DS 207: Introduction to Natural Language Processing

Text Classification

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Slides courtesy: Graham Neubig

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Example: topic classification

- Sports: "Kohli scores another remarkable hundred"
- Politics: "Minister announces new metro plans ahead of elections"
- Entertainment: "A sleeper hit, 12th fail, is praised by many Bollywood actors"
- Finance: "Stocks for Indian delivery startups plummet"

Generative Naive Bayes

$$P(X^{(i)}, y^{(i)}) = P(y^{(i)})\ P(X^{(i)} \mid y^{(i)})$$

$$P(X \mid y) = P(w_1, w_2, w_3, \ldots w_t \mid y)$$

$$P(X \mid y) = \prod_{i}^{t} P(w_i \mid y)$$

$$P(w_i = \text{" Kohli"} \mid y = \text{"sports"})$$

Estimating parameters

$$\mathbf{P}(w_i = \text{"Kohli"} \mid y = \text{"sports"})$$

$$= \frac{\text{count}(w_i = \text{Kohli} \in y = \text{sports})}{\sum_{w \in |V|} \text{count}(w \in y = \text{sports})}$$

Add-α smoothing (or Laplace smoothing)

$$\mathbf{P}(\mathbf{w_i} = \text{"Kohli"} \mid y = \text{"finance"})$$

$$= \frac{\mathbf{count}(w_i = \mathbf{Kohli} \in y = \mathbf{finance}) + \alpha}{\sum_{w \in |V|} (\mathbf{count}(w \in y = \mathbf{finance}) + \alpha)}$$

Evaluation

- Accuracy
- Precision = TP / (Predicted) P
- Recall = TP / (Actual) P
- F1 score

		Predicted condition	
	Total population = P + N	**Predicted positive (PP)**	**Predicted negative (PN)**
Actual condition	**Positive (P)** [a]	**True positive** (TP), hit[b]	**False negative** (FN), miss, underestimation
	Negative (N)[d]	**False positive** (FP), false alarm, overestimation	**True negative** (TN), correct rejection[e]

What metrics are best suited

- Diagnosing rare type of cancer
- Criminal punishment
- Detecting spam
- Recruitment/Filtering based on text in the CVs
- Recommending products/songs/movies

Generative vs Discriminative models

- <u>Generative model</u>: a model that calculates the probability of the input data itself

$P(X)$ — *stand-alone*

$P(X, Y)$ — *joint*

- <u>Discriminative model</u> calculates the probability of a class (or trait) given the data

$P(Y \mid X)$ — *conditional*

Rule based systems: is the headline sports or entertainment?

- **Feature extraction**: Extract the salient features for making the predictions from text

  1. Does the headline contain the word "Kohli"
  2. Does the headline contain the word "win"
  3. Does the headline contain the word "cricket"
  4. Does the headline contain the word "actor"
  5. Does the headline contain the word "show"
  6. Does the headline contain the word "blockbuster"

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$$f(x) = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \qquad W = \begin{bmatrix} +1 \\ +1 \\ +1 \\ -1 \\ -1 \\ -1 \end{bmatrix}$$

A three step process for making predictions

- Feature extraction: Extract the salient features for making the decision from text

$$\mathbf{h} = f(\mathbf{x})$$

- Score calculation: Calculate a score for one or more possibilities

$$s = \mathbf{w} \cdot \mathbf{h} \qquad \mathbf{s} = W\mathbf{h}$$

binary *multi-class*

- Decision function: Choose one of the several possibilities

$$\hat{y} = \text{decide}(\mathbf{s})$$

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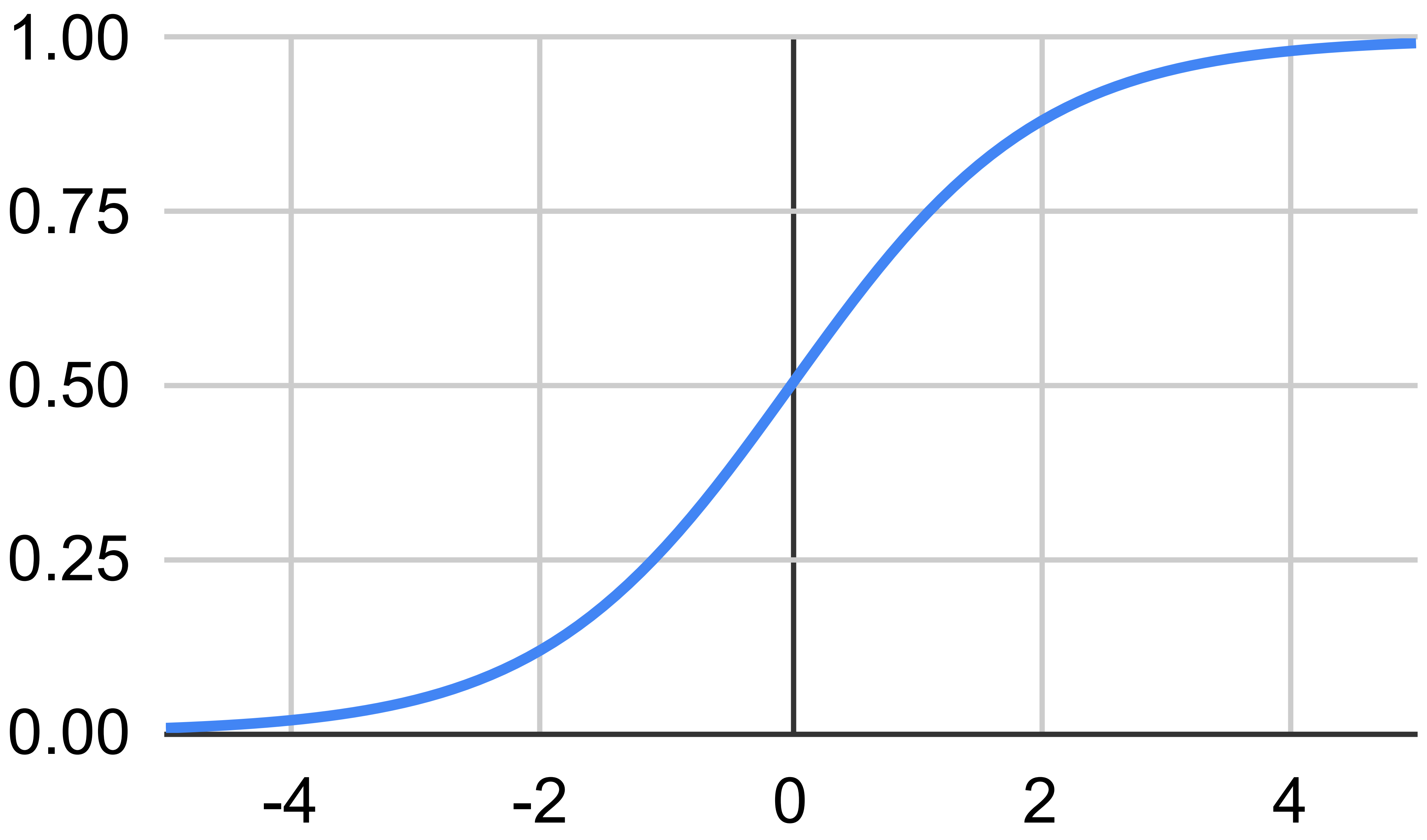
- **Decision:** Convert to a probability:

$P(y|x) = \sigma(s)$ or softmax(**s**)

Sigmoid function

- **Sigmoid can be used for binary decisions**

$$\sigma(s) = \frac{1}{1 + e^{-s}}$$



Softmax

- **Softmax is used for multi-label classification**

$$\textbf{softmax}(s) = \frac{e^{s_i}}{\sum_i^d e^{s_i}}$$

$$s = \begin{pmatrix} -3.2 \\ -2.9 \\ 1.0 \\ 2.2 \\ 0.6 \\ \ldots \end{pmatrix} \longrightarrow p = \begin{pmatrix} 0.002 \\ 0.003 \\ 0.329 \\ 0.444 \\ 0.090 \\ \ldots \end{pmatrix}$$

Softmax

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$$\textbf{softmax}(s) = \frac{e^{s_i}}{\sum_i^d e^{s_i}}$$

$$s = \begin{pmatrix} 1 \\ 6 \\ 2 \end{pmatrix} \longrightarrow p = \begin{pmatrix} 0.006 \\ 0.975 \\ 0.017 \end{pmatrix}$$

Recap: Discriminative models

- **Define a model that calculates probability directly based on parameters W**

$$P(Y|X;W)$$

Computing loss (or error/cost) function

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$$L(W) = -\sum_{x,\, y\ \in\ D} \log P(y \,|\, x; W)$$ **[negative log likelihood]**

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$$L(W) = -\sum_{i}^{n} \Big(y_i \ \log P(y = 1 \,|\, x_i; W) \quad + \quad (1 - y_i) \ \log(P(y = 0 \,|\, x_i; W) \Big)$$

[binary cross entropy]

Learn parameters through gradient descent

- Compute the gradient of the loss function with respect to the parameters

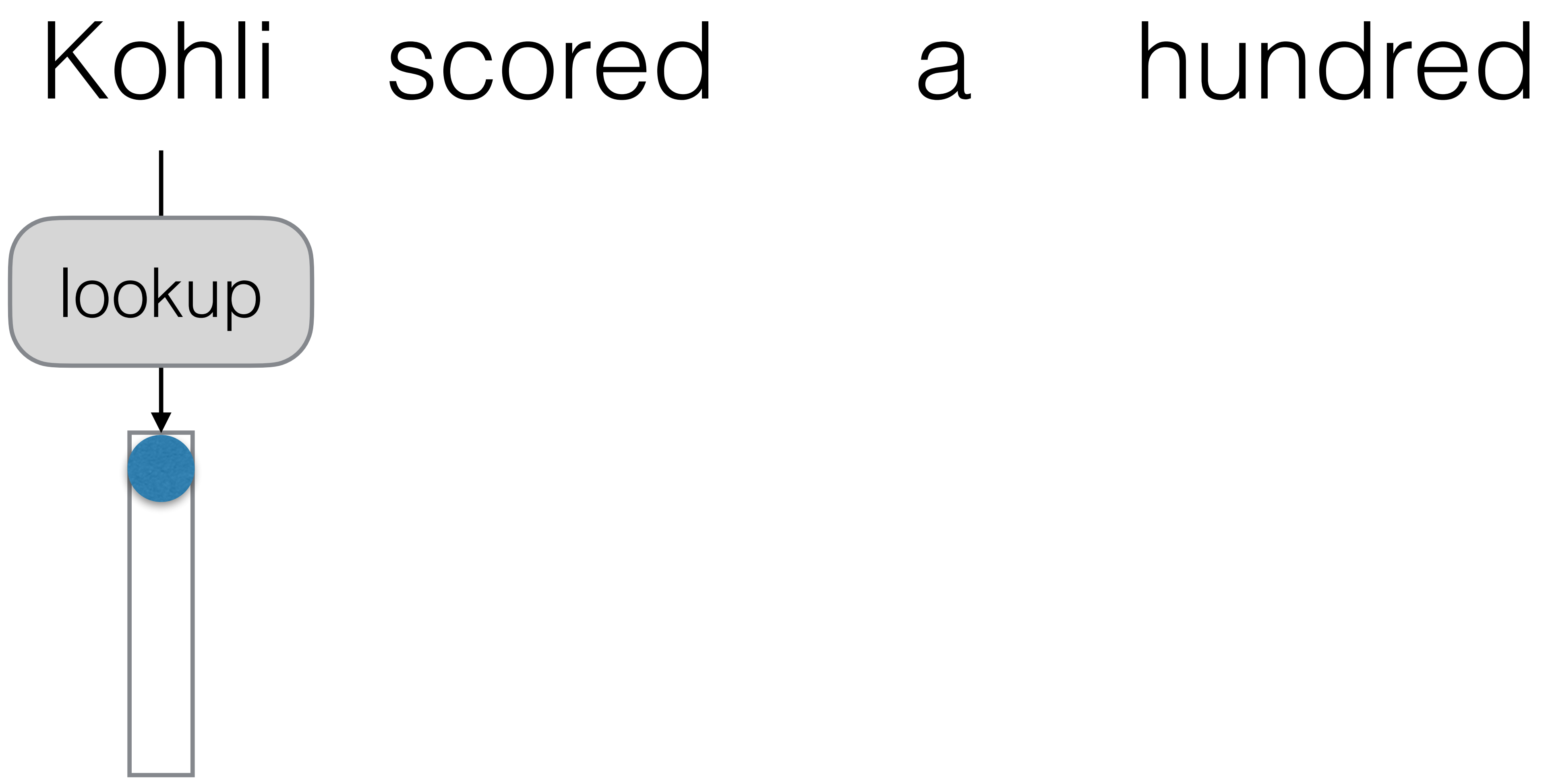
- Keep updating the parameters to move in a direction that decreases the loss

$$W_{t+1} = W_t - \alpha \nabla_{W_t} L(W)$$

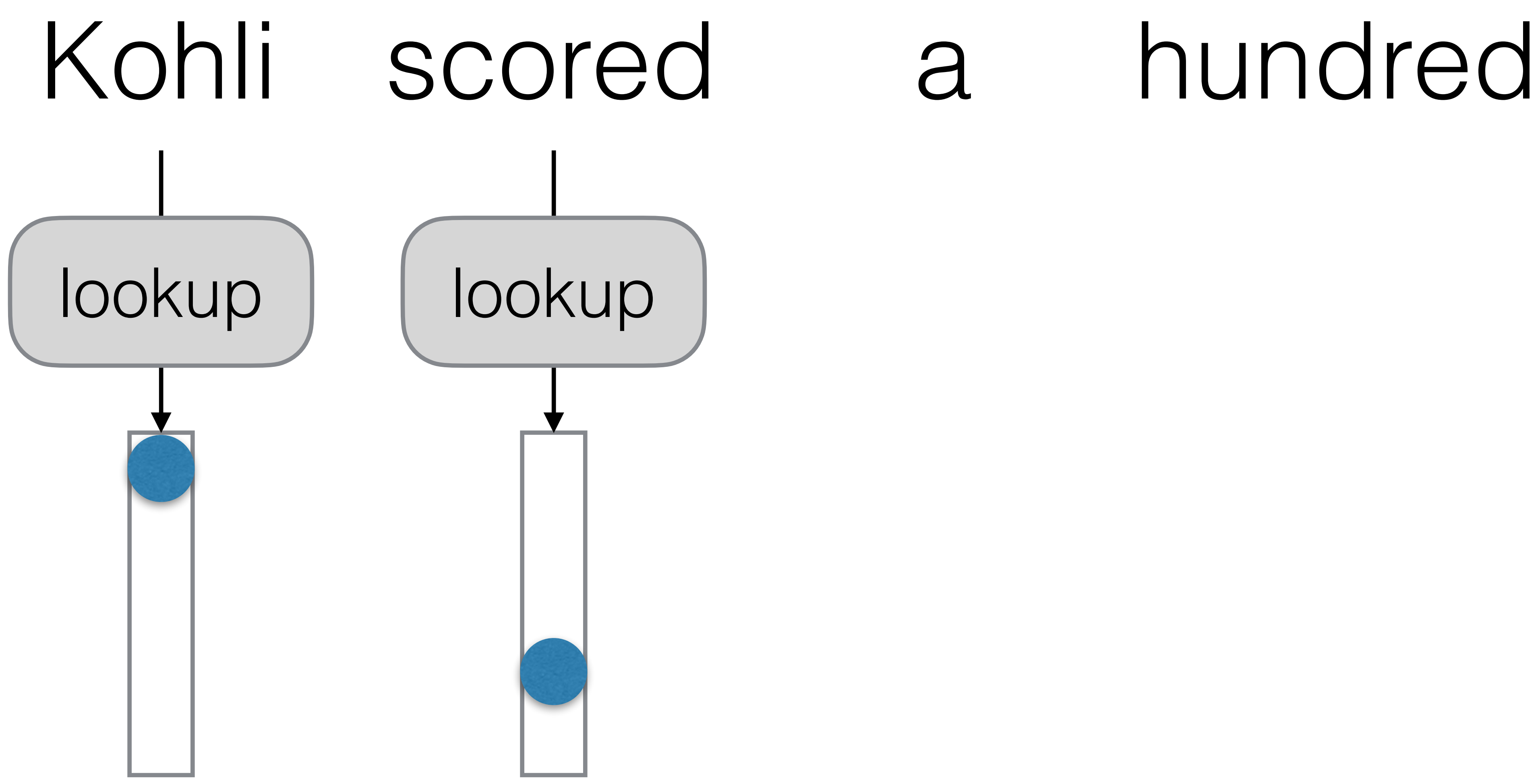
Computational Graph View

Kohli scored a hundred

Computational Graph View



Computational Graph View



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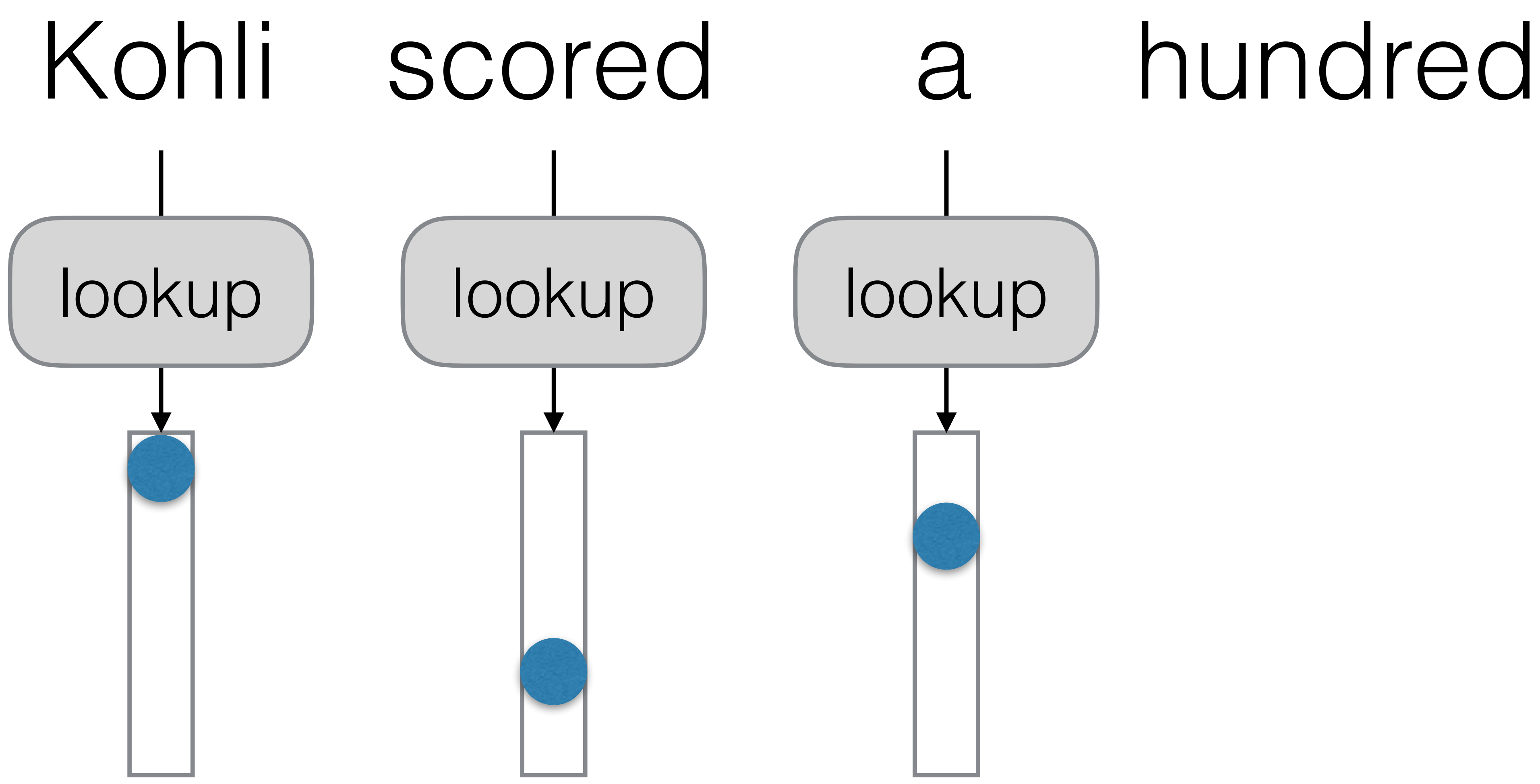

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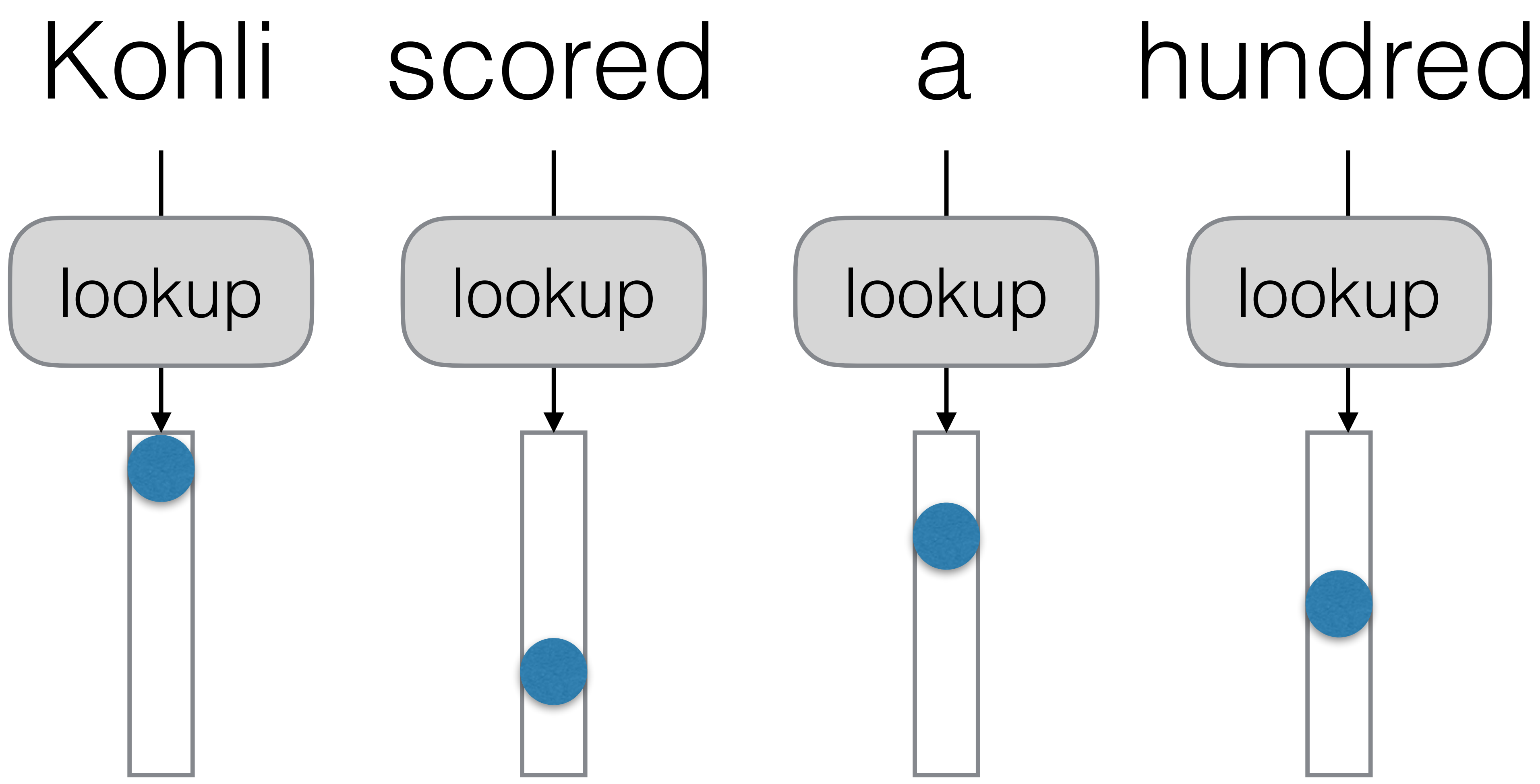

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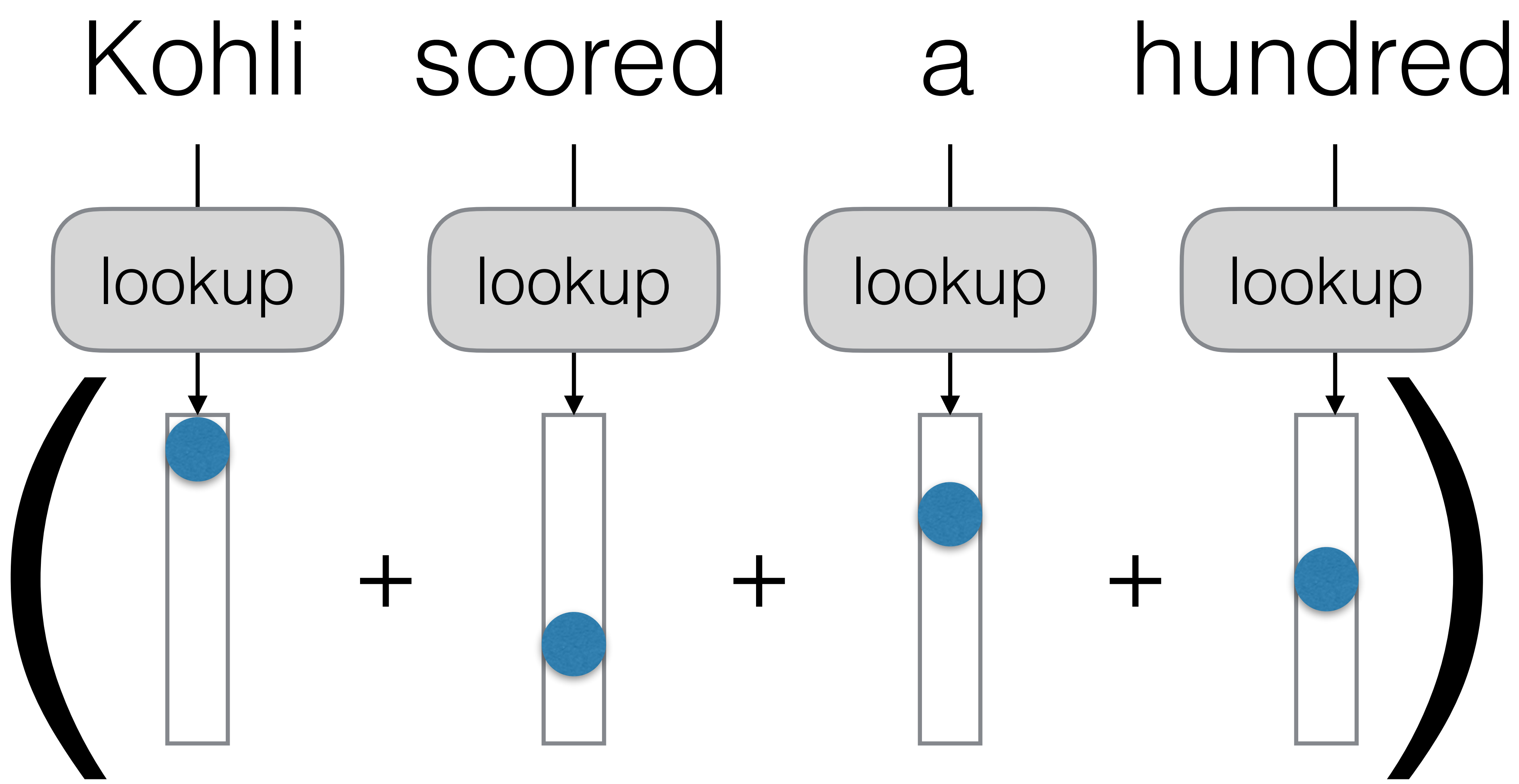

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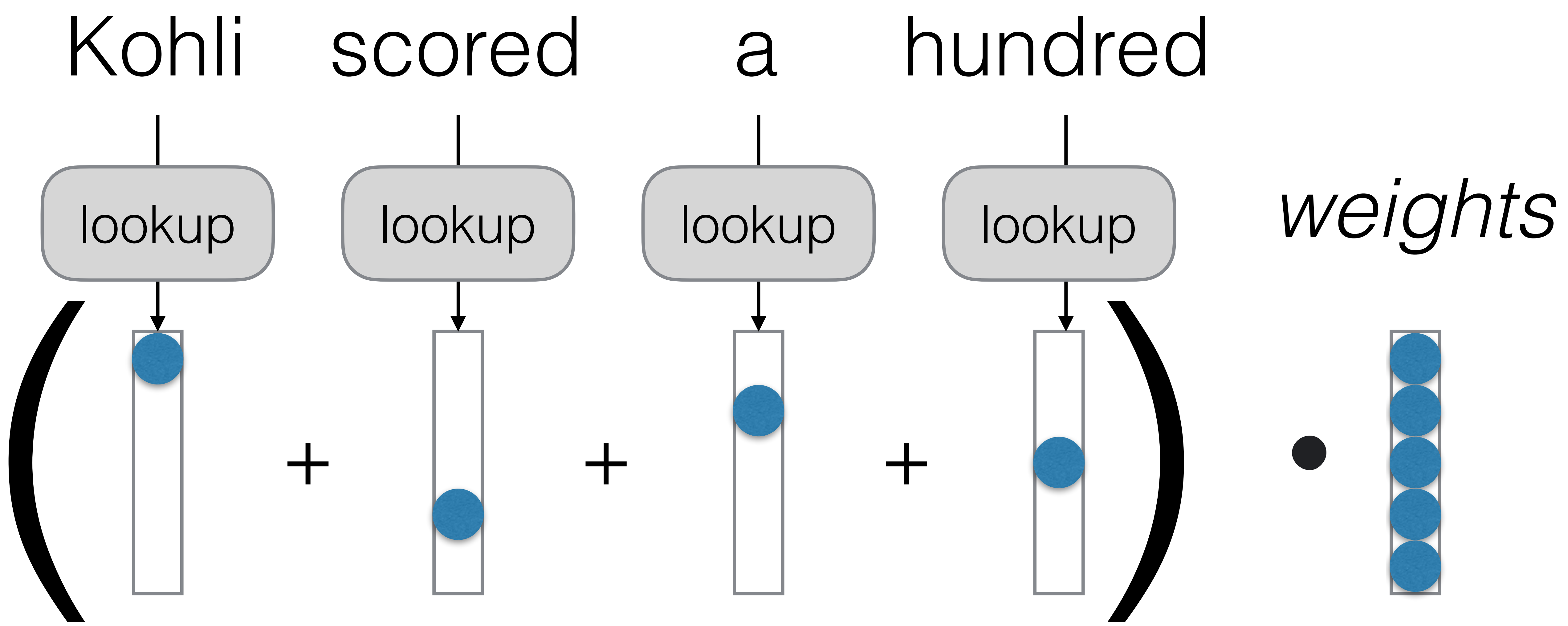

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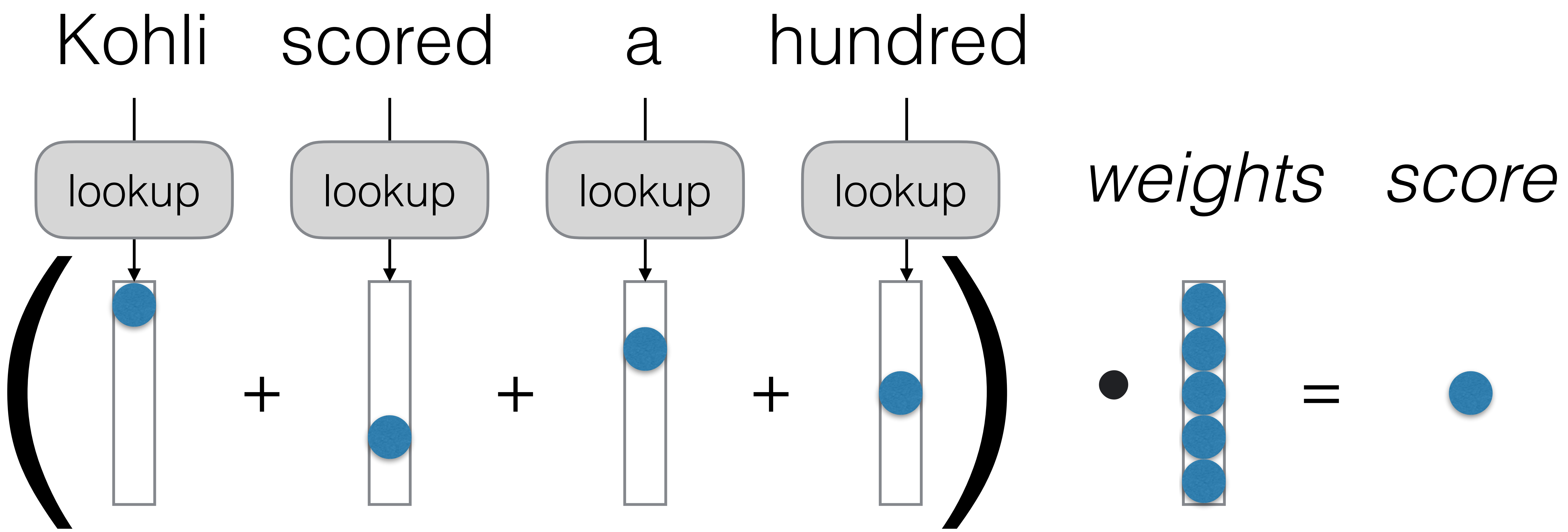

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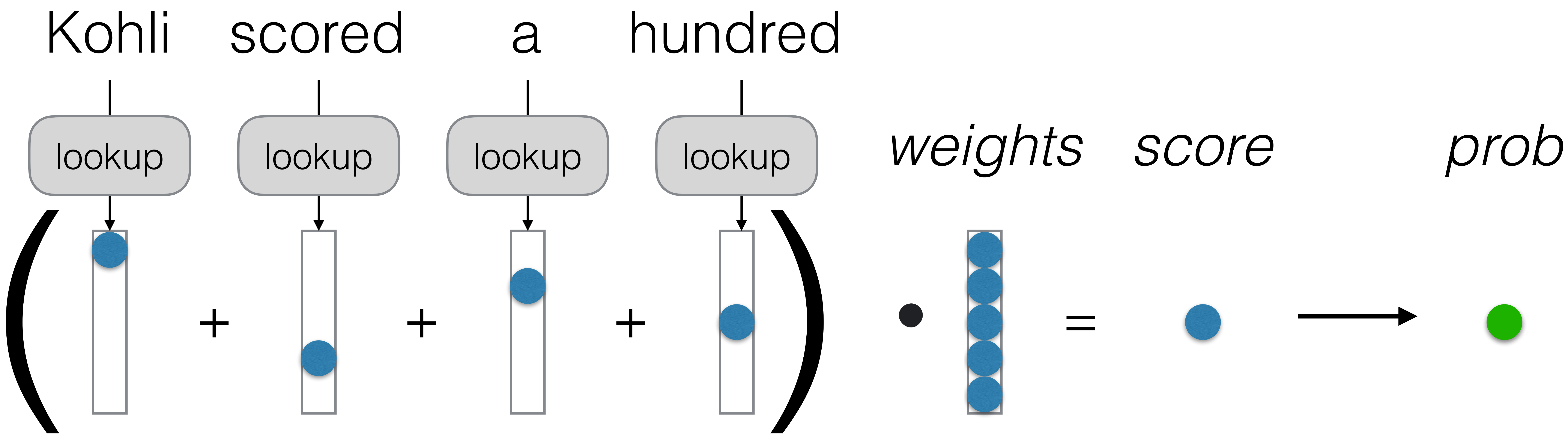

Questions?

Next class: Word2vec