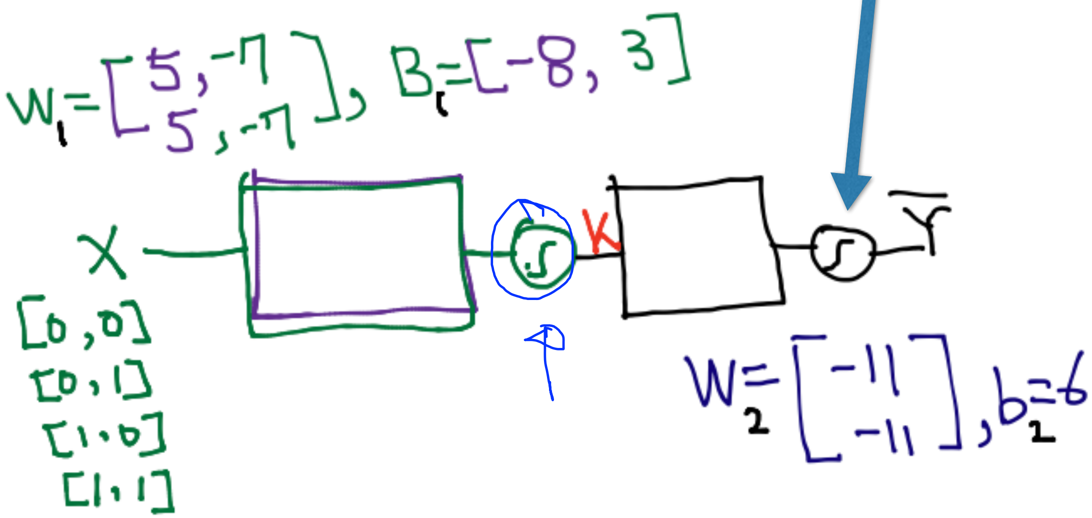
Lecture 10-1

ReLU: Better non-linearity

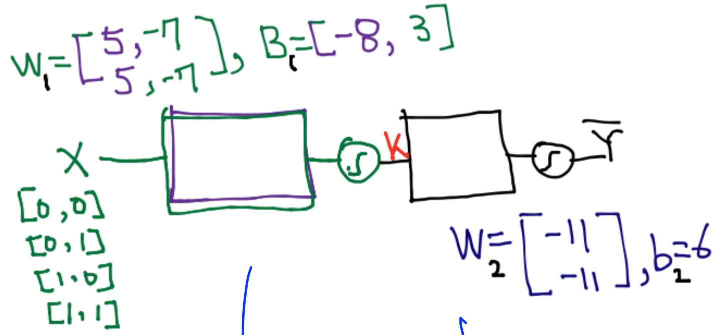
Sung Kim <hunkim+mr@gmail.com>
http://hunkim.github.io/ml/

NN for XOR

Activation function



NN for XOR



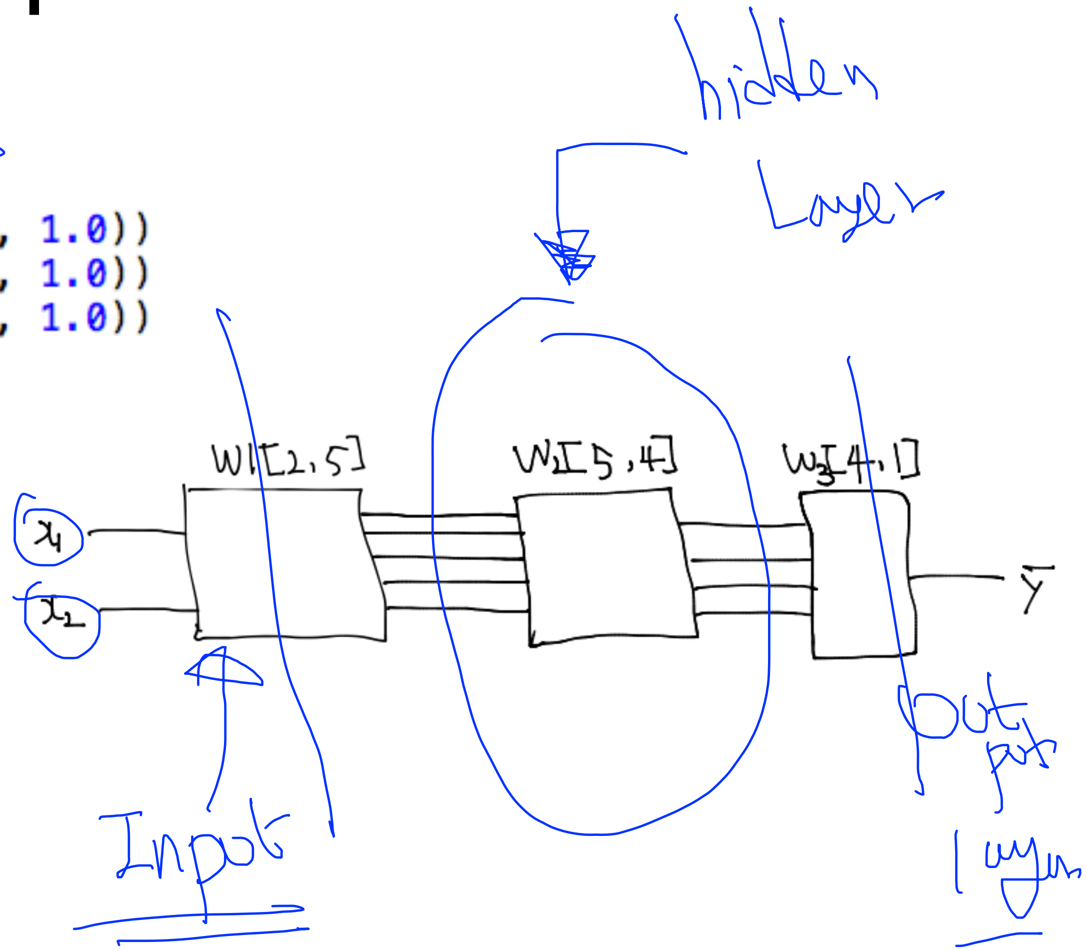

```
W1 = tf.Variable(tf.random_uniform([2, 2], -1.0, 1.0))
W2 = tf.Variable(tf.random_uniform([2, 1], -1.0, 1.0))

b1 = tf.Variable(tf.zeros([2]), name="Bias1")
b2 = tf.Variable(tf.zeros([1]), name="Bias2")

# Our hypothesis
L2 = tf.sigmoid(tf.matmul(X, W1) + b1)
hypothesis = tf.sigmoid(tf.matmul(L2, W2) + b2)
```

Let's go deep & wide!

X5

x1, x2 bias

```
W1 = tf.Variable(tf.random_uniform([2, 5], -1.0, 1.0))
W2 = tf.Variable(tf.random_uniform([5, 4], -1.0, 1.0))
W3 = tf.Variable(tf.random_uniform([4, 1], -1.0, 1.0))

b1 = tf.Variable(tf.zeros([5]), name="Bias1")
b2 = tf.Variable(tf.zeros([4]), name="Bias2")
b3 = tf.Variable(tf.zeros([1]), name="Bias2")

# Our hypothesis
L2 = tf.sigmoid(tf.matmul(X, W1) + b1)
L3 = tf.sigmoid(tf.matmul(L2, W2) + b2)
hypothesis = tf.sigmoid(tf.matmul(L3, W3) + b3)
```



9 hidden layers!

```
W1 = tf.Variable(tf.random_uniform([2, 5], -1.0, 1.0), name = "Weight1")

W2 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight2")
W3 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight3")
W4 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight4")
W5 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight5")
W6 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight6")
W7 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight7")
W8 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight8")
W9 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight9")
W10 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight10")

W11 = tf.Variable(tf.random_uniform([5, 1], -1.0, 1.0), name = "Weight11")

b1 = tf.Variable(tf.zeros([5]), name="Bias1")
b2 = tf.Variable(tf.zeros([5]), name="Bias2")
b3 = tf.Variable(tf.zeros([5]), name="Bias3")
b4 = tf.Variable(tf.zeros([5]), name="Bias4")
b5 = tf.Variable(tf.zeros([5]), name="Bias5")
b6 = tf.Variable(tf.zeros([5]), name="Bias6")
b7 = tf.Variable(tf.zeros([5]), name="Bias7")
b8 = tf.Variable(tf.zeros([5]), name="Bias8")
b9 = tf.Variable(tf.zeros([5]), name="Bias9")
b10 = tf.Variable(tf.zeros([5]), name="Bias10")

b11 = tf.Variable(tf.zeros([1]), name="Bias11")
```

9 hidden layers!

```python
W1 = tf.Variable(tf.random_uniform([2, 5], -1.0, 1.0), name = "Weight1")

W2 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight2")
W3 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight3")
W4 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight4")
W5 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight5")
W6 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight6")
W7 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight7")
W8 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight8")
W9 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight9")
W10 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight10")

W11 = tf.Variable(tf.random_uniform([5, 1], -1.0, 1.0), name = "Weight11")

b1 = tf.Variable(tf.zeros([5]), name="Bias1")
b2 = tf.Variable(tf.zeros([5]), name="Bias2")
b3 = tf.Variable(tf.zeros([5]), name="Bias3")
b4 = tf.Variable(tf.zeros([5]), name="Bias4")
b5 = tf.Variable(tf.zeros([5]), name="Bias5")
b6 = tf.Variable(tf.zeros([5]), name="Bias6")
b7 = tf.Variable(tf.zeros([5]), name="Bias7")
b8 = tf.Variable(tf.zeros([5]), name="Bias8")
b9 = tf.Variable(tf.zeros([5]), name="Bias9")
b10 = tf.Variable(tf.zeros([5]), name="Bias10")

b11 = tf.Variable(tf.zeros([1]), name="Bias11")
```

X

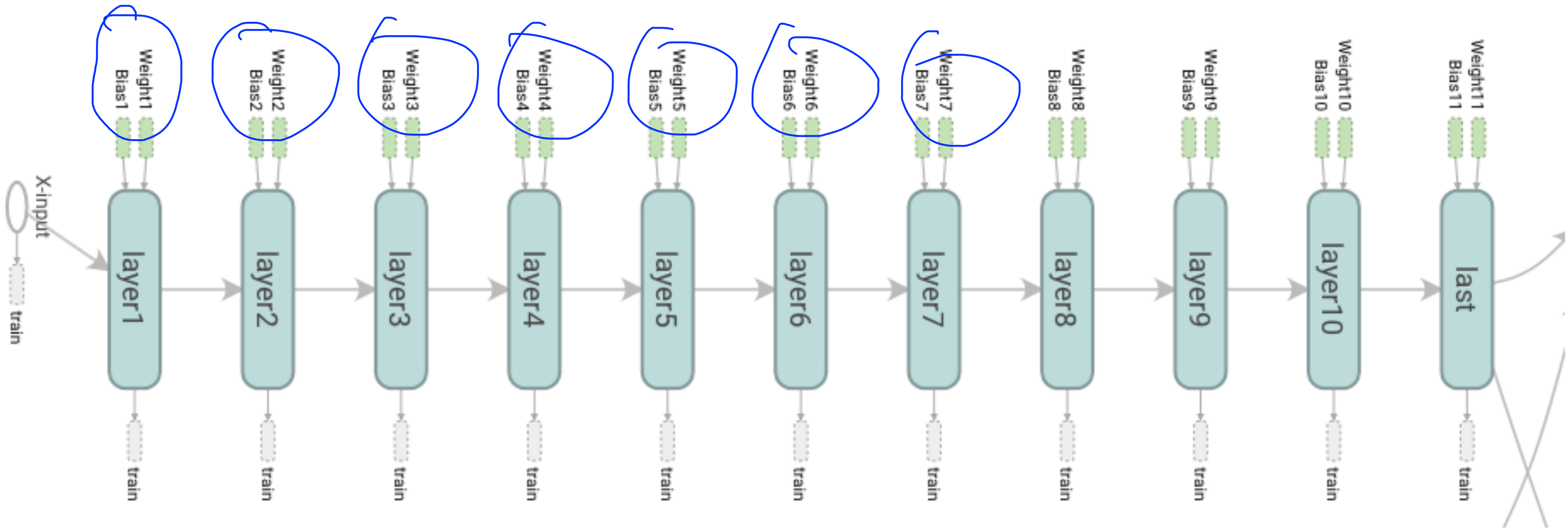
```python
# Our hypothesis
L1 = tf.sigmoid(tf.matmul(X, W1) + b1)
L2 = tf.sigmoid(tf.matmul(L1, W2) + b2)
L3 = tf.sigmoid(tf.matmul(L2, W3) + b3)
L4 = tf.sigmoid(tf.matmul(L3, W4) + b4)
L5 = tf.sigmoid(tf.matmul(L4, W5) + b5)
L6 = tf.sigmoid(tf.matmul(L5, W6) + b6)
L7 = tf.sigmoid(tf.matmul(L6, W7) + b7)
L8 = tf.sigmoid(tf.matmul(L7, W8) + b8)
L9 = tf.sigmoid(tf.matmul(L8, W9) + b9)
L10 = tf.sigmoid(tf.matmul(L9, W10) + b10)

hypothesis = tf.sigmoid(tf.matmul(L10, W11) + b11)
```

9 hidden layers!

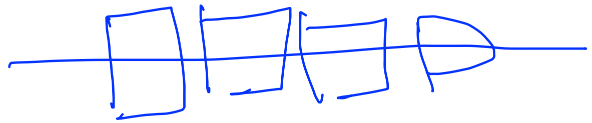
```python
W1 = tf.Variable(tf.random_uniform([2, 5], -1.0, 1.0), name = "Weight1")

W2 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight2")
W3 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight3")
W4 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight4")
W5 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight5")
W6 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight6")
W7 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight7")
W8 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight8")
W9 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight9")
W10 = tf.Variable(tf.random_uniform([5, 5], -1.0, 1.0), name = "Weight10")

W11 = tf.Variable(tf.random_uniform([5, 1], -1.0, 1.0), name = "Weight11")

b1 = tf.Variable(tf.zeros([5]), name="Bias1")
b2 = tf.Variable(tf.zeros([5]), name="Bias2")
b3 = tf.Variable(tf.zeros([5]), name="Bias3")
b4 = tf.Variable(tf.zeros([5]), name="Bias4")
b5 = tf.Variable(tf.zeros([5]), name="Bias5")
b6 = tf.Variable(tf.zeros([5]), name="Bias6")
b7 = tf.Variable(tf.zeros([5]), name="Bias7")
b8 = tf.Variable(tf.zeros([5]), name="Bias8")
b9 = tf.Variable(tf.zeros([5]), name="Bias9")
b10 = tf.Variable(tf.zeros([5]), name="Bias10")

b11 = tf.Variable(tf.zeros([1]), name="Bias11")
```

```python
# Our hypothesis
with tf.name_scope("layer1") as scope:
    L1 = tf.sigmoid(tf.matmul(X, W1) + b1)
with tf.name_scope("layer2") as scope:
    L2 = tf.sigmoid(tf.matmul(L1, W2) + b2)
with tf.name_scope("layer3") as scope:
    L3 = tf.sigmoid(tf.matmul(L2, W3) + b3)
with tf.name_scope("layer4") as scope:
    L4 = tf.sigmoid(tf.matmul(L3, W4) + b4)
with tf.name_scope("layer5") as scope:
    L5 = tf.sigmoid(tf.matmul(L4, W5) + b5)
with tf.name_scope("layer6") as scope:
    L6 = tf.sigmoid(tf.matmul(L5, W6) + b6)
with tf.name_scope("layer7") as scope:
    L7 = tf.sigmoid(tf.matmul(L6, W7) + b7)
with tf.name_scope("layer8") as scope:
    L8 = tf.sigmoid(tf.matmul(L7, W8) + b8)
with tf.name_scope("layer9") as scope:
    L9 = tf.sigmoid(tf.matmul(L8, W9) + b9)
with tf.name_scope("layer10") as scope:
    L10 = tf.sigmoid(tf.matmul(L9, W10) + b10)

with tf.name_scope("last") as scope:
    hypothesis = tf.sigmoid(tf.matmul(L10, W11) + b11)
```

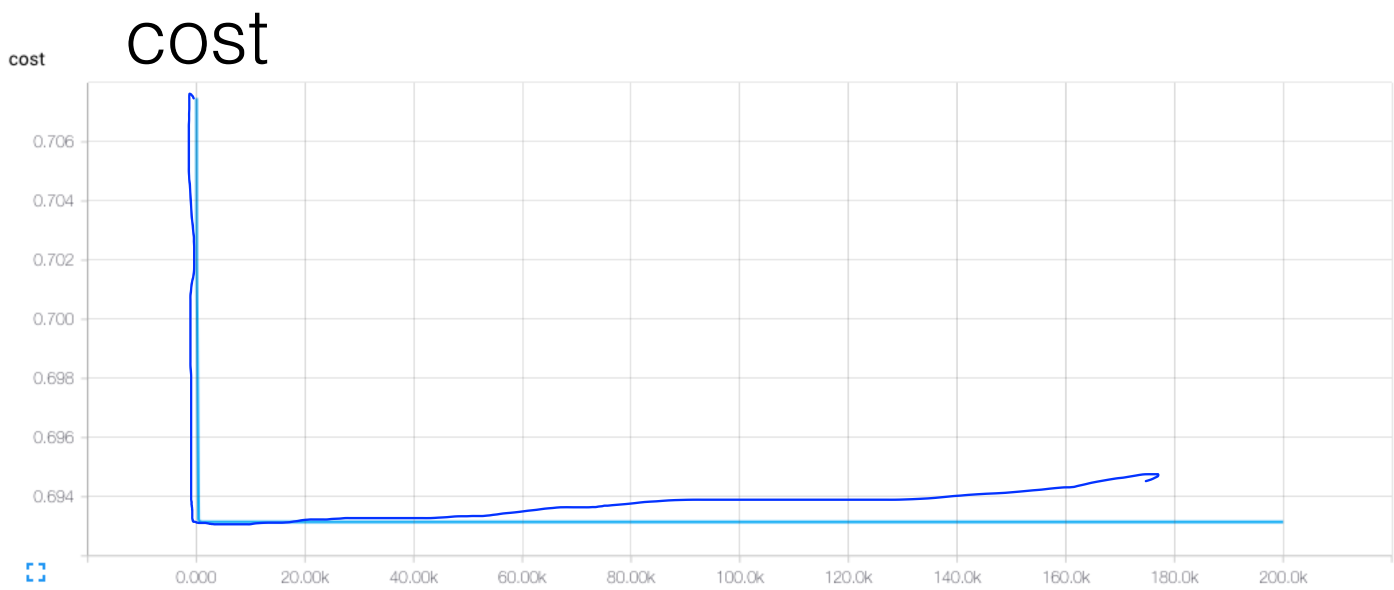
Tensorboard visualization

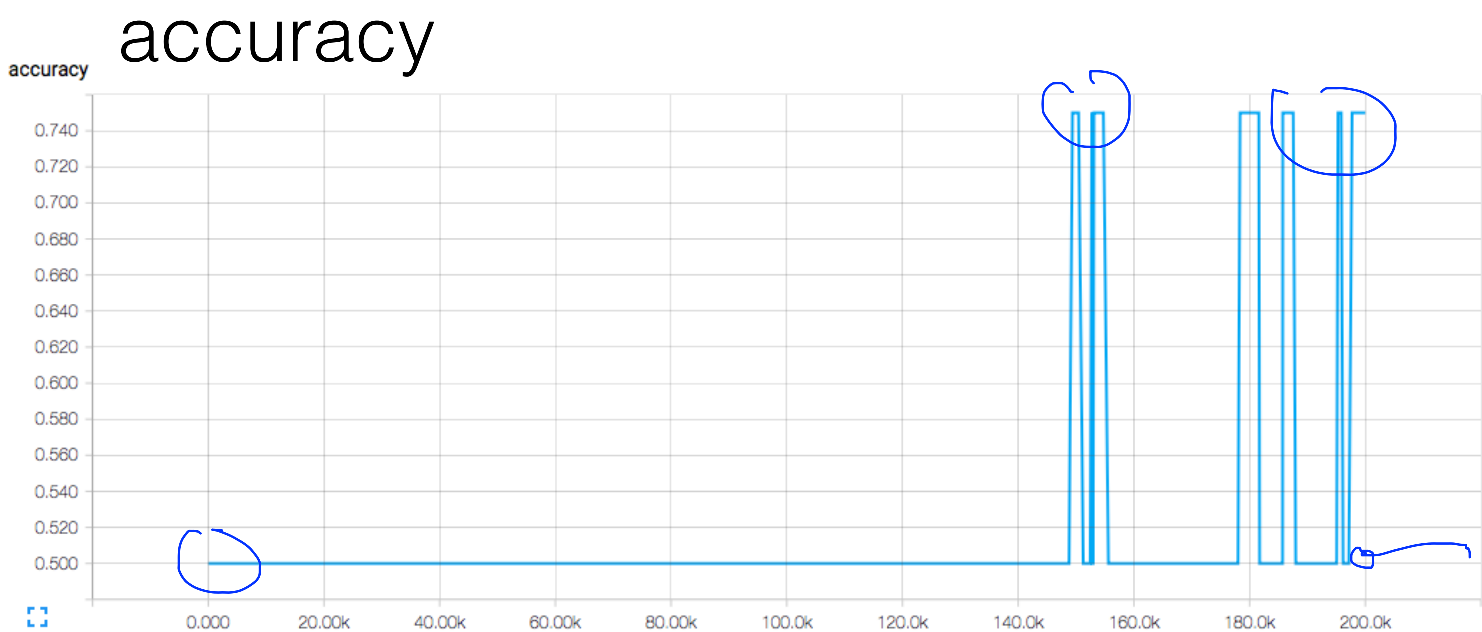


Poor results?



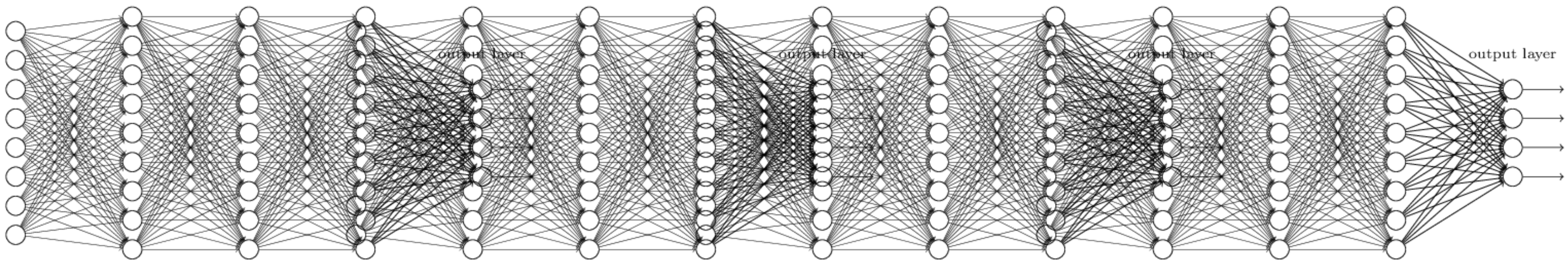
```
196000 [0.69314718, array([[ 0.49999988],
       [ 0.50000006],
       [ 0.49999982],
       [ 0.5       ]], dtype=float32)]
198000 [0.69314718, array([[ 0.49999988],
       [ 0.50000006],
       [ 0.49999982],
       [ 0.5       ]], dtype=float32)]
[array([[ 0.49999988],
       [ 0.50000006],
       [ 0.49999982],
       [ 0.5       ]], dtype=float32), array([[ 0.],
       [ 1.],
       [ 0.],
       [ 1.]], dtype=float32)]
Accuracy: 0.5
```



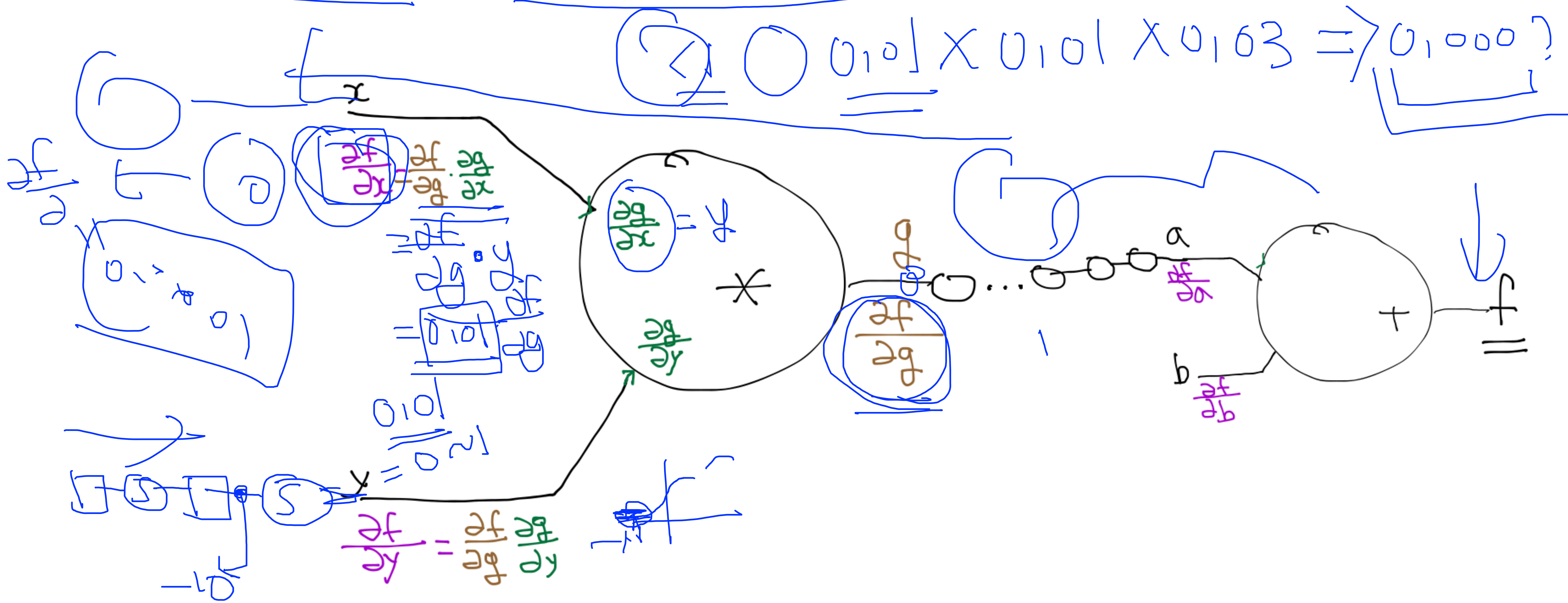


Tensorboard Cost & Accuracy

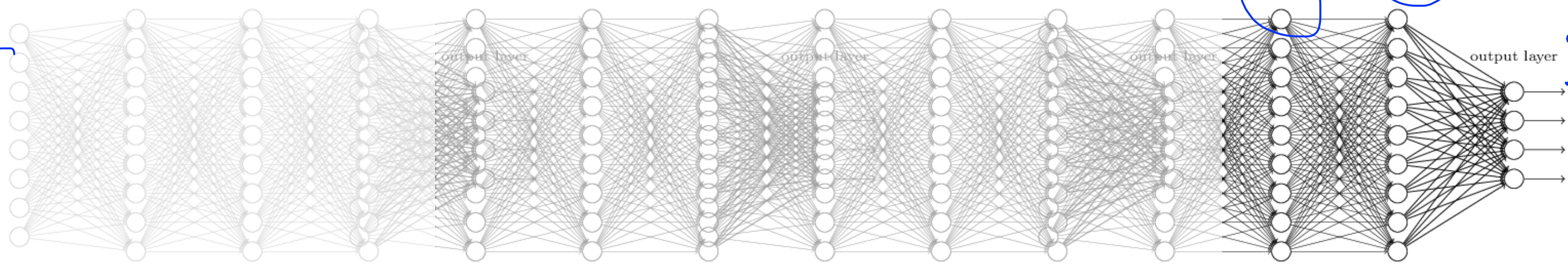
Backpropagation 86



lec 9-2: Backpropagation (chain rule)



Vanishing gradient (NN winter2: 1986-2006)

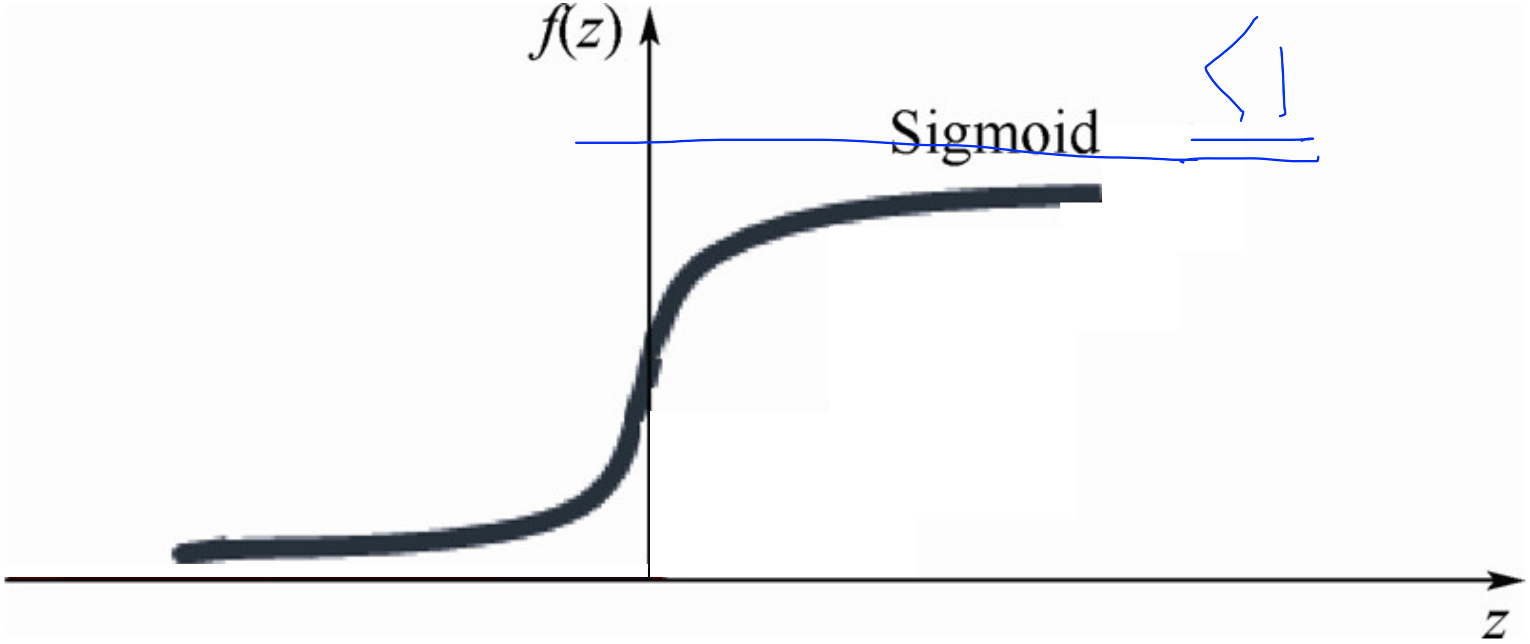


Geoffrey Hinton's summary of findings up to today

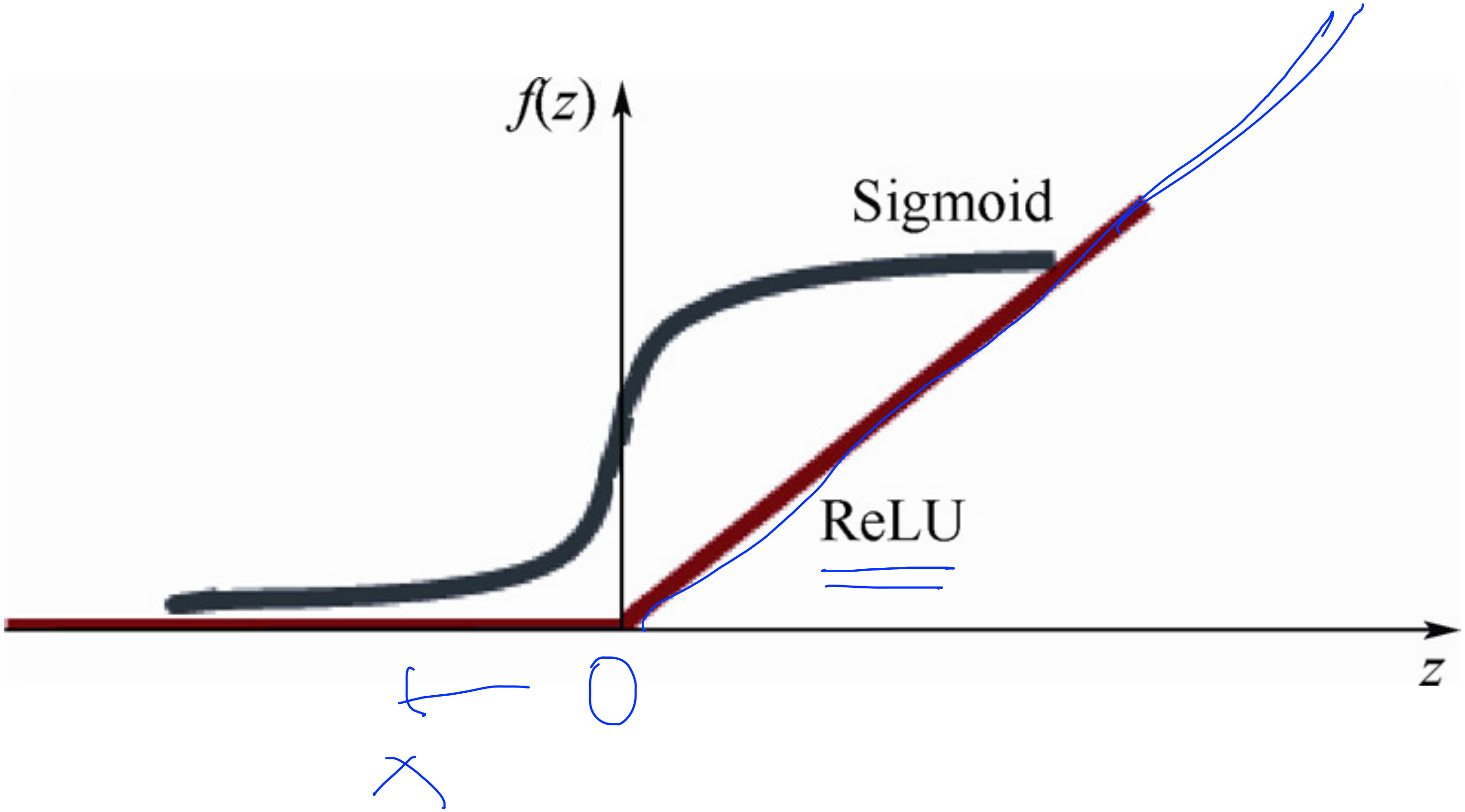
- Our labeled datasets were thousands of times too small.
- Our computers were millions of times too slow.
- We initialized the weights in a stupid way.
- We used the wrong type of non-linearity.

http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning-part-4/

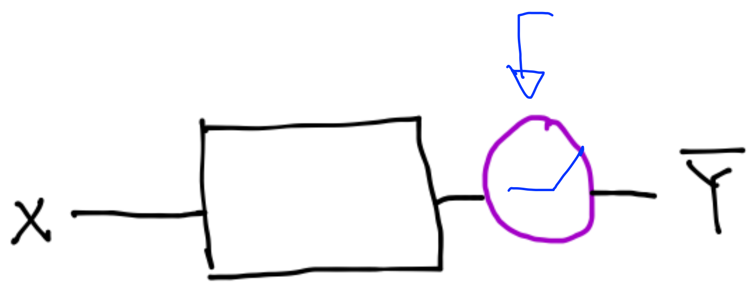
Sigmoid!



Sigmoid!

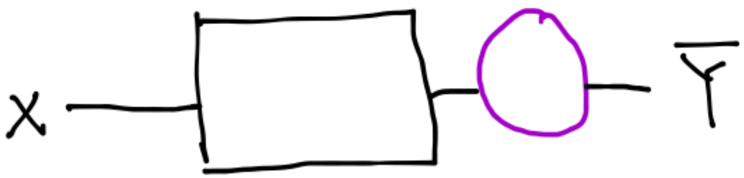


ReLU: Rectified Linear Unit



ReLU: Rectified Linear Unit

max (0, x)



L1 = ~~tf.sigmoid~~(tf.matmul(X, W1) + b1)

L1 = tf.nn.relu(tf.matmul(X, W1) + b1)

ReLu

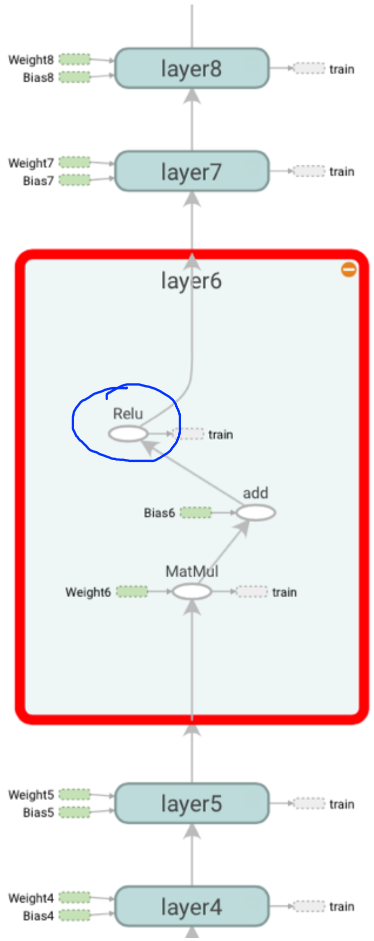
```
# Our hypothesis
with tf.name_scope("layer1") as scope:
    L1 = tf.nn.relu(tf.matmul(X, W1) + b1)
with tf.name_scope("layer2") as scope:
    L2 = tf.nn.relu(tf.matmul(L1, W2) + b2)
with tf.name_scope("layer3") as scope:
    L3 = tf.nn.relu(tf.matmul(L2, W3) + b3)
with tf.name_scope("layer4") as scope:
    L4 = tf.nn.relu(tf.matmul(L3, W4) + b4)
with tf.name_scope("layer5") as scope:
    L5 = tf.nn.relu(tf.matmul(L4, W5) + b5)
with tf.name_scope("layer6") as scope:
    L6 = tf.nn.relu(tf.matmul(L5, W6) + b6)
with tf.name_scope("layer7") as scope:
    L7 = tf.nn.relu(tf.matmul(L6, W7) + b7)
with tf.name_scope("layer8") as scope:
    L8 = tf.nn.relu(tf.matmul(L7, W8) + b8)
with tf.name_scope("layer9") as scope:
    L9 = tf.nn.relu(tf.matmul(L8, W9) + b9)
with tf.name_scope("layer10") as scope:
    L10 = tf.nn.relu(tf.matmul(L9, W10) + b10)

with tf.name_scope("last") as scope:
    hypothesis = tf.sigmoid(tf.matmul(L10, W11) + b11)
```

→ 0 ~ 1

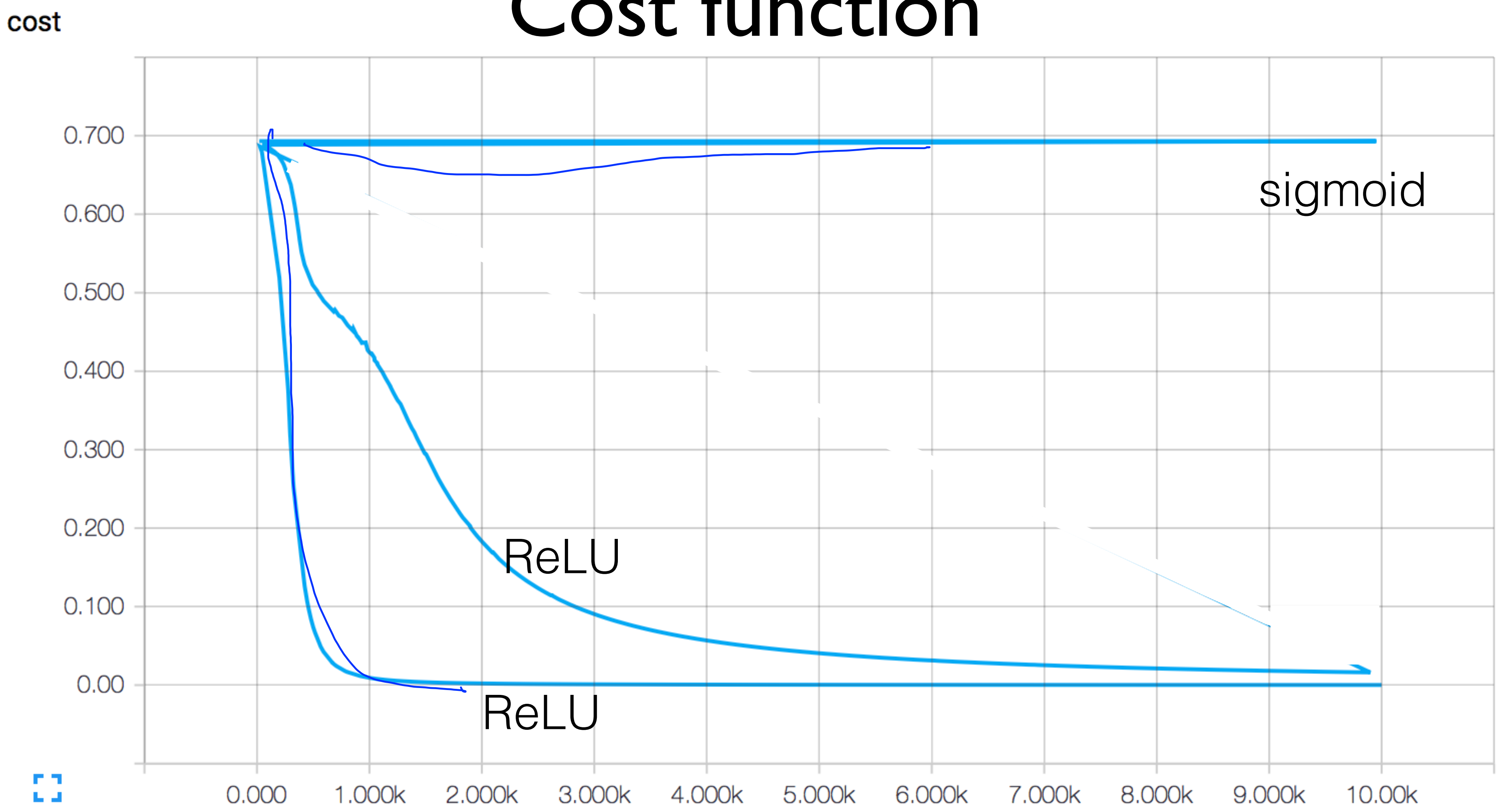
Works very well

```
196000 [2.6226094e-06, array([[  2.59195826e-06],
       [  9.99999642e-01],
       [  9.99994874e-01],
       [  2.43454133e-06]], dtype=float32)]
198000 [2.607708e-06, array([[  2.55822852e-06],
       [  9.99999642e-01],
       [  9.99994874e-01],
       [  2.40260101e-06]], dtype=float32)]
[array([[  2.52509381e-06],
       [  9.99999642e-01],
       [  9.99994874e-01],
       [  2.37124709e-06]], dtype=float32), array([[ 0.],
       [ 1.],
       [ 1.],
       [ 0.]], dtype=float32)]
Accuracy: 1.0
```

Works very well



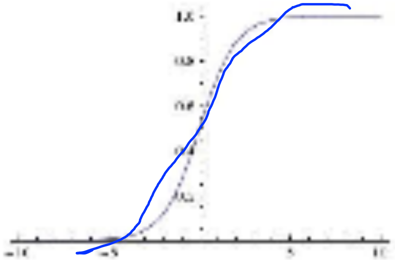
Cost function



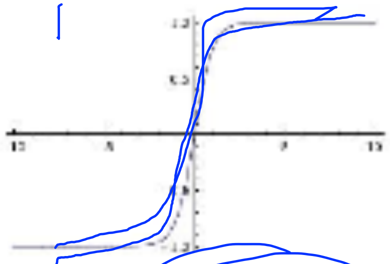
Activation Functions

Sigmoid

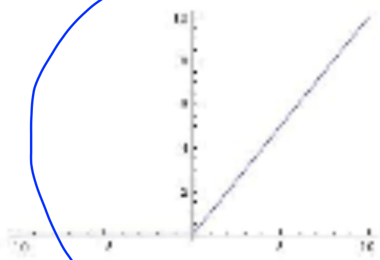
$$\sigma(x) = 1/(1+e^{-x})$$



tanh tanh(x)

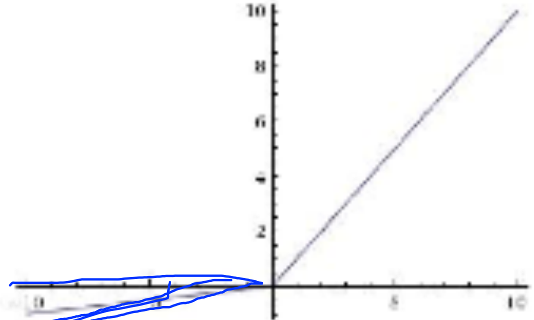


ReLU max(0,x)



Leaky ReLU

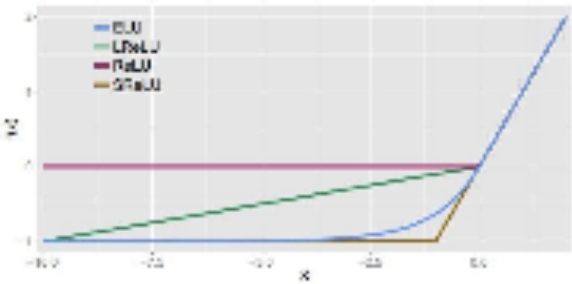
max(0.1x, x)



Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \leq 0 \end{cases}$$



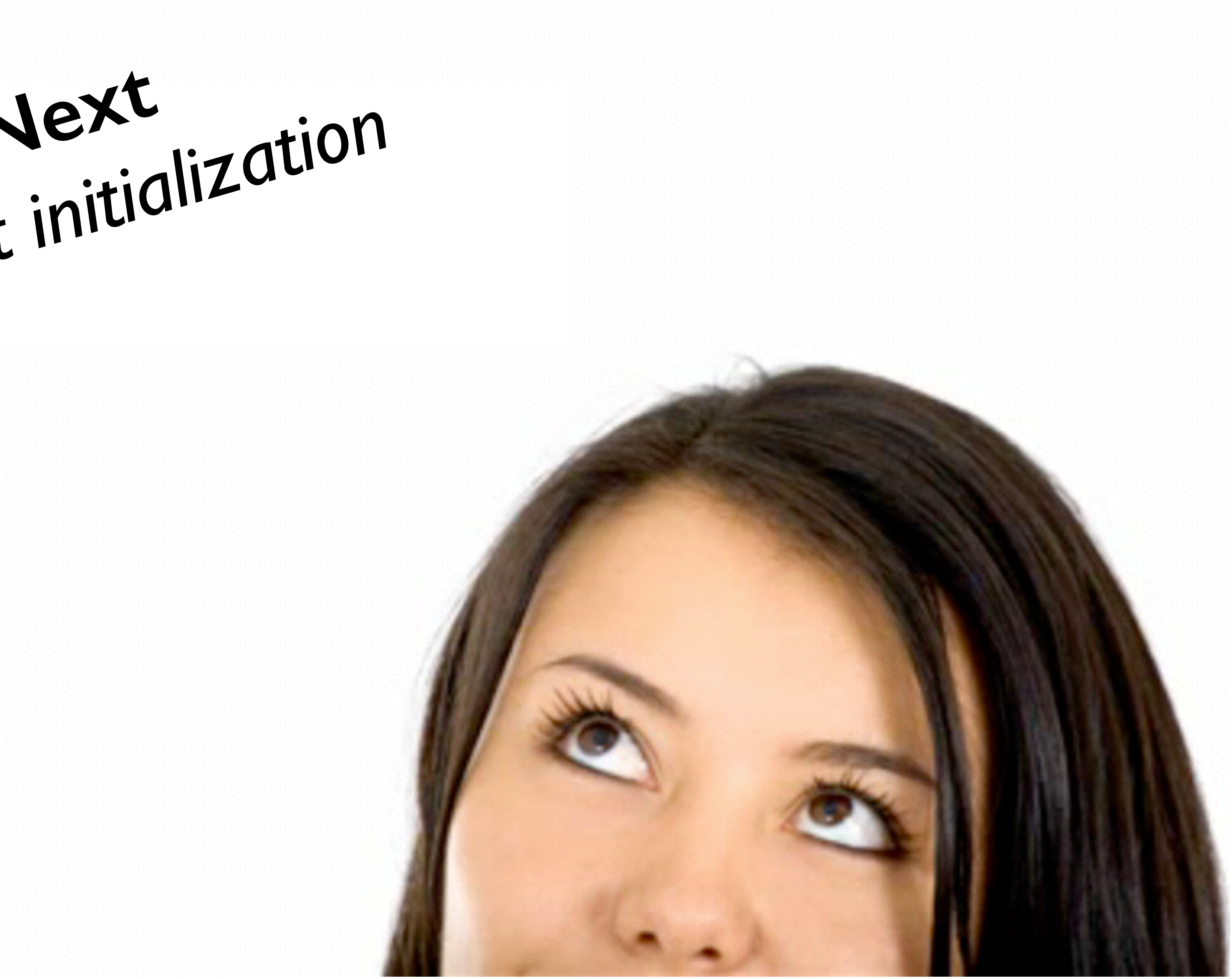
Activation functions on CIFAR-10

maxout	ReLU	VLReLU	tanh	Sigmoid
93.94	**92.11**	92.97	89.28	n/c
93.78	91.74	92.40	89.48	n/c
–	91.93	**93.09**	–	n/c
91.75	90.63	92.27	**89.82**	n/c
n/c†	90.91	92.43	89.54	n/c

[Mishkin et al. 2015]

Next

Weight initialization

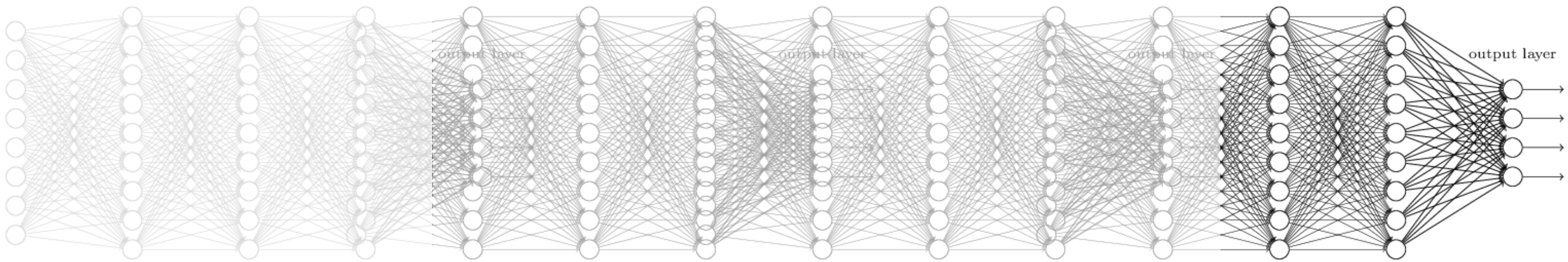


Lecture 10-2

Initialize weights in a smart way

Sung Kim <hunkim+mr@gmail.com>
http://hunkim.github.io/ml/

Vanishing gradient

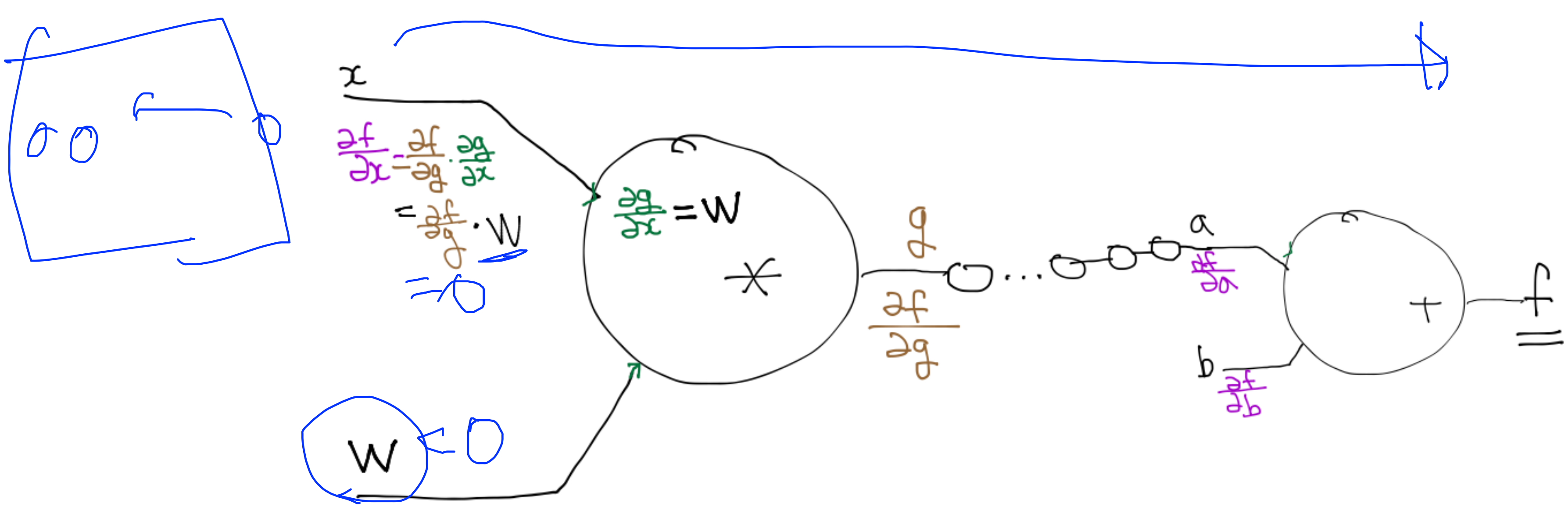


Geoffrey Hinton’s summary of findings up to today

- Our labeled datasets were thousands of times too small.
- Our computers were millions of times too slow.
- We initialized the ~~weights in a stupid way~~.
- We used the wrong type of non-linearity.

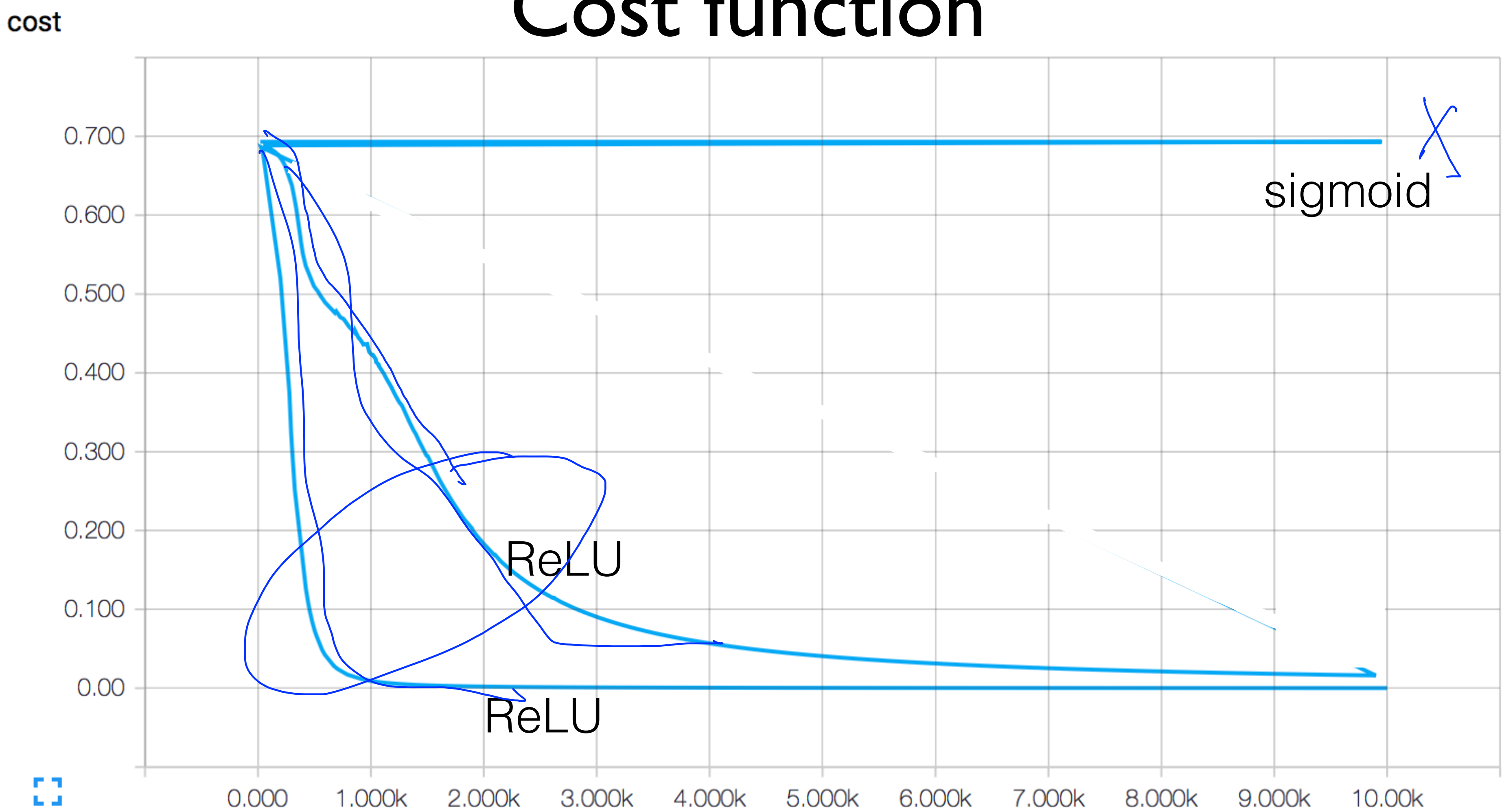
http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning-part-4/

Set all initial weights to 0



http://cs231n.stanford.edu/

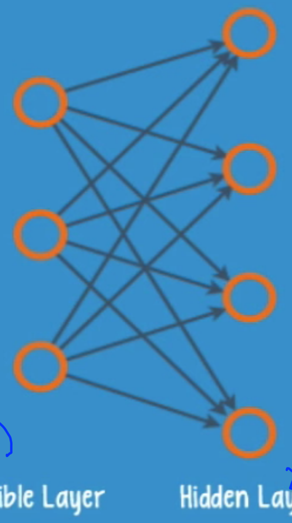
Cost function



Need to set the initial weight values wisely

- Not all 0's
- Challenging issue
- Hinton et al. (2006) "A Fast Learning Algorithm for Deep Belief Nets"
  - Restricted Boatman Machine (RBM)

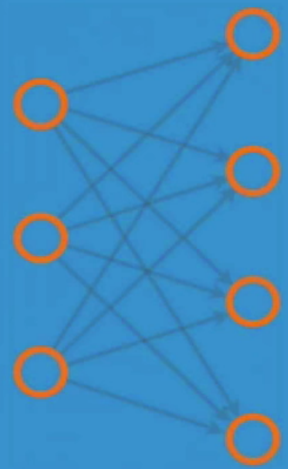
RBM STRUCTURE



RESTRICTION = NO CONNECTIONS WITHIN A LAYER

RECREATE INPUT

Forward



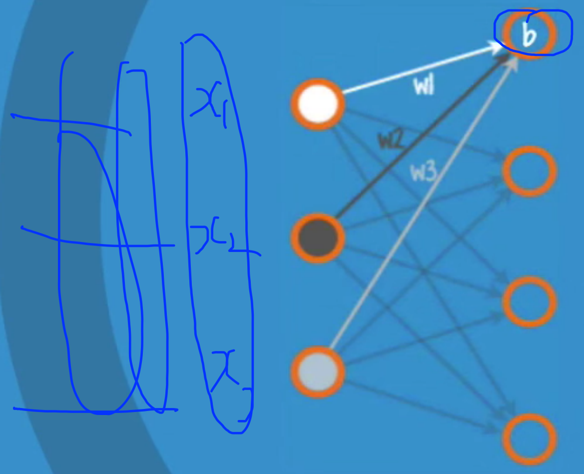
Backward

Become A Better Data Scientist

RECREATE INPUT

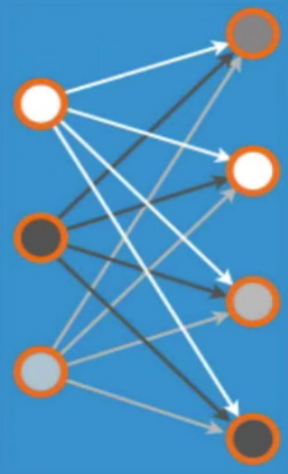
Forward

Backward



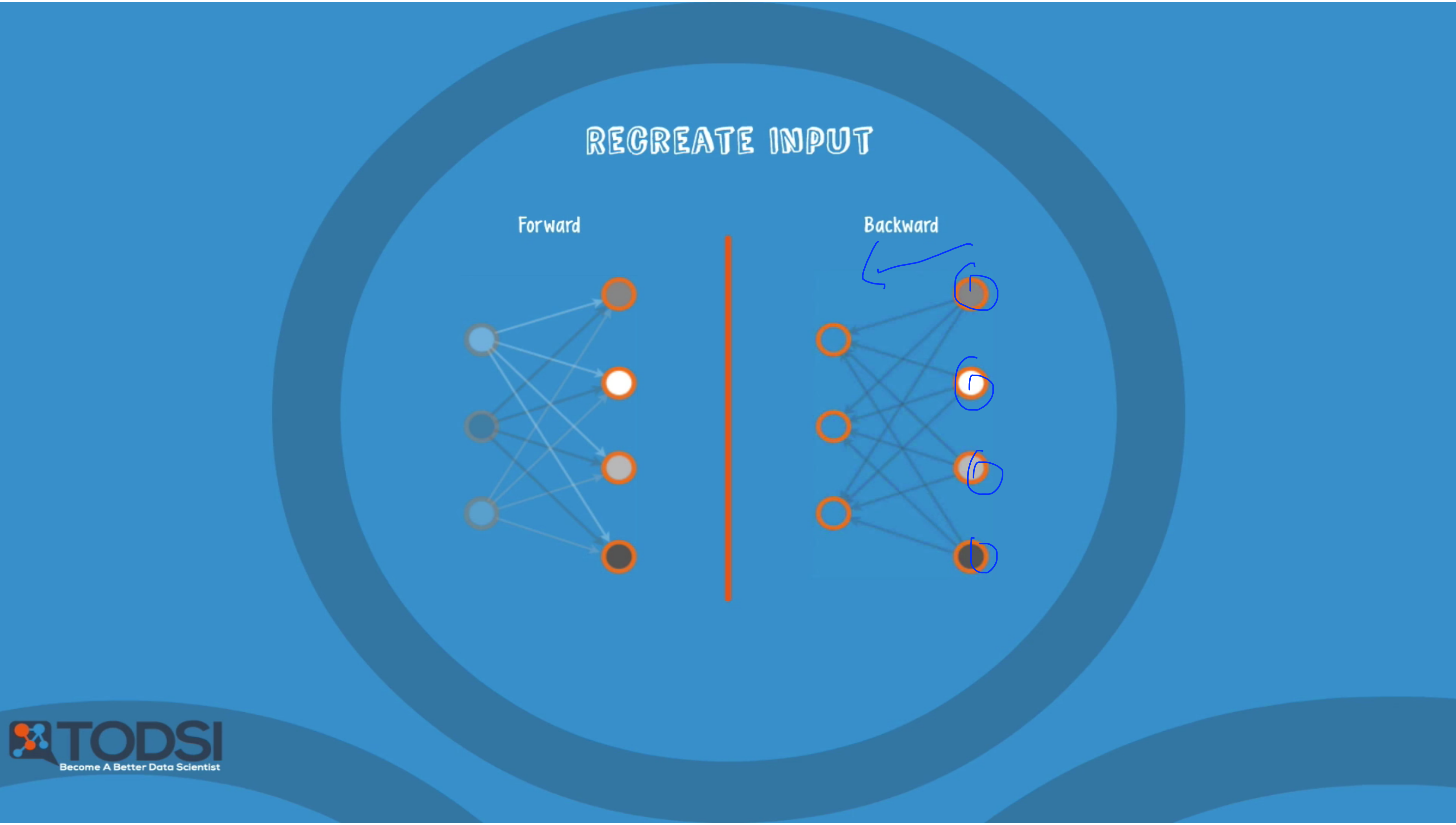
RECREATE INPUT

Forward

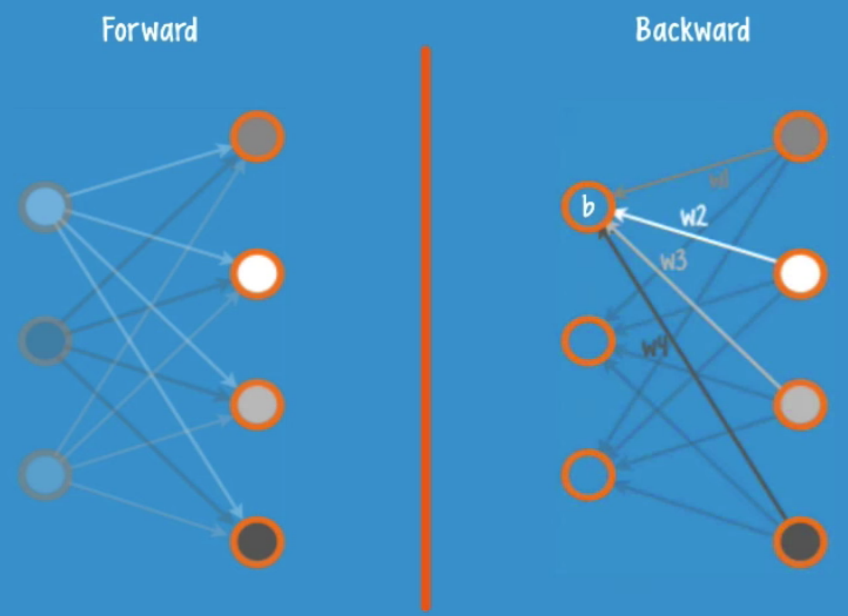


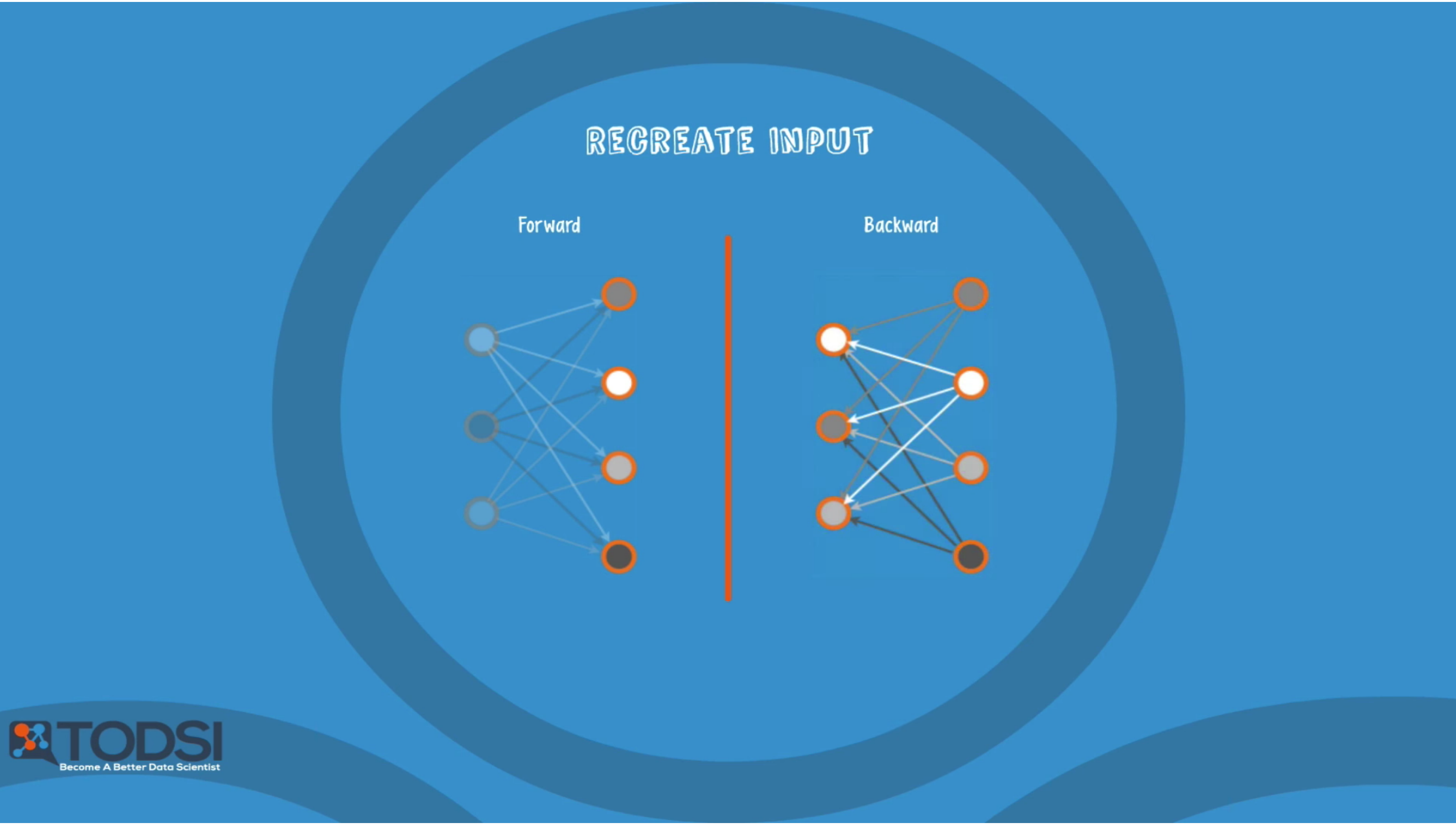
Backward

TODSI
Become A Better Data Scientist

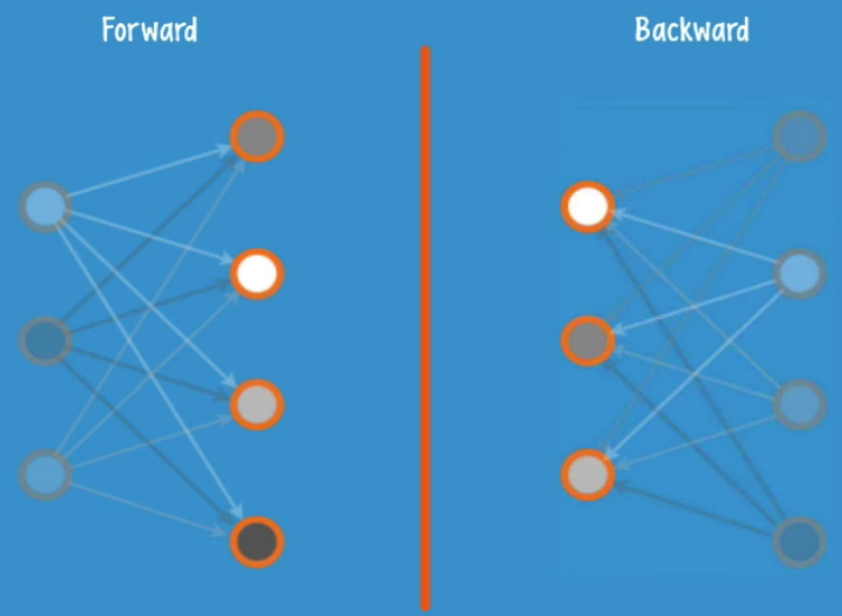

RECREATE INPUT
Forward
Backward
TODSI
Become A Better Data Scientist

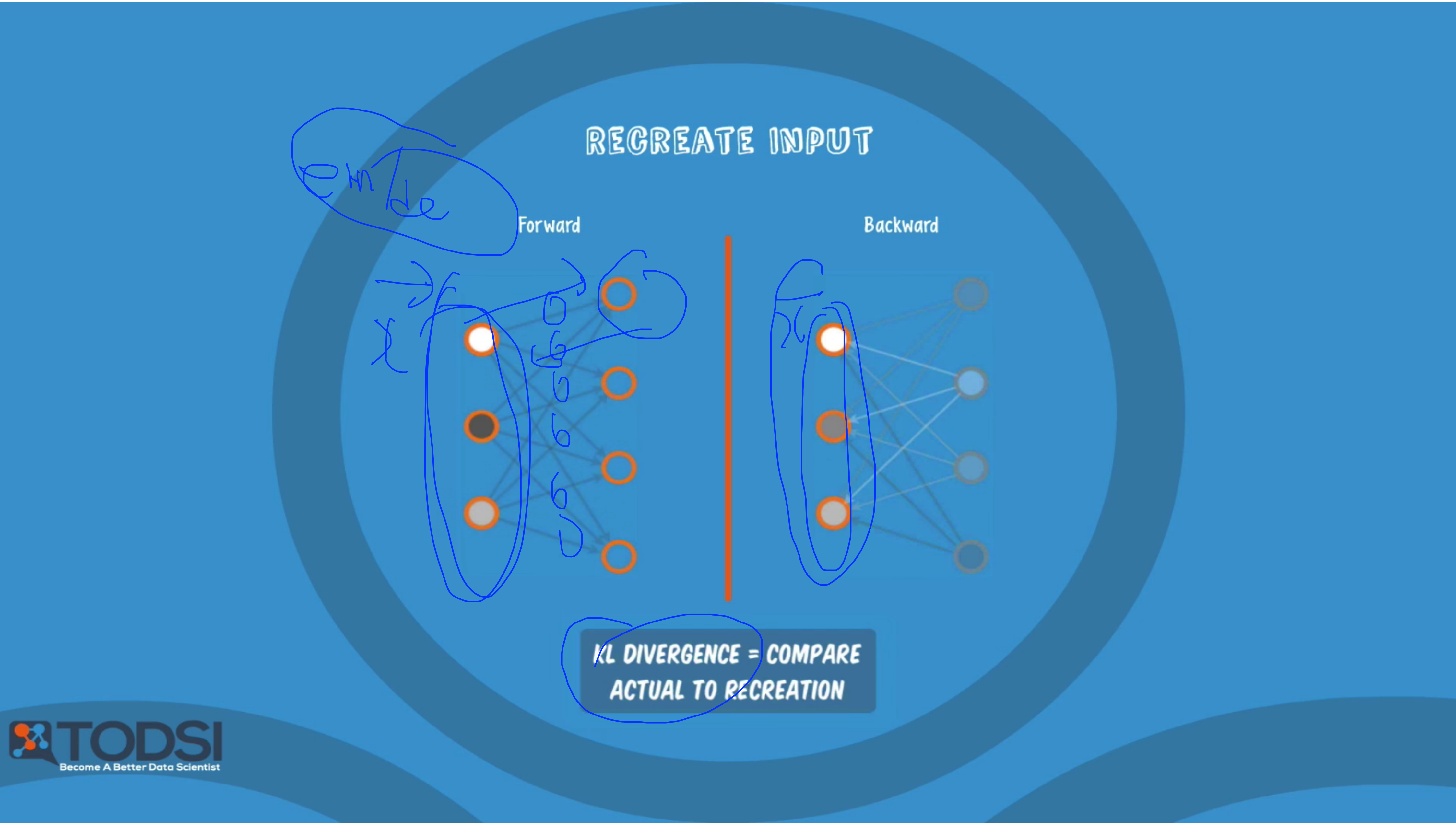
RECREATE INPUT




RECREATE INPUT
Forward
Backward
TODSI
Become A Better Data Scientist

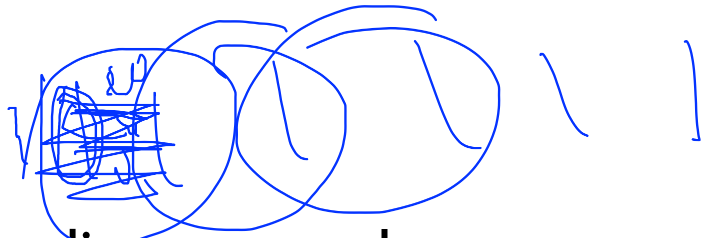
RECREATE INPUT



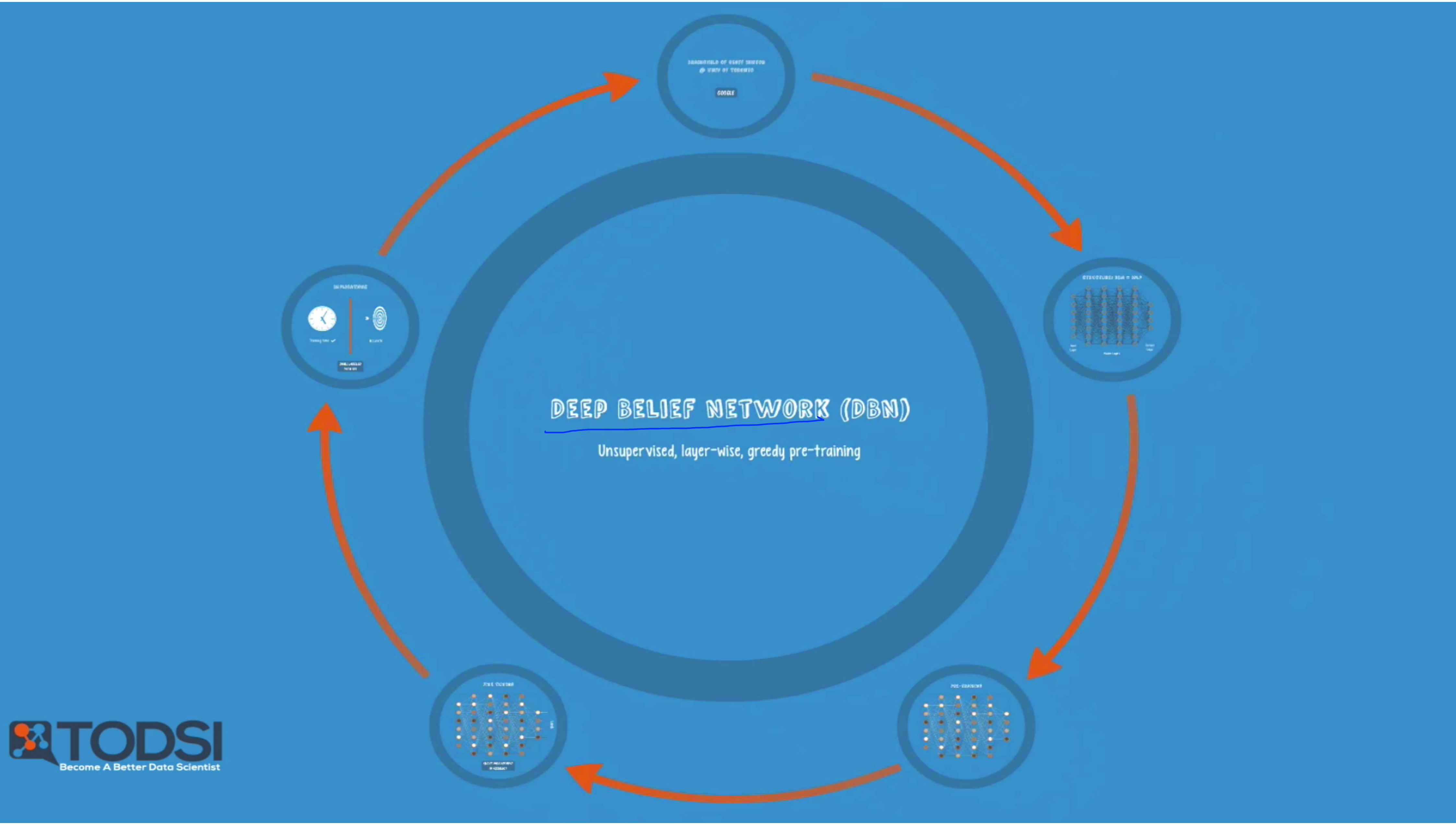


RECREATE INPUT
en/de
Forward
Backward
KL DIVERGENCE = COMPARE ACTUAL TO RECREATION
TODSI
Become A Better Data Scientist

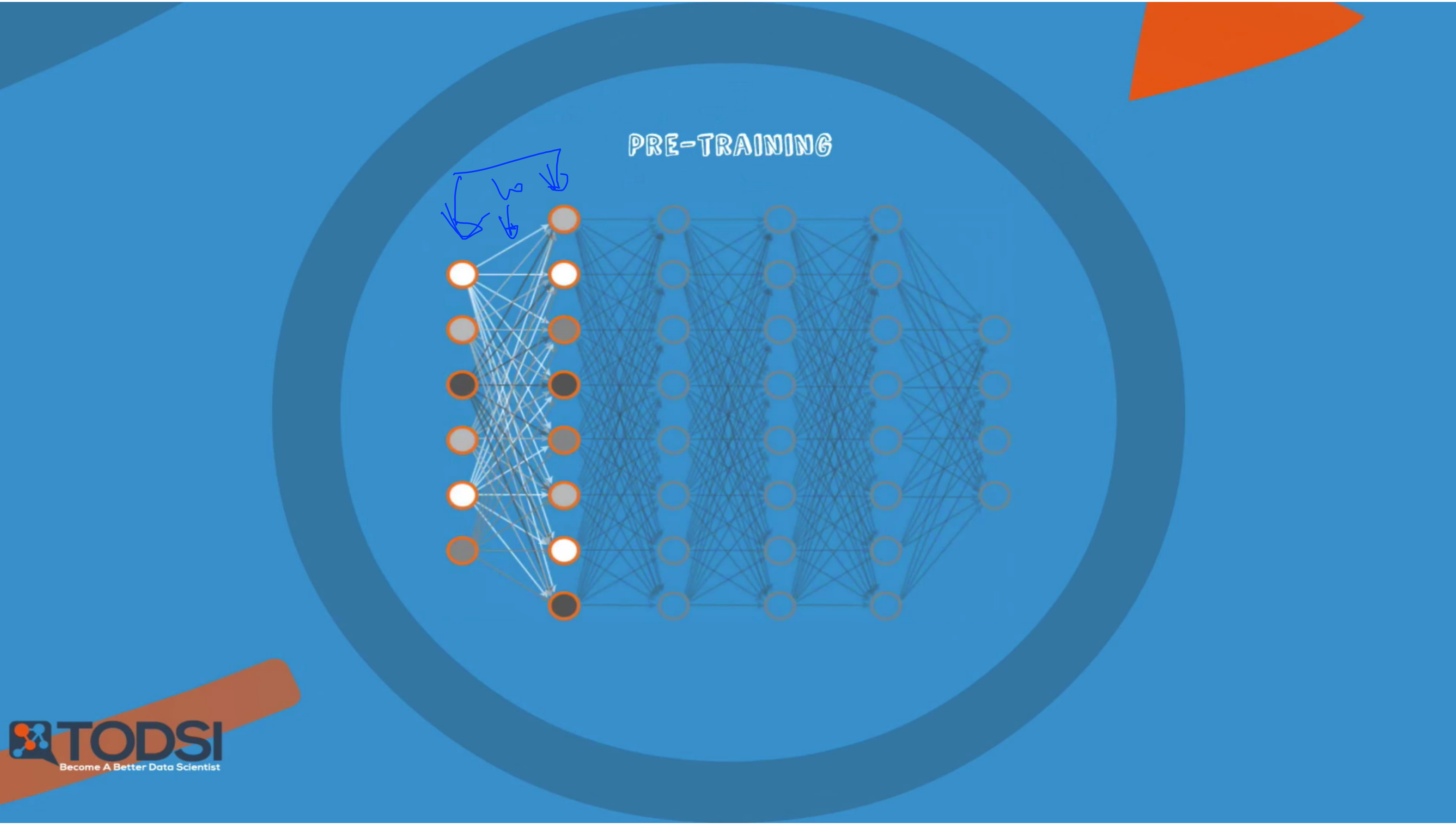
How can we use RBM to initialize weights?

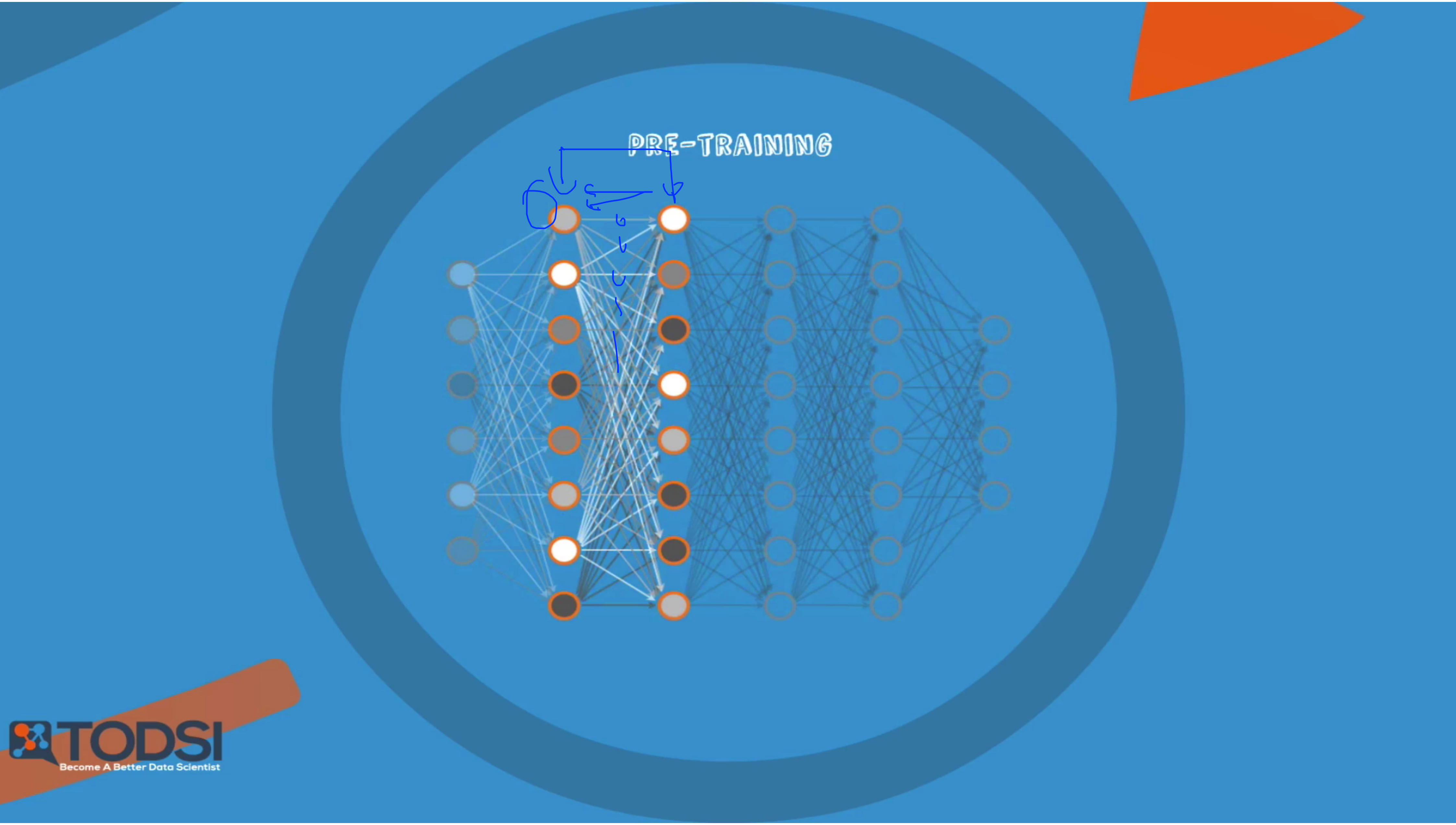


- Apply the RBM idea on adjacent two layers as a pre-training step
- Continue the first process to all layers
- This will set weights
- Example: Deep Belief Network
  - Weight initialized by RBM

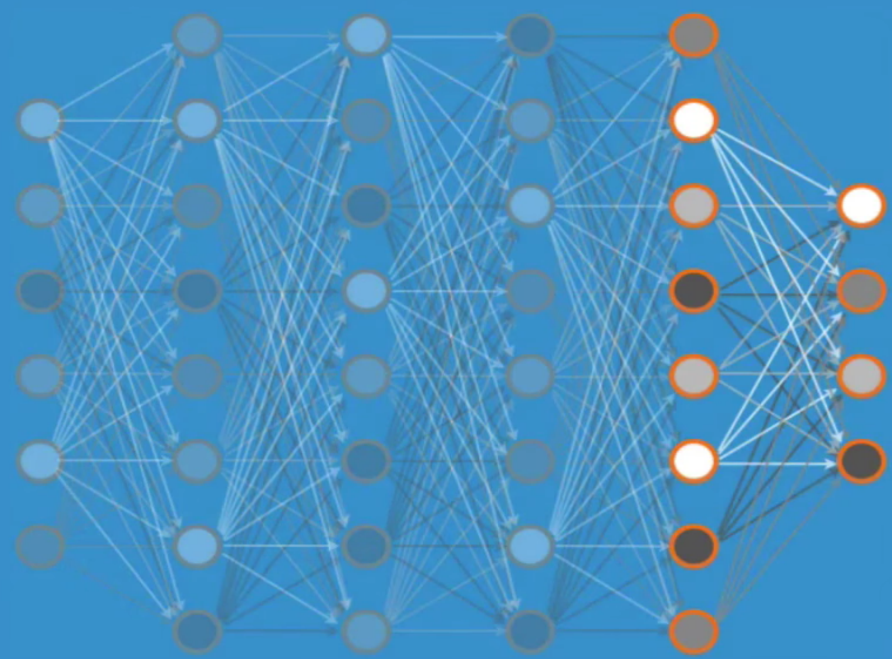

DEEP BELIEF NETWORK (DBN)
Unsupervised, layer-wise, greedy pre-training
TODSI
Become A Better Data Scientist


PRE-TRAINING
TODSI
Become A Better Data Scientist


PRE-TRAINING
TODSI
Become A Better Data Scientist

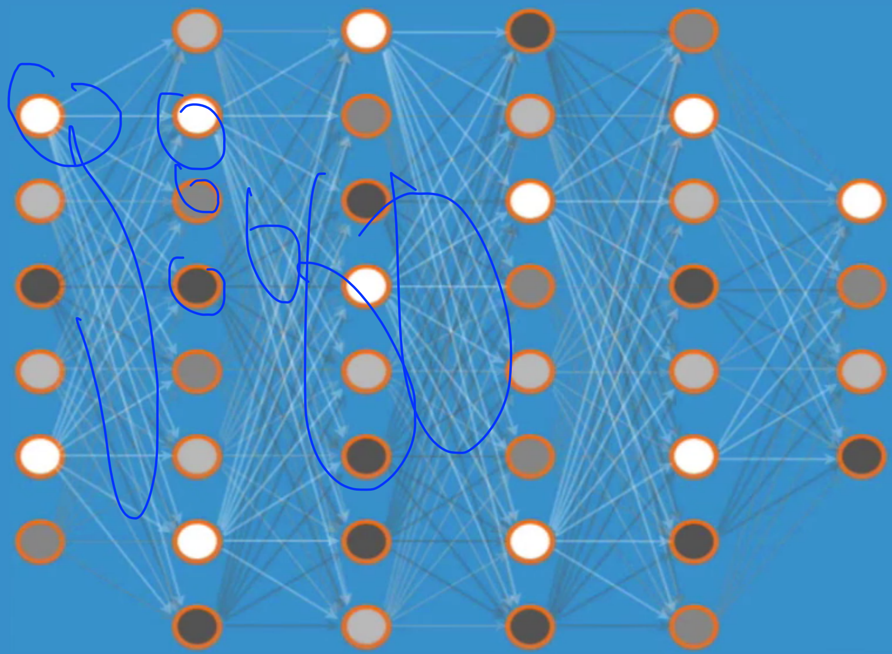

PRE-TRAINING

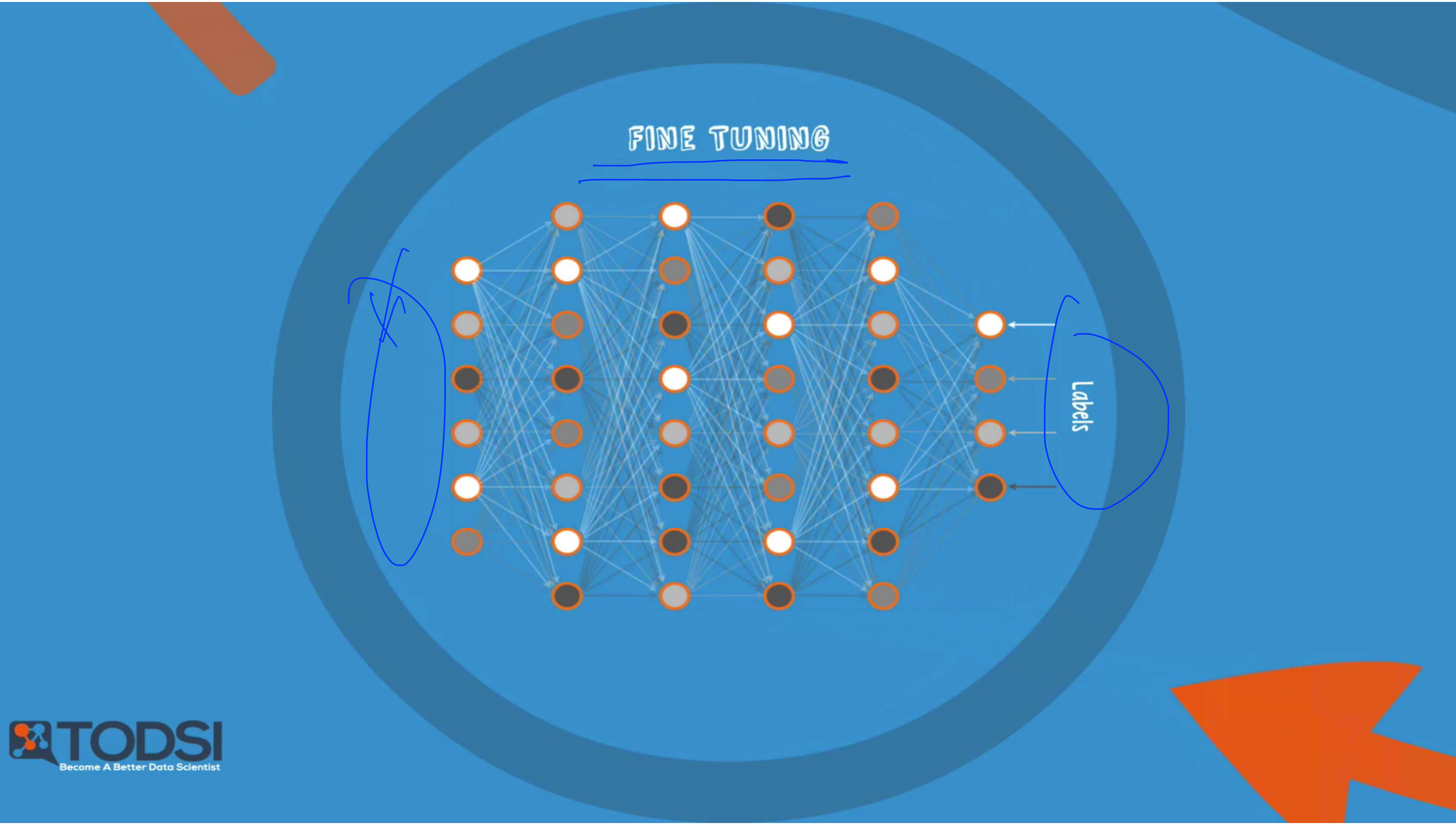
PRE-TRAINING



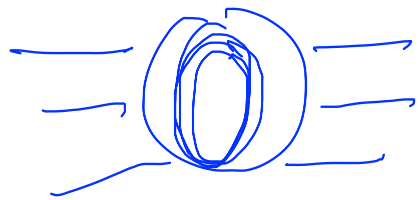
Become A Better Data Scientist

PRE-TRAINING




FINE TUNING
Labels
TODSI
Become A Better Data Scientist

Good news



- No need to use complicated RBM for weight initializations
- Simple methods are OK
  - **Xavier initialization**: X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in International conference on artificial intelligence and statistics, 2010
  - **He's initialization**: K. He, X. Zhang, S. Ren, and J. Sun, "Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification," 2015

Xavier/He initialization

- Makes sure the weights are 'just right', not too small, not too big
- Using number of input (fan_in) and output (fan_out)

```
# Xavier initialization
# Glorot et al. 2010
W = np.random.randn(fan_in, fan_out)/np.sqrt(fan_in)

# He et al. 2015
W = np.random.randn(fan_in, fan_out)/np.sqrt(fan_in/2)
```

http://cs231n.stanford.edu/

prettytensor implementation

```python
def xavier_init(n_inputs, n_outputs, uniform=True):
  """Set the parameter initialization using the method described.
  This method is designed to keep the scale of the gradients roughly the same
  in all layers.
  Xavier Glorot and Yoshua Bengio (2010):
           Understanding the difficulty of training deep feedforward neural
           networks. International conference on artificial intelligence and
           statistics.
  Args:
    n_inputs: The number of input nodes into each output.
    n_outputs: The number of output nodes for each input.
    uniform: If true use a uniform distribution, otherwise use a normal.
  Returns:
    An initializer.
  """
  if uniform:
    # 6 was used in the paper.
    init_range = math.sqrt(6.0 / (n_inputs + n_outputs))
    return tf.random_uniform_initializer(-init_range, init_range)
  else:
    # 3 gives us approximately the same limits as above since this repicks
    # values greater than 2 standard deviations from the mean.
    stddev = math.sqrt(3.0 / (n_inputs + n_outputs))
    return tf.truncated_normal_initializer(stddev=stddev)
```

http://stackoverflow.com/questions/33640581/how-to-do-xavier-initialization-on-tensorflow

Activation functions and initialization on CIFAR-10

Init method	maxout	ReLU	VLReLU	tanh	Sigmoid
LSUV	**93.94**	**92.11**	92.97	89.28	n/c
OrthoNorm	93.78	91.74	92.40	89.48	n/c
OrthoNorm-MSRA scaled	–	91.93	**93.09**	–	n/c
Xavier	91.75	90.63	92.27	**89.82**	n/c
MSRA	n/c†	90.91	92.43	89.54	n/c

[Mishkin et al. 2015]

Still an active area of research

- We don't know how to initialize perfect weight values, yet
- Many new algorithms
  - Batch normalization
  - Layer sequential uniform variance
  - …

Geoffrey Hinton's summary of findings up to today

- Our labeled datasets were thousands of times too small.
- Our computers were millions of times too slow.
- **We initialized the weights in a stupid way.**
- **We used the wrong type of non-linearity.**

http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning-part-4/

Next

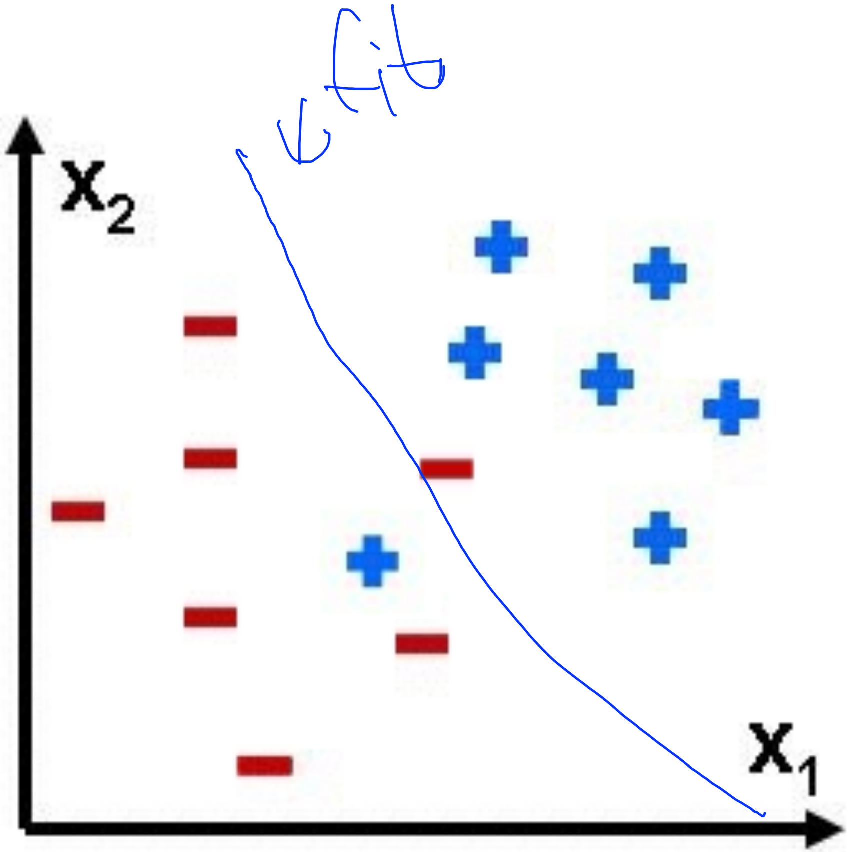
dropout and
model ensemble

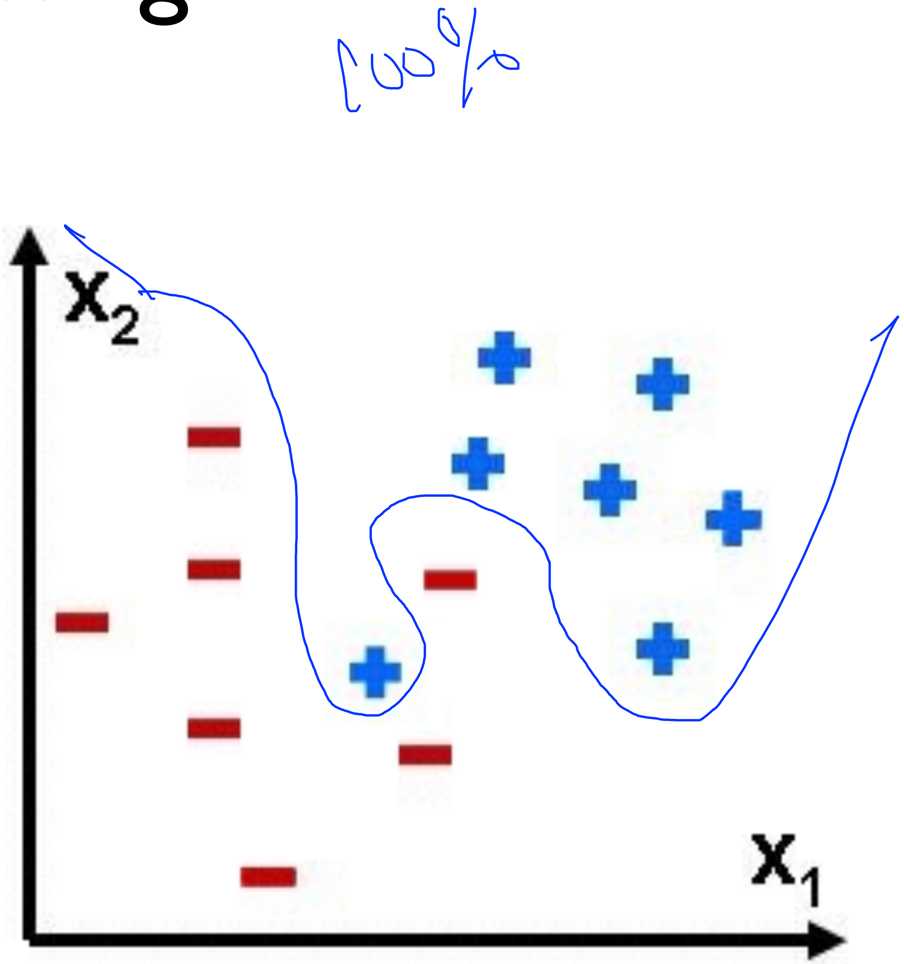
Lecture 10-3

NN dropout and model ensemble

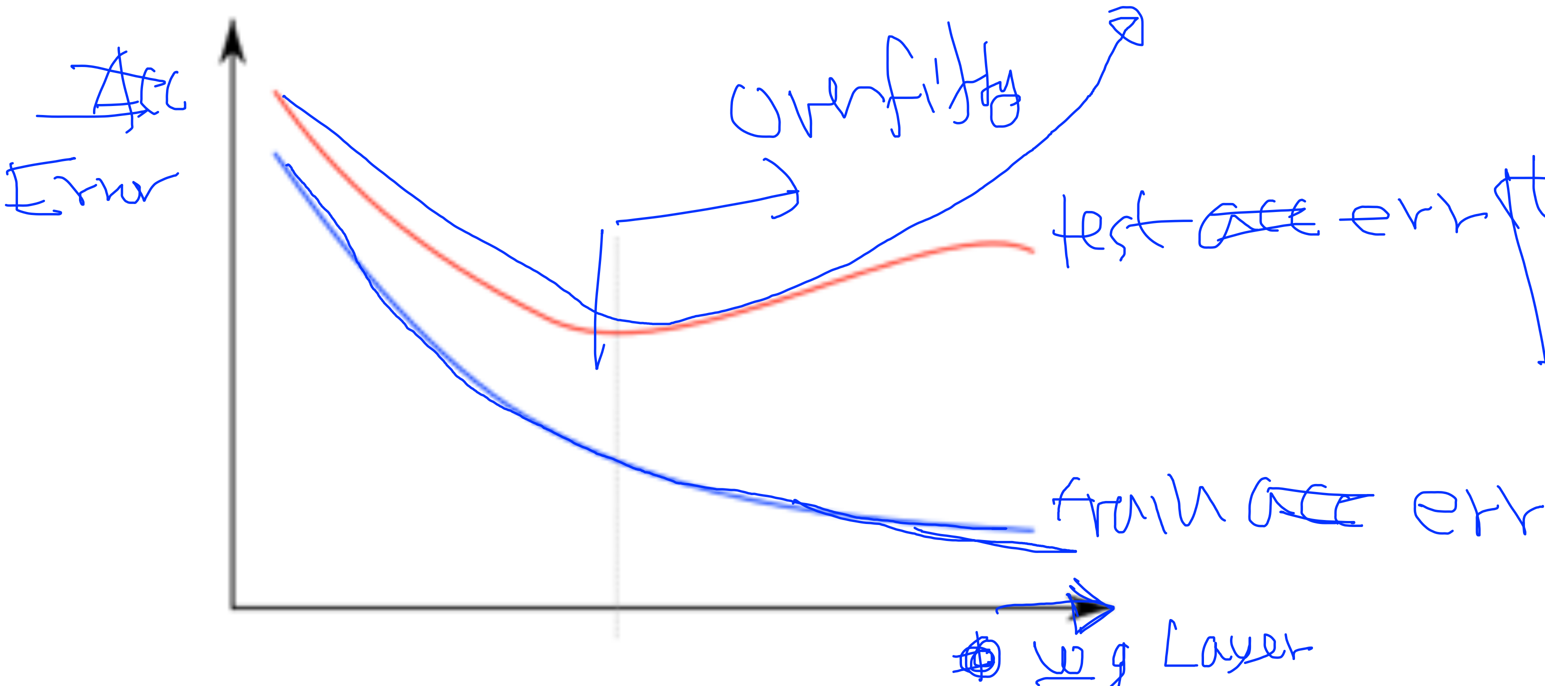
Sung Kim <hunkim+mr@gmail.com>

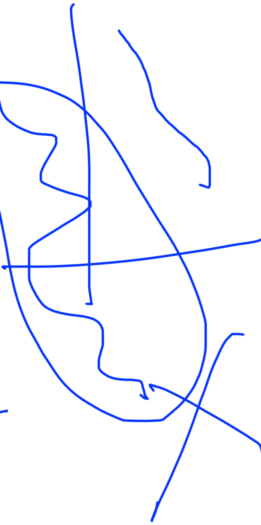
Overfitting





Am I overfitting?





- Very high accuracy on the training dataset (eg: 0.99)
- Poor accuracy on the test data set (0.85)

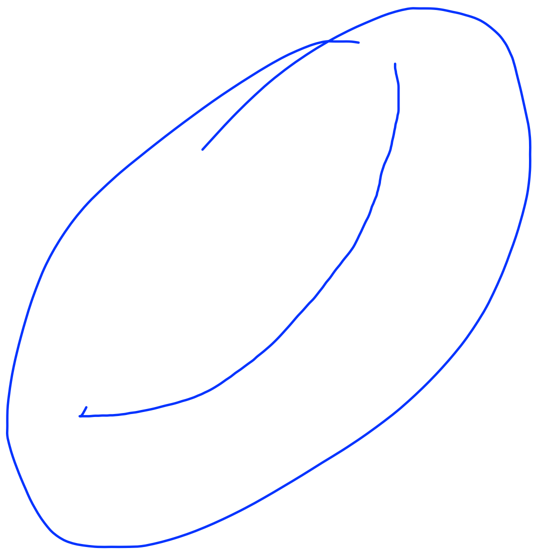
http://cs224d.stanford.edu/syllabus.html

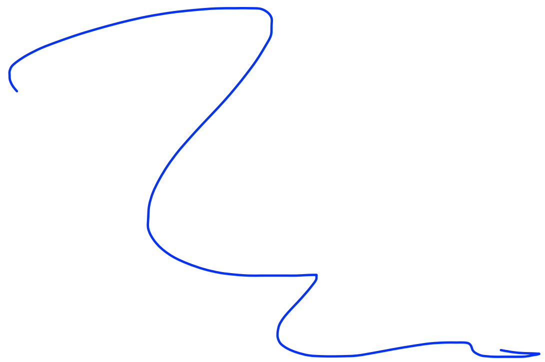
Solutions for overfitting

- More training data!
- ~~Reduce the number of features~~
- **Regularization**

Regularization

- Let’s not have too big numbers in the weight





Regularization

- Let's not have too big numbers in the weight

0.1

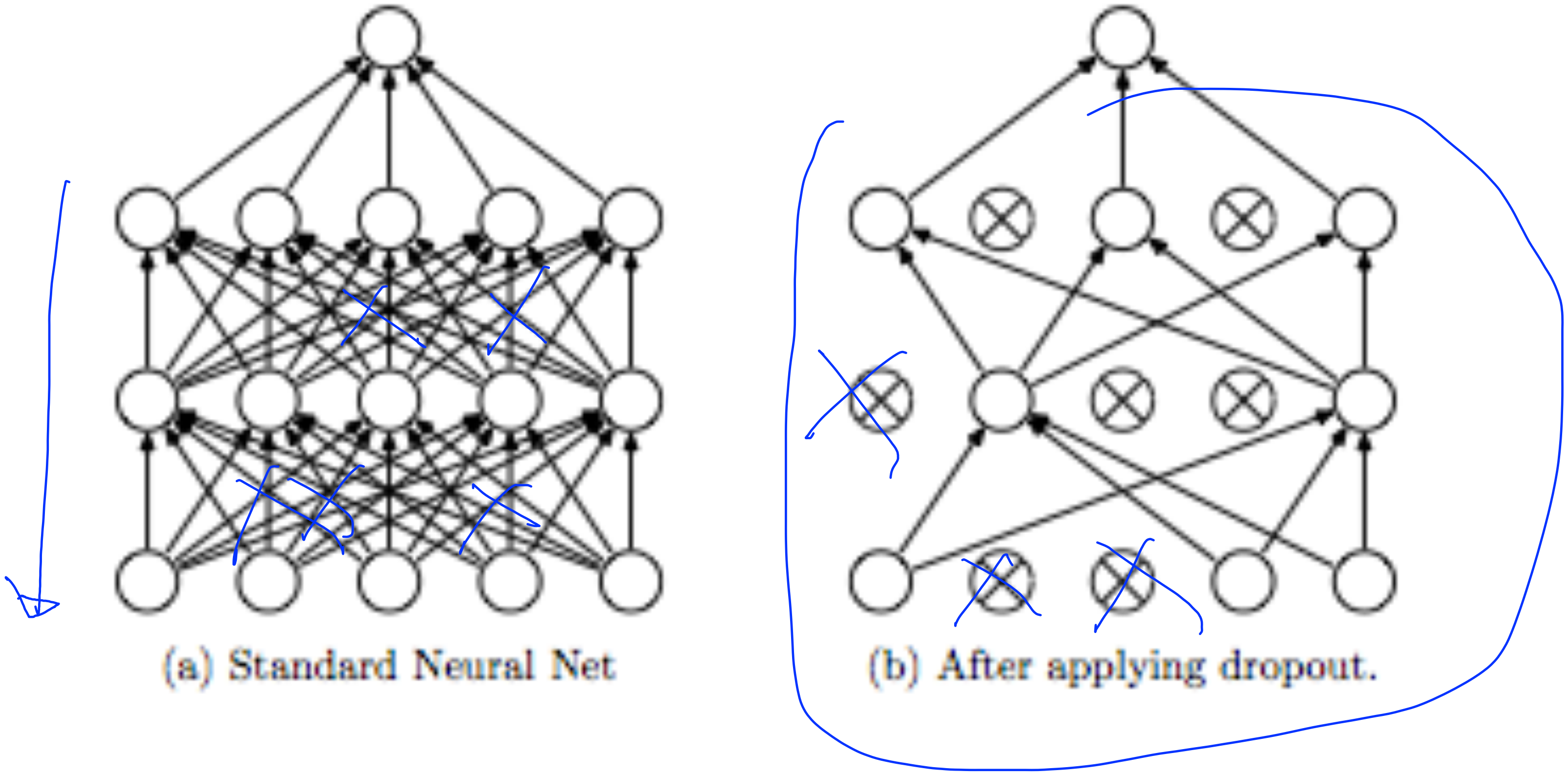
$0 \quad 0.01$

regularization strength

$$\text{cost} + \lambda \sum W^2$$

```
l2reg = 0.001 * tf.reduce_sum(tf.square(W))
```

Dropout: A Simple Way to Prevent Neural Networks from Overfitting [Srivastava et al. 2014]

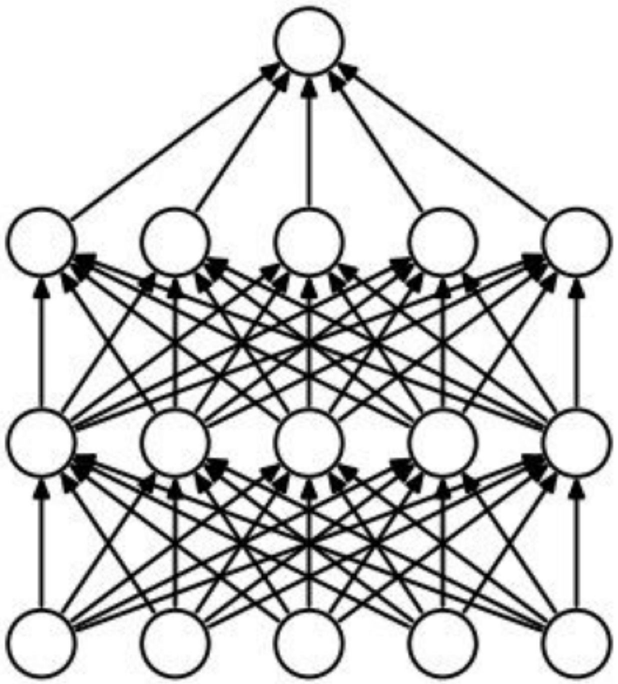


(a) Standard Neural Net

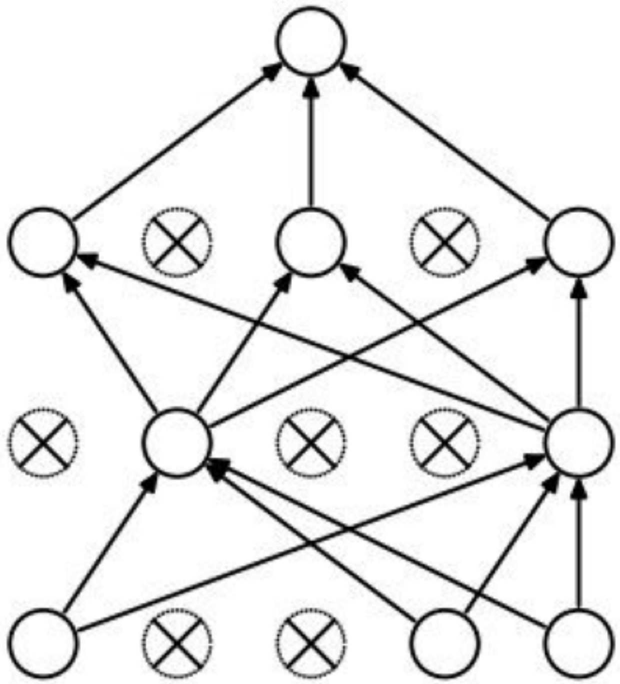
(b) After applying dropout.

Regularization: **Dropout**

"randomly set some neurons to zero in the forward pass"



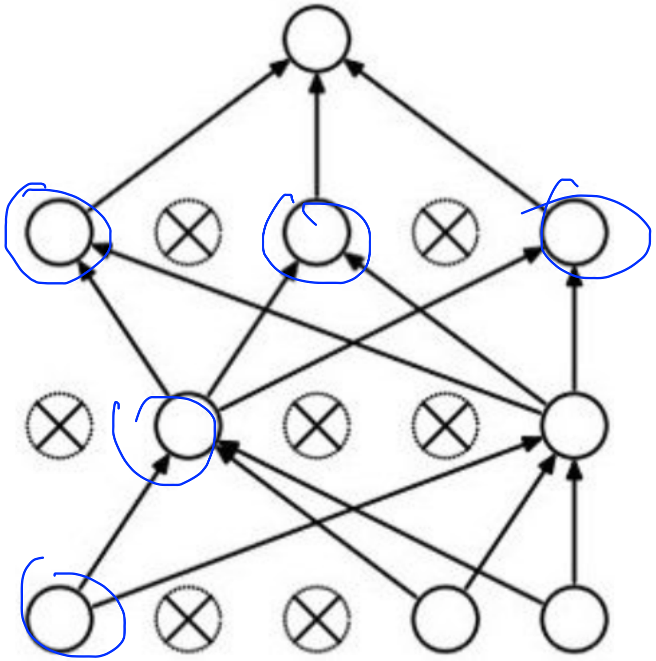
(a) Standard Neural Net



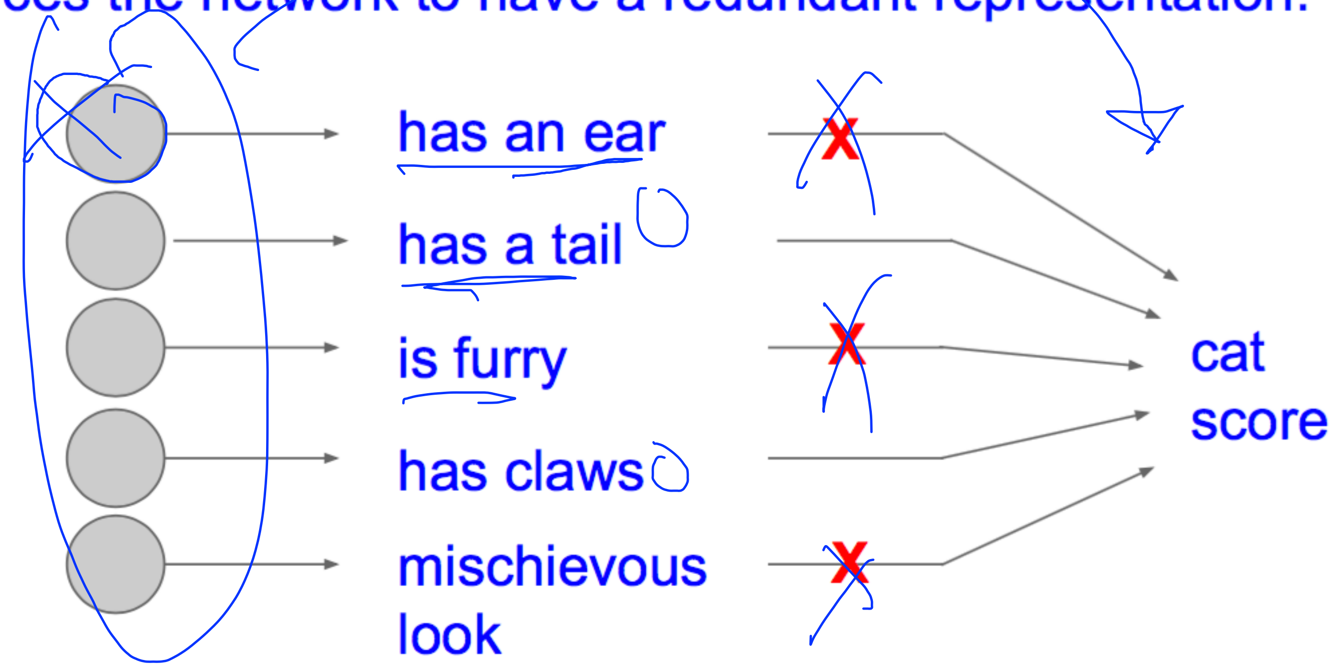
(b) After applying dropout.

[Srivastava et al., 2014]

Waaaait a second…
How could this possibly be a good idea?



Forces the network to have a redundant representation.



TensorFlow implementation

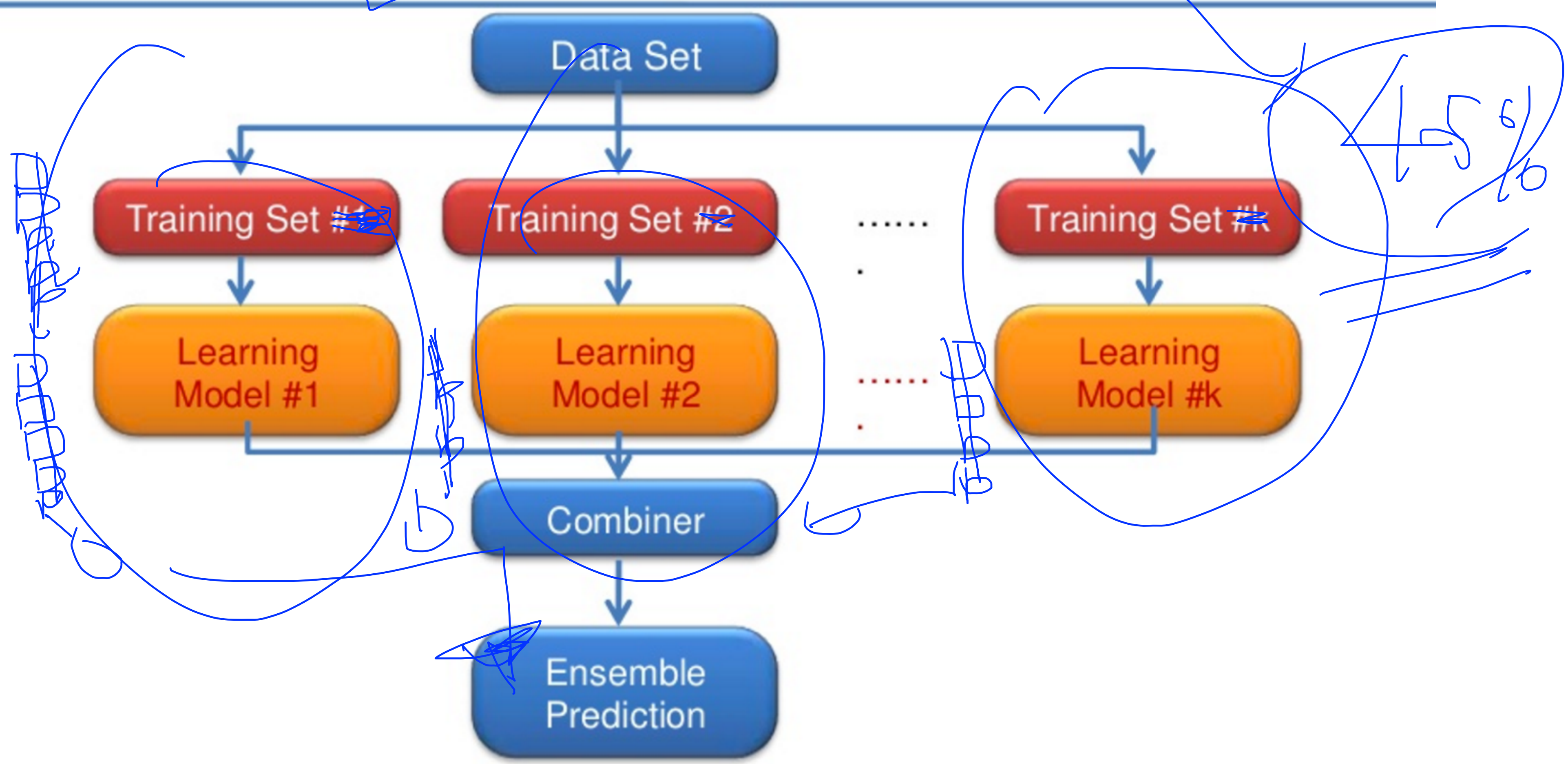
```
dropout_rate = tf.placeholder("float")
_L1 = tf.nn.relu(tf.add(tf.matmul(X, W1), B1))
L1 = tf.nn.dropout(_L1, dropout_rate)
```

0.5

```
TRAIN:
  sess.run(optimizer, feed_dict={X: batch_xs, Y: batch_ys,
  dropout_rate: 0.7})

EVALUATION:
  print "Accuracy:", accuracy.eval({X: mnist.test.images, Y:
  mnist.test.labels, dropout_rate: 1})
```

What is Ensemble?

2%



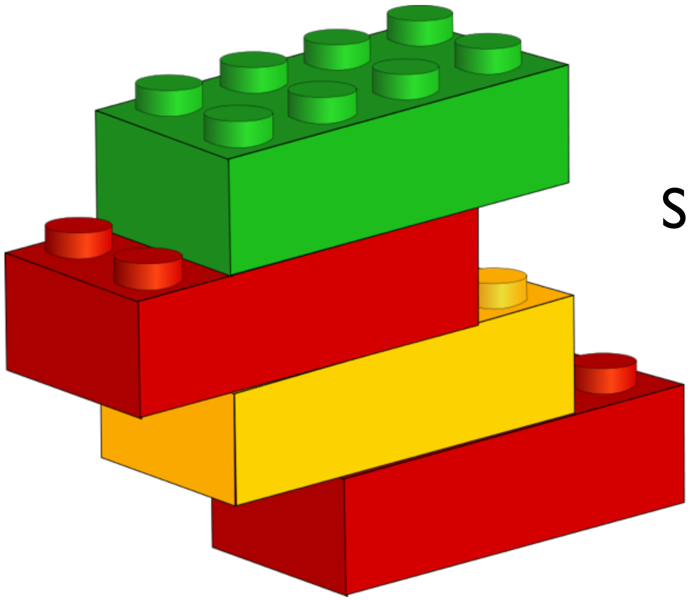
http://www.slideshare.net/sasasiapacific/ipb-improving-the-models-predictive-power-with-ensemble-approaches

Next

NN LEGO Play!

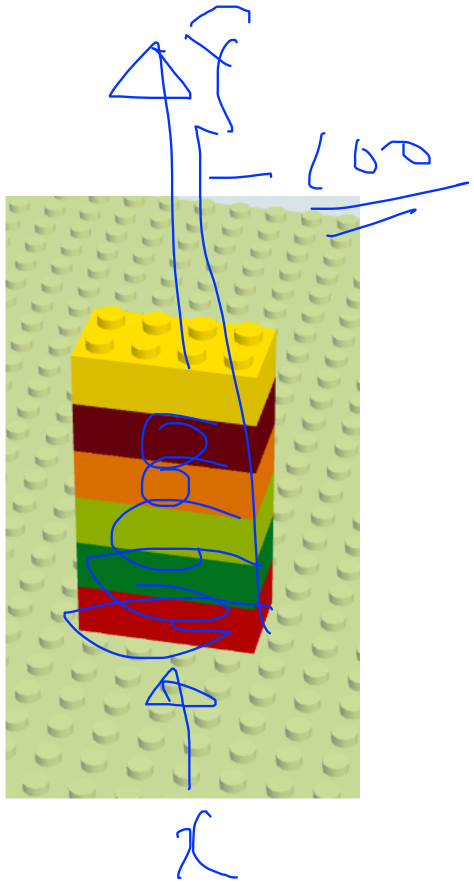
Lecture 10-4

NN LEGO Play



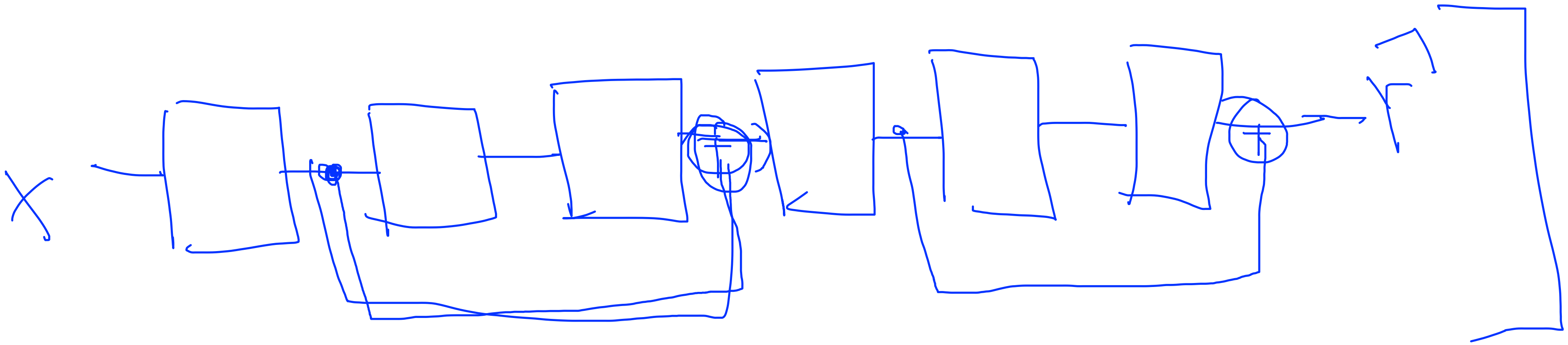
Sung Kim <hunkim+mr@gmail.com>

Feedforward neural network

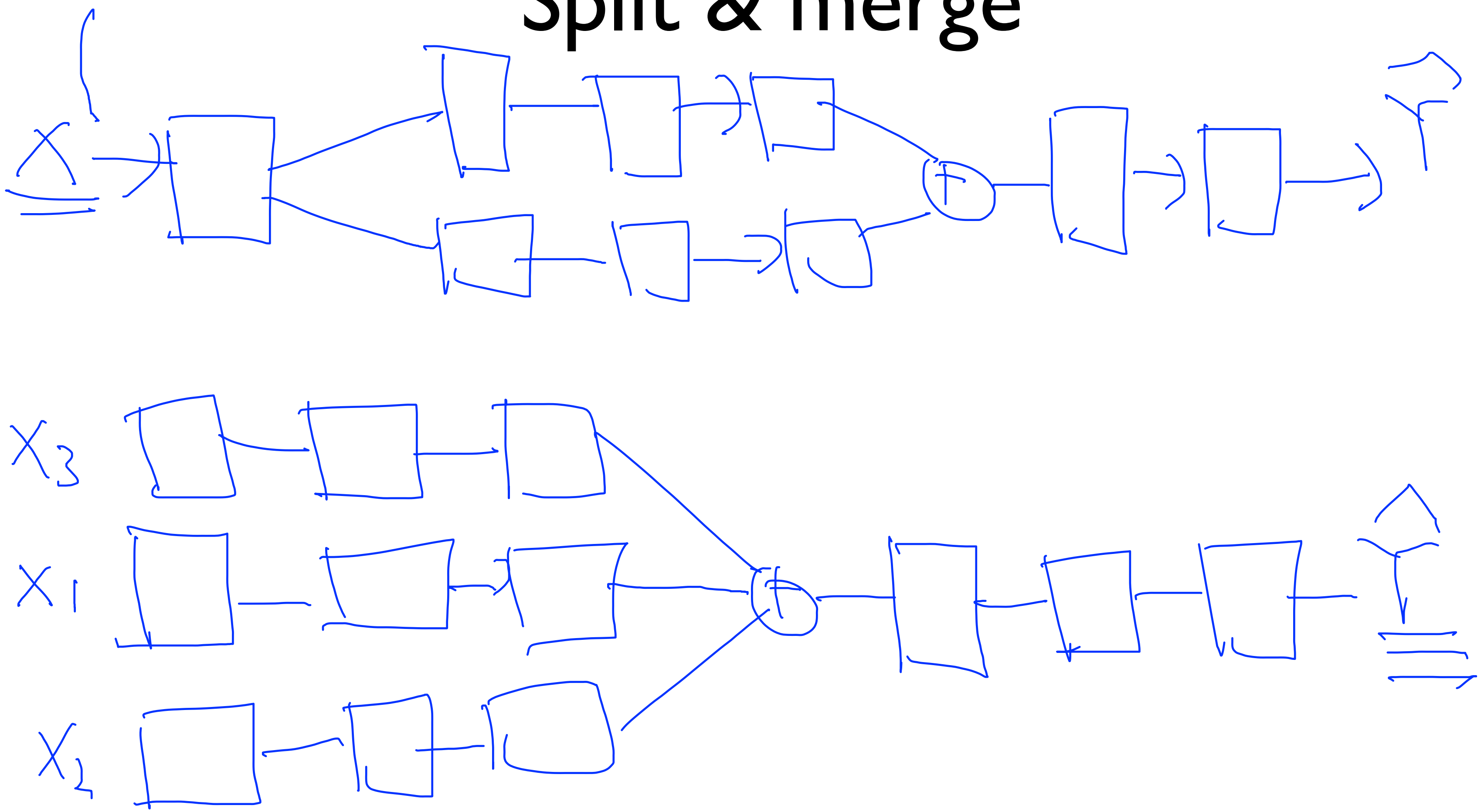


Fast forward

Ho 3%↓

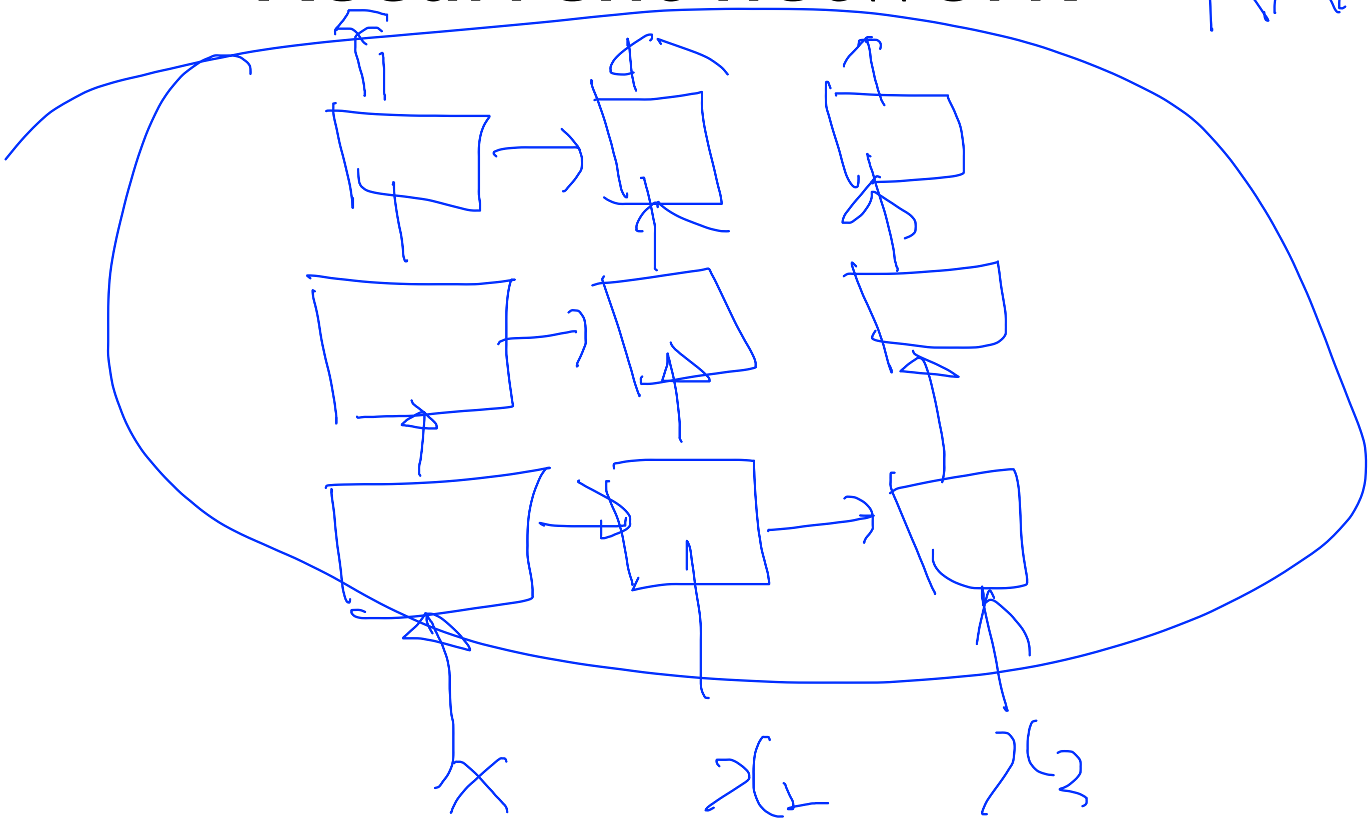


Split & merge

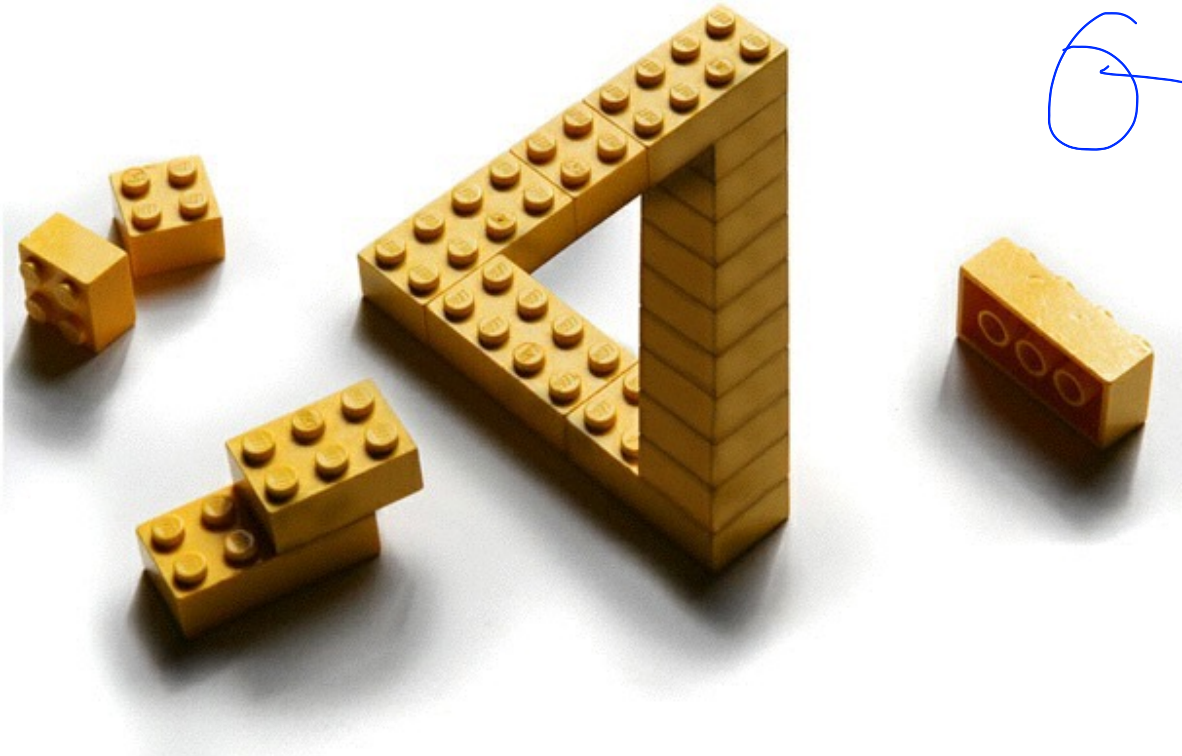


Recurrent network

RNN



'The only limit is your imagination'



http://itchyi.squarespace.com/thelatest/2012/5/17/the-only-limit-is-your-imagination.html