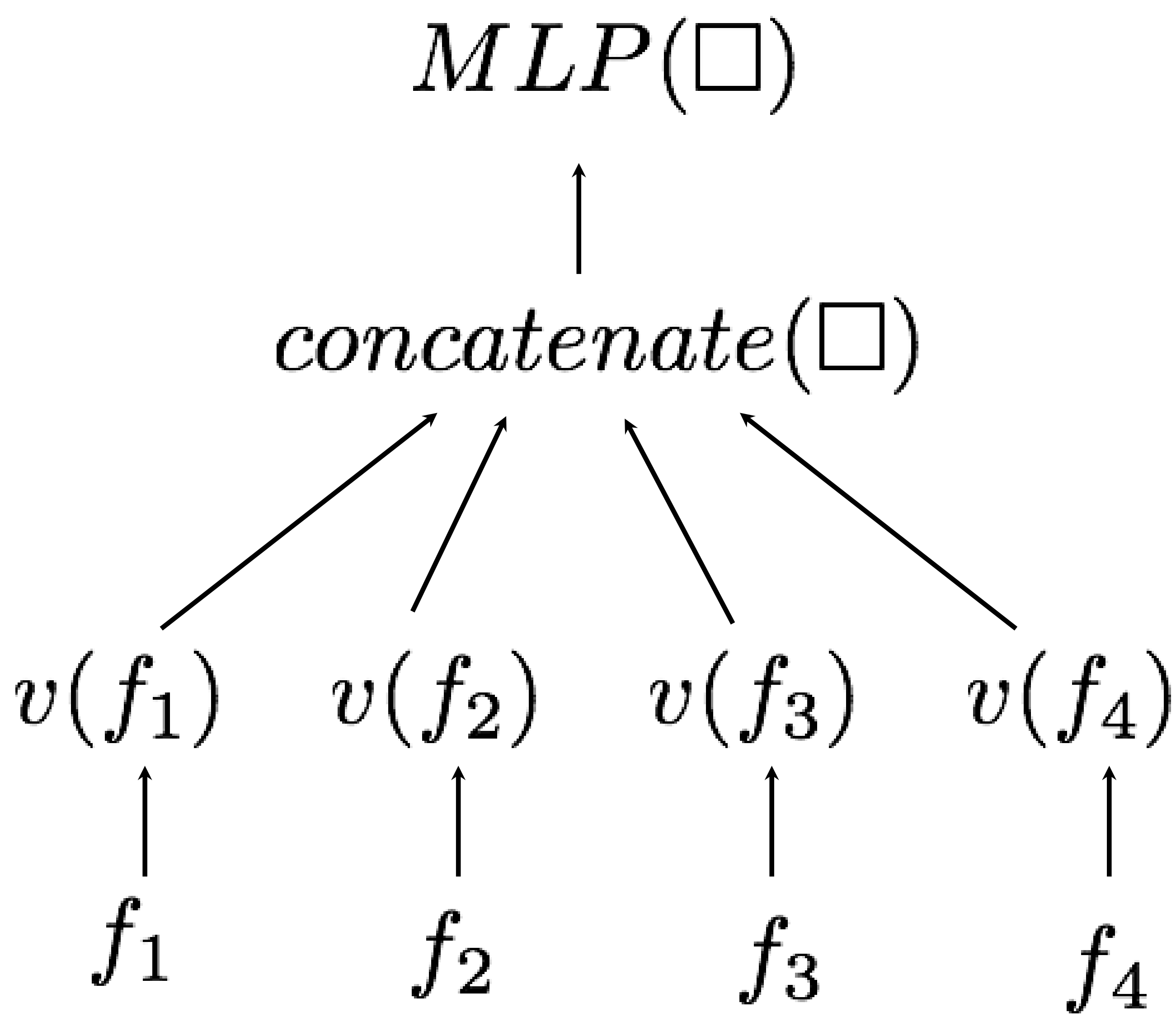
"feature embeddings"

- Each feature is assigned a vector.
- The input is a combination of feature vectors.
- The feature vectors are **parameters of the model** and are trained jointly with the rest of the network.
- **Representation Learning**: similar features will receive similar vectors.

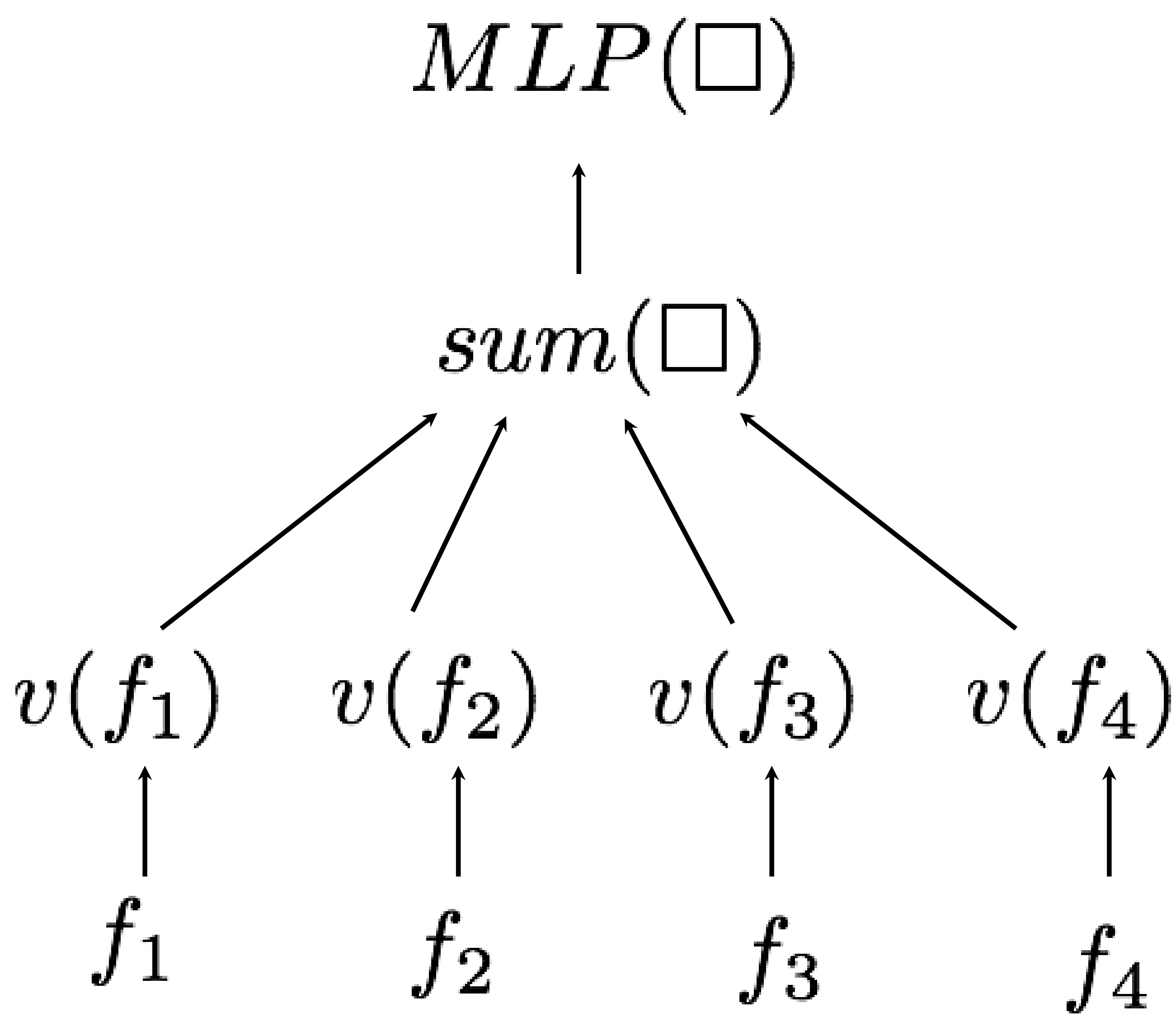
"feature embeddings"



"feature embeddings"



"feature embeddings"



Concat vs. Sum

- **Concatenating** feature vectors: the "roles" of each vector is retained.

$$concat\left(v(\text{"}the\text{"}), v(\text{"}thirsty\text{"}), v(\text{"}dog\text{"})\right)$$

prev word | current word | next word

- Different features can have vectors of different dim.

- Fixed number of features in each example (need to feed into a fixed dim layer).

Concat vs. Sum

- **Summing** feature vectors: "bag of features"

$$sum\left(v(\text{"}the\text{"}), v(\text{"}thirsty\text{"}), v(\text{"}dog\text{"})\right)$$

word word word

- Different feature vectors should have same dim.

- Can encode arbitrary number of features.

Concat vs. Sum

- **Summing** feature vectors: "bag of features"

$$sum\left(v(\text{"}the\text{"}), v(\text{"}thirsty\text{"}), v(\text{"}dog\text{"})\right)$$

word word word

- Different feature vectors should have same dim.

- Can encode **arbitrary number of features.**

Continuous Bag of Words (CBOW)

$$CBOW(f_1, ..., f_k) = \frac{1}{k}\sum_{i=1}^{k} v(f_i)$$

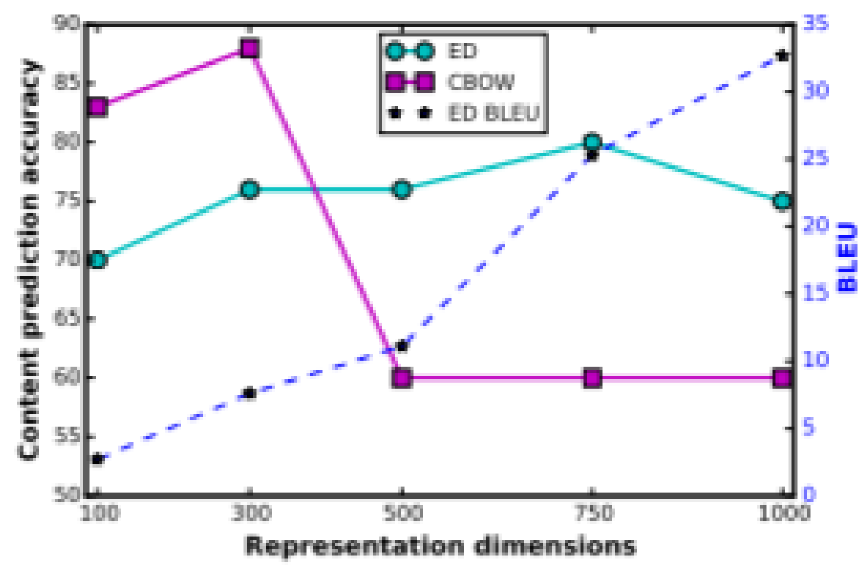
- a popular choice in document classification.
- can assign a different weight to each feature:

$$WCBOW(f_1, ..., f_k) = \frac{1}{\sum_{i=1}^{k} a_i}\sum_{i=1}^{k} a_i v(f_i)$$

Surprising Power of CBOW

$$CBOW(f_1, ..., f_k) = \frac{1}{k}\sum_{i=1}^{k} v(f_i)$$

Given CBOW vector and word vector,
can we predict if word is in cbow?



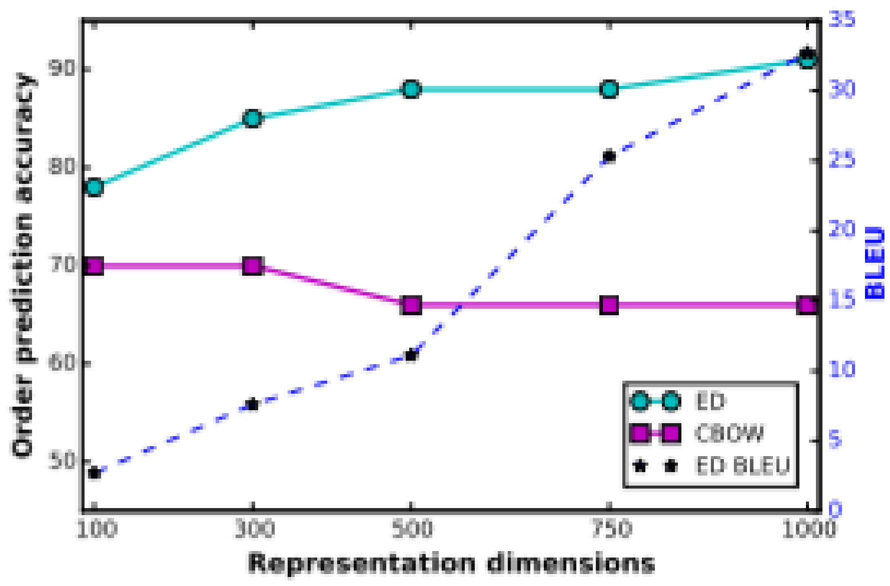
Fine-grained Analysis of Sentence Embeddings Using Auxiliary Prediction Tasks

Yossi Adi[1,2], Einat Kermany[2], Yonatan Belinkov[3], Ofer Lavi[2], Yoav Goldberg[1]

Surprising Power of CBOW

$$CBOW(f_1, ..., f_k) = \frac{1}{k}\sum_{i=1}^{k} v(f_i)$$

Given CBOW vector and two word vectors,
can we predict which word appeared before the other?



FINE-GRAINED ANALYSIS OF SENTENCE EMBEDDINGS USING AUXILIARY PREDICTION TASKS

Yossi Adi[1,2], Einat Kermany[2], Yonatan Belinkov[3], Ofer Lavi[2], Yoav Goldberg[1]

Surprising Power of CBOW

$$CBOW(f_1, ..., f_k) = \frac{1}{k}\sum_{i=1}^{k} v(f_i)$$

Given CBOW vector
can we predict sentence length?

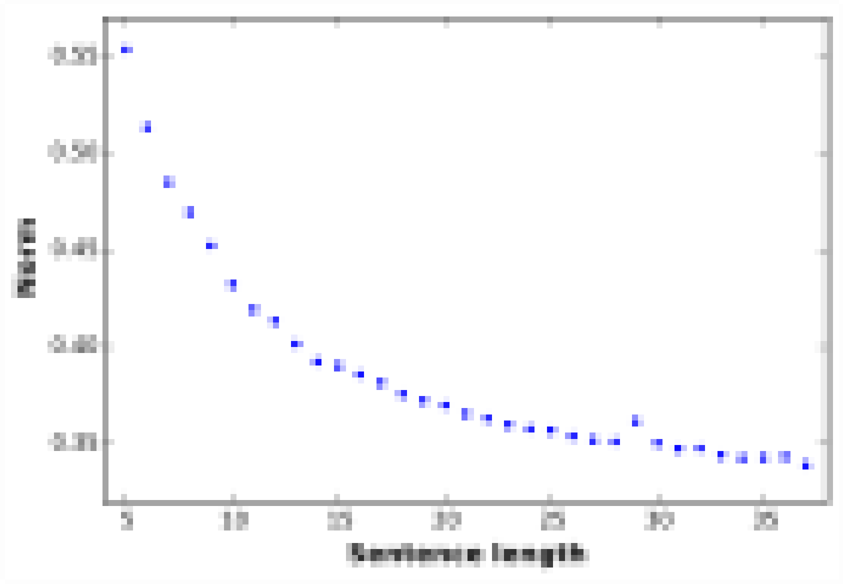
FINE-GRAINED ANALYSIS OF SENTENCE EMBEDDINGS USING AUXILIARY PREDICTION TASKS

Yossi Adi[1,2], Einat Kermany[2], Yonatan Belinkov[3], Ofer Lavi[2], Yoav Goldberg[1]

Surprising Power of CBOW

$$CBOW(f_1, ..., f_k) = \frac{1}{k}\sum_{i=1}^{k} v(f_i)$$

Given CBOW vector
can we predict sentence length?



(b) Average embedding norm vs. sentence length for CBOW with an embedding size of 300.

how come?

Deep Unordered Composition Rivals Syntactic Methods for Text Classification

Mohit Iyyer,[1] Varun Manjunatha,[1] Jordan Boyd-Graber,[2] Hal Daumé III[1]
[1]University of Maryland, Department of Computer Science and UMIACS
[2]University of Colorado, Department of Computer Science
{miyyer,varunm,hal}@umiacs.umd.edu, Jordan.Boyd.Graber@colorado.edu

"Document Averaging Networks"

text classification

scores of labels

$$\uparrow$$

$$softmax(\square)$$

$$\uparrow$$

$$CBOW(\square)$$

$$\uparrow$$

$$w_1, ..., w_n$$

"neural bag of words"

scores of labels

$$\uparrow$$

$$softmax(\square)$$

$$\uparrow$$

$$g^2(\mathbf{W}^2\square + \mathbf{b}^2)$$

$$\uparrow$$

$$g^1(\mathbf{W}^1\square + \mathbf{b}^1)$$

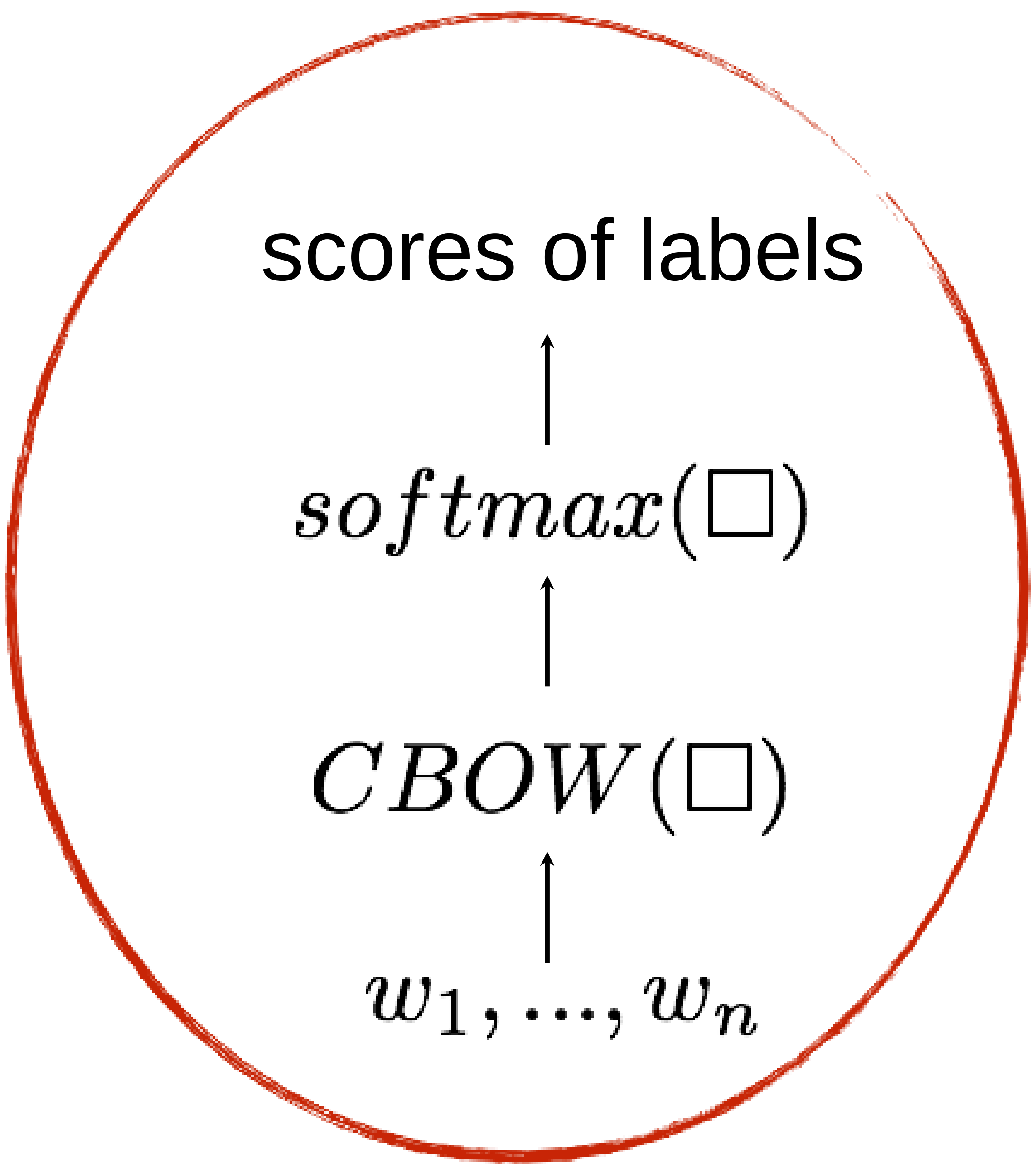
$$\uparrow$$

$$CBOW(\square)$$

$$\uparrow$$

$$w_1, ..., w_n$$

"deep averaging network"



"neural bag of words"

If each feature is bigram,
works great.

Moving to unigrams, large drop.

Unigrams + MLP --> better
but not like bigrams.

Importance of Ngrams

- While we can ignore global order in many cases...
- ... local ordering is still often very important.
- Local sub-sequences encode useful structures.

Importance of Ngrams

- While we can ignore global order in many cases...
- ... local ordering is still often very important.
- Local sub-sequences encode useful structures.

(so why not just assign a vector to each ngram?)

ConvNets

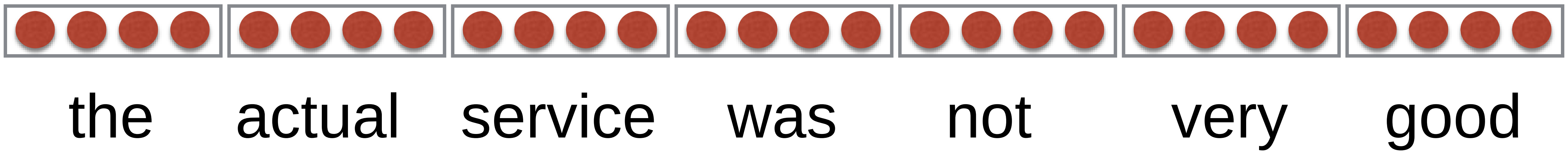
special architecture for local predictors

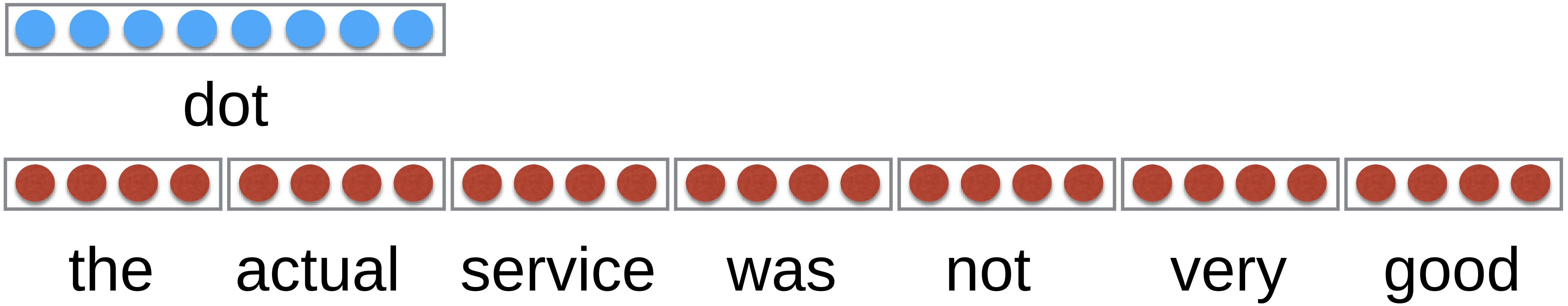
ConvNets

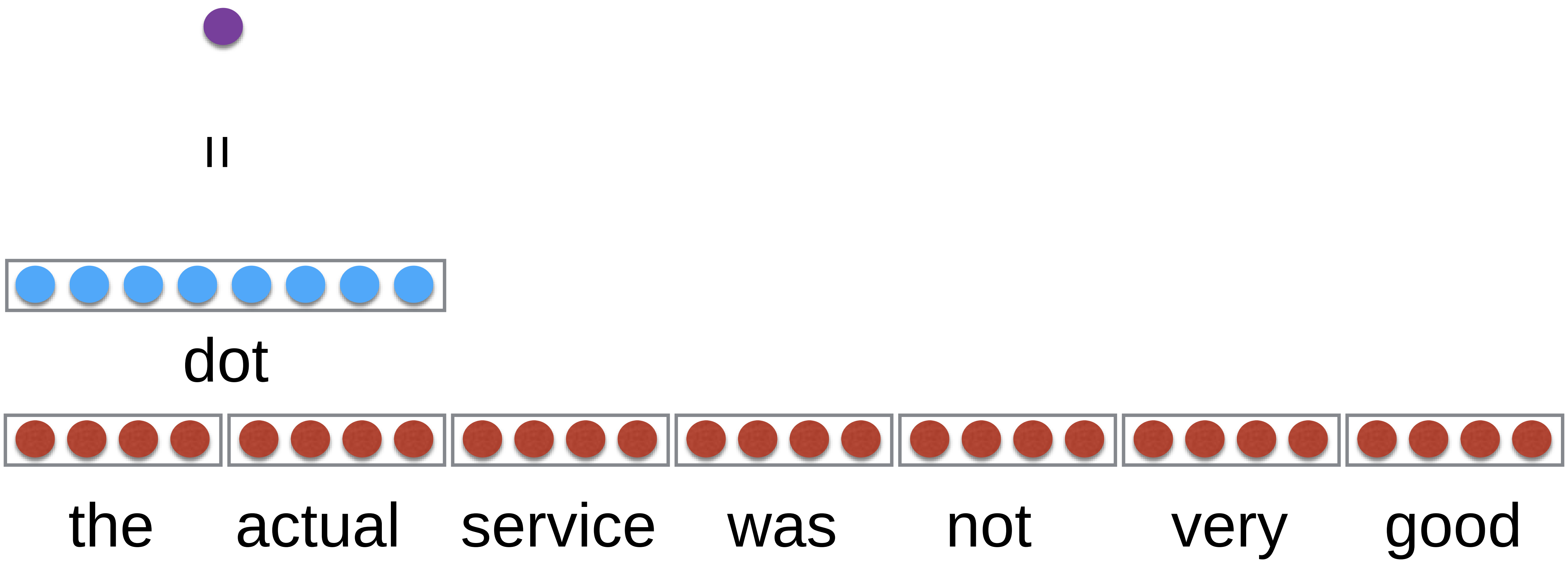
- CBOW allows encoding arbitrary length sequences, but loses all order information.
- Some local order (i.e. bigrams, trigrams) is informative. Yet, we do not care about exact position in the sequence. (think "good" vs. "not good")
- ConvNets (in language) allow to identify informative local predictors.
- Works by moving a shared function (feature extractor) over a sliding window, then pooling results.

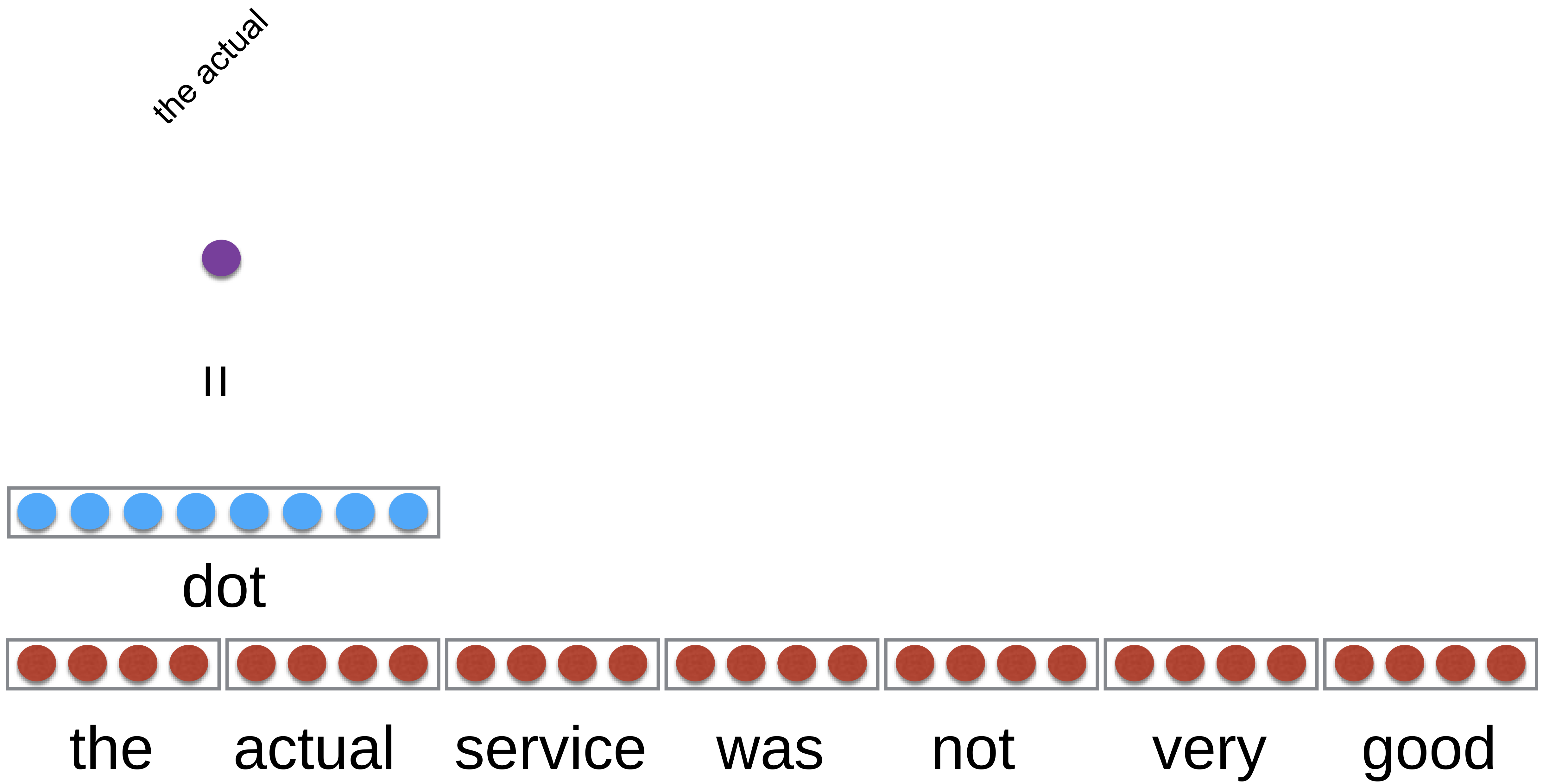
ConvNets

- ConvNets have huge success in computer vision.
- It allows invariance to object position.
- It allows composing large predictors from small.

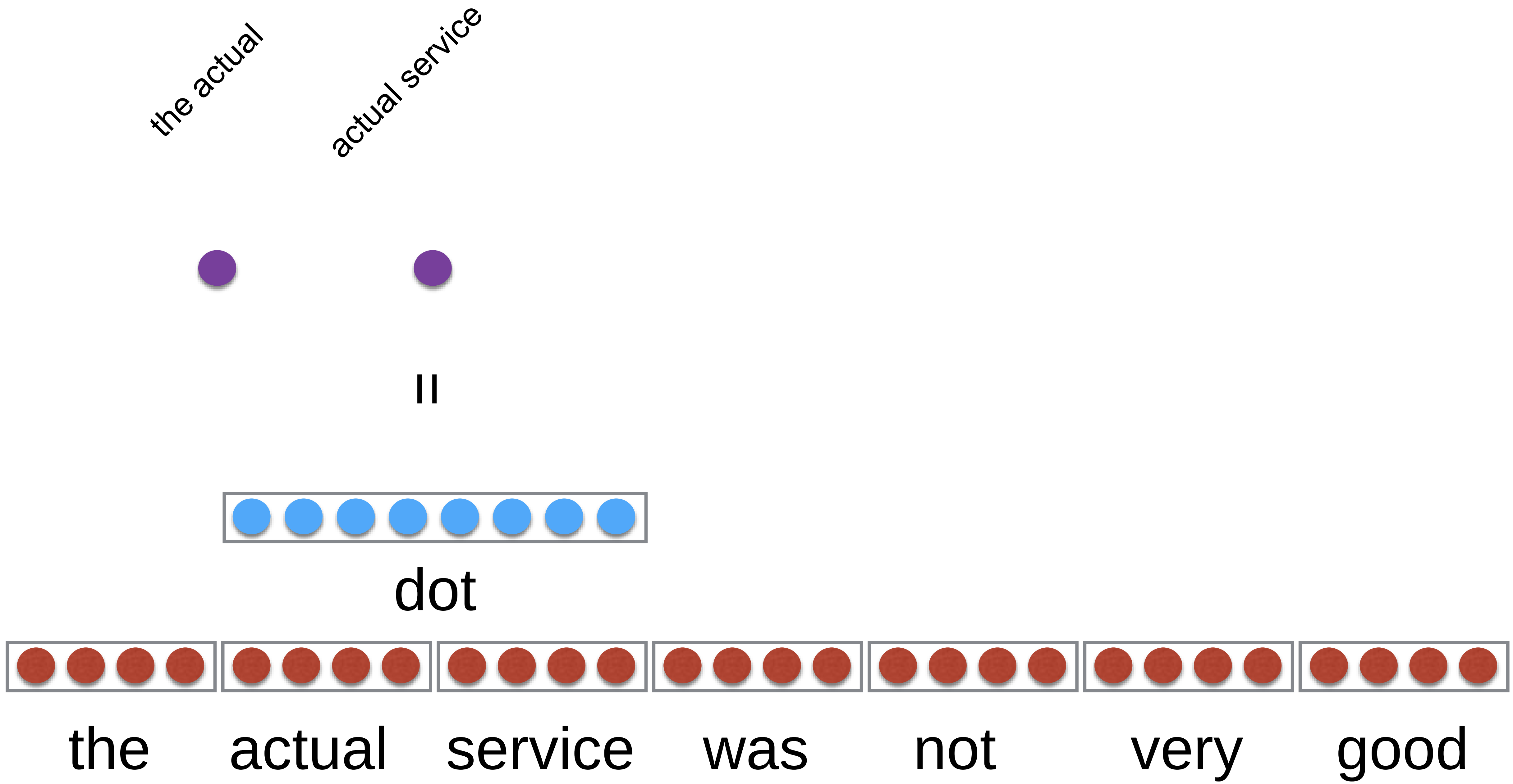

the
actual
service
was
not
very
good


dot
the
actual
service
was
not
very
good

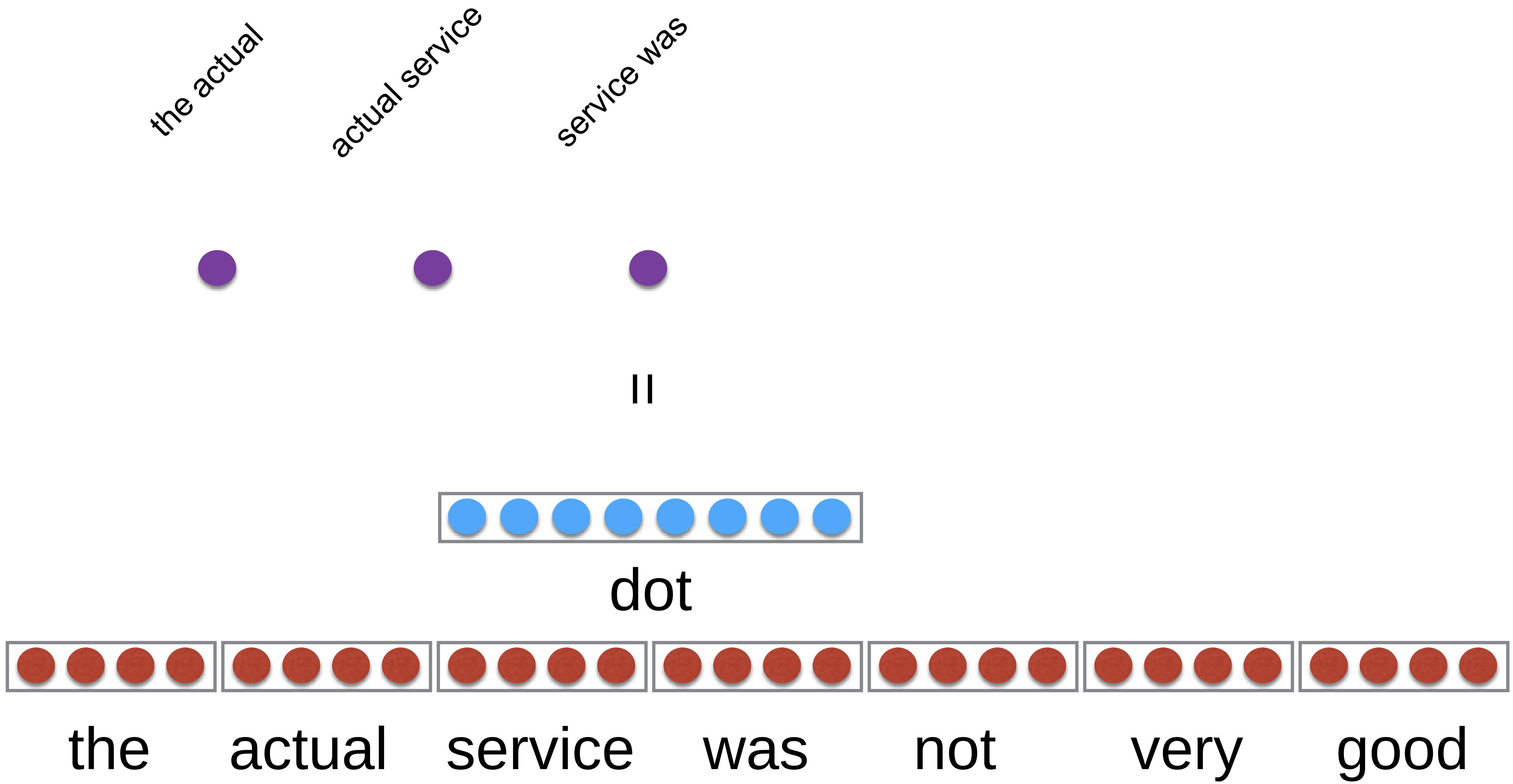

=
dot
the
actual
service
was
not
very
good



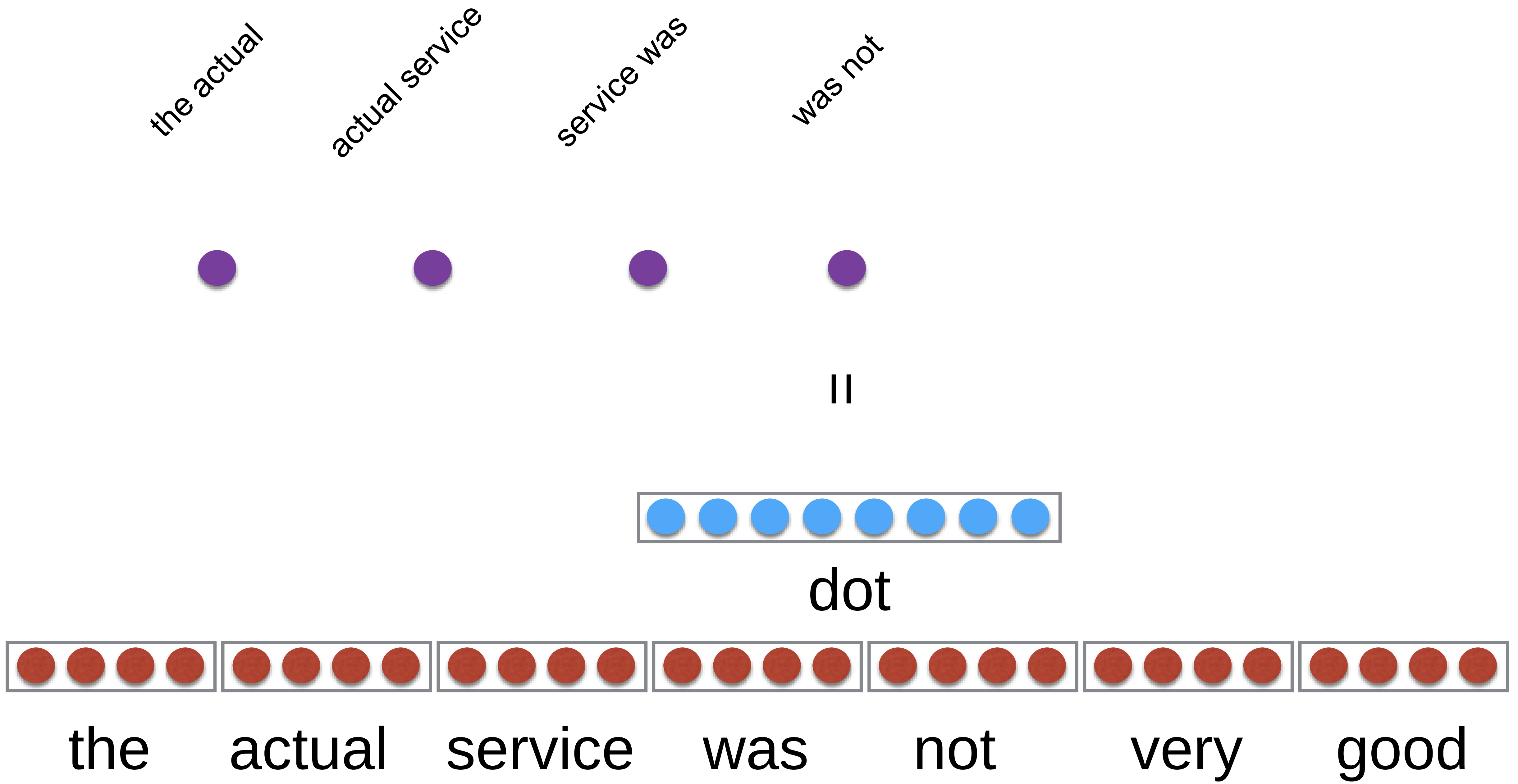
the actual
=
dot
the
actual
service
was
not
very
good

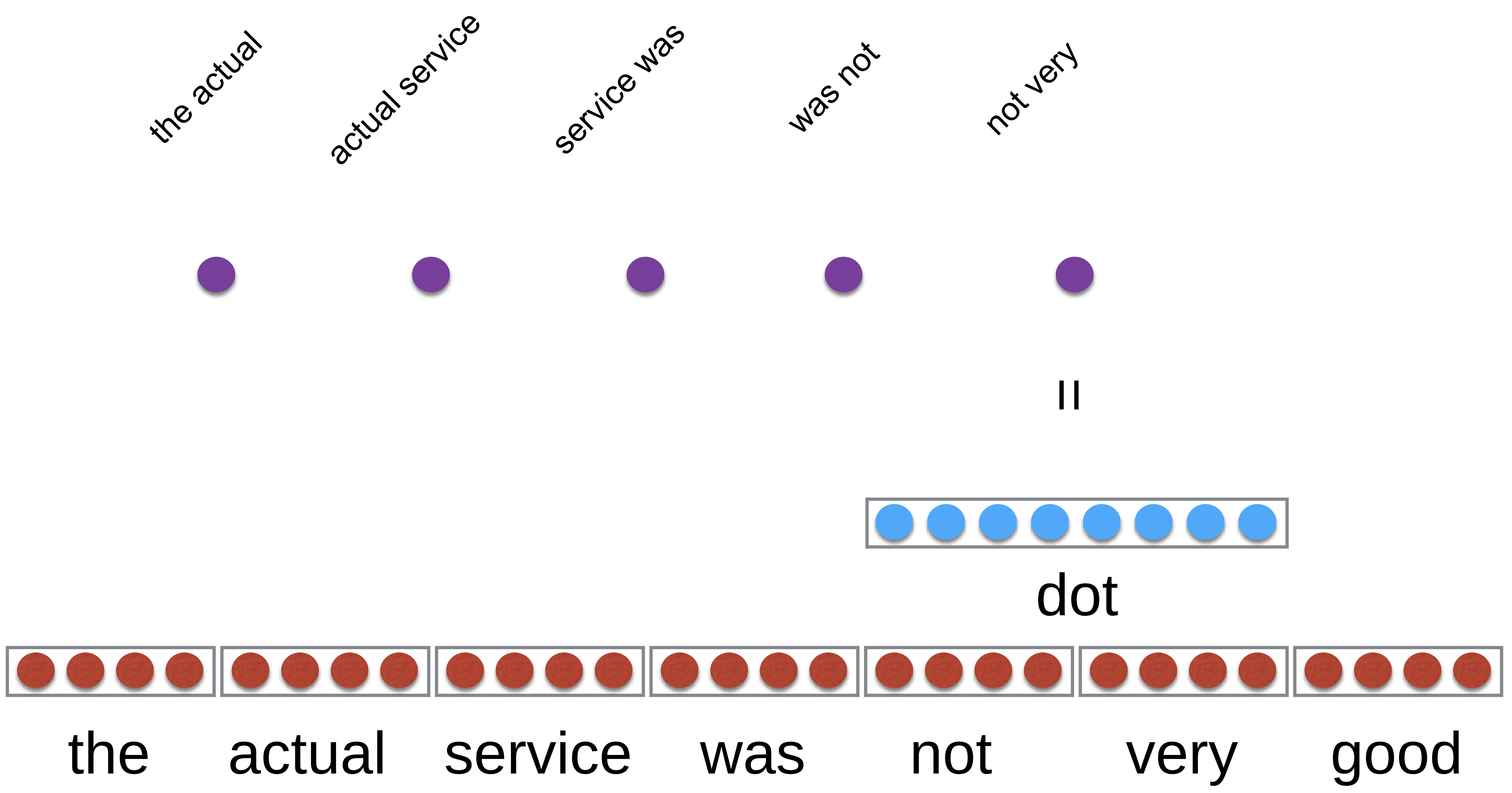


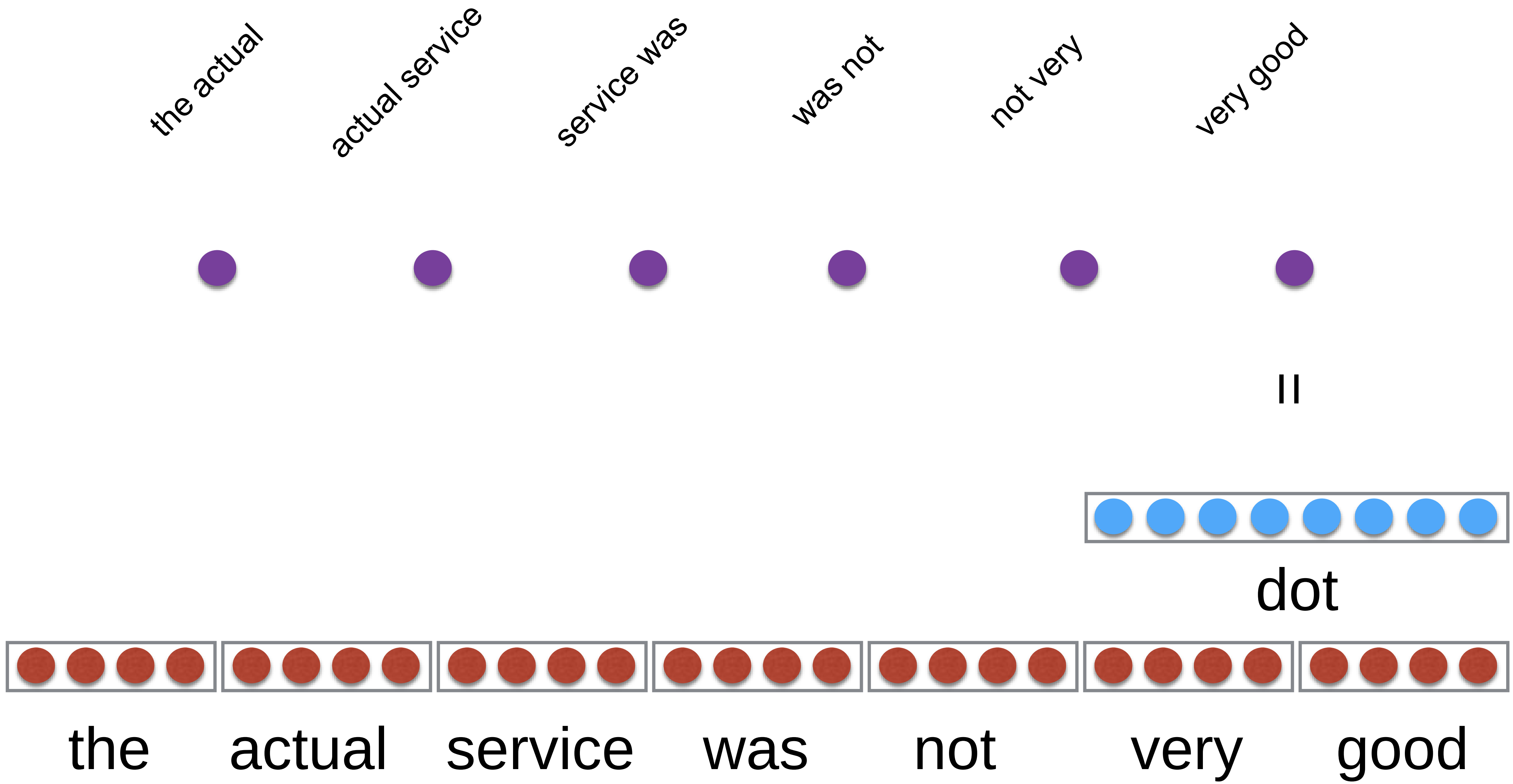
the actual
actual service
=
dot
the
actual
service
was
not
very
good



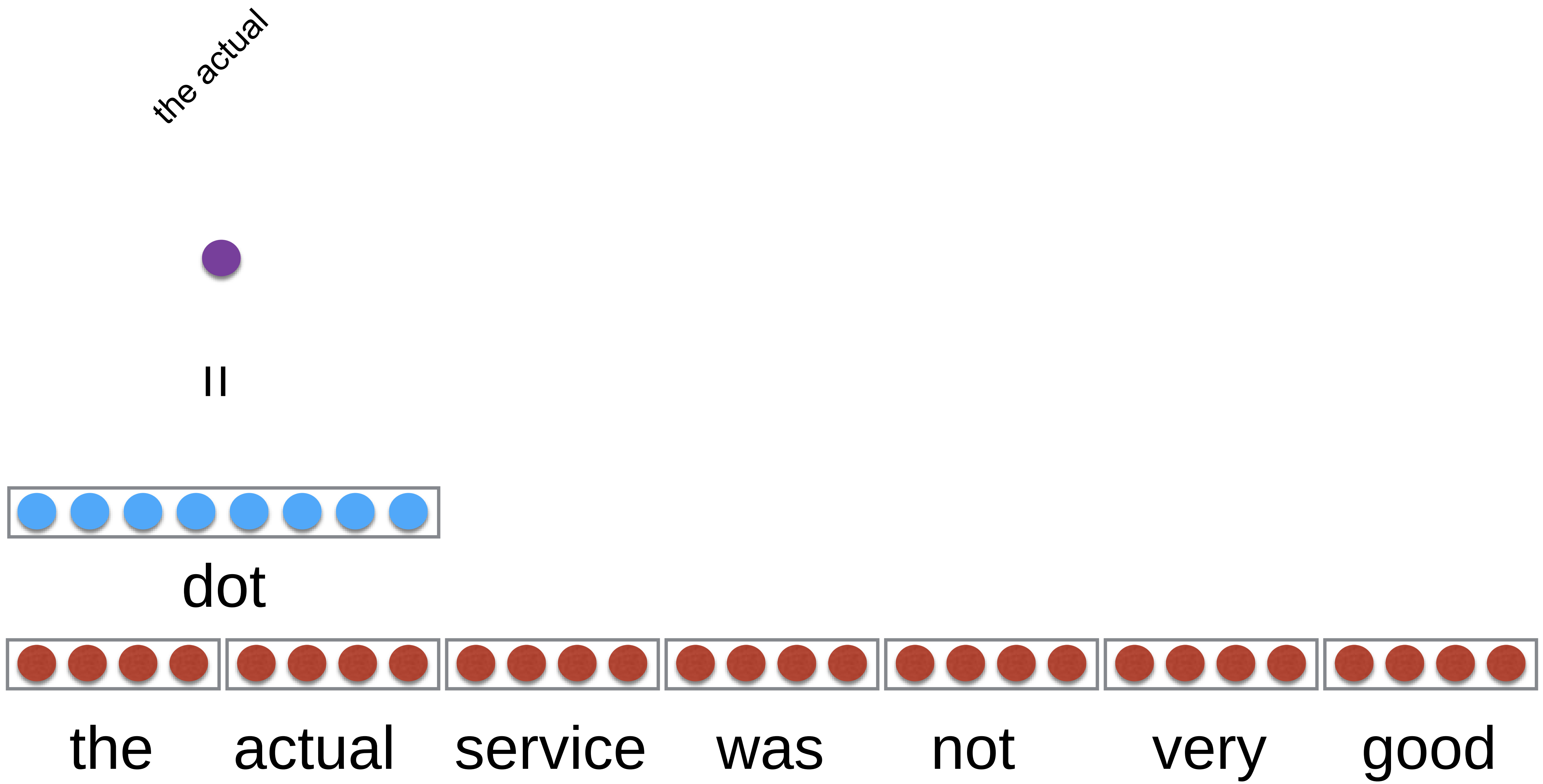
the actual
actual service
service was
=
dot
the
actual
service
was
not
very
good

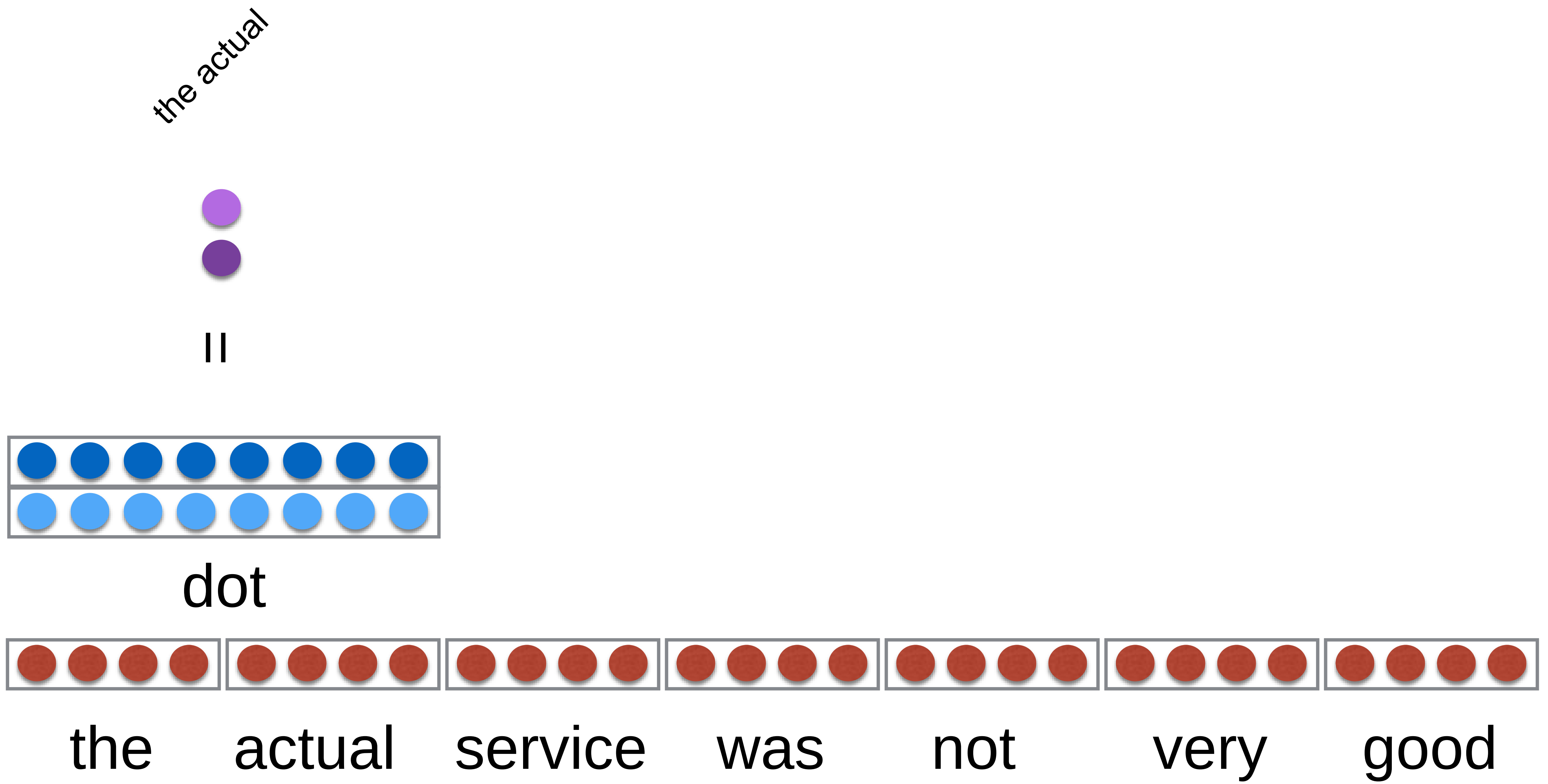

the actual
actual service
service was
was not
=
dot
the
actual
service
was
not
very
good


the actual
actual service
service was
was not
not very
=
dot
the
actual
service
was
not
very
good

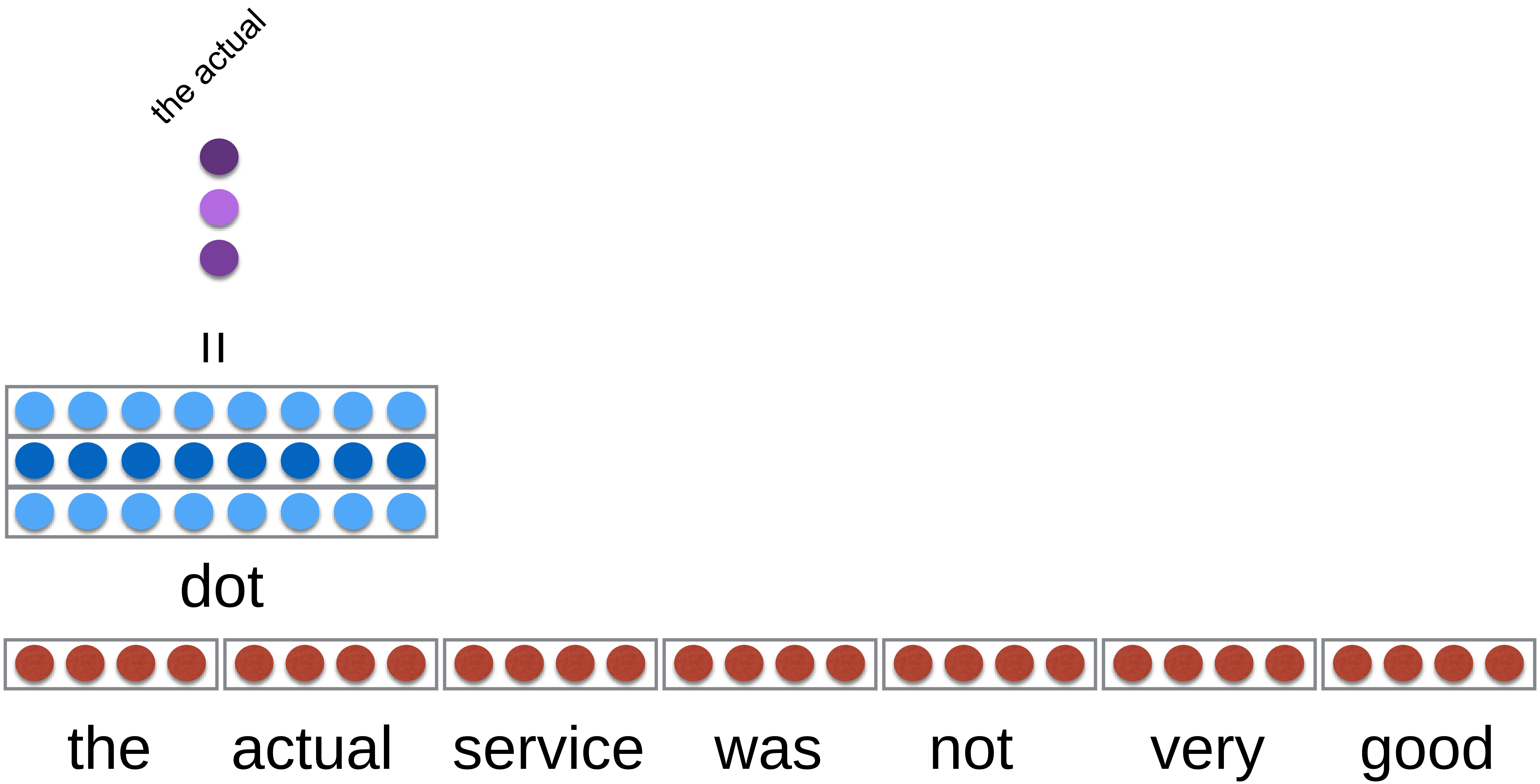


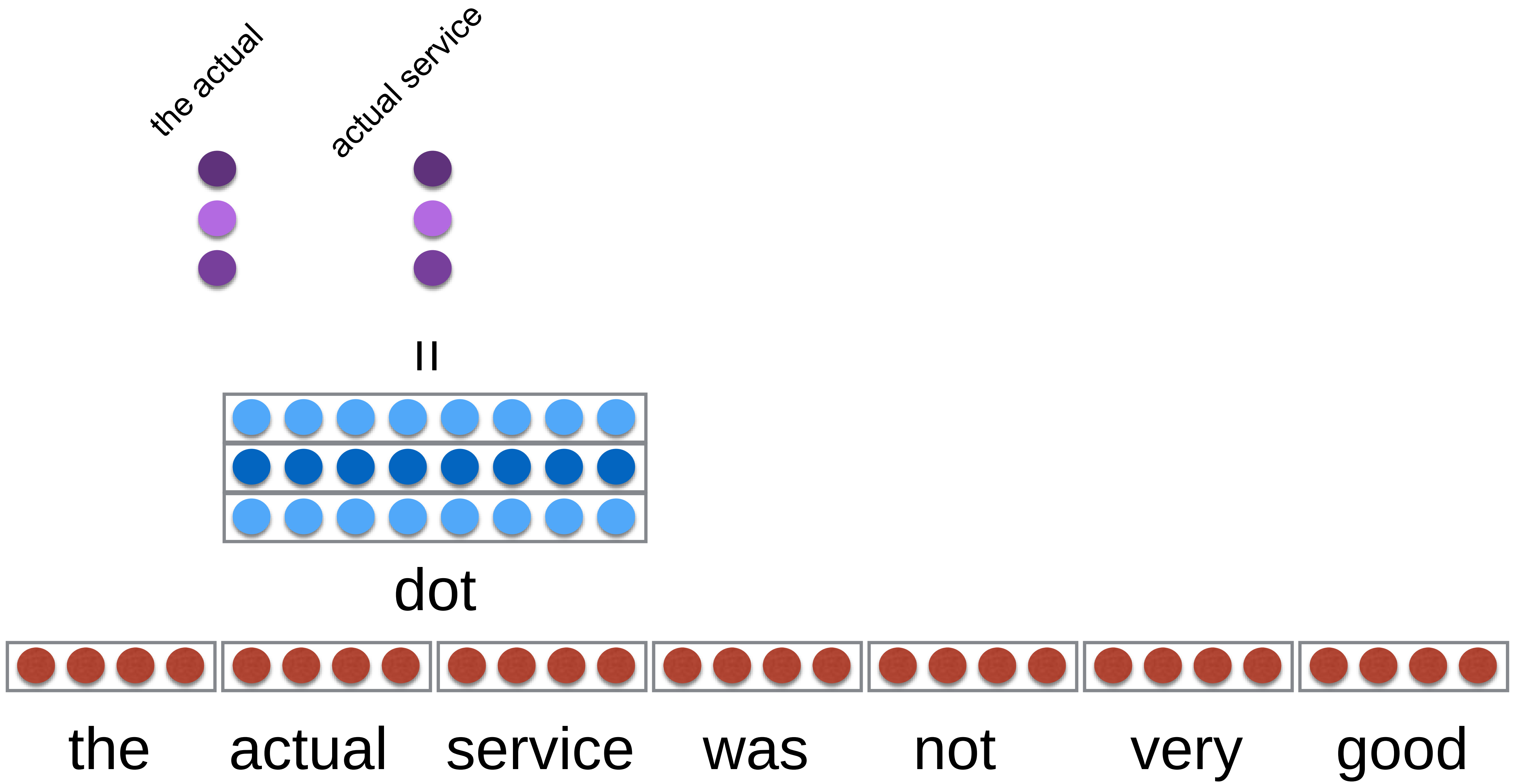
the actual
actual service
service was
was not
not very
very good
=
dot
the
actual
service
was
not
very
good

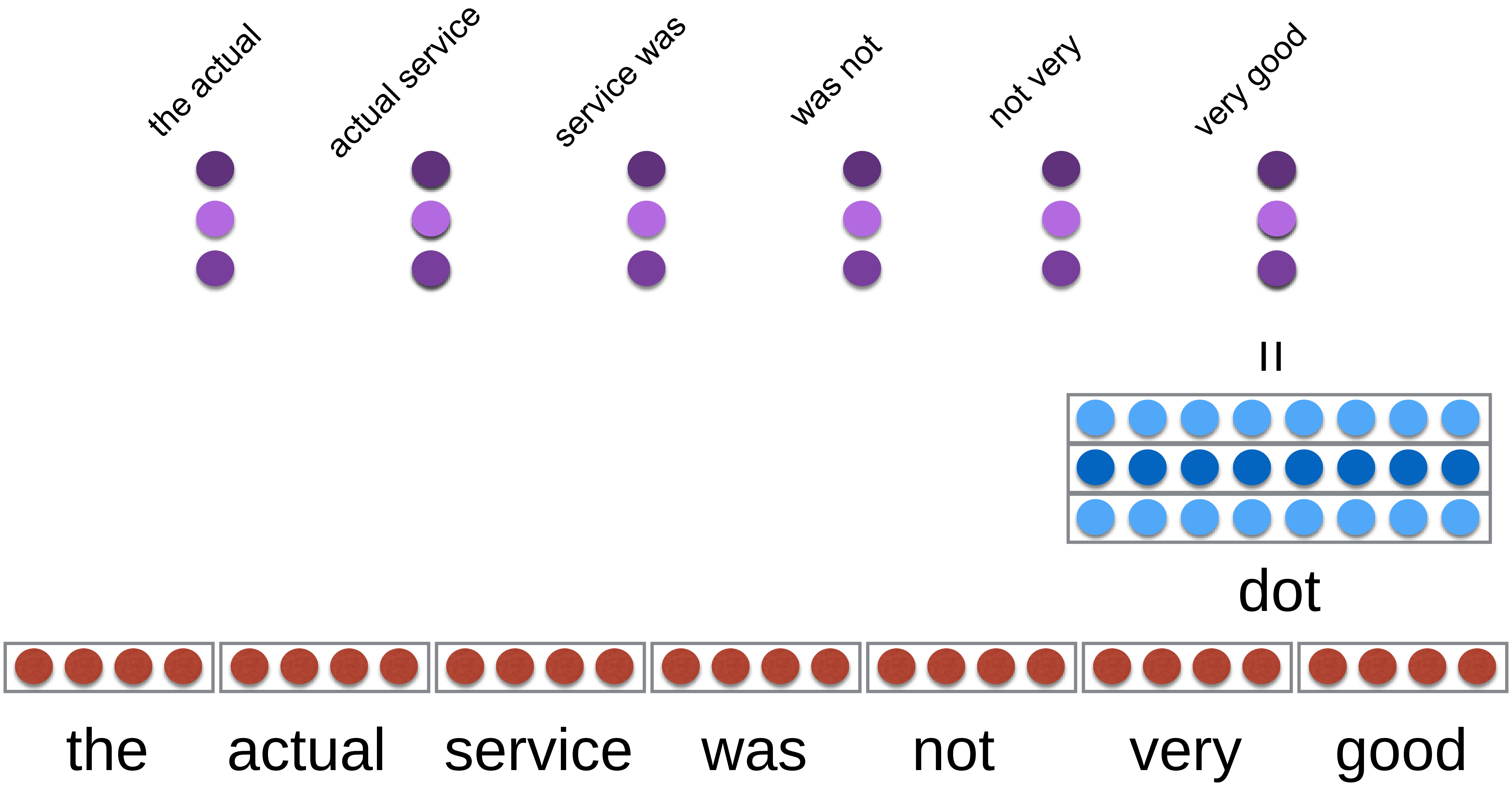

the actual
=
dot
the
actual
service
was
not
very
good



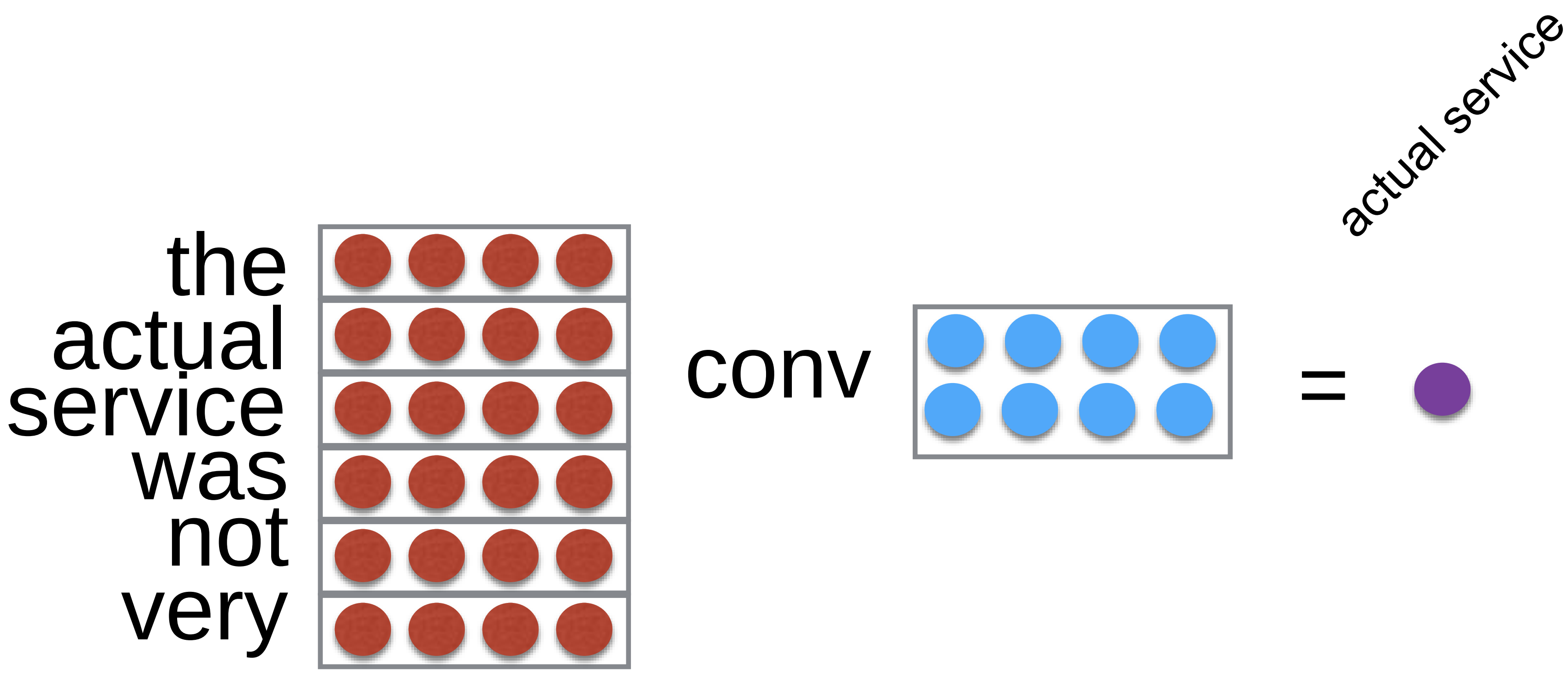
the actual
=
dot
the
actual
service
was
not
very
good


the actual
=
dot
the
actual
service
was
not
very
good

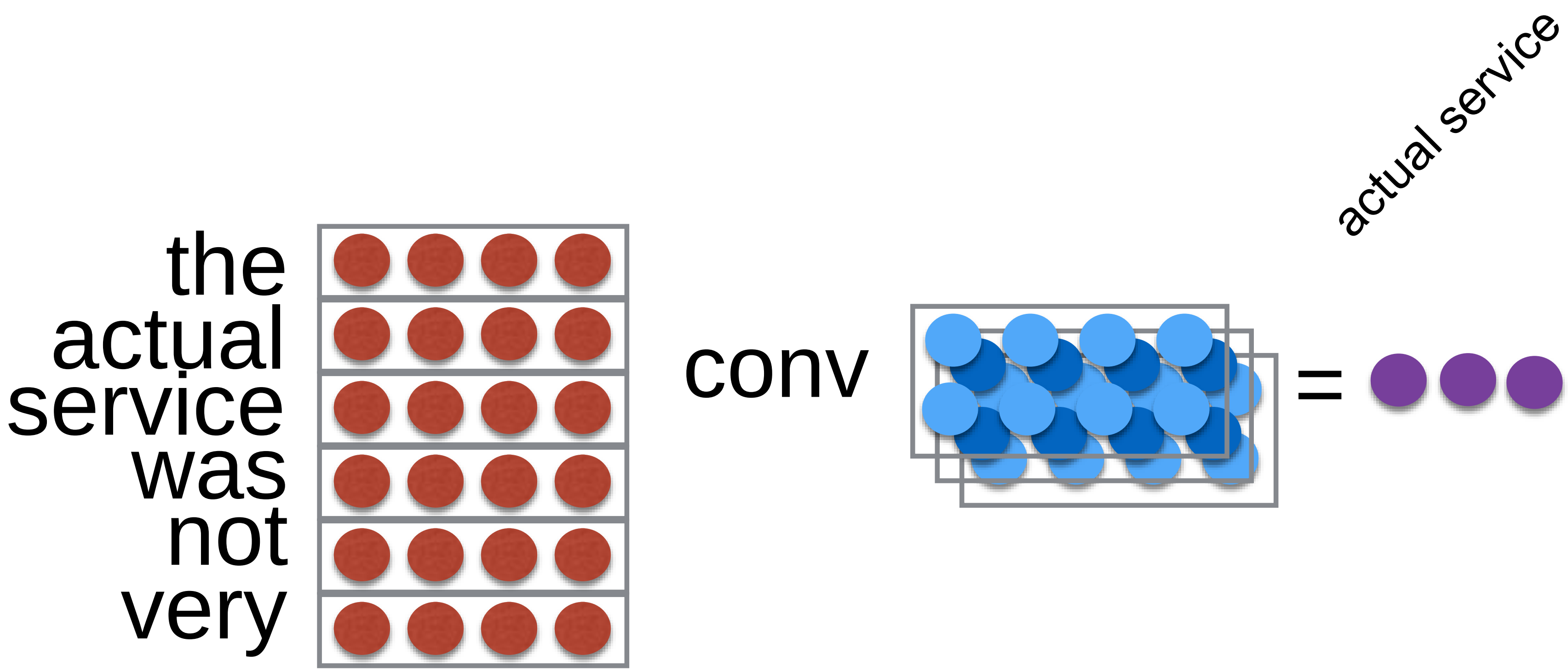

the actual
actual service
=
dot
the
actual
service
was
not
very
good



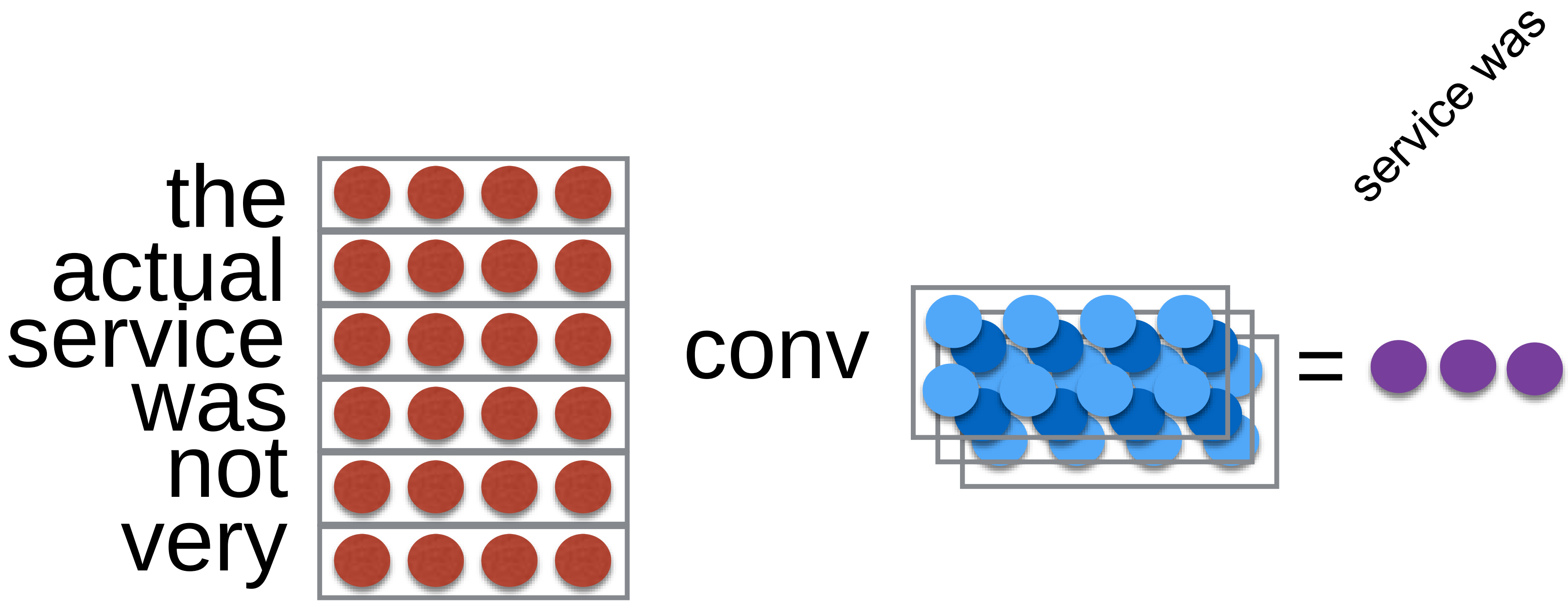
the actual
actual service
service was
was not
not very
very good
=
dot
the
actual
service
was
not
very
good



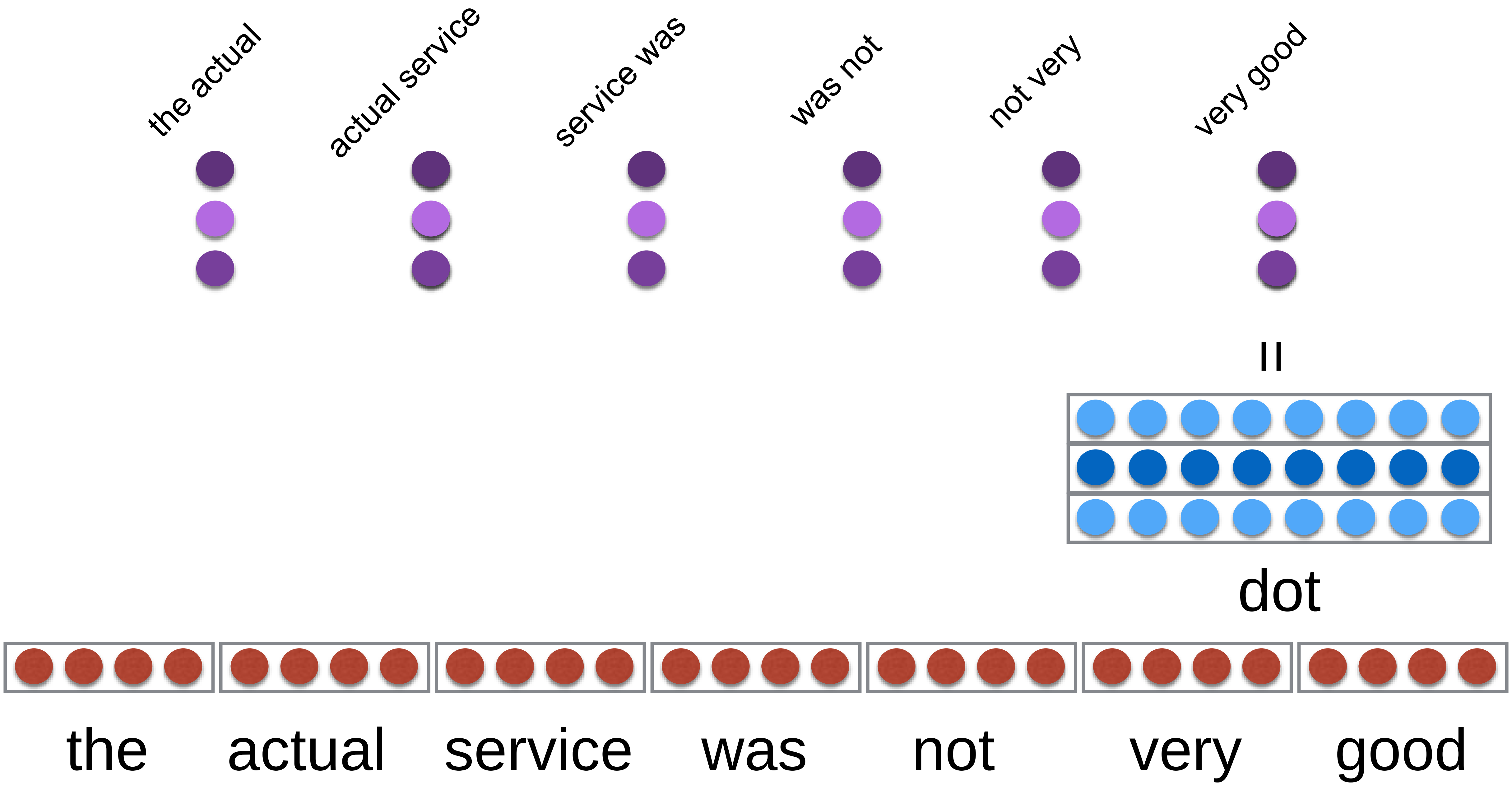
(another way to represent text convolutions)



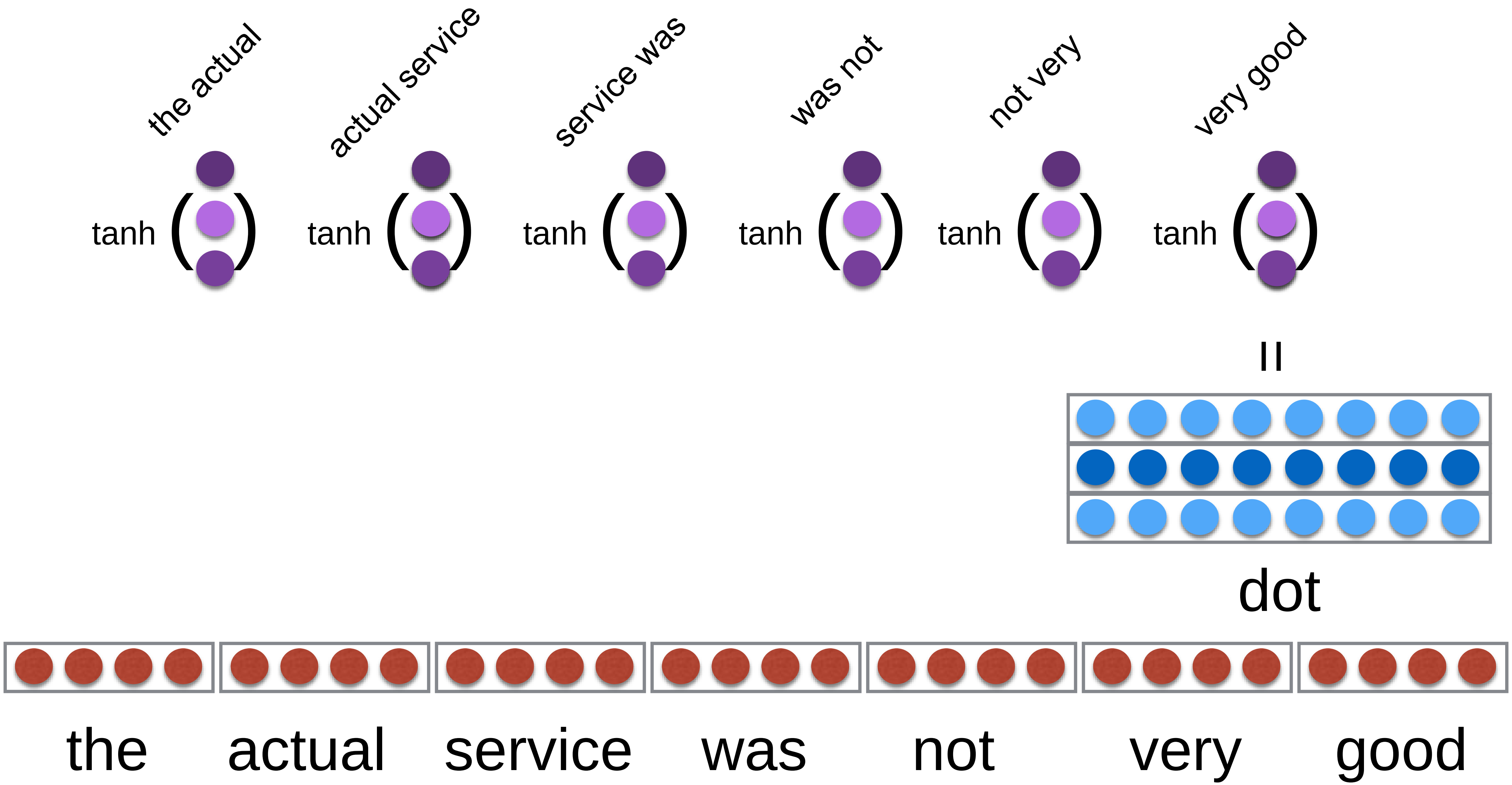
(another way to represent text convolutions)



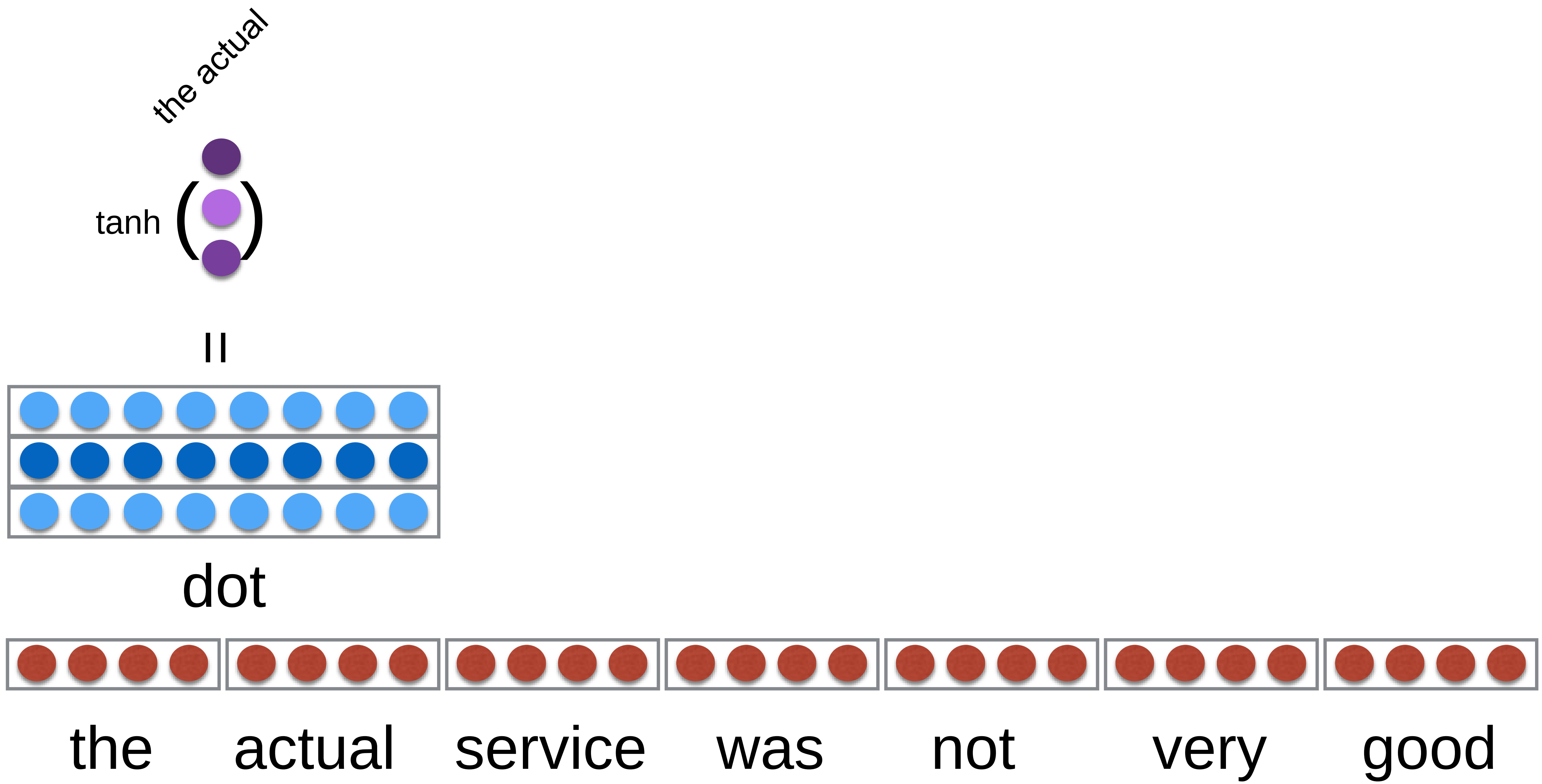
(another way to represent text convolutions)



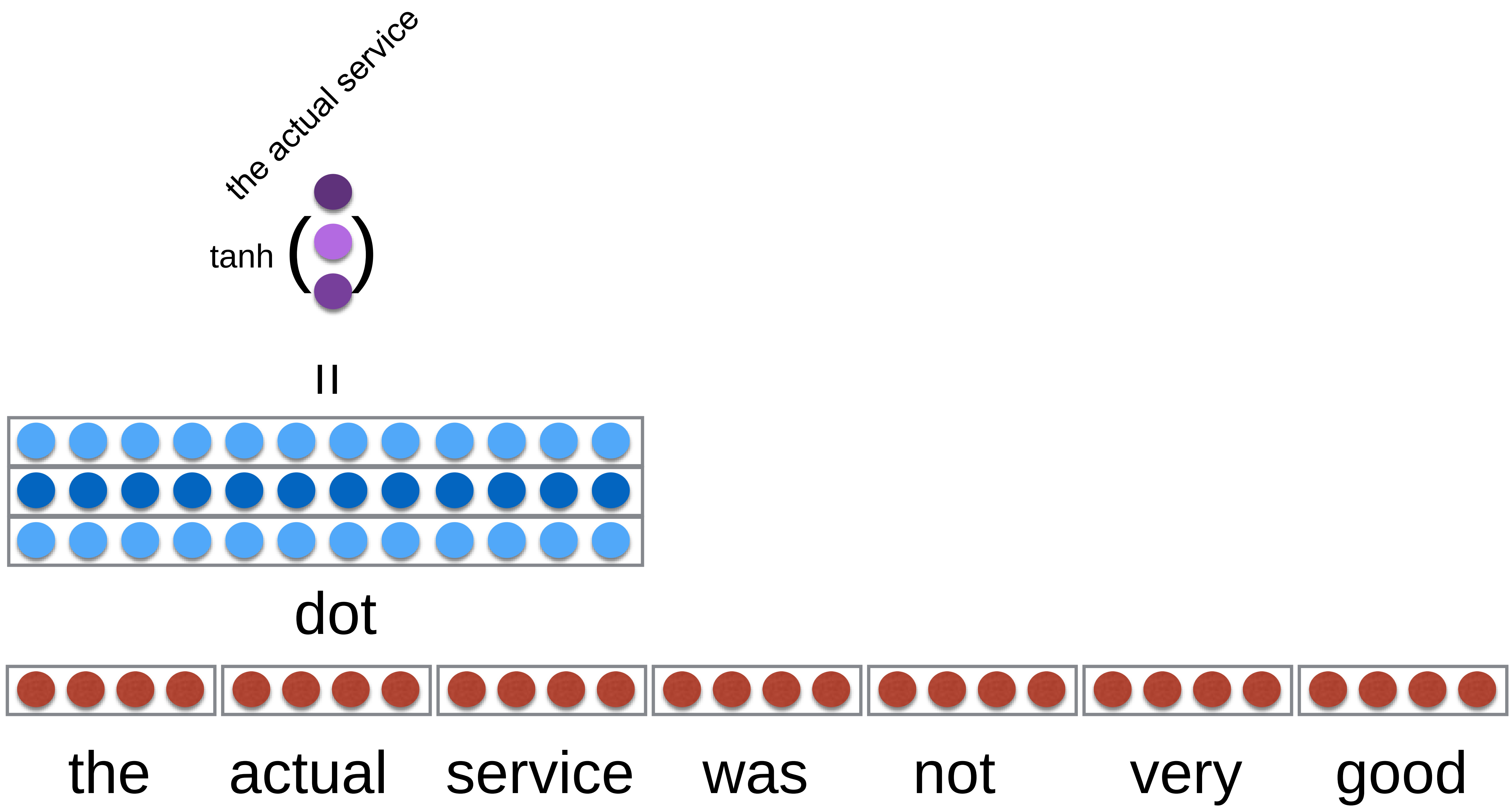
**(we'll focus on the 1-d view here,
but remember they are equivalent)**



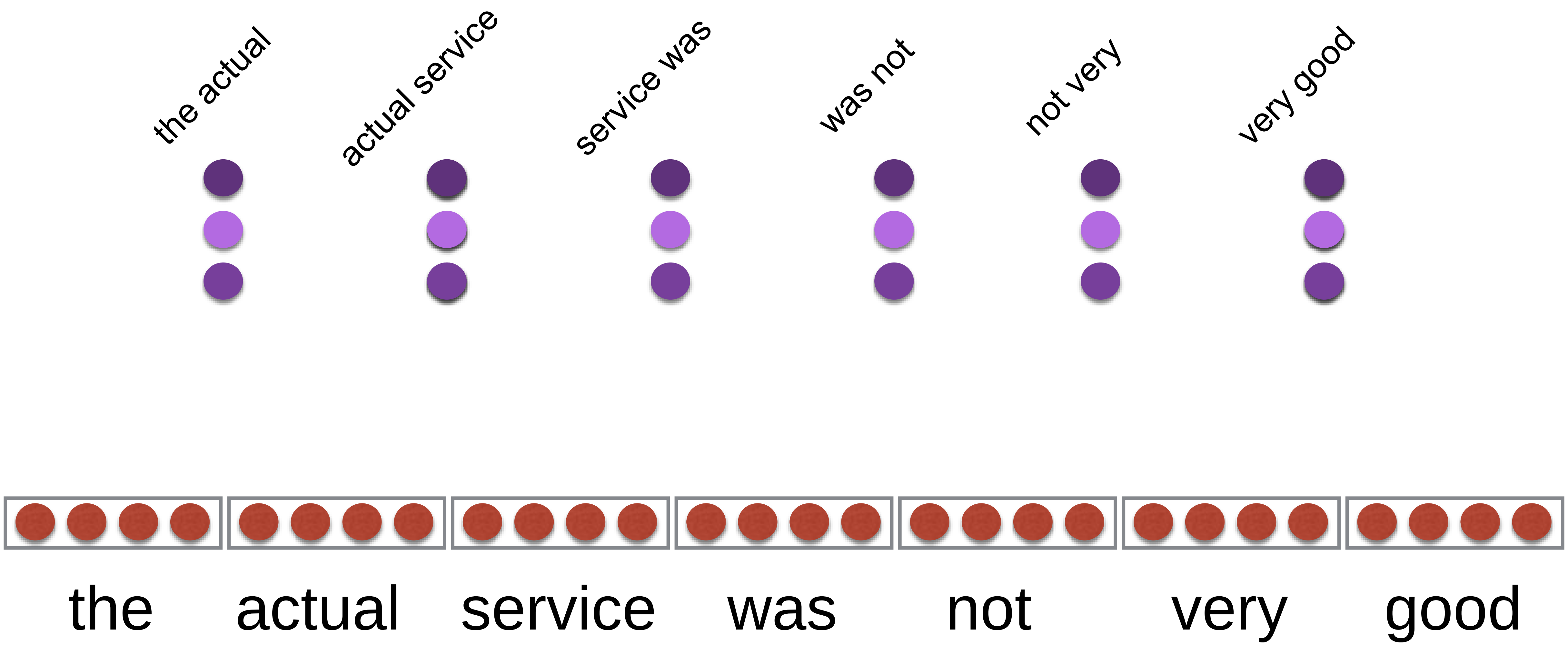
(usually also add non linearity)



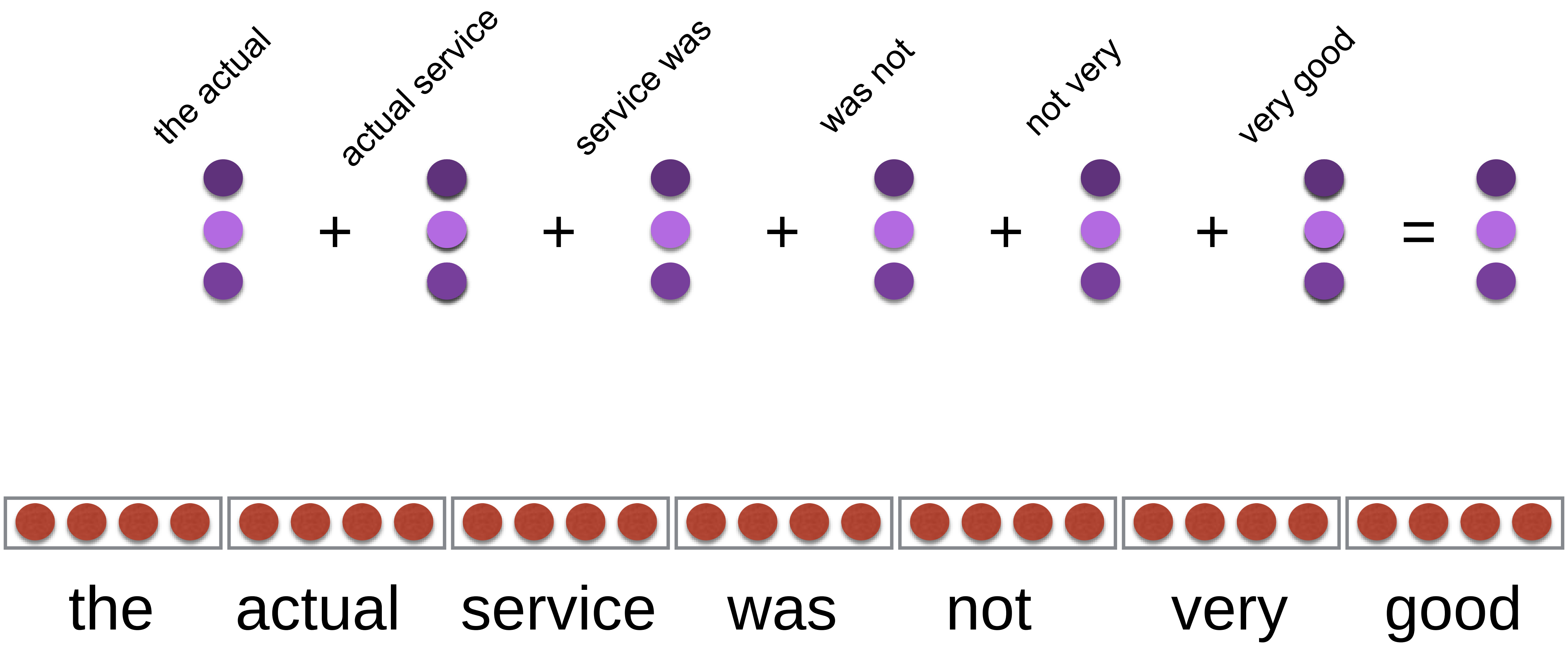
(can have larger filters)



(can have larger filters)



we have the ngram vectors. now what?



can do "pooling"

"Pooling"

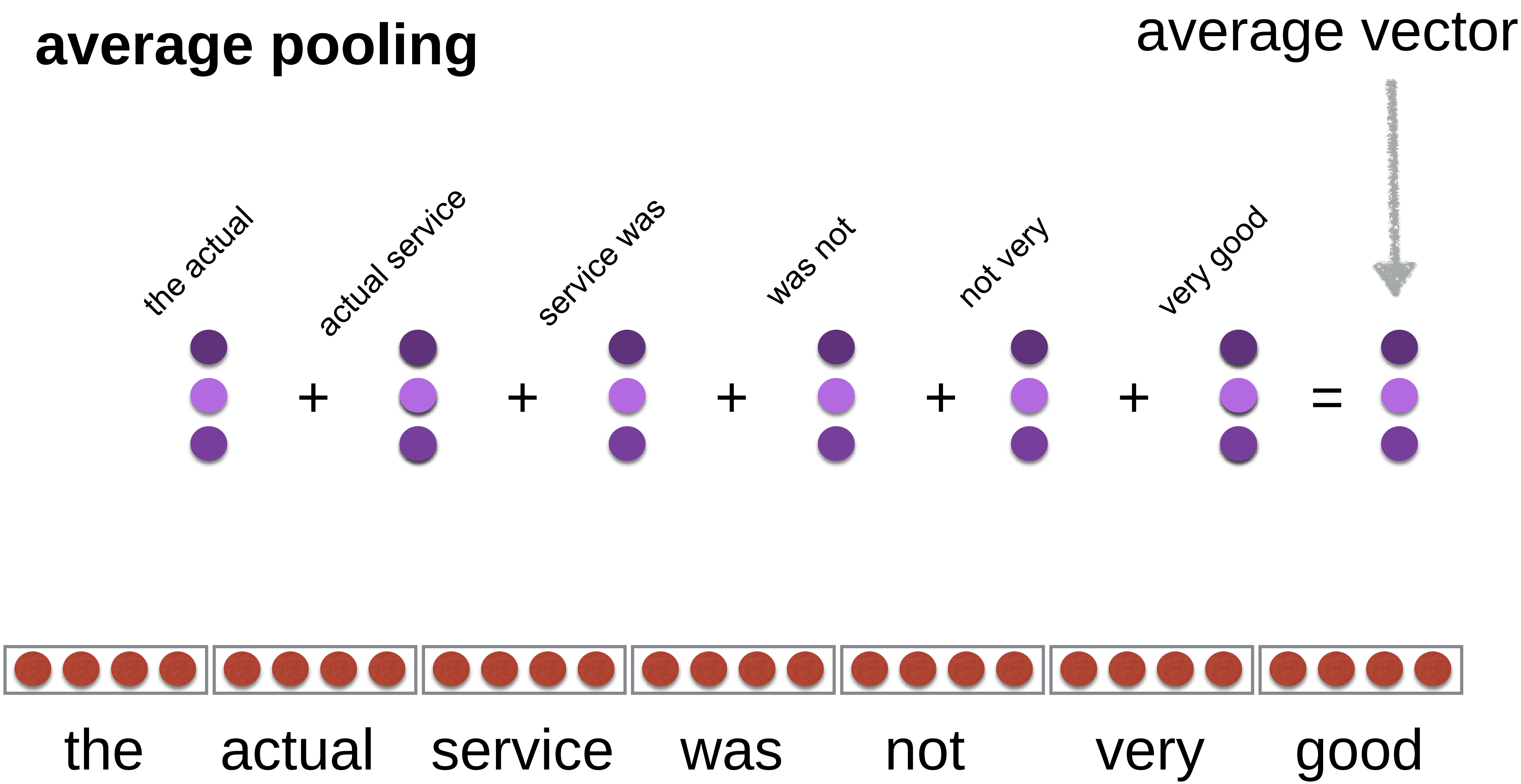
Combine K vectors into a single vector

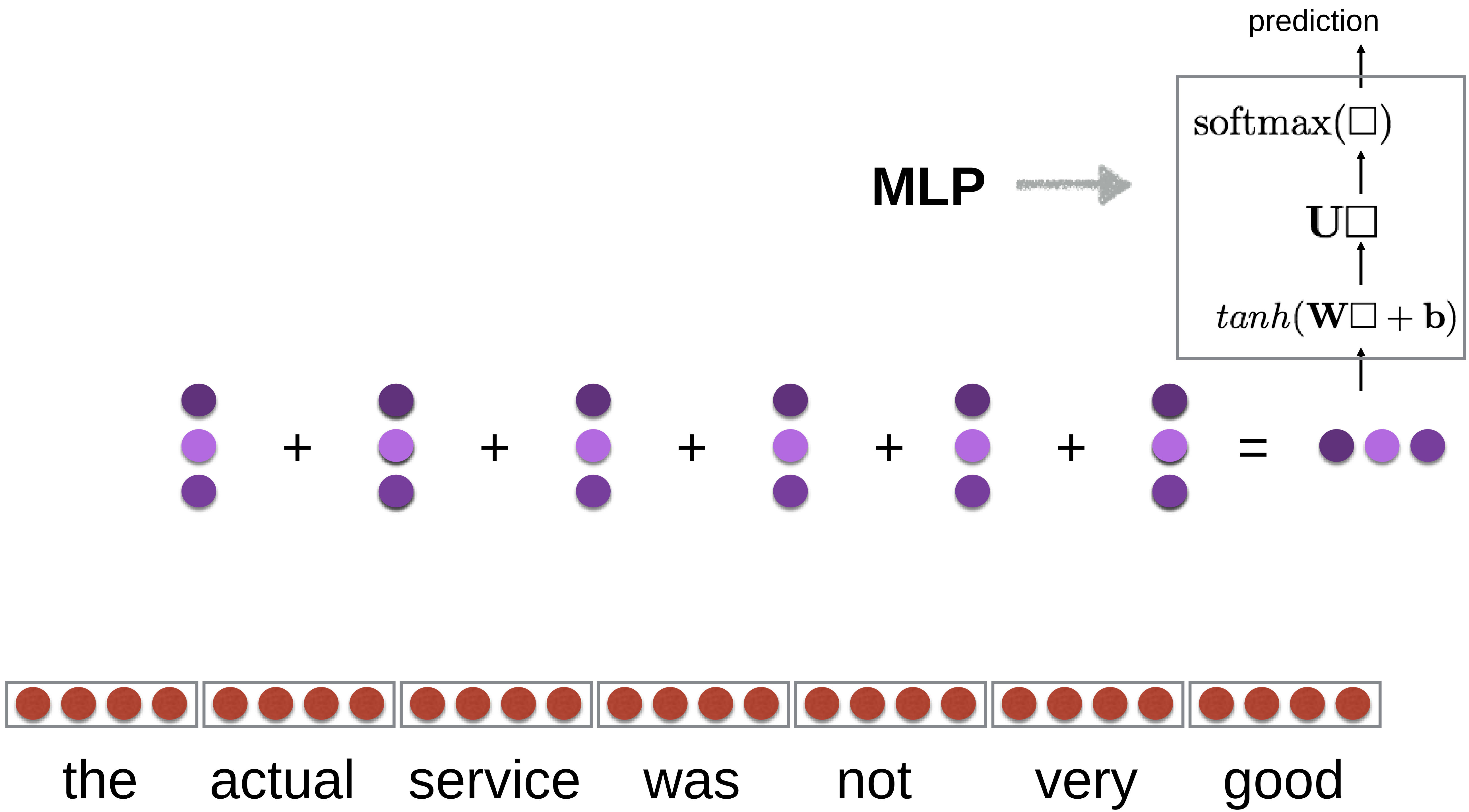
"Pooling"

Combine K vectors into a single vector

This vector is a summary of the K vectors, and can be used for prediction.

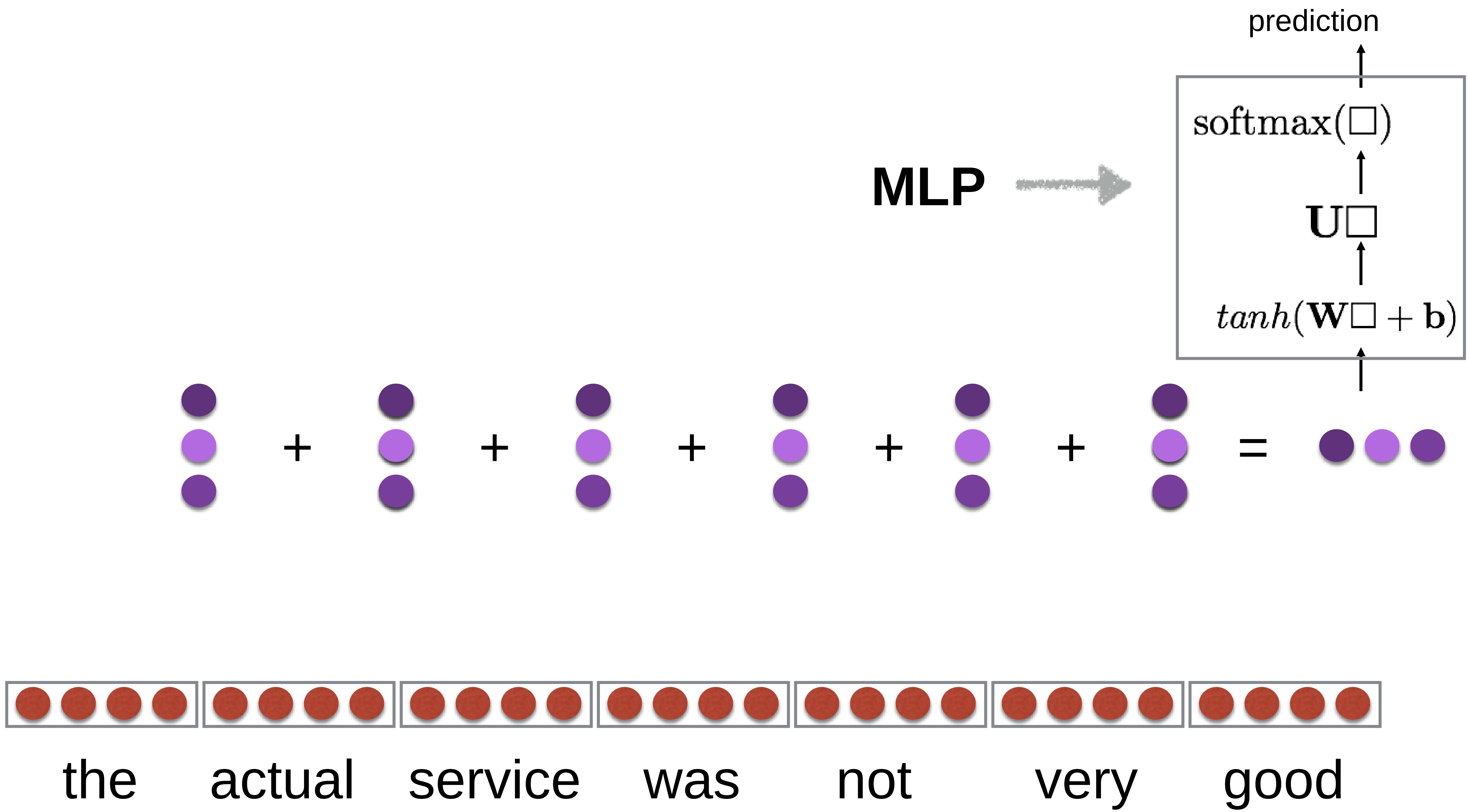
average pooling





train end-to-end for some task

(train the MLP, the filter matrix, and the embeddings together)



train end-to-end for some task

(train the MLP, the filter matrix, and the embeddings together)

the vectors learn to capture what's important

we have the ngram vectors. now what?

Can look at the differences between terms.

microsoft *office* software		car *body* shop	
Free *office* 2000	0.550	car *body* kits	0.698
download *office* excel	0.541	auto *body* repair	0.578
word *office* online	0.502	auto *body* parts	0.555
apartment *office* hours	0.331	wave *body* language	0.301
massachusetts *office* location	0.293	calculate *body* fat	0.220
international *office* berkeley	0.274	forcefield *body* armour	0.165

Table 2: Sample word n-grams and the cosine similarities between the learned word-n-gram feature vectors of "*office*" and "*body*" in different contexts after the CLSM is trained.

A Latent Semantic Model with Convolutional-Pooling Structure for Information Retrieval

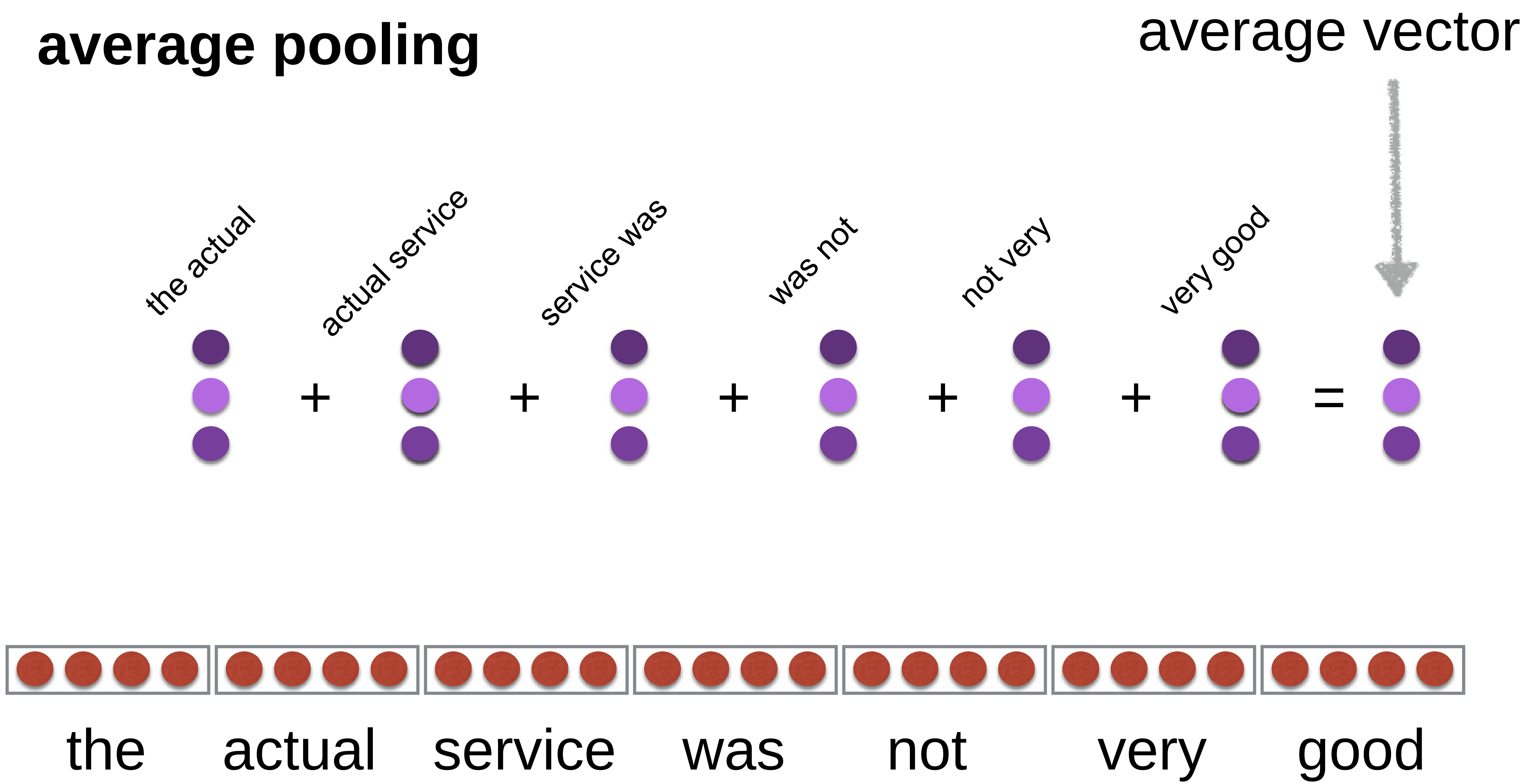
Yelong Shen
Microsoft Research
Redmond, WA, USA
yeshen@microsoft.com

Xiaodong He
Microsoft Research
Redmond, WA, USA
xiaohe@microsoft.com

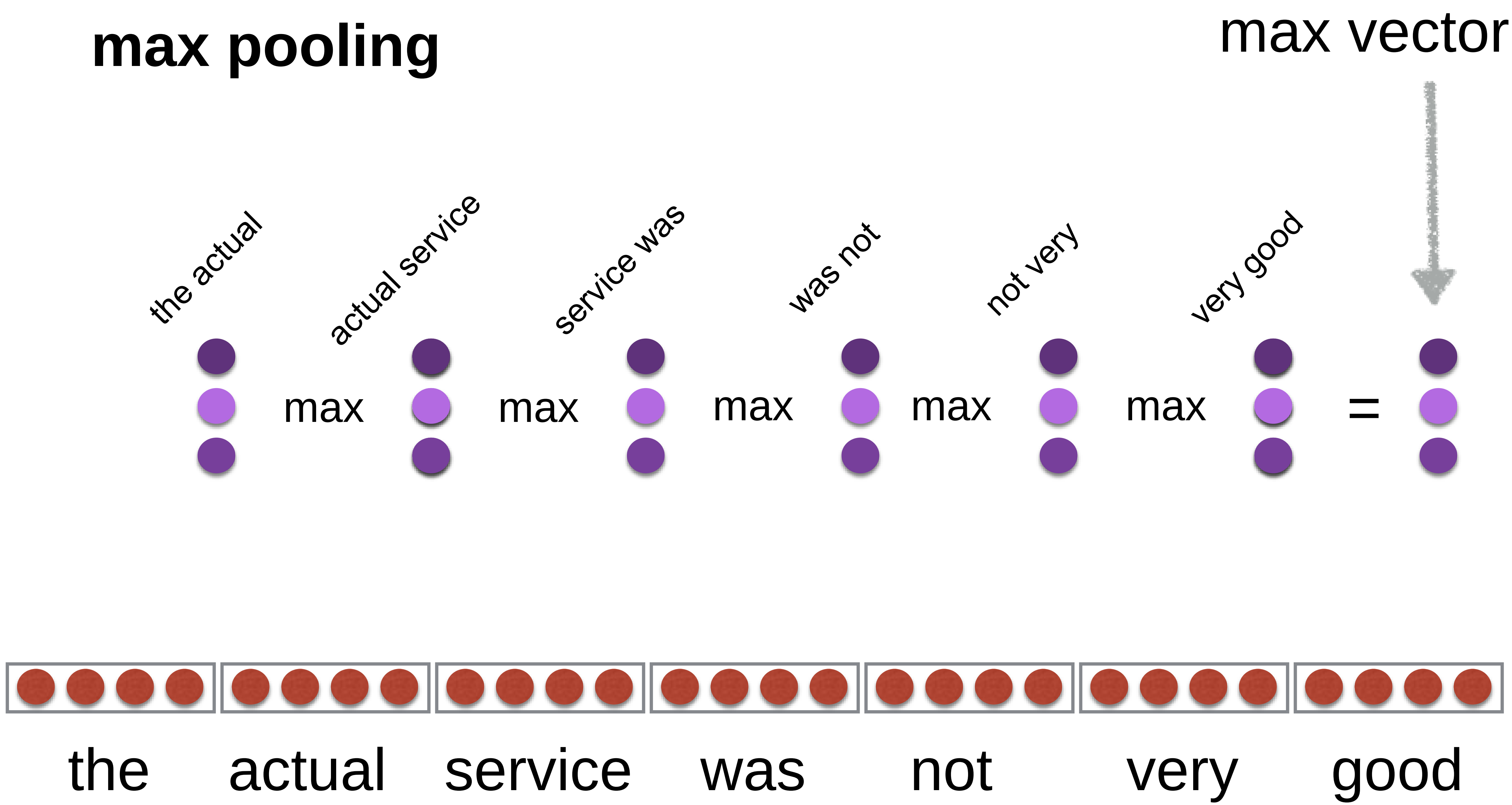
Jianfeng Gao
Microsoft Research
Redmond, WA, USA
jfgao@microsoft.com

Li Deng
Microsoft Research
Redmond, WA, USA
deng@microsoft.com

Grégoire Mesnil
University of Montréal
Montréal, Canada
gregoire.mesnil@umontreal.ca

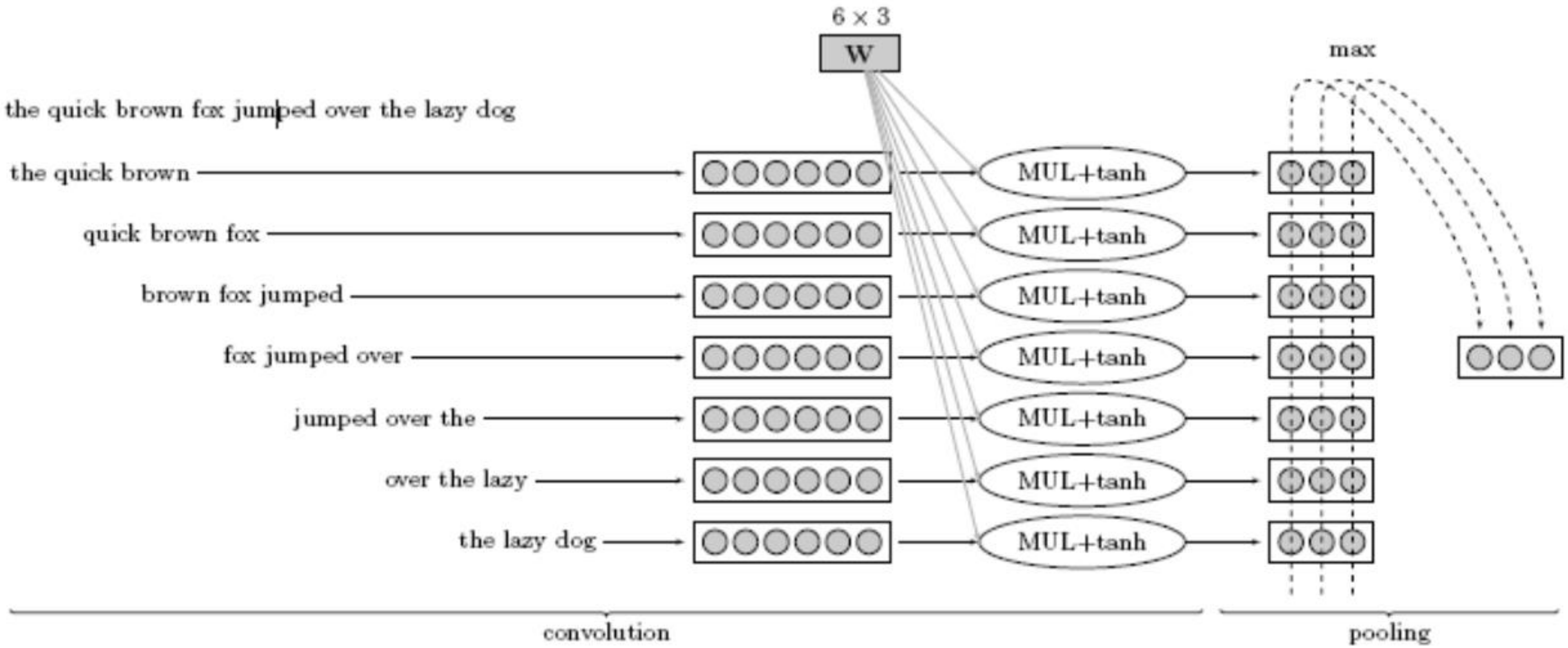

average pooling
average vector
the actual
actual service
service was
was not
not very
very good
+
+
+
+
+
=
the
actual
service
was
not
very
good

max pooling

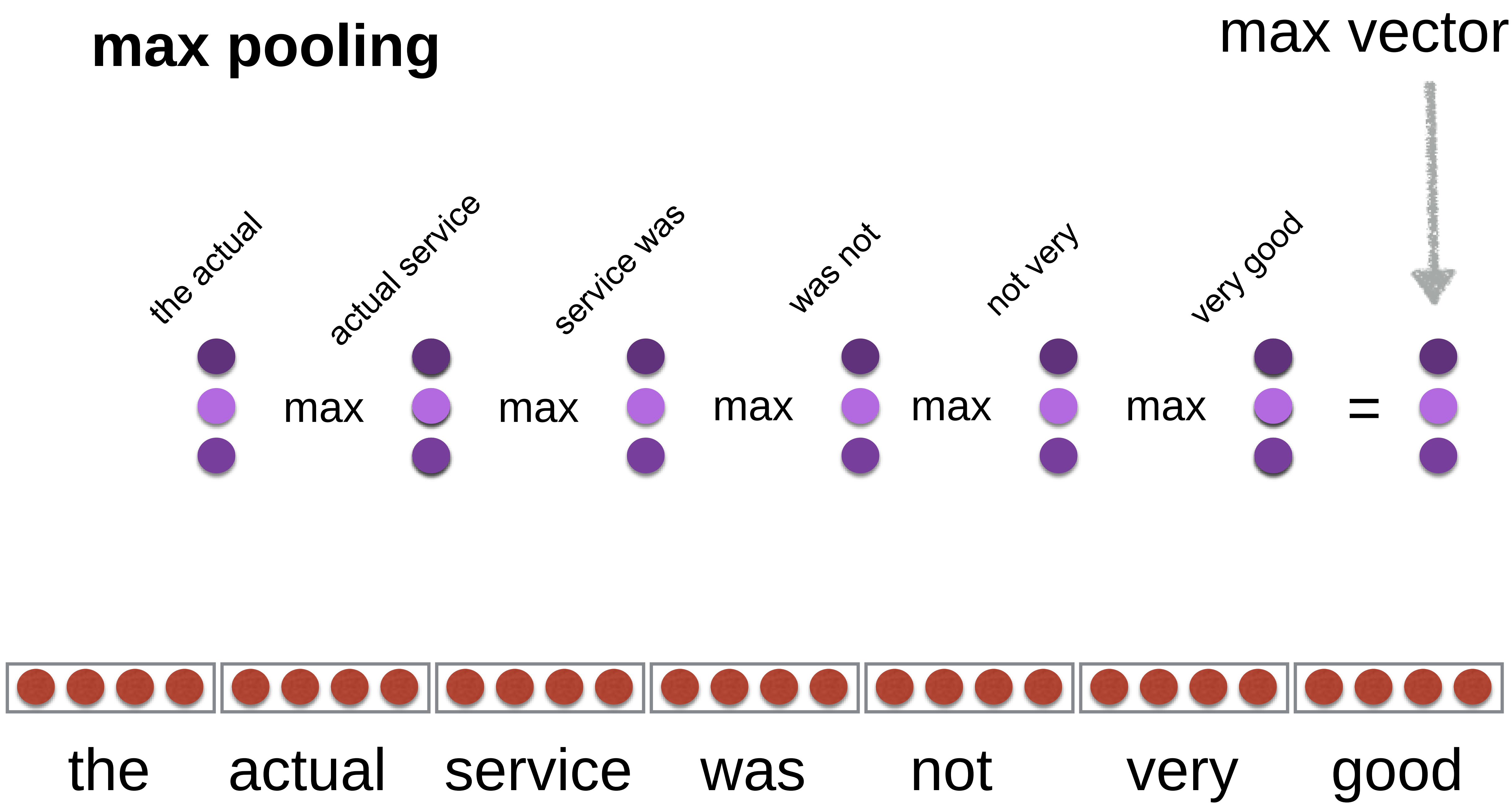


(max in each coordinate)

Another way to draw this:



max pooling



max vs average – discuss

Zhang, Y., & Wallace, B. (2015). A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification

one benefit of max-pooling: it's "**interpretable**"

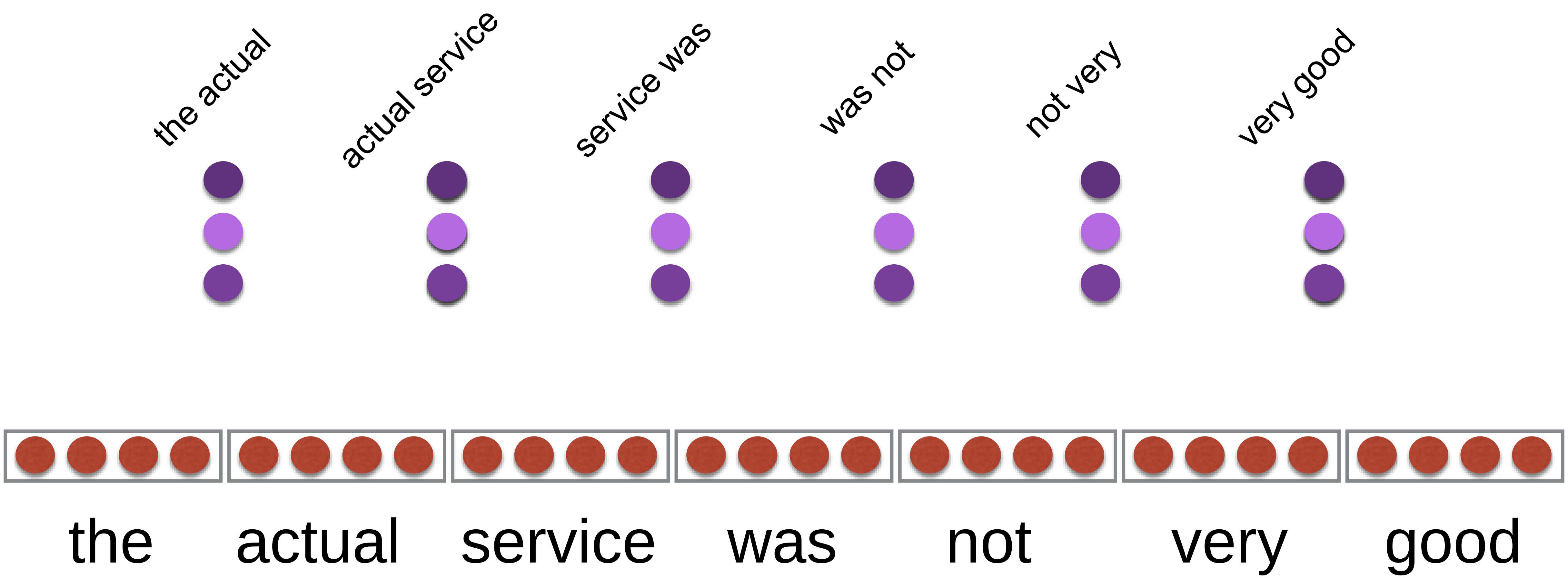
we can know where each element
in the summary vector came from

Examples of resulting "summaries"

microsoft **office excel** could allow remote **code execution**
welcome to the **apartment office**
online **body fat** percentage **calculator**
online **auto body** repair **estimates**
vitamin a the **health** benefits given by **carrots**
calcium supplements and **vitamin d** discussion stop **sarcoidosis**

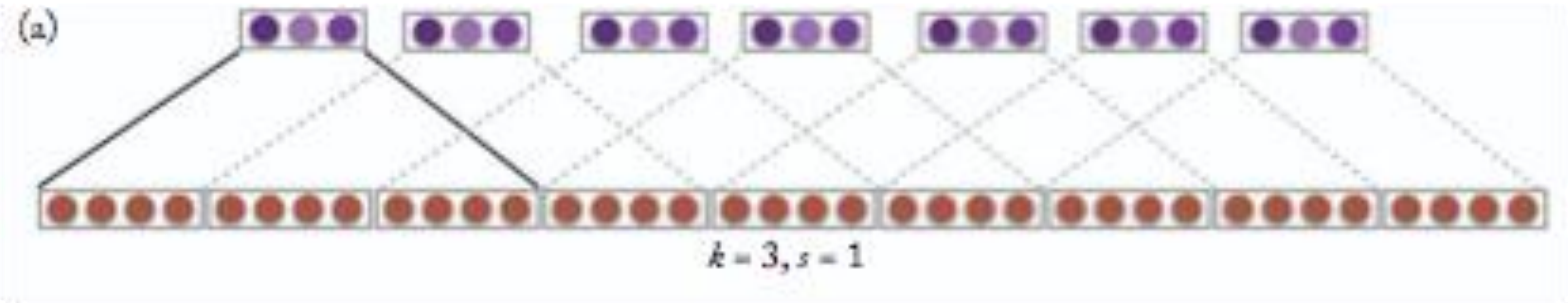
Table 3: Sample document titles. We examine the five most active neurons at the max-pooling layer and highlight the words in **bold** who win at these five neurons in the *max* operation. Note that, the feature of a word is extracted from that word together with the context words around it, but only the center word is highlighted in bold.

Strides



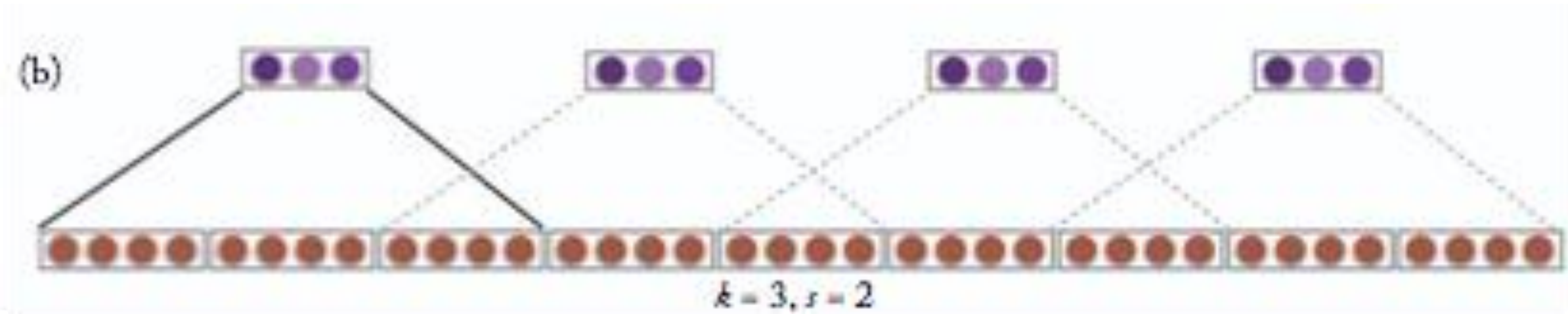
strides = how much you move

Strides



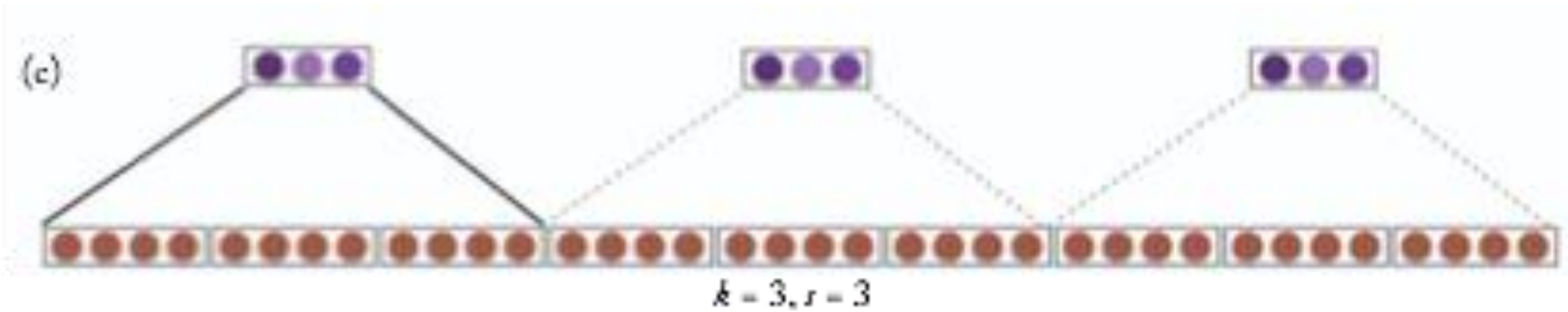
k = 3, stride = 1

Strides



k = 3, stride = 2

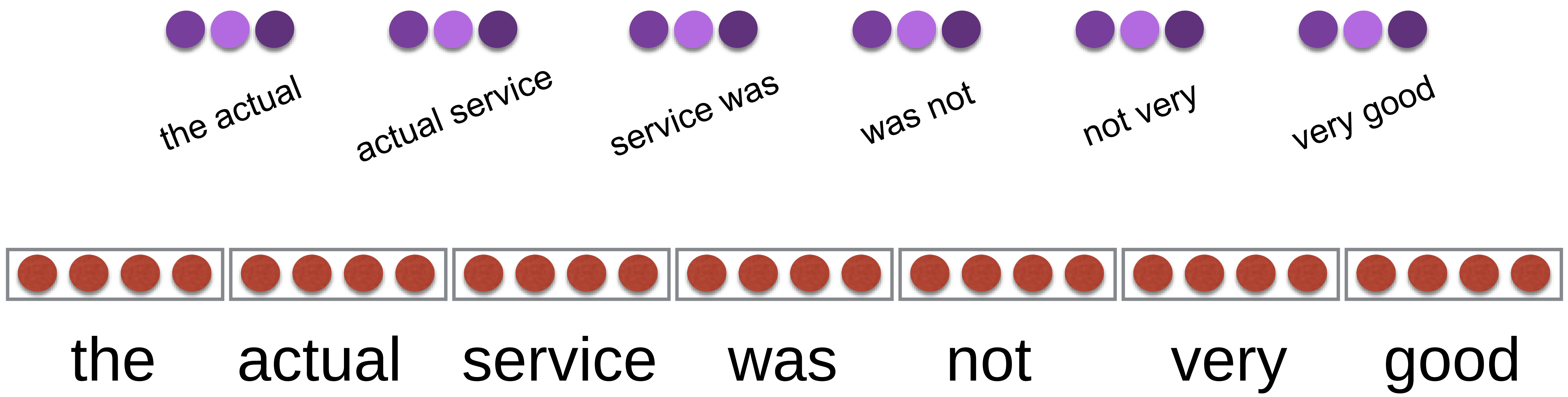
Strides



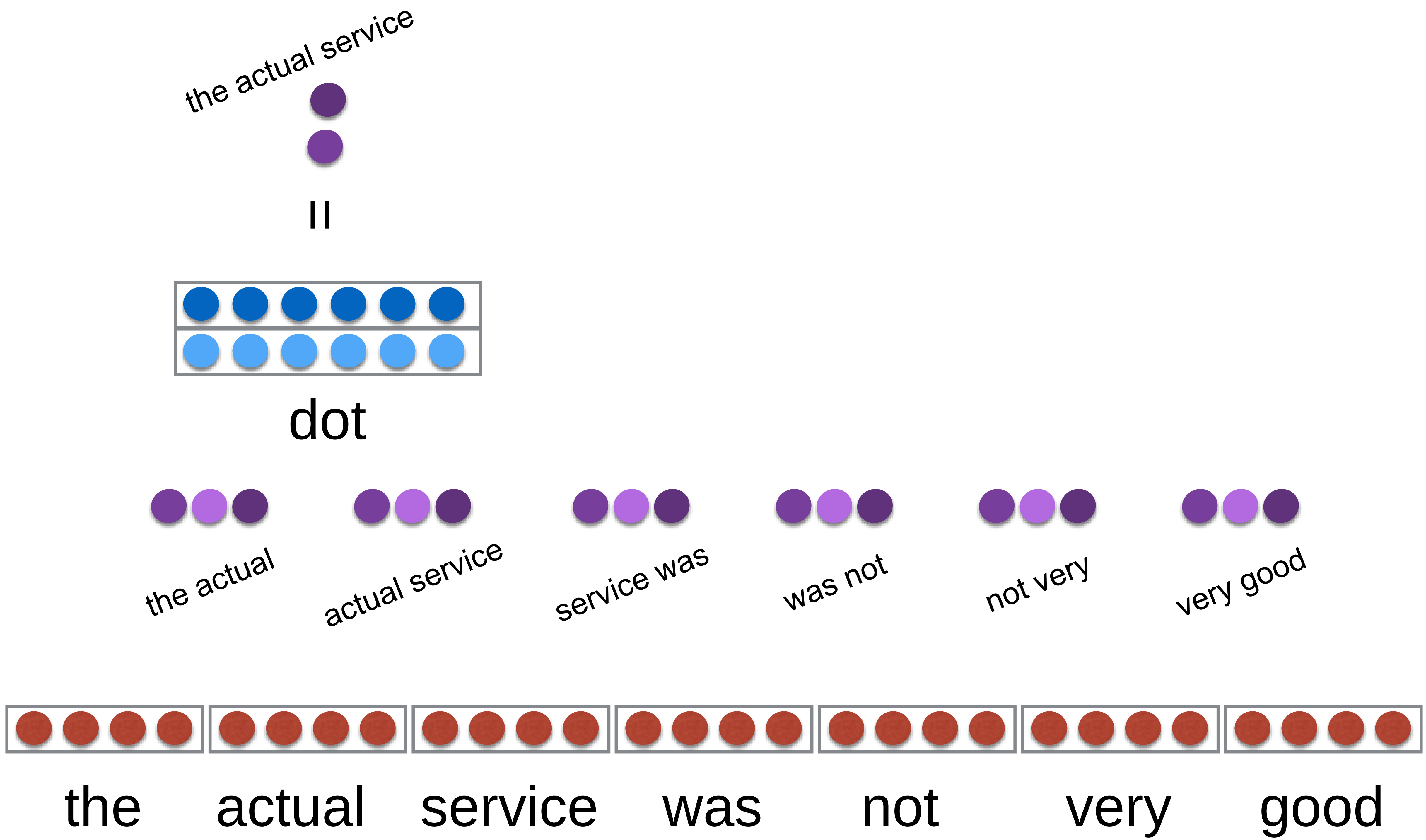
k = 3, stride = 3

Hierarchy

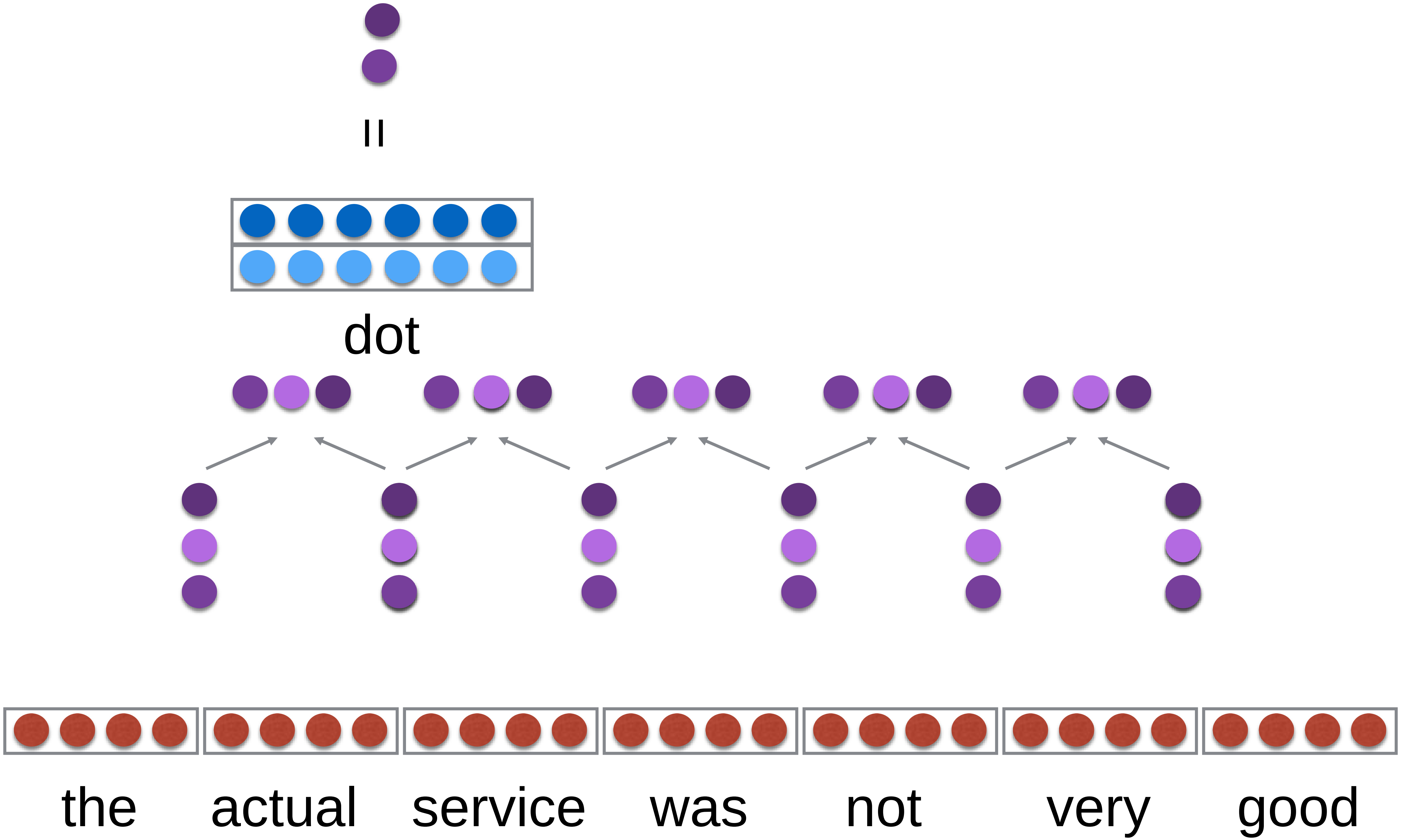
Hierarchy



can have hierarchy

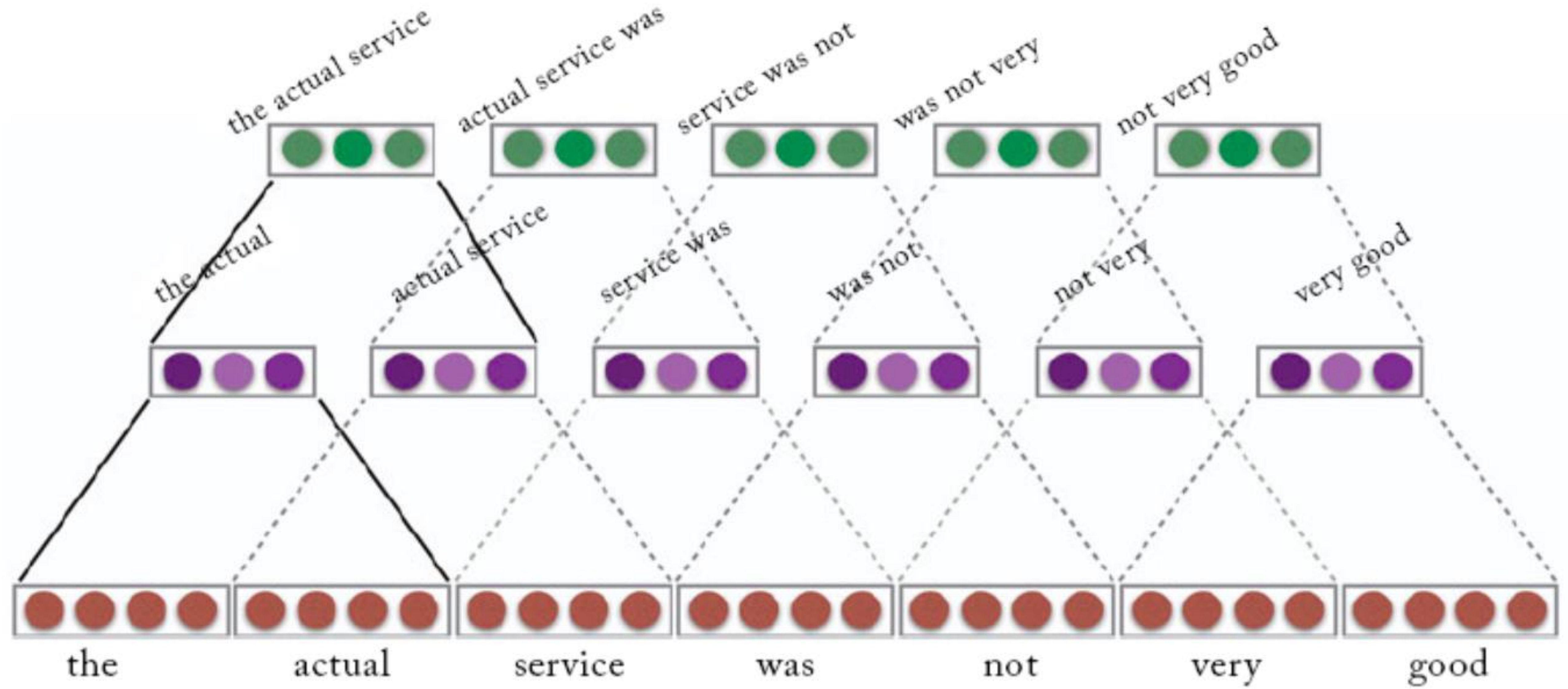


can have hierarchy



(can combine: **pooling + hierarchy)**

Hierarchy



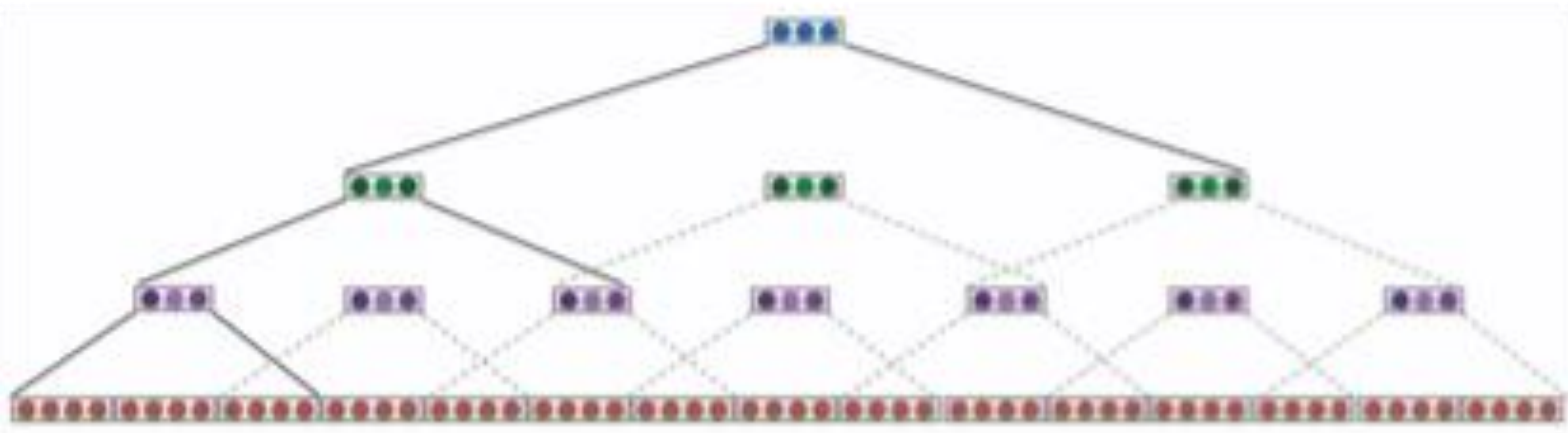
2-layer hierarchical conv with k=2

Dilated Convolutions

we want to cover more of the sequence

idea: strides + hierarchy

Dilated Convolutions



dilated convolution, k=3

idea: strides + hierarchy

ConvNets Summary

- Shared matrix used as feature detector.
- Extracts interesting ngrams.
- Pool ngrams to get fixed length representation.
- Max-pooling works well.
    - Max vs. Average pooling.
- Use hierarchy / dilation to expand coverage.
- Train end-to-end.

Alternative: Hashing Trick

- ConvNet is an architecture for finding good ngrams.
- But if we know ngrams are important, why not just have ngram embeddings (ngram vectors)?
- --> for large vocabulary, not scalable.

  Can't represent all ngrams, don't know which are important.

Alternative: Hashing Trick

- **Problem**: our ngram vocabulary size if 10^9
- **Solution**: use smaller space via hashing,
  allow feature clashes.

Hashing Trick

- We have > 10^9 different ngrams.
- We can afford ~10^6 different embeddings.
- Map each ngram to a number in [0, 10^6]
- Use the corresponding embedding vector.
- Clashes will happen, but it will probably be ok.
  - Even safer: map each ngram to two numbers using two different hash functions, sum the vectors.

Hashing Trick vs ConvNets

- What are the benefits of using bag of ngrams?
- What are the benefits of using ConvNet (ngram detector)?
- Does it matter if the vocabulary size is small or large?

(discuss)