Women Techmakers

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IWD Extended Summit

Machine Learning with TensorFlow

Who are we?

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Software Engineer at LinkedIn

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Agenda

1. Introduction to ML and Neural Networks

2. Codelab: Sign Language Recognition using TensorFlow

Introduction to ML and Neural Networks

01

What is AI?

At the core of every computer program there is a mathematical function at work. It could be as simple as computing the interest on an outstanding loan or as complex as flying an aircraft on autopilot. *Artificial Intelligence*, or *AI*, is a generic name for a computer program whose core mathematical function has been created (almost) automatically; and *Machine Learning*, or *ML*, refers to a collection of techniques which offer ways of creating AI.

Namit Chaturvedi
(PhD in theoretical computer science,
Applied Research Engineer at LinkedIn)

Types of Machine Learning Problems

Machine Learning

Supervised

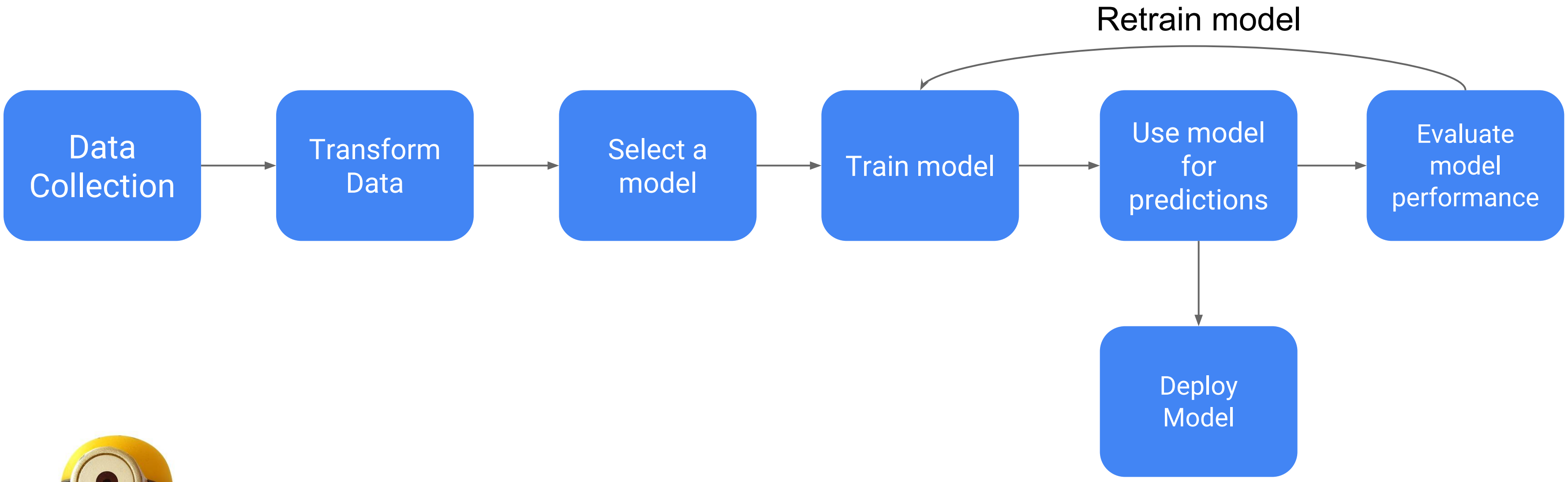
- Classification
- Regression

Unsupervised

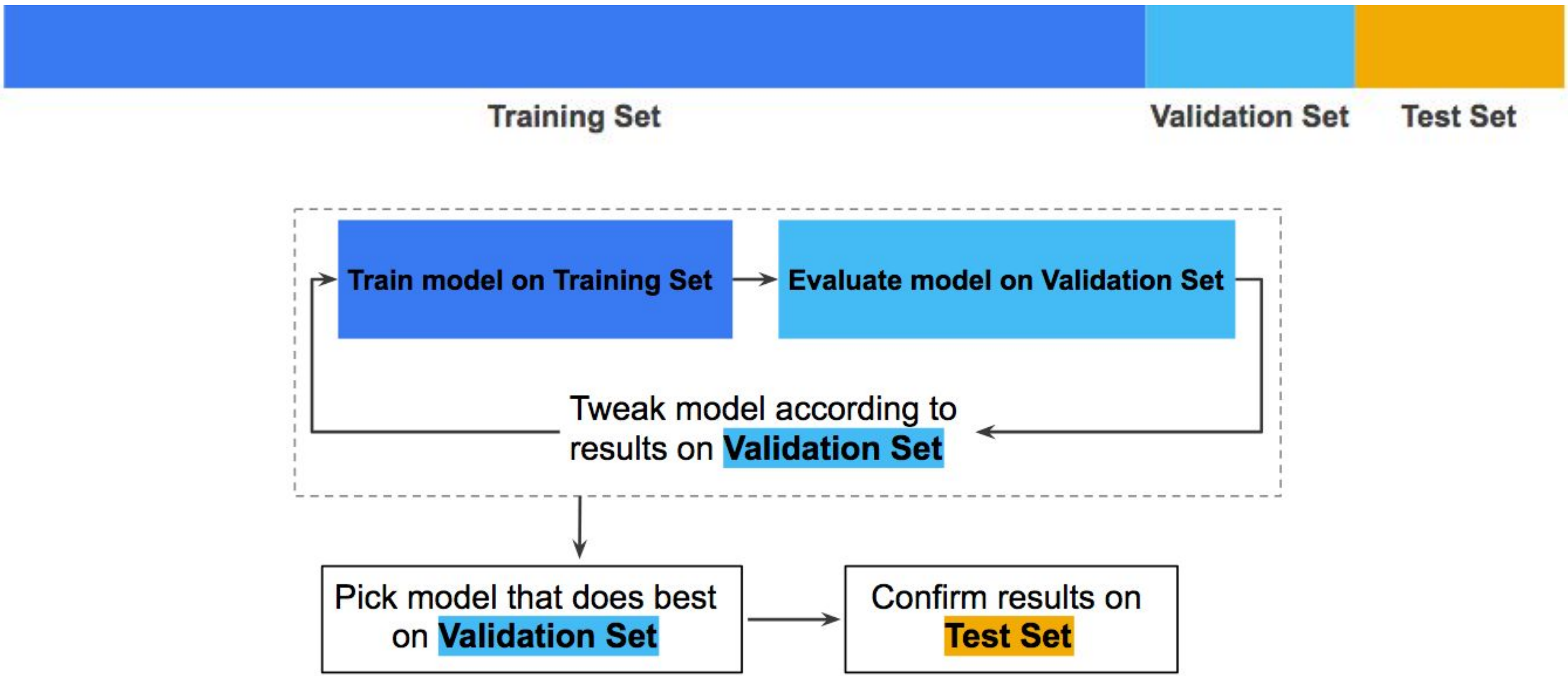
- Clustering
- Association Mining

Reinforcement

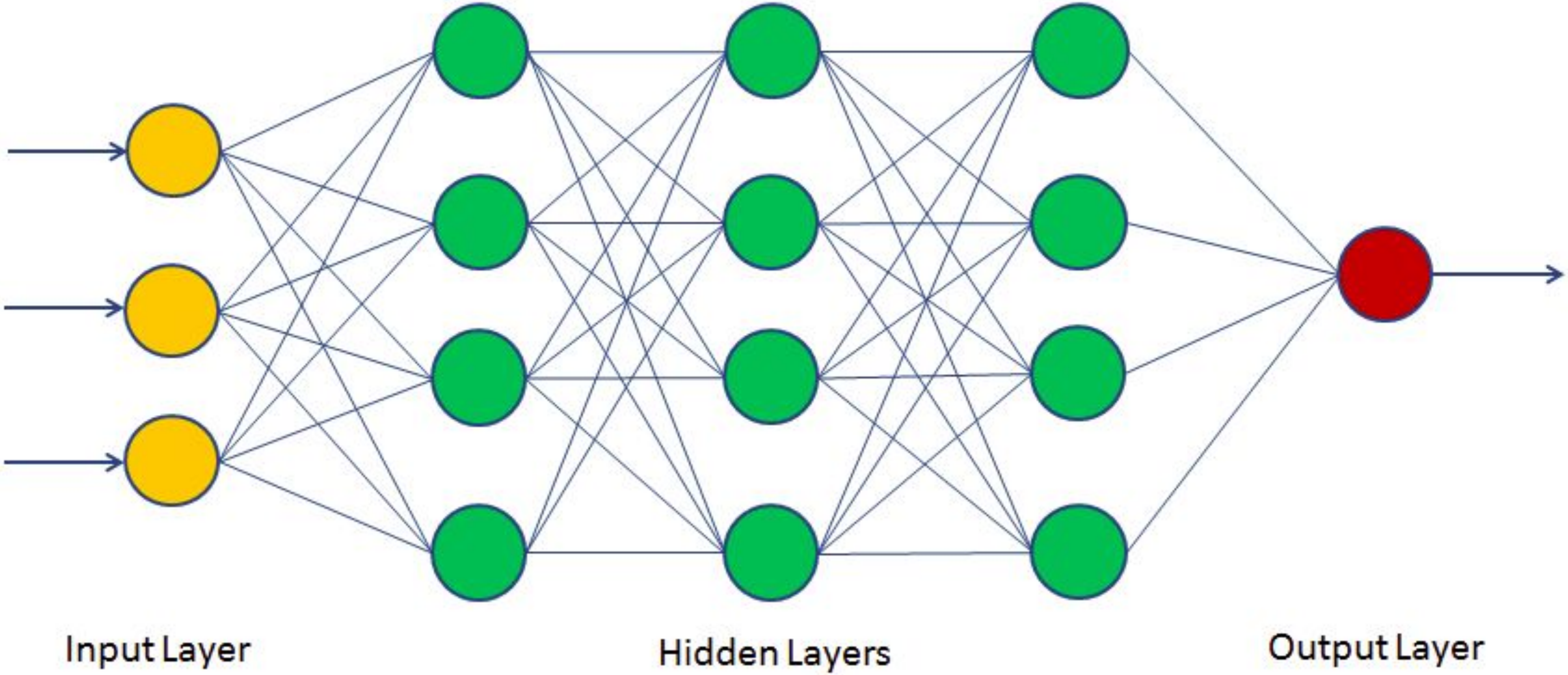
End to End ML Pipeline



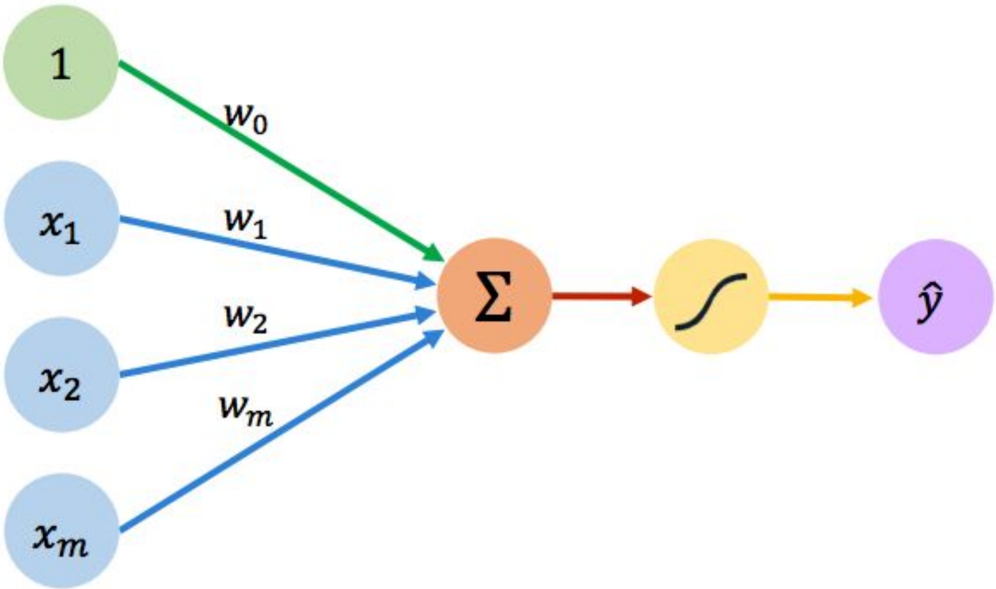
Preparing your dataset:



Neural Network



The Perceptron



Linear combination of inputs

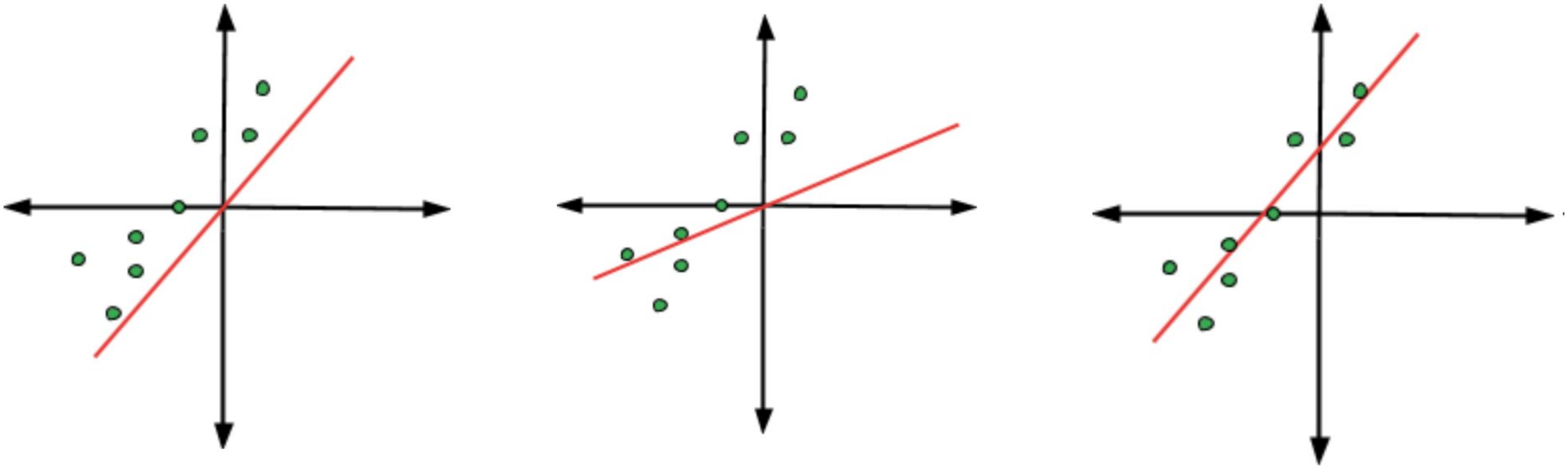
Output

$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i \, w_i \right)$$

Non-linear activation function

Bias

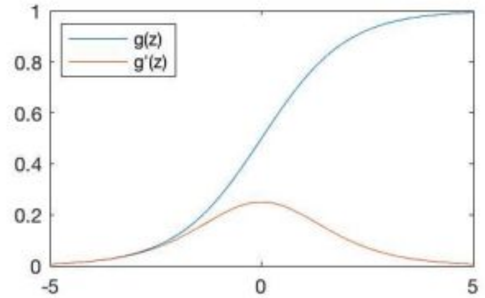
Bias



$y = w_1 x$ $y = w_2 x$ $y = w_0 + w_1 x$

Activation Functions: Introduce Non-Linearity

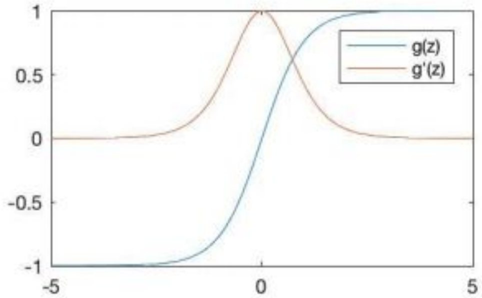
Sigmoid Function



$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

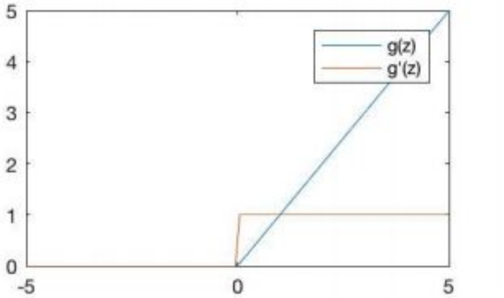
Hyperbolic Tangent



$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

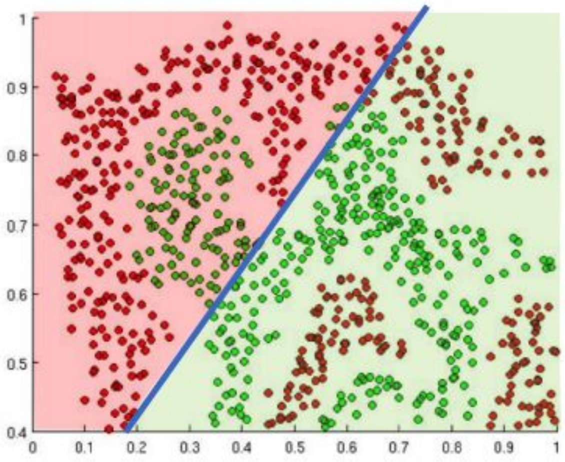
Rectified Linear Unit (ReLU)



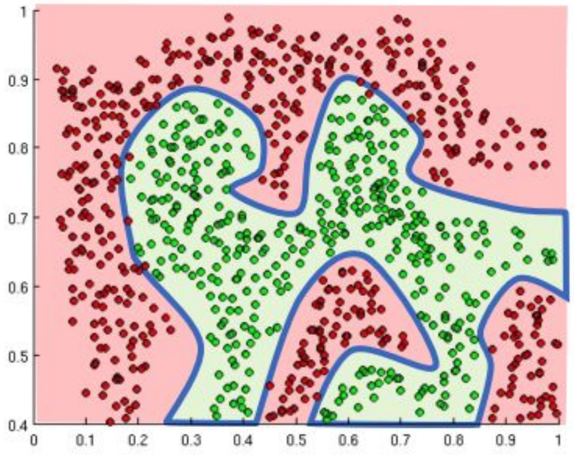
$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

Activation Functions: Introduce Non-Linearity



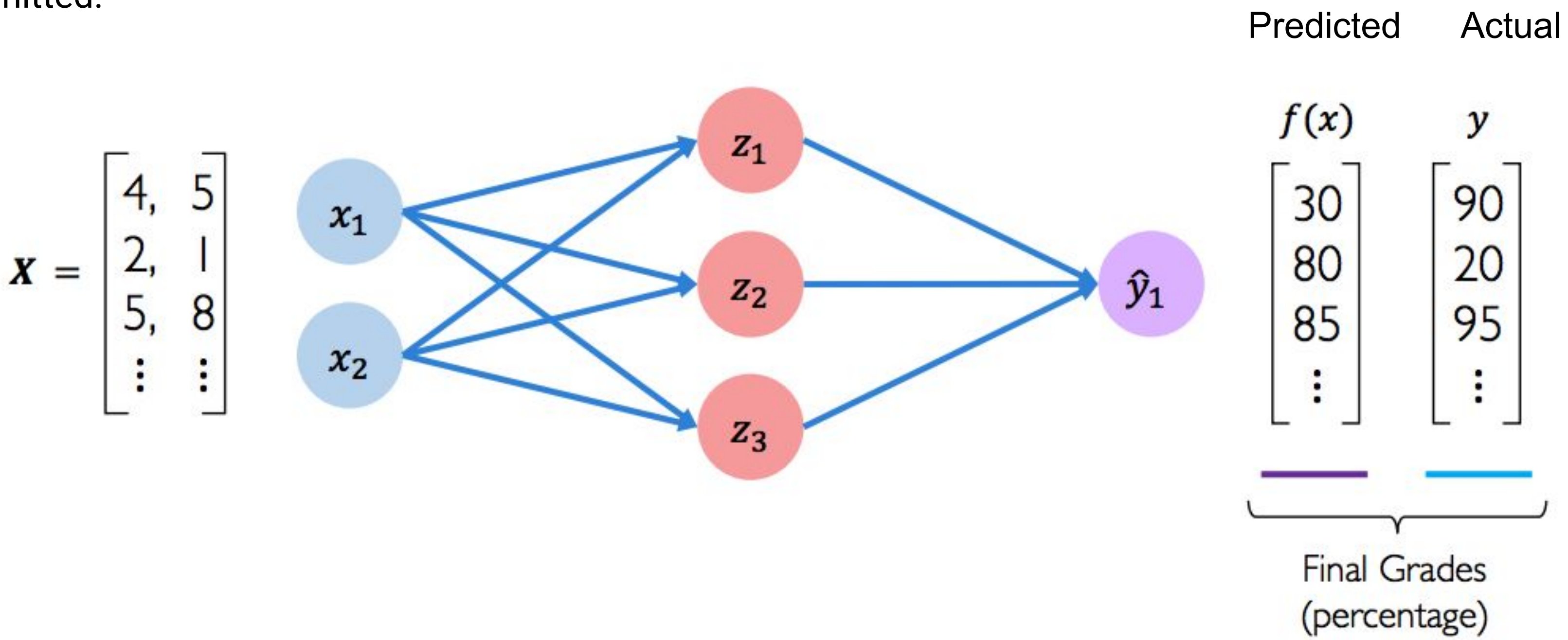
Linear Activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

Example Neural Network

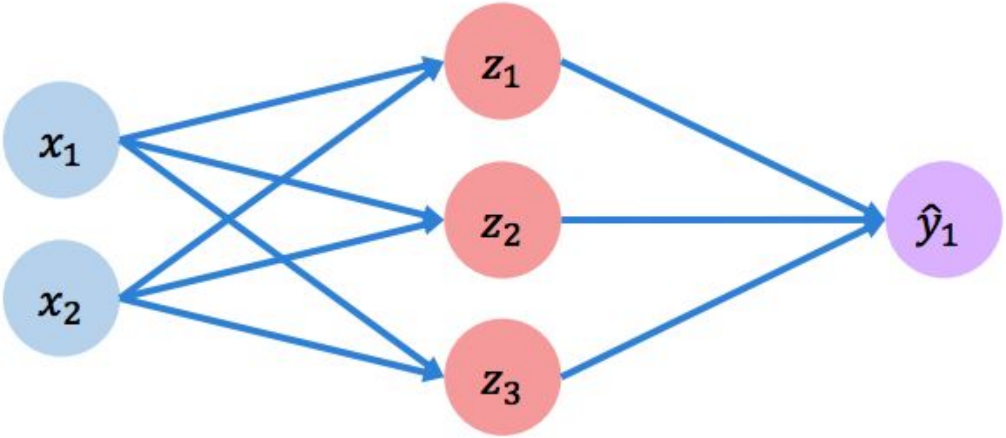
For example: Predicting the final exam score (on 100) of a student given features like number of lectures attended, and number of assignments submitted.



Mean Squared Loss

For example: Predicting the final grade of a student given features like number of lectures attended, and number of assignments submitted.

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$



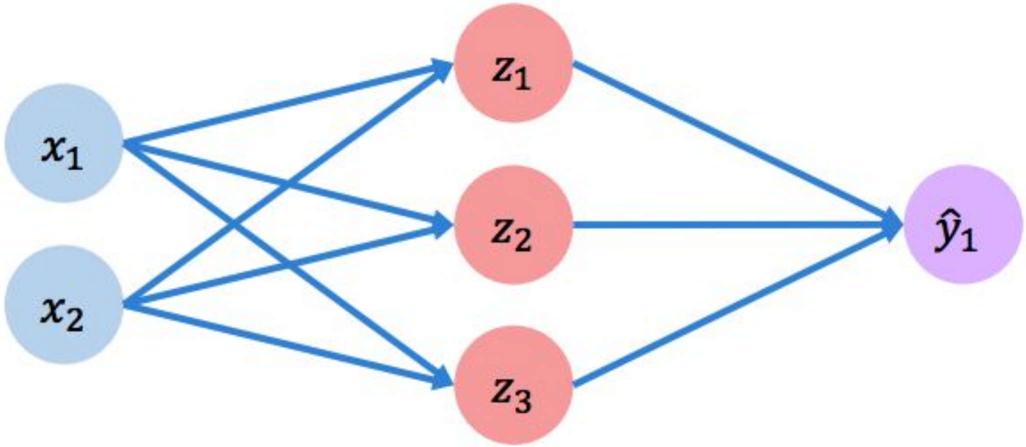
$$\underbrace{\begin{array}{cc} \text{Predicted} & \text{Actual Score} \\ f(x) & y \\ \begin{bmatrix} 30 \\ 80 \\ 85 \\ \vdots \end{bmatrix} & \begin{bmatrix} 90 \\ 20 \\ 95 \\ \vdots \end{bmatrix} \end{array}}_{\text{Final Grades (percentage)}}$$

$$\boldsymbol{J}(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n}\Big(\underbrace{y^{(i)}}_{\text{Actual}} - \underbrace{f\big(x^{(i)};\boldsymbol{W}\big)}_{\text{Predicted}}\Big)^2$$

Cross-Entropy Loss

For example: Classifying whether a student will pass or not given features like number of lectures attended, and number of assignments submitted.

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$

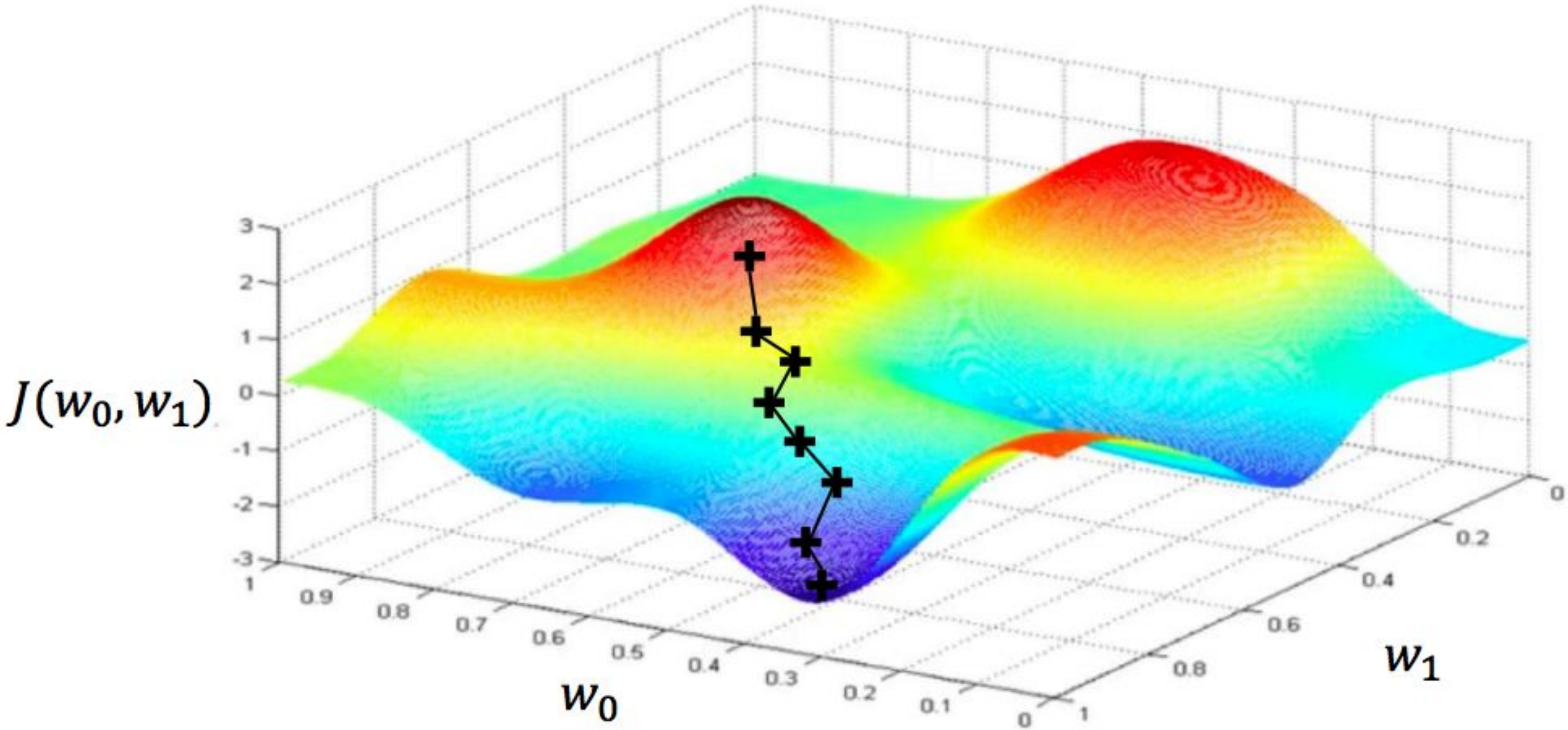


Predicted	Actual Score
$f(x)$	y

$$f(x) = \begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} \qquad y = \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix}$$

$$J(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n} \underbrace{y^{(i)}}_{\text{Actual}} \log\Big(\underbrace{f\big(x^{(i)};\boldsymbol{W}\big)}_{\text{Predicted}}\Big) + (1-\underbrace{y^{(i)}}_{\text{Actual}})\log\Big(1-\underbrace{f\big(x^{(i)};\boldsymbol{W}\big)}_{\text{Predicted}}\Big)$$

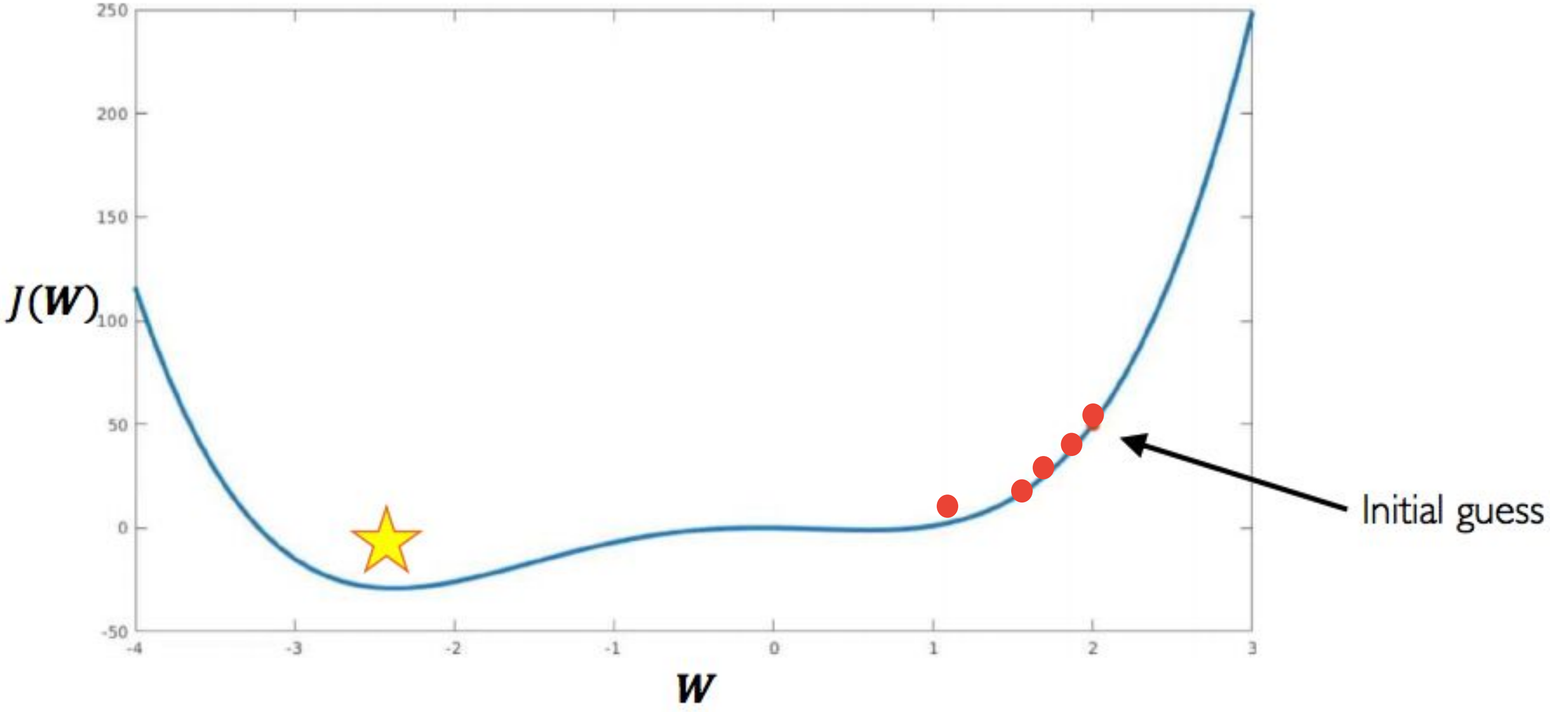
Visualizing our Loss Function



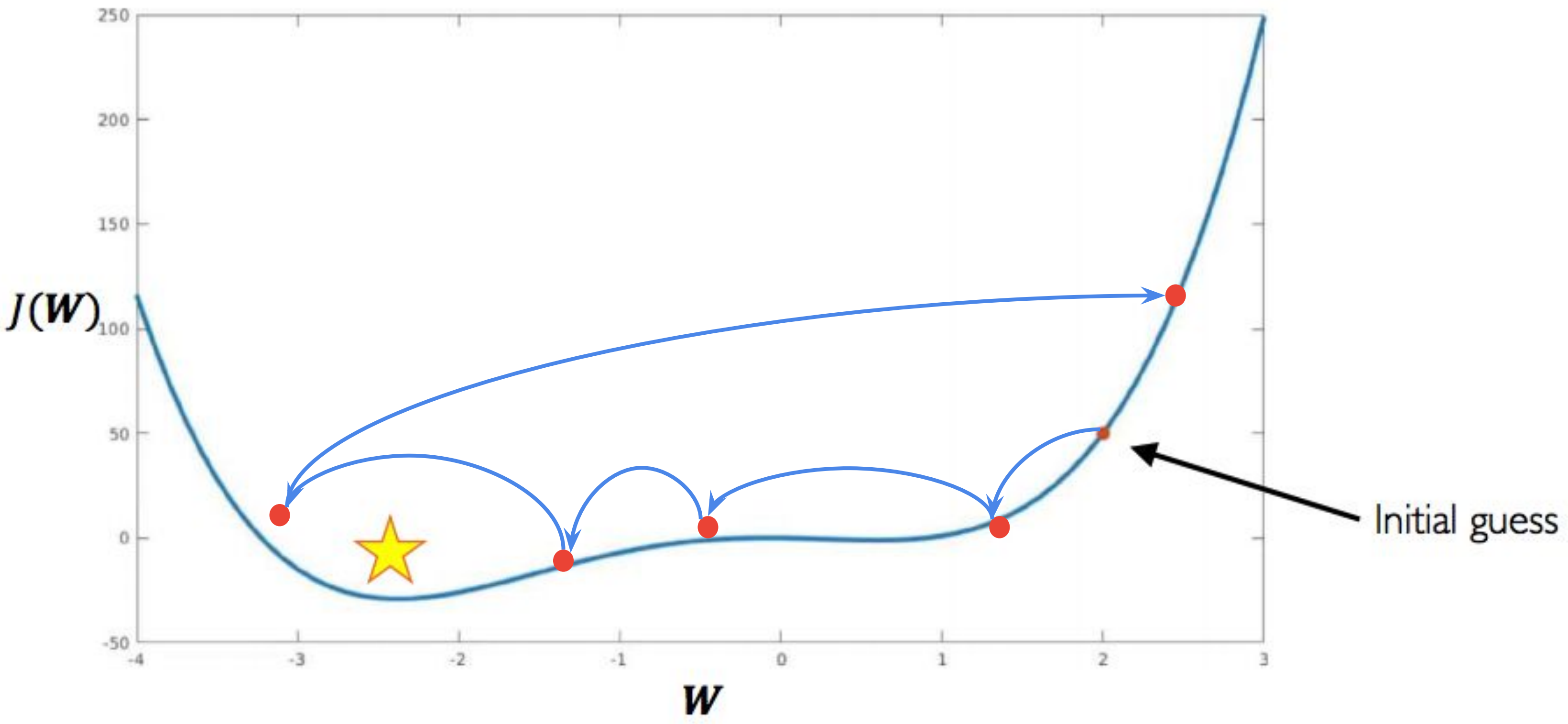
Gradient Descent Algorithm

1. Initialize weights randomly $\sim\mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
4. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Return weights

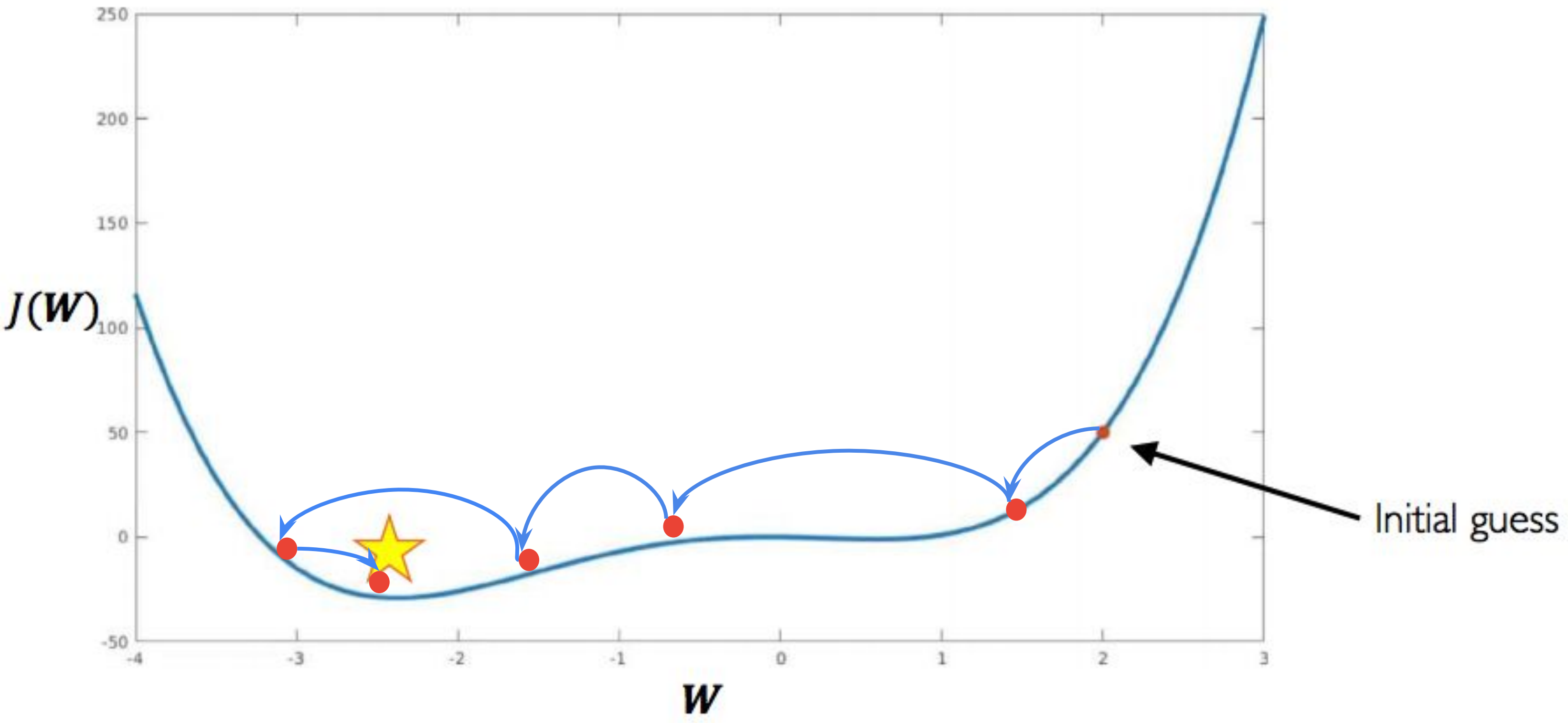
Low Learning Rate



High Learning Rate



Good Learning Rate



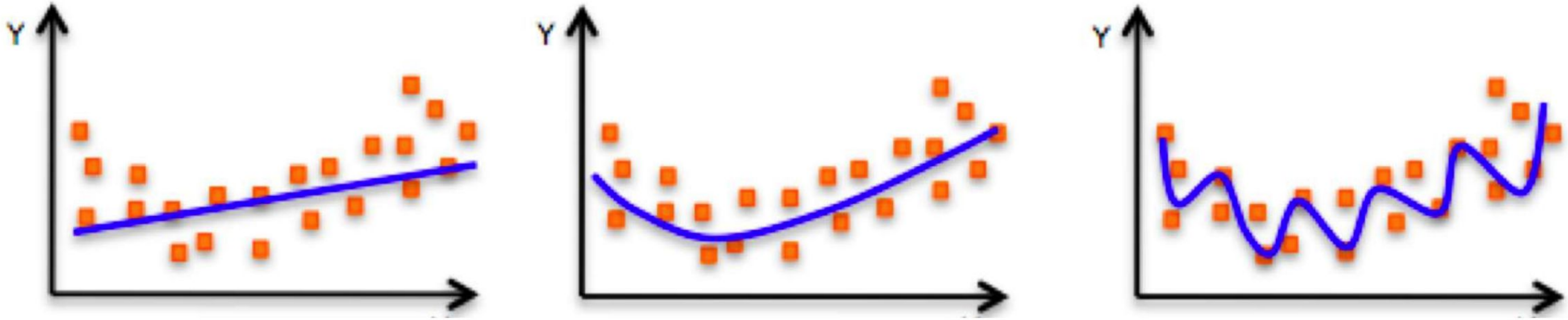
Adaptive Learning Rate Algorithms

- Momentum
- Adagrad
- Adadelta
- Adam
- RMSProp

Batch Size and Epochs

1. Initialize weights randomly $\sim\mathcal{N}(0, \sigma^2)$
2. Loop
3. Pick single data point $\boldsymbol{i}$
4. Compute gradient, $\frac{\partial J_i(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
6. Return weights

Problem of Overfitting



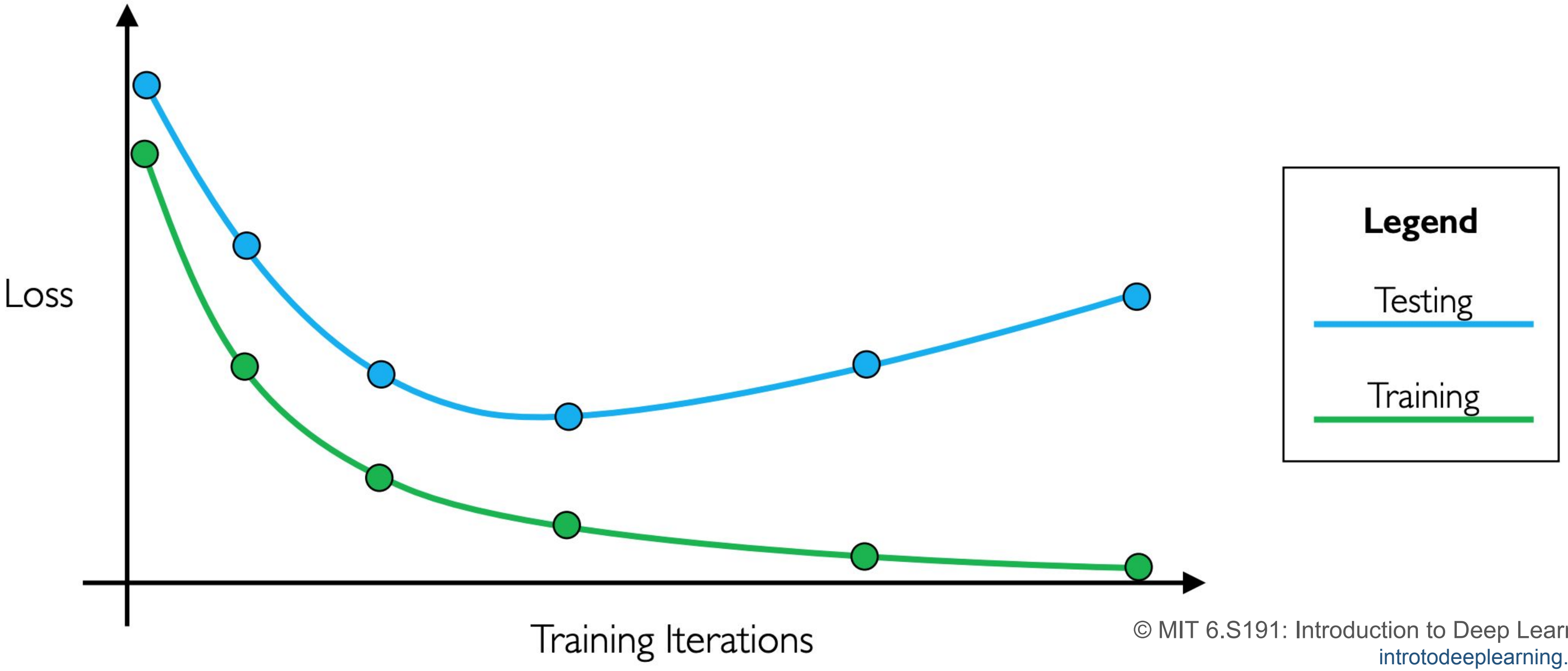
Underfitting
Model does not have capacity to fully learn the data

← **Ideal fit** →

Overfitting
Too complex, extra parameters, does not generalize well

Early Stopping

Stop training before we start overfitting.



Early Stopping

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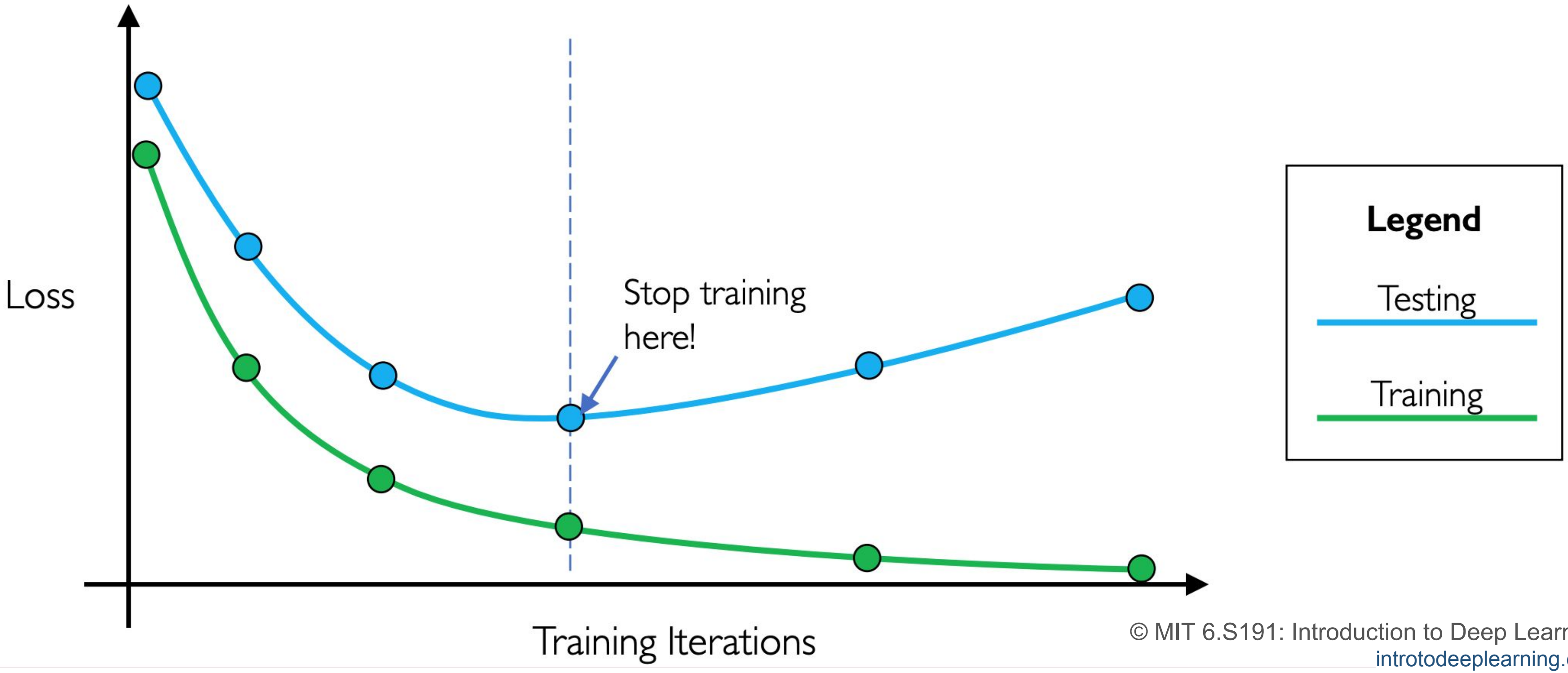
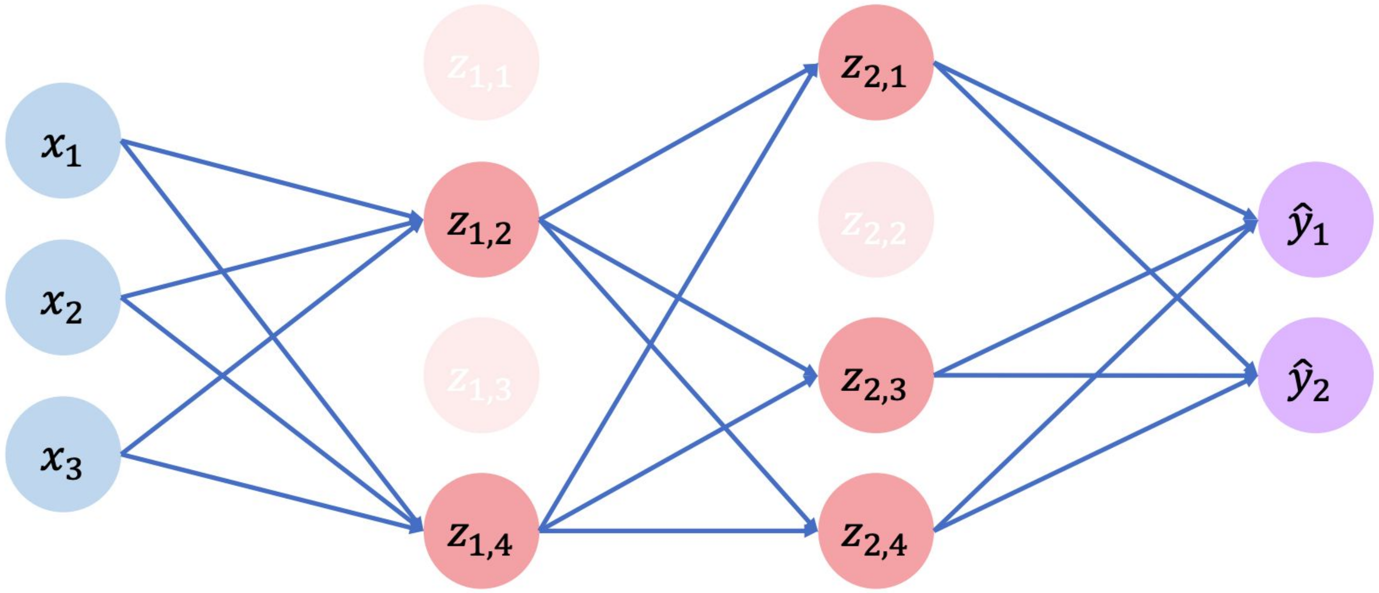


Dropouts

Randomly set some activations to 0



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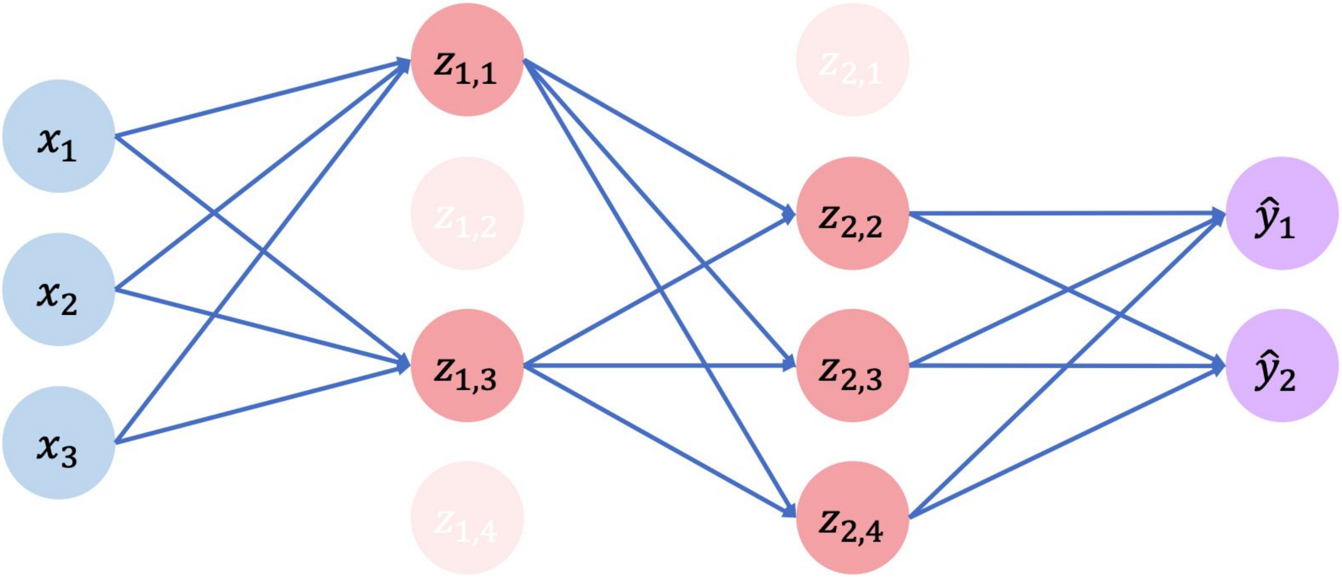
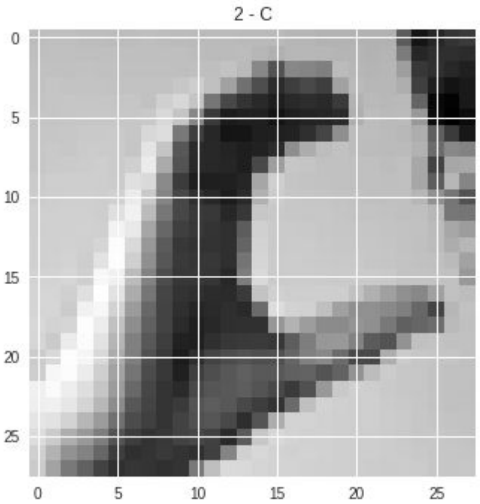


Hands On: Solving a Classification Problem using TensorFlow

Demo

Recognizing Sign Language from Images



Input Image

```
187 188 188 187 187 ....... 28 columns
188 189 189 188 188
...
...
...
191 193 192 192 192 ....... 28 rows
```

Pixel Representation
of 28 x 28 image

$$\begin{array}{c} A \\ B \\ C \\ D \\ \ldots \end{array} \begin{bmatrix} 0.01 \\ 0.003 \\ 0.98 \\ 0.02 \\ \end{bmatrix}$$

Classification Result

Output of the model produces a probability score for the image belonging to a particular class.

http://bit.ly/iwdcolab

Any Questions?

Slides, Code and Links

can be found at github.com/anisham197/WTMExtendedSummit/

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References

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- http://ruder.io/optimizing-gradient-descent/