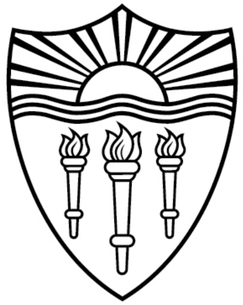
CSCI 544: Applied Natural Language Processing

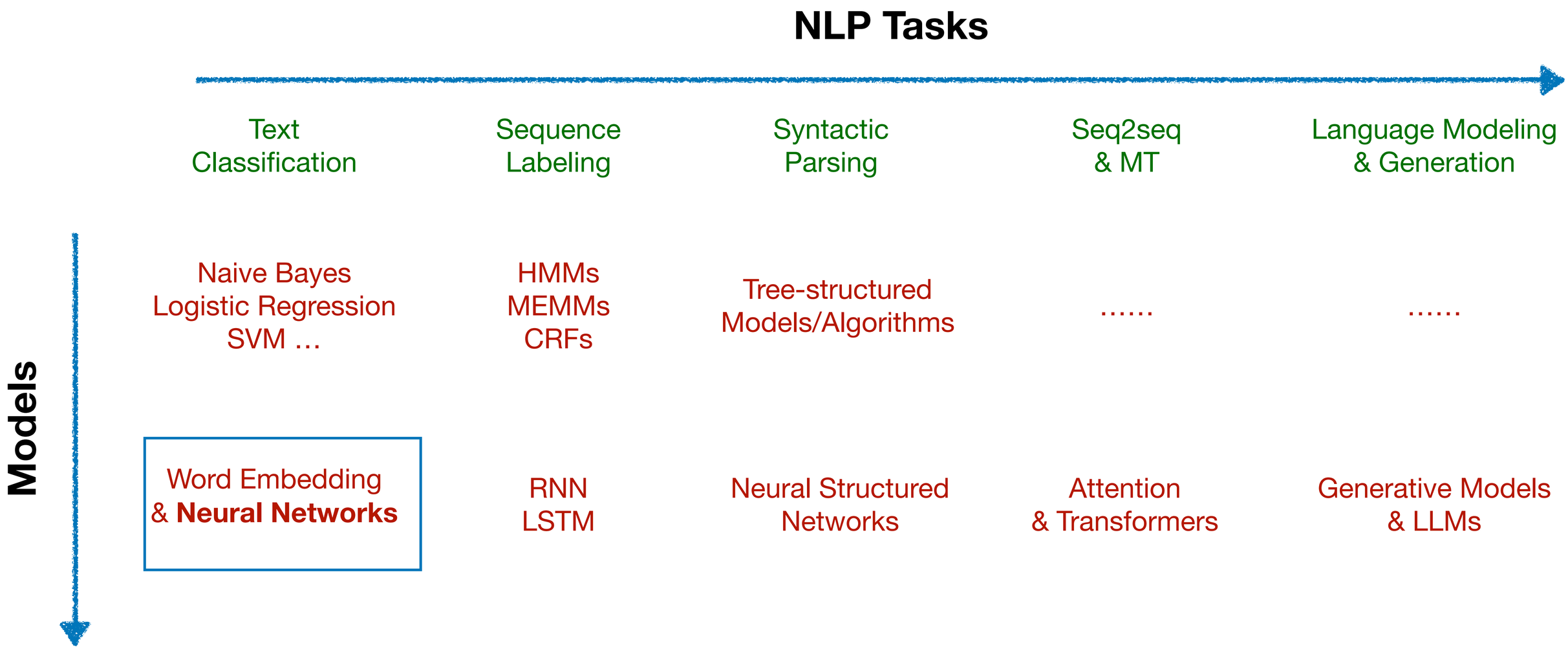
Deep Neural Networks for NLP

Xuezhe Ma (Max)



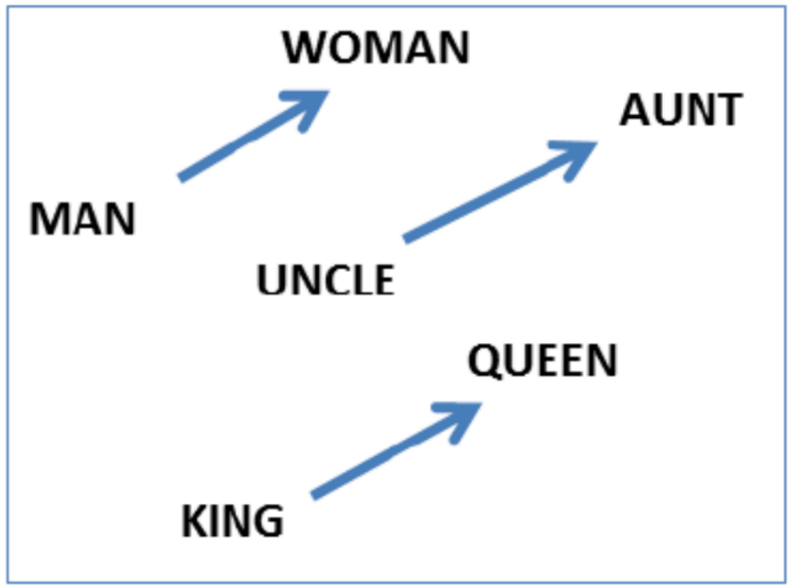
USC University of Southern California

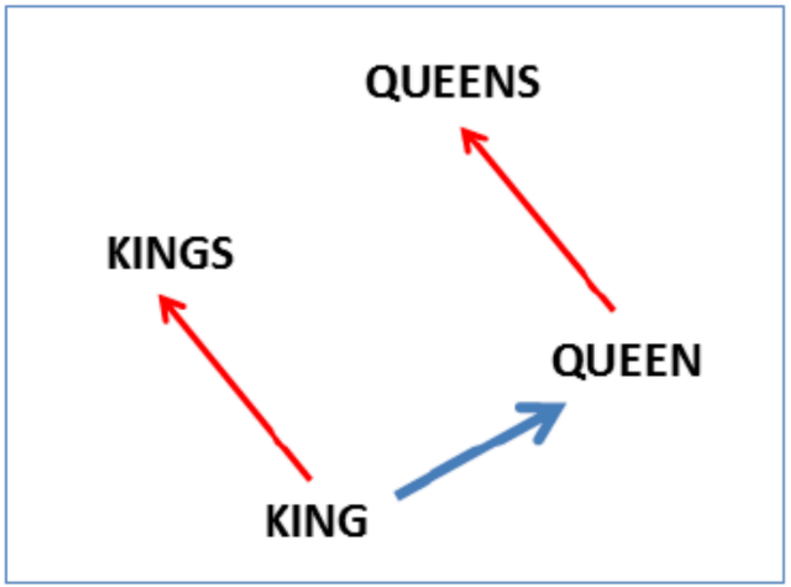
Course Organization



Recap: Problems of Traditional Text Classification

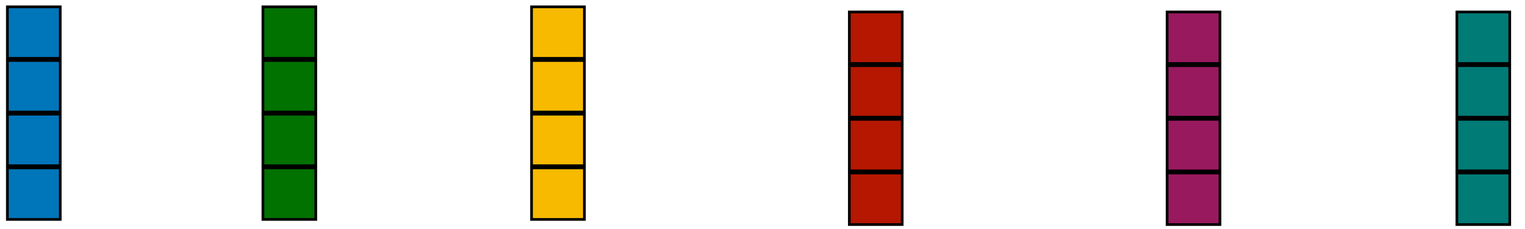
- **Insufficient attention on feature representations**
  - Bag of words & TF-IDF
  - Only frequency information, not semantic meaning of each word (last lecture)
  - No contextual information (this lecture)





Apply Word Embeddings to Tasks

- **Classification**
  - We need a single feature vector to feed into ML classifiers



I **am** **a** **student** **at** **USC**

Element-wise pooling: $y = \textbf{pool}(x_1, \ldots, x_n)$

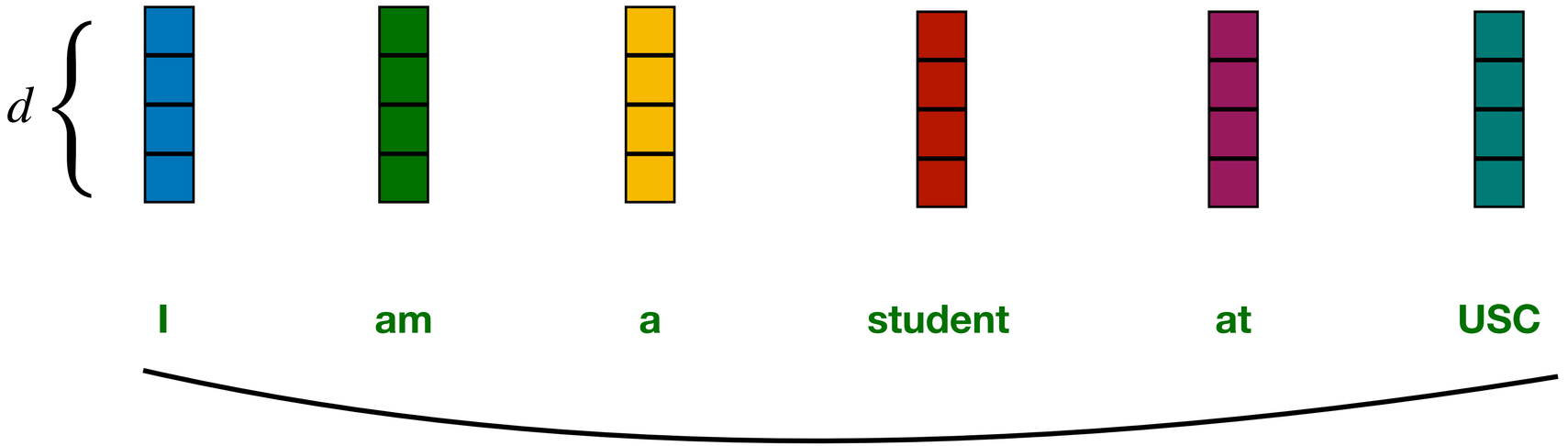
e.g. AVG, MAX

No contextual information!

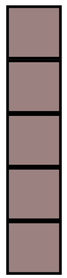
Goal: One Vector to Represent a Document

- **Classification**
  - We need a single feature vector to feed into ML classifiers

$X \in \mathbb{R}^{n \times d}$ Word Embeddings



$$y = f(x_1, \ldots, x_n) \in \mathbb{R}^{d'}$$



Contextual information in y!

Compositionality

Bat

hit bat

hit with bat

It is (almost) infeasible to manually define semantic compositionality

Goal: One Vector to Represent a Document

- **Classification**
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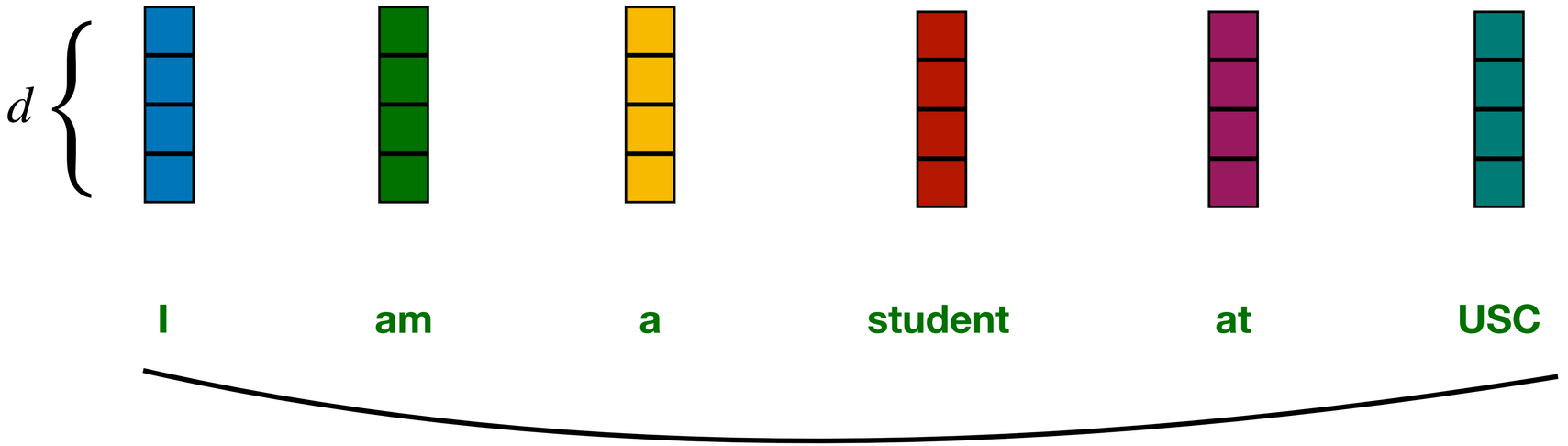
$X \in \mathbb{R}^{n \times d}$ Word Embeddings



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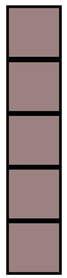


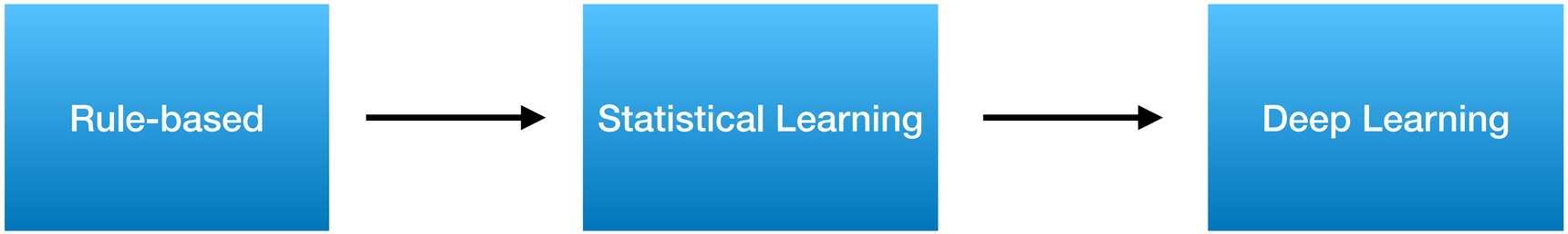
Contextual information in y!

Feature Representations:

Engineering vs. Learning

Why deep learning?

Evolution of NLP



1950 **1990** **2010**

manually design rules

- manually design features
- learn rules

- manually design neural networks
- learn features

more learning, less human knowledge

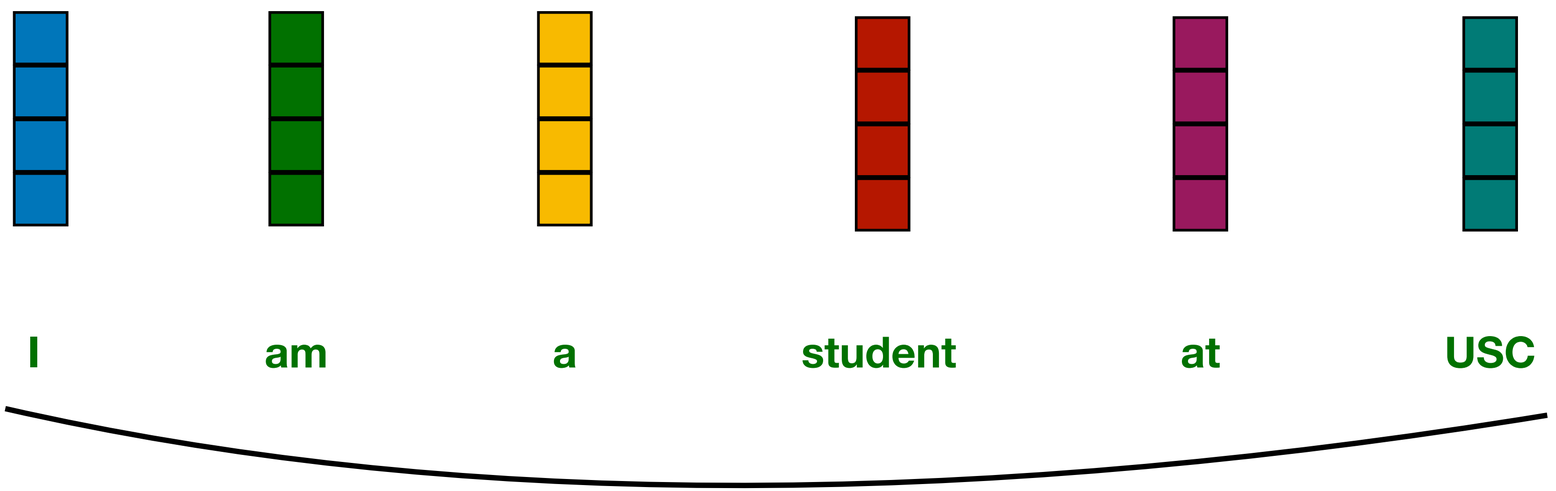
Outline

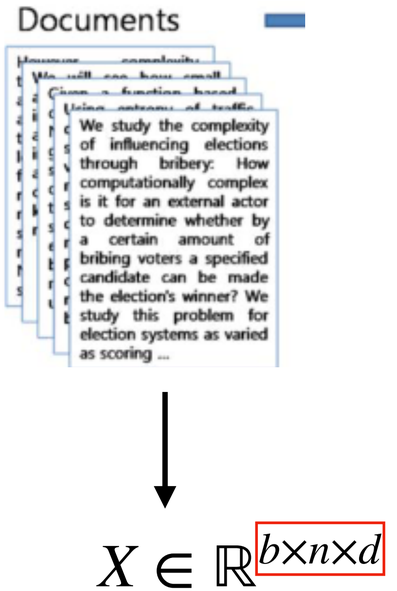
- **A Brief Introduction of Some Neural Networks**
  - Feedforward Neural Networks
  - Convolutional Neural Networks (CNNs)
  - Recurrent Neural Networks (RNNs) (next lecture)

Deep Neural Networks

Deep Neural Networks: Basic Concepts

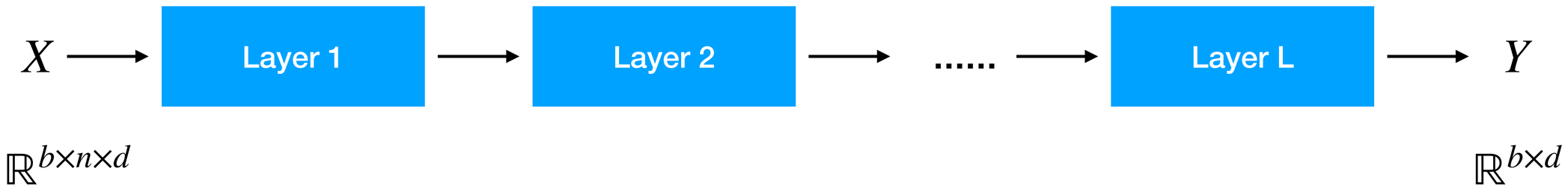
- **The dimension of batch**
  - Each document is a sequence of embedding vectors (one vector per word)
  - We once fead multiple documents to as input a DNN





Deep Neural Networks: Basic Concepts

- **A deep neural network consists of multiple layers**
  - Different layers may have different architectures and serve different purposes
  - Each layer maintains its own (learnable) parameters
  - Each layer may require specific shape of its input X

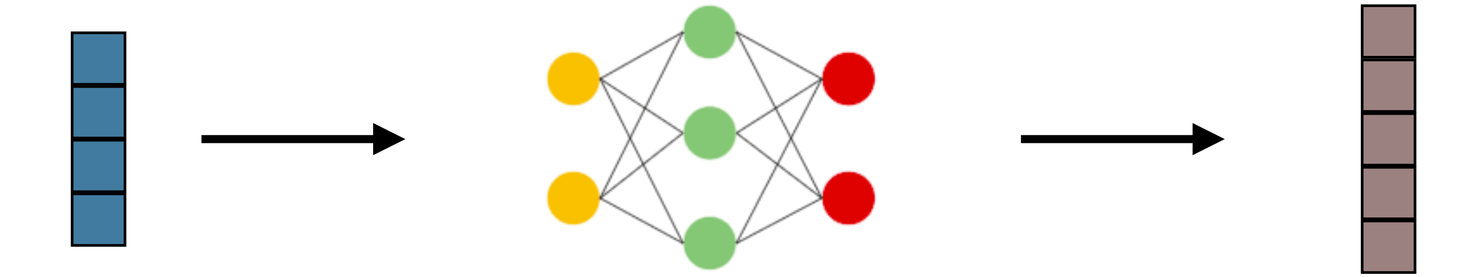


Feedforward Neural Networks

- **One layer of Feedforward neural network**

$$f : \mathbb{R}^d \rightarrow \mathbb{R}^{d'}$$

d and d' are pre-defined hyper-parameters



$X \in \mathbb{R}^d$

$Y \in \mathbb{R}^{d'}$

$$Y = f(X) = \sigma(W \cdot X + b)$$

non-linear function

parameters

Feedforward Neural Networks

- **One layer of Feedforward neural network**

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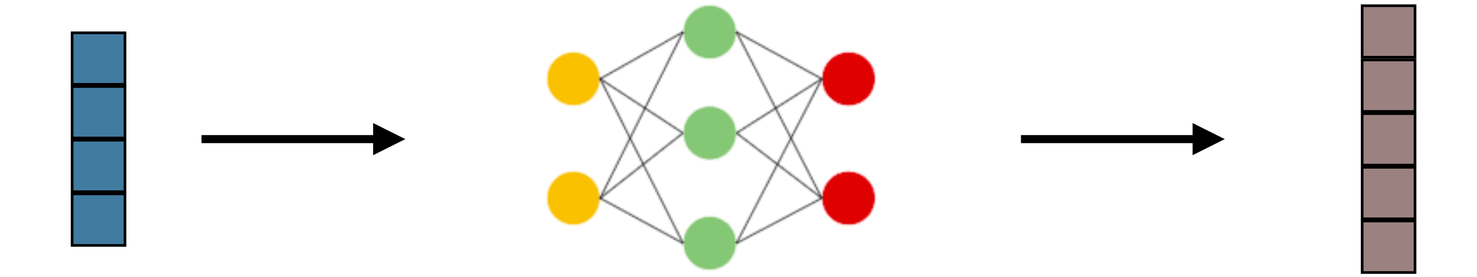


$X \in \mathbb{R}^d$

$Y \in \mathbb{R}^{d'}$

$$Y = f(X) = \sigma(W \cdot X + b)$$

non-linear function

parameters

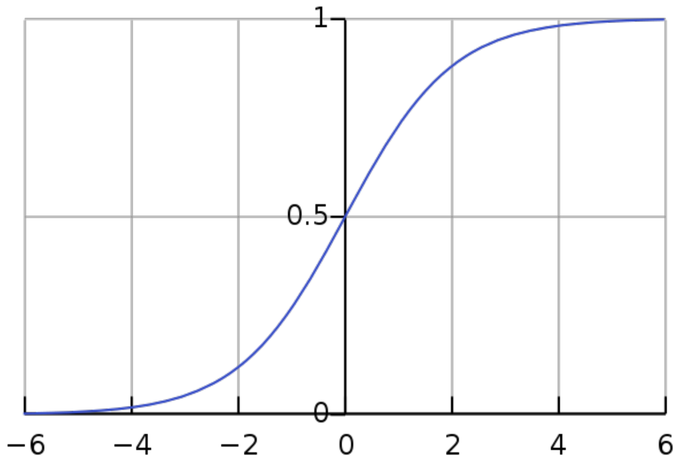
What is the shape of W and b when d, d' are given?

$W \in \mathbb{R}^{d \times d'}$, $b \in \mathbb{R}^{d'}$

Non-linear Functions

- **A.k.a Activation functions**

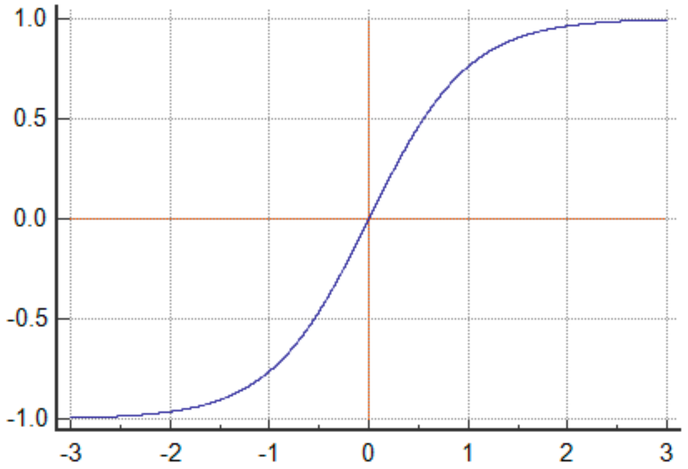
Sigmoid function



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

range $(0,1)$

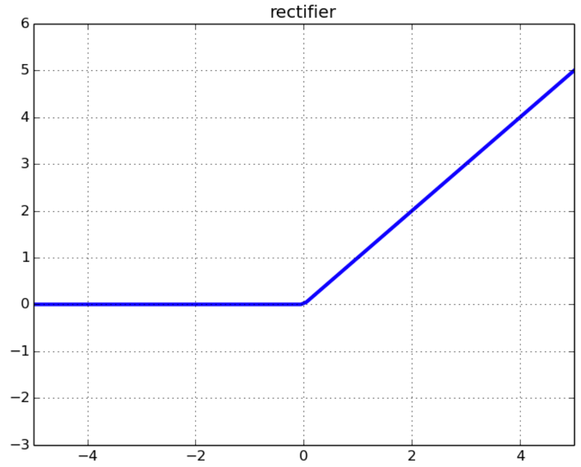
tanh function



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

range $(-1,1)$

ReLU function



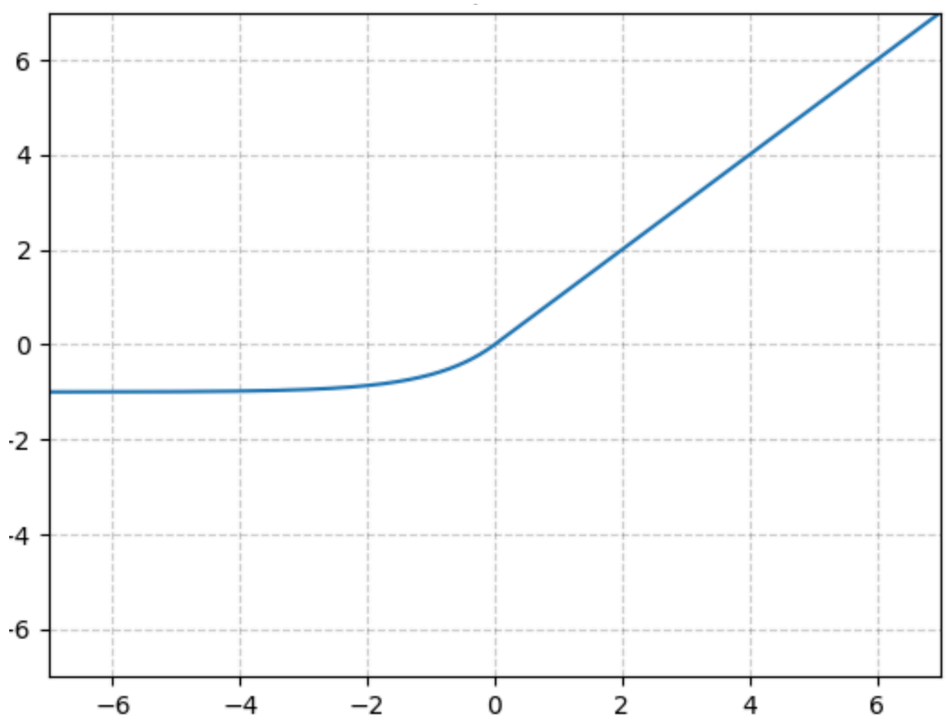
$$x = \max(0,\ x)$$

range $(0,\infty)$

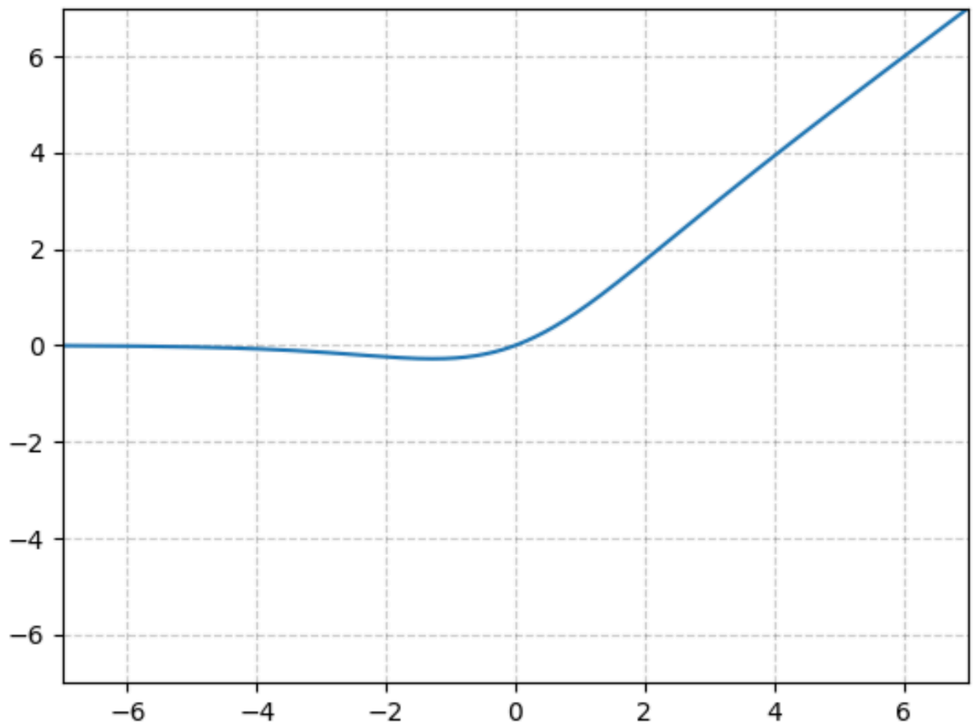
Non-linear Functions

- **Variants of ReLU**

ELU



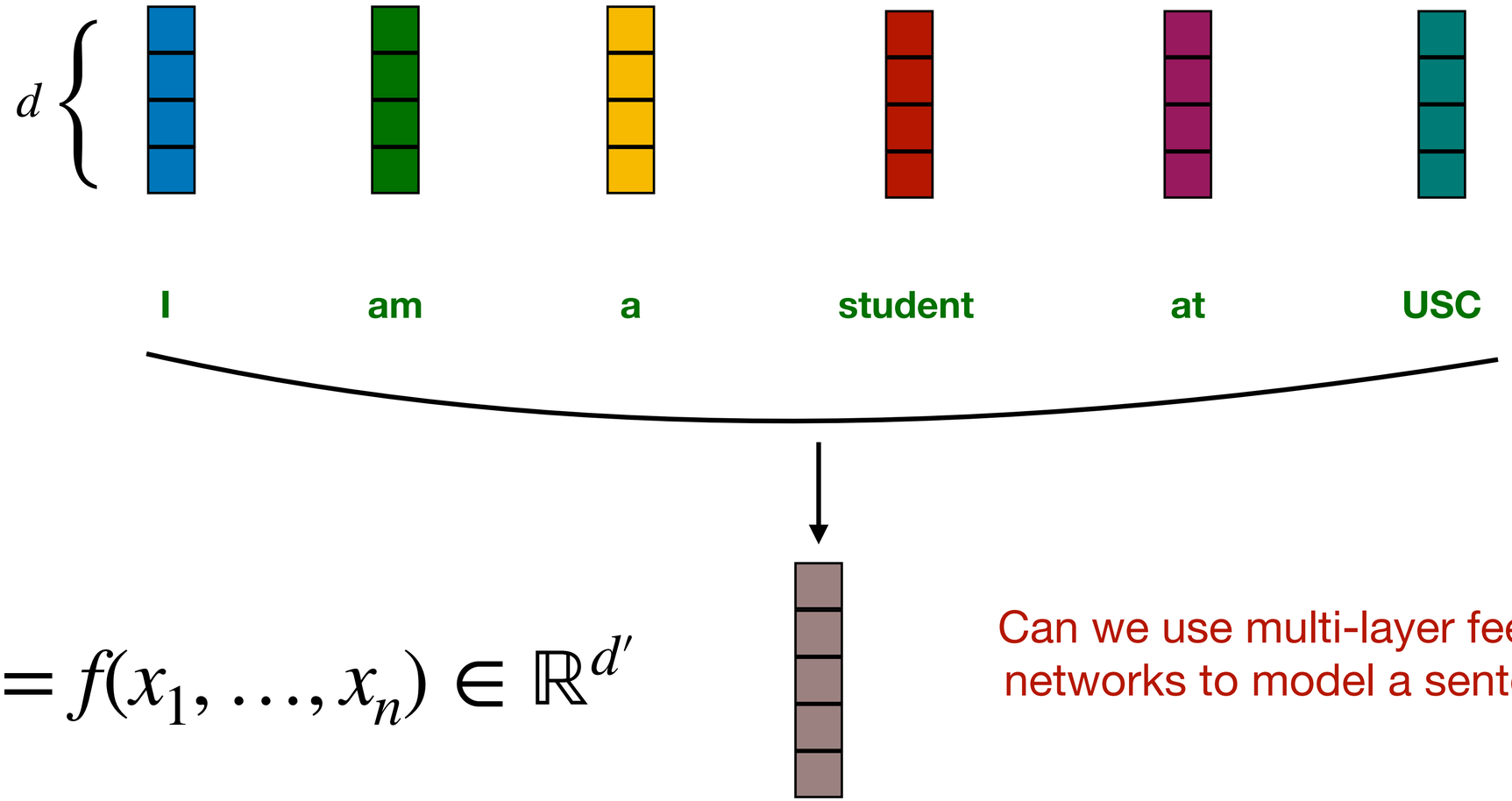
SiLU



Goal: One Vector to Represent a Document

- **Classification**
  - We need a single feature vector to feed into ML classifiers

$X \in \mathbb{R}^{n \times d}$ Word Embeddings



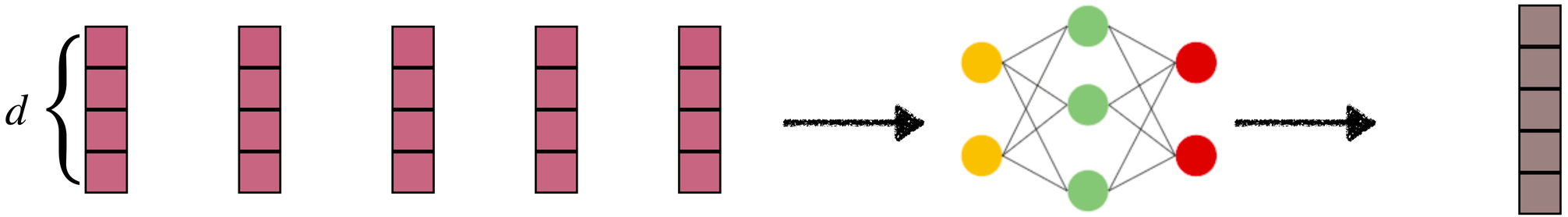
$$y = f(x_1, \ldots, x_n) \in \mathbb{R}^{d'}$$

Can we use multi-layer feed forward neural networks to model a sentence/document?

FeedForward Networks for Our Goal?

$X \in \mathbb{R}^{n \times d}$ Word Embeddings

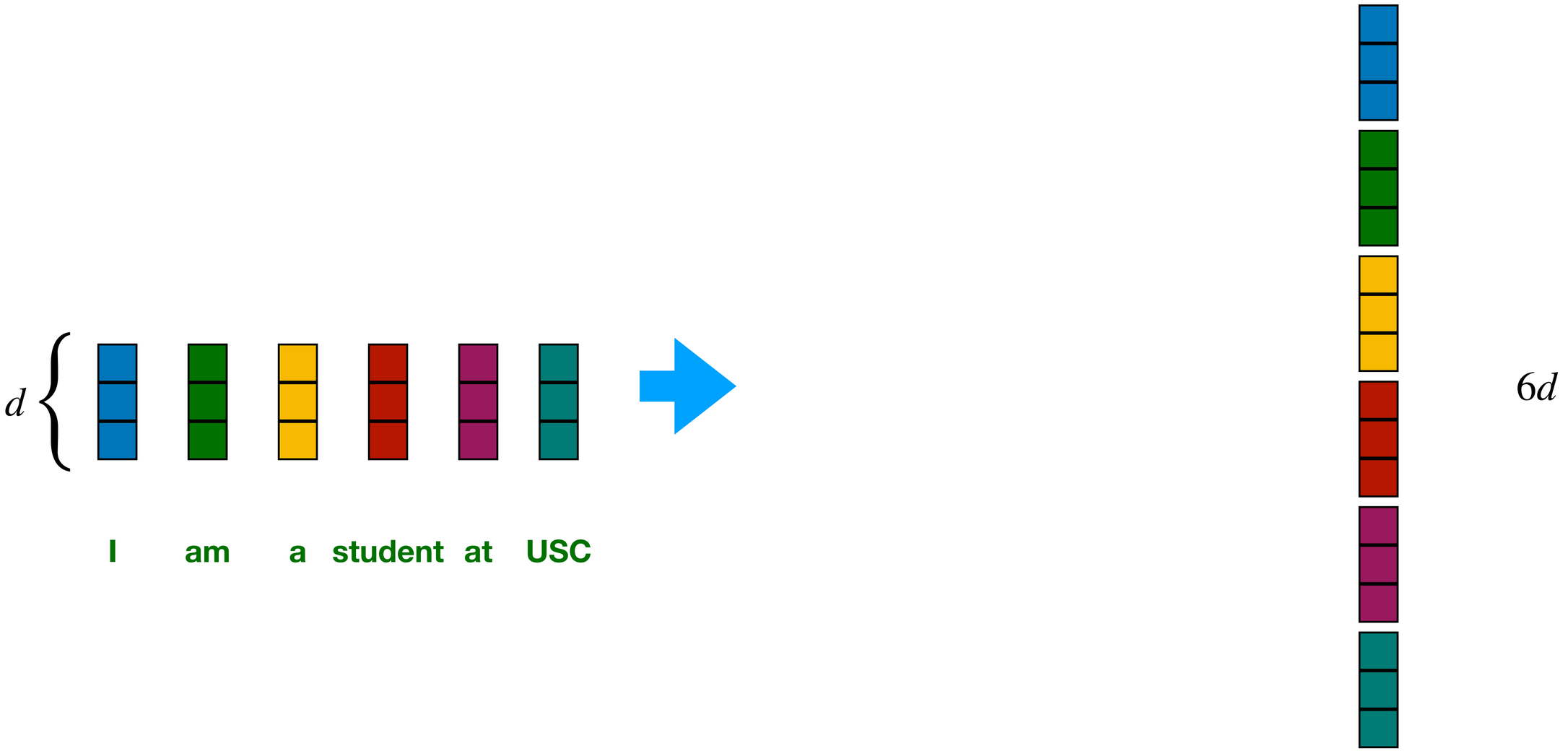
$Y \in \mathbb{R}^{d'}$



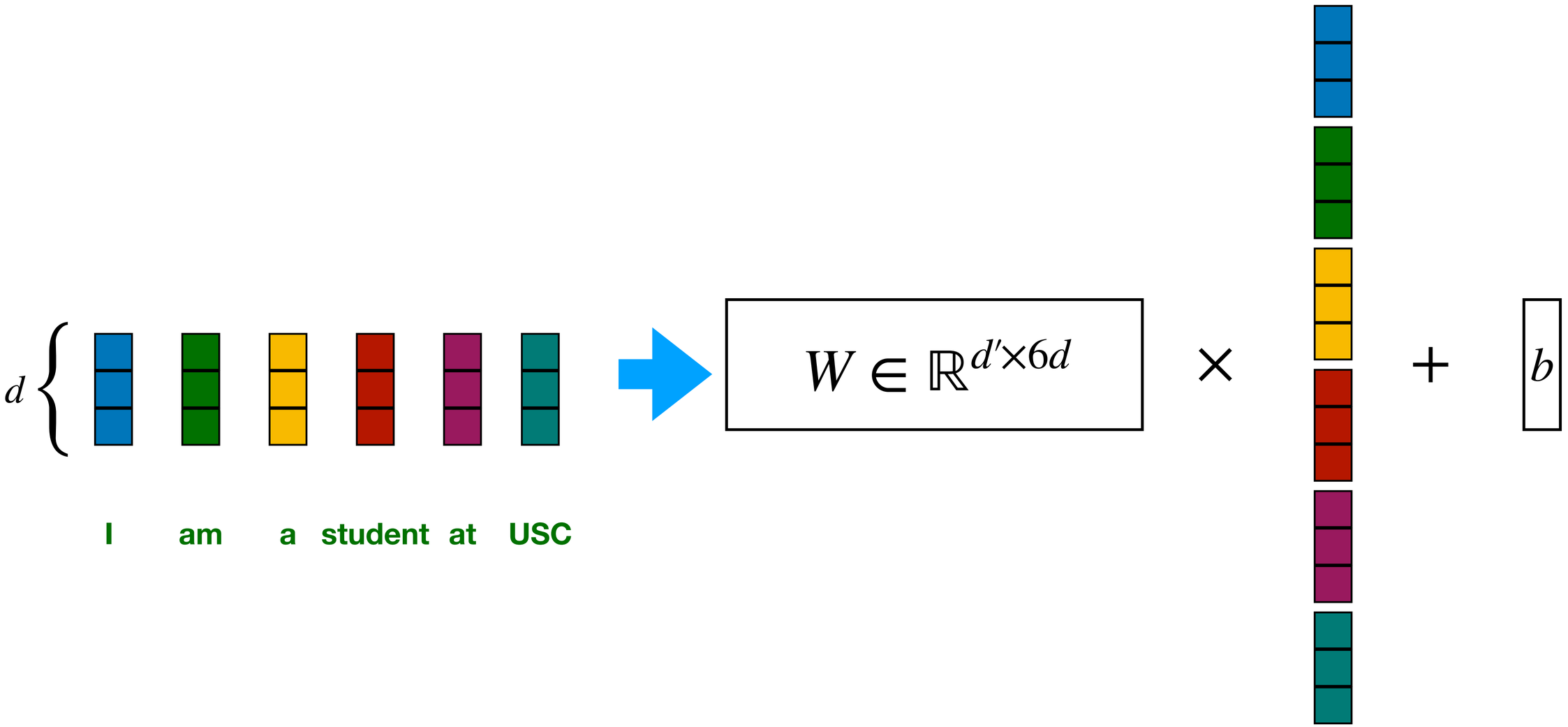
Max is working at USC

Simple Solution: flatten X to a one-dimensional vector, then feed it into a FFN?

FeedForward Networks for Our Goal?

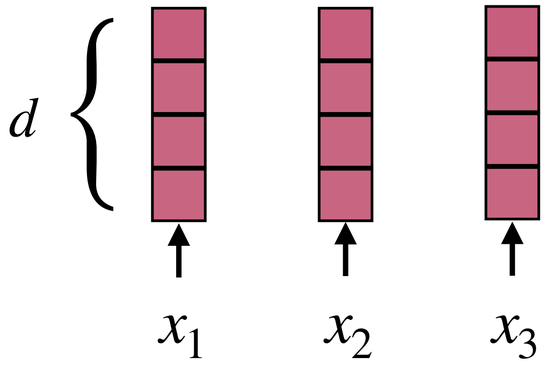


FeedForward Networks for Our Goal?



Modeling Sentences with Various Lengths

- **FFNs cannot model sentences with various lengths.**
  - The input and output dimensions need be pre-defined for each layer



$$f : \mathbb{R}^{3\times d} \rightarrow \mathbb{R}^{d'}$$

$$X \in \mathbb{R}^{3\times d}$$

Modeling Sentences with Various Lengths

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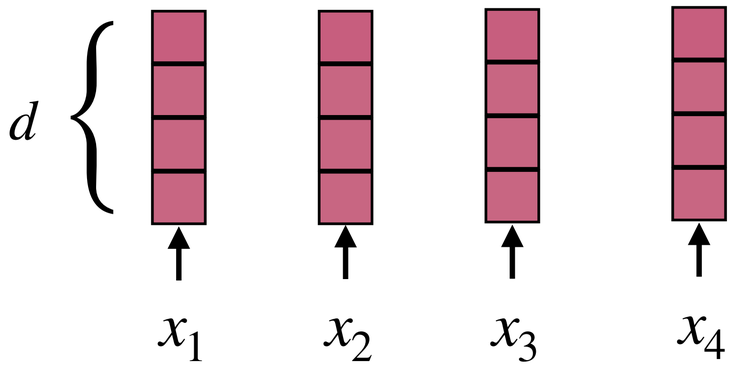
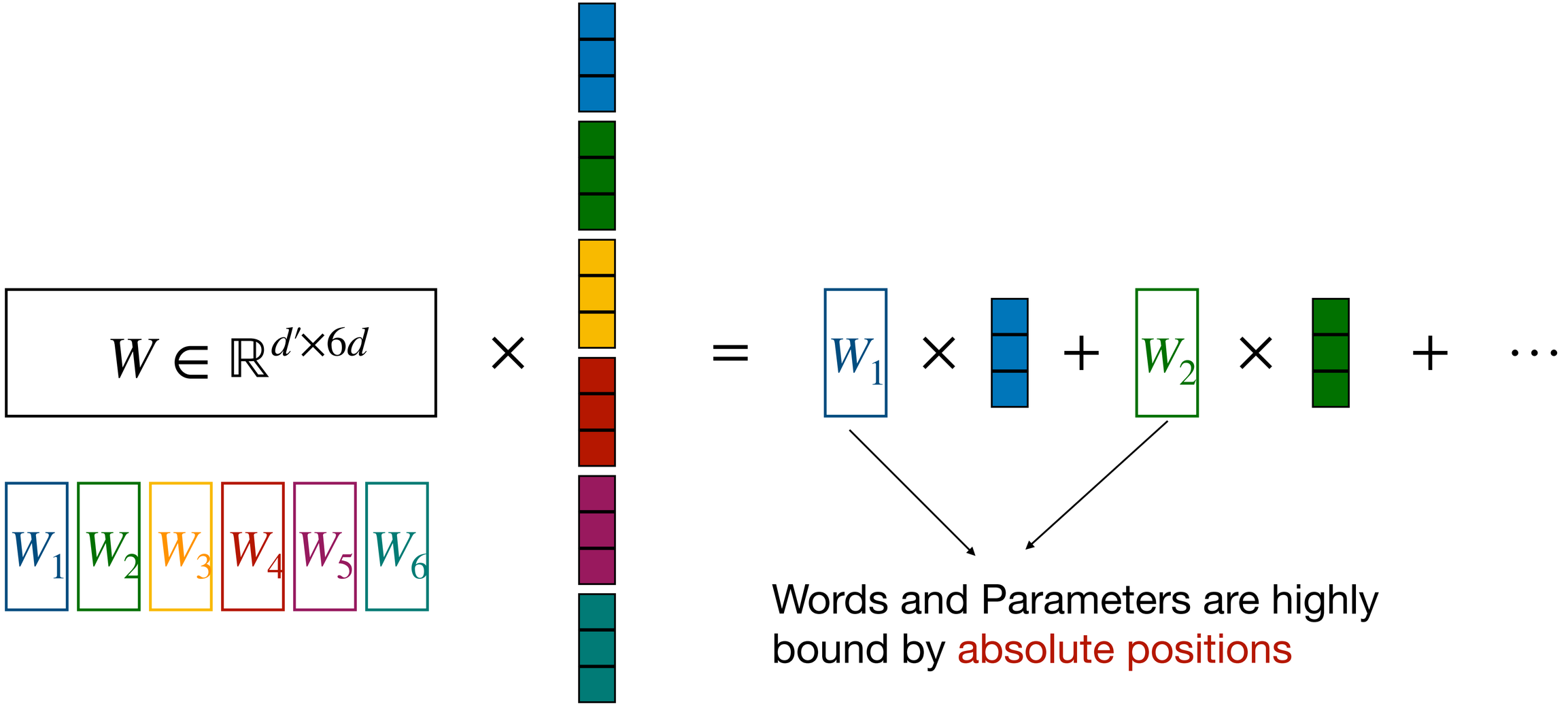


$$f : \mathbb{R}^{3\times d} \rightarrow \mathbb{R}^{d'}$$

$$X \in \mathbb{R}^{4\times d}$$

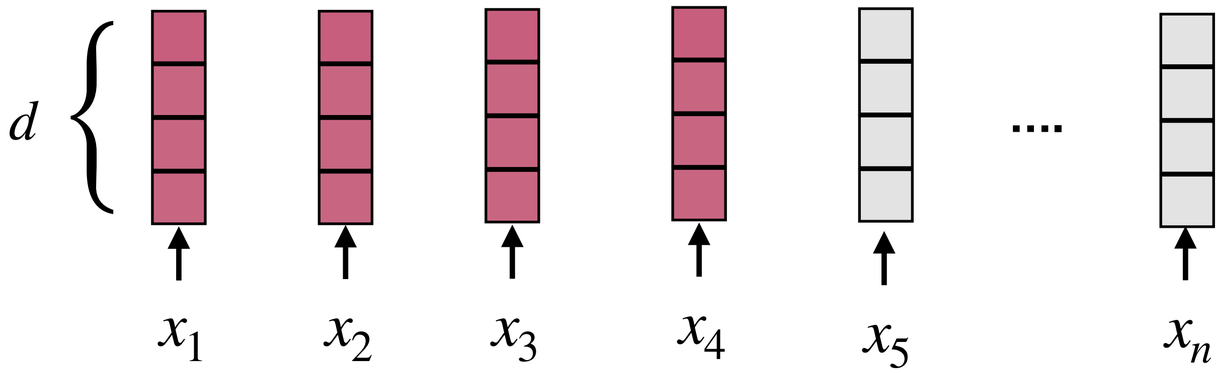
Why not set a maximum length?

FeedForward Networks for Our Goal?



Modeling Sentences with Various Lengths

- **FFNs cannot model sentences with various lengths.**
  - The input and output dimensions need be pre-defined for each layer
  - The parameter W would be too large for long sentences $W \in \mathbb{R}^{n \times d \times d'}$



$X \in \mathbb{R}^{n \times d}$

Why not applying FFN on each vector individually?

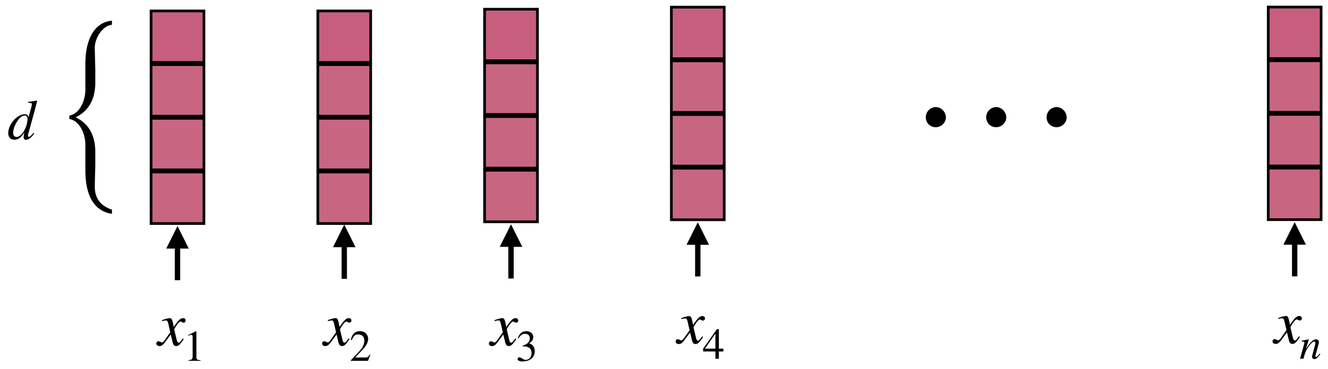
Still no context information!

Convolutional Neural Networks (CNNs)

- **Basic Idea:** only model a segment of input with fixed window-size

$$f : \mathbb{R}^{k \times d} \rightarrow \mathbb{R}^{d'}$$ k is the window size

shape of the parameter W is $\mathbb{R}^{k \times d \times d'}$



$$X \in \mathbb{R}^{n \times d}$$

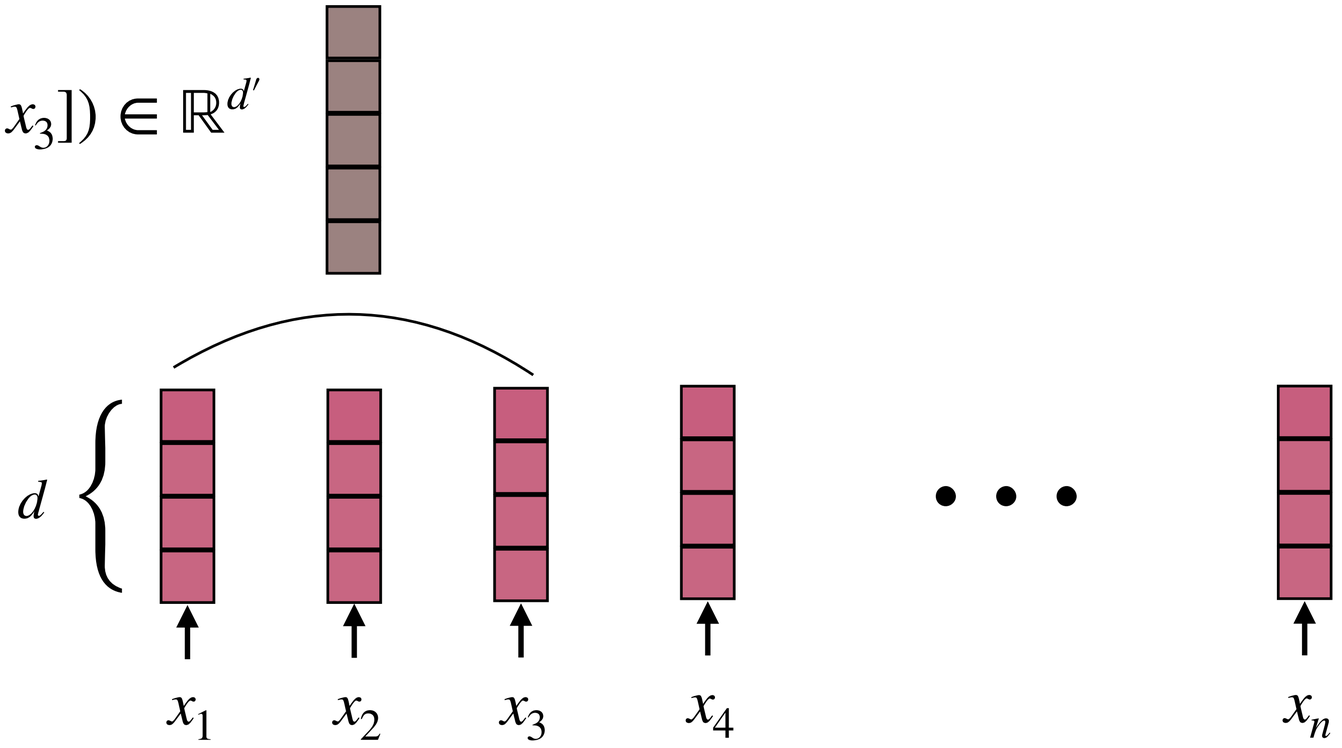
Convolutional Neural Networks (CNNs)

- **Basic Idea:** only model a segment of input with fixed window-size

$f : \mathbb{R}^{k \times d} \rightarrow \mathbb{R}^{d'}$ k is the window size

$k = 3$

$y_1 = f([x_1, x_2, x_3]) \in \mathbb{R}^{d'}$



$X \in \mathbb{R}^{n \times d}$

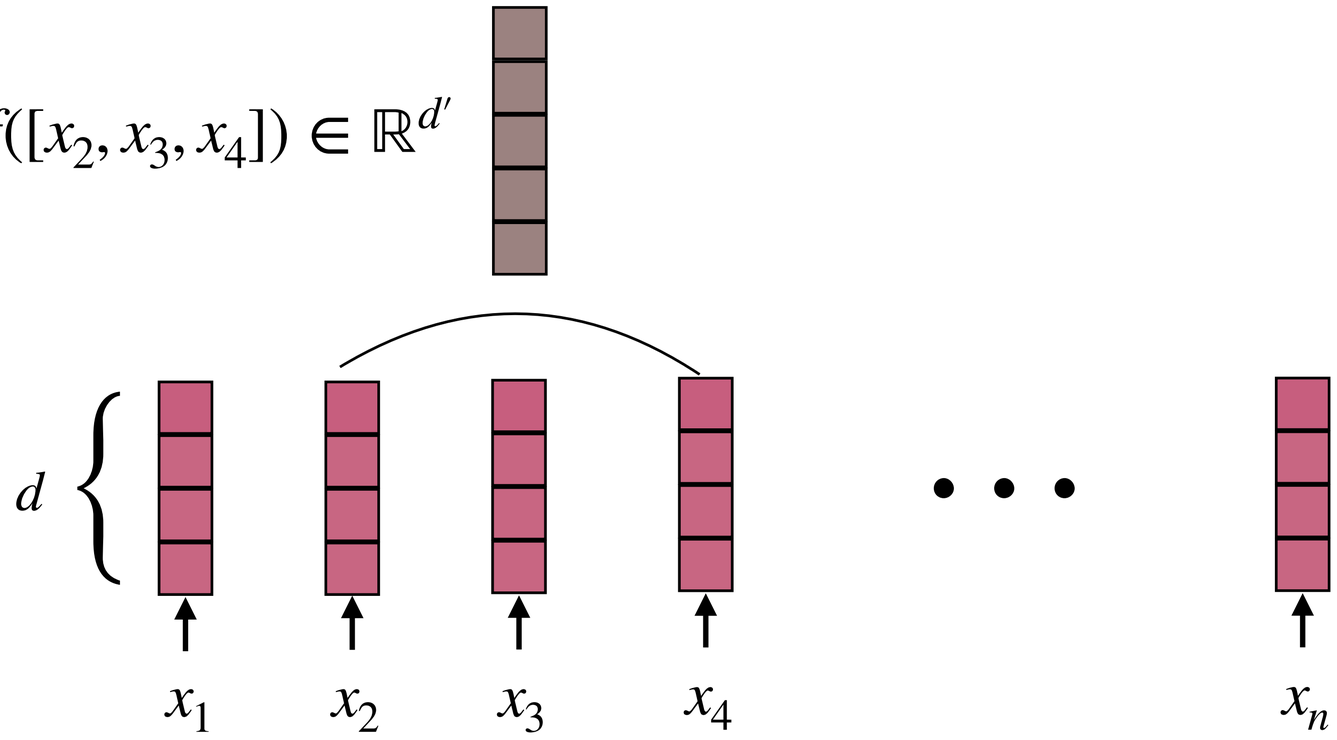
Convolutional Neural Networks (CNNs)

- **Basic Idea:** only model a segment of input with fixed window-size

$f : \mathbb{R}^{k \times d} \rightarrow \mathbb{R}^{d'}$ k is the window size

$k = 3$

$y_2 = f([x_2, x_3, x_4]) \in \mathbb{R}^{d'}$



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Convolutional Neural Networks (CNNs)

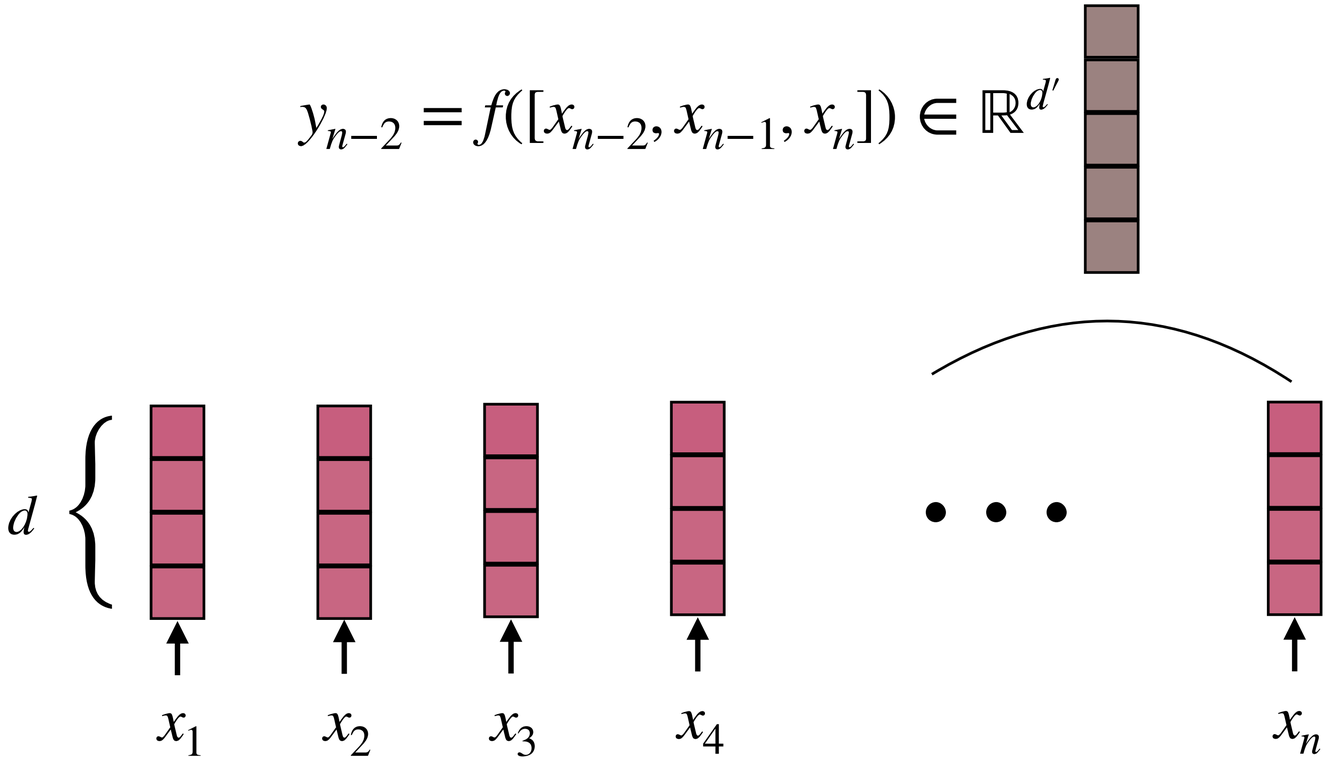
- **Basic Idea:** only model a segment of input with fixed window-size

$k = 3$

$$f : \mathbb{R}^{k \times d} \rightarrow \mathbb{R}^{d'}$$

k is the window size

$$y_{n-2} = f([x_{n-2}, x_{n-1}, x_n]) \in \mathbb{R}^{d'}$$



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Convolutional Neural Networks (CNNs)

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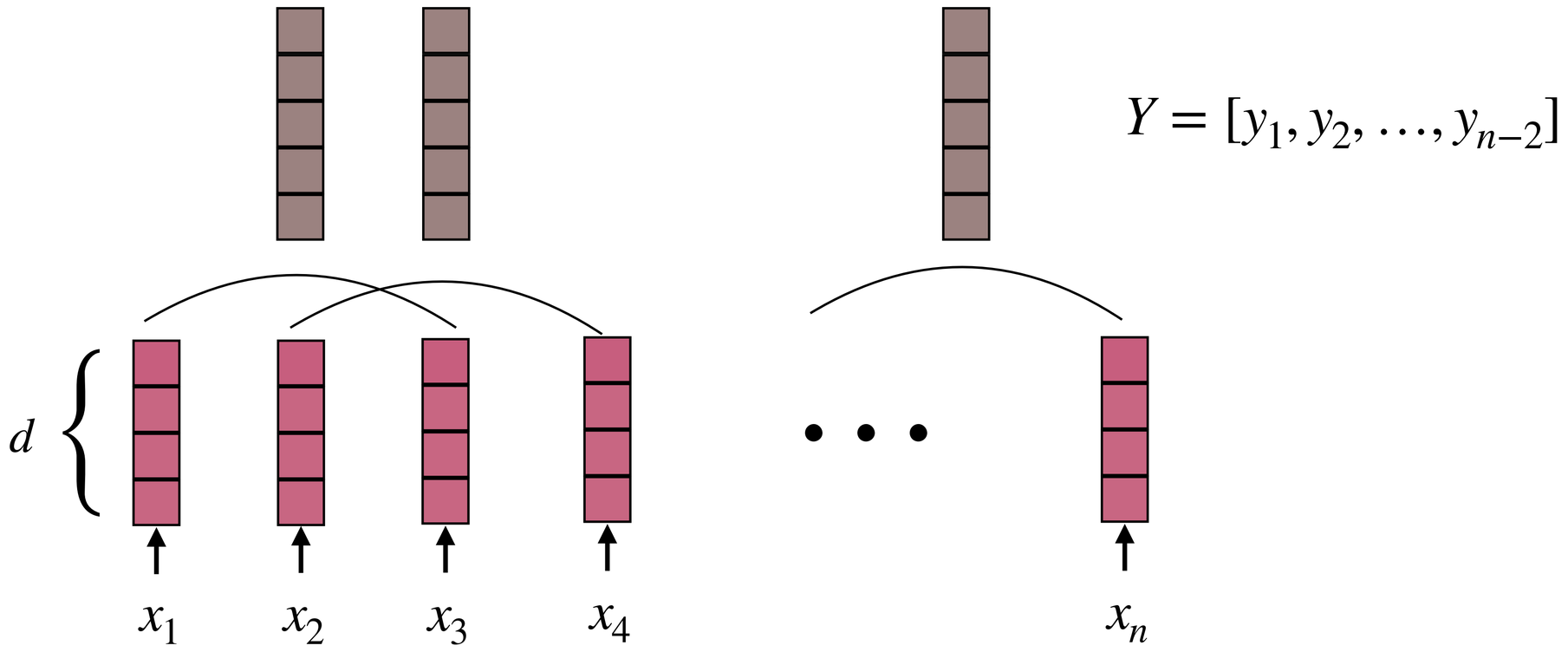

$Y = [y_1, y_2, \ldots, y_{n-2}]$

$X \in \mathbb{R}^{n \times d}$

Convolutional Neural Networks (CNNs)

- **Basic Idea:** only model a segment of input with fixed window-size

$k = 3$

$f : \mathbb{R}^{k \times d} \rightarrow \mathbb{R}^{d'}$

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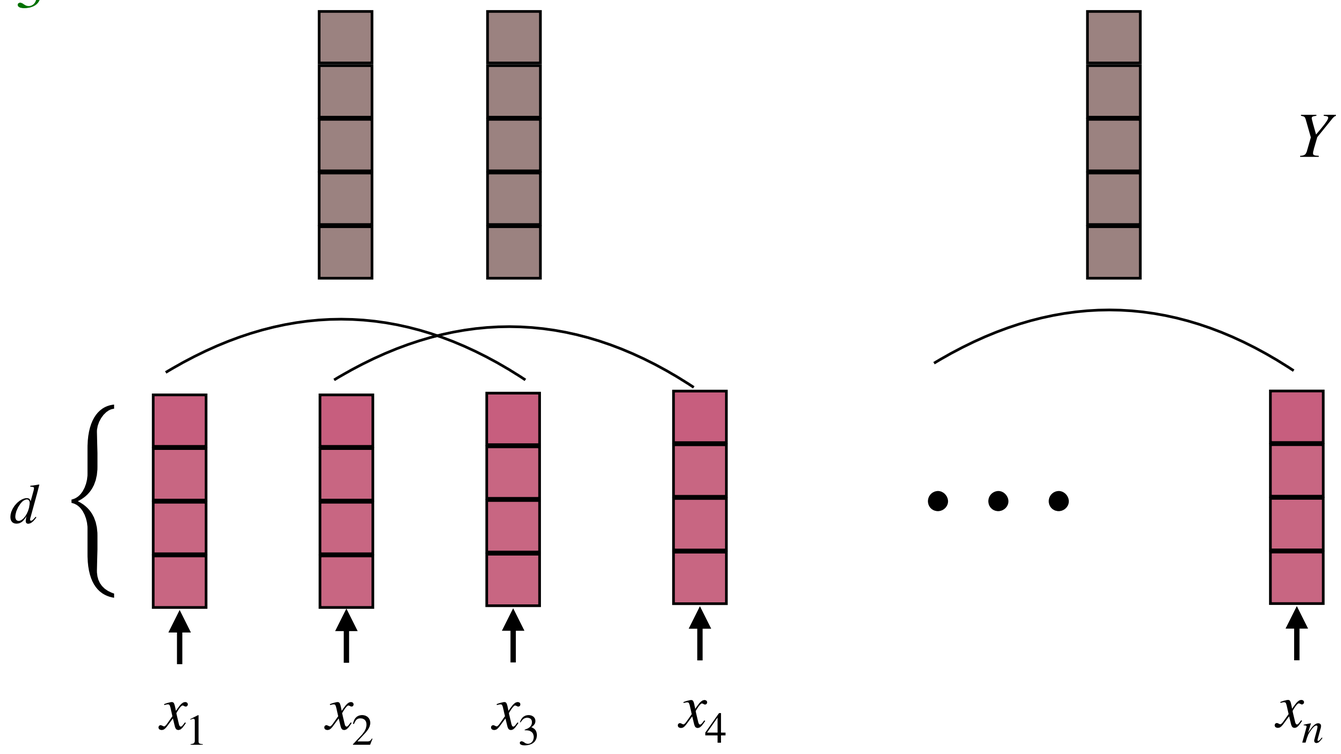

$Y = [y_1, y_2, \ldots, y_{n-2}]$

What if we want Y contains n vectors?

$X \in \mathbb{R}^{n \times d}$

Convolutional Neural Networks (CNNs)

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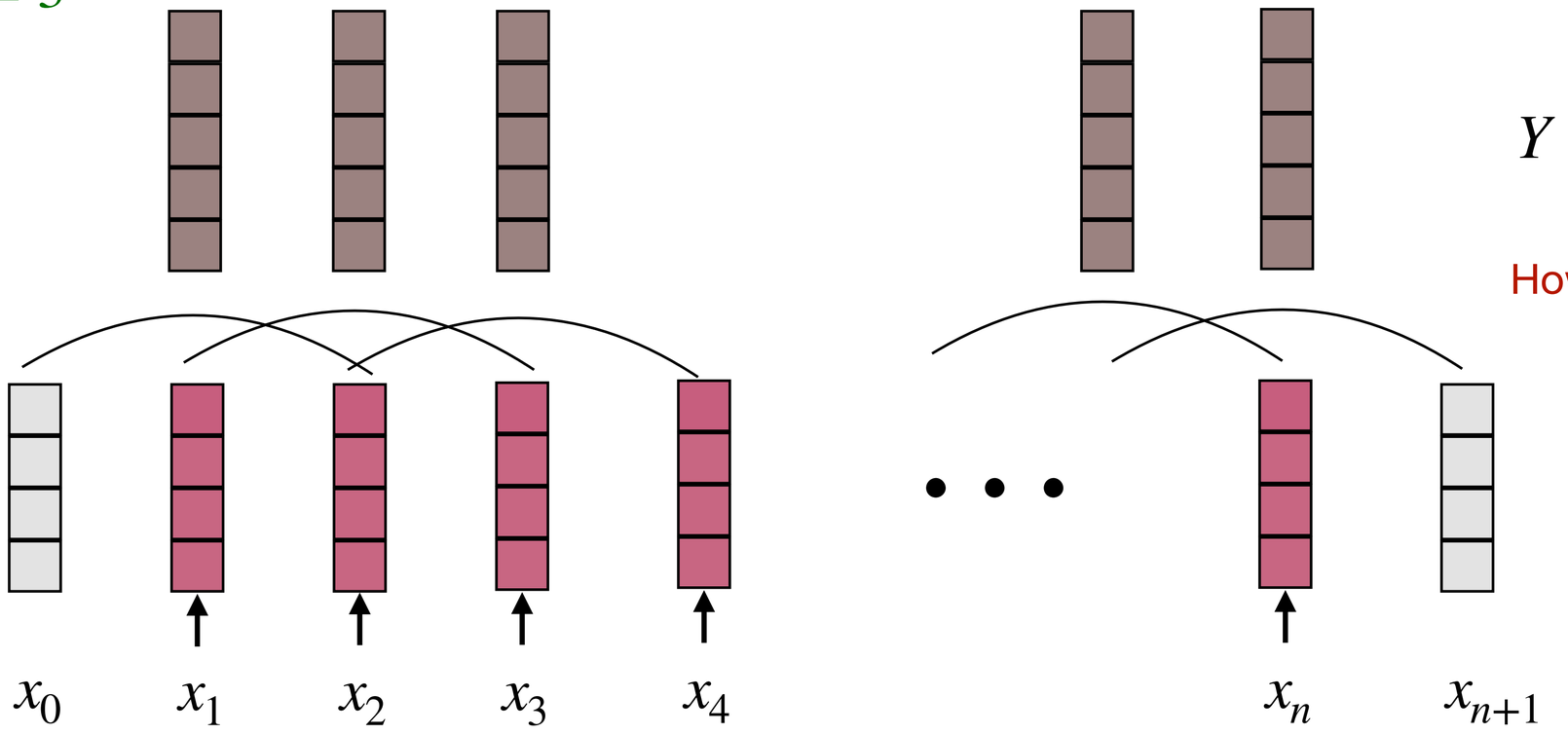


$Y = [y_1, y_2, \ldots, y_n] \in \mathbb{R}^{n \times d'}$

How to compress Y into a single vector?

Pooling!

$X \in \mathbb{R}^{n \times d}$

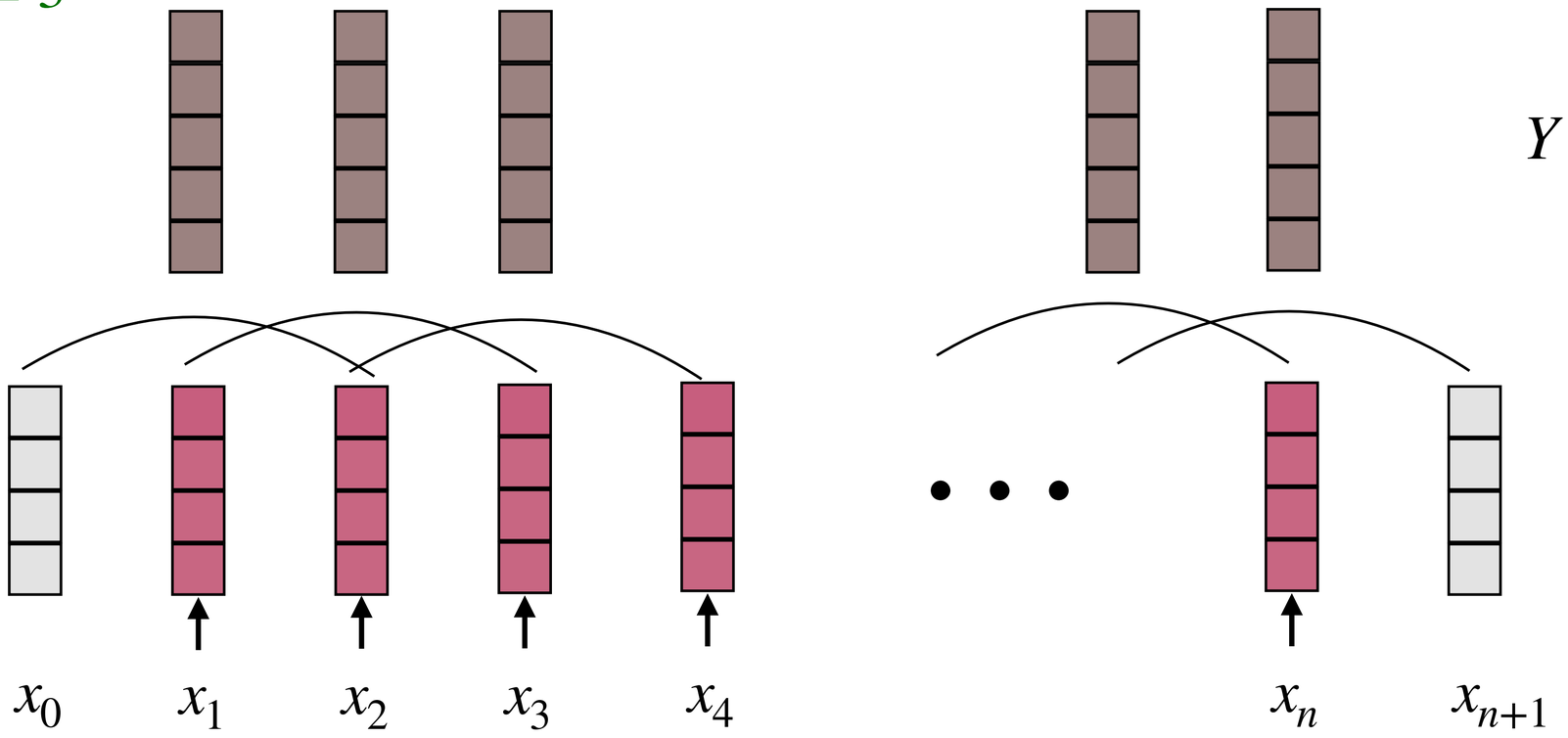
Convolutional Neural Networks (CNNs)

- **Basic Idea:** only model a segment of input with fixed window-size

$k = 3$

$f : \mathbb{R}^{k \times d} \rightarrow \mathbb{R}^{d'}$

k is the window size



$X \in \mathbb{R}^{n \times d}$

$Y = [y_1, y_2, \ldots, y_n] \in \mathbb{R}^{n \times d'}$

Pros:

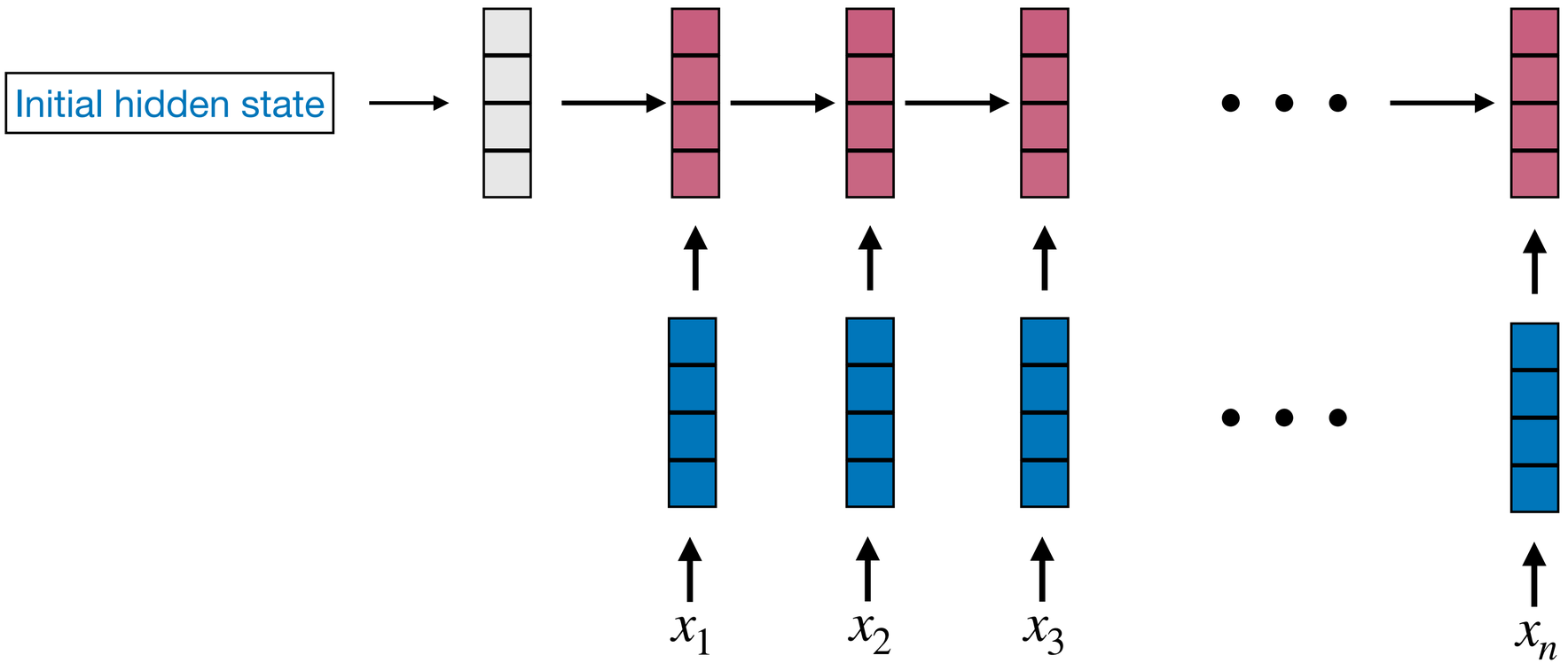
- Simple architecture
- Parallel computation

Cons:

- Small context window
- Not good at modeling long dependencies

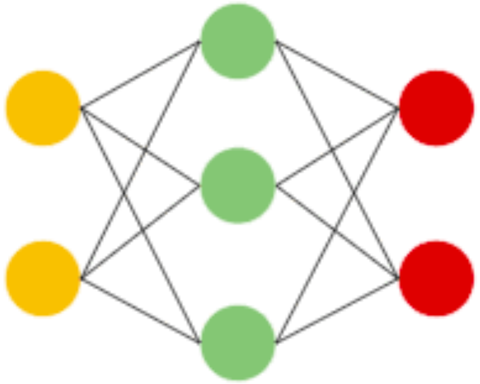
Recurrent Neural Networks

- **Recurrent Neural Networks (RNNs)**
  - Re-using one feed forward network in a recurrent way

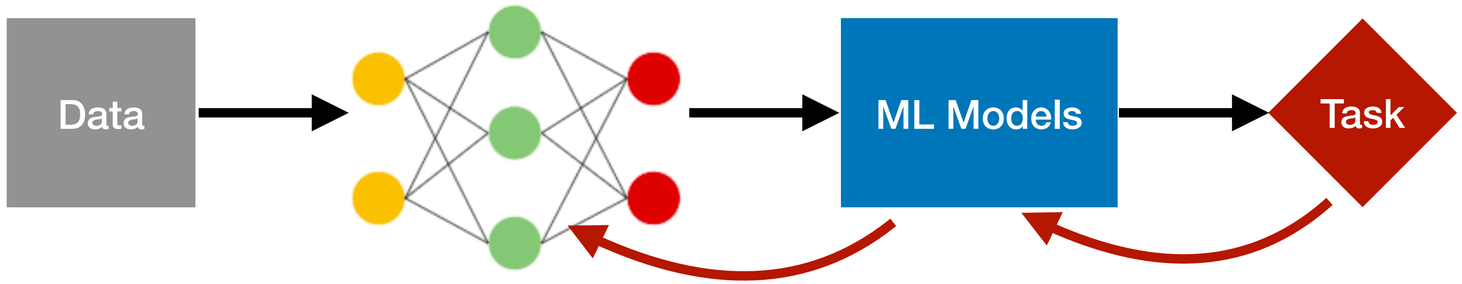


We leave RNN to the next lecture

How to learn a neural network



Deep Learning System



Automatically learning feature representations for the end task

Deep Learning a.k.a Representation Learning

Training a DNN

- **Algorithm: gradient descent in a mini-batch**
  - Batch size is a hyper-parameter
- **Gradient calculation: back-propagation**
  - $W \leftarrow W - \gamma \nabla_W L(X)$
- **Initialization of parameters**
  - Very important!
  - Different layers may have different initialization strategy
  - A commonly used one for FFN: $W \in \mathbb{R}^{d \times d'}$, $W \sim N(0, \frac{1}{\sqrt{d}})$

Back-Propagation

- **One sentence to describe back-propagation**
  - The chain rule of differential/gradient

$$y = f(x) = f(g_1(x), g_2(x), \ldots, g_K(x))$$

$$\nabla_x y = \sum_{j=1}^{K} \nabla_{g_j} y \cdot \nabla_x g_j(x)$$

Back-Propagation: first derive the gradient of each layer (or even each operation), then apply chain rule to compute the gradient of the whole network

Back-Propagation

- **A simple example:**

$$y = (x + 1) \times 2$$

+ operation

x operation

PyTorch implements gradient calculation for the whole set of commonly used operations

Back-Propagation

- **Back-Propagation is NOT the most efficient way to compute gradients**

$$y = f(x) + g(x) - g(x)$$

Manually:

$$\nabla_x y = \nabla f(x)$$

Back-Propagation:

$$\nabla_x y = \nabla f(x) + \boxed{\nabla g(x) - \nabla g(x)}$$

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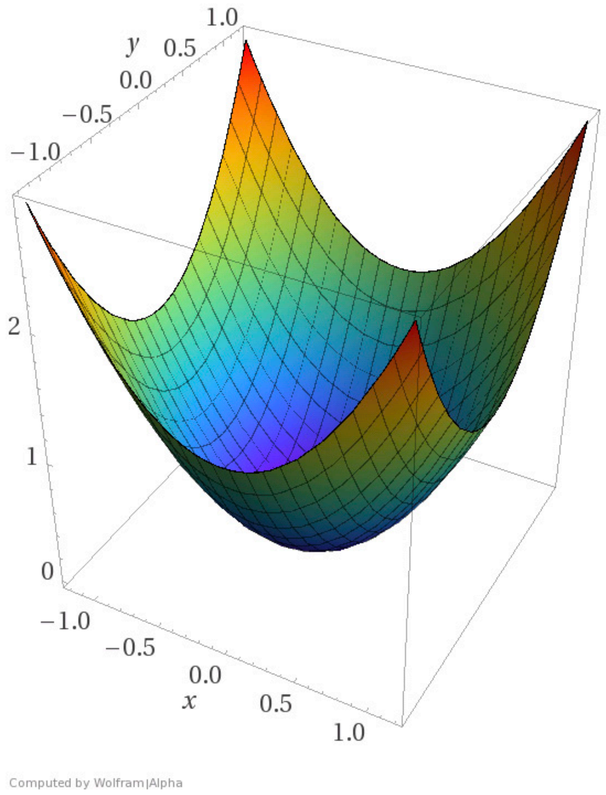
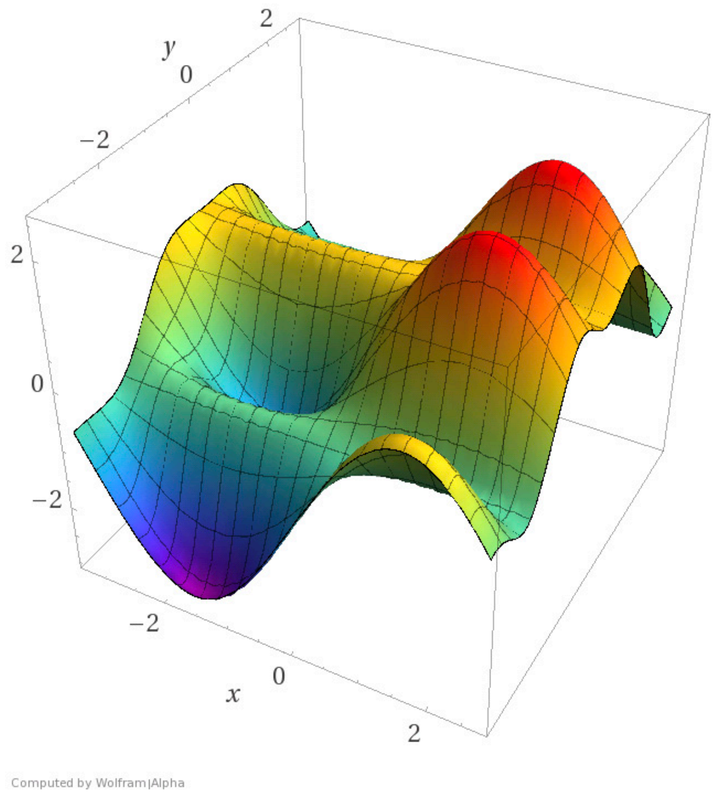
Training a Deep Neural Network is Challenging

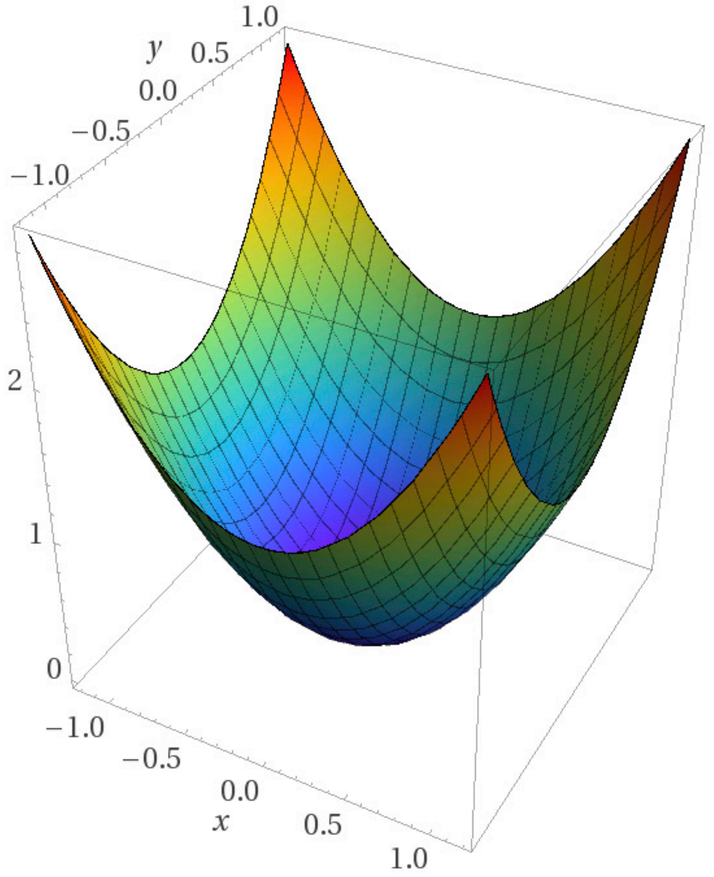
- **DNNs are non-convex**





Training a Deep Neural Network is Challenging

- **Convex optimization is relatively easy**
  - Only one optimal point, which is the global optimum
  - Initialization only impacts converging speed but not convergence point



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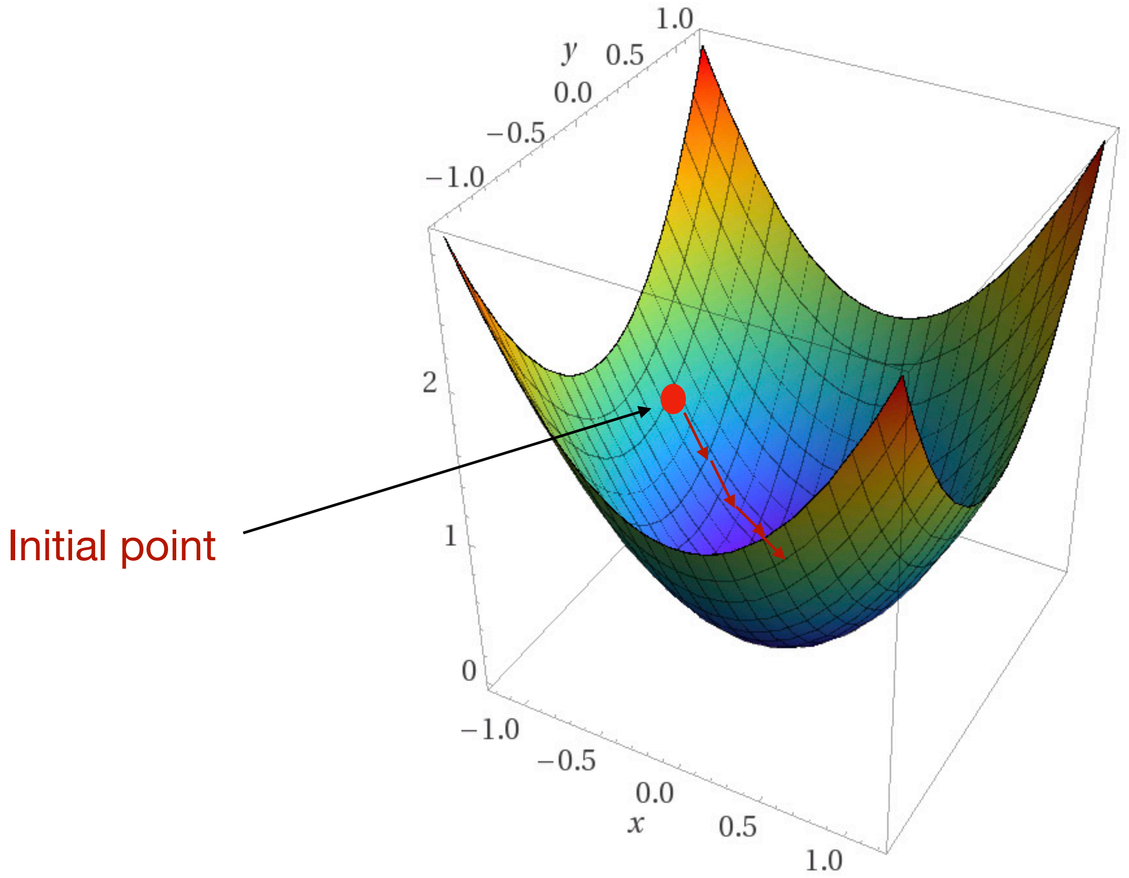

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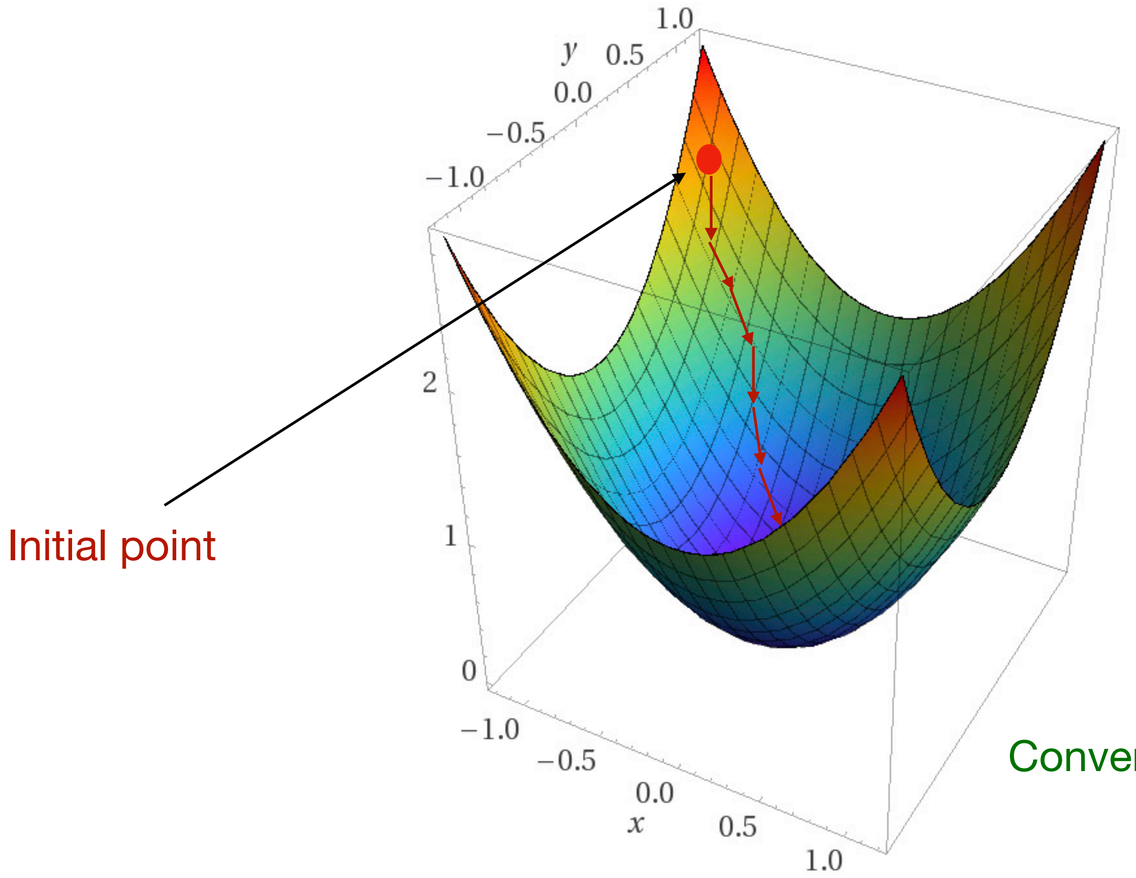
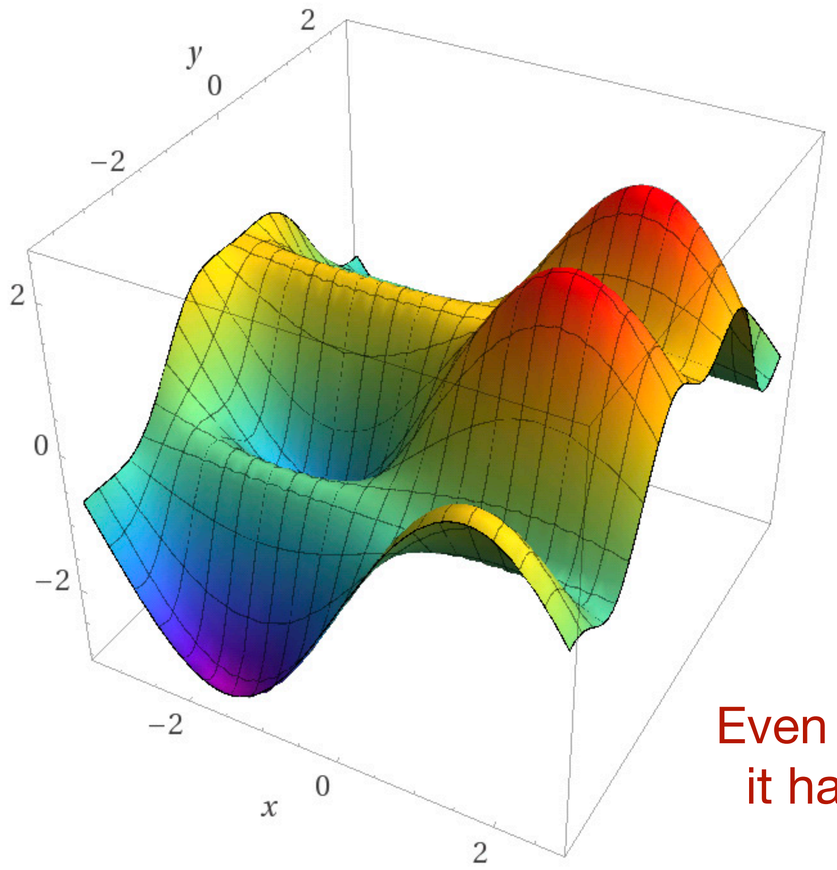


Converge to the same optimum with more steps

Training a Deep Neural Network is Challenging

- **Non-Convex optimization is extremely hard**
  - Multiple local optimal points
  - Initialization impacts the final convergence point



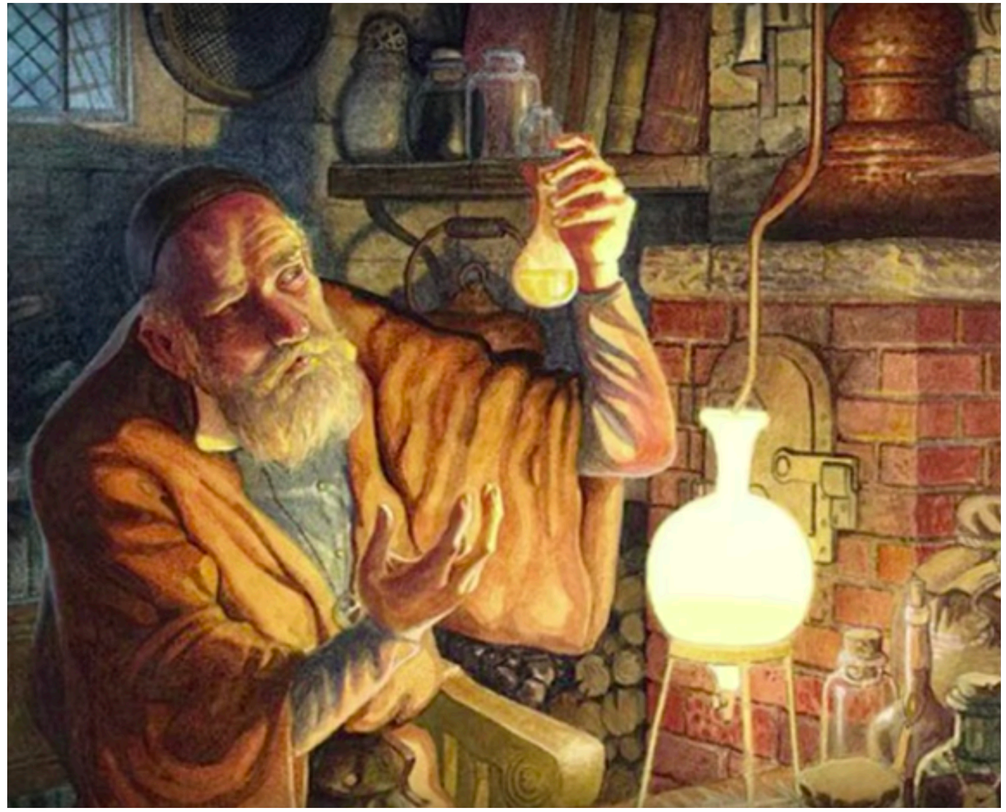
Even the most powerful model, we are not sure if it has converged to the global optimum or not!

Results

	Movie Review	Sentiment Analysis
SVM	77.3	82.9
Tree-CRF	77.7	85.4
CNNs (2-layers)	**81.5**	**87.2**

Before Building Your DNNs

- DNNs are non-convex
- No rigorous theoretical supports, but only empirical evidences



Rahimi@NIPS2017:
Has Deep Learning Become Alchemy?

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Q&A