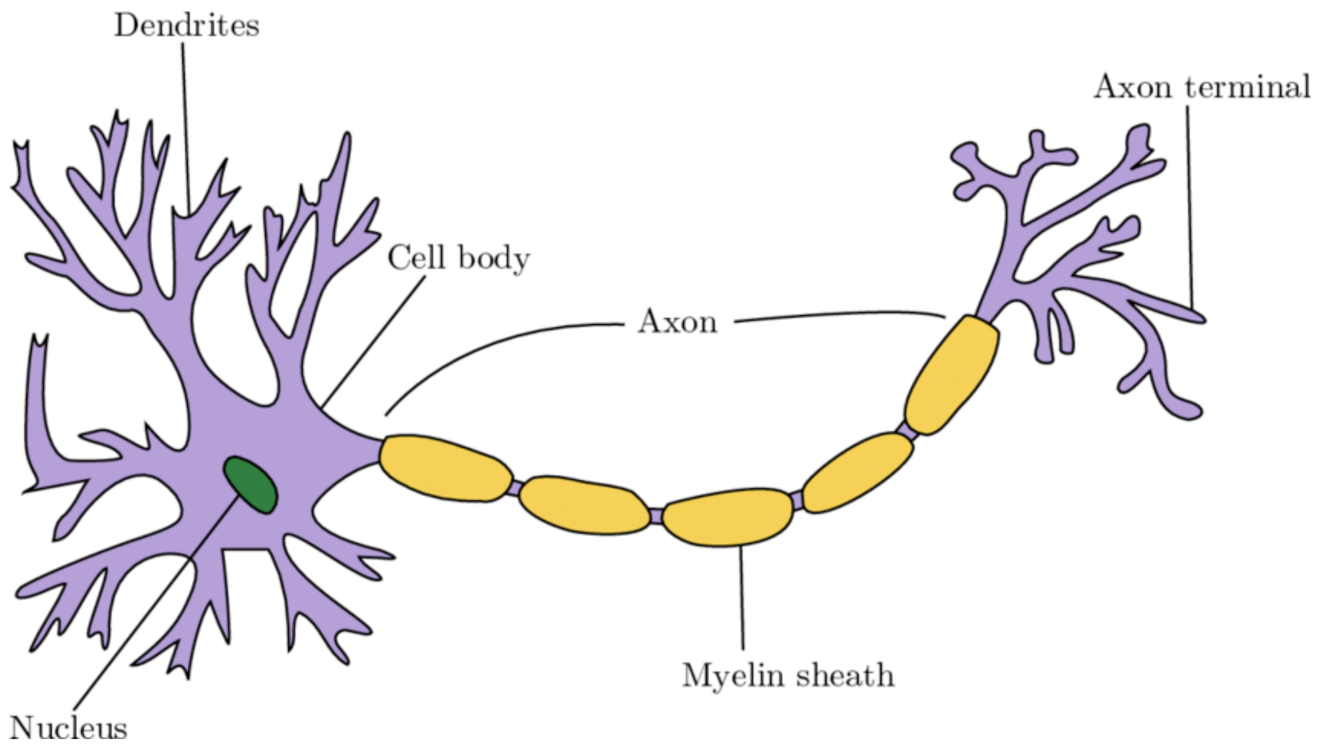
Neural Network Models

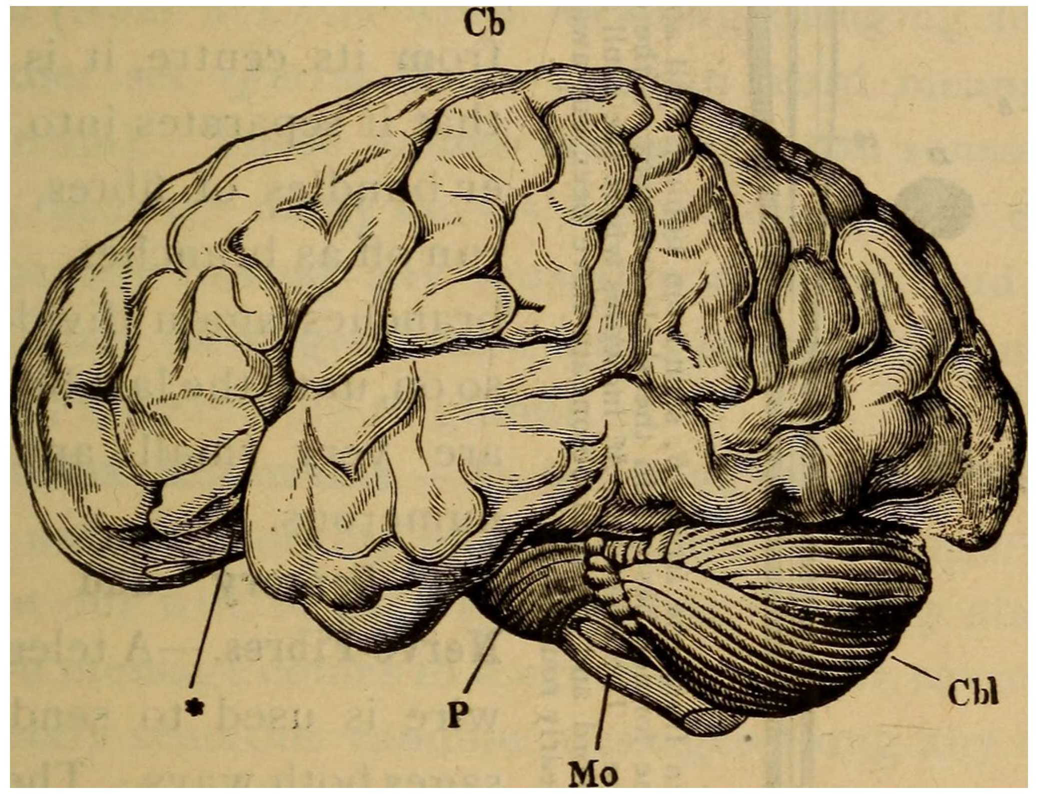
for natural language processing

Thomas Brochhagen // Session 05, 2024 // NLP@MLTA; Computational MorphoSyntax@CCiL

Neural Network Model

Neural Network Model

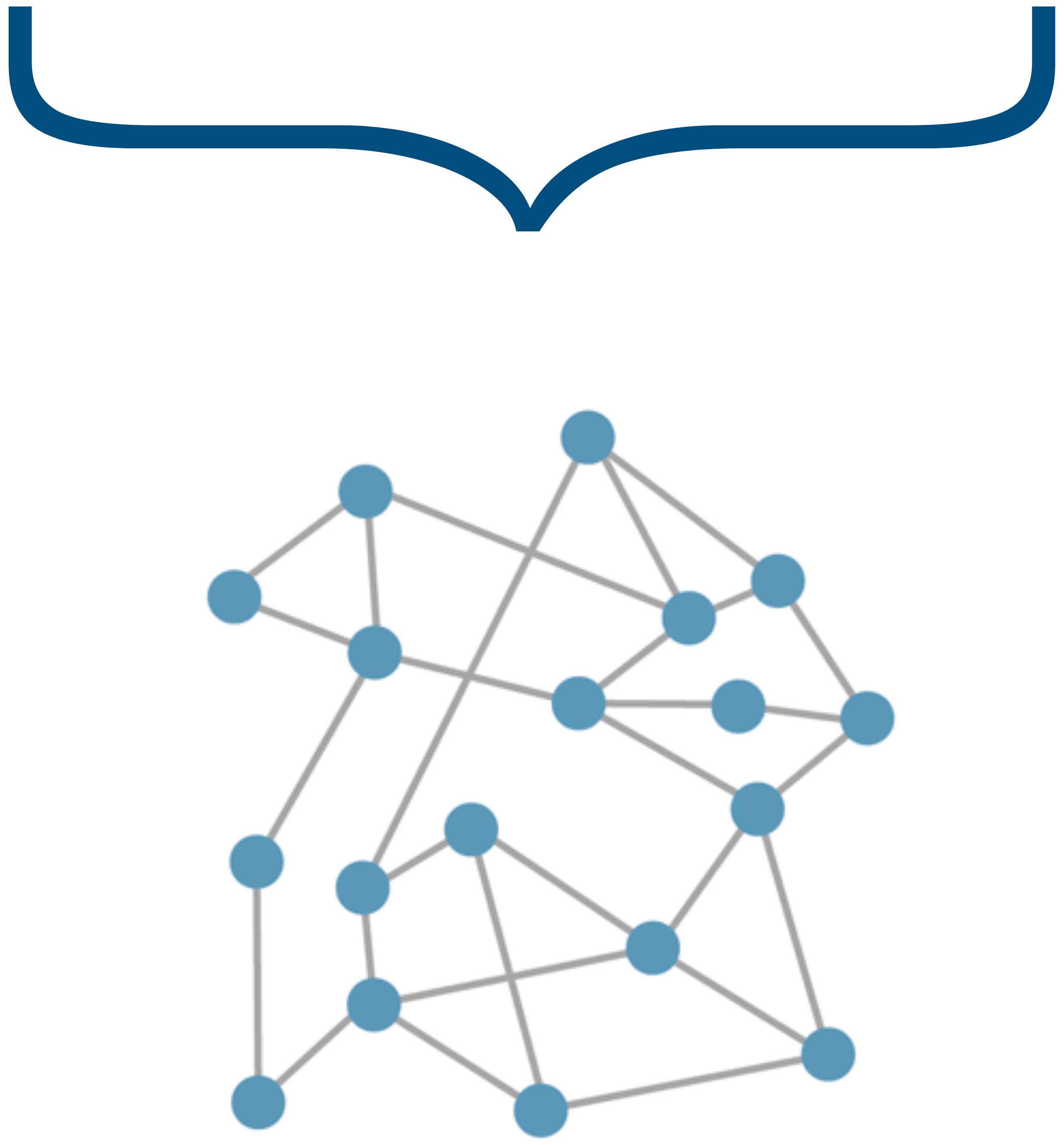




Neural Network Model

Distributed architecture
Connectionist basis

Neural Network Model



What is a model?

Neural Network **Model**

Useful representation

Often but not always an abstraction

~~Neural~~ Network Model

Models

For any word from vocabulary, with a single guess

1. predict its frequency

2. predict the next word

Loss/cost function

$\lambda(y, \hat{y}) = (y - \hat{y})^2$	quadratic loss
$\lambda(y, \hat{y}) = \max(0, 1 - y \cdot \hat{y})$	hinge loss
$\log p(y \mid \theta)$	log predictive density

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To be a good model, you need to know what you will be evaluated on!

Loss/cost function

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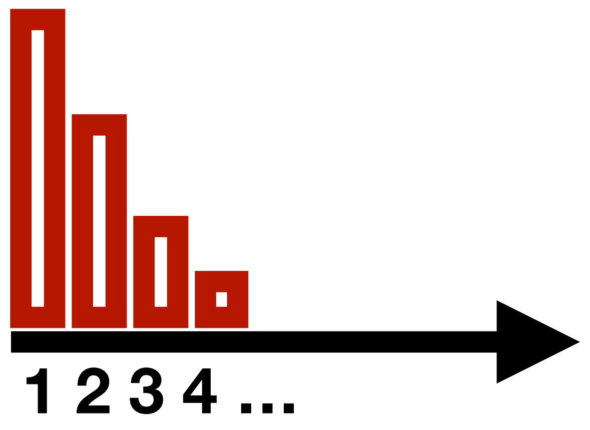
$\lambda(y, \hat{y}) = \text{max}(0,1 - y \cdot \hat{y})$	hinge loss
$\log p(y \mid \theta)$	log predictive density

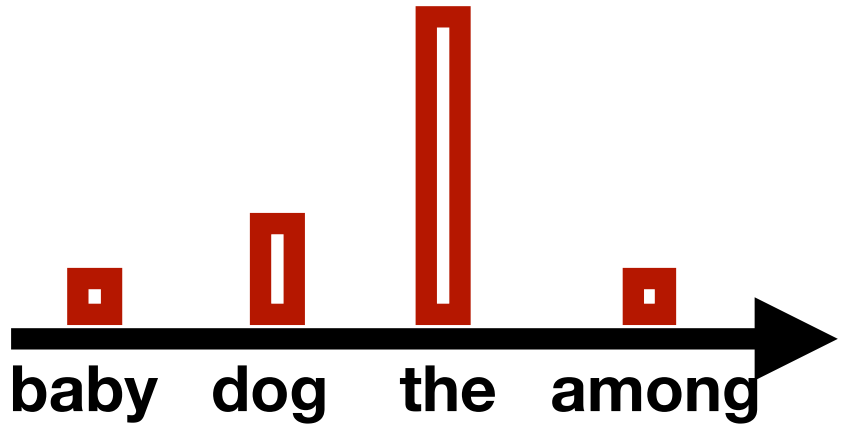
There is no free lunch

For any word v from vocabulary of size |V|, with a single guess

1. predict its frequency



2. predict the next word



For any word v from vocabulary of size |V|, with a single predictor

1. predict its frequency

2. predict the next word

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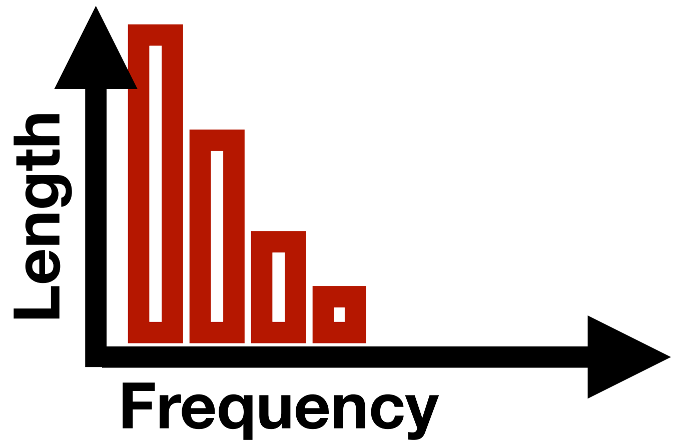
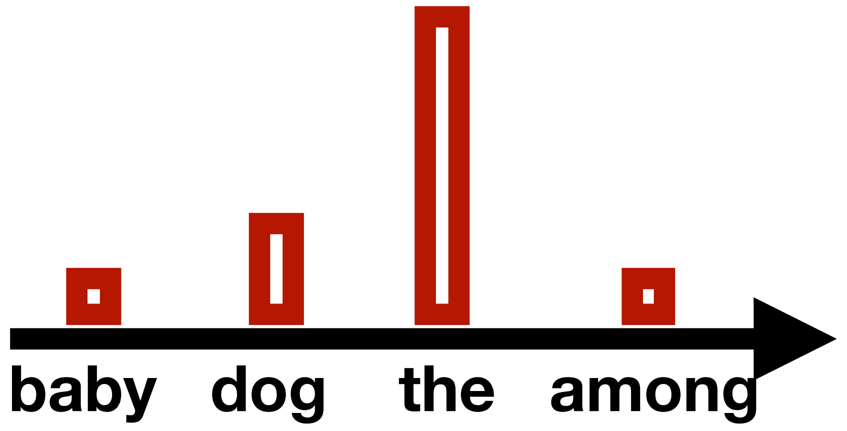


2. predict the next word



For any word v from vocabulary of size |V|, with a **multiple predictors**

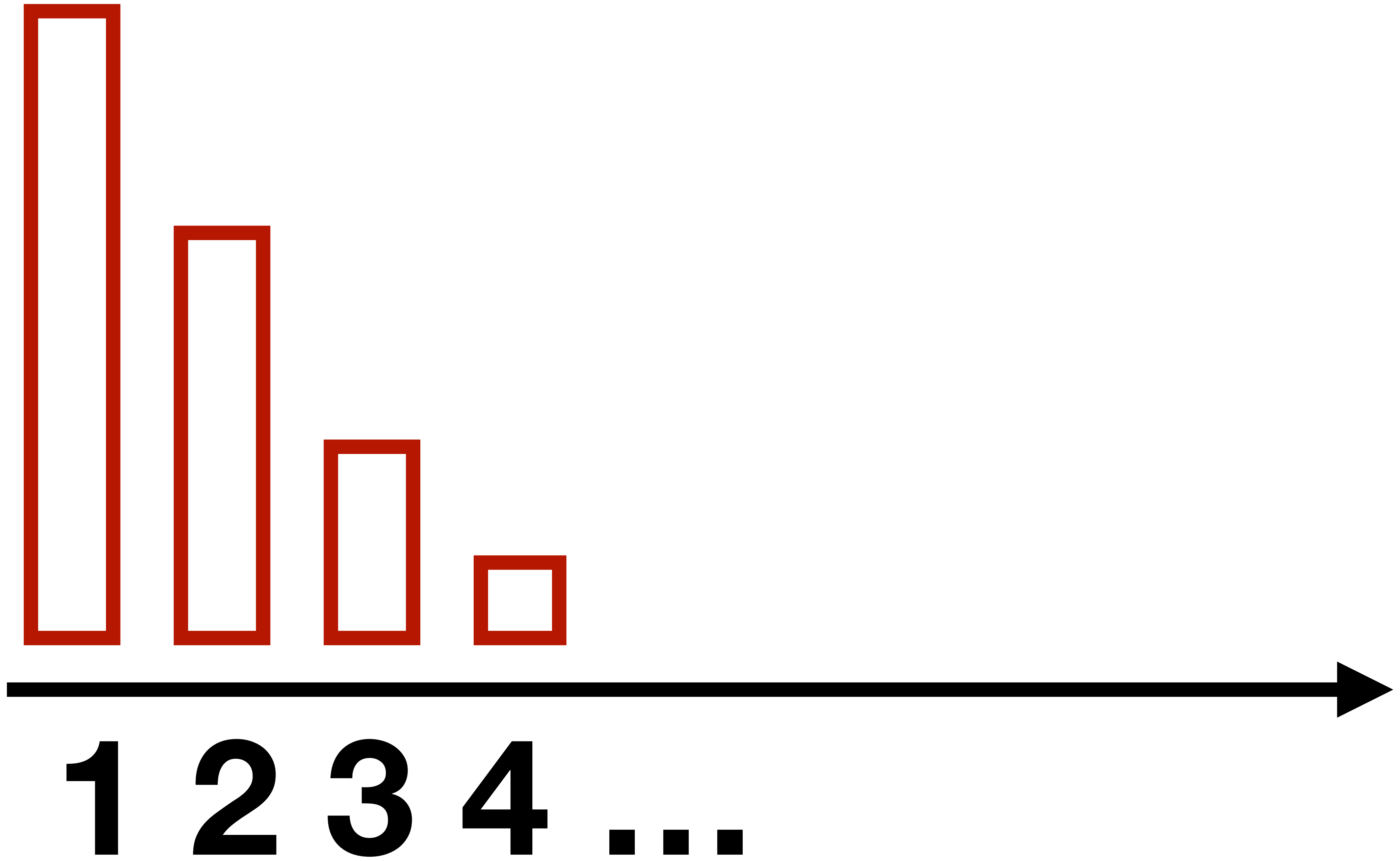
1. predict its frequency

2. predict the next word

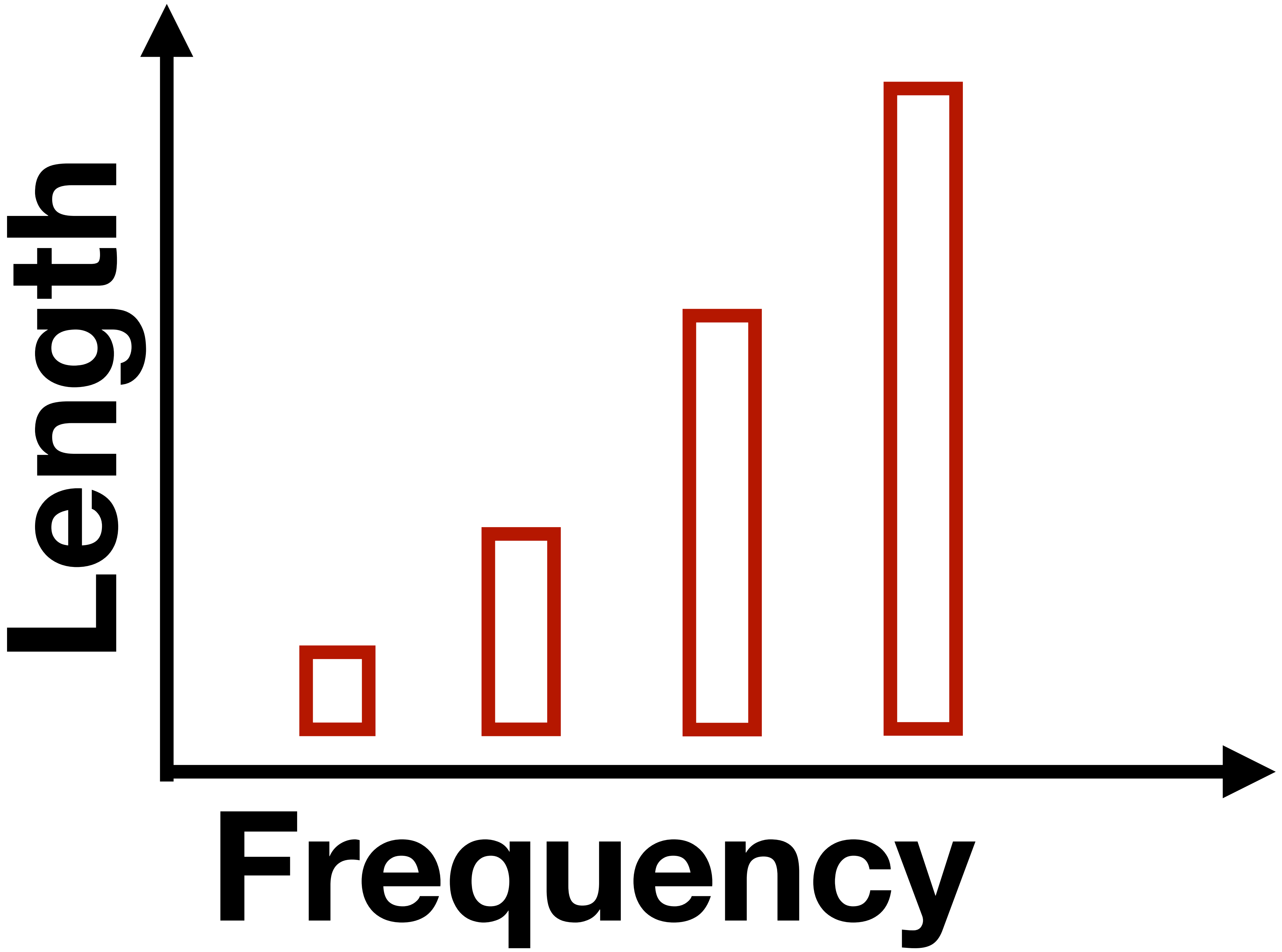
How can the multiple predictors be combined?

Linear models and non-linearity

$$\text{frequency}_i = \beta_0$$



$$\text{frequency}_i = \beta_0 + \beta_1 \text{length}_i$$



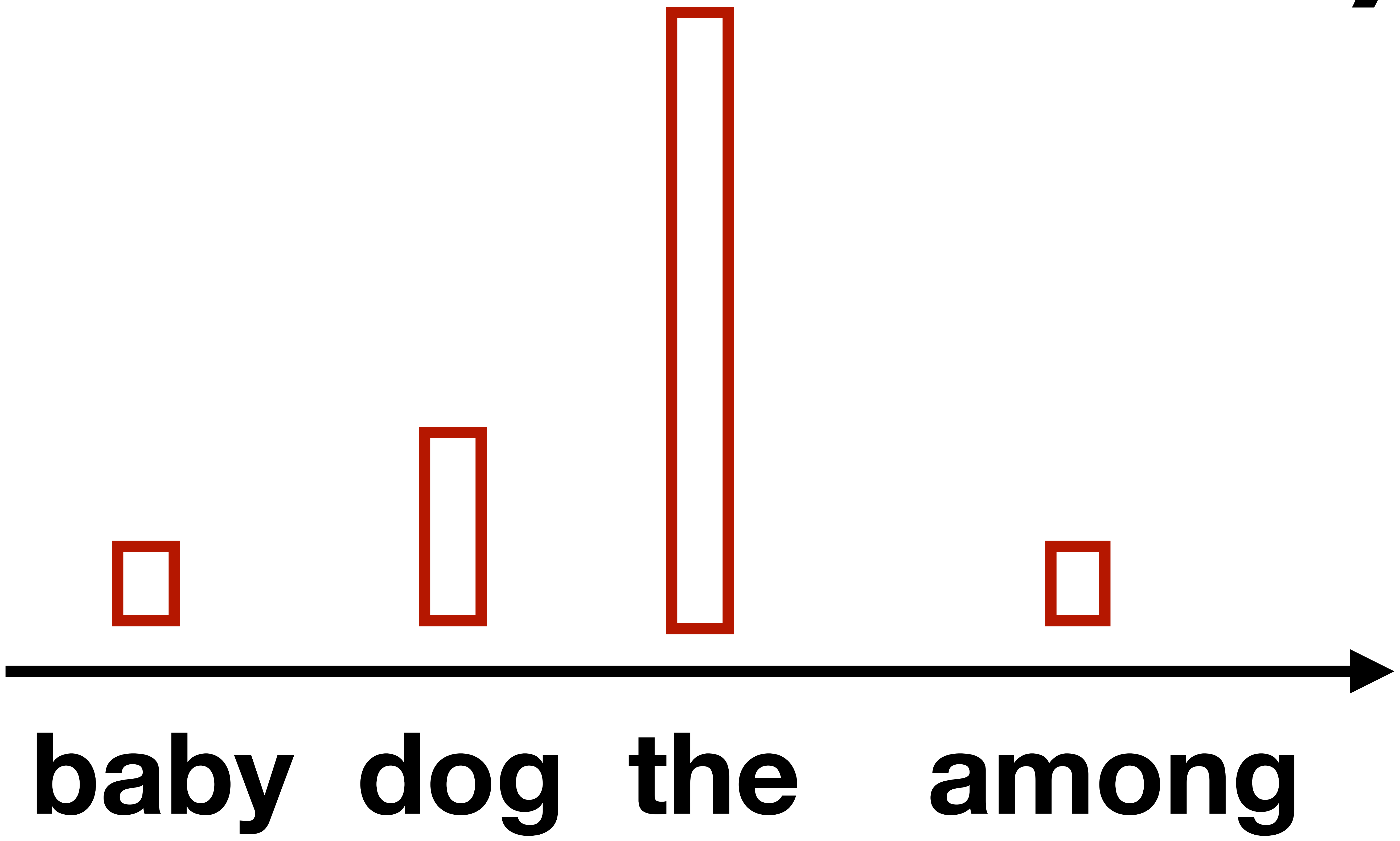
$$\text{frequency}_i = \beta_0 + \beta_1 \text{length}_i + \beta_2 \text{pos}_i$$

$$\text{frequency}_i = \beta_0 + \beta_1 \text{length}_i \times \beta_2 \text{pos}_i$$

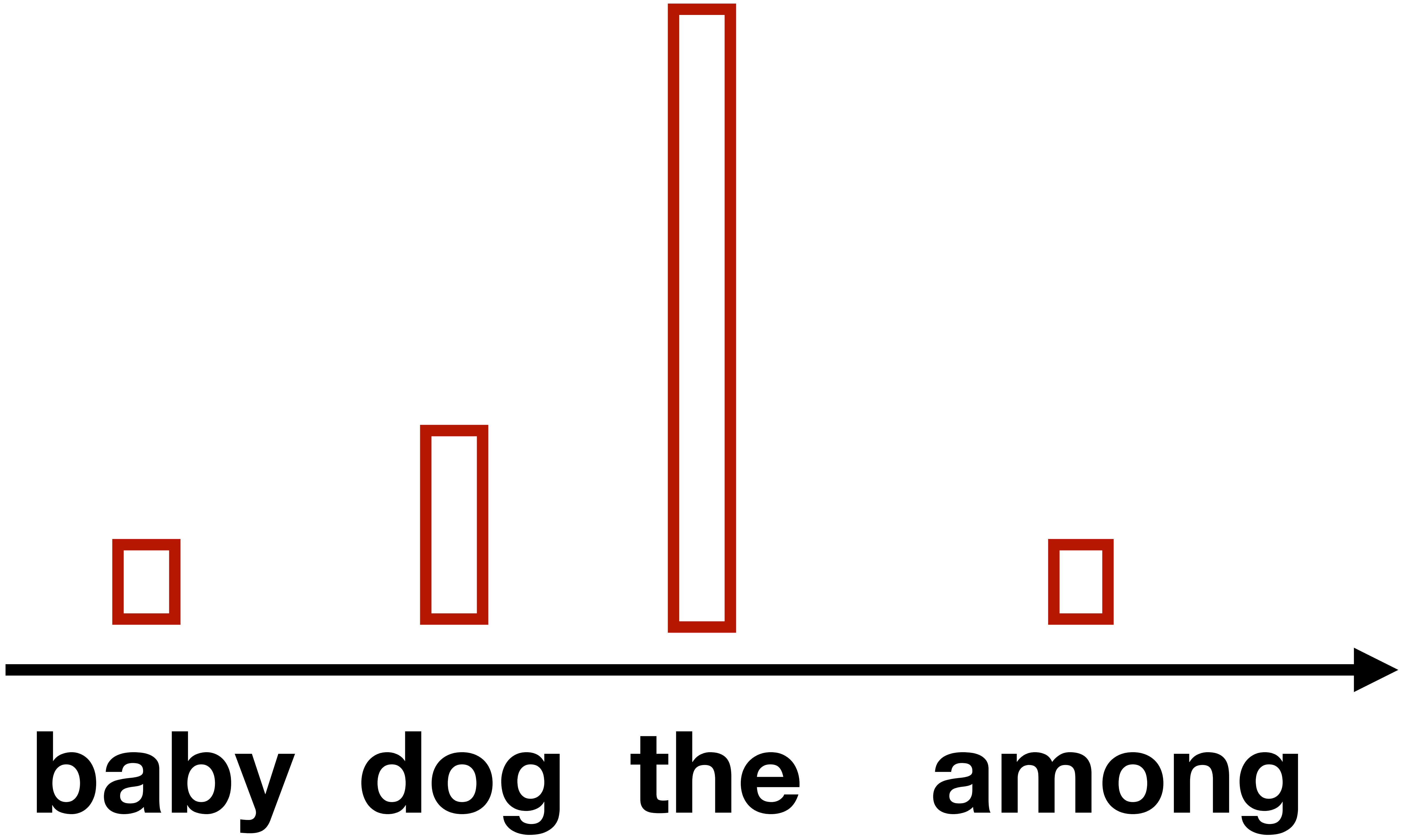
$$\cdots$$

You can keep making this more complex. The point is that this the outcome of a linear combination of parameters

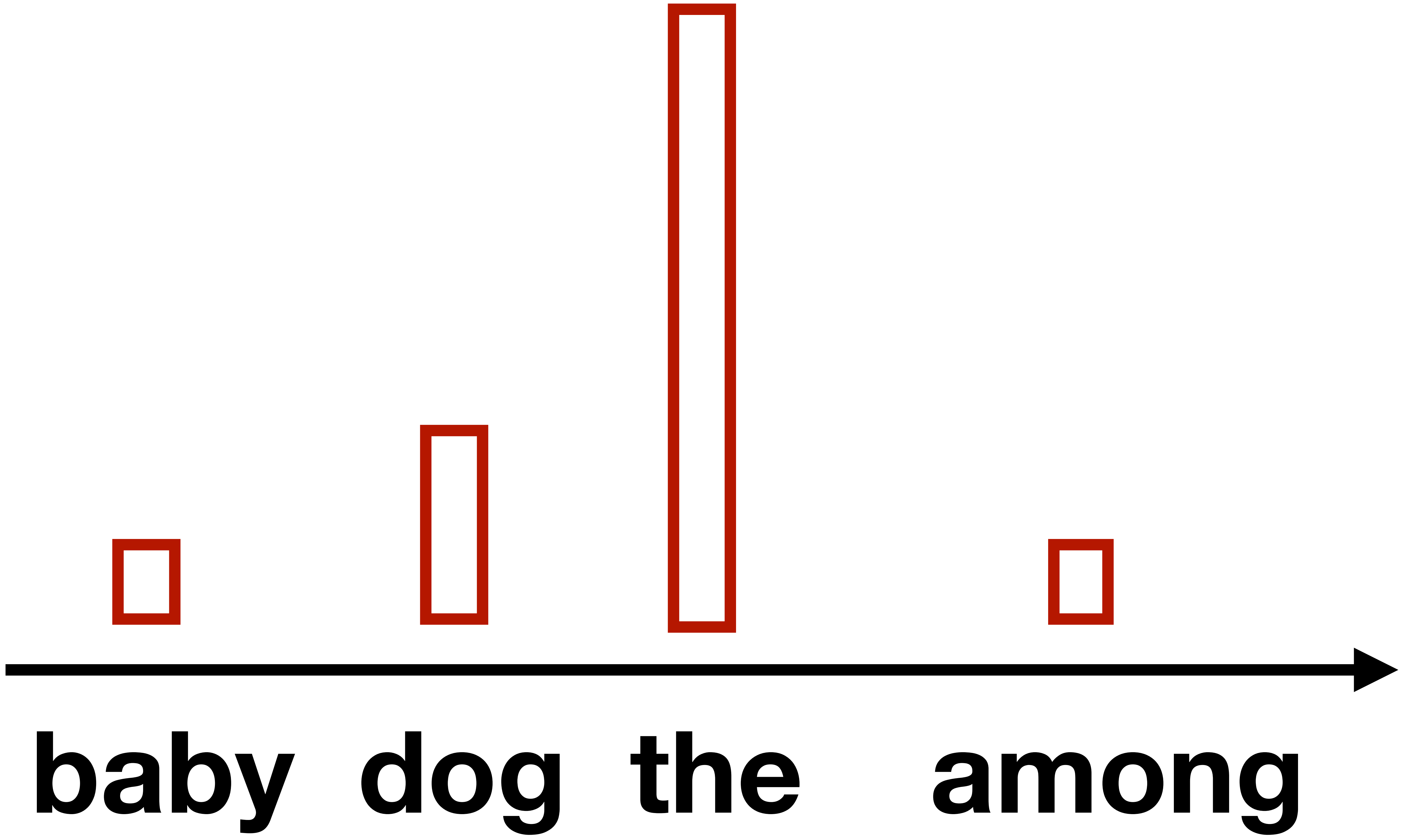
$$\text{next word}_i = \beta_0$$

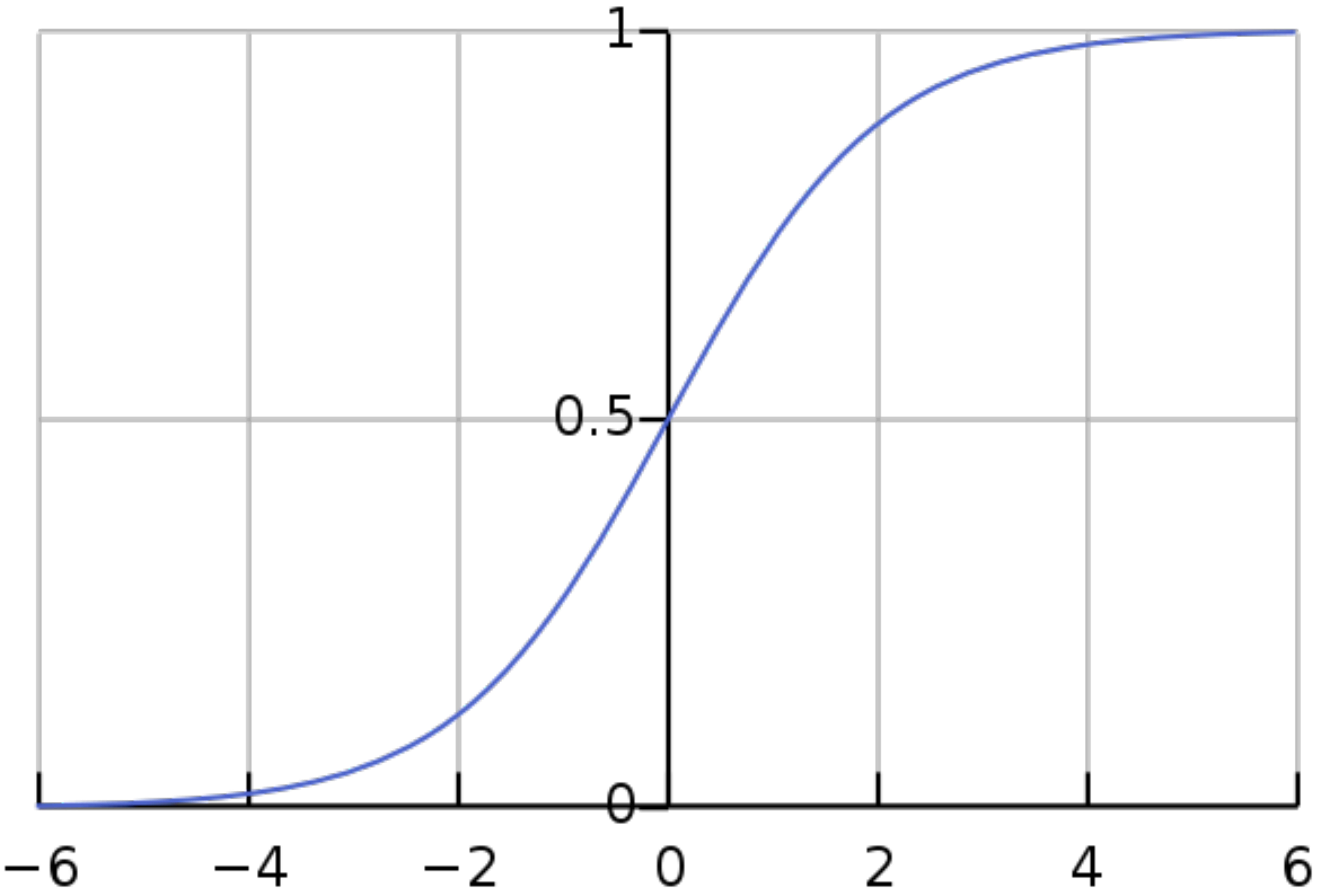


$$\text{pr}(\text{next word}_i) = \beta_0$$



$$\text{pr}(\text{next word}_i) = f(\beta_0)$$





Non-linearity, at last!

Generalized linear models are still linear models even though they use a non-linear transformation

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NNs scale up these ideas but are non-linear and have many parameters with no clear semantics behind them

Neural Network models

Non-linearity: Many phenomena are non-linear, so linearity is a potentially unnecessary constraint in the relationship between input and output

Parameters with no clear semantics: Automatically induced from data with no need to match architecture to phenomenon*

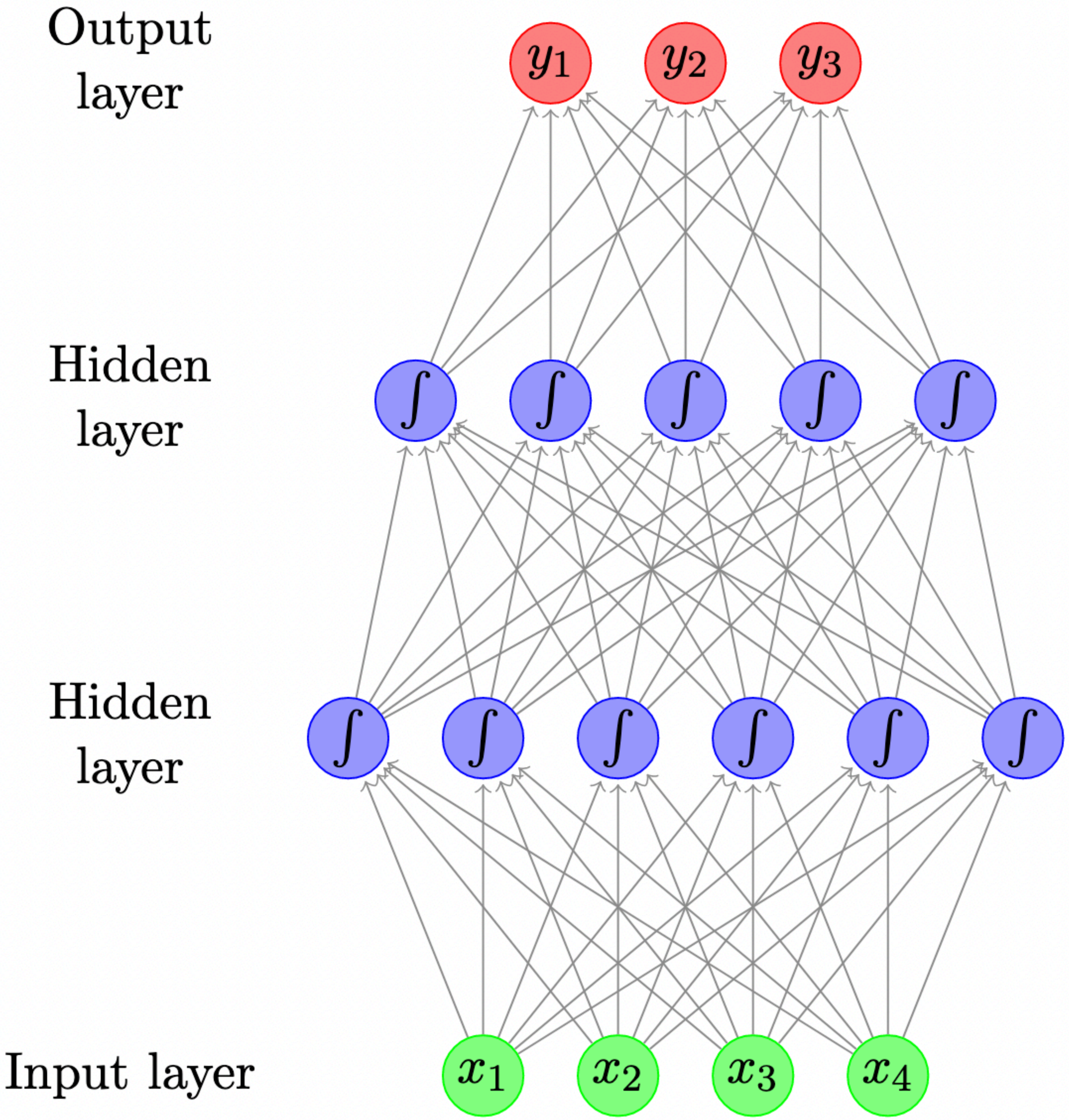
Many parameters: Can be an issue but doesn’t need to be

Dense representations

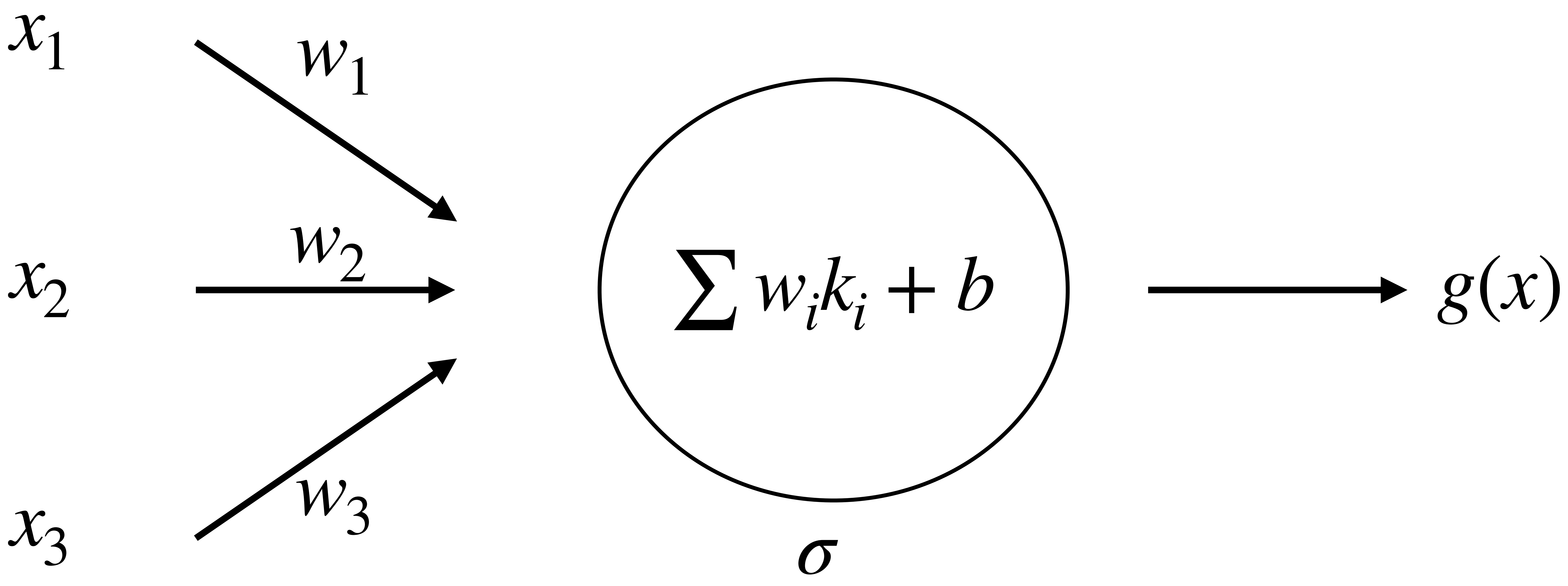
Feed-forward NN

$$[x_1, \ldots, x_{d_{in}}] \quad \Rightarrow \quad \text{NN}(\,\cdot\,) \quad \Rightarrow [y_1, \ldots, y_{d_{out}}]$$

Feed-forward NN

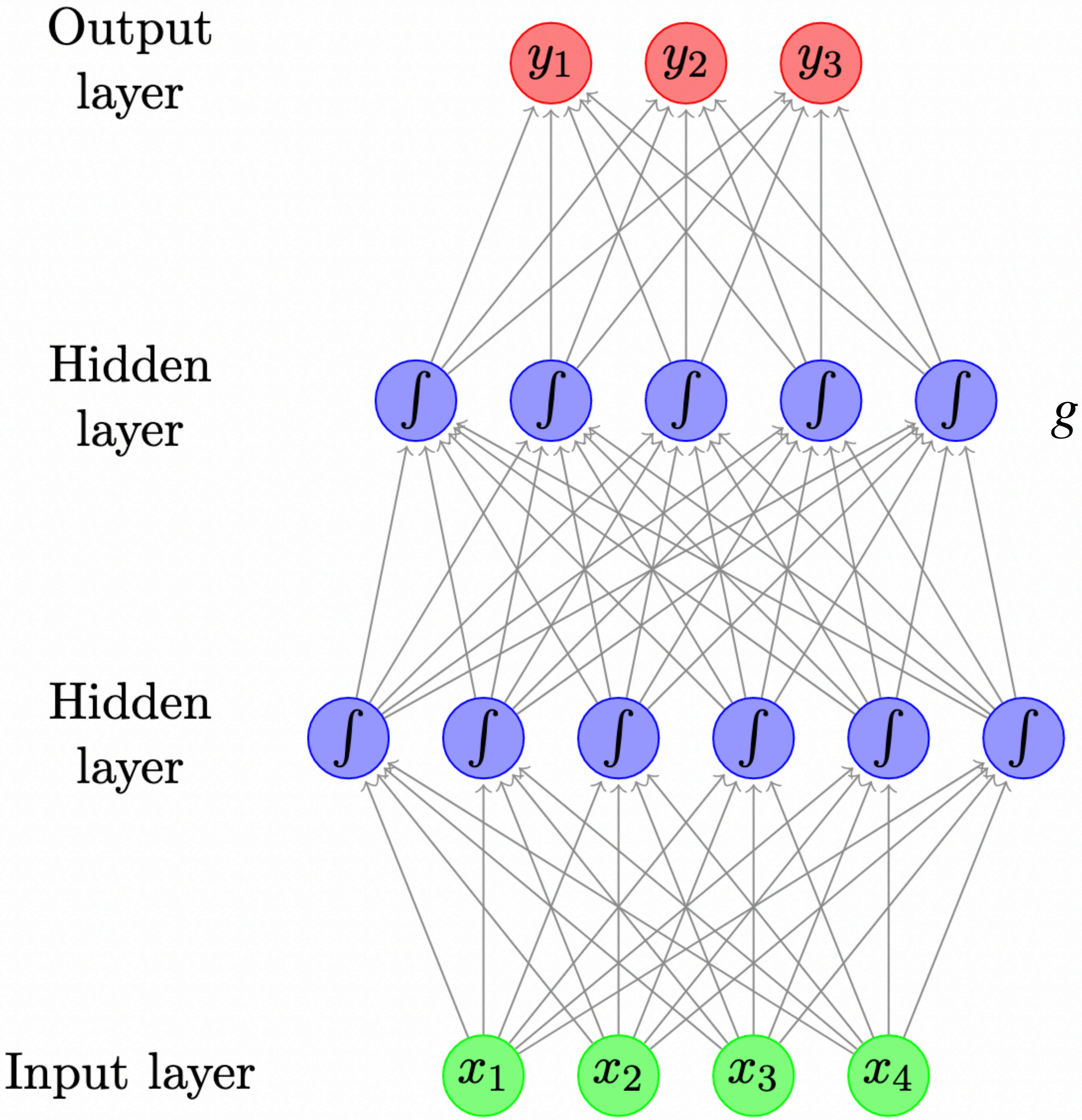


Feed-forward NN



$$\sigma\left(\sum_1^3 w_i k_i + b\right) = g(x)$$

Feed-forward NN



$$g^2(g^1(xW^1 + b^1)W^2 + b^2)$$

$$g^1(xW^1 + b^1)$$

$$x \in \mathbb{R}^{d_{in}}$$

Decisions for the modeller/engineer

1. Number of dimensions

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7.Training regime
(e.g., stochastic gradient descent + flavor;
batching; drop-out)