EEP 596: LLMs: From Transformers to GPT || Lecture 2

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Univ. of Washington, Seattle

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Outline for Lecture

- Motivation for DL

Deep Learning

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- Motivation for DL
- DL Applications

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- DL Applications
- DL History

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- Motivation for DL
- DL Applications
- DL History
- Logistic Regression

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- Training and Back-propagation

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- Training and Back-propagation
- Over-fitting and Hyper-parameters

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- DL History
- Logistic Regression
- Deep Learning Models
- Activation functions
- Tensorflow Demo
- Training and Back-propagation
- Over-fitting and Hyper-parameters
- Other DL architectures

(Part of DL Course)

Deep Learning Reference

Deep Learning

Great reference for the theory and fundamentals of deep learning: Book by Goodfellow and Bengio et al Bengio et al

Deep Learning History

Introduction to Deep Learning

Deep Learning

1. Lot of buzz around Deep Learning in the ~~past decade and a half~~! 2decades

Transformers

LLMs

Introduction to Deep Learning

Deep Learning

1. Lot of buzz around Deep Learning in the past decade and a half!
2. Deep Learning refers to Neural Networks that is a loose approximation of how the brain works

Applications of Deep Learning

Applications

1. Self-driving cars

Applications of Deep Learning

Applications

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2. Sentiment analysis

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8. Auto-complete search results.

Many more!

Applications of Deep Learning

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7. Auto-complete sentence in Emails. How many of us use this?
8. Auto-complete search results.
9. Chat bots - Like ChatGPT/Sparrow/Anthropic, etc LLMs

Email auto-complete

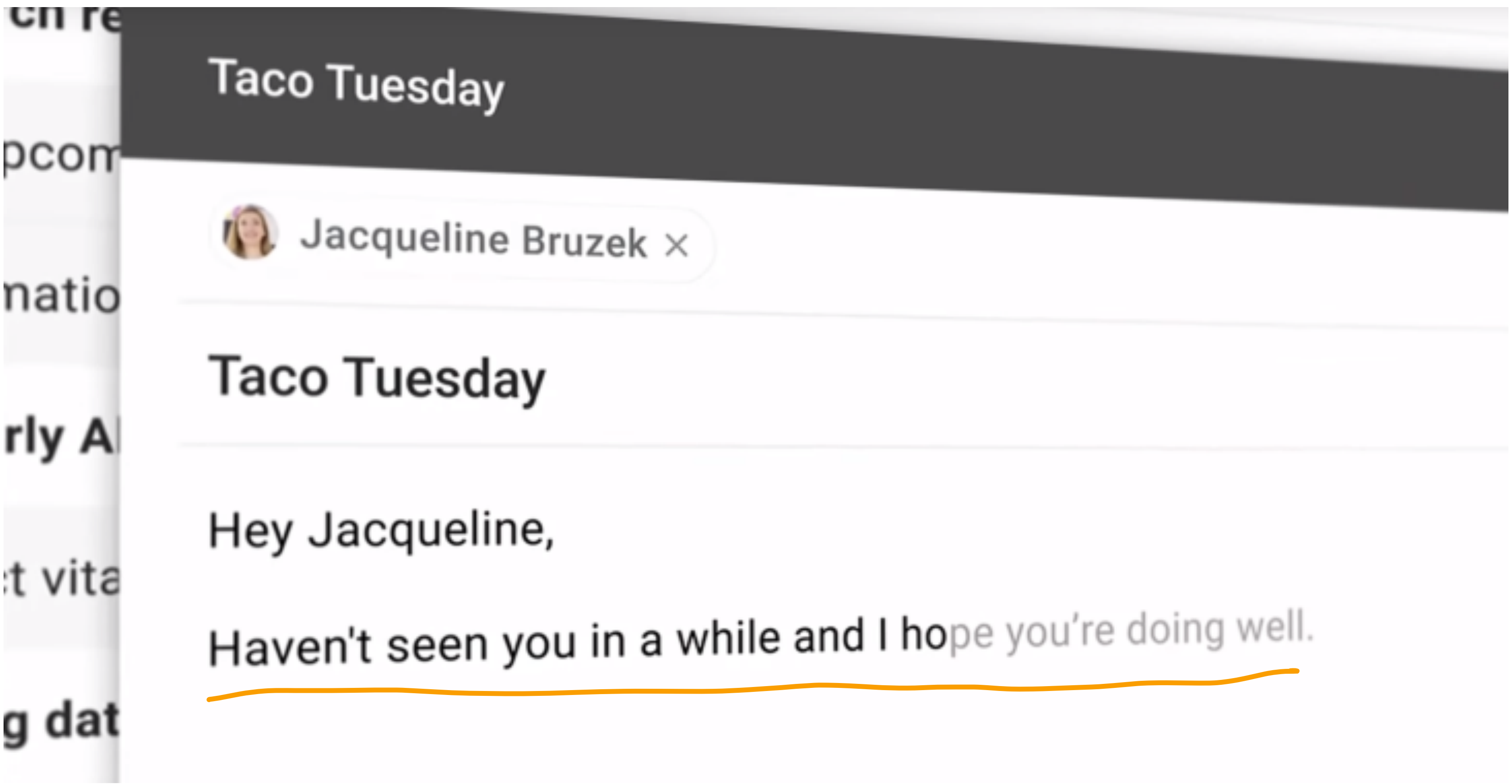
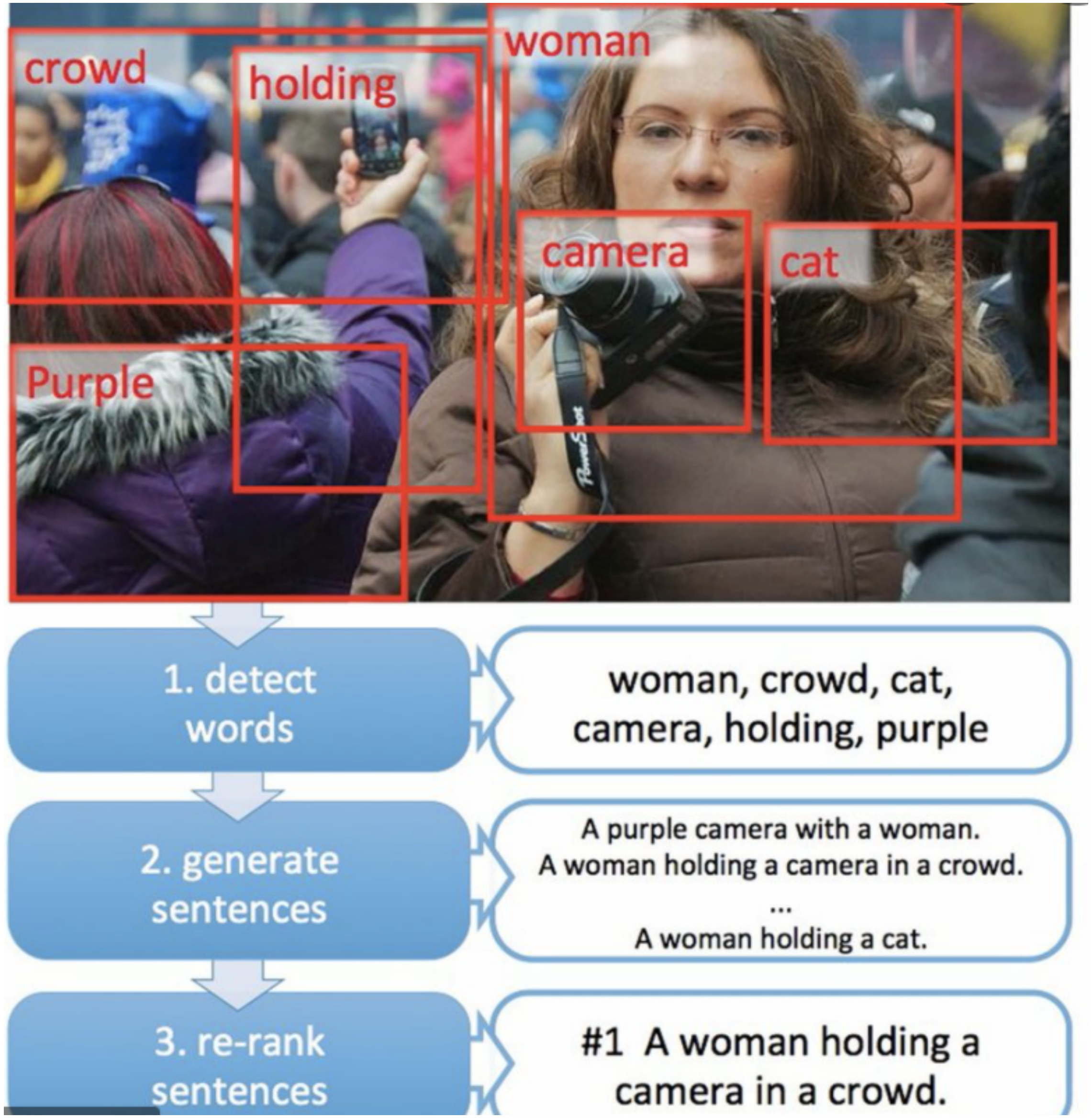


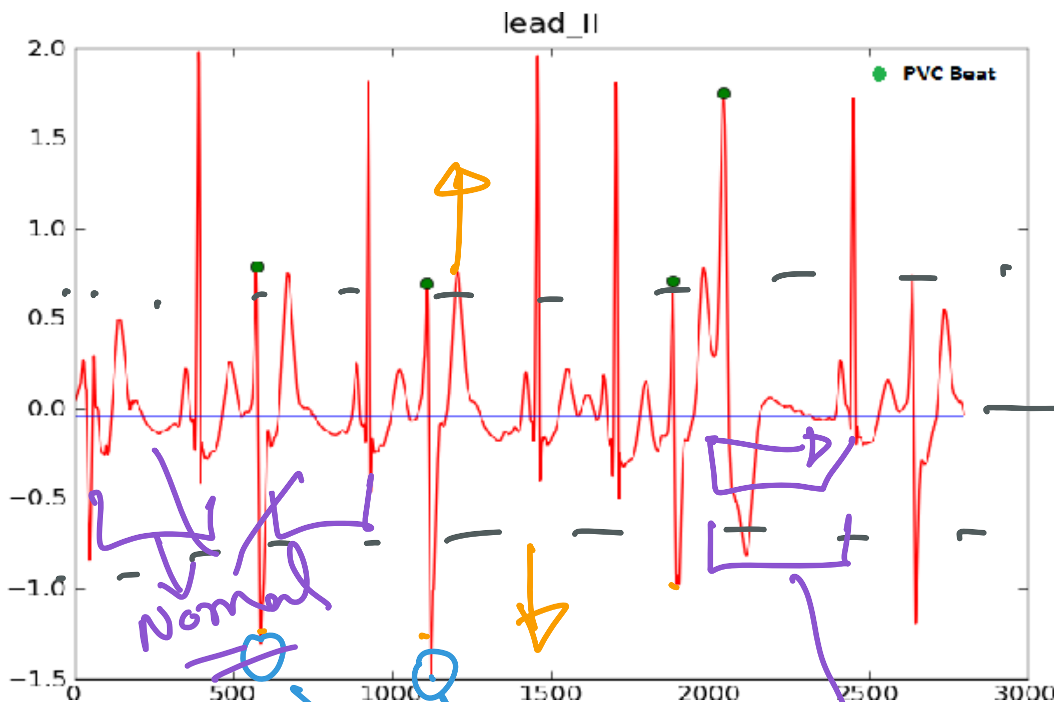
Image to Text!



Computer Vision Research

Arrhythmia Detection

ML Task:
Anomaly Detection



Normal

2 SD

Mean

2 SD

Point Anomalies

Arrhythmic Heart Beat

Brief History of Deep Learning

- **1965:** First deep-learning model came out in 1965 by Ivakhenko et al. Didn't use back-propagation for training but sequential least squares fit.
- **1979:** Earliest Convolutional Neural Network (CNN) by Fukushima et al.

  → Back bone to train a NN
- **1985:** Earliest back-propagation in 1985 by Hinton et al
- **1989:** Application of back-prop for recognizing MNIST hand-written digits at Bell labs by Yann LeCun
- **1993:** **LeNet** by Yann LeCun. The beginning of the **X-Nets** where X could be Alex, Inception, etc
- **1997:** Discovery of recurrent Neural Nets - RNN and LSTMs in 1997 by Horchreiter and Schmidhuber.

Brief History of Deep Learning

- **1997 - 2006:** GPUs got faster - 1000x computational speed improvement
- **2011:** Ciresan et al showed that you can train a CNN without pre-trained weights just with good computational power.
- **2012:** Beginning of ILSVRC competition for improving image-net data set performance.
- **2017:** Transformers arrive on the scene with Vaswani et al and begin the **Language Model revolution**.
- **2020:** Transformer gets applied to Vision as well and matches CNN in performance through the Vi-Transformer.
- **2022:** ChatGPT (based on transformers) arrives on the scene and puts AI on the world map!

2011

DL based Vision models

2010-2017 LSTMs & RNN

"Attention is all you need"

2022 - 2024

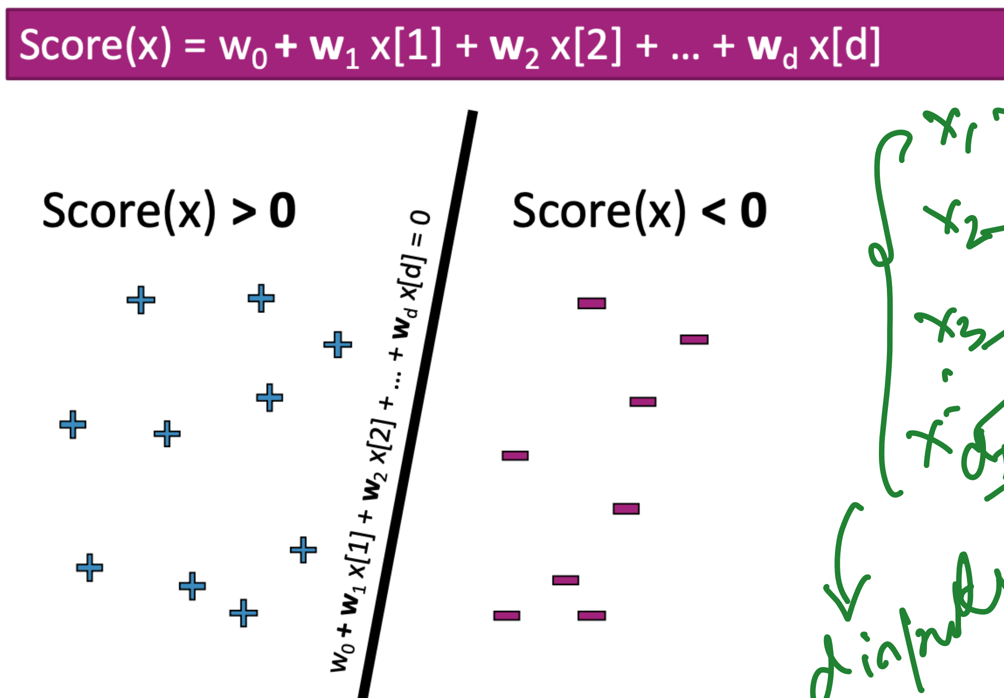
Perceptron to Deep Neural Networks/Deep Learning

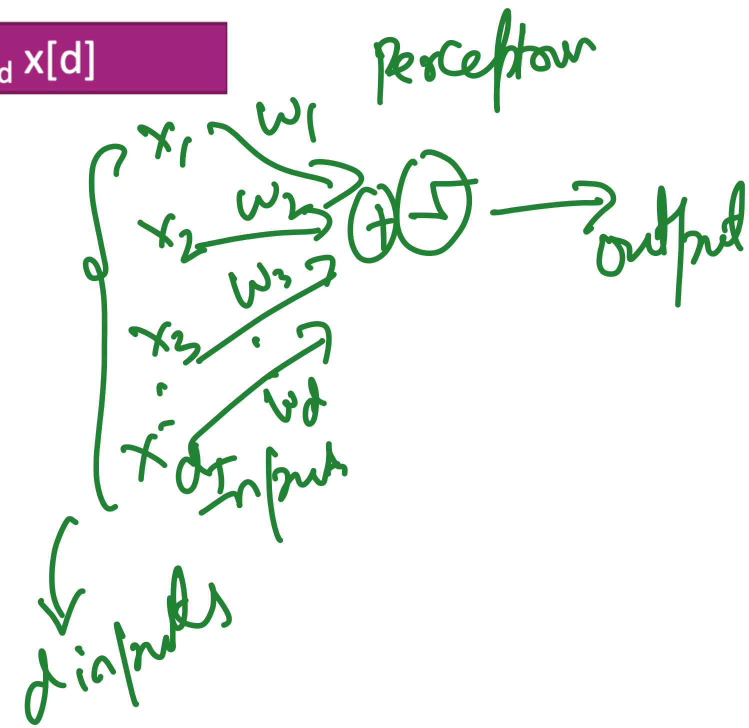
Logistic Regression to Deep Learning

Linear to Non-linear Models

Let's work through the nitty-gritties of the logistic regression model and neural network model!

Perceptron



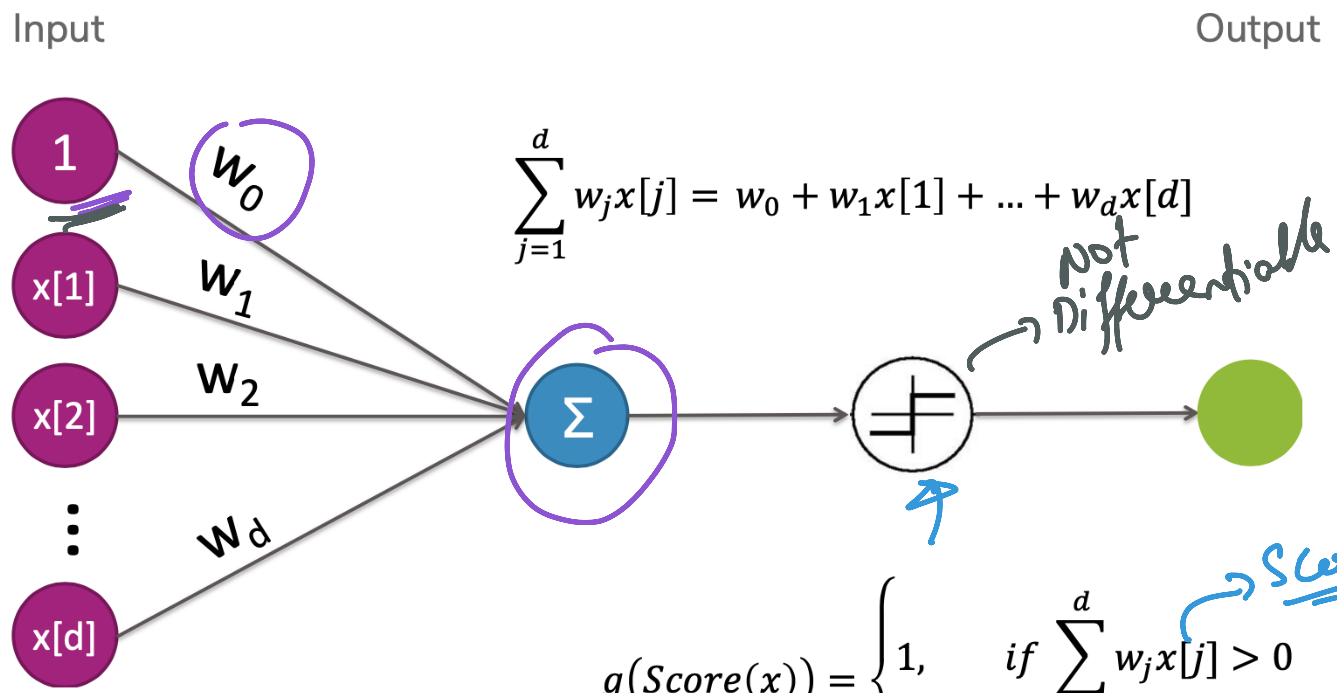


$w^T x = w_1 x_1 + w_2 x_2 + \dots + w_d x_d$

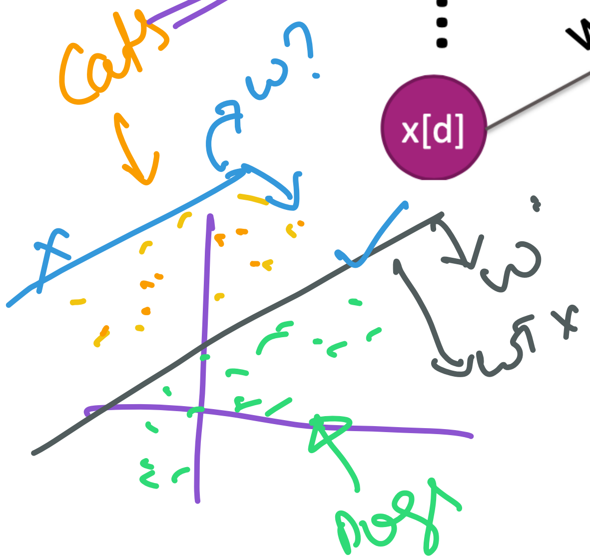
Learn the weights in training

Perceptron

$$\sum_{j=1}^{d} w_j x[j] = w_0 + w_1 x[1] + \ldots + w_d x[d]$$



Discriminate Cat Images from Dogs



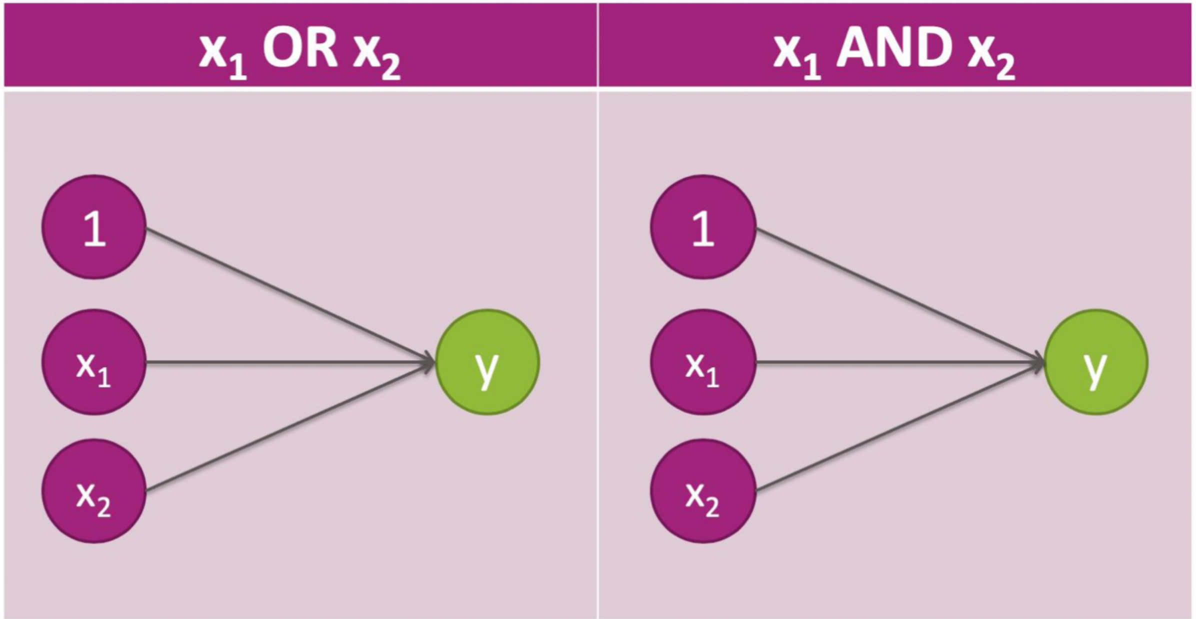
$$g(Score(x)) = \begin{cases} 1, & \text{if } \underbrace{\sum_{j=1}^{d} w_j x[j]}_{} > 0 \\ 0, & \text{otherwise} \end{cases}$$

→ Score

Data		Score		
Cat → x	→	$w^T x$	> 0 →	Cat
Dog → x^2	→	$w^T x^2$	< 0 →	Dog

OR and AND Functions

What can a perceptrons represent?



x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	1

x_1	x_2	y
0	0	0
0	1	0
1	0	0
1	1	1

Perceptron to Logistic Regression

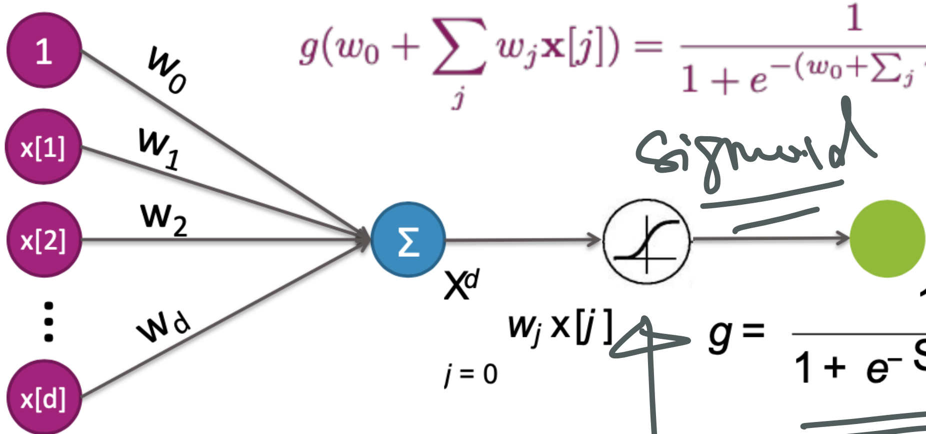
Perceptron → Logistic Regresn

↓

1 Layer NN

$$g(w_0 + \sum_j w_j \mathbf{x}[j]) = \frac{1}{1 + e^{-(w_0 + \sum_j w_j \mathbf{x}[j])}}$$

Sigmoid



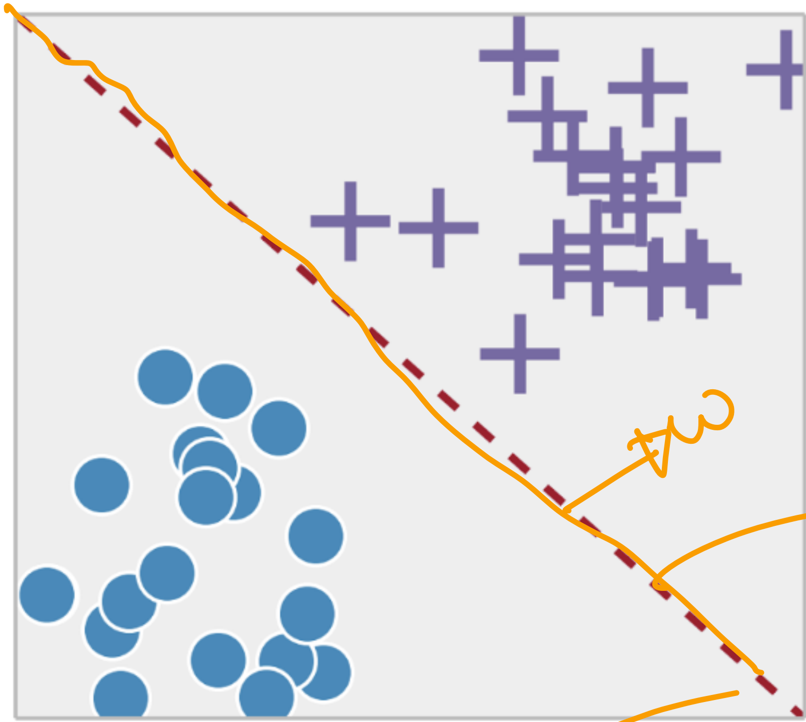
$\sum_{j=0}^{d} w_j \, x[j]$

$$g = \frac{1}{1 + e^{-\mathrm{Score}(x)}}$$

→ Probabilities

→ 0 and

Logistic Regression



w

→ Linear Separator

Linear combination of weights & data
(w) (x)

LR fundamentals

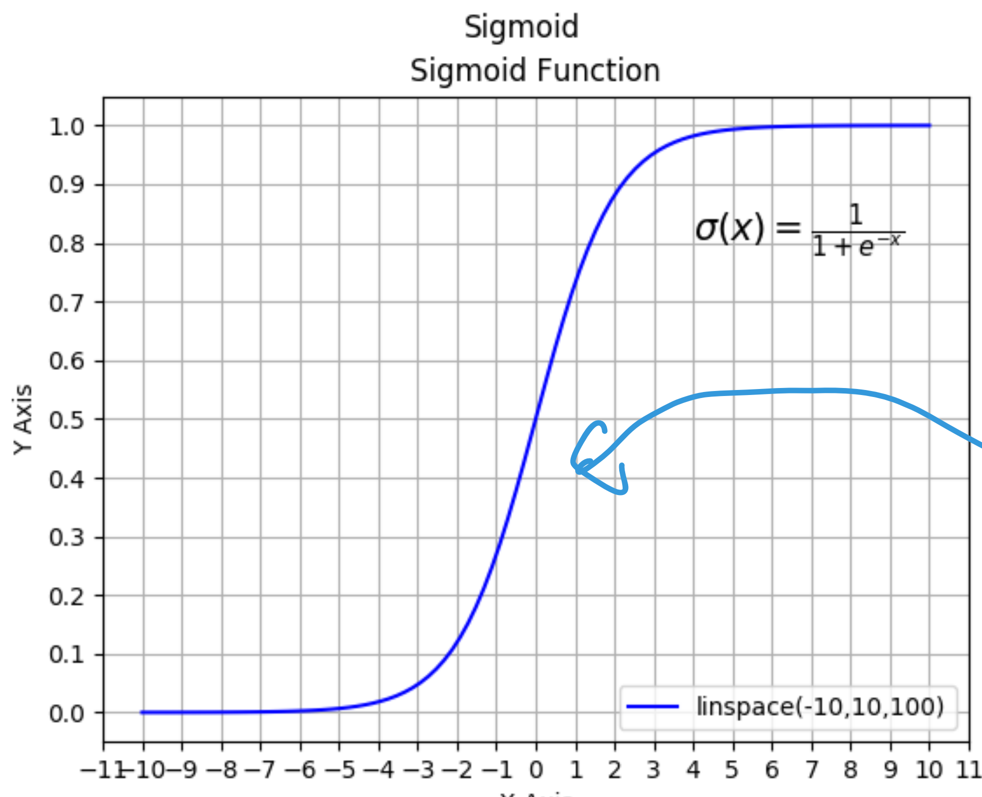
- Linear Model → Linear combination of weights & data
- Want score $w^T x^i > 0$ for $y_i = +1$ and $w^T x_i < 0$ for $y_i = -1$!
- If linearly separable data, above is feasible. Else, minimize error in separability!!

Logistic Regression

Probability for a class

In LR, the score, $w^T x$ is converted to a probability through the sigmoid function. So we can talk about $P(\hat{y^i} = +1)$ or $P(\hat{y^i} = -1)$

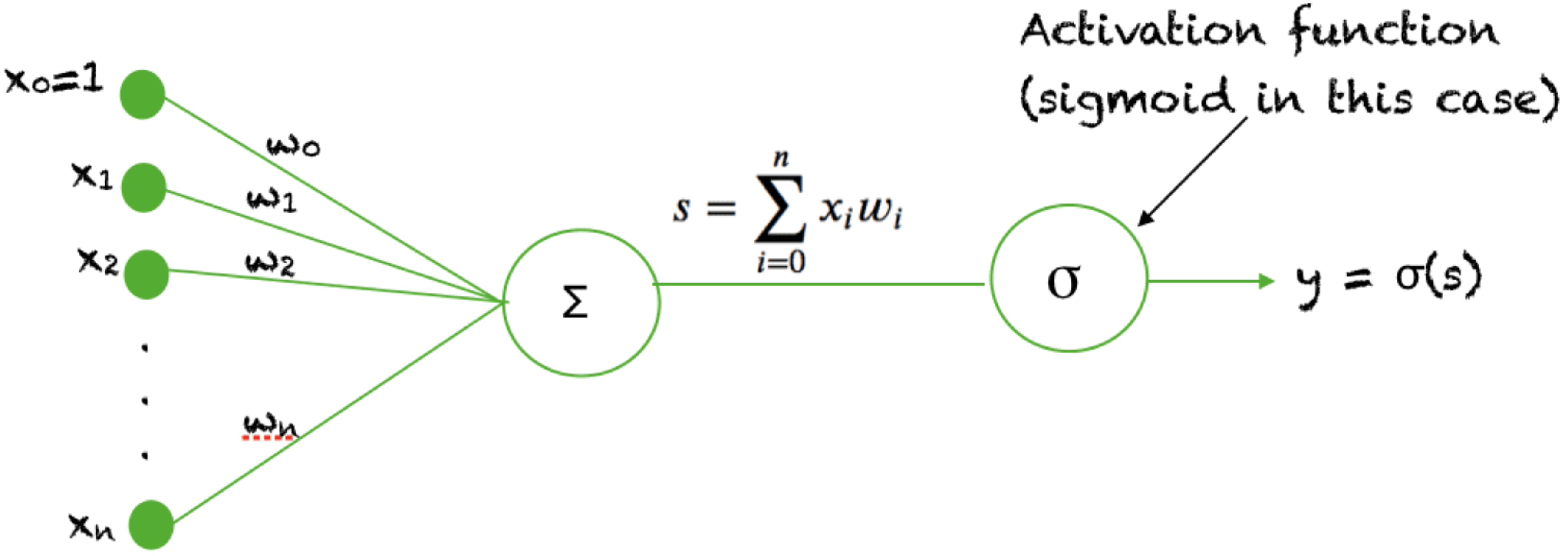
Sigmoid Function



$p(x \text{ is Cat}) = \frac{1}{1+e^{-w^T x}}$

$0 \le p \le 1$

LR represented Graphically



Logistic Regression

LR Prediction

$$\hat{y}_i = \frac{1}{1 + e^{-\hat{w}^T x^i}}$$

LR Loss

Assume that $y_i = 0$ or $y_i = 1$ (i.e. the negative class has a label 0). Then the binary cross-entropy loss applies to LR:

$$\min_w y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$

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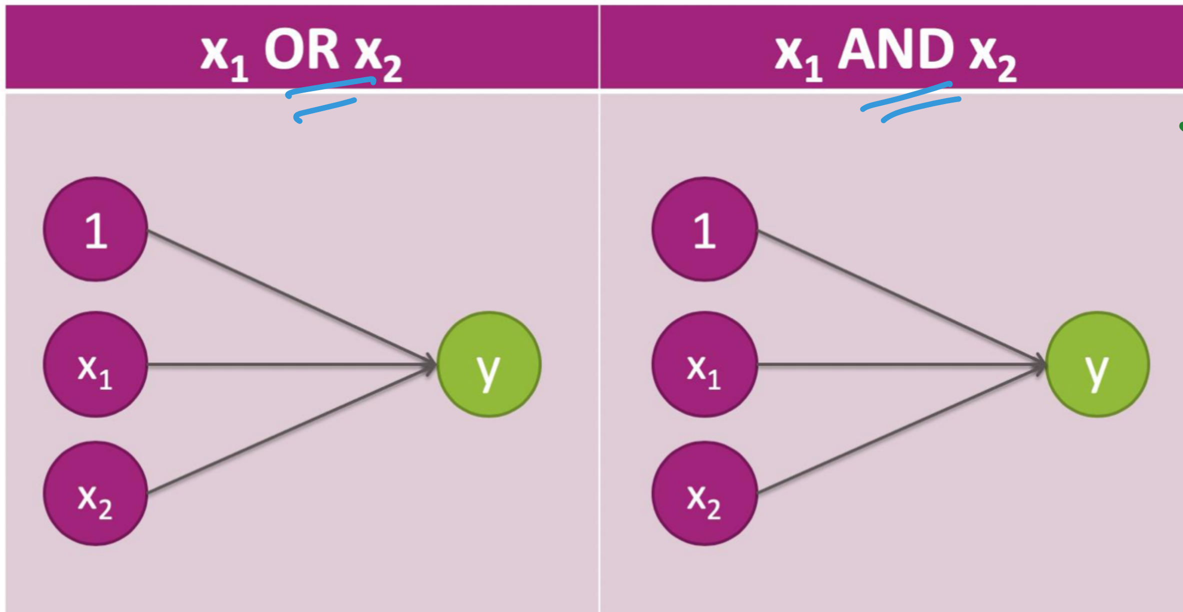

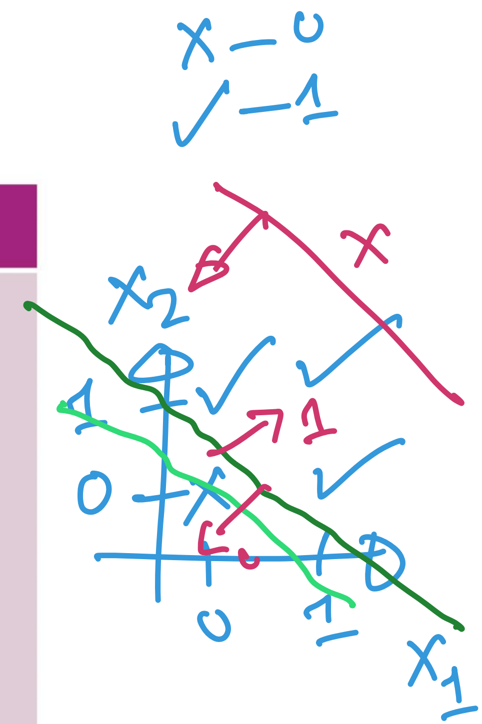

x_1	x_2	y
0	0	0
0	1	1
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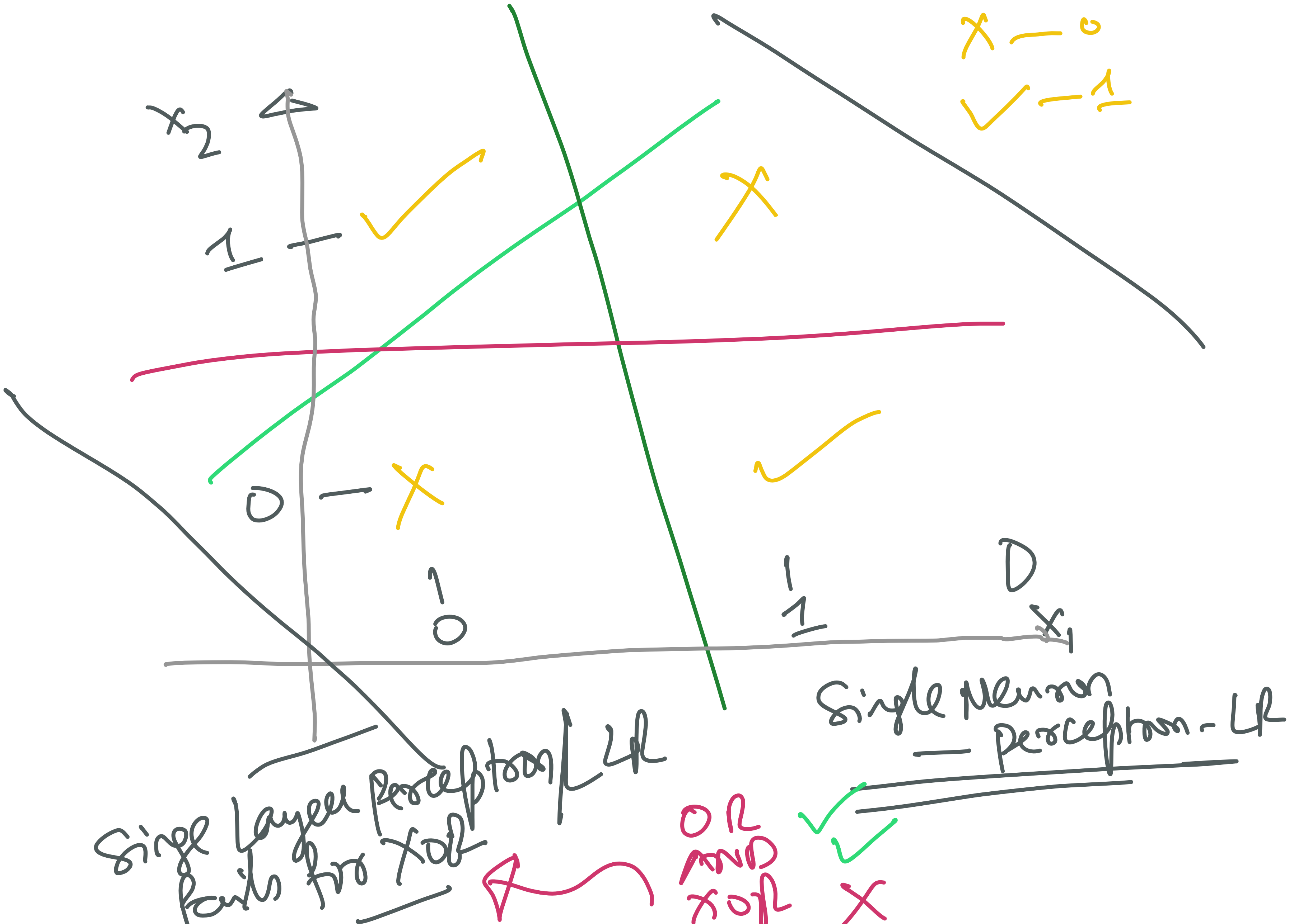
1	1	1

Learning XOR



XOR through Multi-layer perceptron

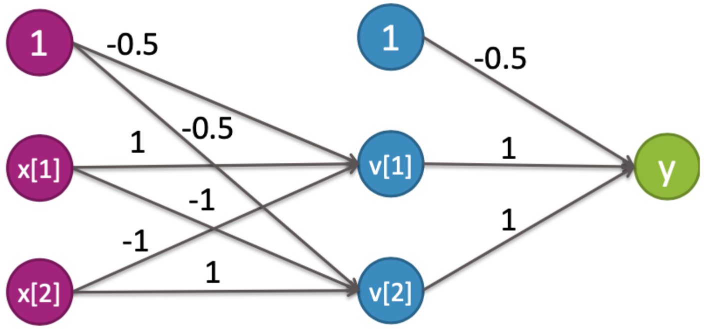
This is a 2-layer neural network

$y = x[1]\ XOR\ x[2] = (x[1]\ AND\ !\, x[2])\ OR\ (!\, x[1]\ AND\ x[2])$

$v[1] = (x[1]\ AND\ !\, x[2])$
$\quad = g(-0.5 + x[1] - x[2])$

$v[2] = (!\, x[1]\ AND\ x[2])$
$\quad = g(-0.5 - x[1] + x[2])$

$y = v[1]\ OR\ v[2]$
$\quad = g(-0.5 + v[1] + v[2])$

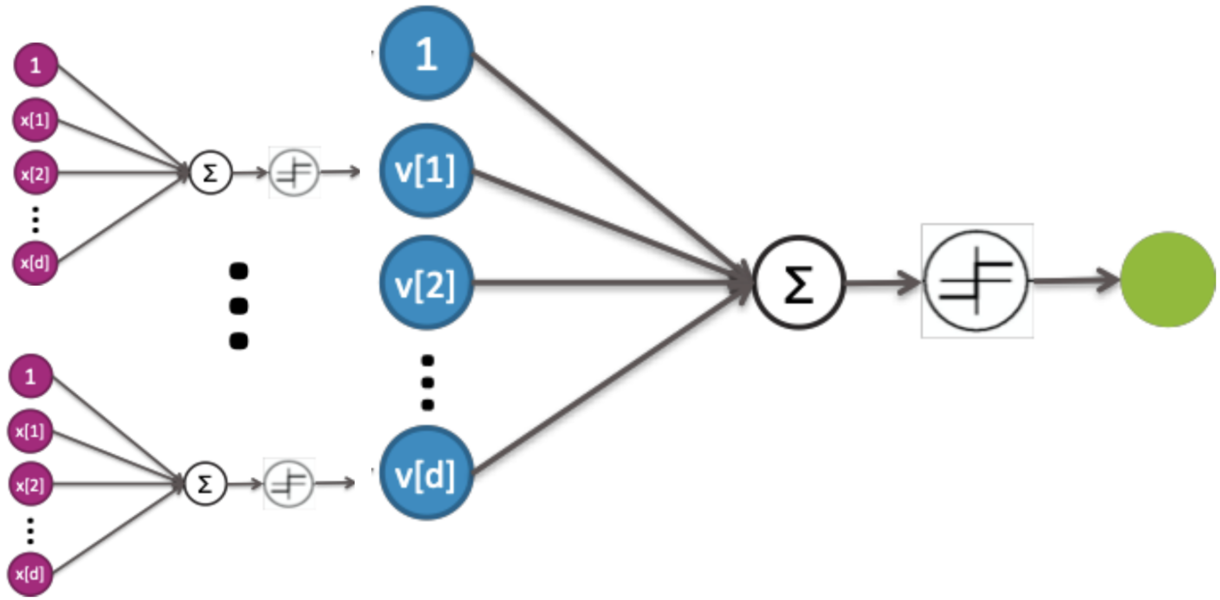


ICE #1

Which methods can learn the XOR function?

1. Logistics Regression
2. Naive Bayes Classifier
3. Decision Trees
4. Support Vector Machines

Multi-Layer Perceptron (MLP)



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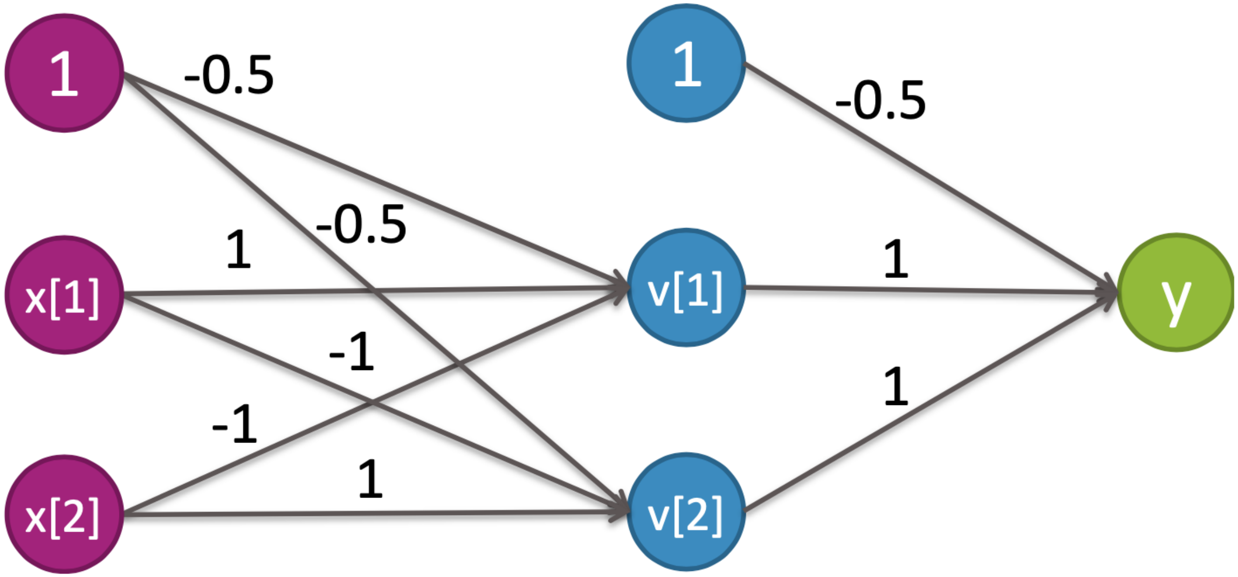
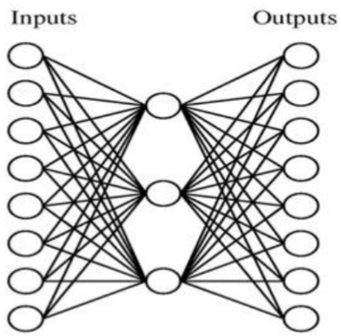


2 Layer Neural Network

Two layer neural network (alt. one hidden-layer neural network)



Single

$$out(x) = g\left(w_0 + \sum_j w_j x[j]\right)$$

1-hidden layer

$$out(x) = g\left(w_0 + \sum_k w_k g\left(w_0^{(k)} + \sum_j w_j^{(k)} x[j]\right)\right)$$

Deep Learning: Activations, FFN and more

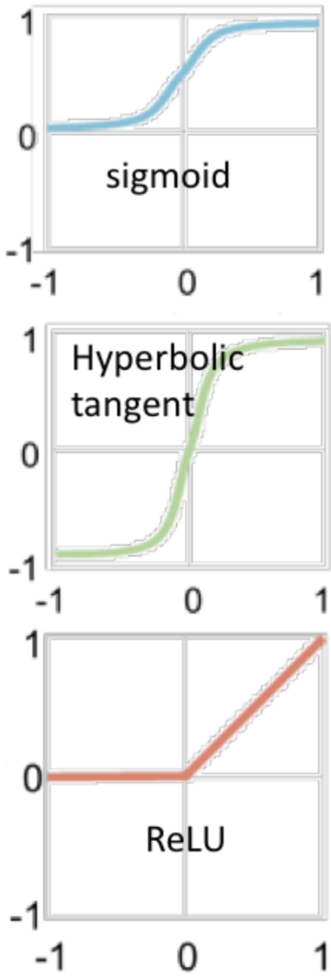
Choices for Non-Linear Activation Function

•Sigmoid
-Historically popular, but (mostly) fallen out of favor
•Neuron's activation saturates
(weights get very large -> gradients get small)
•Not zero-centered -> other issues in the gradient steps
-When put on the output layer, called "softmax" because interpreted as class probability (soft assignment)

•Hyperbolic tangent $g(x) = \tanh(x)$
-Saturates like sigmoid unit, but zero-centered

•Rectified linear unit (ReLU) $g(x) = x^+ = \max(0,x)$
-Most popular choice these days
-Fragile during training and neurons can "die off"… be careful about learning rates
-"Noisy" or "leaky" variants

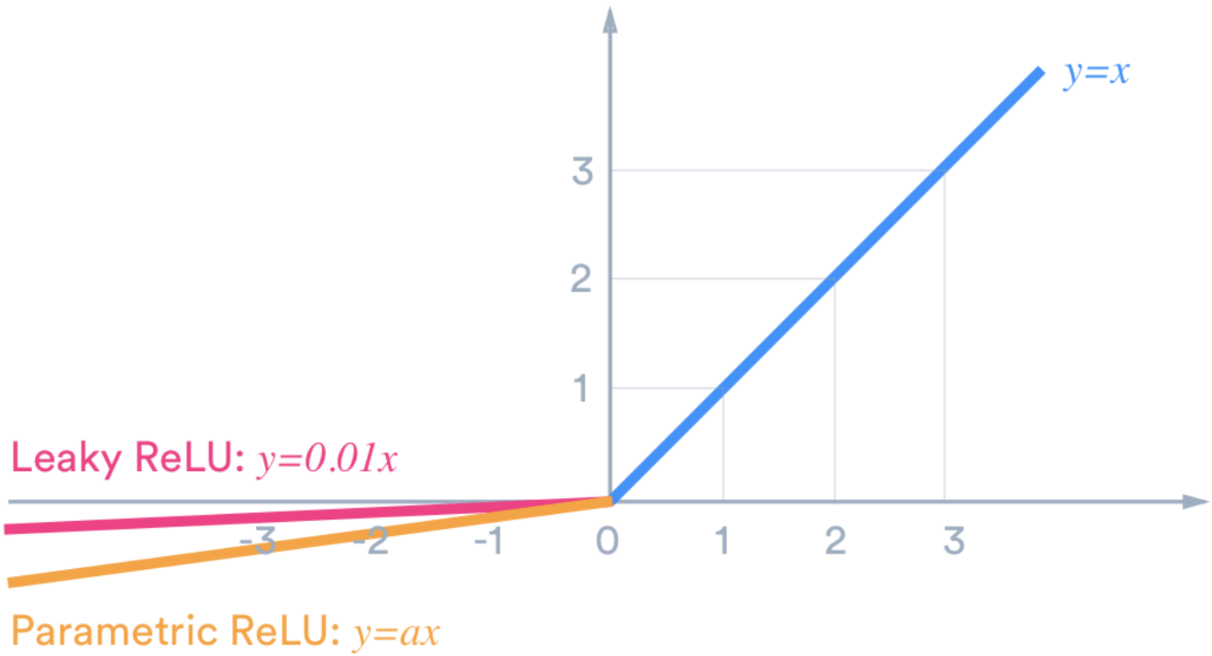
•Softplus $g(x) = \log(1+\exp(x))$
-Smooth approximation to rectifier activation



Gradient of Sigmoid and RELU

Sigmoid vs RELU

RELU vs Leaky RELU



Tensorflow Playground Demo

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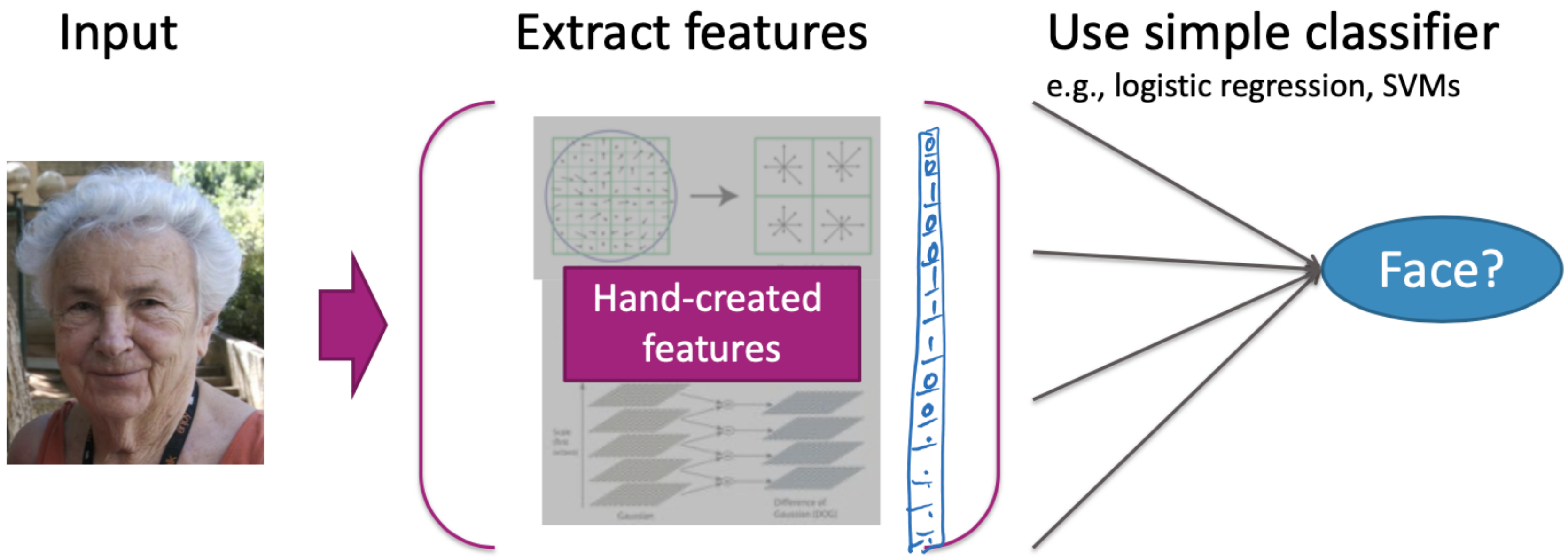
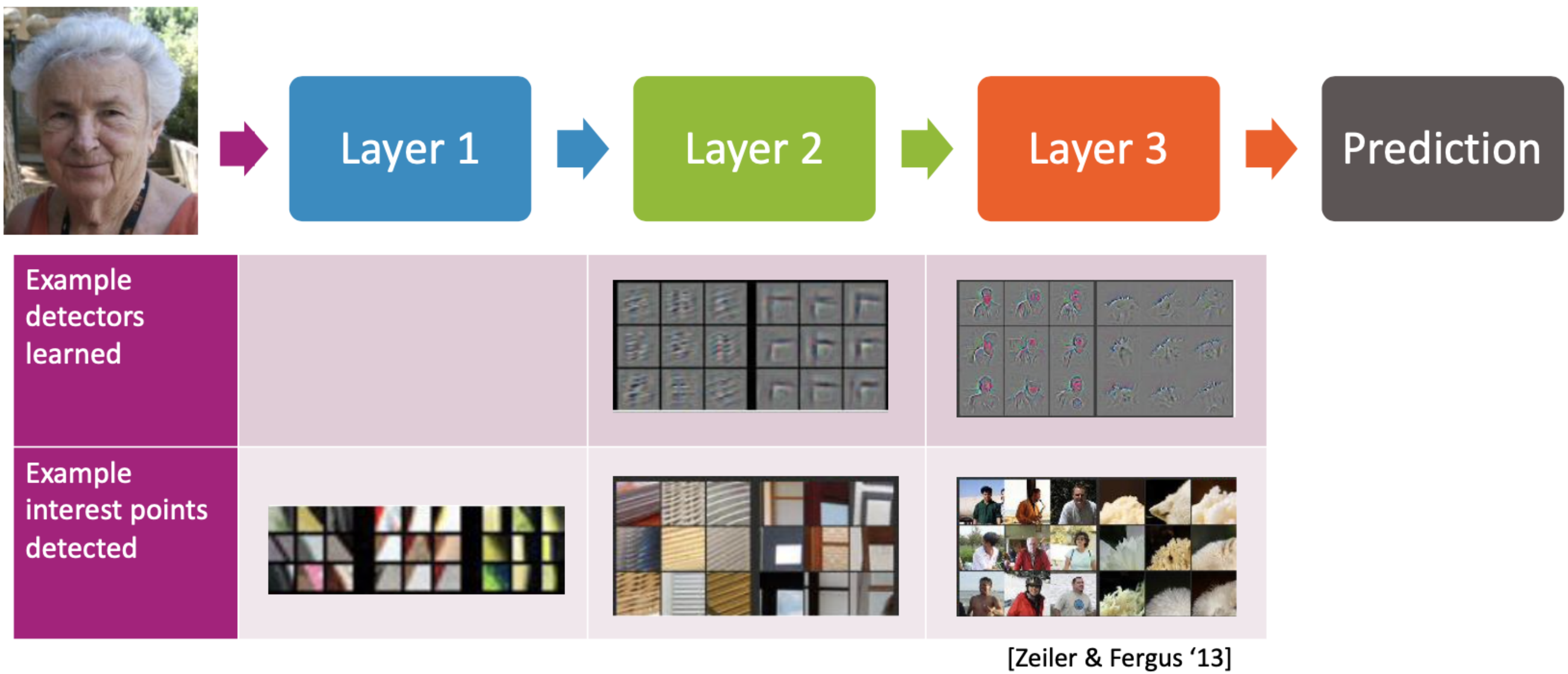
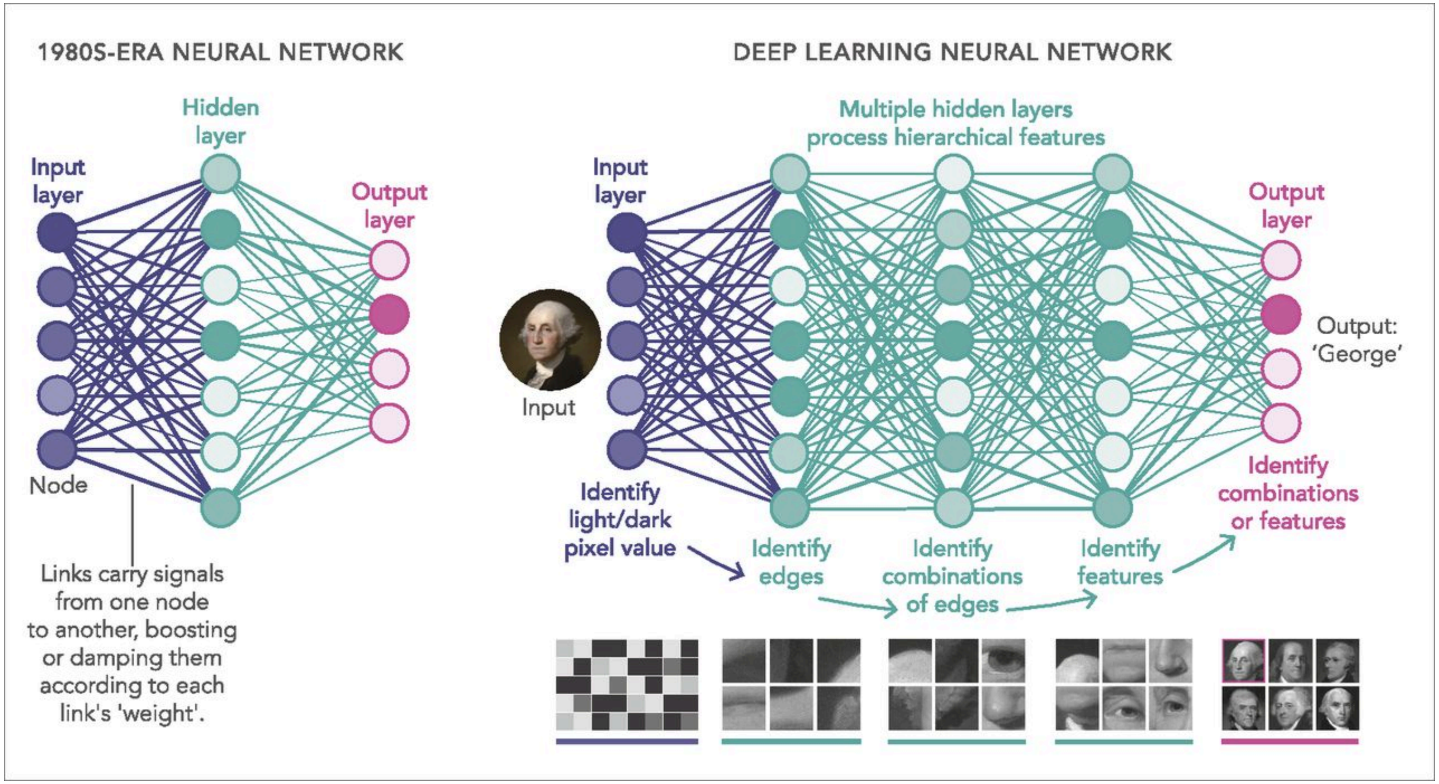
Computer vision before deep learning



Computer vision after deep learning



Feed-forward Deep Learning Architecture Example



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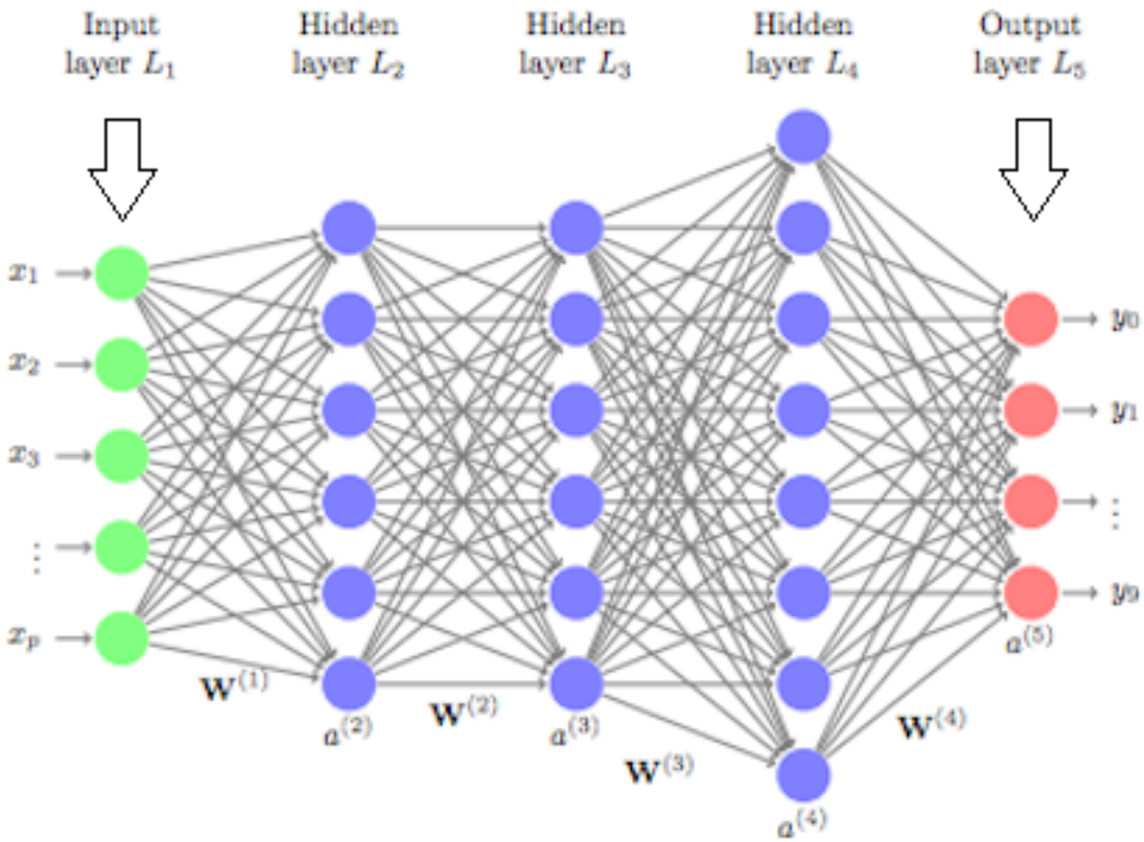

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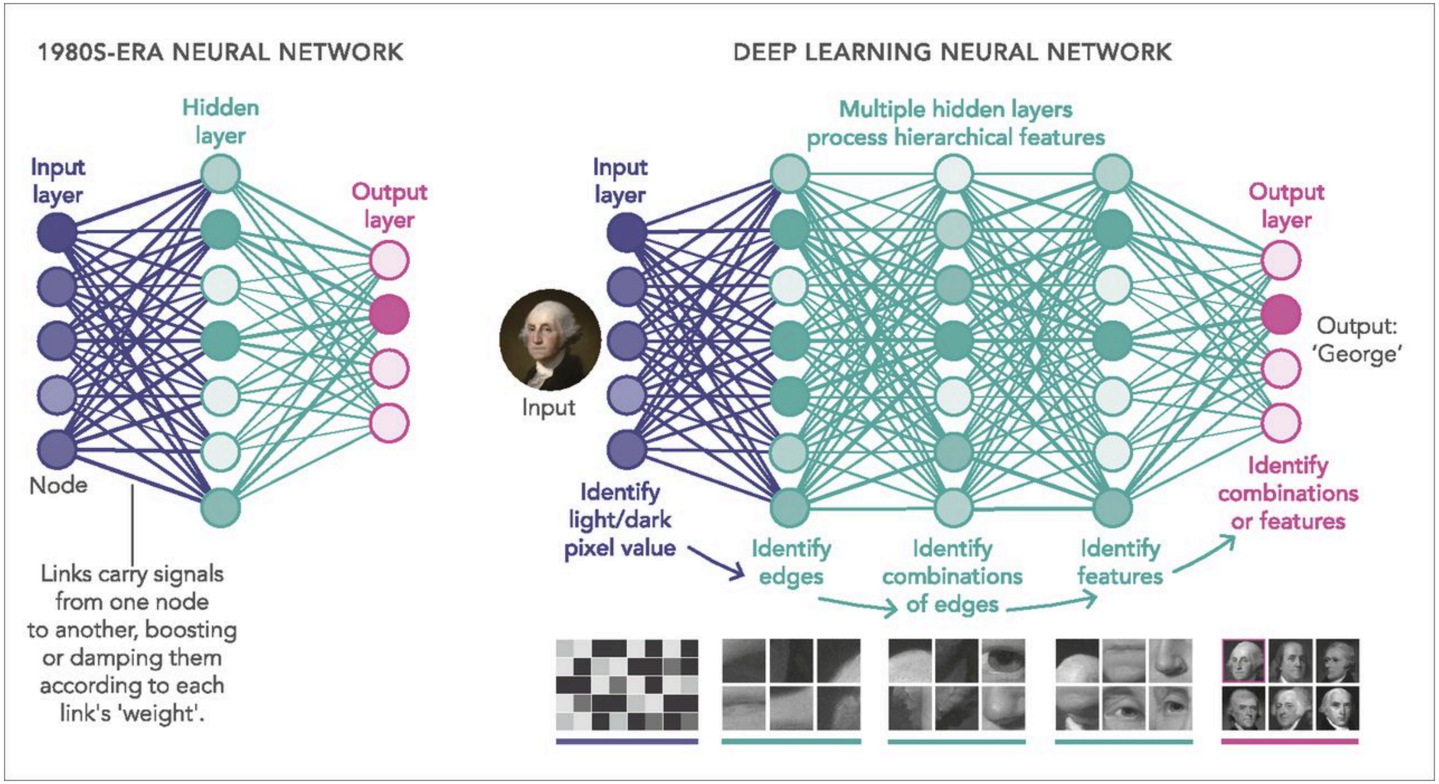

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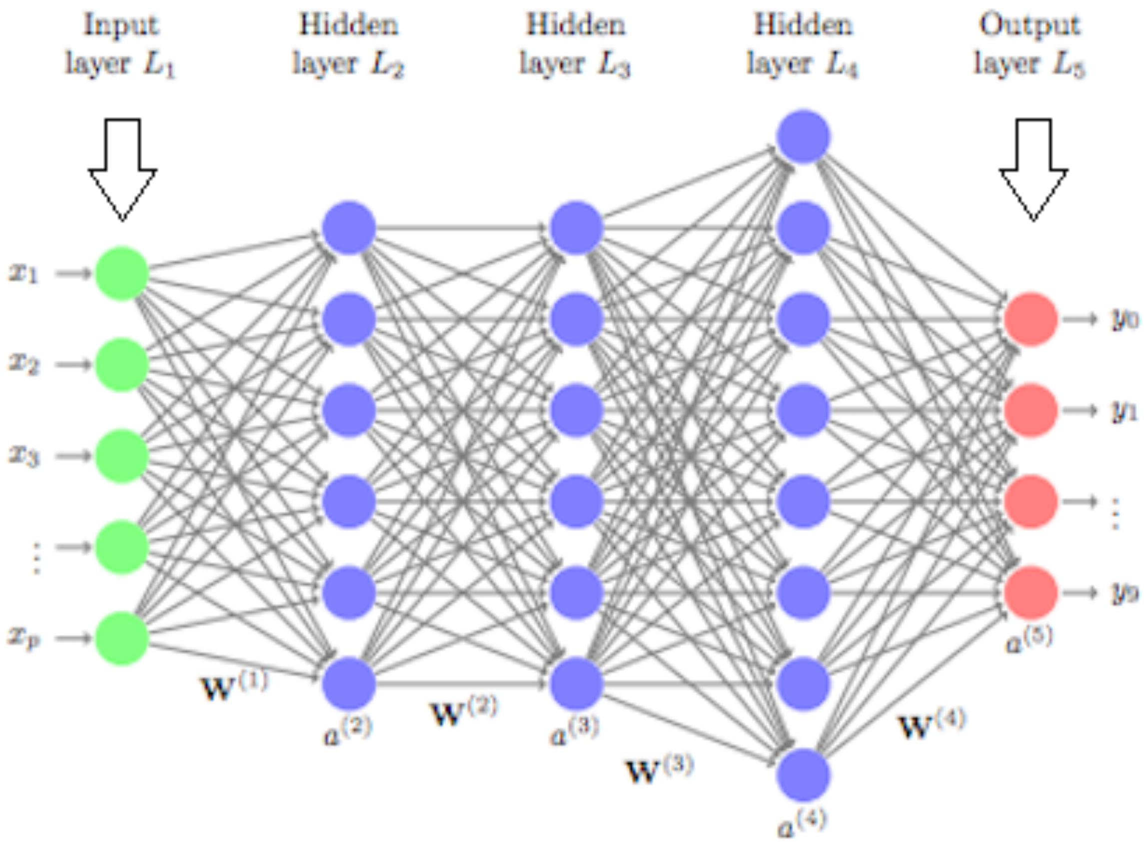

ICE #2

Compute the number of parameters in DNN model

Consider a DNN model with 3 hidden layers where each hidden layer has 1000 neurons. Let the input layer be raw pixels from a 100x100 image and the output layer has 10 dimensions, let's say for a 10 class image classification example. How many total parameters exist in the DNN model?

1. 10 million parameters
2. 11 million parameters
3. 12 million parameters
4. 13 million parameters

Training a DNN

SGD with mini-batch

SGD mini-batch is the staple diet. However there are some **learning rate schedulers** that are known to work better for DNNs - Such as Adagrad and more recently, ADAM. ADAM adapts the learning rate to each individual parameter instead of having a global learning rate.

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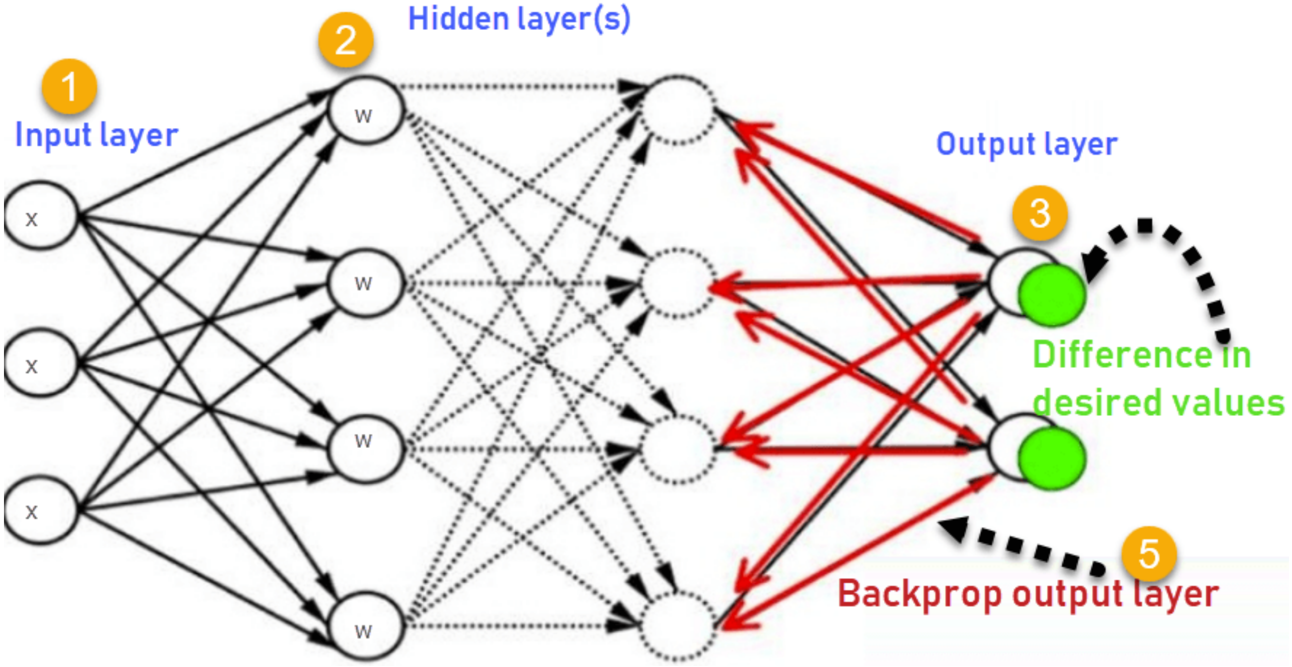
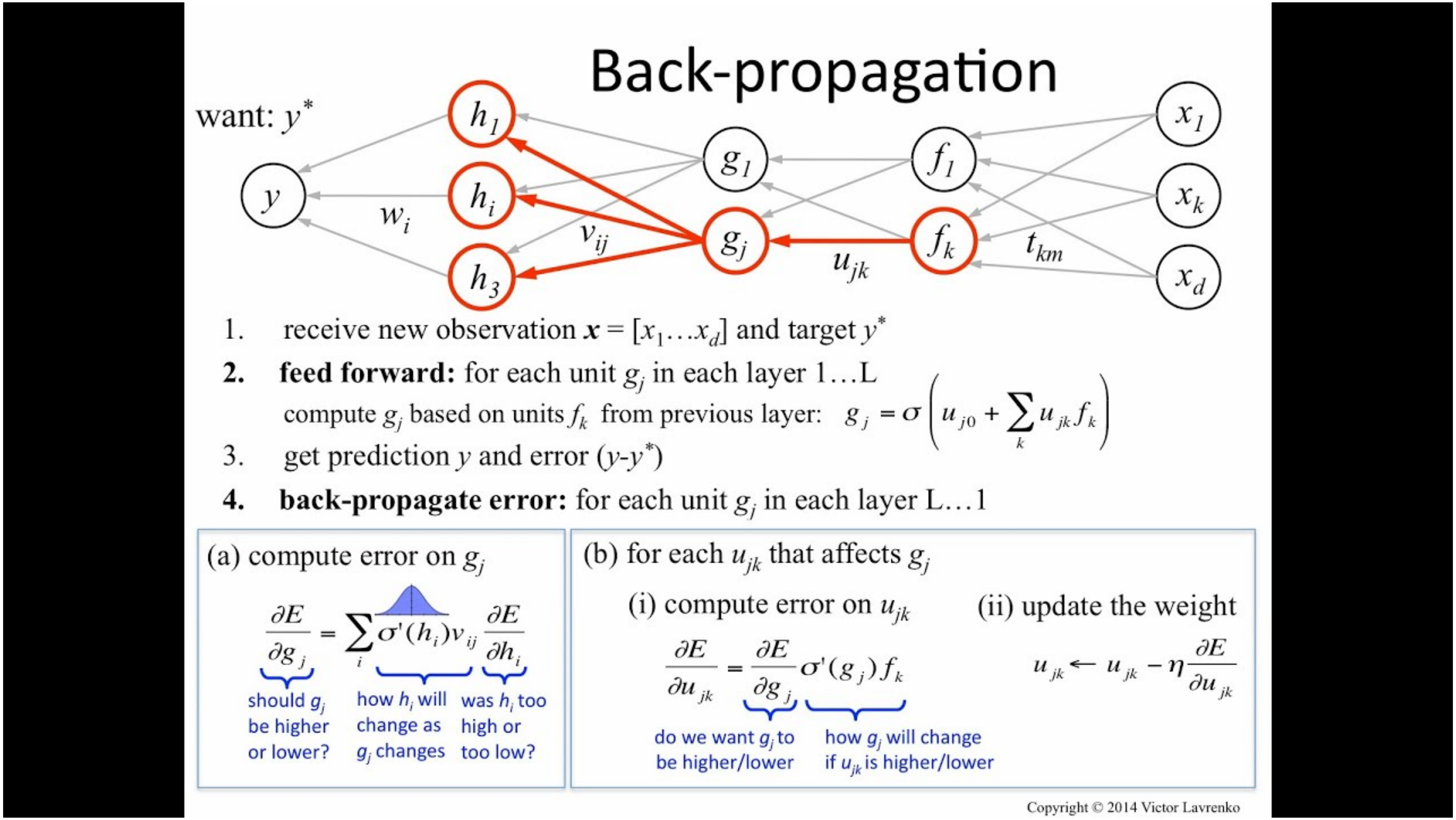
How do we compute gradient in a DNN?

Back-propagation!

Forward Propagation vs Back-propagation



Back Propagation explained



Back Propagation Summary

Back Prop

Back prop is one of the fundamental backbones of the training modules behind deep learning and beyond (including for example ChatGPT). What exactly is back prop? It is just a way to unravel gradient computation in the neural network. Back prop is how we would **compute the gradient** in a neural network.

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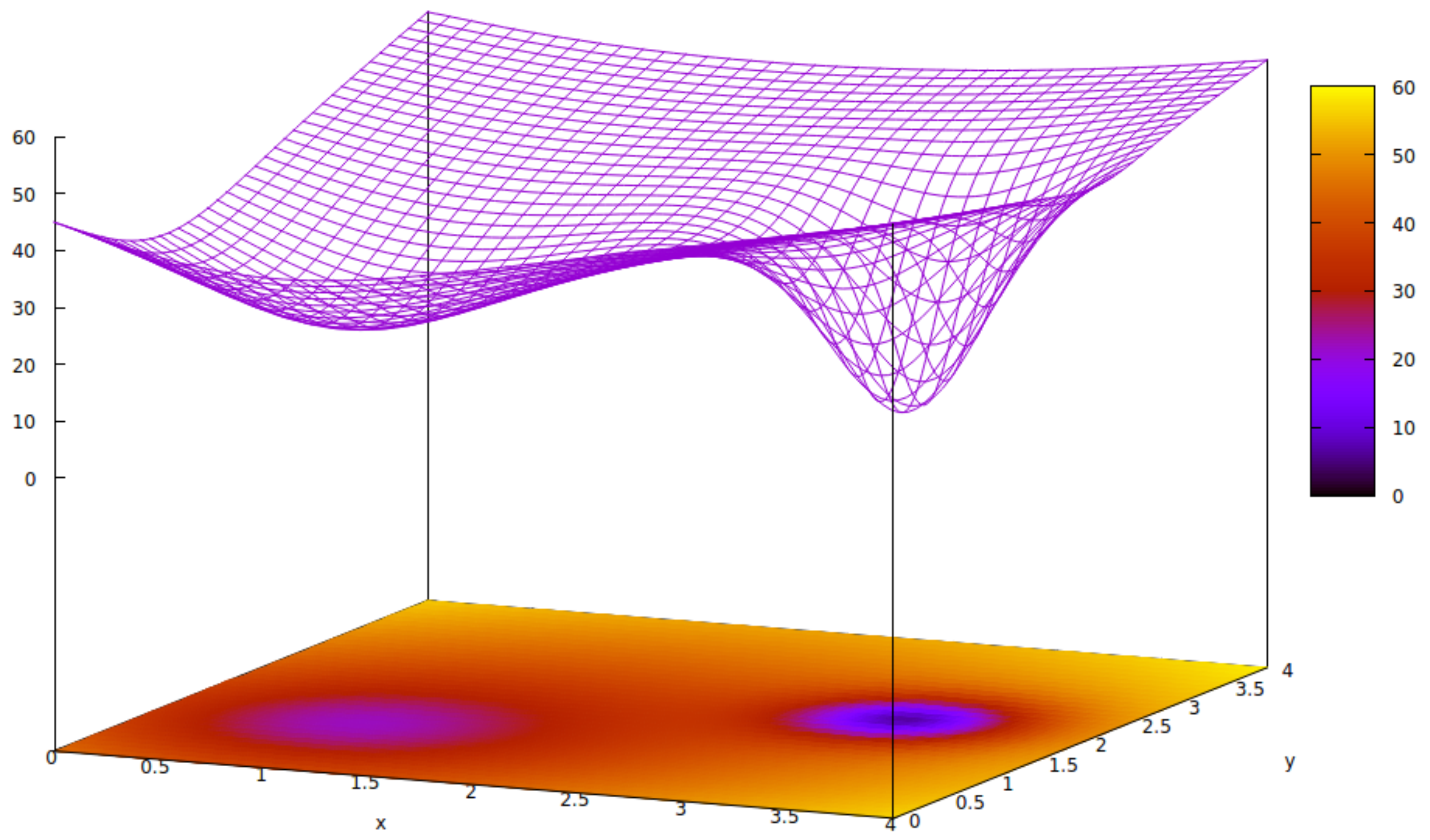
Back Prop as information flow

It can also be thought of as flow information from the error in the output (the loss function) down to the weights. Update the weights so we don't make **this error** next time around. Back prop is a way to do **gradient descent in neural networks!**

Good vs Bad Local minima



Hyper-parameters in Deep Learning

ICE #3: Which of the following is not a hyper-parameter in deep learning?

1. Learning rate
2. Number of Hidden Layers
3. Number of neurons per hidden layer
4. All of the above

Hyper-parameters in Deep Learning

Hyper-parameters

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Hyper-parameters in Deep Learning

Hyper-parameters

1. Learning rate
2. Number of Hidden Layers
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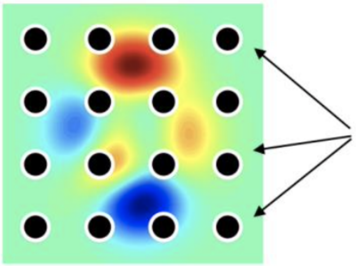
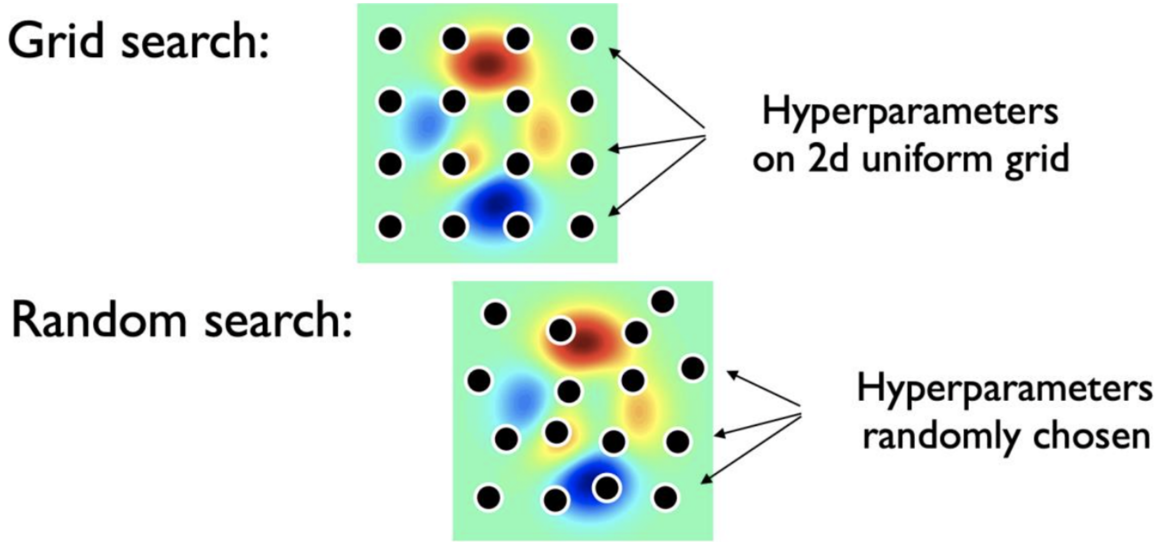
4. Type of non-linear activation function used
5. Anything else?

Hyper-parameter tuning methods

Grid search:



Hyper-parameter tuning methods



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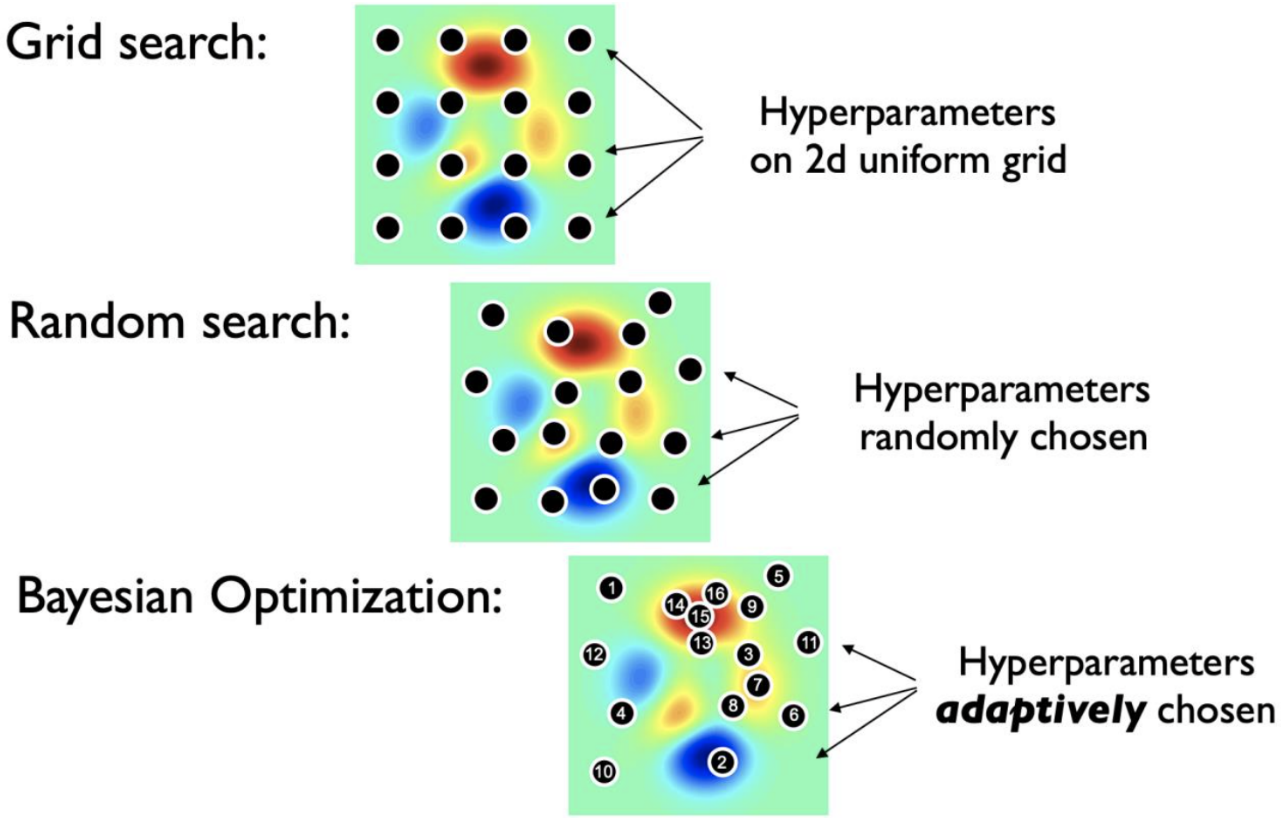

Over-fitting in DNNs

How to handle over-fitting in DNNs

1. A DNN model with 100 million parameters and only 100k data points or even a million data points will overfit unless we take care of over-fitting.

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5. Early stopping is also a great strategy! Stop training the DL model when the validation error starts increasing. How's this different from regular validation we were doing earlier??

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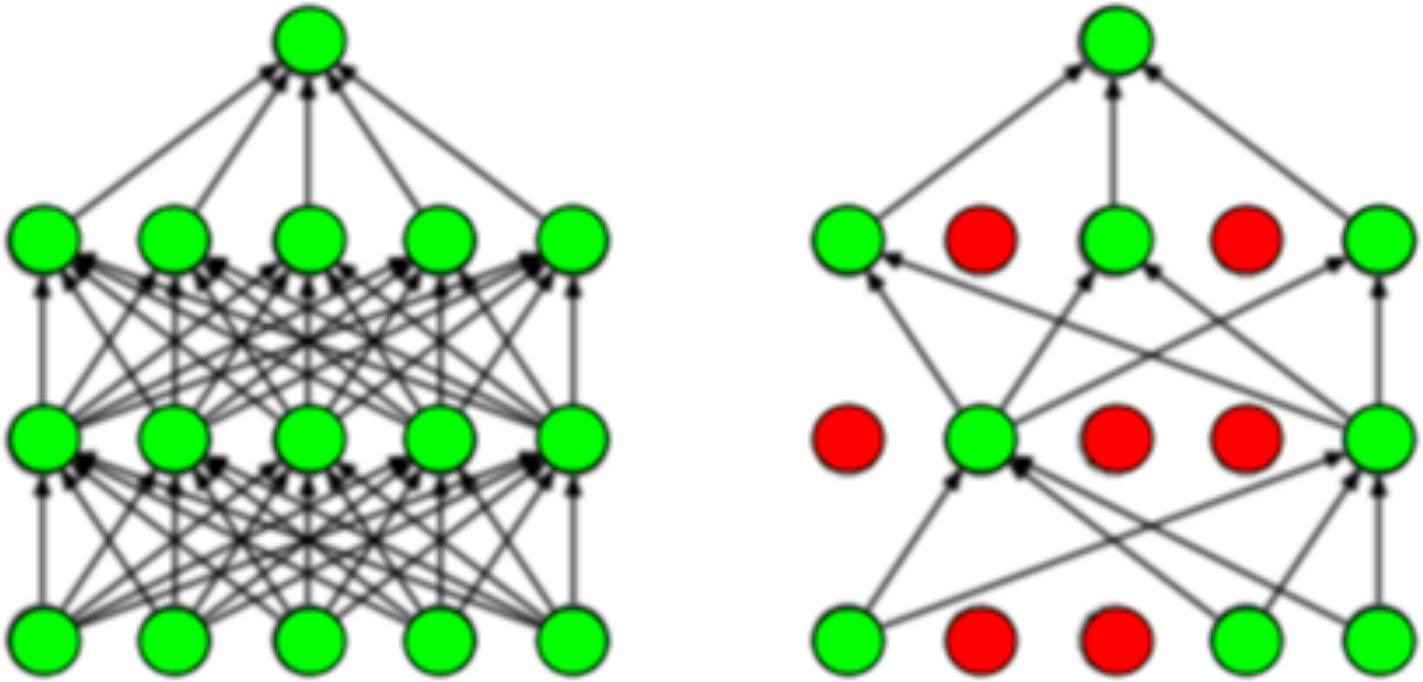
6. Book by Yoshua Bengio has tons of details and great reference for Deep Learning!

Taking care of Over-fitting: Dropouts



(a) Standard Neural Net

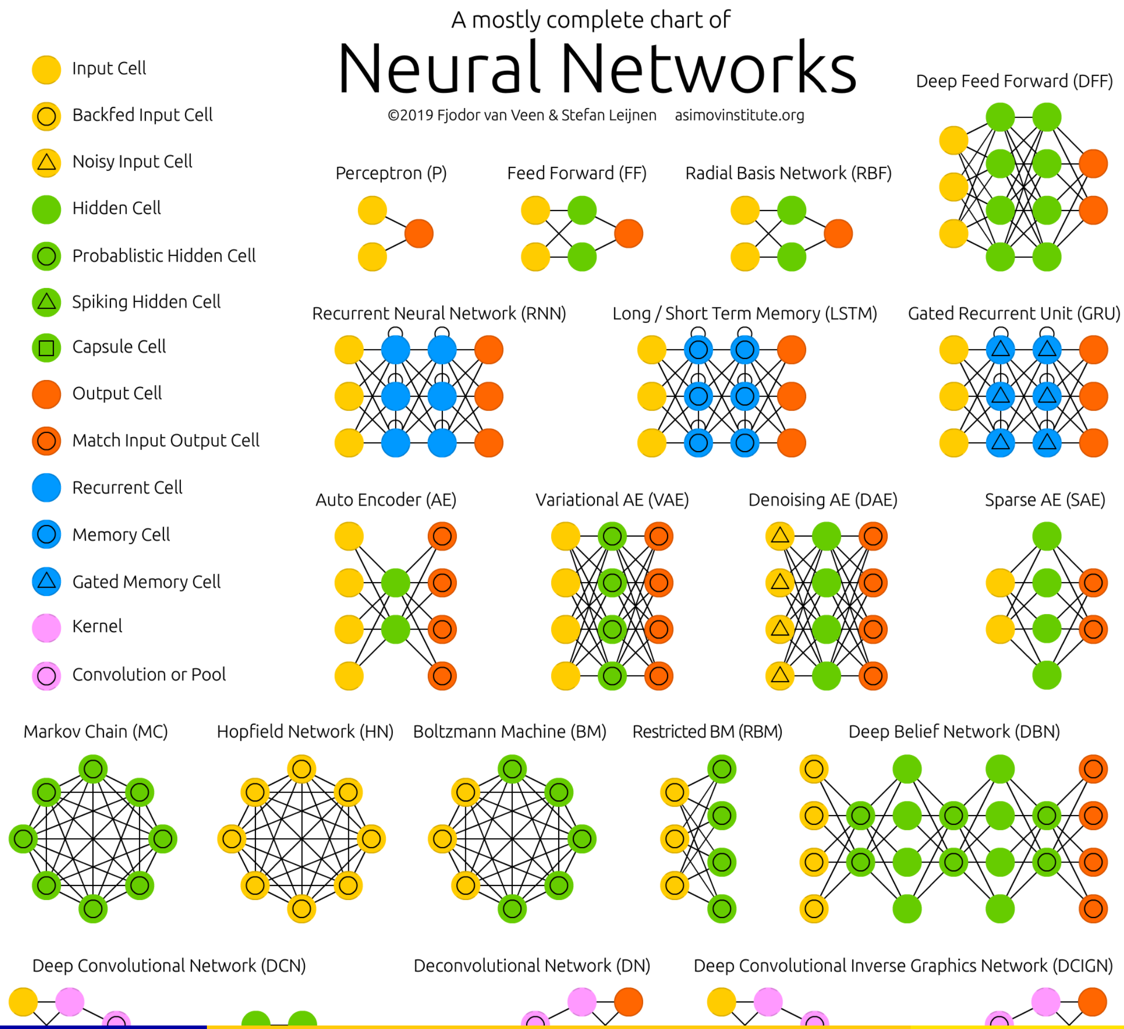
(b) After applying dropout.

Tensorflow Playground Demo

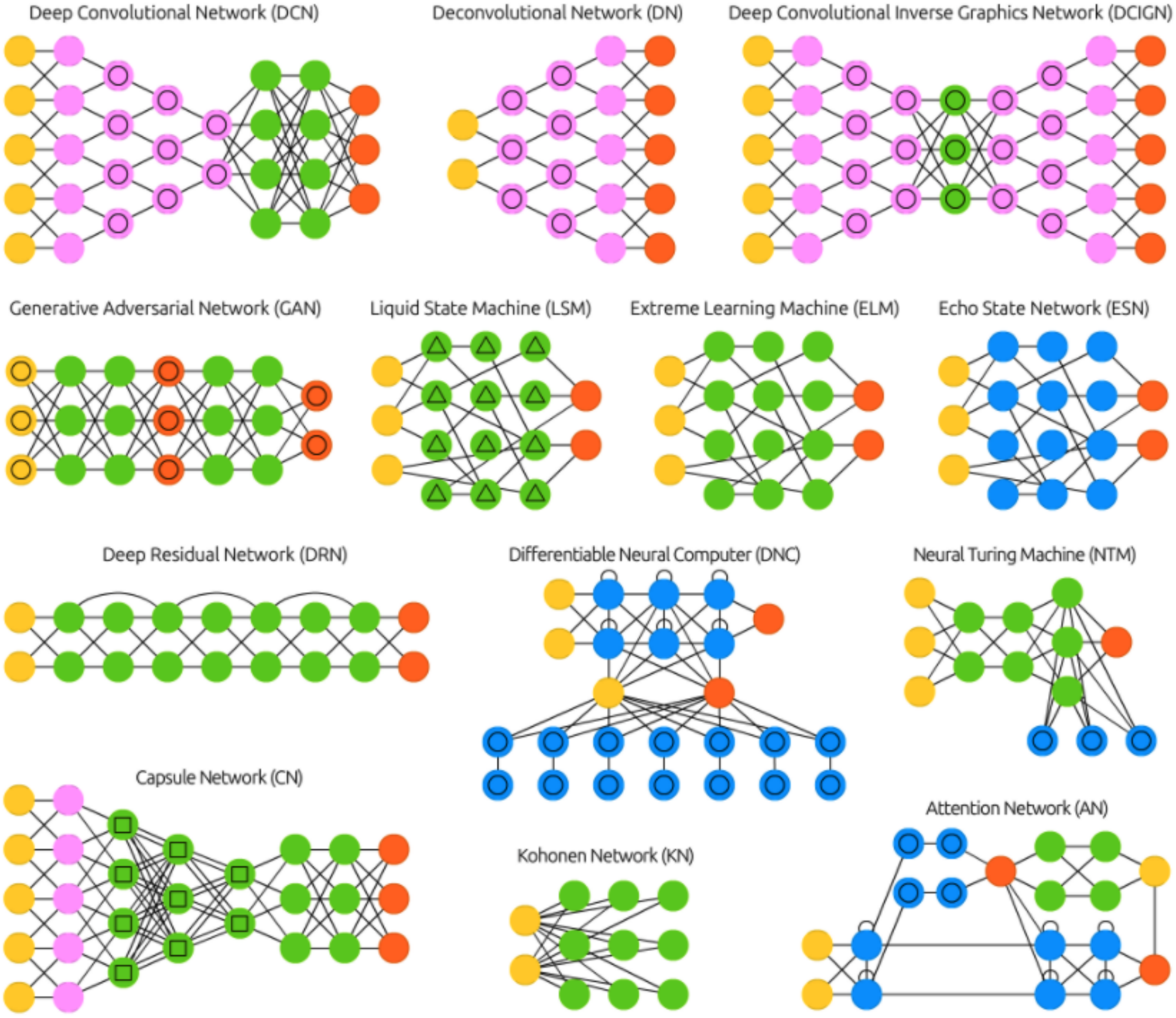
Tensorflow Playground Demo

Neural Networks Zoo

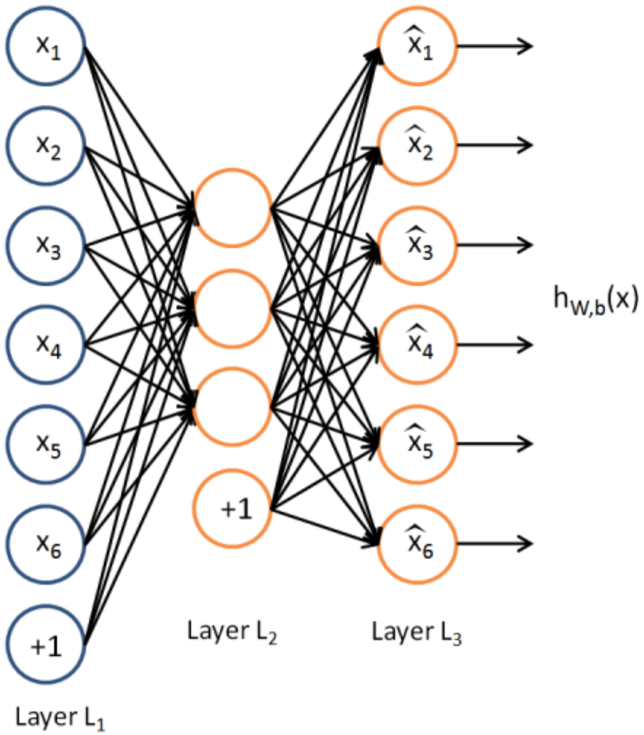
Zoo Reference



Neural Networks Zoo



Auto Encoders



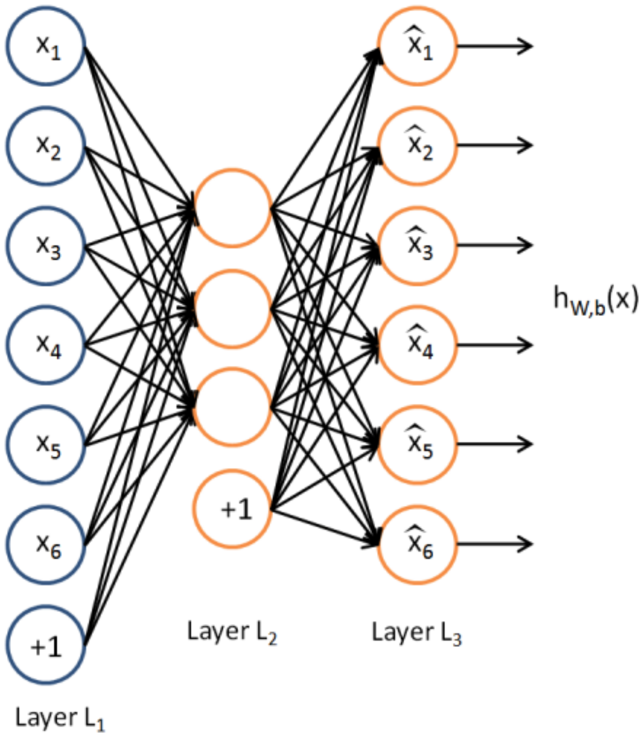
ICE #4

PCA vs Auto Encoder

Which of the following statements are true ?

1. Both PCA and Auto Encoders serve the purpose of dimensionality reduction
2. They are both linear models but one uses a neural nets architecture and the other is based on projections
3. PCA is robust to outliers while Auto Encoders are not
4. Auto Encoders are as better than Glove Embeddings to find low-dim embeddings for words

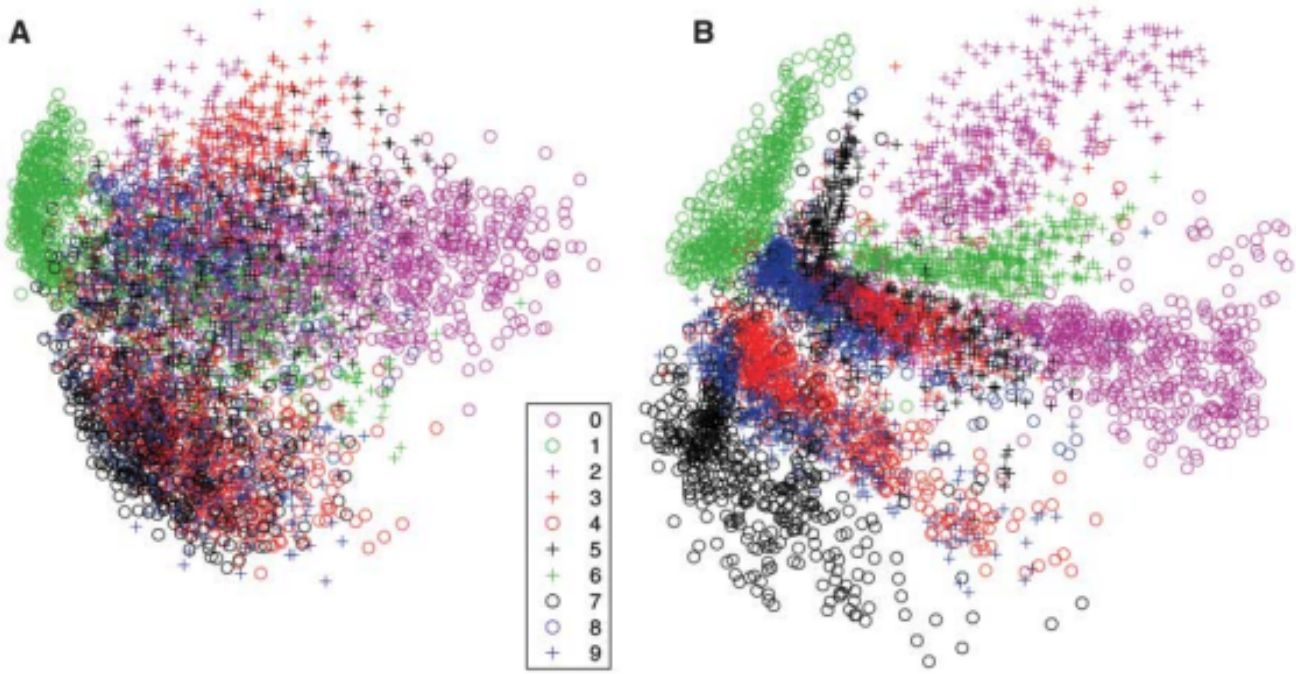
PCA vs Auto-Encoders



AutoEncoders and Dimensionality Reduction

Reading Reference for AE Dimensionality Reduction

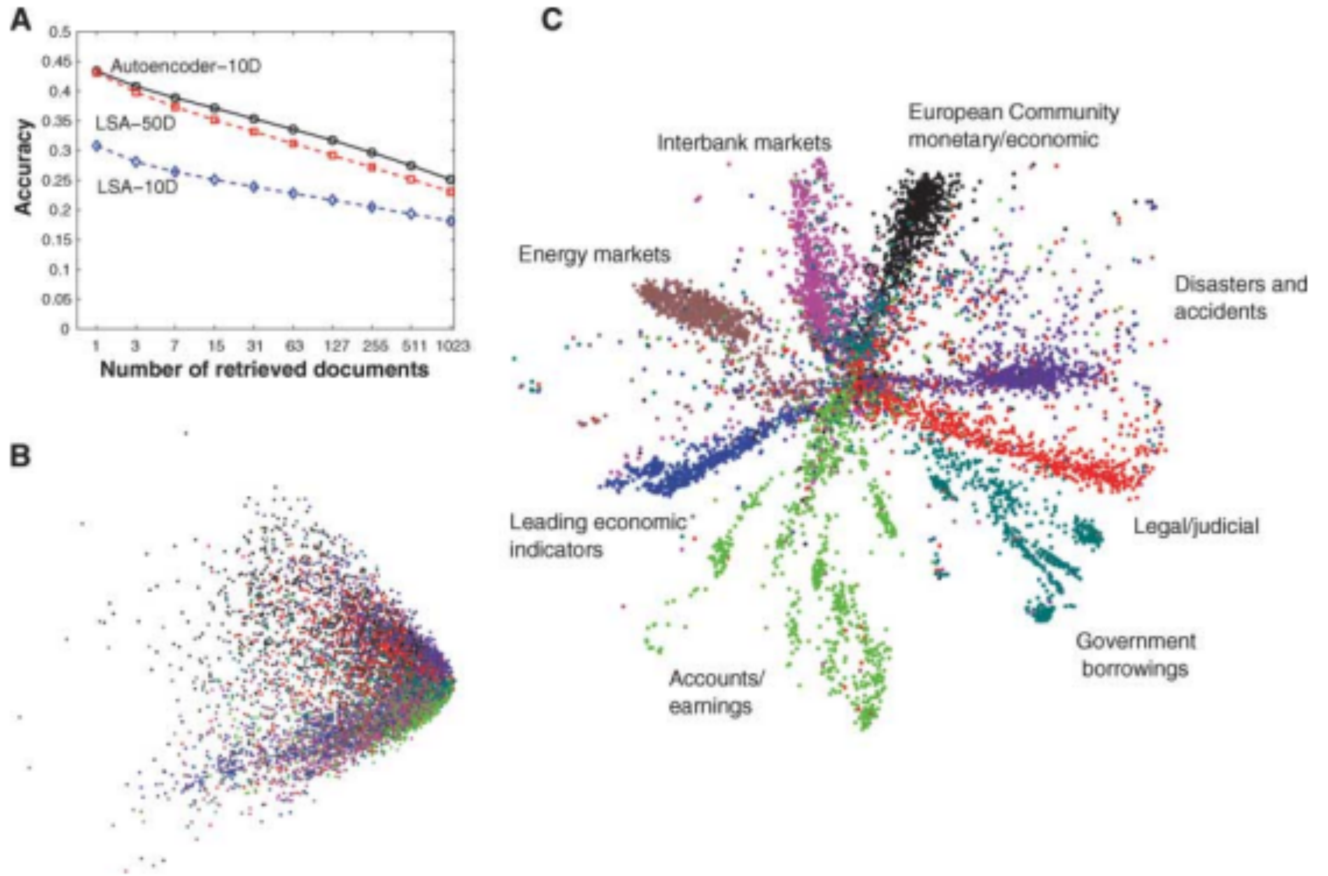
Fig. 3. (**A**) The two-dimensional codes for 500 digits of each class produced by taking the first two principal components of all 60,000 training images. (**B**) The two-dimensional codes found by a 784-1000-500-250-2 autoencoder. For an alternative visualization, see (*8*).



AutoEncoders and Dimensionality Reduction

Reading Reference for AE Dimensionality Reduction

Fig. 4. **(A)** The fraction of retrieved documents in the same class as the query when a query document from the test set is used to retrieve other test set documents, averaged over all 402,207 possible queries. **(B)** The codes produced by two-dimensional LSA. **(C)** The codes produced by a 2000-500-250-125-2 autoencoder.



AutoEncders Summary

1. Auto-Encoders are a method for dimensionality reduction and can do better than PCA for visualization

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AutoEncders Summary

1. Auto-Encoders are a method for dimensionality reduction and can do better than PCA for visualization
2. Use Neural Networks architecture and hence can encode non-linearity in the embeddings
3. Anything else?
4. Auto Encoders can learn convolutional layers instead of dense layers - Better for images! More flexibility!!

Removing obstacles in images

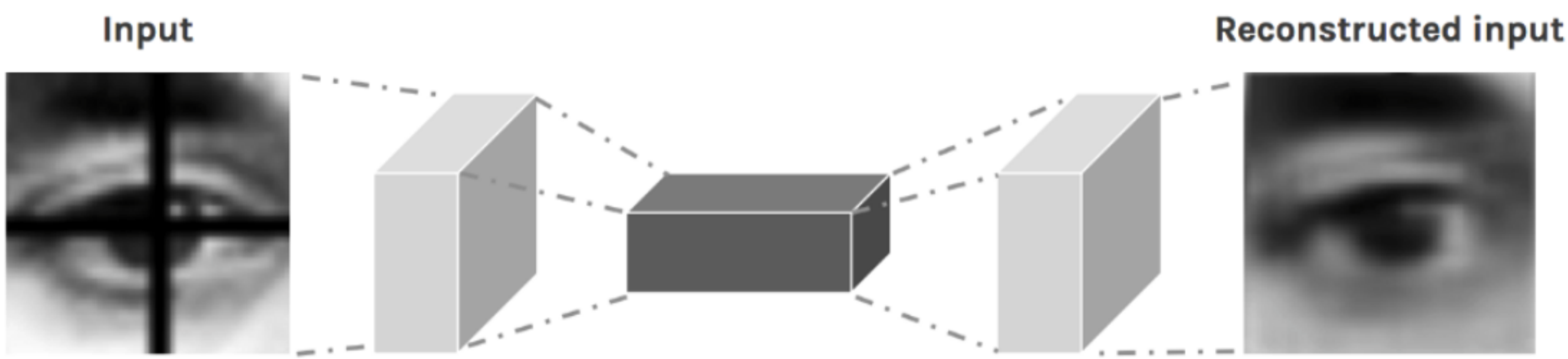


Figure 12: Reconstructed image from missing image [14]

Removing obstacles in images

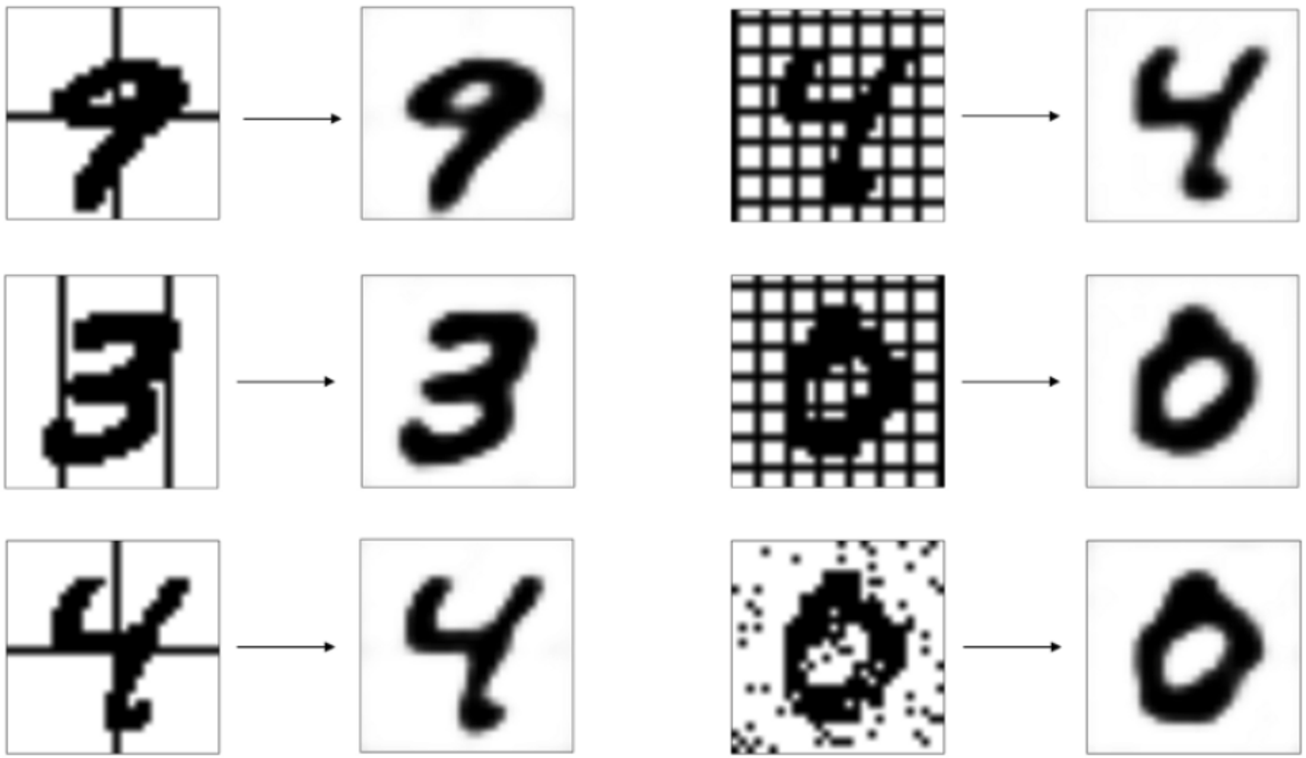
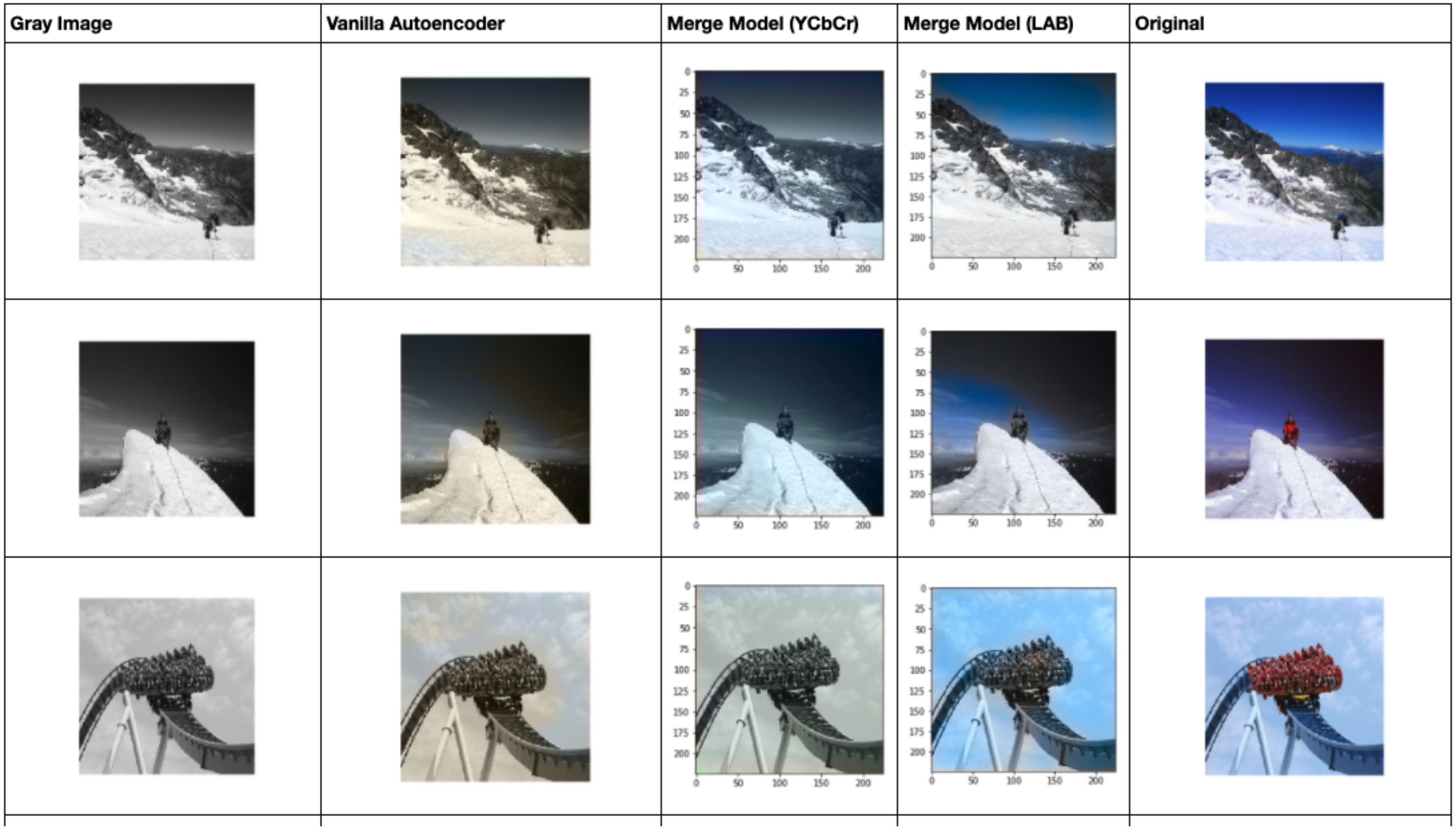
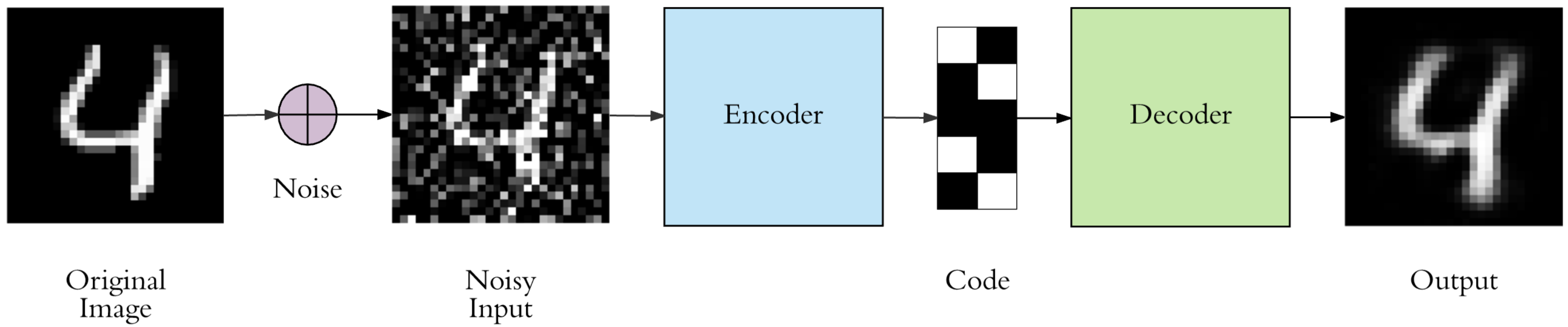


Figure 13: Source [15]

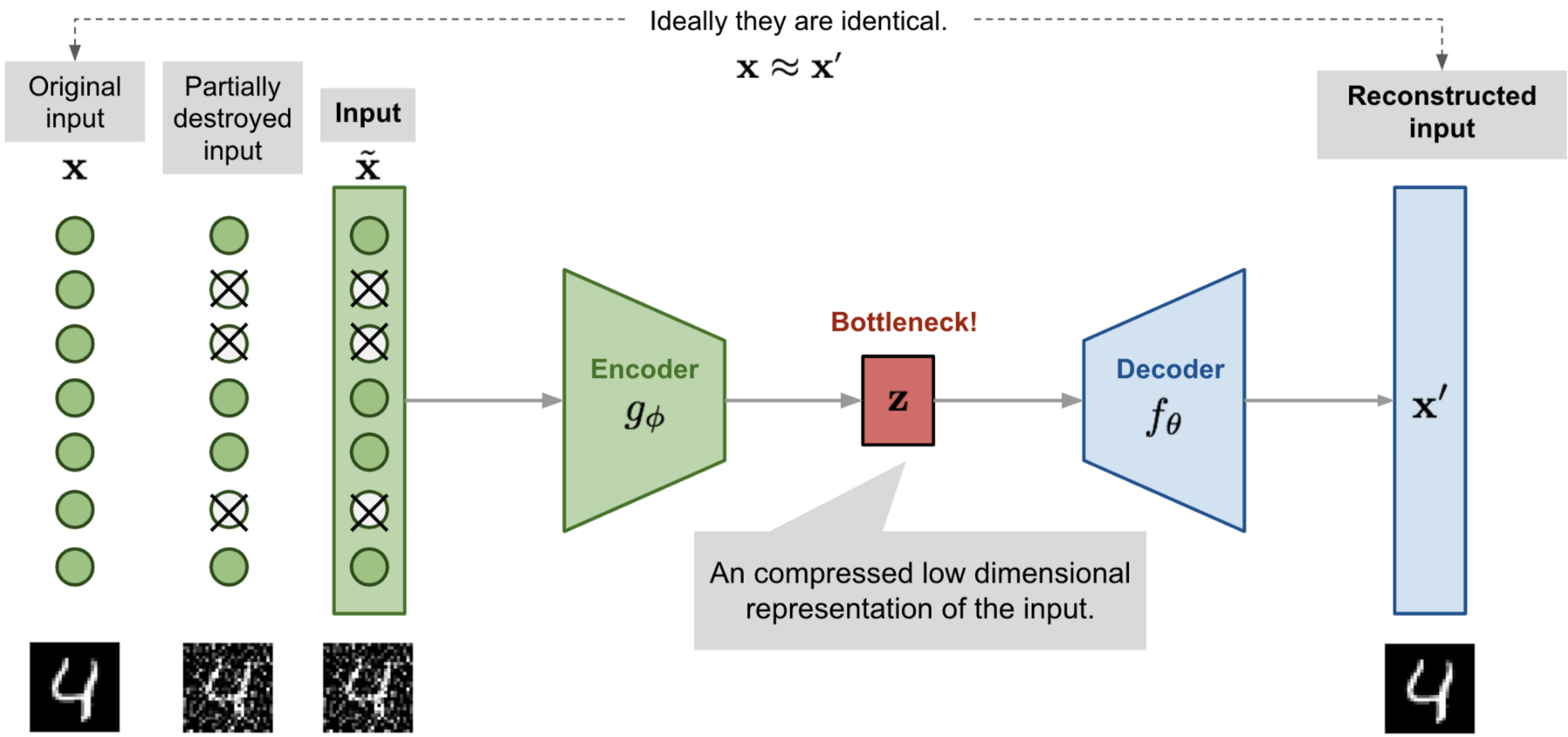
Coloring Images



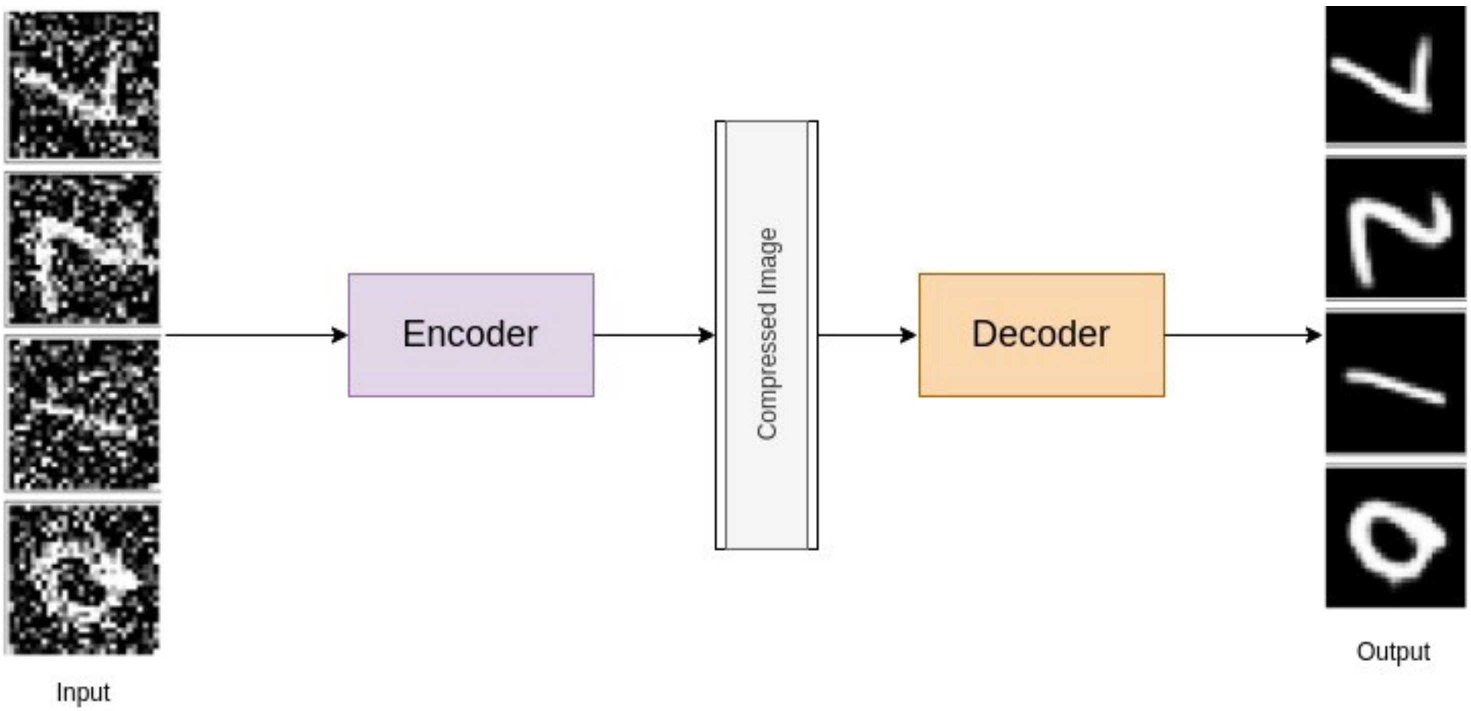
De-noising Auto Encoders



De-noising Auto Encoders



De-noising Auto Encoders



De-noising Auto Encoders

Details

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- Difference: Noise is injected in the inputs on purpose but output is a clean data point.

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- This forces the Auto Encoder to “de-noise” data, esp. useful for images!

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- Just like an Auto Encoder
- Difference: Noise is injected in the inputs on purpose but output is a clean data point.
- This forces the Auto Encoder to "de-noise" data, esp. useful for images!
- Esp. useful for a category of objects or images (e.g. digit recognition or face recognition, etc)

ICE #5

Unsupervised Learning

Which of these is NOT an example of unsupervised learning?

1. Perceptron
2. Auto Encoder
3. De-noising Auto Encoder
4. K-means++
5. None of the above
6. All of the above

Breakouts Time 1

5 mins

Discuss in your groups what are some real-world applications of any or many of the Auto Encoder Architectures we discussed so far you can think of in your area of work or in a standard context e.g. images.

Sequence structure in NLP

Example

I love this car!   Positive Sentiment

Sequence structure in NLP

Example

I love this car! Positive Sentiment

Example

I am not sure I love this car! Negative Sentiment

Sequence structure in NLP

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I love this car! Positive Sentiment

Example

I am not sure I love this car! Negative Sentiment

Example

I don't think its a bad car at all! $\rightarrow$ Positive Sentiment

Sequence structure in NLP

Example

I love this car! Positive Sentiment

Example

I am not sure I love this car! Negative Sentiment

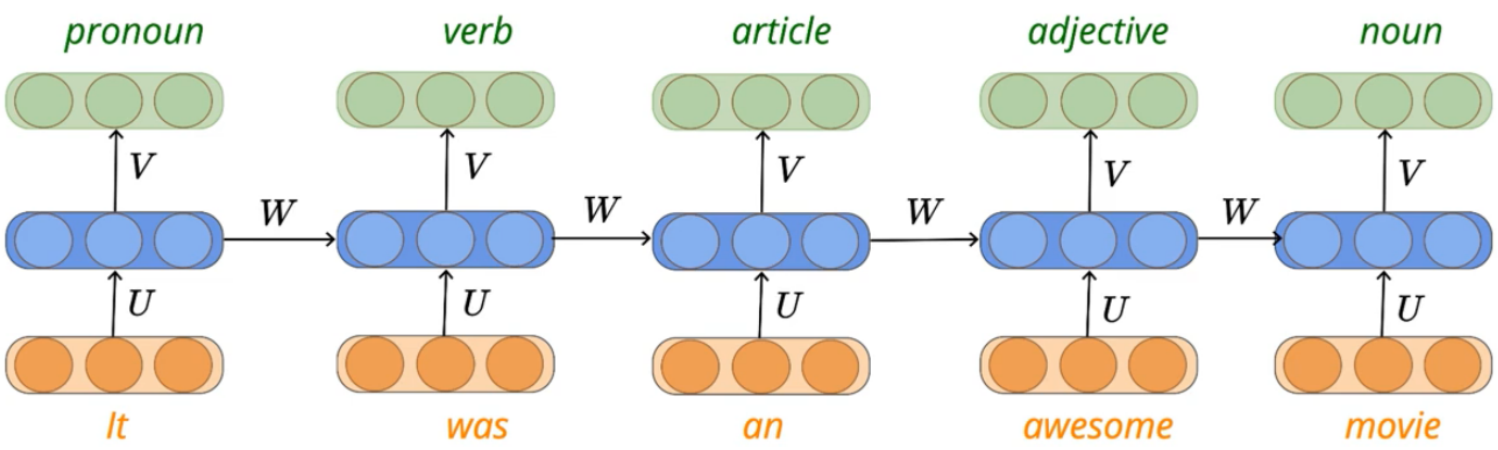
Example

I don't think its a bad car at all! $\rightarrow$ Positive Sentiment

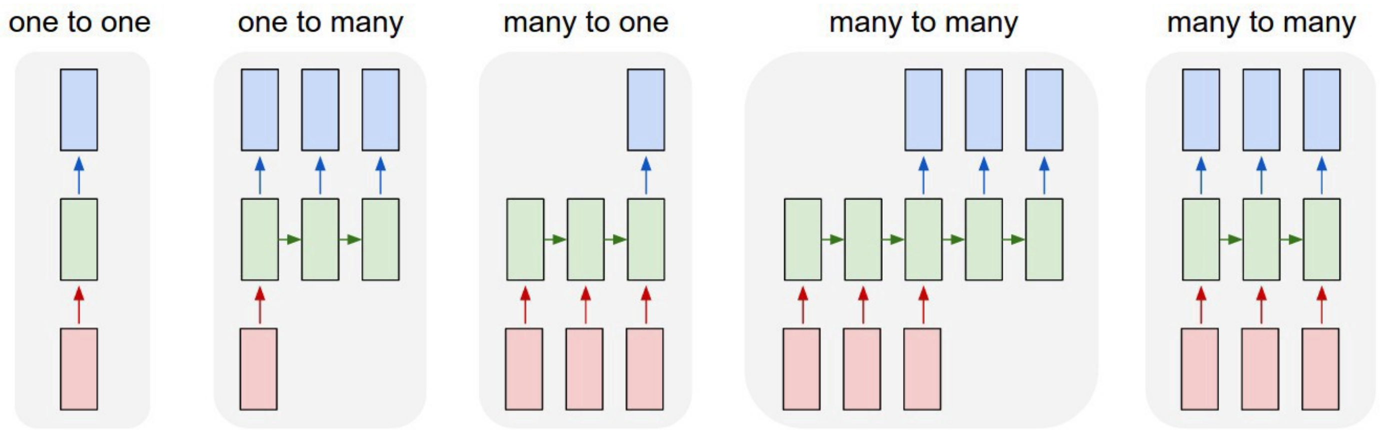
Example

Have to carry the **context(state)** from some-time back to fully understand what's happening!

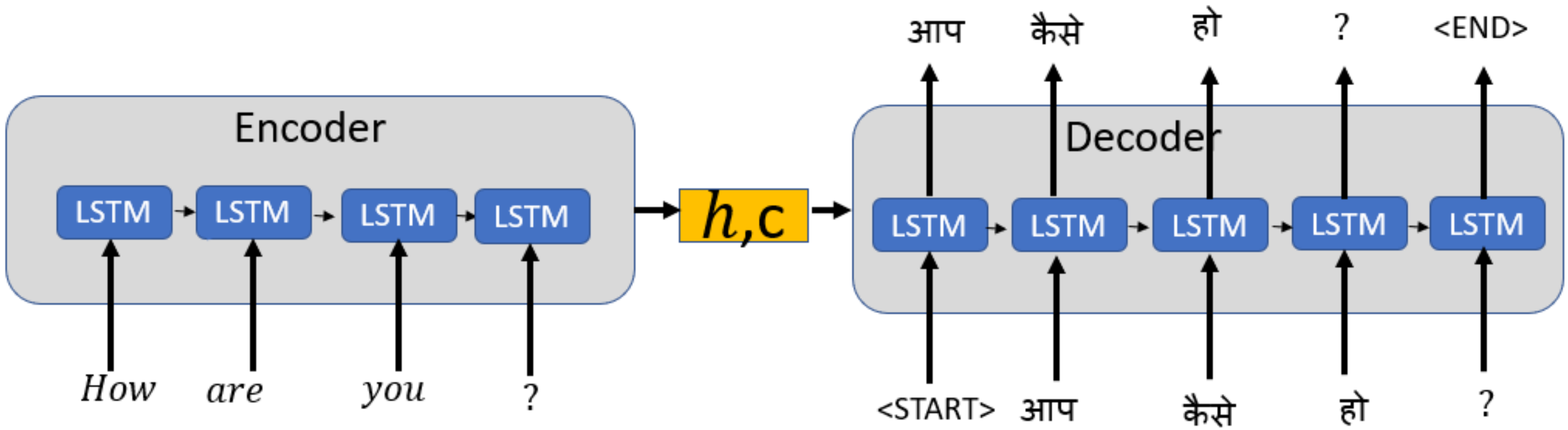
Sequence to Sequence Model (LSTM) Applications



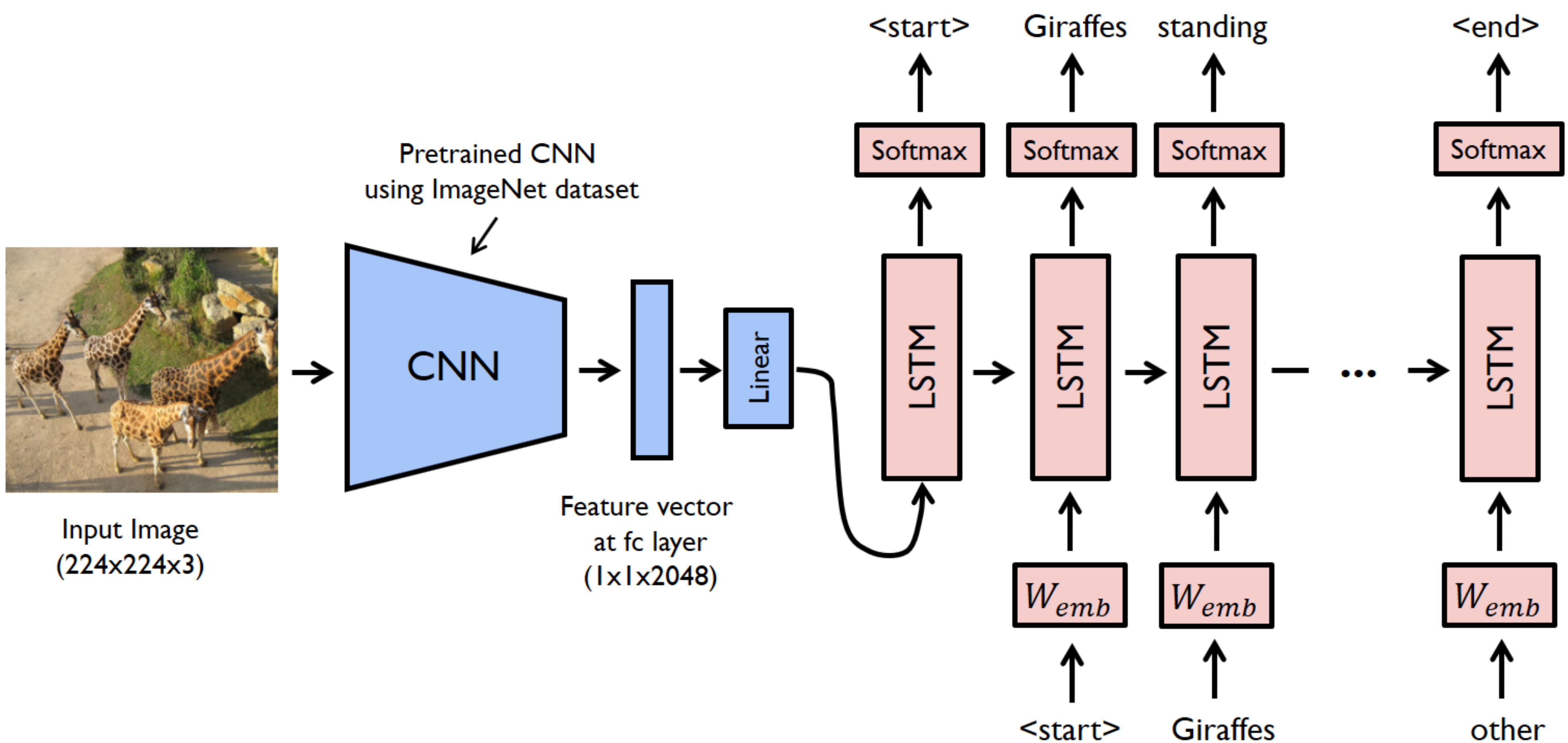
Sequence to Sequence Model (LSTM) Applications



Sequence to Sequence Model (LSTM) Applications



Sequence to Sequence Model (LSTM) Applications



Breakouts Time #2

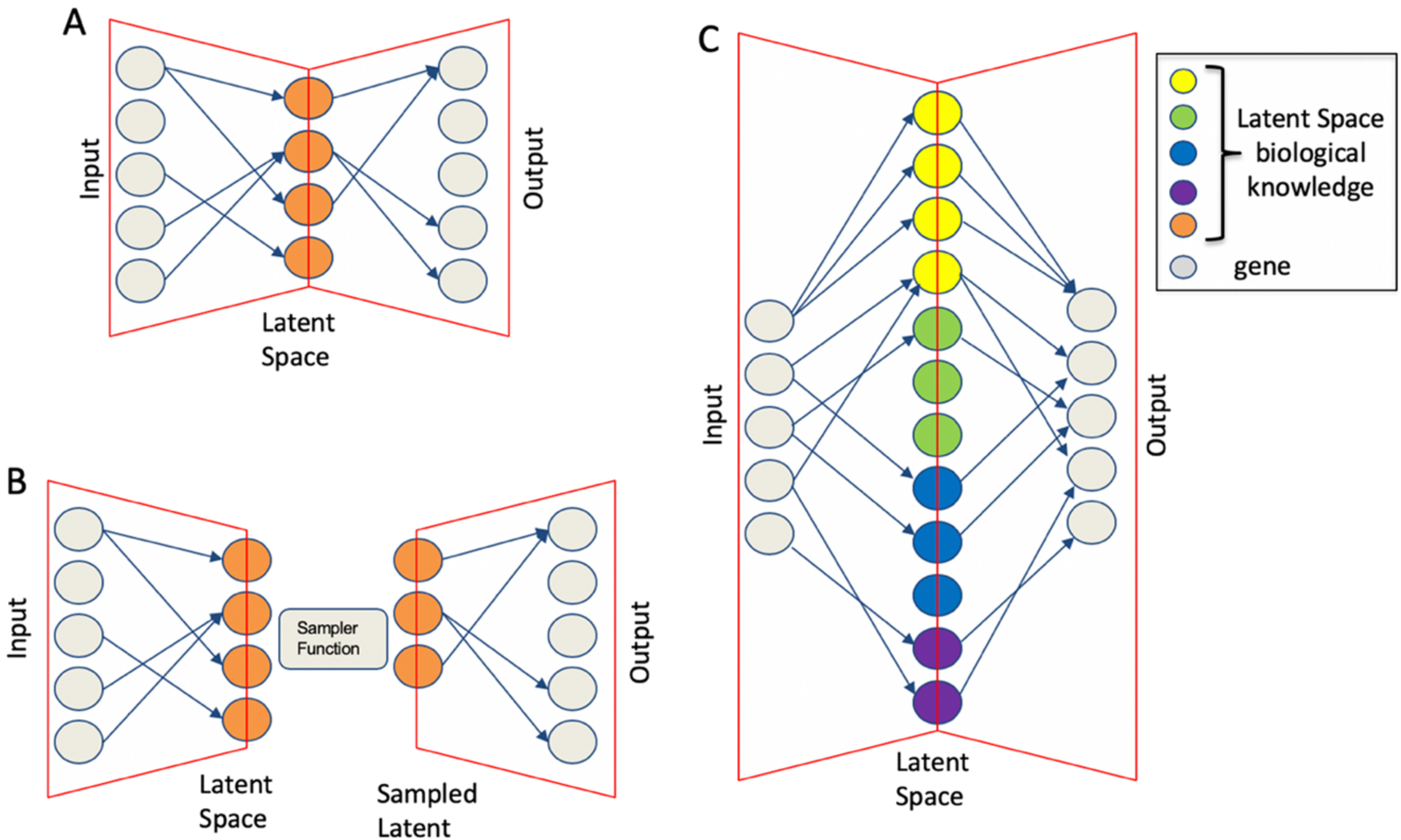
Auto-complete — 5 mins

Let's say you are tasked with building an in-email auto-completion application, which can help complete partial sentences into full sentences through suggestions (auto-complete). How would you use what we have learned so far to model this? What architecture would you use? What would be your data? And what are some pitfalls or painpoints your model should address?

Extra Slides

Sparse Auto Encoders

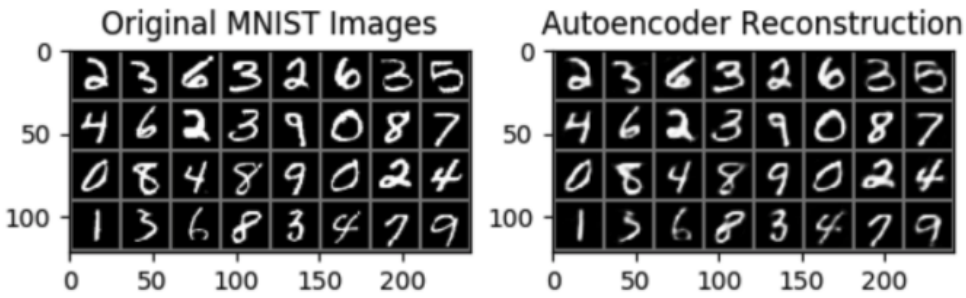
Sparse AE



Sparse Auto Encoders

Sparse AE

Reference



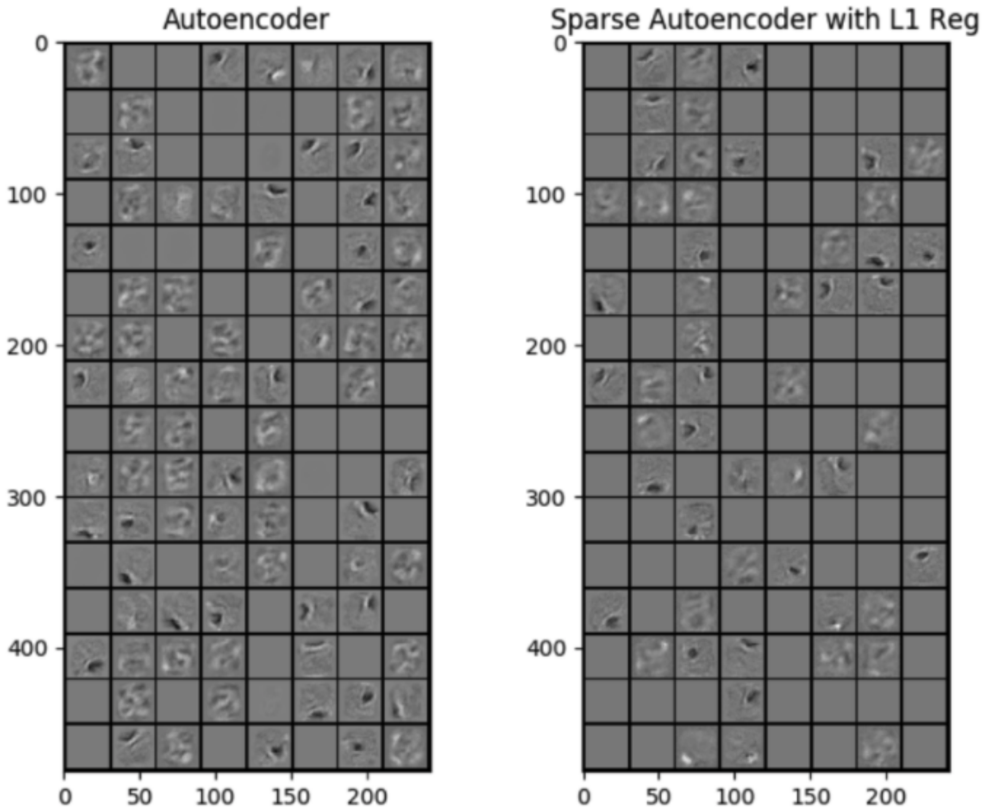
Methods	Best MSE Loss (MNIST or CIFAR-10)
Simple Autoencoder	0.0318 (MNIST)
Sparse Autoencoder (L1 reg)	0.0301 (MNIST)

Experiment Results

Sparse Auto Encoders

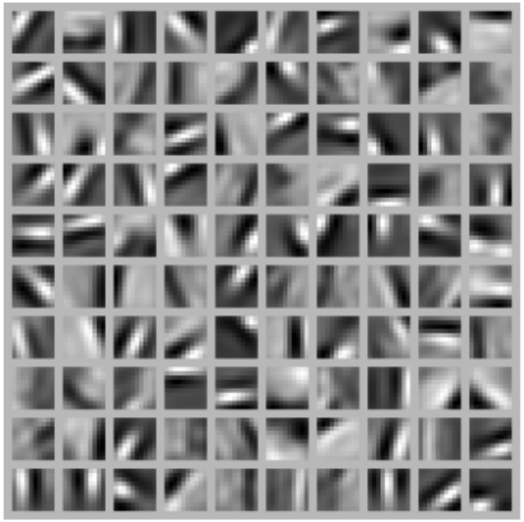
Sparse AE

Reference



Sparse Auto Encoders

Input Image that maximizes activations for each neuron in hidden layer!



Sparse De-noising Auto Encoders