Deep Learning for Visual Recognition
- Week 3

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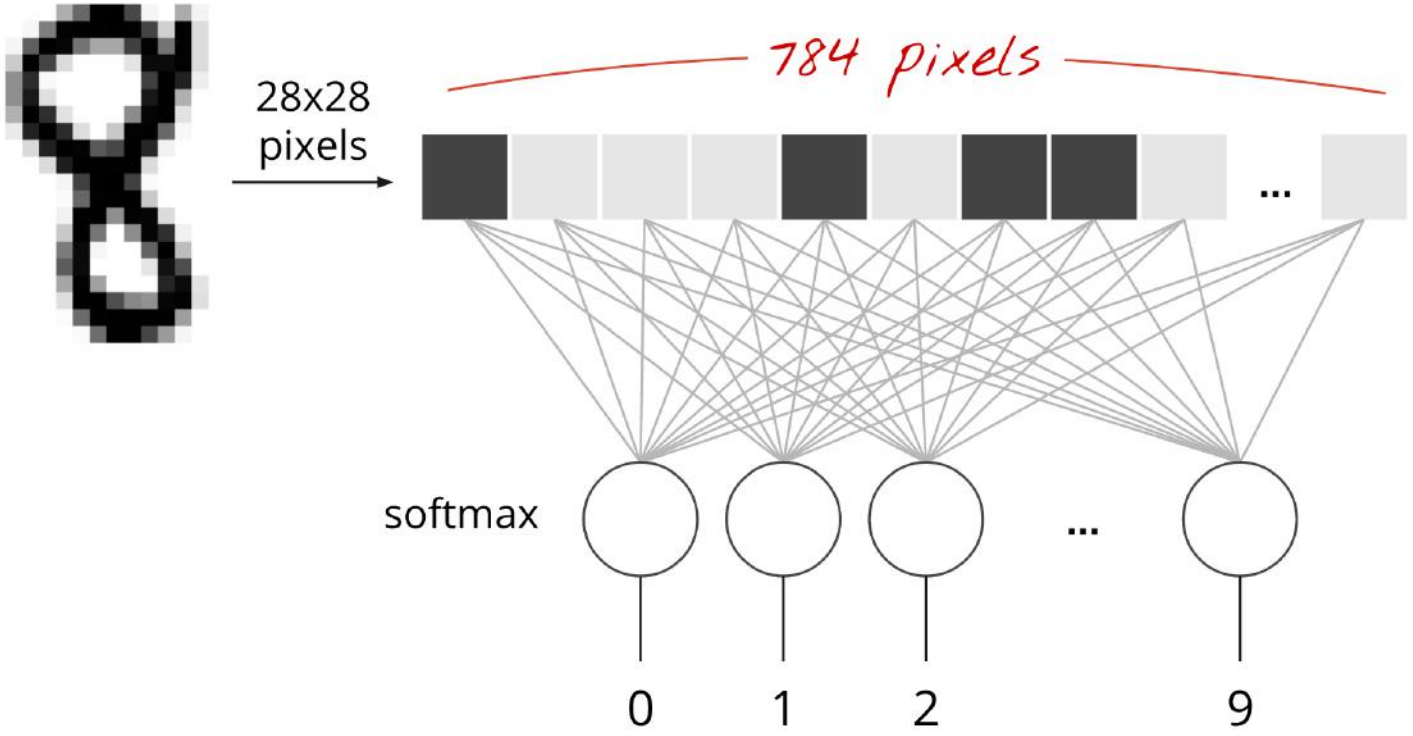
Class 11
Review of CNNs

The contents of following section is borrowed from google cloud platform blog : https://goo.gl/Qc6Qbu

Softmax Classification



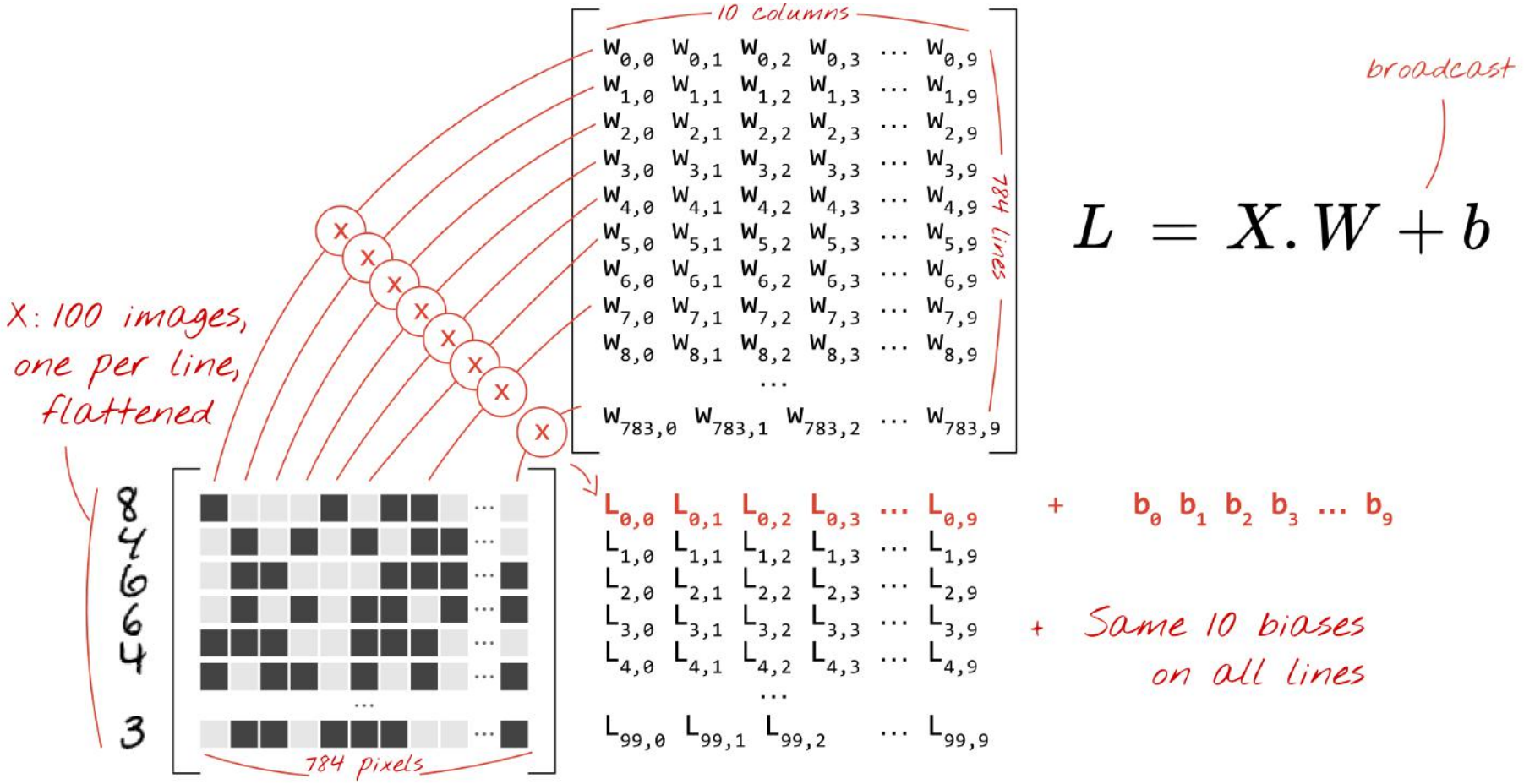
weighted sum of all pixels + bias

$$softmax(L_n) = \frac{e^{L_n}}{||e^{L}||}$$

neuron outputs

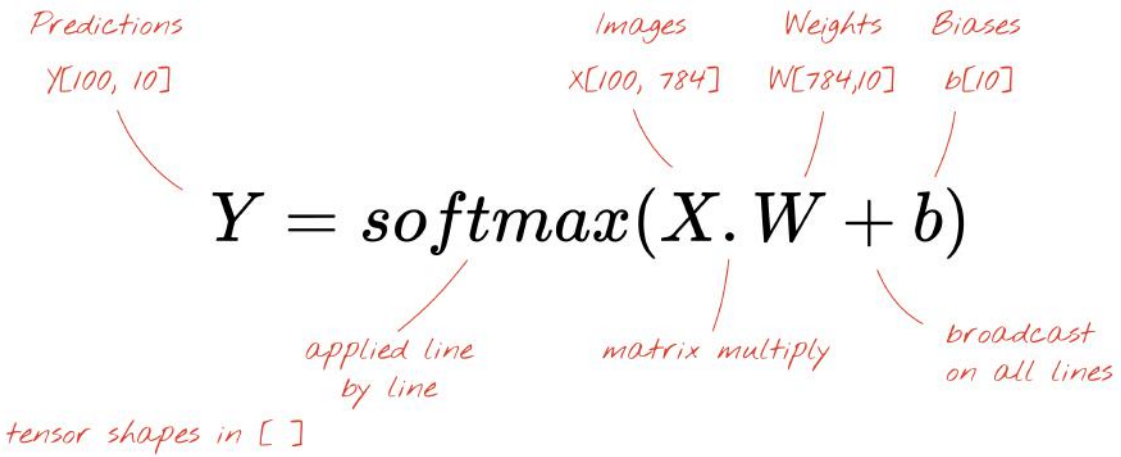
Softmax Classification

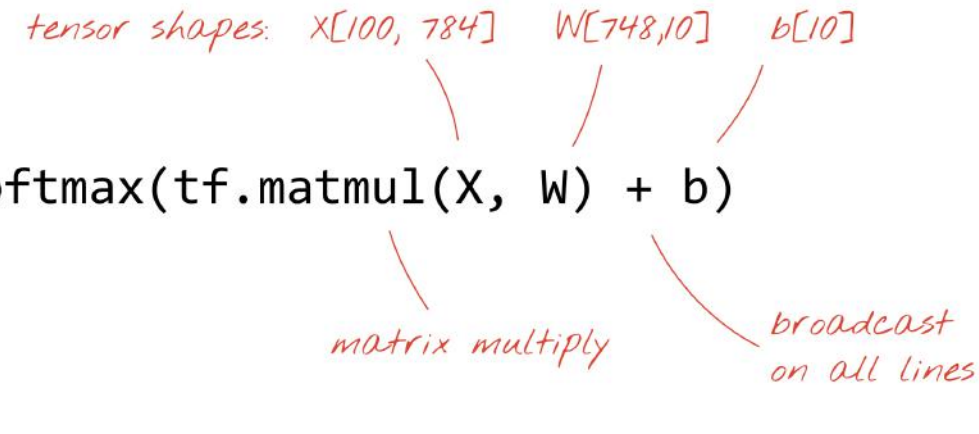
- Matrix Notation



Softmax Classification

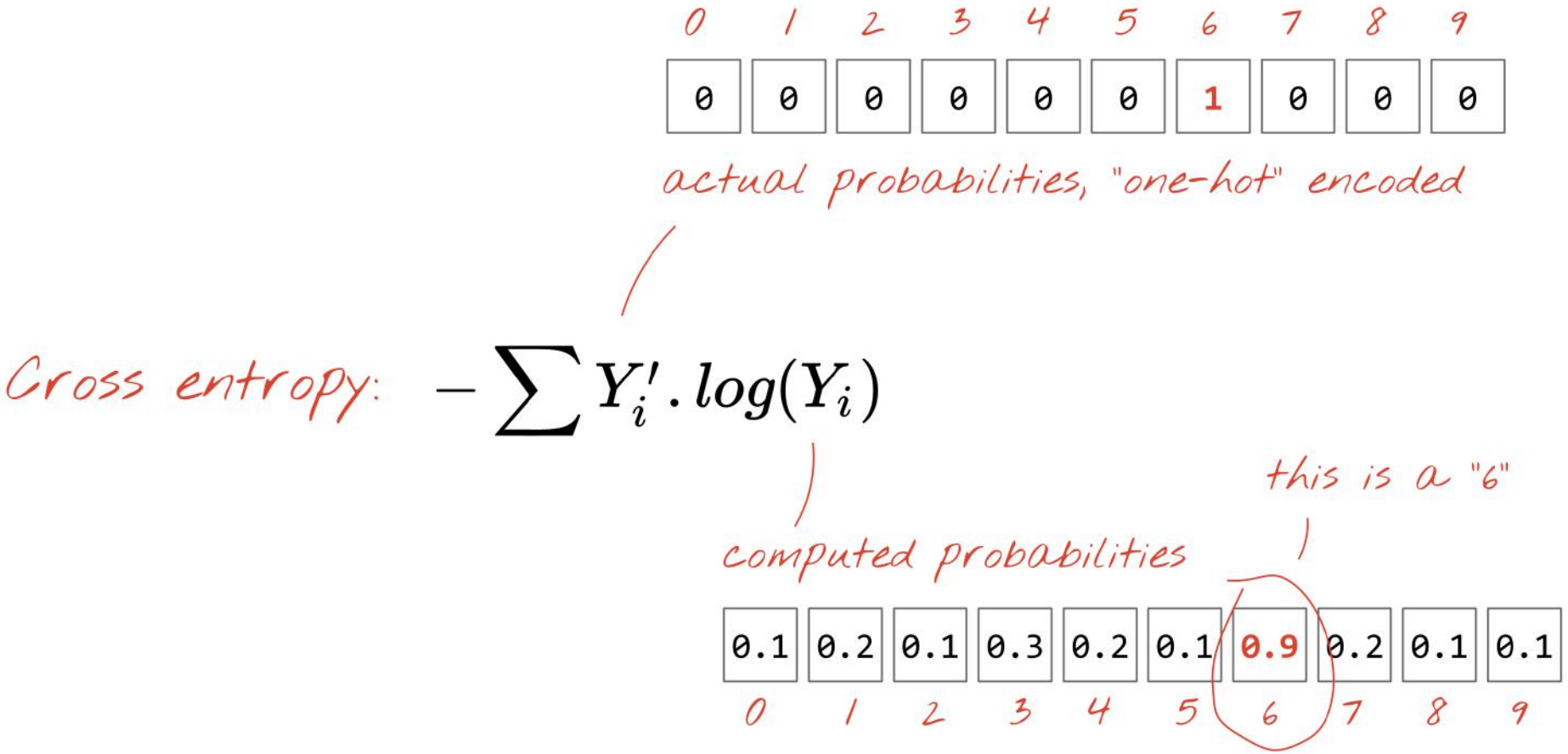
- Batch Notation





Softmax Classification

- Loss Function



Softmax Classification

- Full Python Code

initialisation

```
import tensorflow as tf


X = tf.placeholder(tf.float32, [None, 28, 28, 1])
W = tf.Variable(tf.zeros([784, 10]))
b = tf.Variable(tf.zeros([10]))
init = tf.initialize_all_variables()
```

model

```
# model
Y=tf.nn.softmax(tf.matmul(tf.reshape(X,[-1, 784]), W) + b)

# placeholder for correct answers
Y_ = tf.placeholder(tf.float32, [None, 10])
```

success metrics

```
# loss function
cross_entropy = -tf.reduce_sum(Y_ * tf.log(Y))

# % of correct answers found in batch
is_correct = tf.equal(tf.argmax(Y,1), tf.argmax(Y_,1))
accuracy = tf.reduce_mean(tf.cast(is_correct,tf.float32))
```

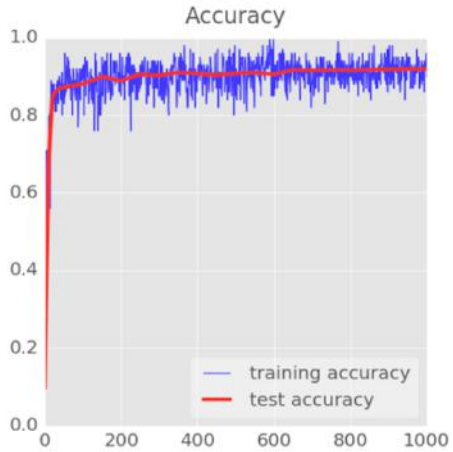
training step

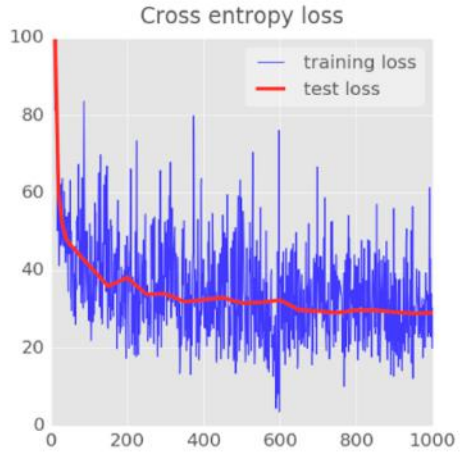
```
optimizer = tf.train.GradientDescentOptimizer(0.003)
train_step = optimizer.minimize(cross_entropy)


sess = tf.Session()
sess.run(init)

for i in range(10000):
      # load batch of images and correct answers
      batch_X, batch_Y = mnist.train.next_batch(100)
      train_data={X: batch_X, Y_: batch_Y}

      # train
      sess.run(train_step, feed_dict=train_data)

      # success ? add code to print it
      a,c = sess.run([accuracy, cross_entropy], feed=train_data)

      # success on test data ?
      test_data={X:mnist.test.images, Y_:mnist.test.labels}
      a,c = sess.run([accuracy, cross_entropy], feed=test_data)
```

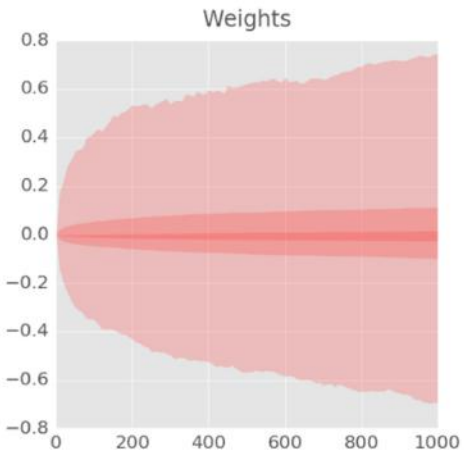
Run

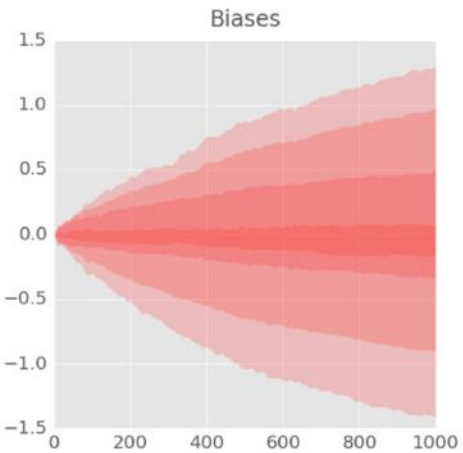
Softmax Classification

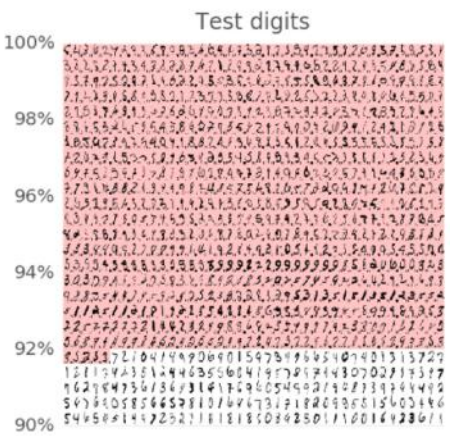
- Lets Run! : ./tensorflow-mnist/mnist_1.0_softmax.py





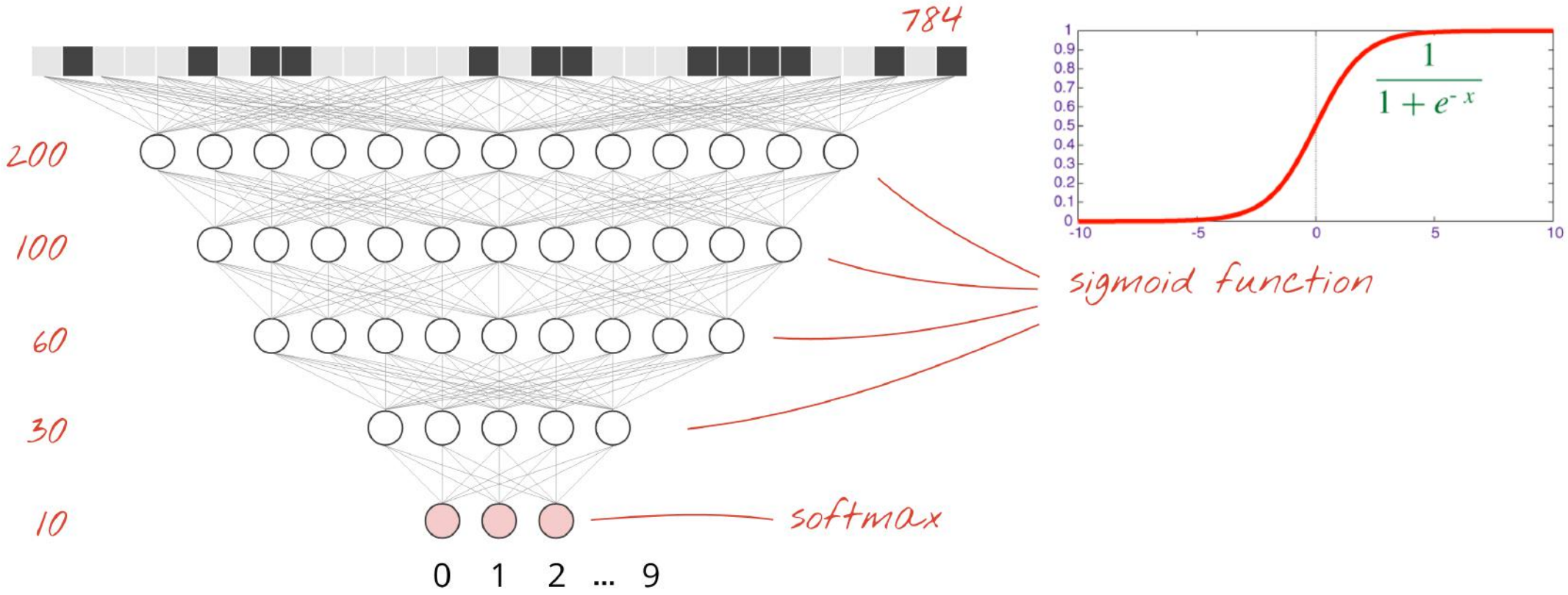






Multi-layered Perceptron

- Model Architecture



Multi-layered Perceptron

- TensorFlow Code

```
K = 200
L = 100
M = 60
N = 30

W1 = tf.Variable(tf.truncated_normal([28*28, K] ,stddev=0.1))
B1 = tf.Variable(tf.zeros([K]))
W2 = tf.Variable(tf.truncated_normal([K, L], stddev=0.1))
B2 = tf.Variable(tf.zeros([L]))
W3 = tf.Variable(tf.truncated_normal([L, M], stddev=0.1))
B3 = tf.Variable(tf.zeros([M]))
W4 = tf.Variable(tf.truncated_normal([M, N], stddev=0.1))
B4 = tf.Variable(tf.zeros([N]))
W5 = tf.Variable(tf.truncated_normal([N, 10], stddev=0.1))
B5 = tf.Variable(tf.zeros([10]))
```

weights initialised with random values

weights and biases

```
X = tf.reshape(X, [-1, 28*28])

Y1 = tf.nn.sigmoid(tf.matmul(X, W1) + B1)
Y2 = tf.nn.sigmoid(tf.matmul(Y1, W2) + B2)
Y3 = tf.nn.sigmoid(tf.matmul(Y2, W3) + B3)
Y4 = tf.nn.sigmoid(tf.matmul(Y3, W4) + B4)
Y = tf.nn.softmax(tf.matmul(Y4, W5) + B5)
```

Multi-layered Perceptron

- Truncated Normal Distribution

`tf.truncated_normal(shape, mean=0.0, stddev=1.0, dtype=tf.float32, seed=None, name=None)` {#truncated_normal}

Outputs random values from a truncated normal distribution.

The generated values follow a normal distribution with specified mean and standard deviation, except that values whose magnitude is more than 2 standard deviations from the mean are dropped and re-picked.

Args:

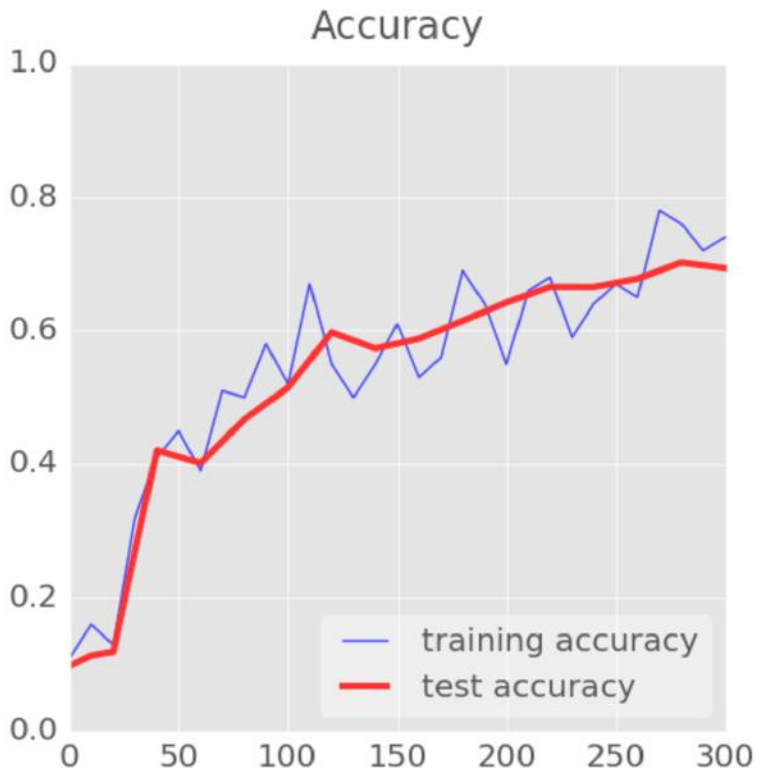
- **`shape`**: A 1-D integer Tensor or Python array. The shape of the output tensor.
- **`mean`**: A 0-D Tensor or Python value of type `dtype`. The mean of the truncated normal distribution.
- **`stddev`**: A 0-D Tensor or Python value of type `dtype`. The standard deviation of the truncated normal distribution.
- **`dtype`**: The type of the output.
- **`seed`**: A Python integer. Used to create a random seed for the distribution. See `set_random_seed` for behavior.
- **`name`**: A name for the operation (optional).

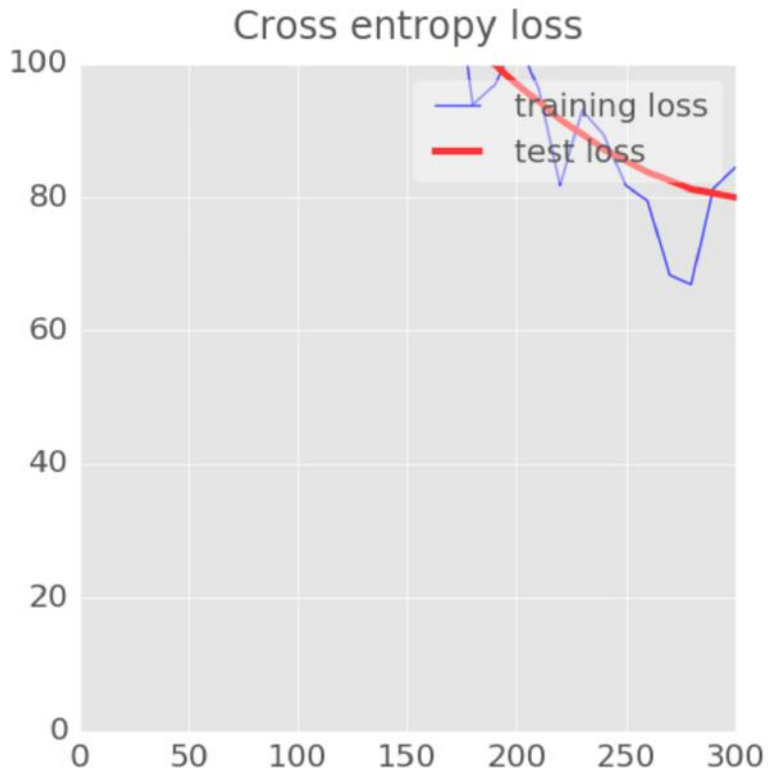
Returns:

A tensor of the specified shape filled with random truncated normal values.

Multi-layered Perceptron

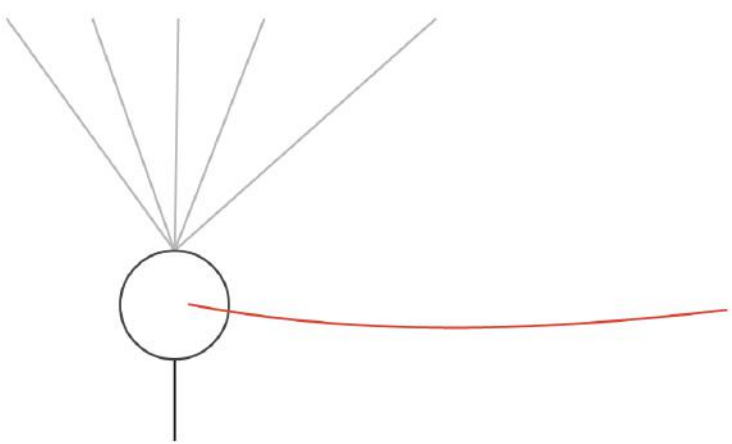
- Lets Run ! : ./tensorflow-mnist/mnist_2.0_five_layers_sigmoid.py
  - Result : Slow Start.

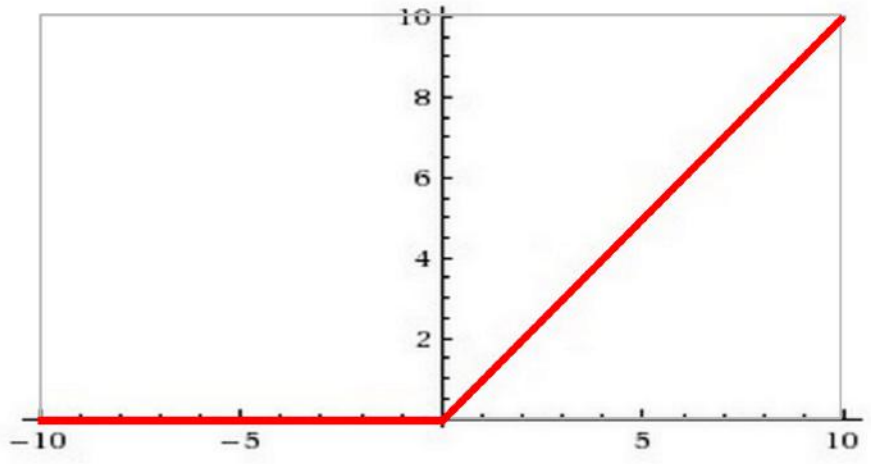




Multi-layered Perceptron

- Rectified Linear Unit

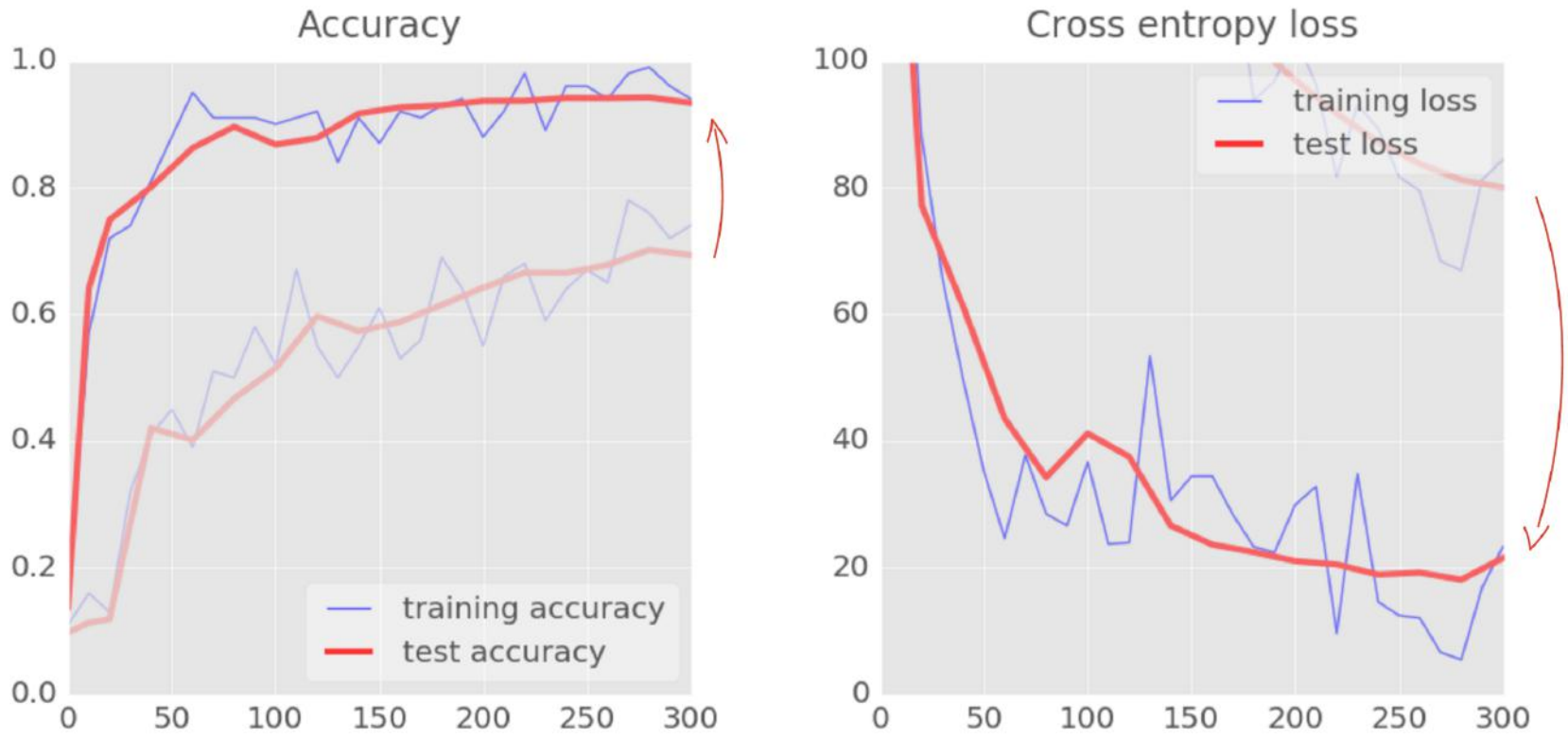





```
Y = tf.nn.relu(tf.matmul(X, W) + b)
```

Multi-layered Perceptron

- Lets Run ! : ./tensorflow-mnist/mnist_2.1_five_layers_relu.py

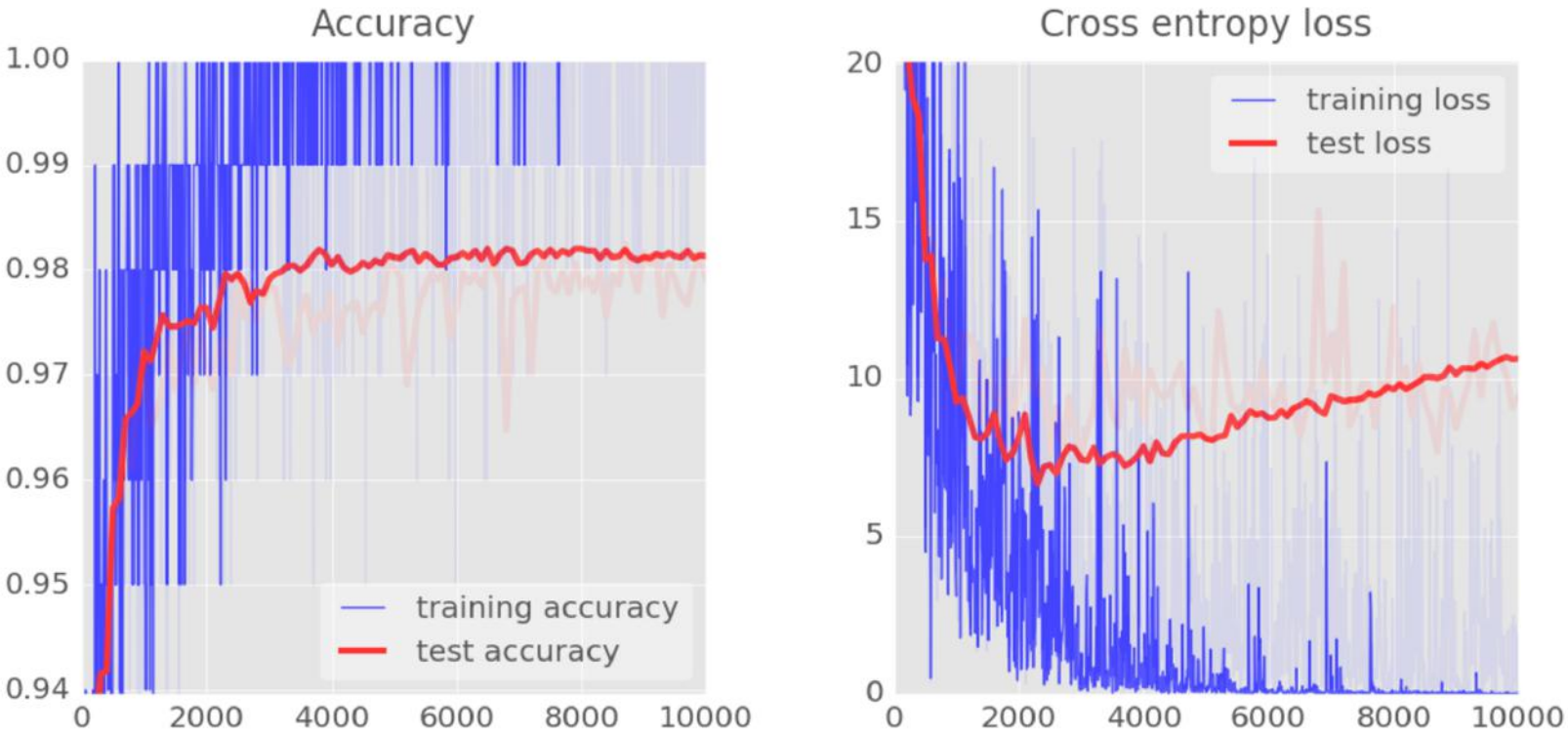


Multi-layered Perceptron

- Problem : Noisy Convergence -> Learning Rate Decay

Multi-layered Perceptron

- Let's Run ! : ./tensorflow-mnist/mnist_2.2_five_layers_relu_lrdecay.py

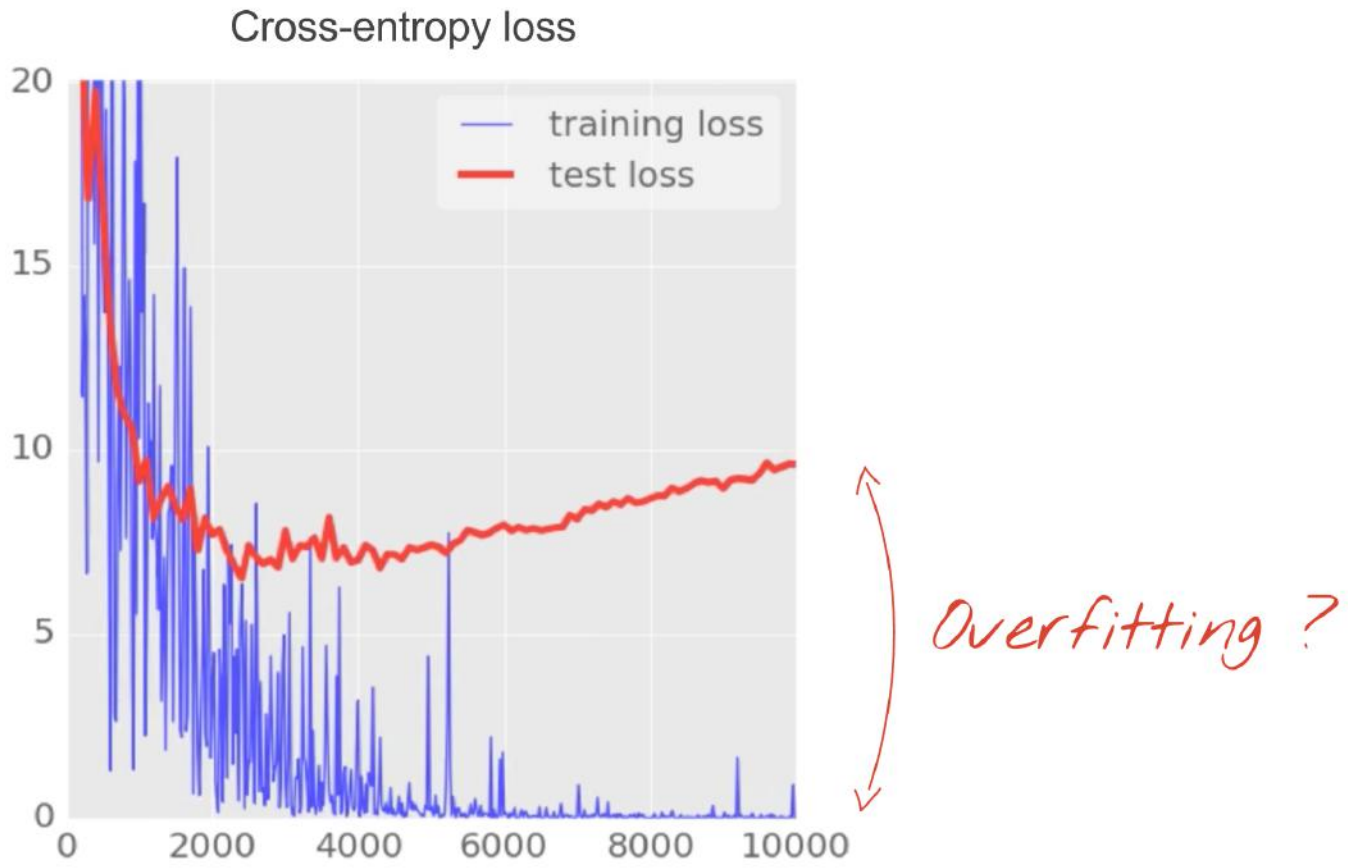


Learning rate 0.003 at start then dropping exponentially to 0.0001

```
learning_rate = min_learning_rate + (max_learning_rate - min_learning_rate) * math.exp(-i/decay_speed)
```

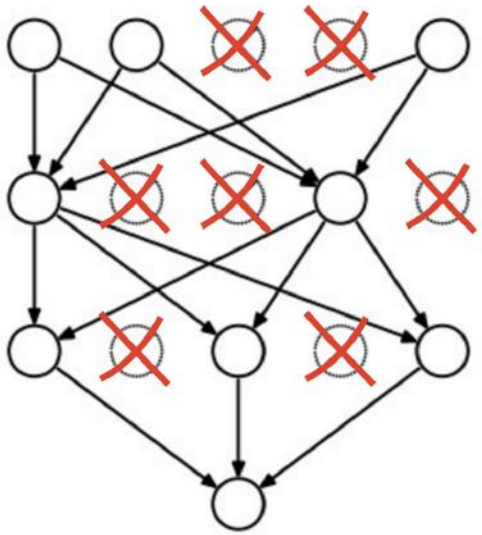
Multi-layered Perceptron

- Problem : Overfitting -> Dropout

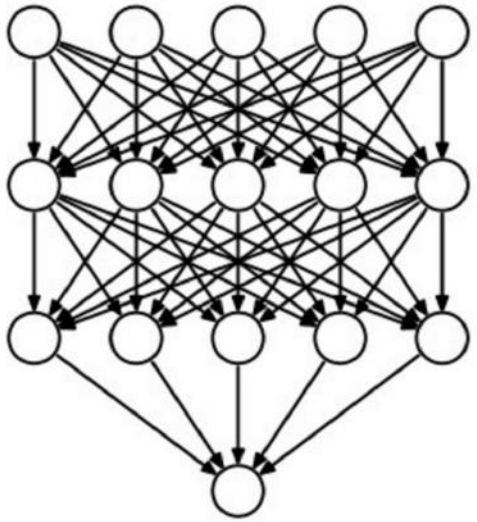


Multi-layered Perceptron

- Dropout



TRAINING
pKeep=0.75

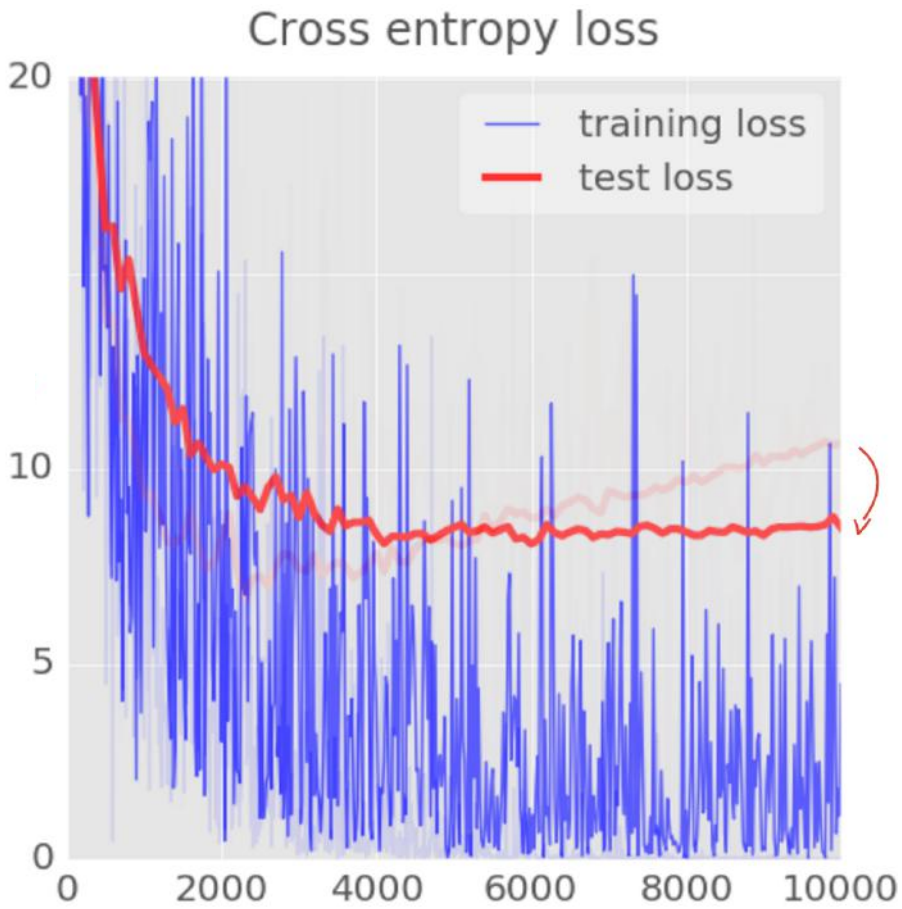


EVALUATION
pKeep=1

```
pkeep =
tf.placeholder(tf.float32)

Yf = tf.nn.relu(tf.matmul(X, W) + B)
Y  = tf.nn.dropout(Yf, pkeep)
```

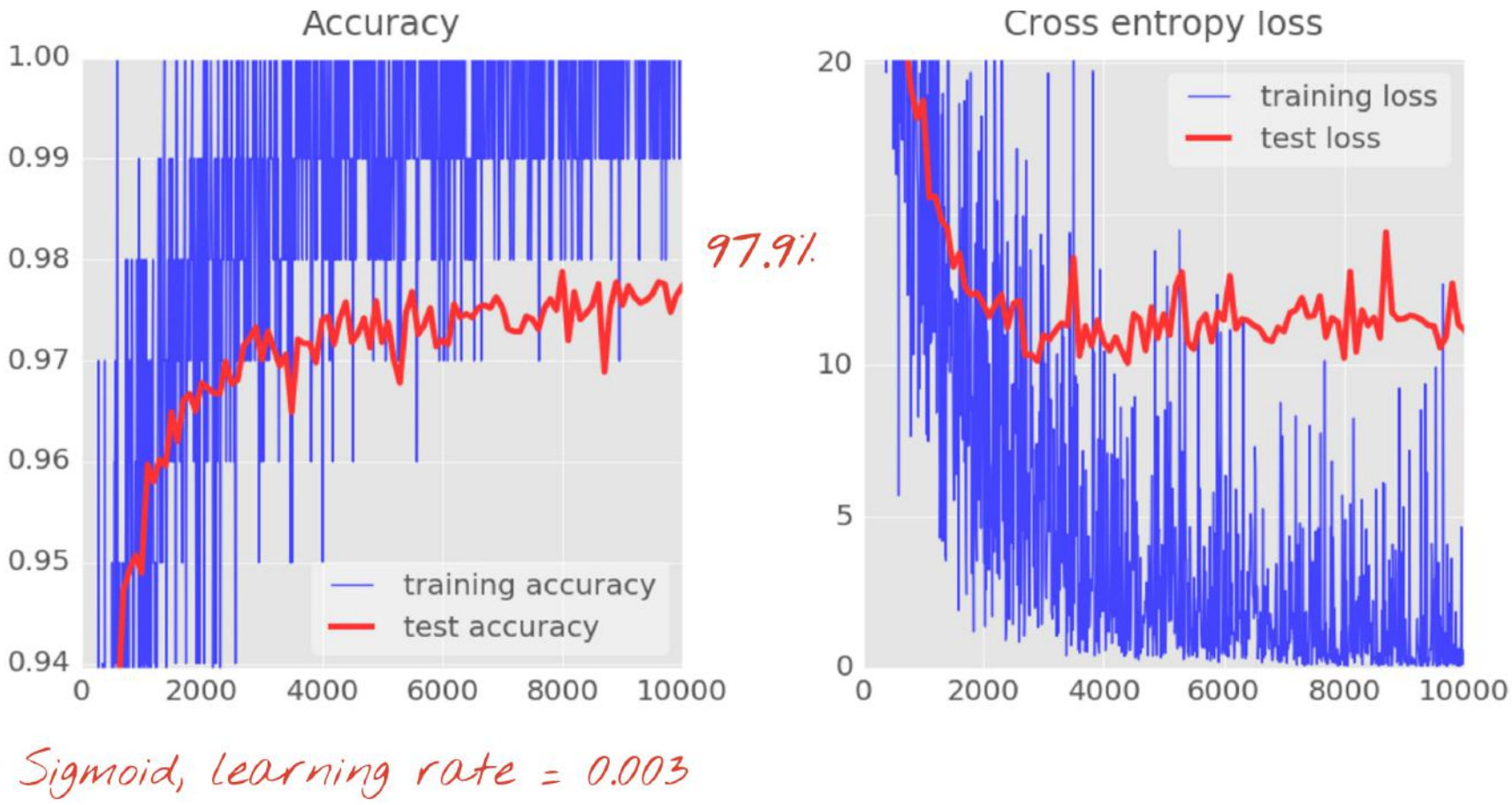
Multi-layered Perceptron

- Let’s Run ! : ./tensorflow-mnist/mnist_2.3_five_layers_relu_lrdecay_dropout.py



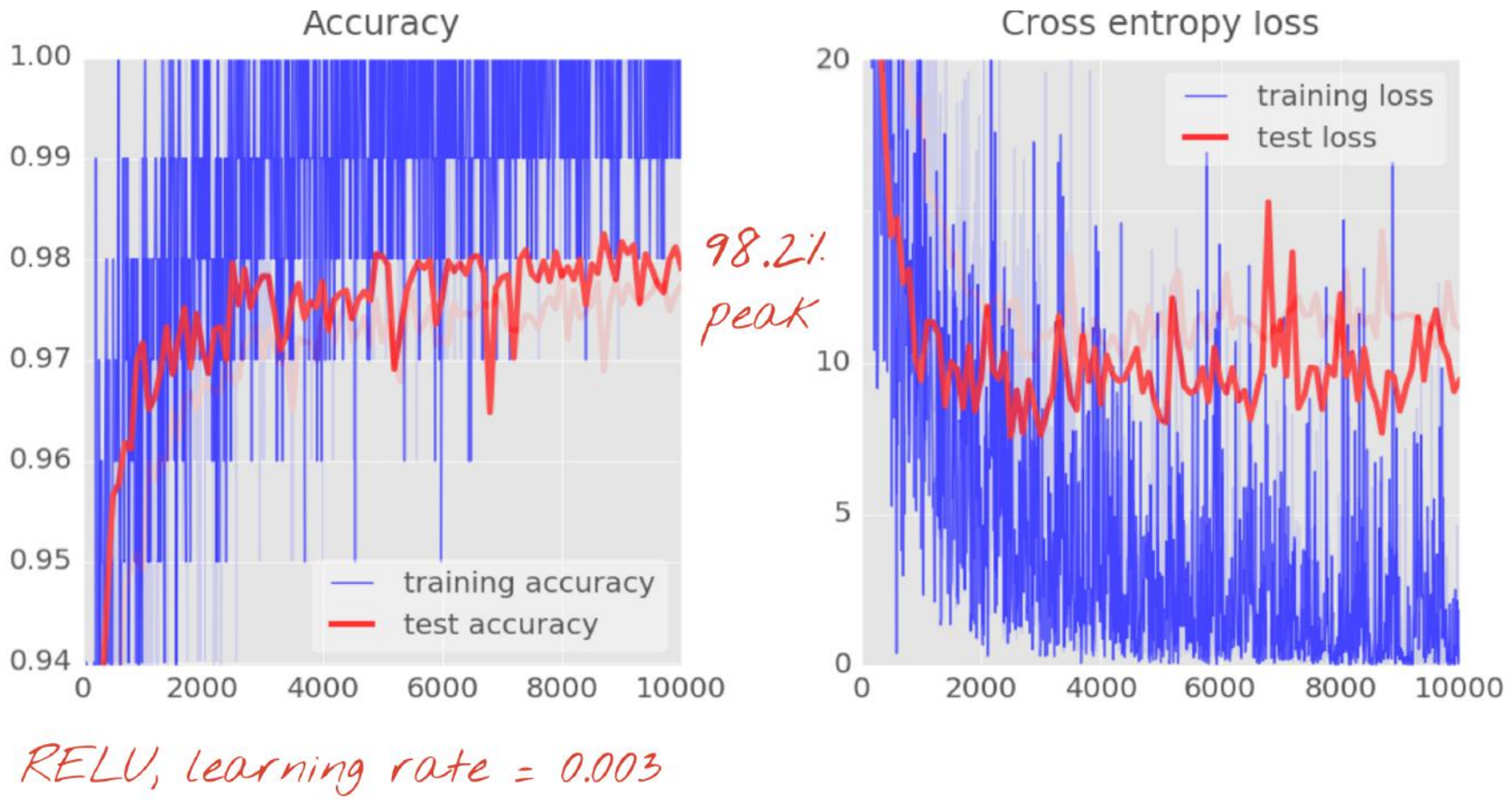
Multi-layered Perceptron

- All the Recipes



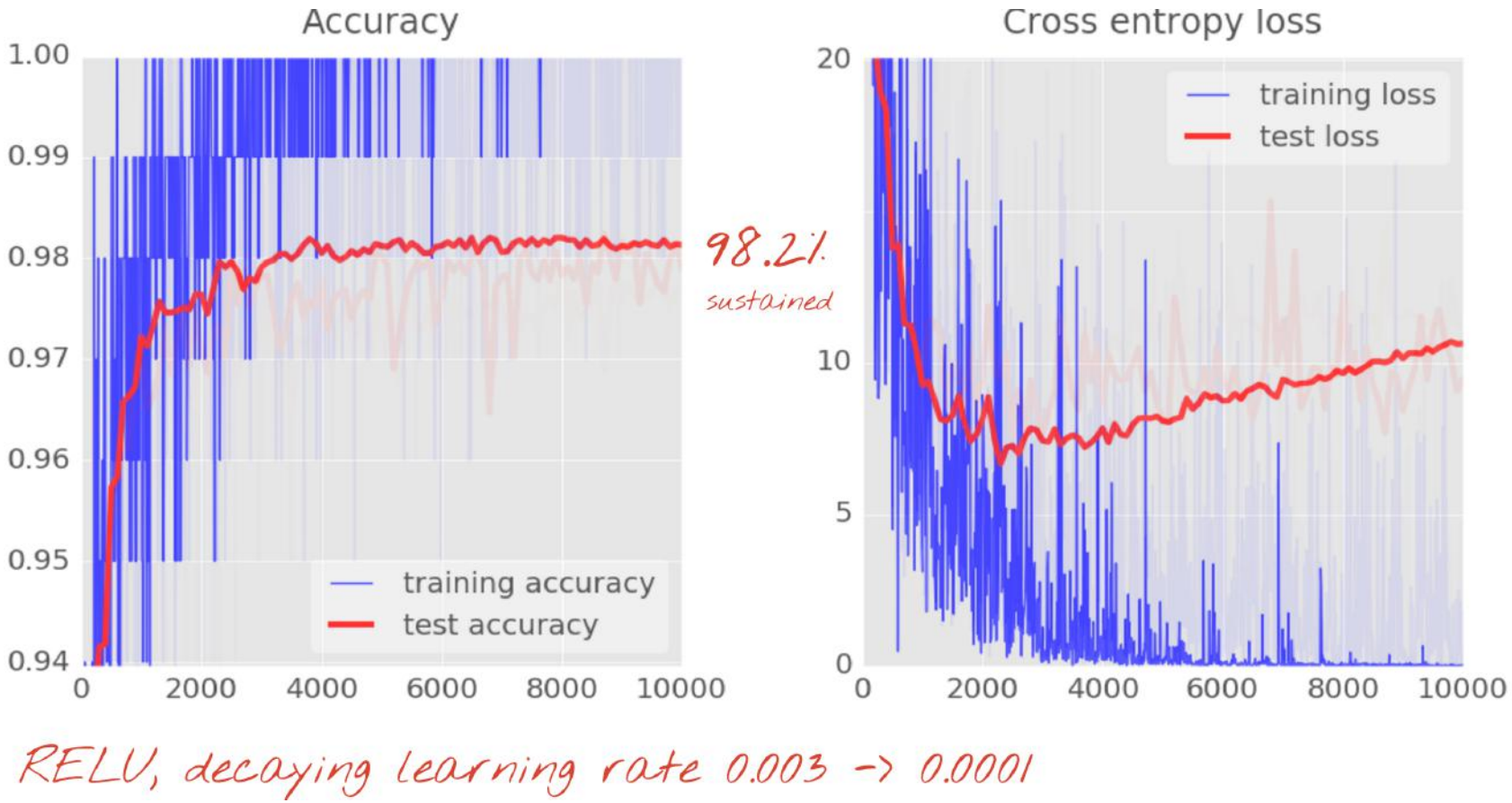
Multi-layered Perceptron

- All the Recipes



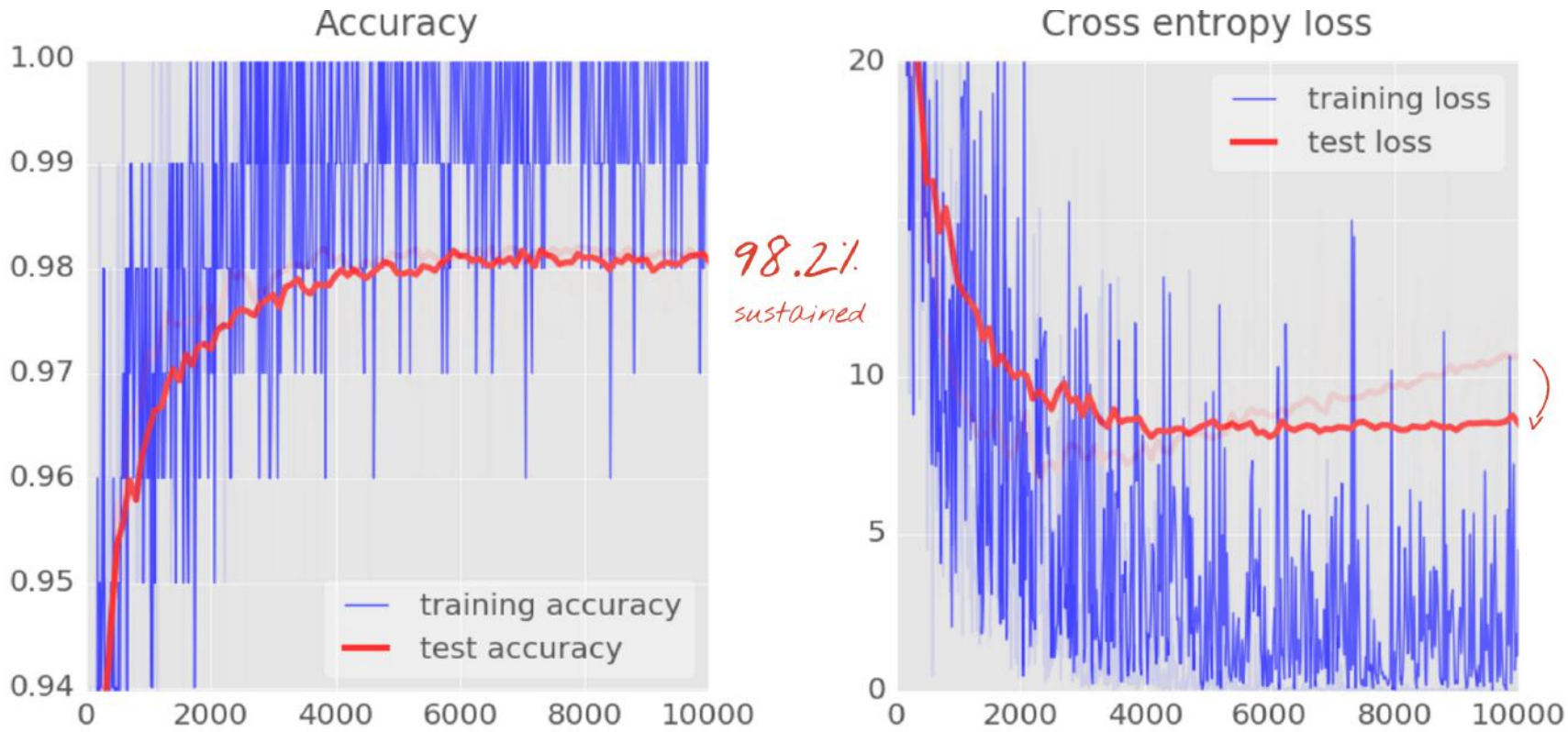
Multi-layered Perceptron

- All the Recipes



Multi-layered Perceptron

- All the Recipes



Multi-layered Perceptron

- One-more Thing : tf.get_variable()

```
tf.get_variable(name, shape=None, dtype=None, initializer=None,
regularizer=None, trainable=True, collections=None, caching_device=None,
partitioner=None, validate_shape=True, custom_getter=None)
```

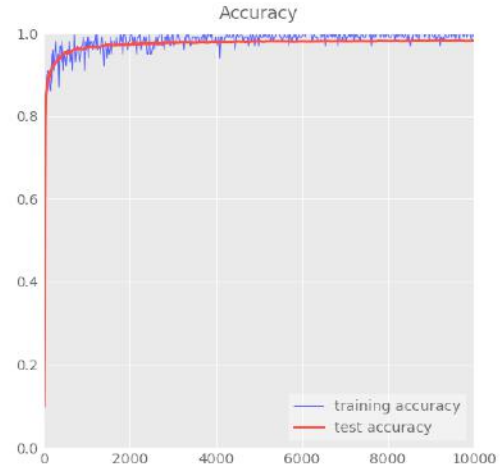
Gets an existing variable with these parameters or create a new one.

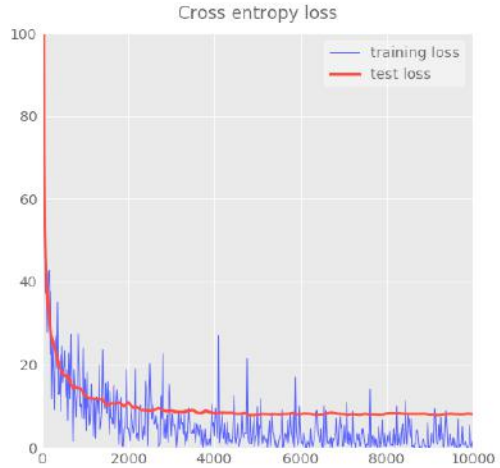
This function prefixes the name with the current variable scope and performs reuse checks. See the Variable Scope How To for an extensive description of how reusing works. Here is a basic example:

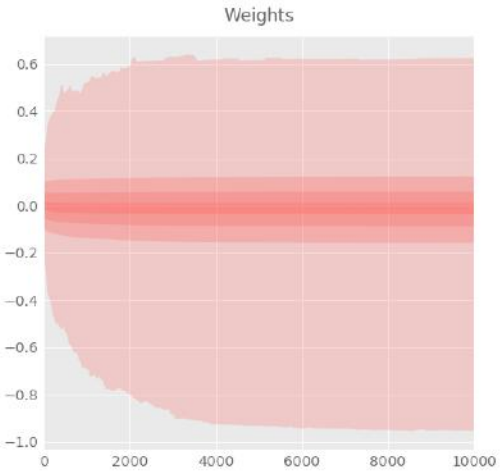
```
with tf.variable_scope("foo"):
    v = tf.get_variable("v", [1])  # v.name == "foo/v:0"
    w = tf.get_variable("w", [1])  # w.name == "foo/w:0"
with tf.variable_scope("foo", reuse=True)
    v1 = tf.get_variable("v")  # The same as v above.
```

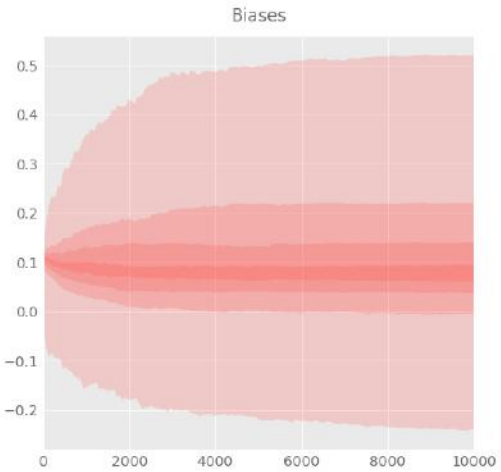
Multi-layered Perceptron

- Before : 98.25%



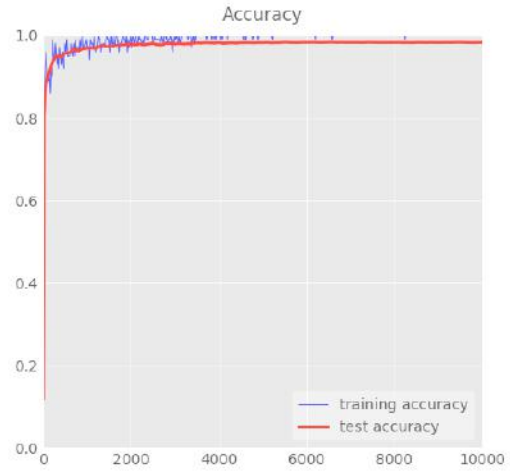


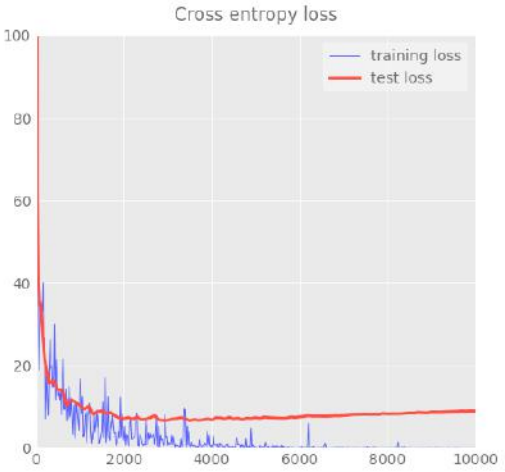


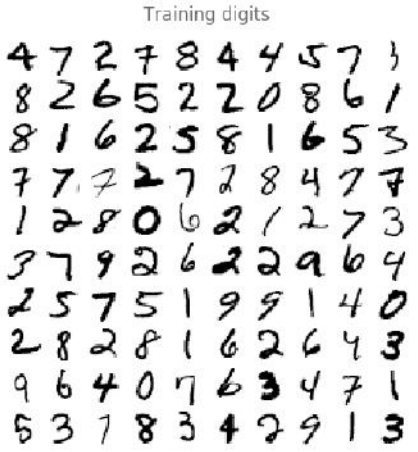


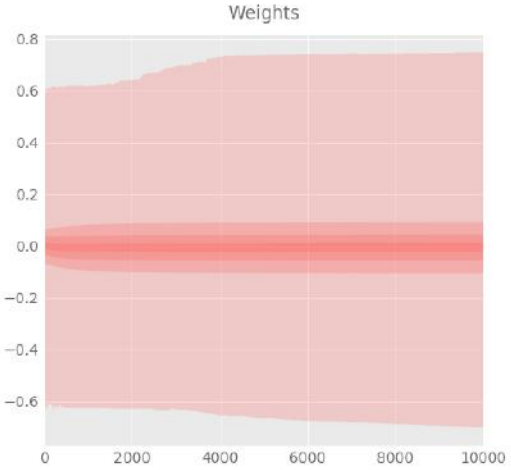
Multi-layered Perceptron

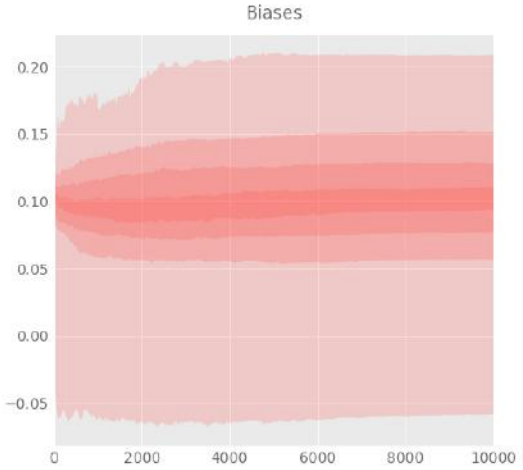
- After : 98.39%

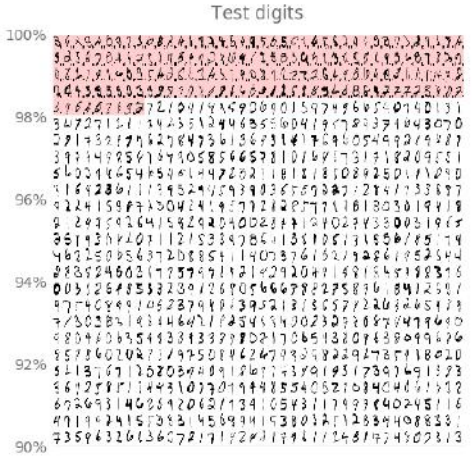






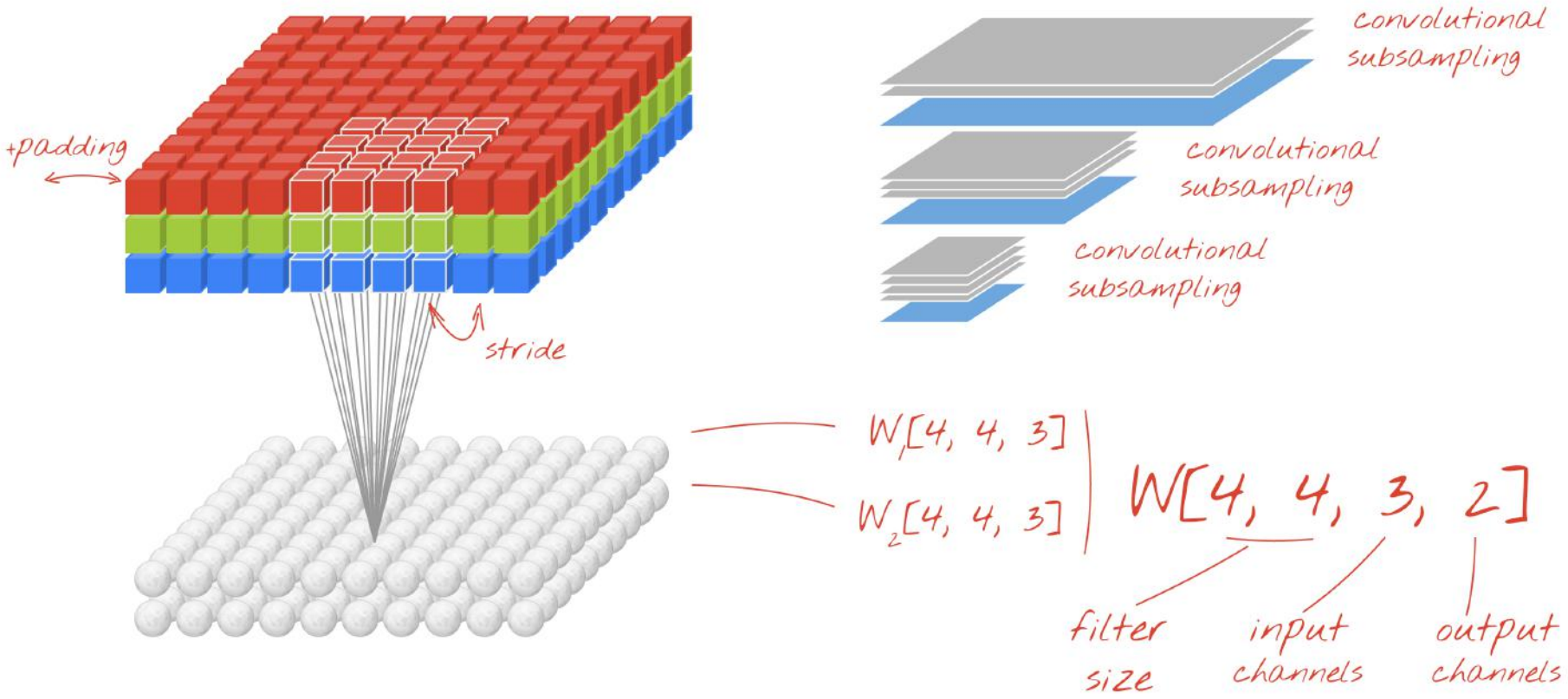






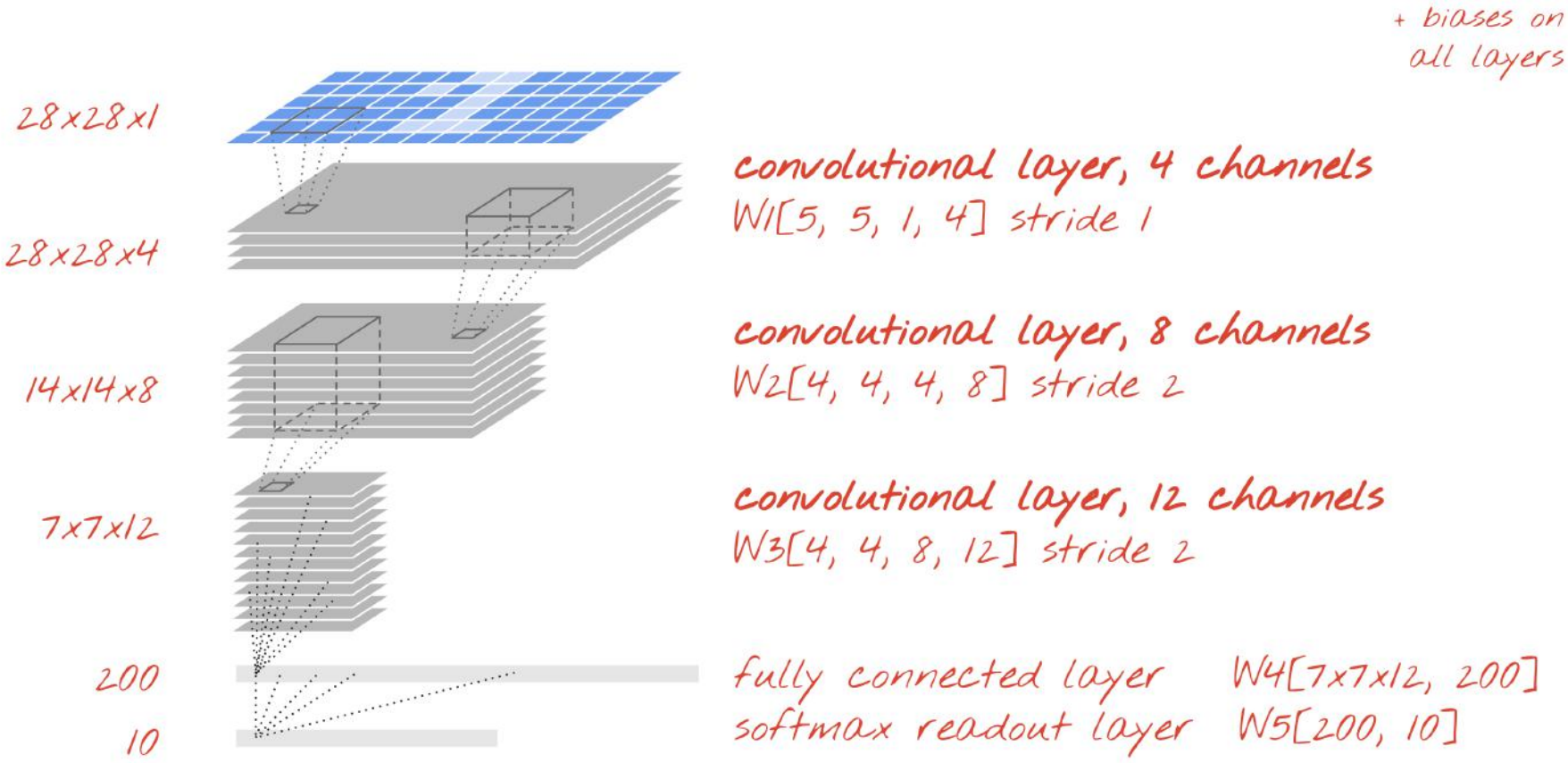
Convolutional Neural Network

- Convolution Layer



Convolutional Neural Network

- Architecture – Smaller Network



Convolutional Neural Network

- Code – Smaller Network

filter size / input channels / output channels

```
K=4
L=8
M=12

W1 = tf.Variable(tf.truncated_normal([5, 5, 1, K] ,stddev=0.1))
B1 = tf.Variable(tf.ones([K])/10)
W2 = tf.Variable(tf.truncated_normal([5, 5, K, L] ,stddev=0.1))
B2 = tf.Variable(tf.ones([L])/10)
W3 = tf.Variable(tf.truncated_normal([4, 4, L, M] ,stddev=0.1))
B3 = tf.Variable(tf.ones([M])/10)

N=200

W4 = tf.Variable(tf.truncated_normal([7*7*M, N] ,stddev=0.1))
B4 = tf.Variable(tf.ones([N])/10)
W5 = tf.Variable(tf.truncated_normal([N, 10] ,stddev=0.1))
B5 = tf.Variable(tf.zeros([10])/10)
```

weights initialised with random values

input image batch X[100, 28, 28, 1] / weights / stride / bia

```
Y1 = tf.nn.relu(tf.nn.conv2d(X, W1, strides=[1, 1, 1, 1], padding='SAME') +
Y2 = tf.nn.relu(tf.nn.conv2d(Y1, W2, strides=[1, 2, 2, 1], padding='SAME')
Y3 = tf.nn.relu(tf.nn.conv2d(Y2, W3, strides=[1, 2, 2, 1], padding='SAME')

YY = tf.reshape(Y3, shape=[-1, 7 * 7 * M])

Y4 = tf.nn.relu(tf.matmul(YY, W4) + B4)
Y  = tf.nn.softmax(tf.matmul(Y4, W5) + B5)
```

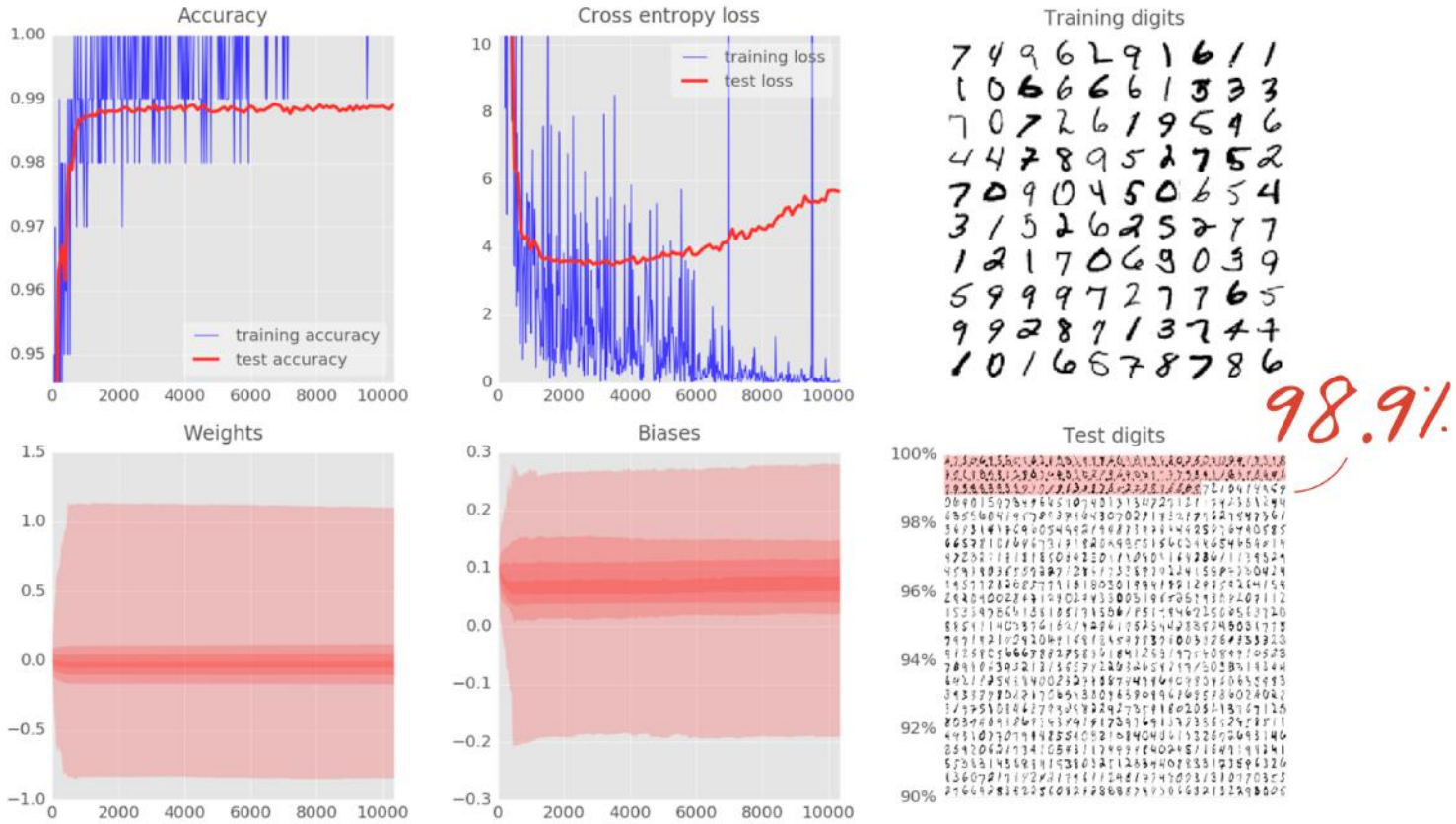
flatten all values for fully connected layer

Y3

YY

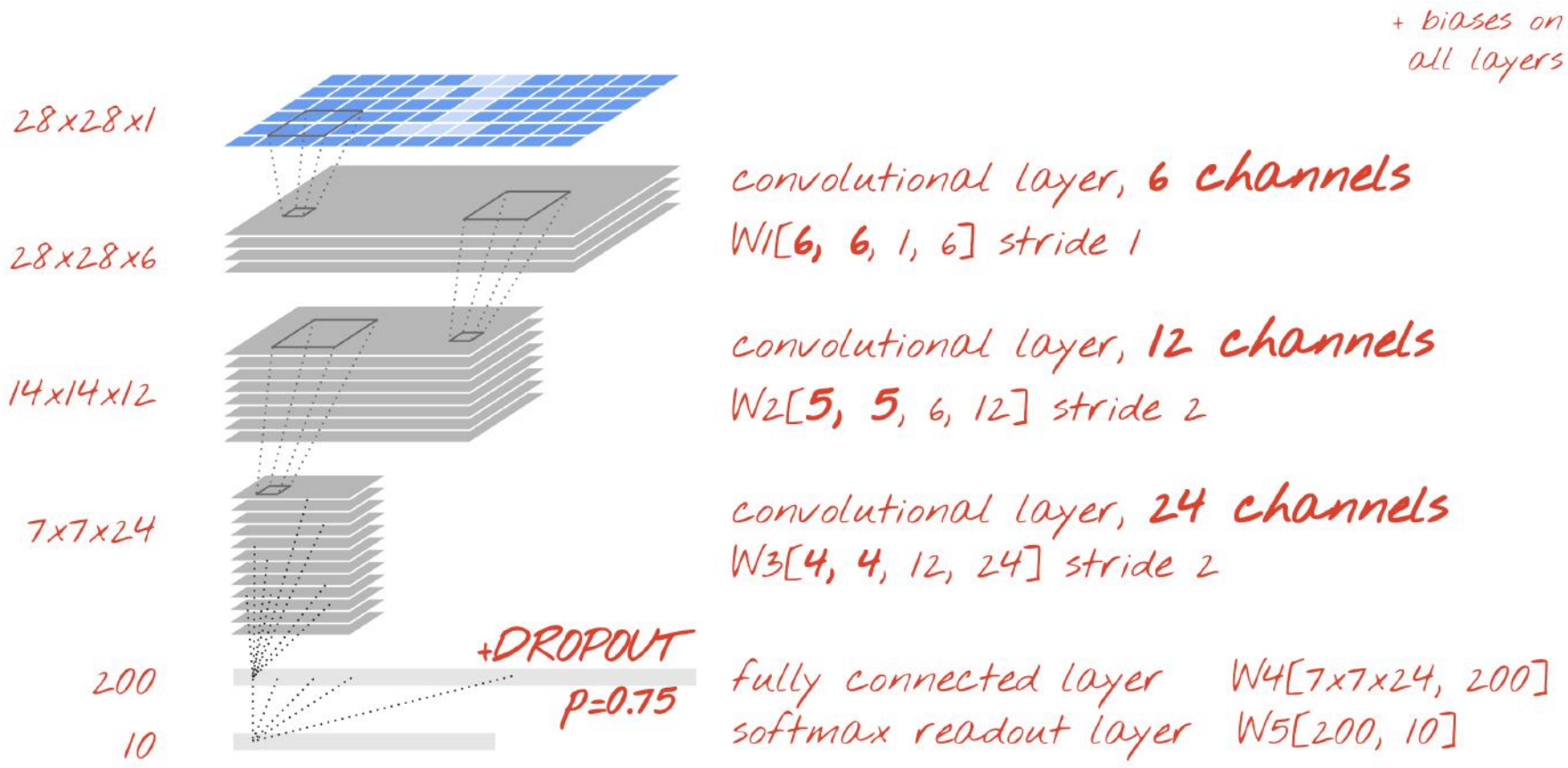
Convolutional Neural Network

- Let's Run – ./tensorflow-mnist/mnist_3.0_convolutional.py
  - Problem : Overfitting -> Bigger Network with Regularization



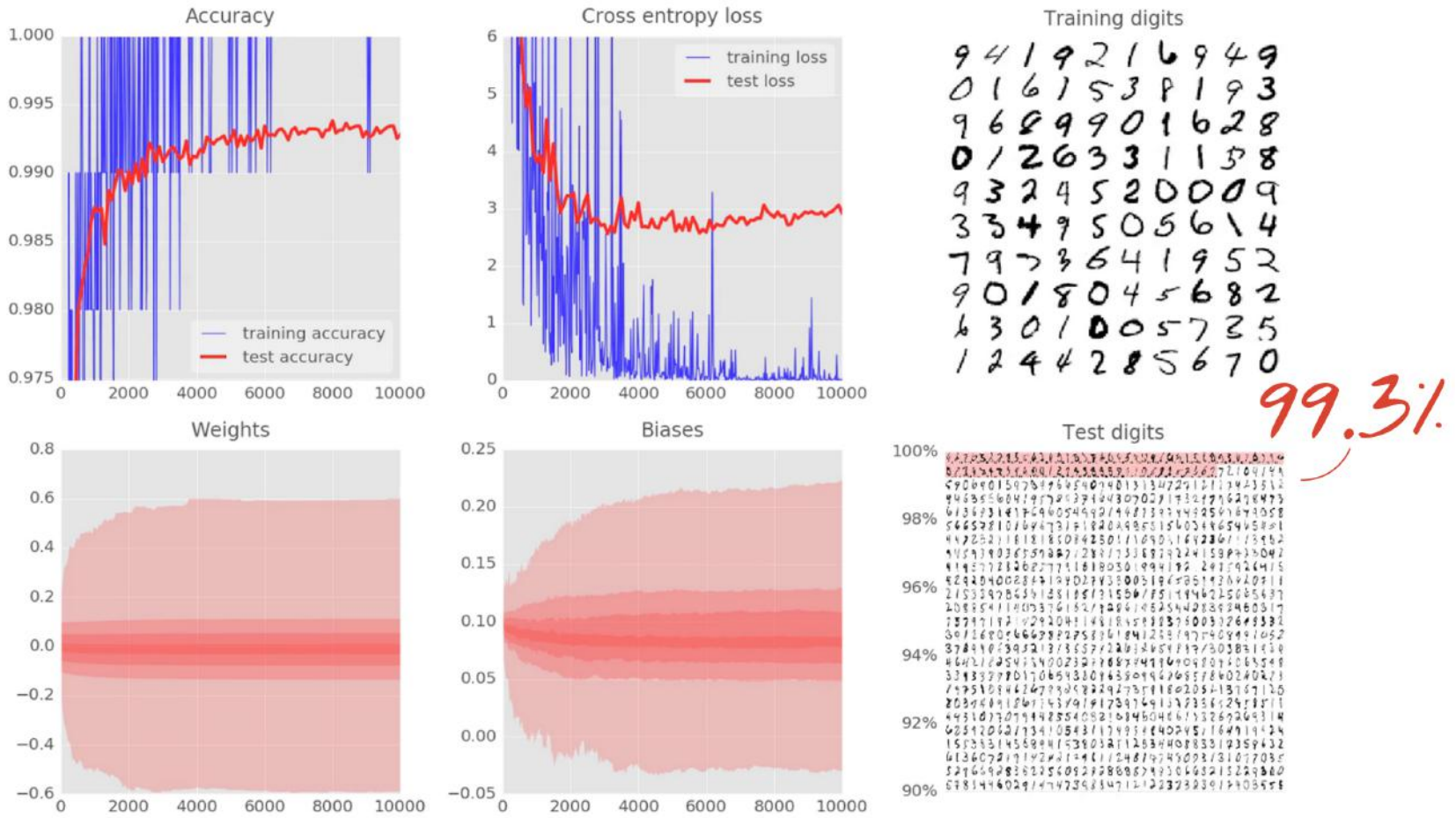
Convolutional Neural Network

- Architecture – Bigger Network



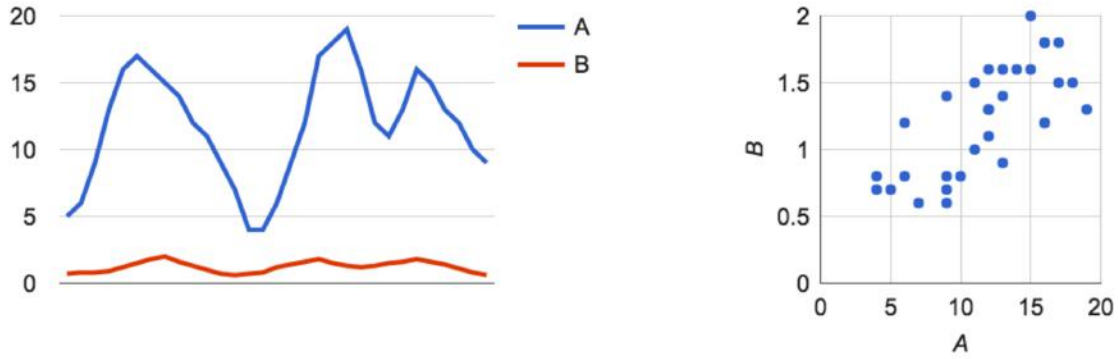
Convolutional Neural Network

- Let’s Run ! : ./tensorflow-mnist/mnist_3.1_convolutional_bigger_dropout.py

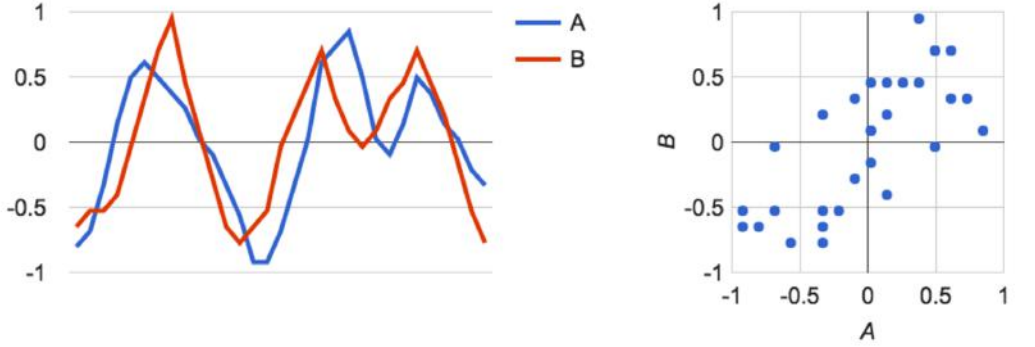


Batch Normalization

- Data Whitening



Data: large values, different scales, skewed, correlated

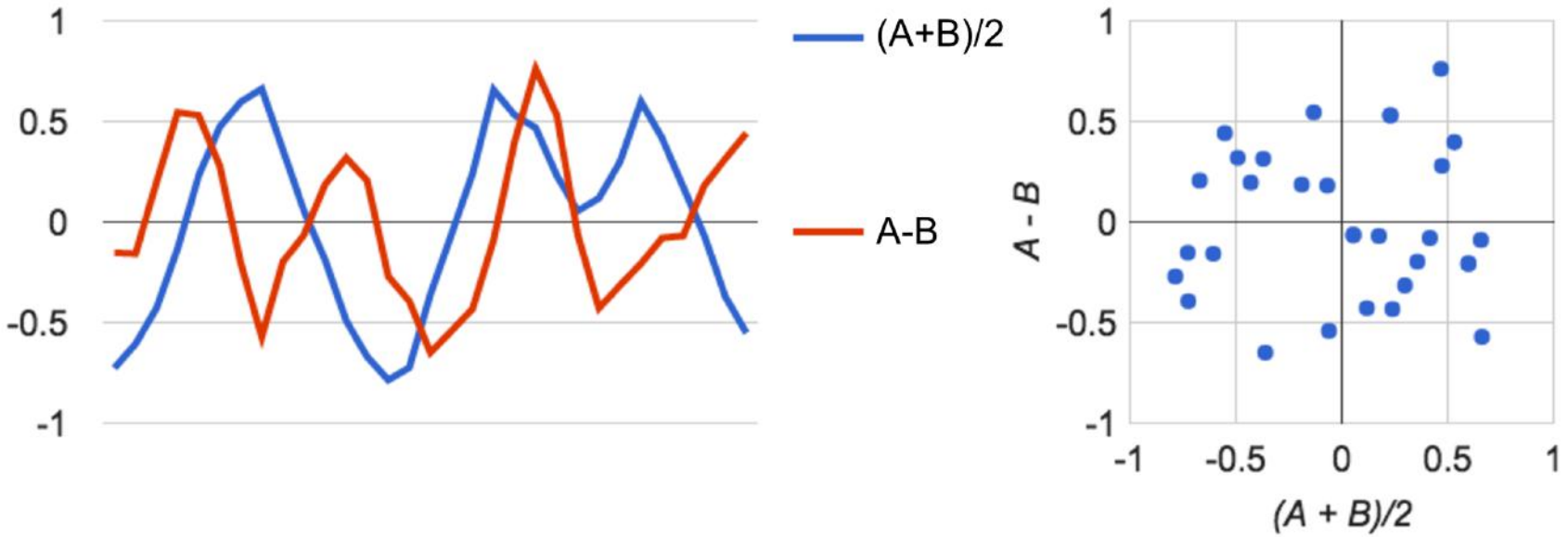


Modified data: centered around zero, rescaled...

Subtract average
Divide by std dev

Batch Normalization

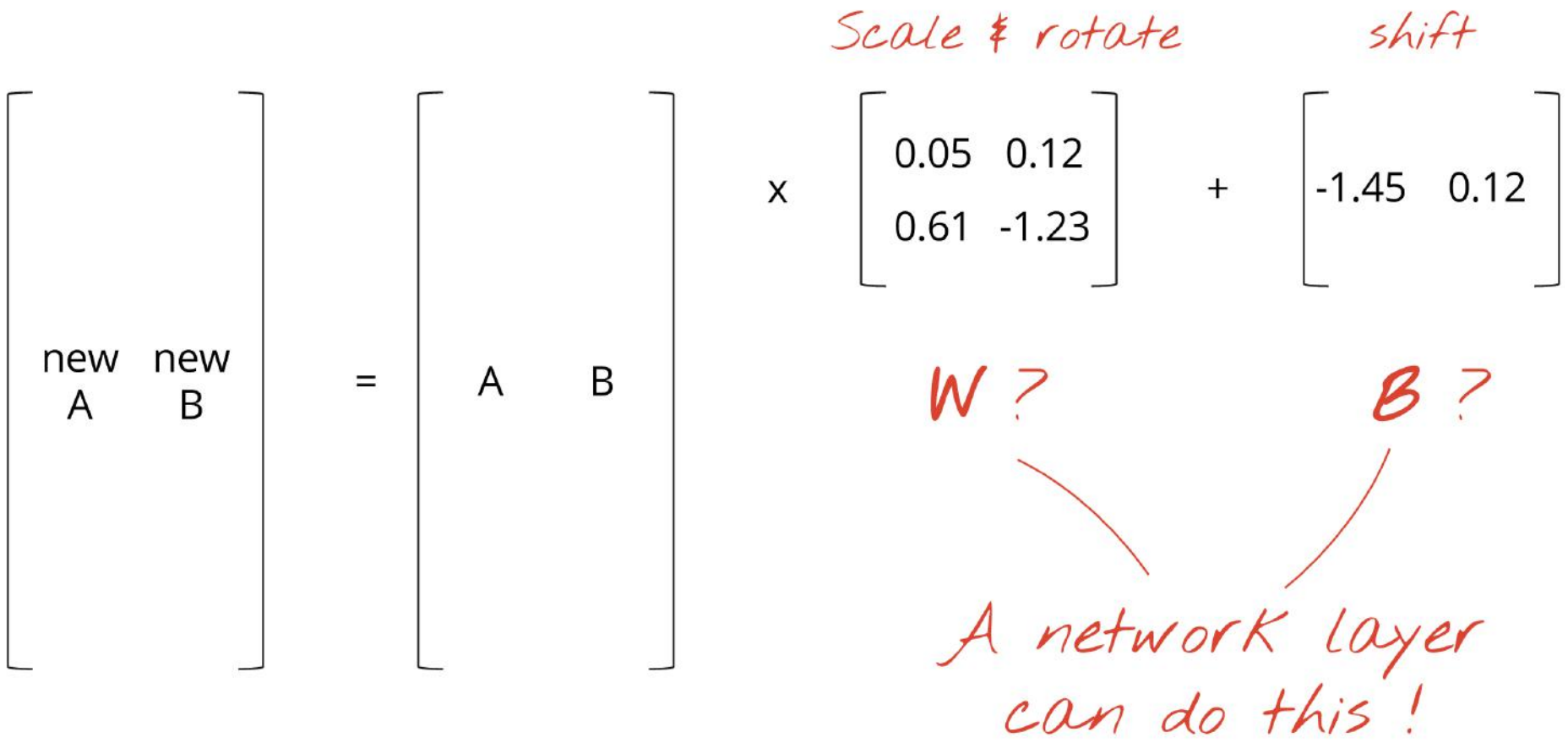
- Data Whitening



Modified data: ... and decorrelated (that was almost a Principal Component Analysis)

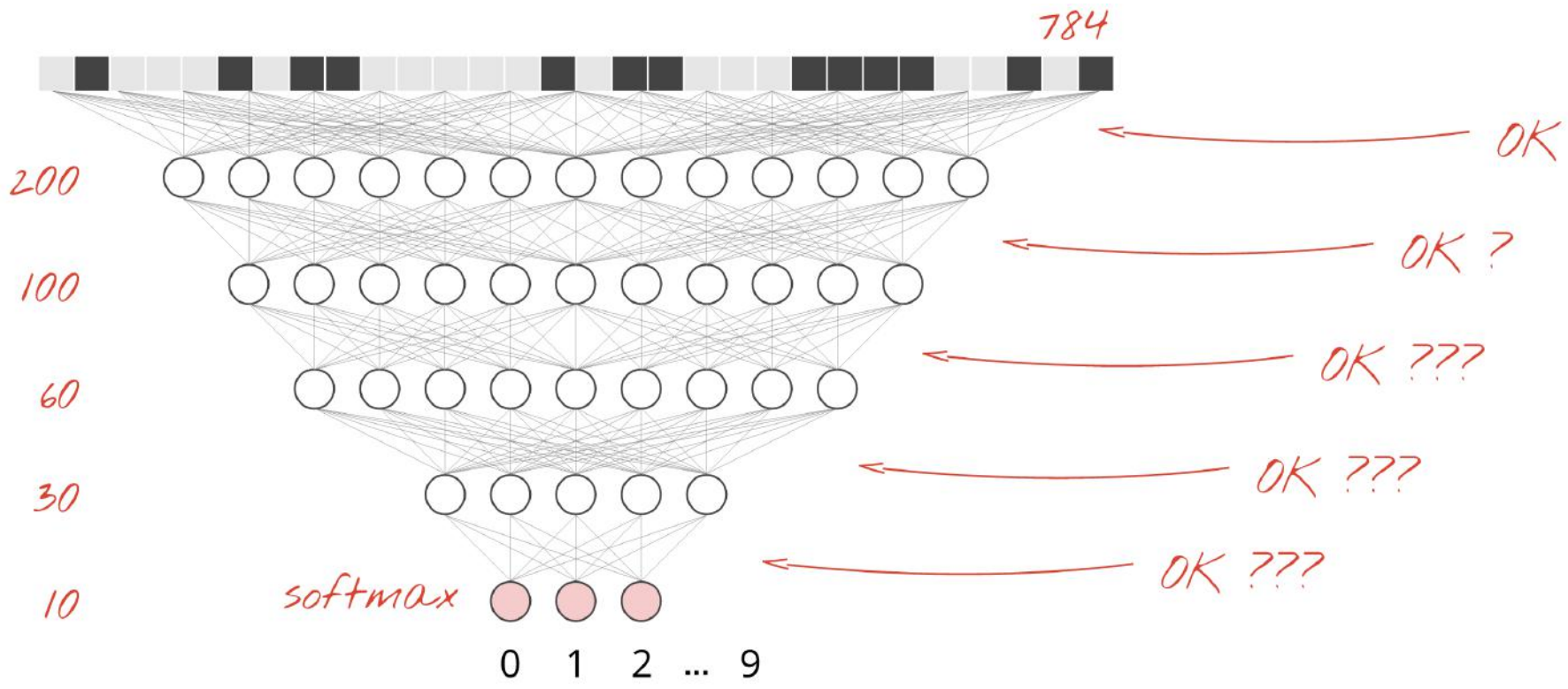
Batch Normalization

- Data Whitening



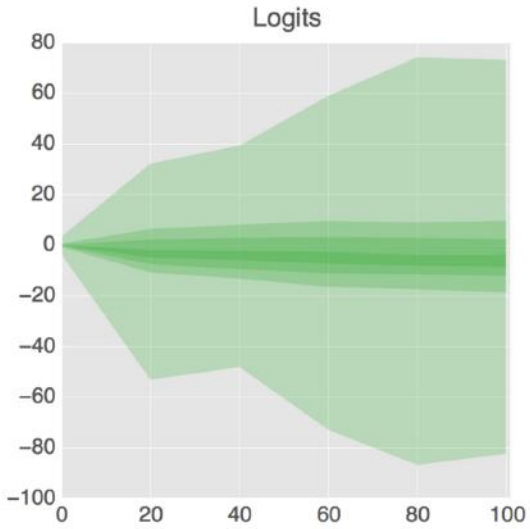
Batch Normalization

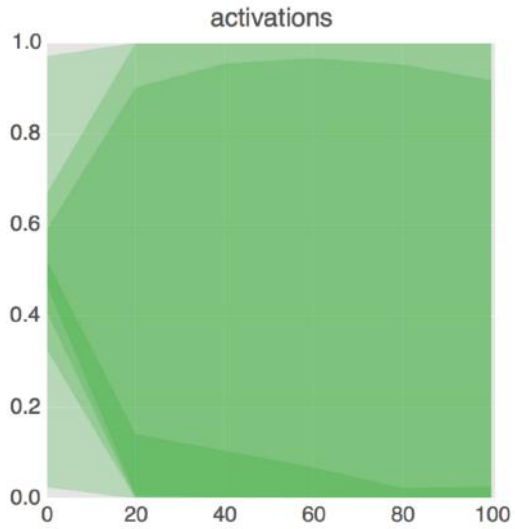
- Let's Get Back to MLP

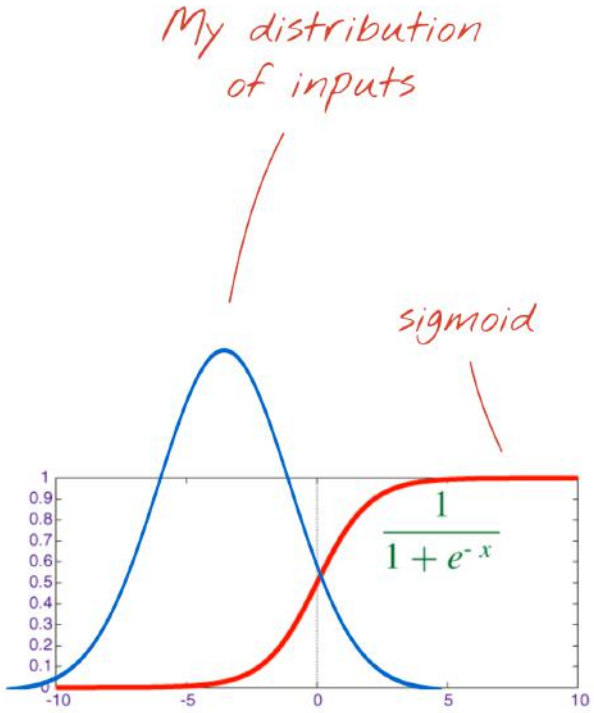


Batch Normalization

- Let's Get Back to MLP
  - Problem : Saturating Activations







Batch Normalization

- Batch Normalization

Compute average and variance on mini-batch

"logit" = weighted sum + bias

Center and re-scale logits
before the activation function
(decorrelate ? no, too complex)

$$\hat{x} = \frac{x - avg_{batch}(x)}{stdev_{batch}(x) + \epsilon}$$

Add learnable scale and offset
for each logit so as to restore expressiveness

one of each per neuron

$$BN(x) = \alpha\hat{x} + \beta$$

Try α=stdev(x) and β=avg(x) and you have $BN(x) = x$

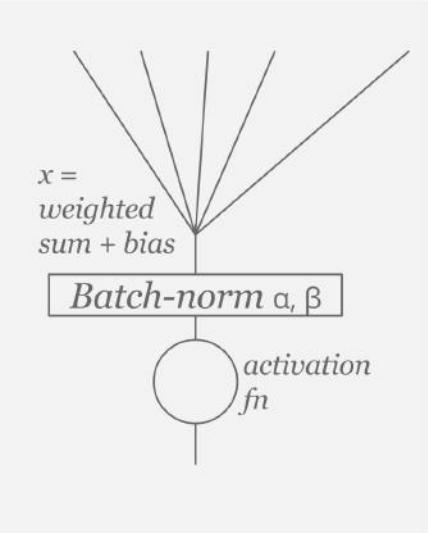
Batch Normalization

- Batch Normalization

depends from:
weights, biases, images

depends from:
same weights and biases, images
only one set of weights and biases in a mini-batch

$$\hat{x} = \frac{x - avg_{batch}(x)}{stdev_{batch}(x) + \epsilon}$$

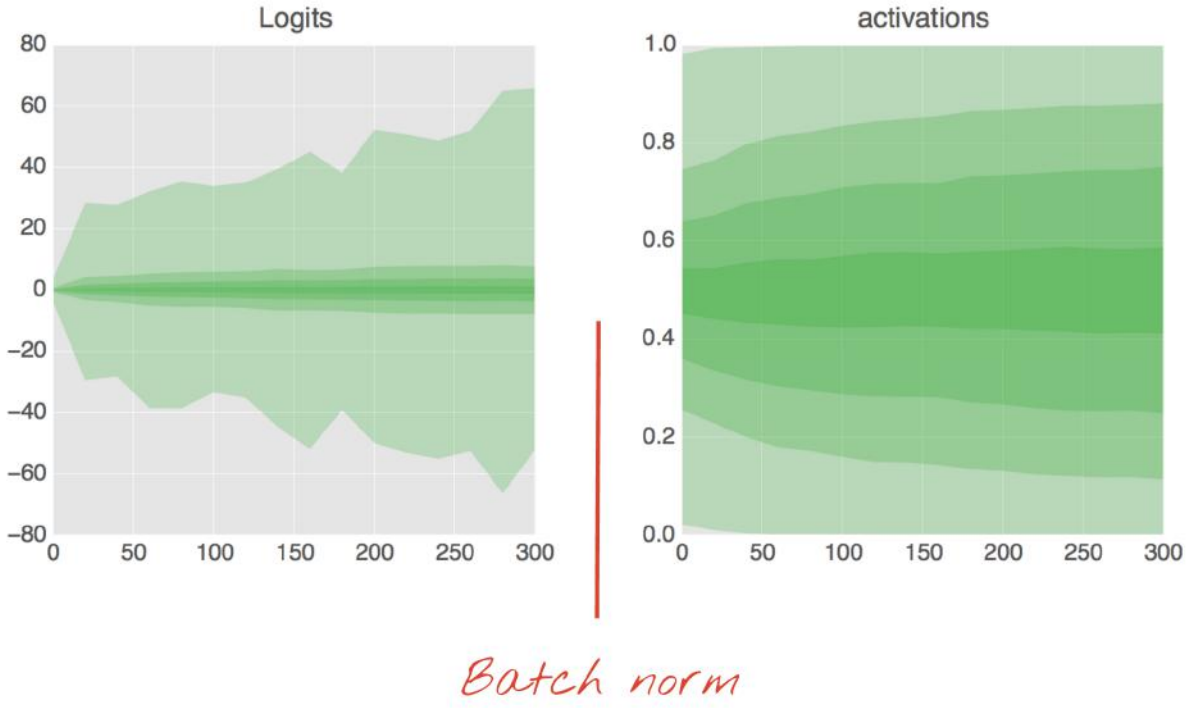


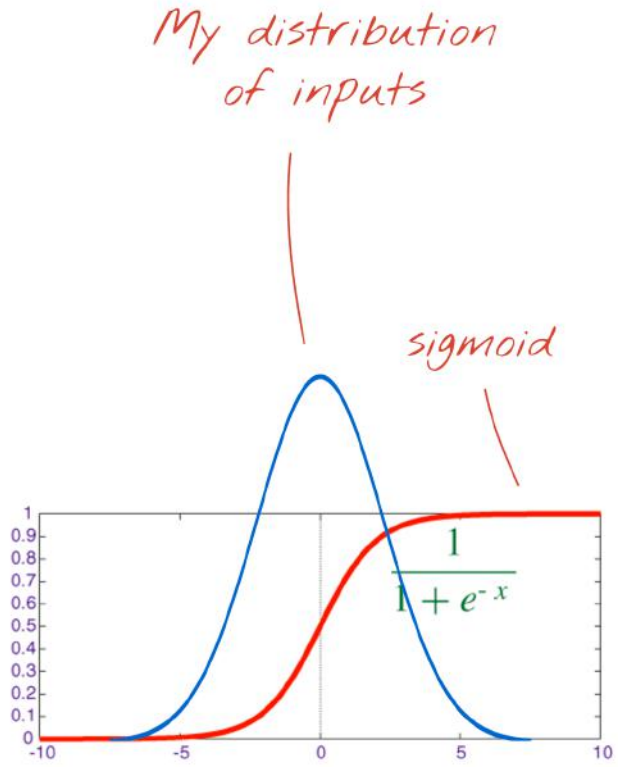
$$BN(x) = \alpha\hat{x} + \beta$$

=> BN is differentiable relatively to weights, biases, α and β
It can be used as a layer in the network, gradient calculations will still work

Batch Normalization

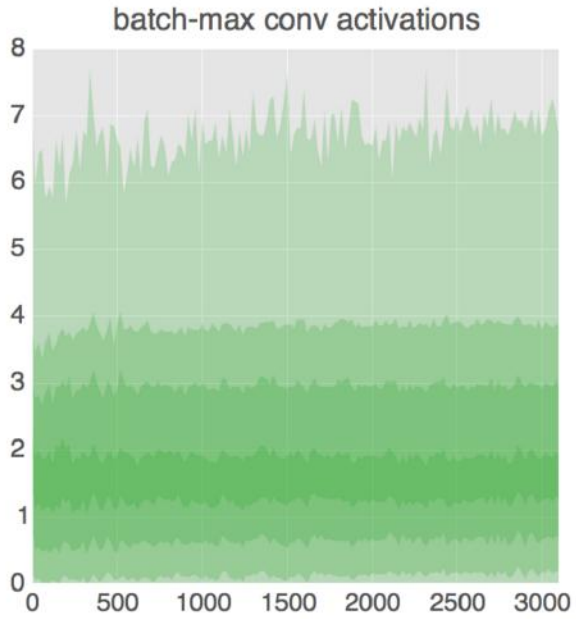
- Let's Run ! : ./tensorflow-mnist/mnist_4.0_batchnorm_five_layers_sigmoid.py

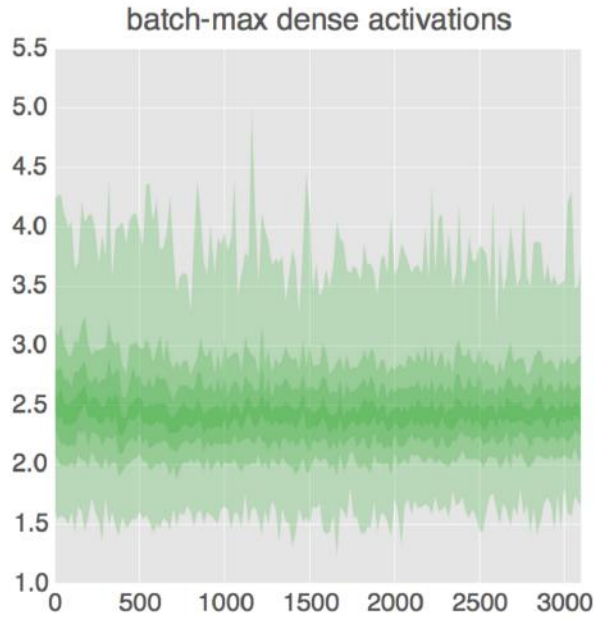


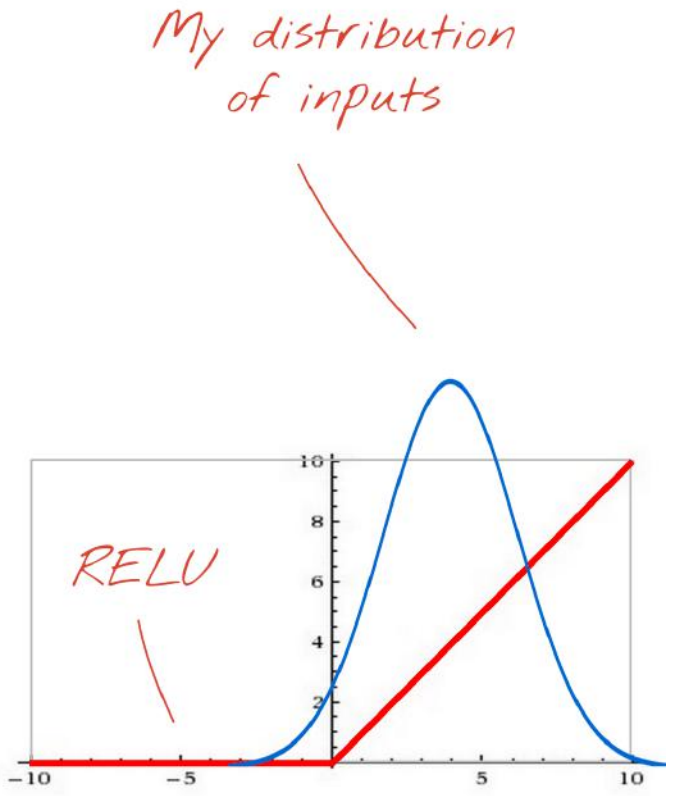


Batch Normalization

- Let's Run ! : ./tensorflow-mnist/mnist_4.1_batchnorm_five_layers_relu.py
  - Max activations for each neuron



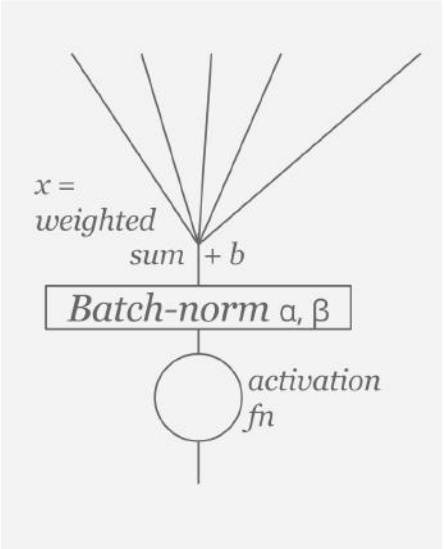




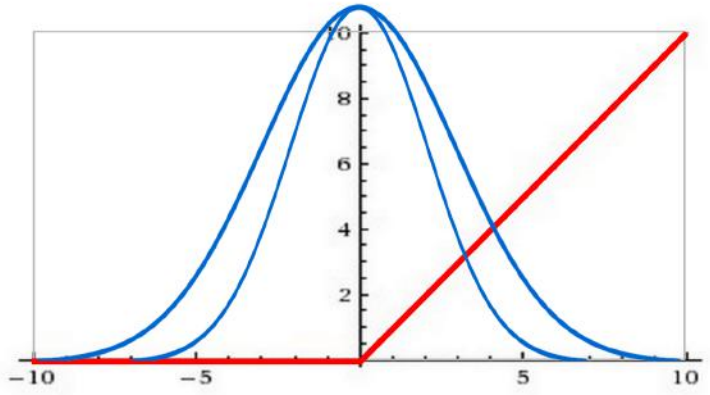
Batch Normalization

- Batch Normalization Done Right

biases :
no longer useful



Per neuron:	relu	sigmoid
without BN	**bias**	**bias**
With BN	**β**	**α, β**

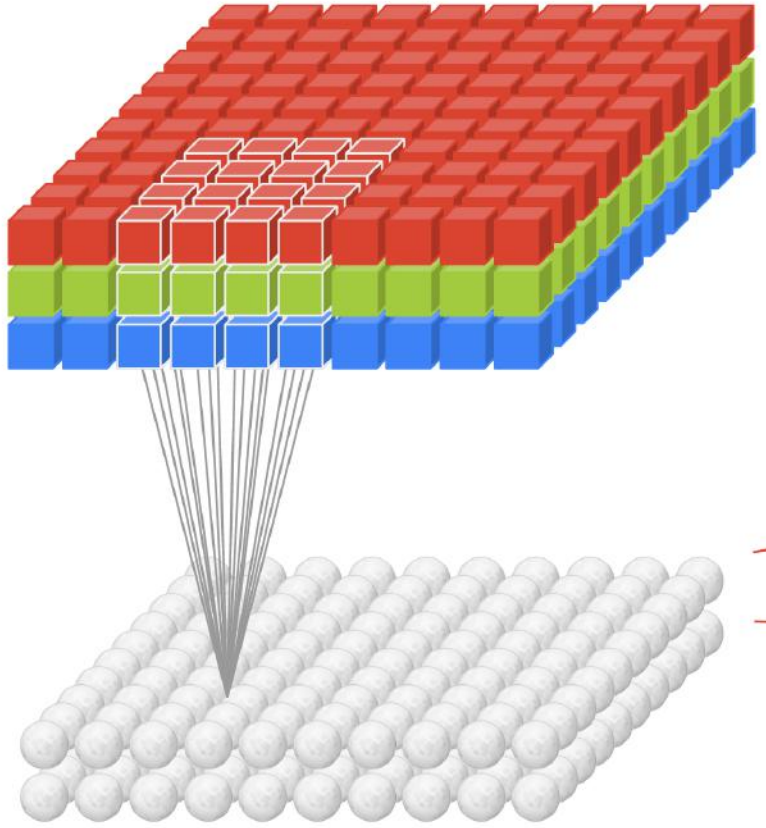


when activation fn is RELU
α is not useful
It does not modify output distrib.

+You can go faster: use higher learning rate
+BN also regularises: lower or remove dropout

Batch Normalization

- Batch Normalization in Convolution Layers



Each neuron or patch has a value:

- per image in the batch
- per x position
- per y position

=> compute avg and stdev across all `batchsize x width x height` values

$W_1[4, 4, 3]$ — b_1 α_1 β_1

$W_2[4, 4, 3]$ — b_2 α_2 β_2

Still, one bias, scale or offset per neuron

Batch Normalization

- Batch Normalization at Test Time

$$\hat{x} = \frac{x - avg_?(x)}{stdev_?(x) + \epsilon}$$

Stats on what ?

- Last batch: no
- all images: yes (but not practical)
- => Exponential moving average during training

Define one offset and/or scale per neuron

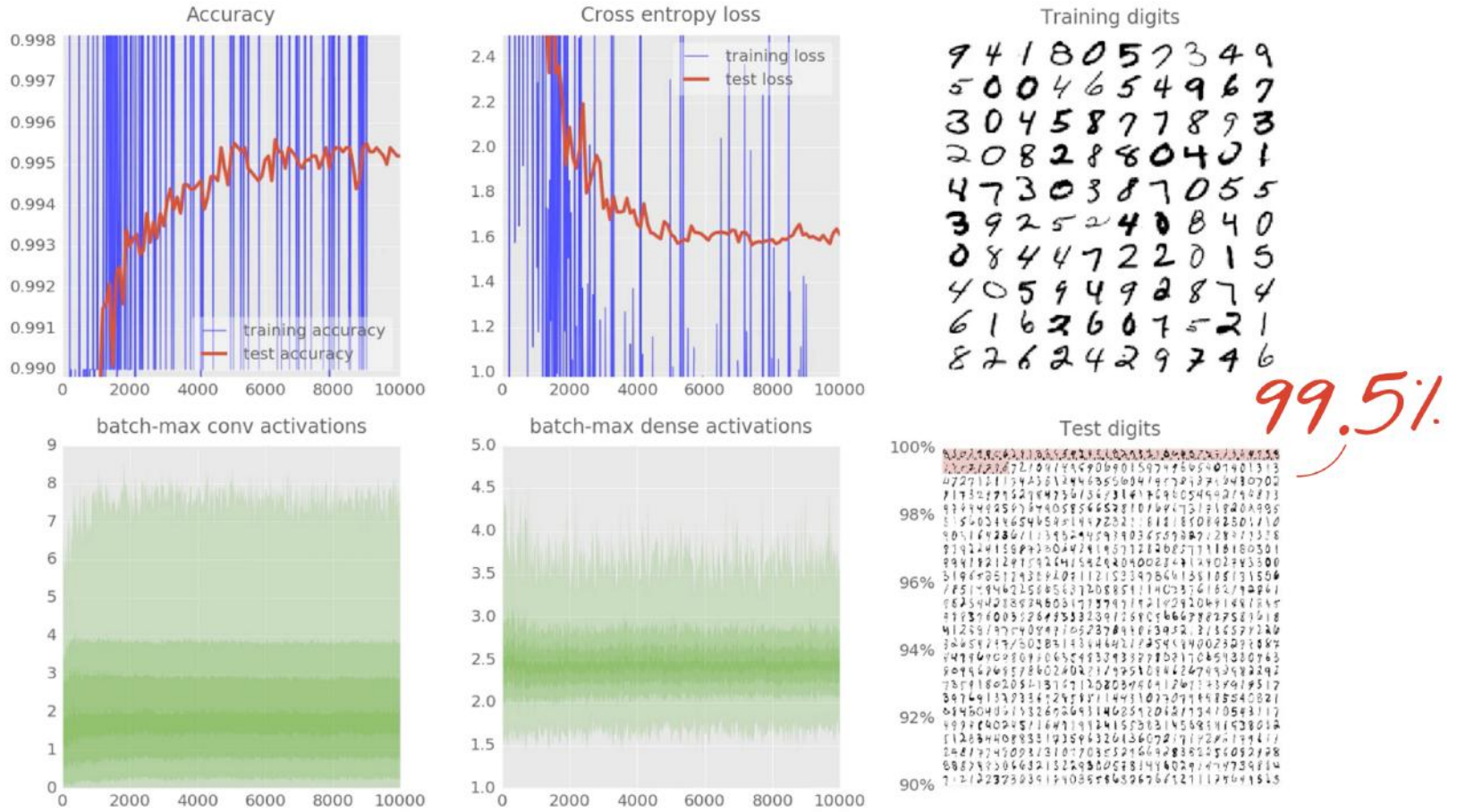
```
def batchnorm_layer(Ylogits, is_test, Offset, Scale, iteration, convolutional=False):
    exp_moving_avg = tf.train.ExponentialMovingAverage(0.9999, iteration)
    if convolutional:    # avg across batch, width, height
        mean, variance = tf.nn.moments(Ylogits, [0, 1, 2])
    else:
        mean, variance = tf.nn.moments(Ylogits, [0])
    update_moving_averages = exp_moving_avg.apply([mean, variance])
    m = tf.cond(is_test, lambda: exp_moving_avg.average(mean), lambda: mean)
    v = tf.cond(is_test, lambda: exp_moving_avg.average(variance), lambda: variance)
    Ybn = tf.nn.batch_normalization(Ylogits, m, v, Offset, Scale, variance_epsilon=1e-5)
    return Ybn, update_moving_averages
```

don't forget to execute this (sess.run)

apply activation fn on Ybn

Batch Normalization

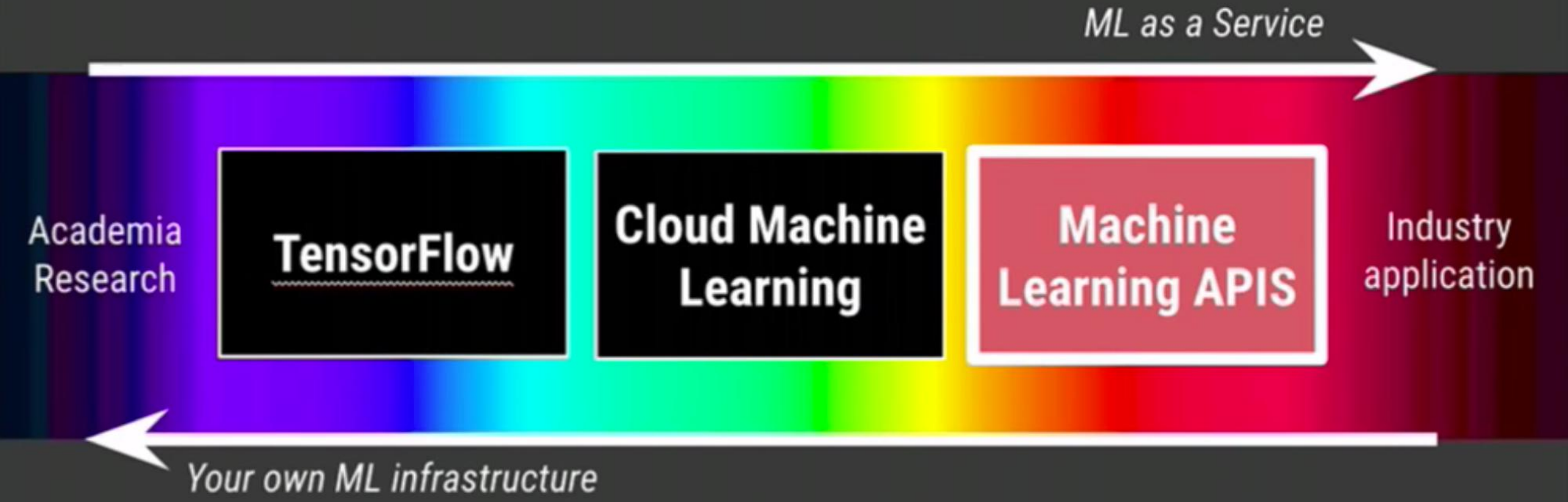
- Let’s Run ! : ./tensorflow-mnist/mnist_4.2_batchnorm_convolutional.py



Class 12

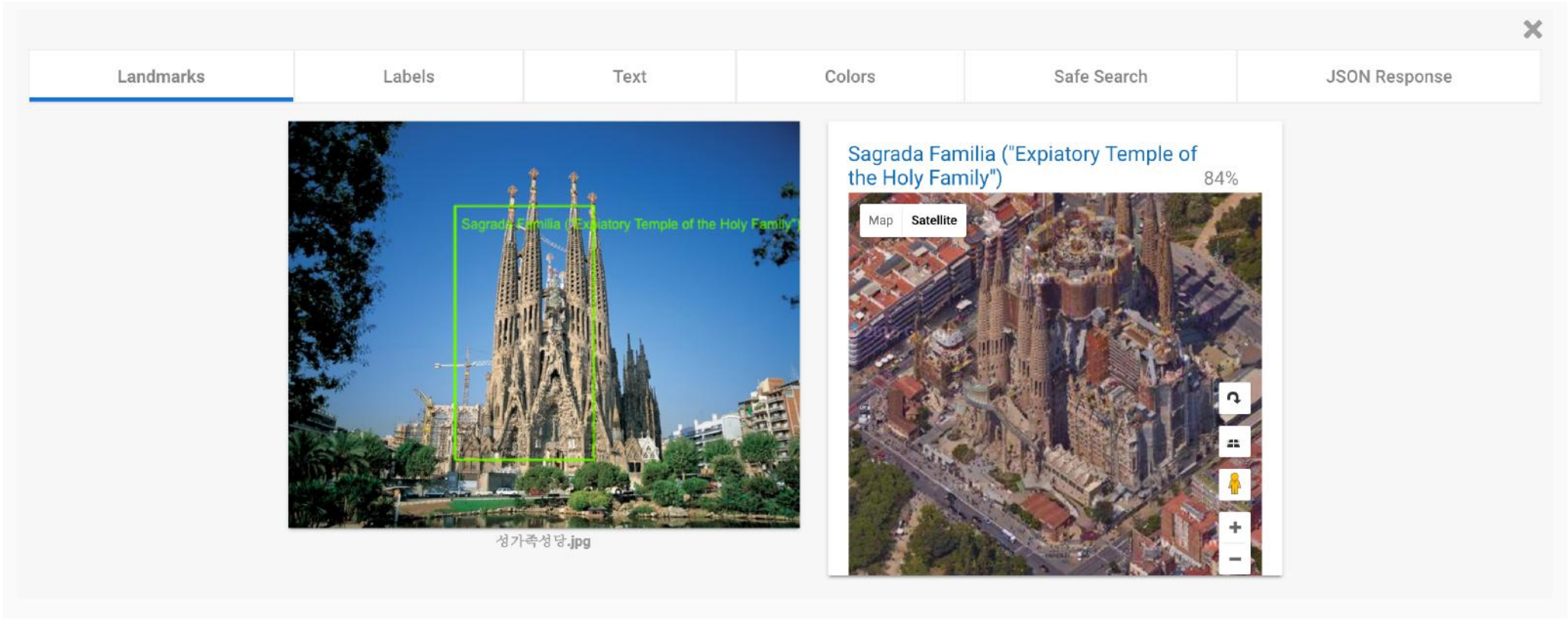
Google Cloud Platforms for Service Development

The Machine Learning Spectrum



Google Cloud Vision API

- https://cloud.google.com/vision/



Google Cloud Vision API

Feature Type	Description
LABEL_DETECTION	Add labels based on image content (see Detecting Labels)
TEXT_DETECTION	Perform Optical Character Recognition (OCR) on text within the image (see Detecting Text)
SAFE_SEARCH_DETECTION	Determine image safe search properties on the image (see Detecting Safe Search Properties)
FACE_DETECTION	Detect faces within the image (see Detecting Faces)
LANDMARK_DETECTION	Detect geographic landmarks within the image (see Detecting Landmarks)
LOGO_DETECTION	Detect company logos within the image (see Detecting Logos)
IMAGE_PROPERTIES	Compute a set of properties about the image (such as the image's dominant colors) (see Detecting Image Properties)

Google Cloud Vision API

Feature	1 - 1000 units/month	1001- 1,000,000 units/month	1,000,001 to 5,000,000 units/month	5,000,001 - 20,000,000 units/month
Label Detection	Free	$1.50	$1.50	$1.00
OCR	Free	$1.50	$1.50	$0.60
Explicit Content Detection	Free		Now free with Label Detection*	
Facial Detection	Free	$1.50	$1.50	$0.60
Landmark Detection	Free	$1.50	$1.50	$0.60
Logo Detection	Free	$1.50	$1.50	$0.60
Image Properties	Free	$1.50	$1.50	$0.60

Google Cloud Vision API – Using Cloud SDK

- Install Google Cloud SDK
  - https://cloud.google.com/sdk/docs/
- Install Google Cloud Vision API
  - https://cloud.google.com/vision/docs/reference/libraries#client-libraries-install-python
- Hands-on
  - https://github.com/KyuhwanJung/tensorflow_tutorial/tree/master/part3/notebook

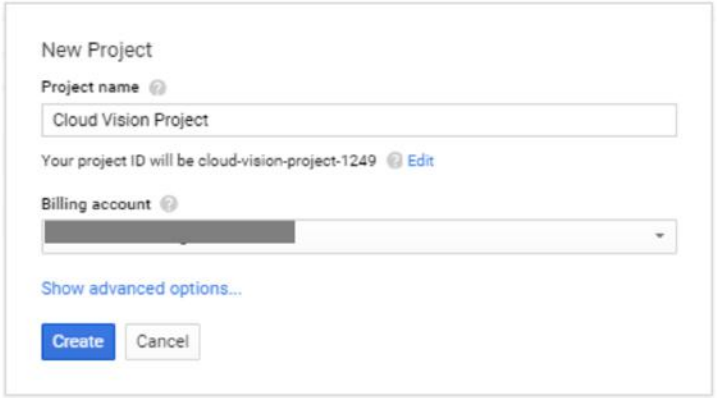
Google Cloud Vision API

- Using Vision API outside of Google Cloud SDK

1. Create Google Cloud Platform Project

Head over to the Google Cloud Platform Developers Console and login with your account. Ensure that you have a Billing Account setup with Google Cloud Platform.

Go to the list of all projects for your account and click on the Create Project button to create a new project. This will bring up the form as shown below:



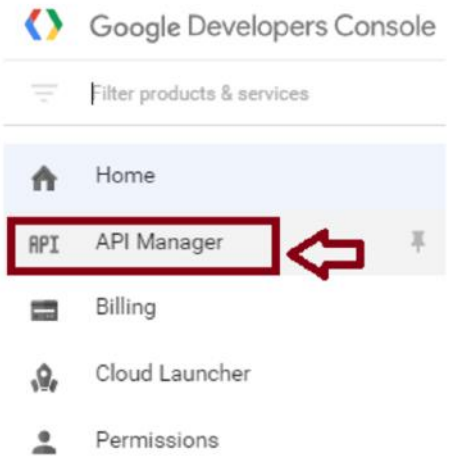
Enter a name for your project and select the Billing account that you want to apply to your project. Click on Create.

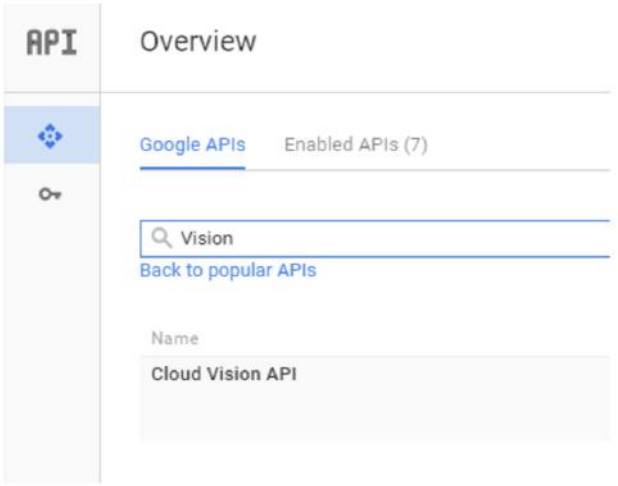
Google Cloud Vision API

- Using Vision API outside of Google Cloud SDK

2. Enable Google Cloud Vision API for Your Project

The next step is to enable the Cloud Vision API for your project. Click on the hamburger menu on top and then on API Manager as shown below:





The Cloud Vision API is not enabled for your project. Google provides several APIs and we need to find the Cloud Vision API. Enter the word "Vision" in the filter field as shown below and Cloud Vision API should come up as shown below:

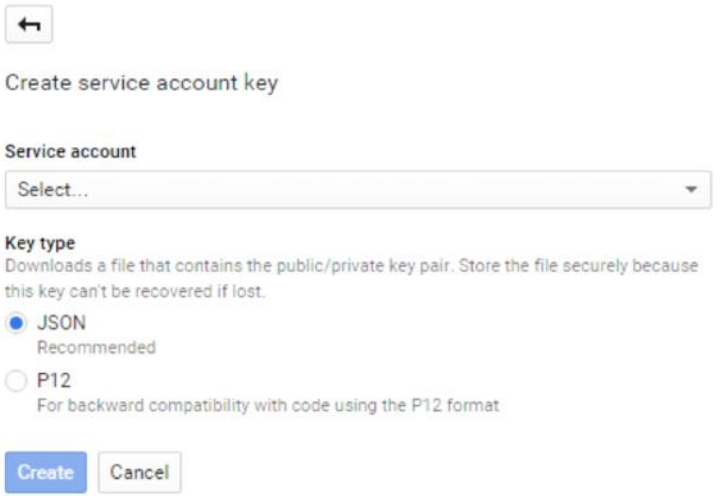
Google Cloud Vision API

- Using Vision API outside of Google Cloud SDK

3. Getting Credentials

Visit the API Manager link again from the hamburger menu and click on Credentials. This will bring up a choice of what kind of Authentication mechanism that we want. For maximum flexibility, we will go with the Service Account Key, which will allow us access to the Vision API from applications running and is recommended for production use. Plus with the Application Credentials feature, authentication and authorization has been greatly simplified for the Google APIs.

Once you select the Service Account Key, you will see a screen as shown below:



Google Cloud Vision API

- Using Vision API outside of Google Cloud SDK

4. Use the Application Default Credentials

This feature makes it dead simple to integrate authentication to Google APIs in your applications. Check out the documentation.

All we need to do is set an environment variable named GOOGLE_APPLICATION_CREDENTIALS and its value will be the JSON key file that we just downloaded in the previous step.

So go ahead and set the environment variable value as shown below:

On a Mac / Linux, you can do the following:

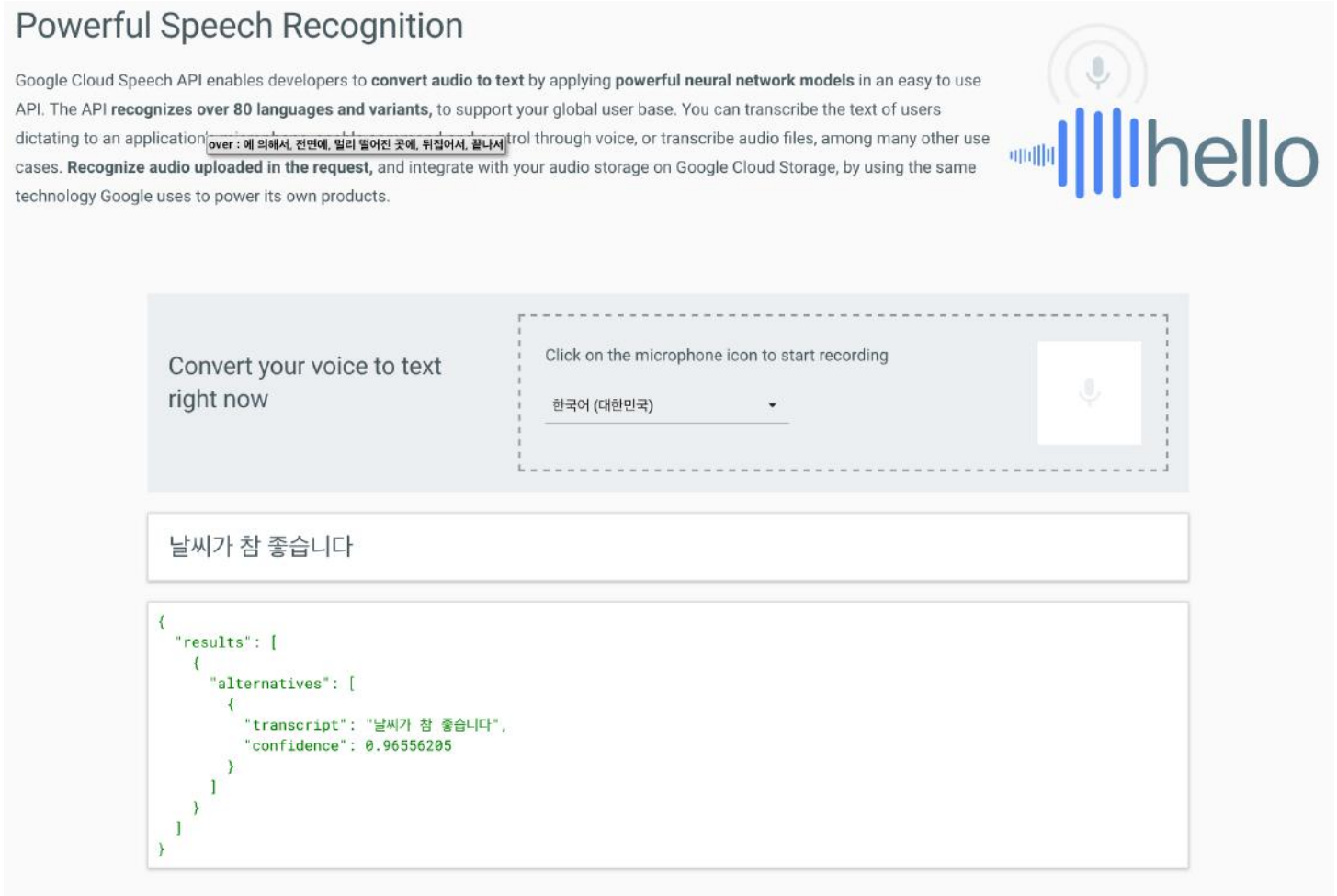
```
$ export GOOGLE_APPLICATION_CREDENTIALS=<Path To Your JSON Key File>
```

On Windows, you can do the following:

```
SET GOOGLE_APPLICATION_CREDENTIALS=<Path To Your JSON Key File>
```

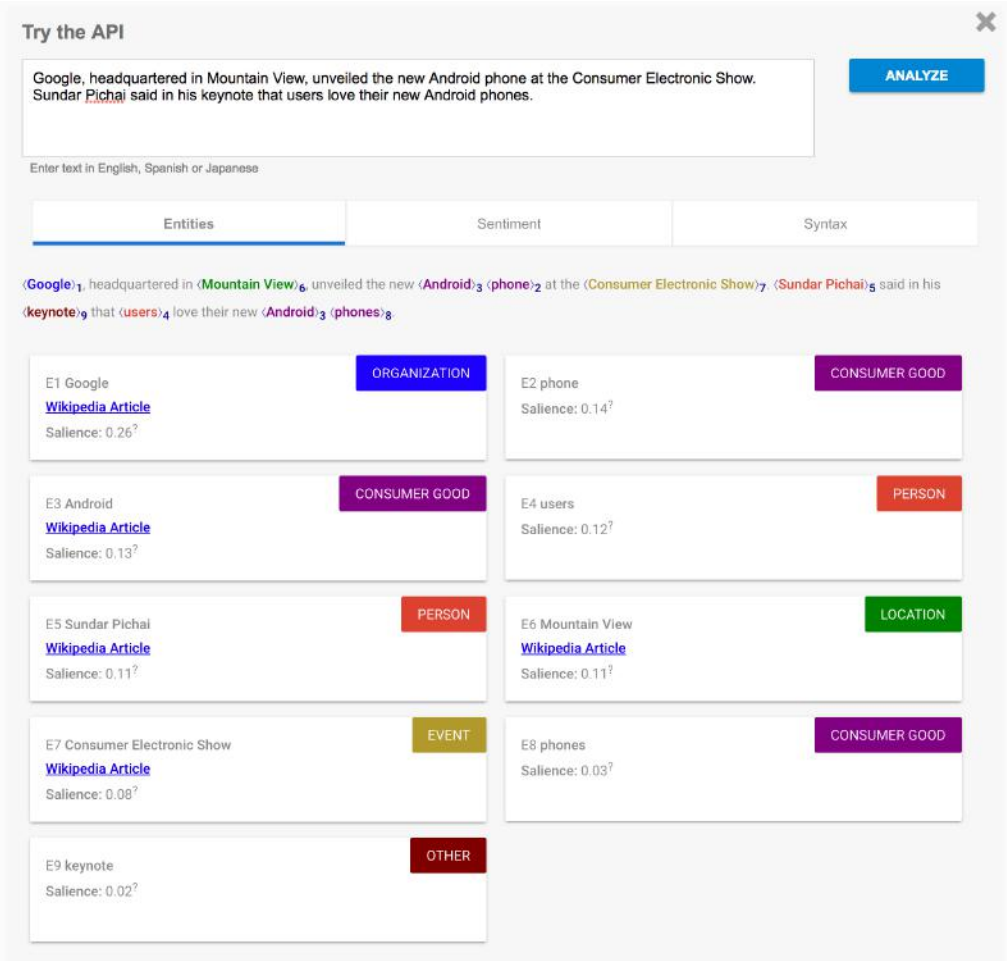
Google Cloud Speech API

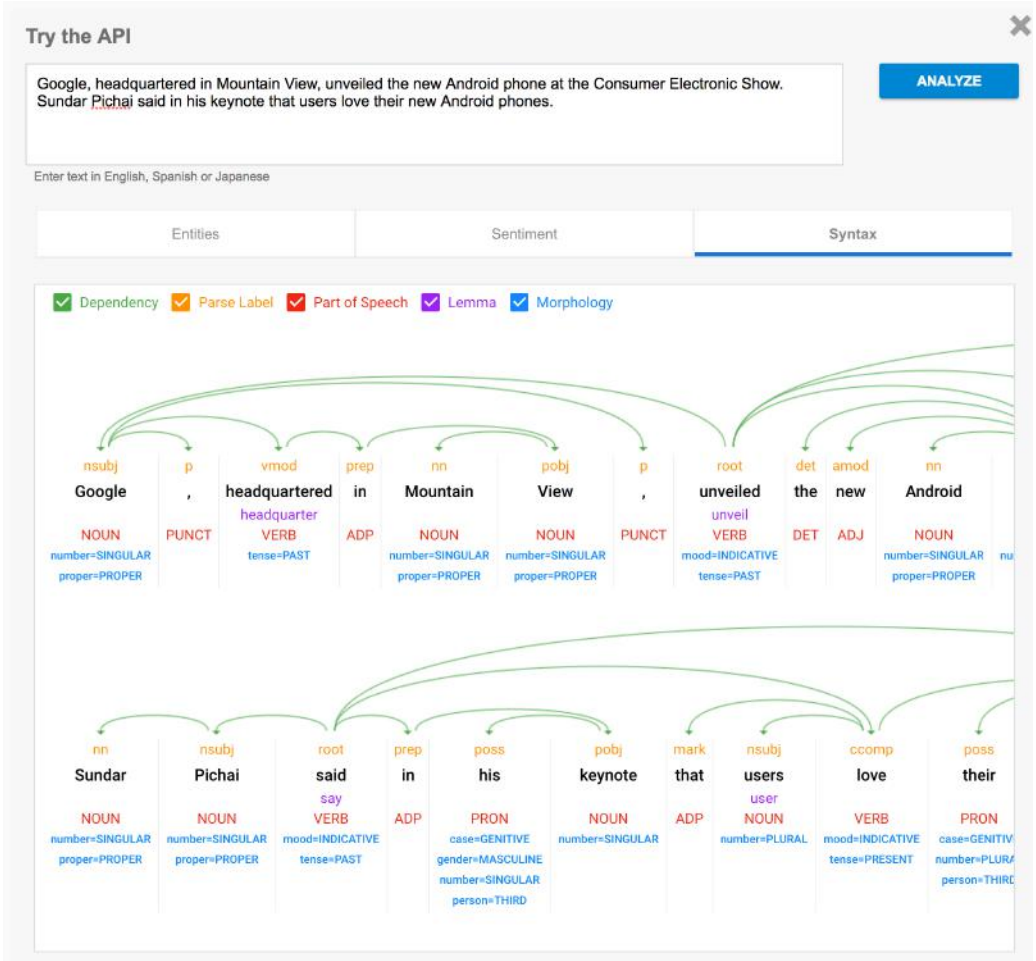
- https://cloud.google.com/speech/



Google Cloud Natural Language API

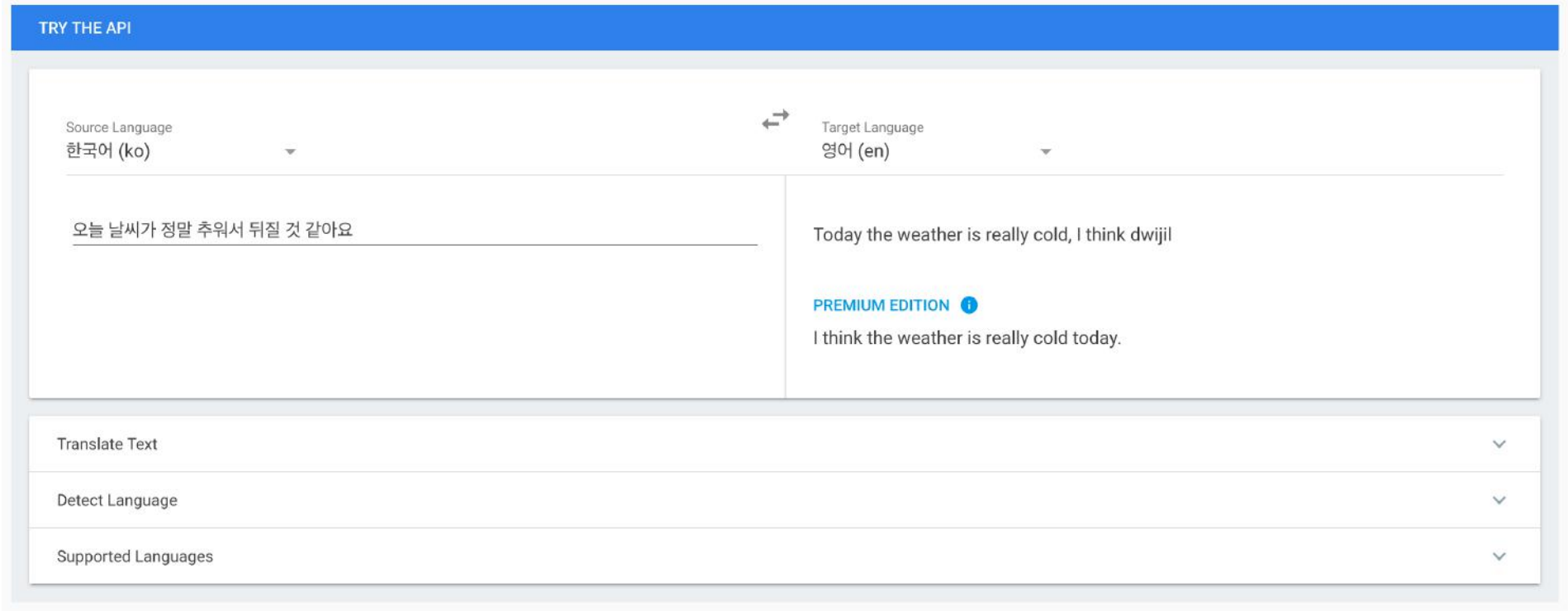
- https://cloud.google.com/natural-language/





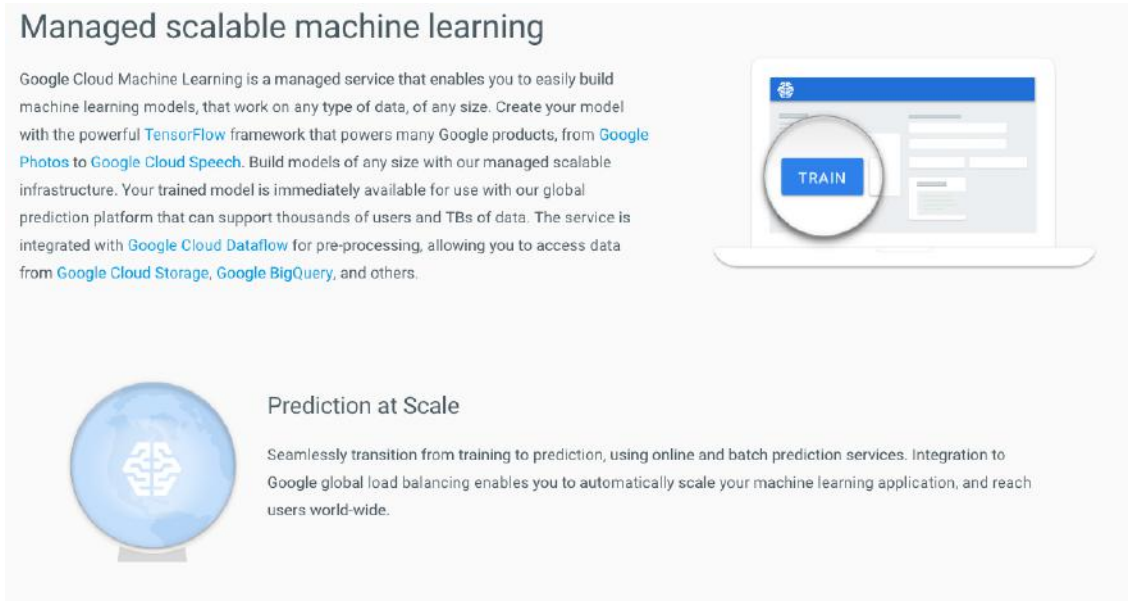
Google Cloud Natural Language API

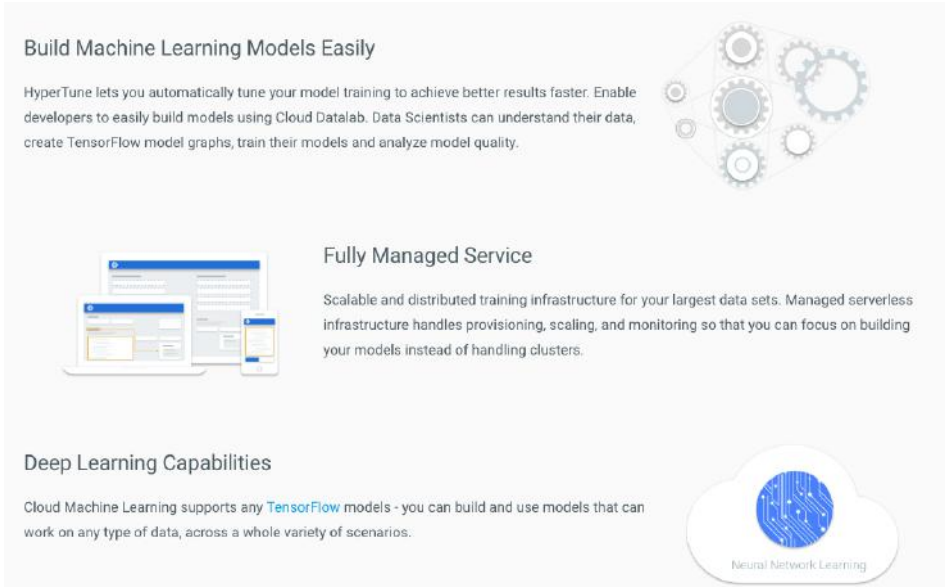
- https://cloud.google.com/translate/



Google Cloud Machine Learning

- https://cloud.google.com/ml/





Class 13
CNNs for Semantics Segmentation

Problem of Semantic Segmentation

- Level of Problem Difficulty

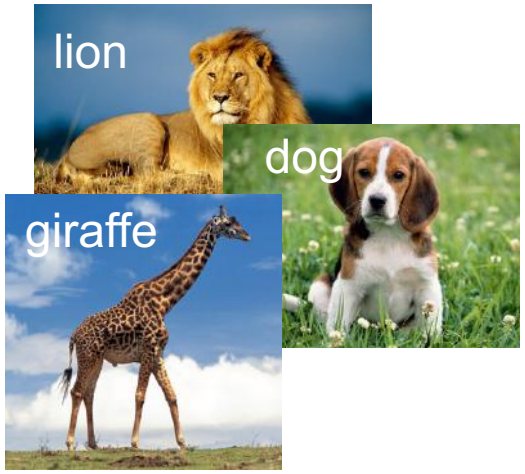
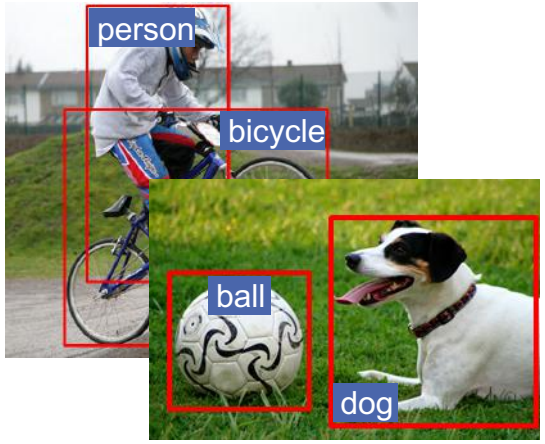
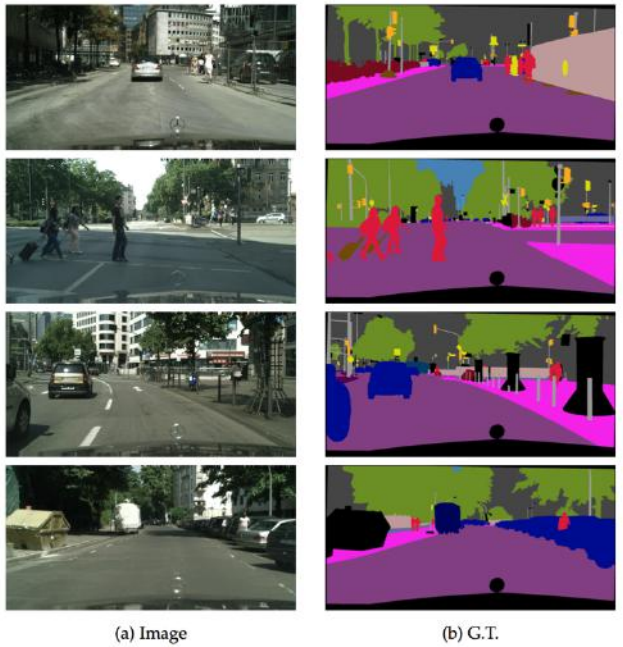


Image Classification



Object Detection

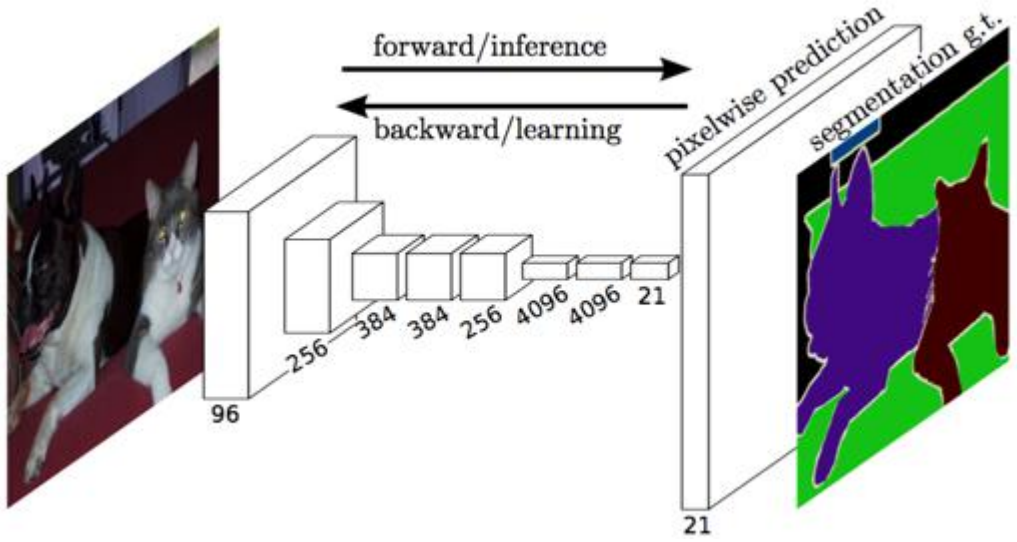
Semantic Segmentation

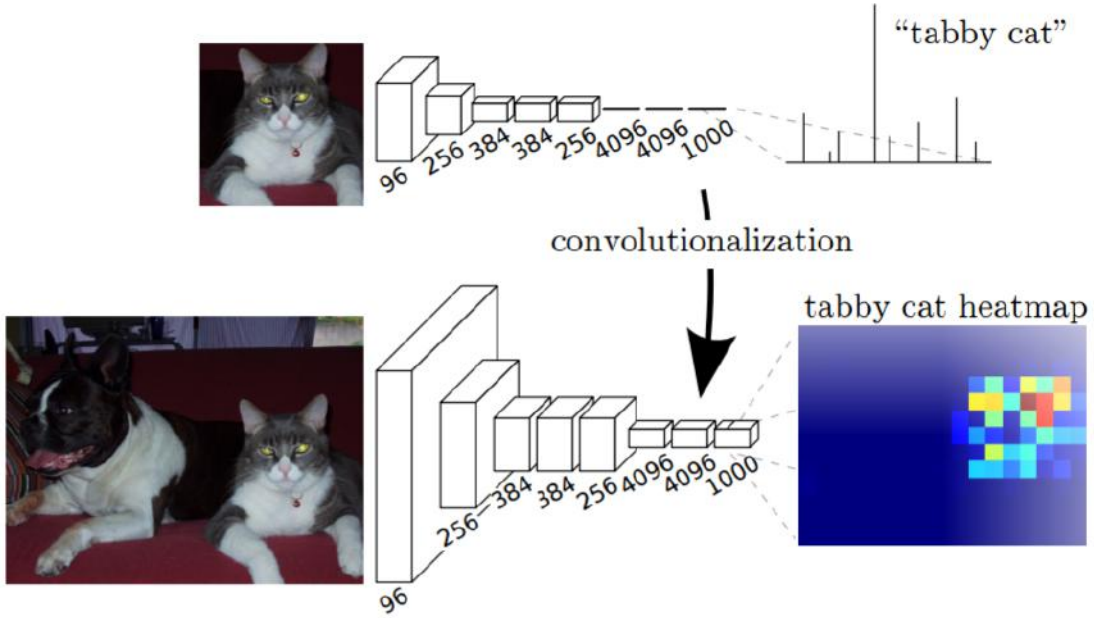


(a) Image (b) G.T.

Fully Convolutional Neural Network (FCN)

- End-to-end CNN for Semantic Segmentation





Fully Convolutional Neural Network (FCN)

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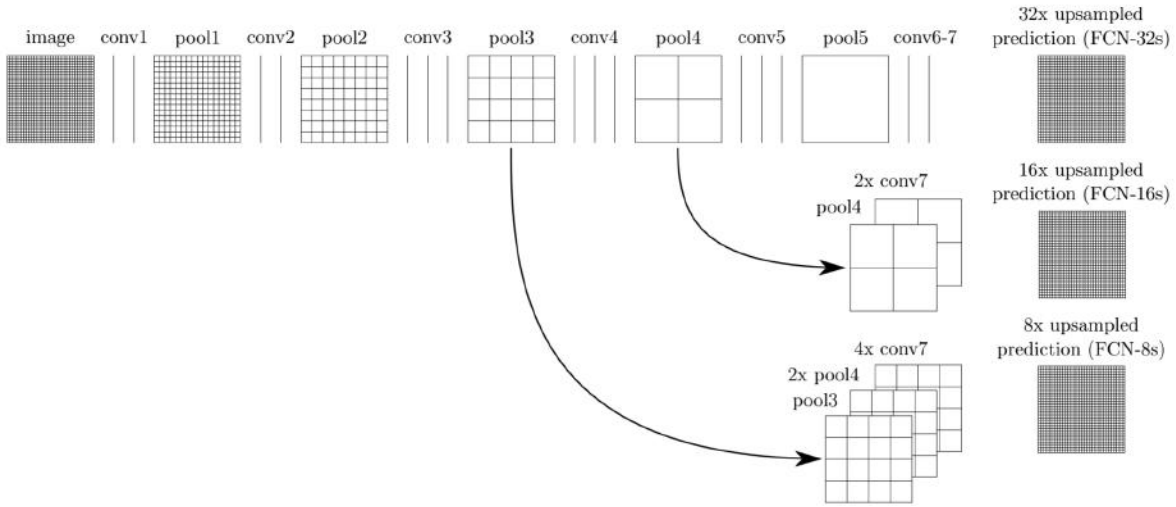
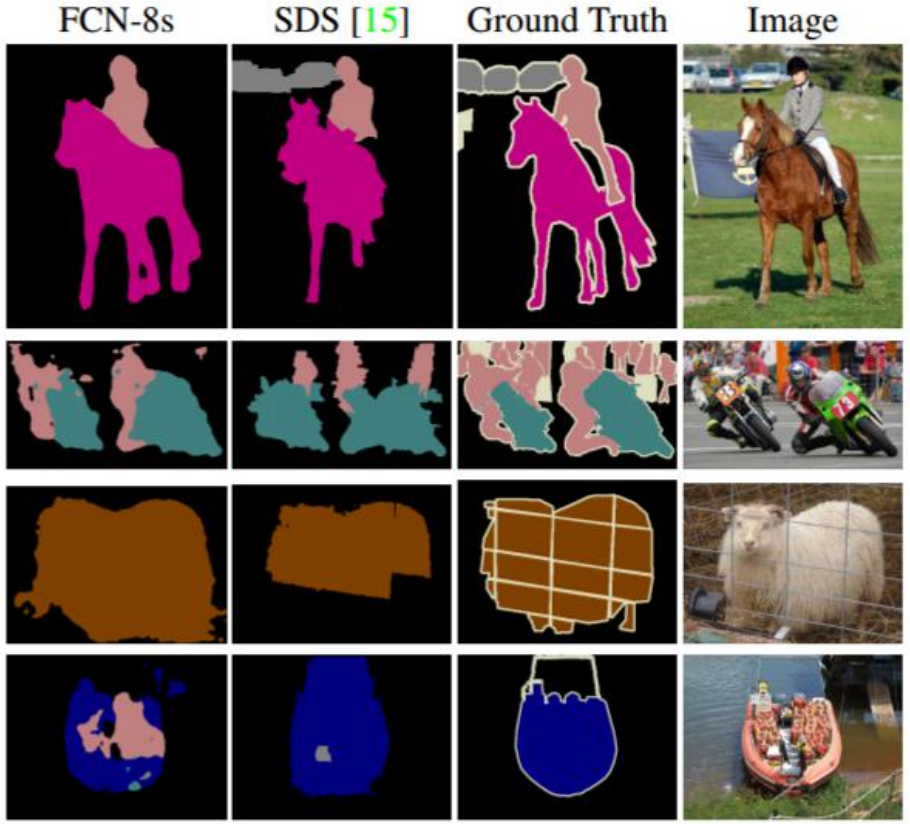
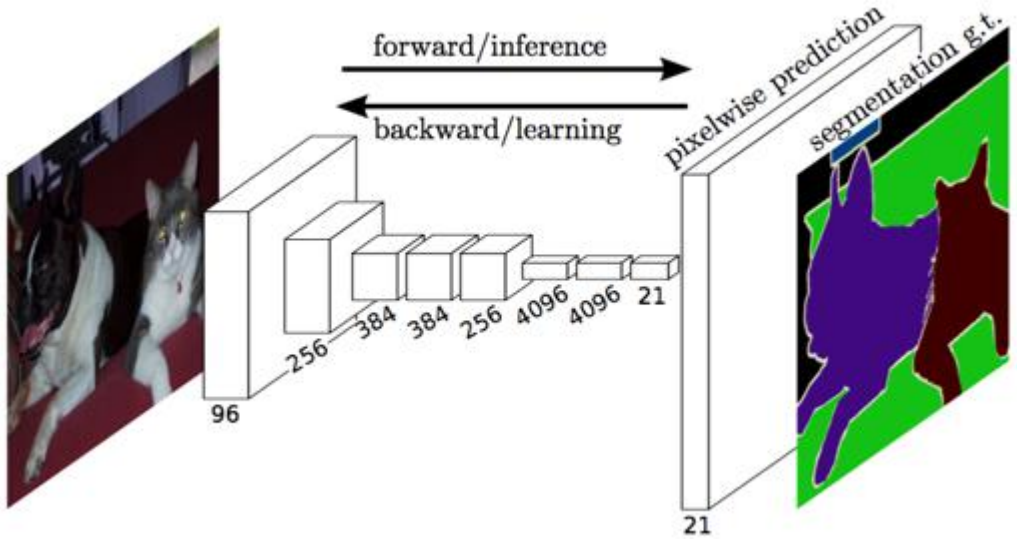
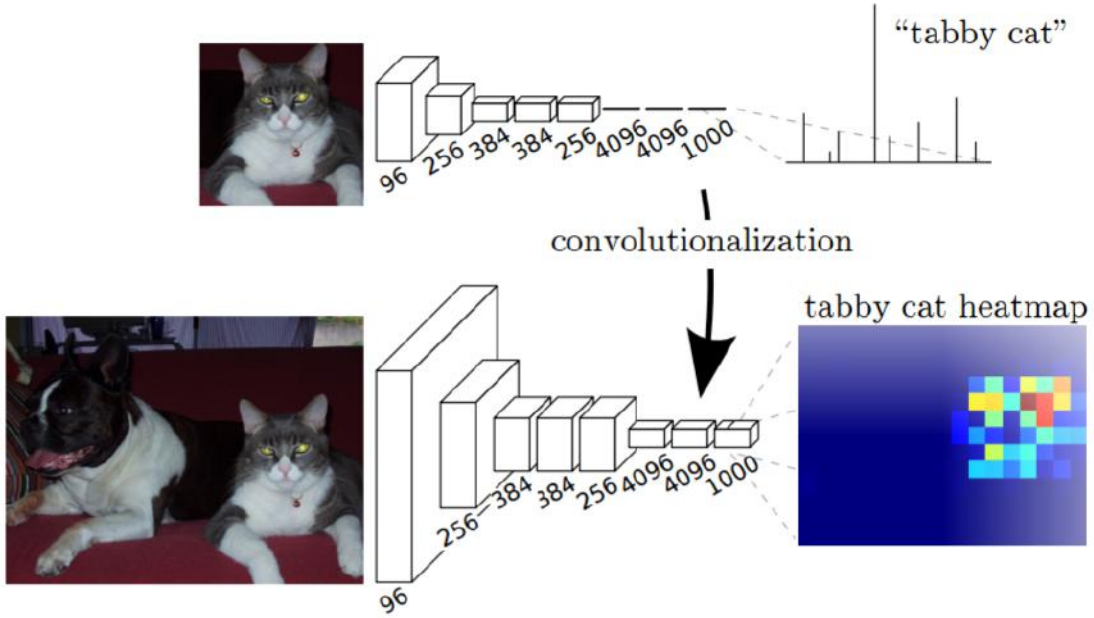




Fully Convolutional Neural Network (FCN)

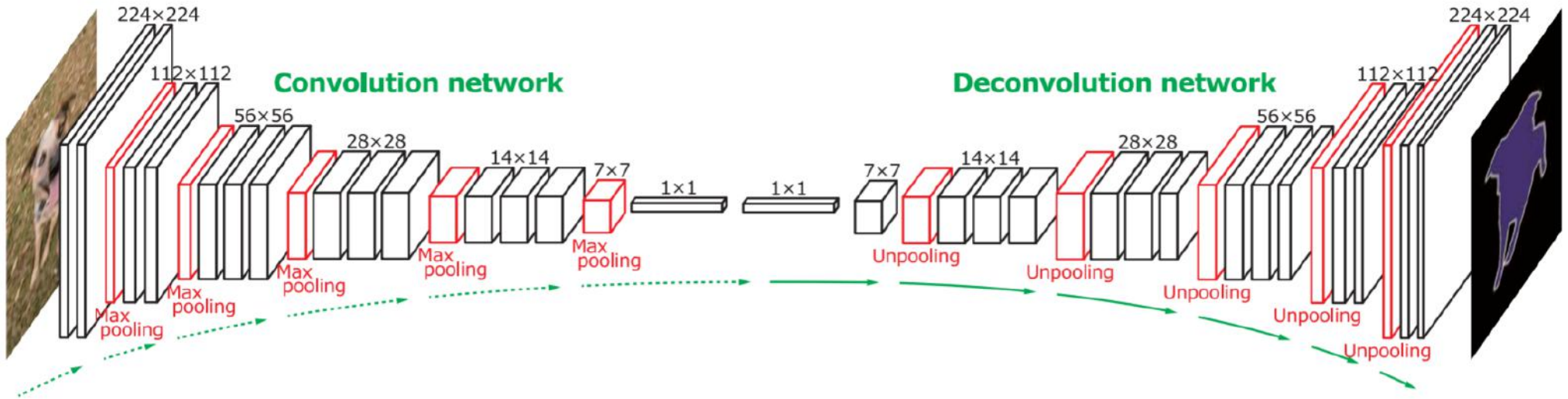
- End-to-end CNN for Semantic Segmentation





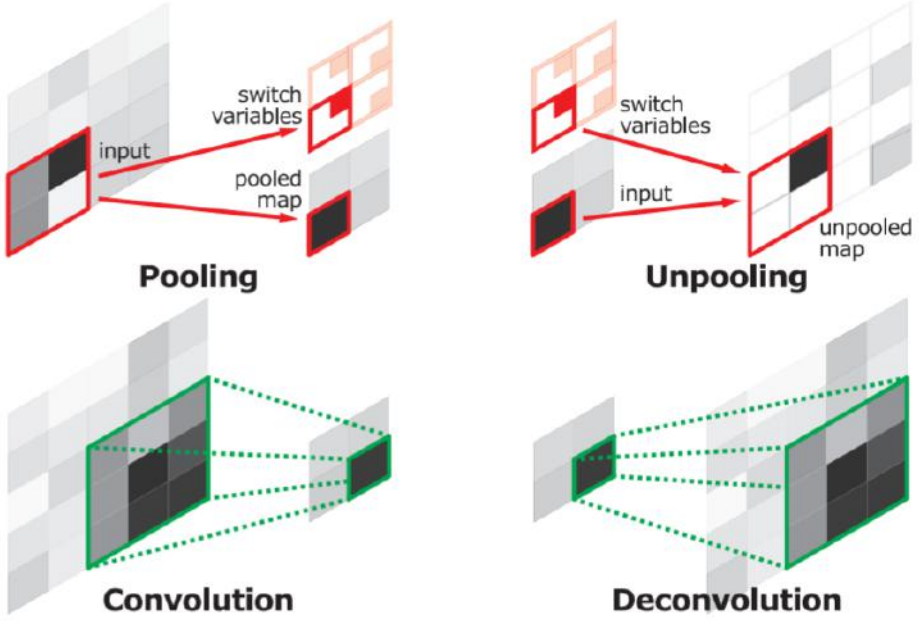
DeconvNet

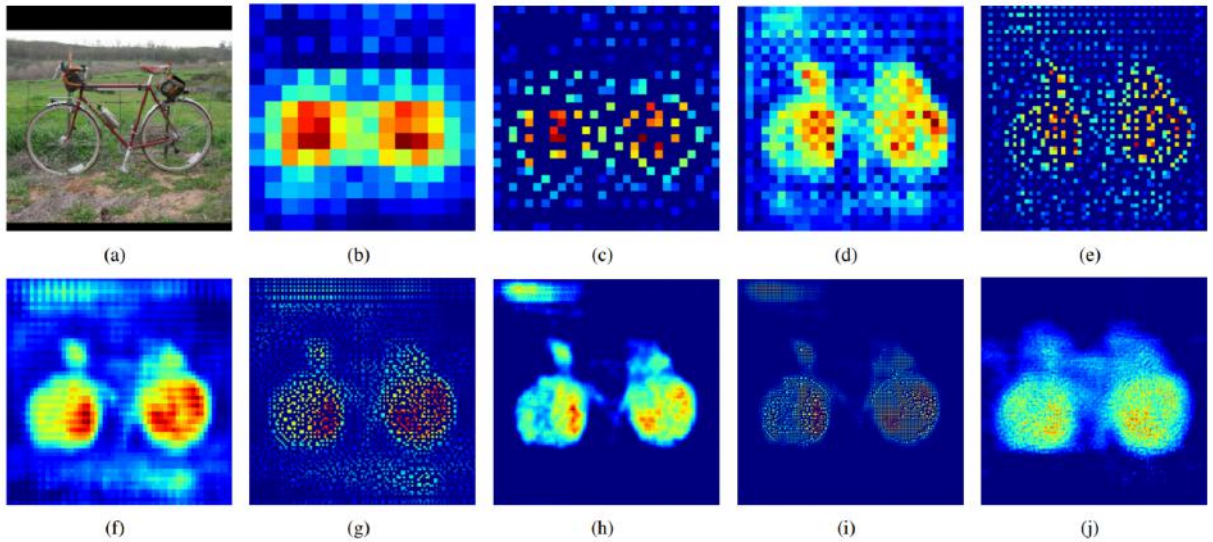
- Deconvolutional Neural Network with UnPooling Operation



DeconvNet

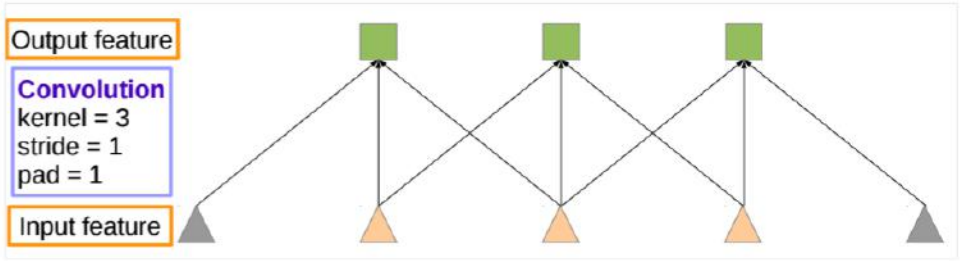
- Deconvolutional Neural Network with UnPooling Operation



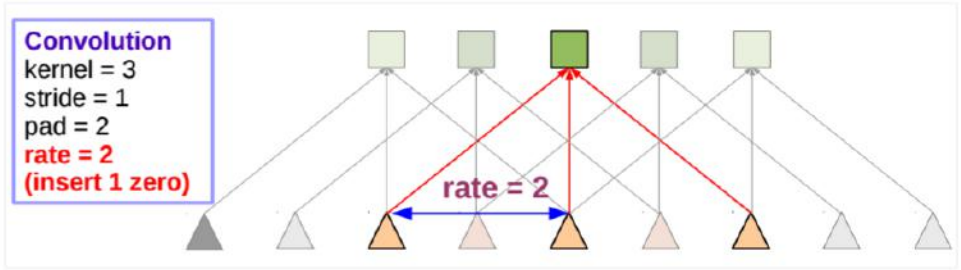


DeepLab

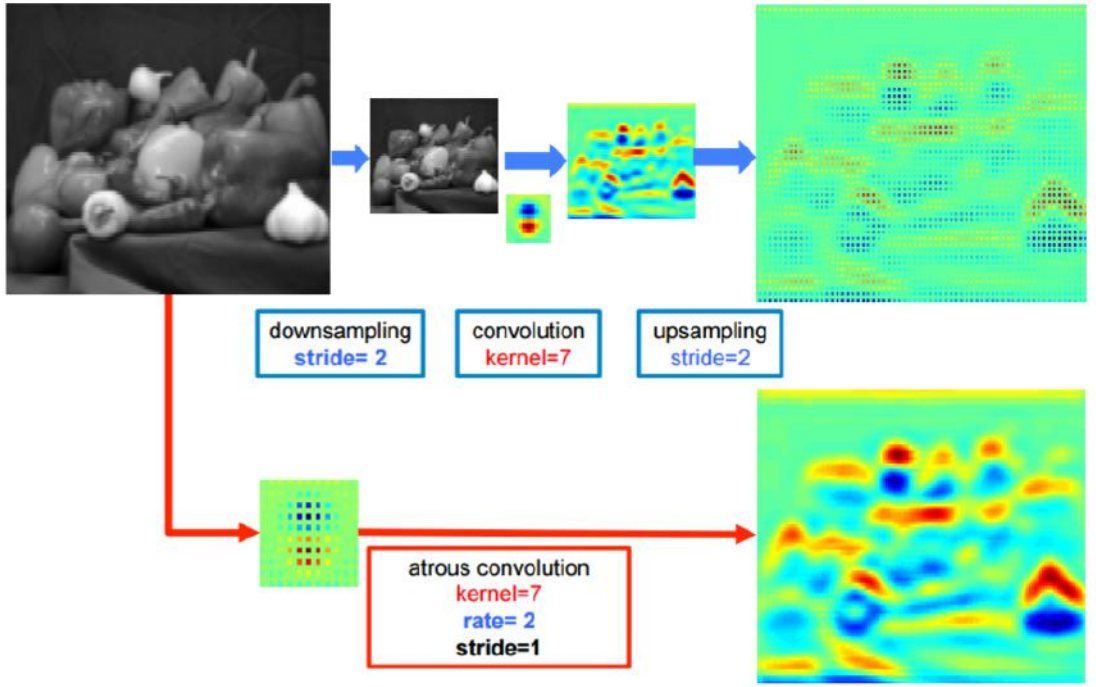
- Enlarging Field of View using Atrous Convolution



(a) Sparse feature extraction

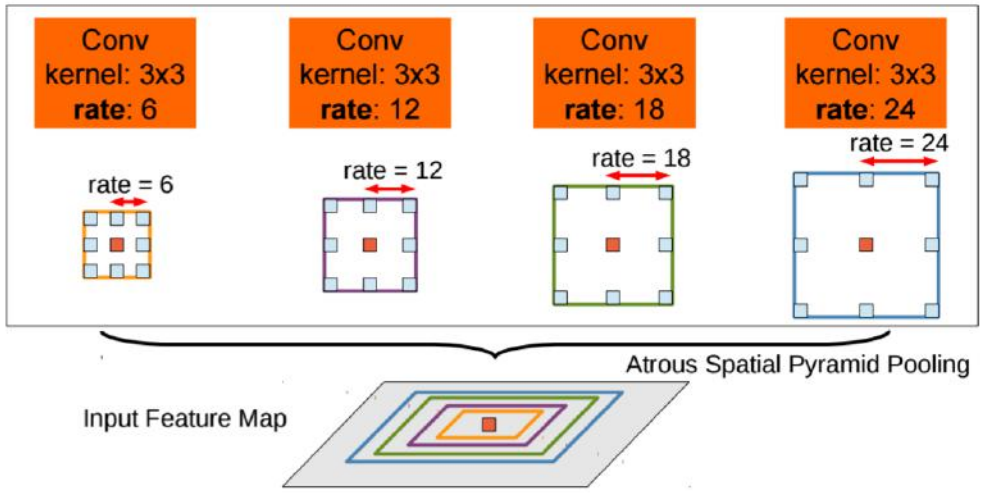


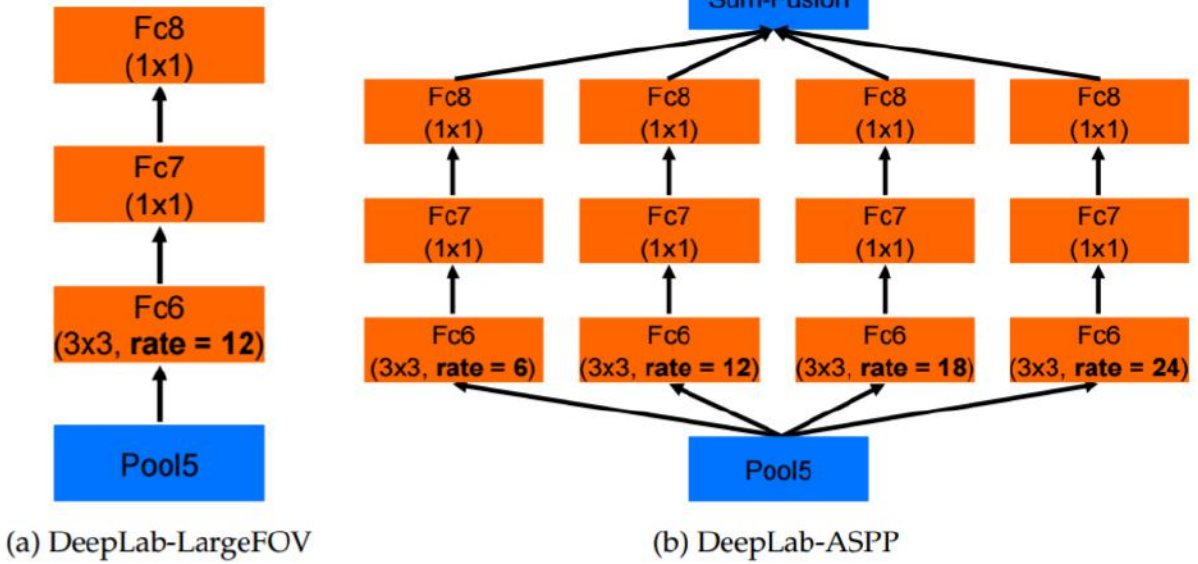
(b) Dense feature extraction



DeepLab

- Using Multiple 'Rate' for Multi-scale Object Segmentation

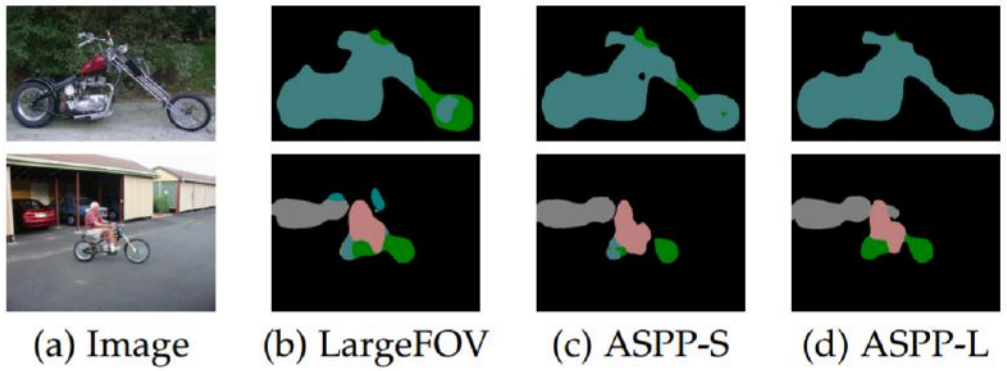


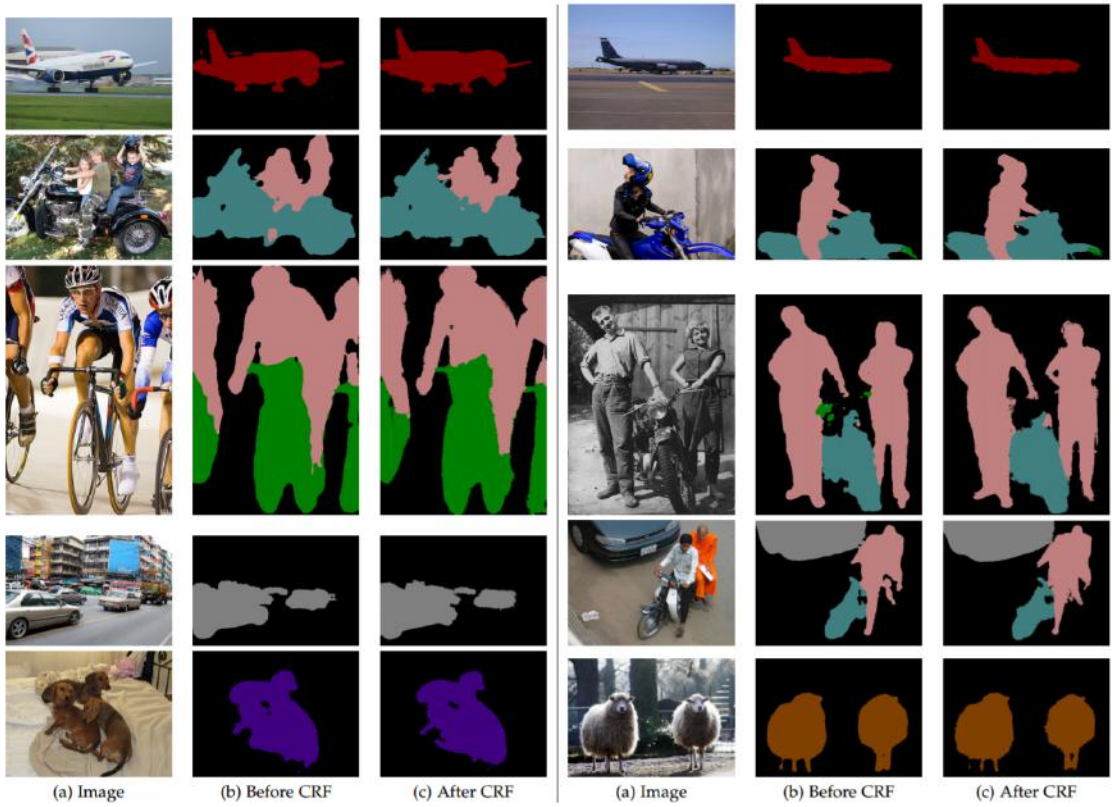


(a) DeepLab-LargeFOV (b) DeepLab-ASPP

DeepLab

- Shows State-of-the-art Performance on VOC 2012 after CRF

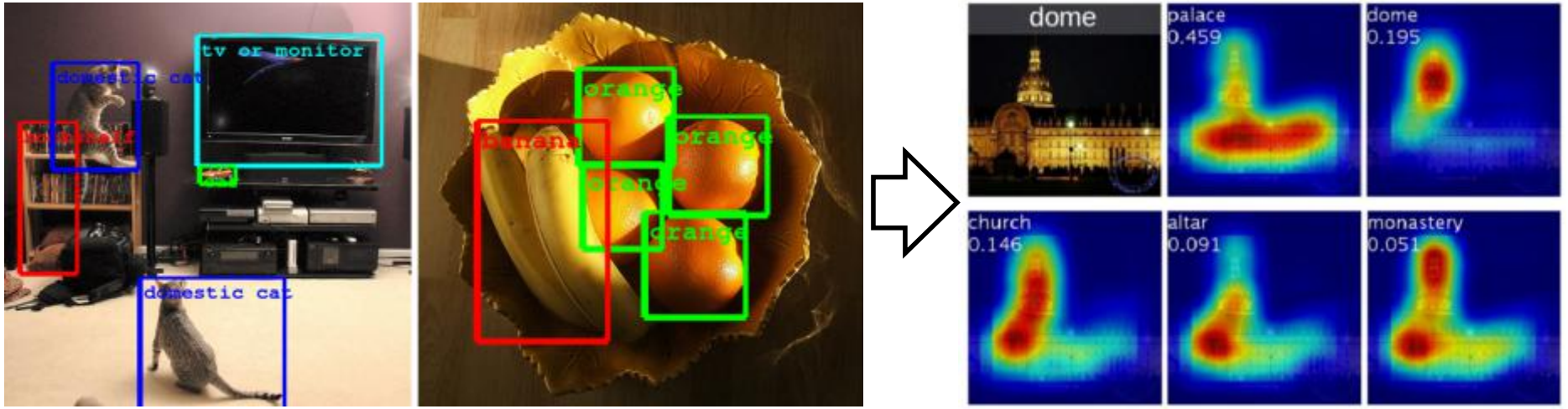




Class 14
CNNs for Weakly Supervised Learning

Weakly Supervised Learning

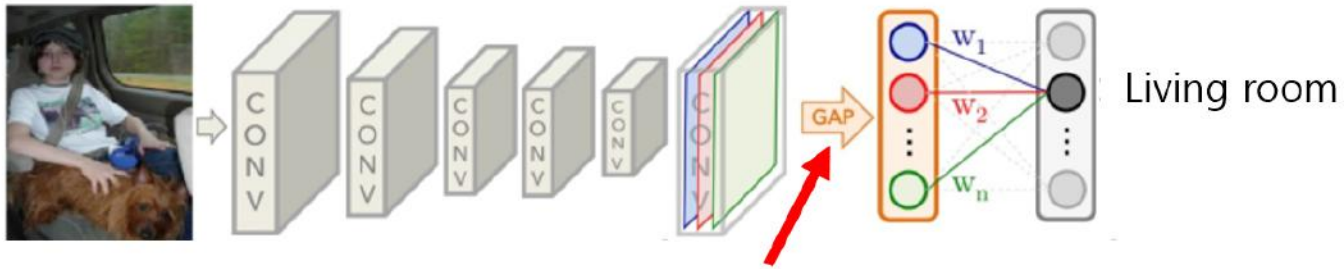
- Problem Definition
  - What if we have only image-level annotations while we need to precisely locate the region of target object?



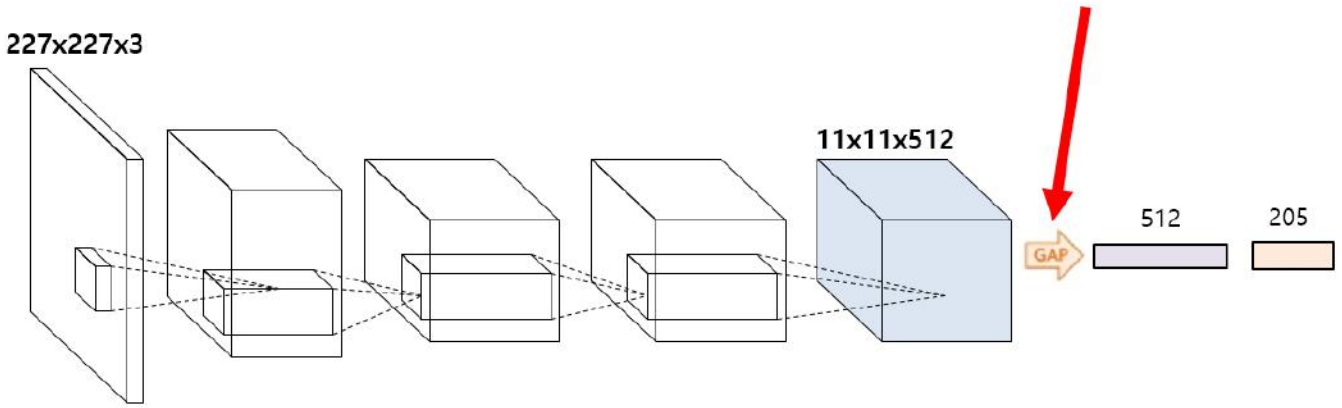
Weakly Supervised Learning

- Class Activation Map Approach

AlexNet+GAP+places205



11x11 Avg Pooling: Global Average Pooling (GAP)




```
('data', (10, 3, 227, 227))
('conv1', (10, 96, 55, 55))
('pool1', (10, 96, 27, 27))
('norm1', (10, 96, 27, 27))
('conv2', (10, 256, 27, 27))
('pool2', (10, 256, 13, 13))
('norm2', (10, 256, 13, 13))
('conv3', (10, 384, 13, 13))
('conv4', (10, 384, 13, 13))
('conv5', (10, 384, 13, 13))
('pool5', (10, 384, 11, 11))
('conv6', (10, 512, 11, 11))
('conv7', (10, 512, 11, 11))
('pool8_global', (10, 512, 1, 1))
('fc9', (10, 205))
('prob', (10, 205))
→ alexnetplusCAM_places205
```

Weakly Supervised Learning

- Class Activation Map Approach
  - Identify important image regions by projecting back the weights of output layer to convolutional feature maps.
  - CAMs can be generated for each class in single image.
  - Regions for each categories are different in given image.

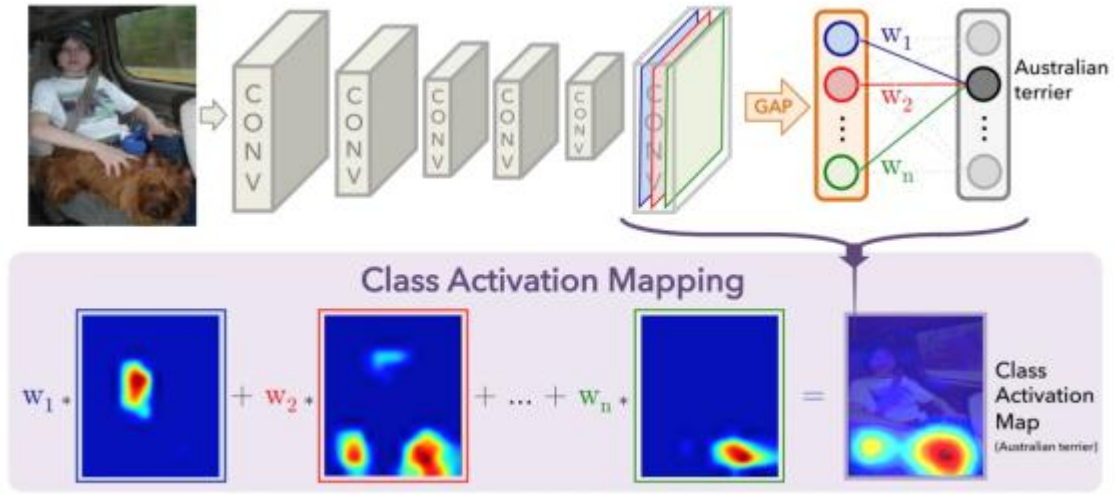


Figure 2. Class Activation Mapping: the predicted class score is mapped back to the previous convolutional layer to generate the class activation maps (CAMs). The CAM highlights the class-specific discriminative regions.

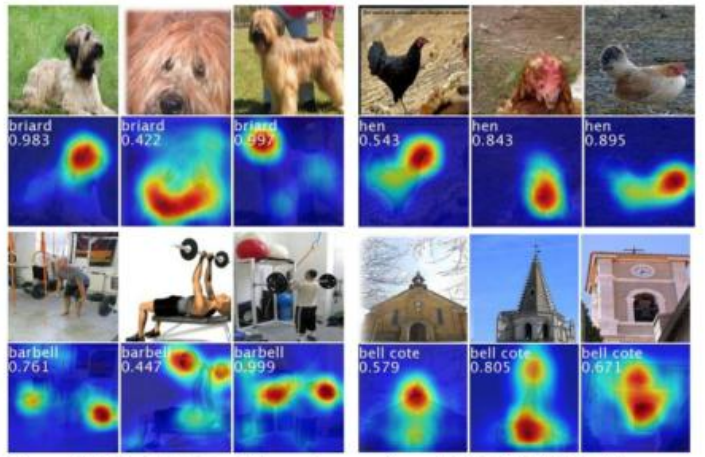


Figure 3. The CAMs of four classes from ILSVRC [20]. The maps highlight the discriminative image regions used for image classification e.g., the head of the animal for *briard* and *hen*, the plates in *barbell*, and the bell in *bell cote*.

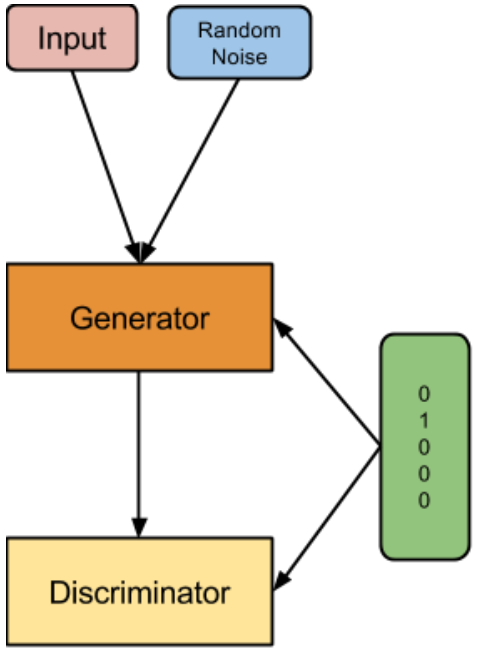
Class 15
Generative Adversarial Networks

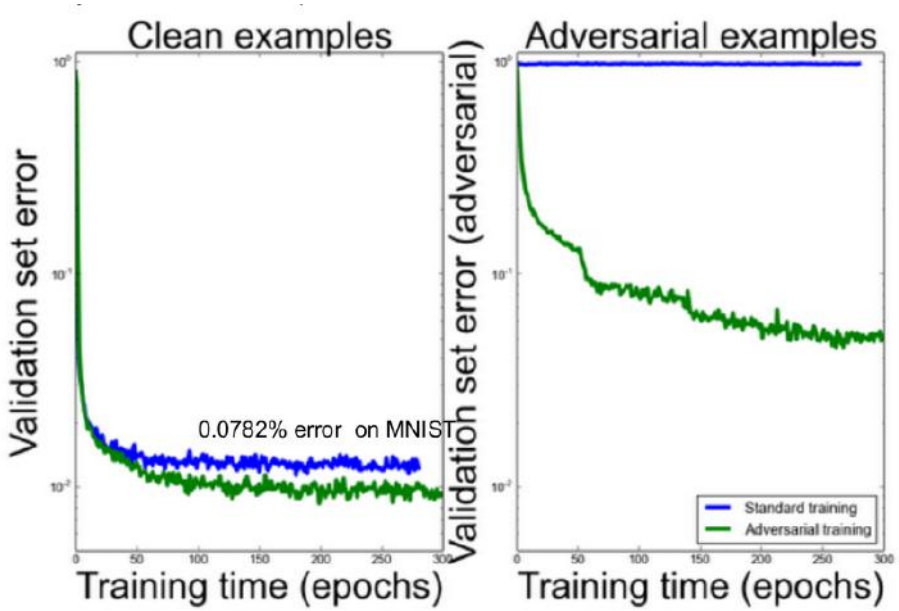
Generative Models

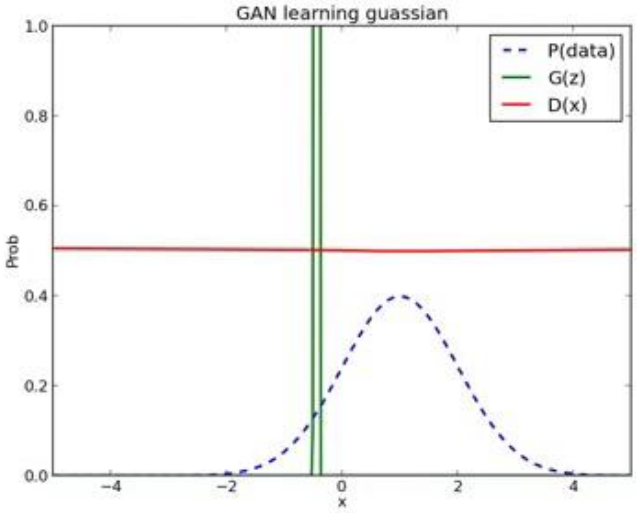
- Definition
  - A model for randomly generating observable data values, typically given some hidden parameters
  - “What I cannot created, I do not understand.”
- Examples
  - We can distinguish Chinese from Japanese but we cannot speak them.
  - Kids can read numbers and characters but cannot write down them.
- Deep Generative Models
  - Auto-Encoders : AE, Denoising AE, Sparse AE, Variational AE
  - Generative Adversarial Networks : GAN, DCGAN, InfoGAN,

Generative Adversarial Networks (NIPS 2014)

- Generator vs Discriminator
  - Simpler generative model than MCMC-based or variational inference-based models.

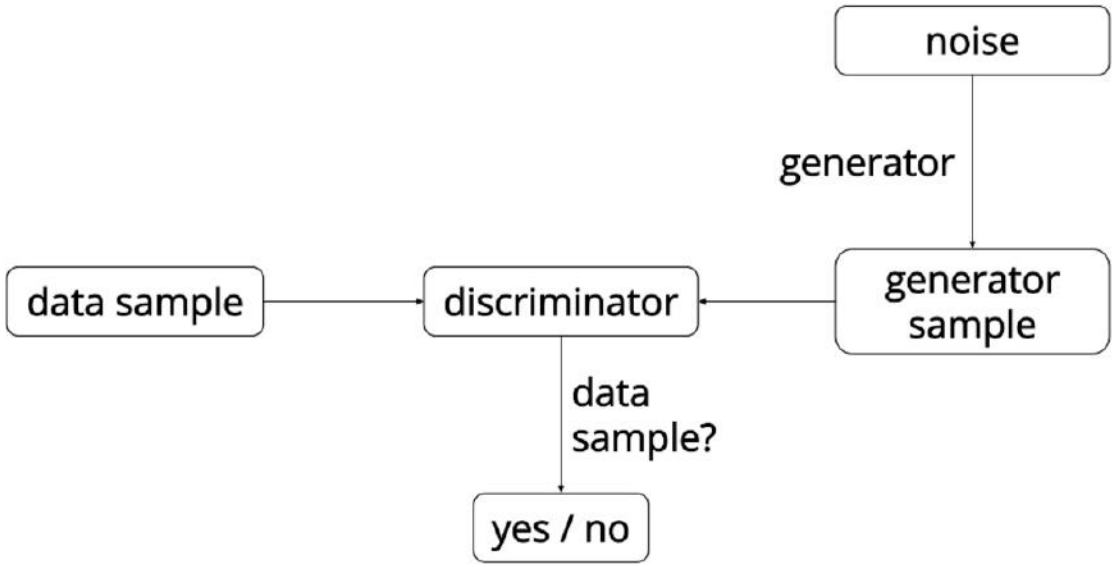






Generative Adversarial Networks (NIPS 2014)

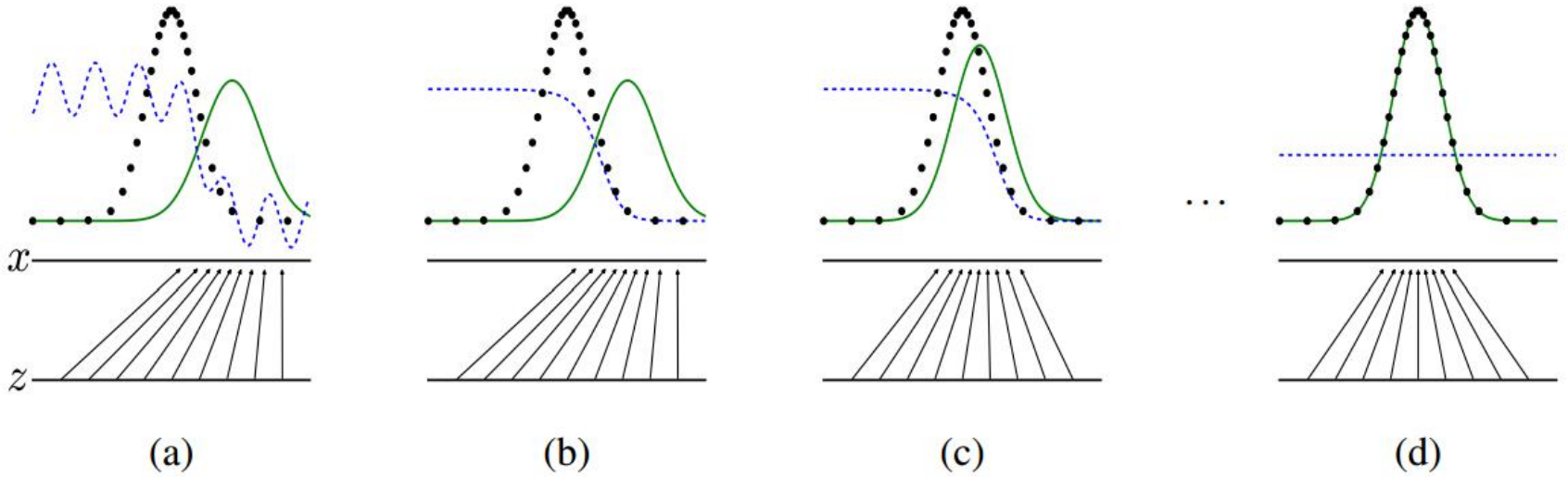
- 1D Example



Generative Adversarial Networks (NIPS 2014)

- MinMax Problem for Generator and Discriminator
  - Minimize for G, maxize for D.
  - D discriminate whether the input is from data or generative model.
  - G generate sample from

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$



Generative Adversarial Networks (NIPS 2014)

- The Algorithm

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Training D to convergence is expensive.
Therefore, train D k step and train G slowly.

In the early phase D is confident and gradient is small
Instead we can max D(G(z))

Generative Adversarial Networks (NIPS 2014)

- Theoretical Results
  - Optimality for D

Proposition 1. *For G fixed, the optimal discriminator D is*

$$D_G^*(\boldsymbol{x}) = \frac{p_{data}(\boldsymbol{x})}{p_{data}(\boldsymbol{x}) + p_g(\boldsymbol{x})}$$

  - Optimality for G

Theorem 1. *The global minimum of the virtual training criterion $C(G)$ is achieved if and only if $p_g = p_{data}$. At that point, $C(G)$ achieves the value $-\log 4$.*

  - Convergence Analysis

Proposition 2. *If G and D have enough capacity, and at each step of Algorithm 1, the discriminator is allowed to reach its optimum given G, and p_g is updated so as to improve the criterion*

$$\mathbb{E}_{\boldsymbol{x}\sim p_{data}}[\log D_G^*(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{x}\sim p_g}[\log(1 - D_G^*(\boldsymbol{x}))]$$

then p_g converges to p_{data}

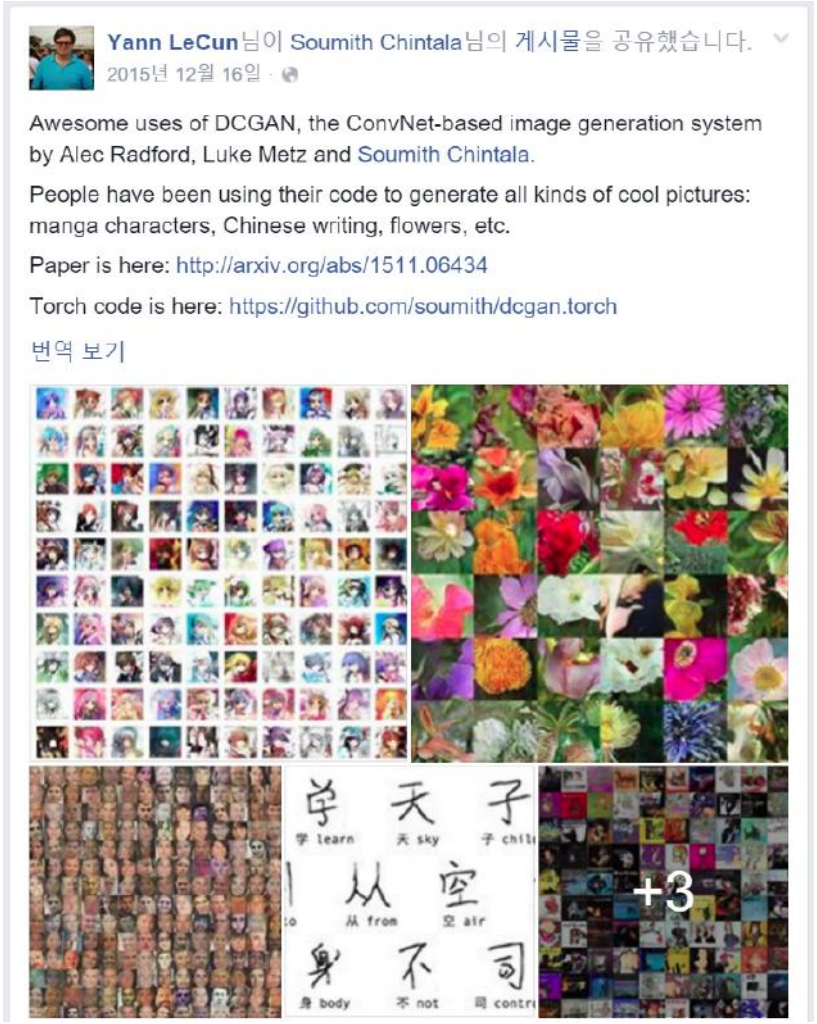
Generative Adversarial Networks (NIPS 2014)

- Experimental Results
  - D : MLP with maxout activation and dropout
  - G : MLP with ReLU and sigmoid activation

Deep Convolutional GAN (ICLR 2016)

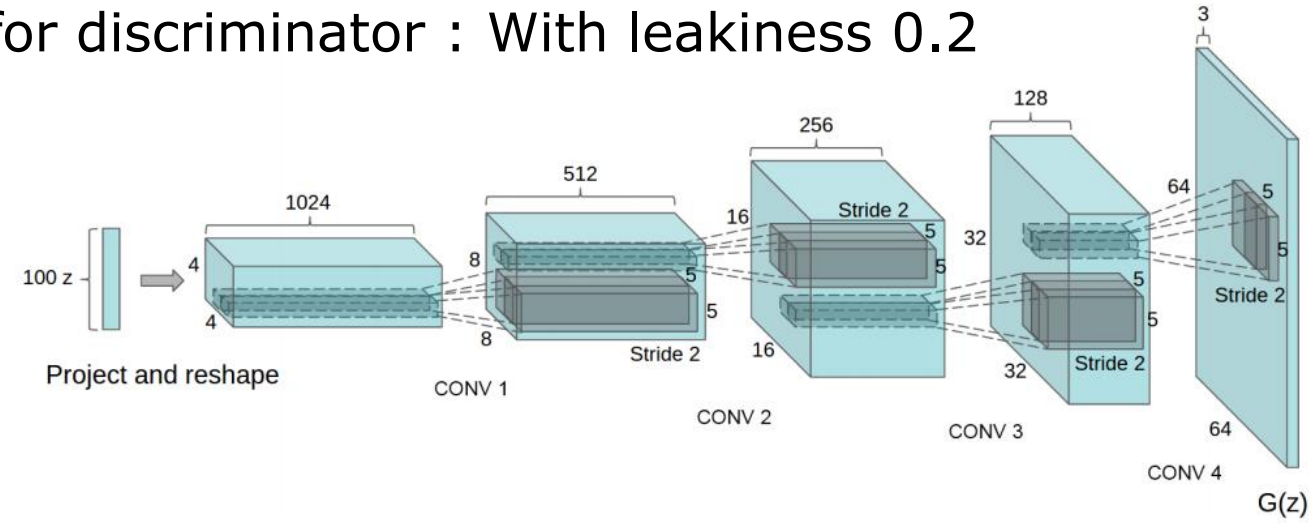
- Bridging Gap between Supervised and Unsupervised Feature Learning
  - CNNs have mainly used for supervised tasks.
  - There are unlimited images without labels.
  - CNNs are good at dealing with Images.
  - How can we used CNNs to extract good representation of images without supervision?

- There have been some image generators
  - Yes. For example GAN and its laplacian pyramid extension, VAE, RNN, DeConvNet, …
  - However, training network was unstable and the generated images were blurry or noisy.



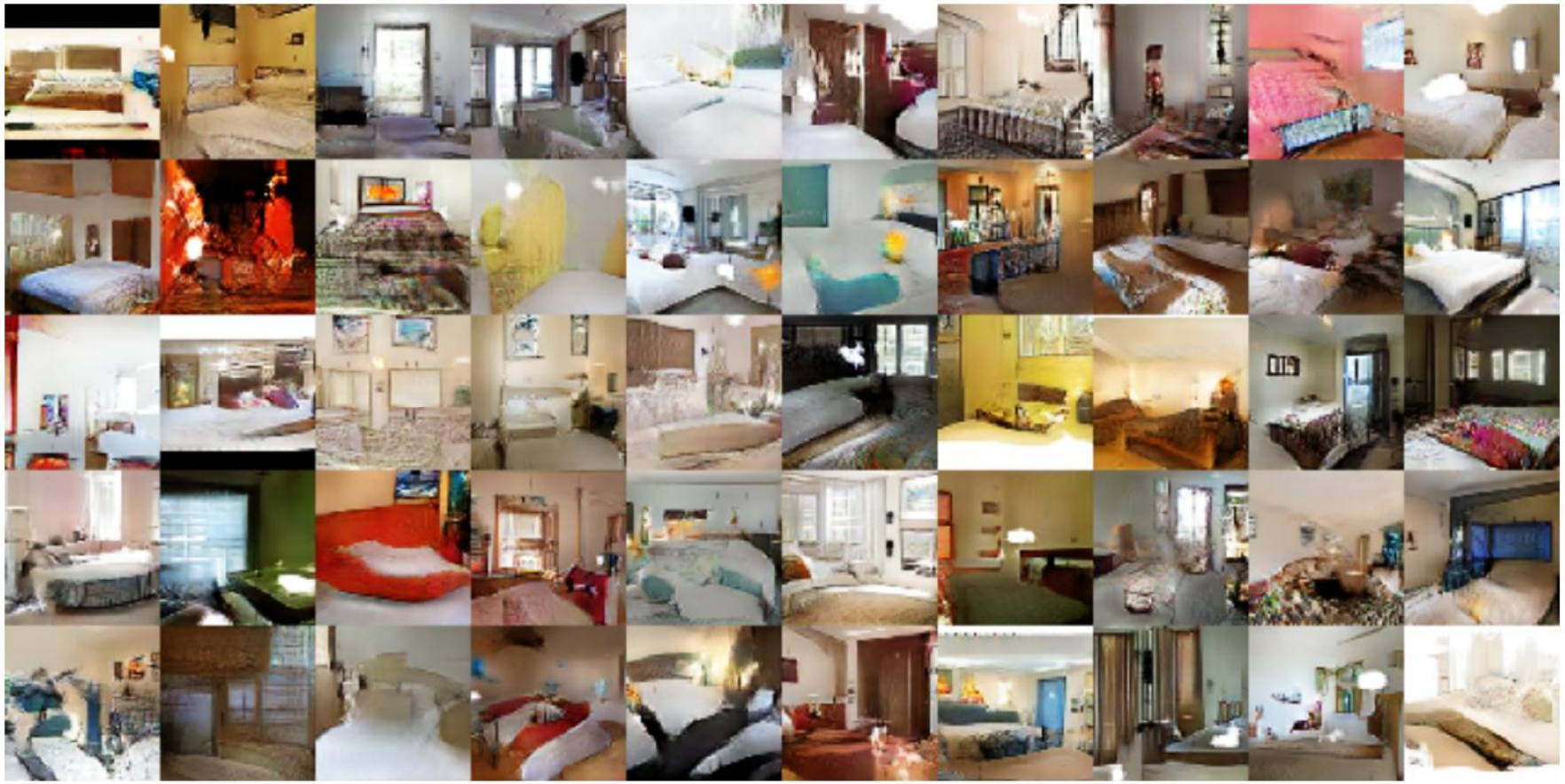
Deep Convolutional GAN (ICLR 2016)

- Recipes Making CNNs Work for GAN
  - All ConvNet : Replace pooling layer with strided convolutions.
  - No FC layers : Directly connecting last conv features to the input of generator and output of discriminator.
  - Batch normalization : Stabilizing learning process and help training deeper generator.
  - ReLU activation for generator : Except the output layer which uses Tanh
  - LeakyReLU for discriminator : With leakiness 0.2



Deep Convolutional GAN (ICLR 2016)

- Generated Samples – Large-scale Scene Understanding

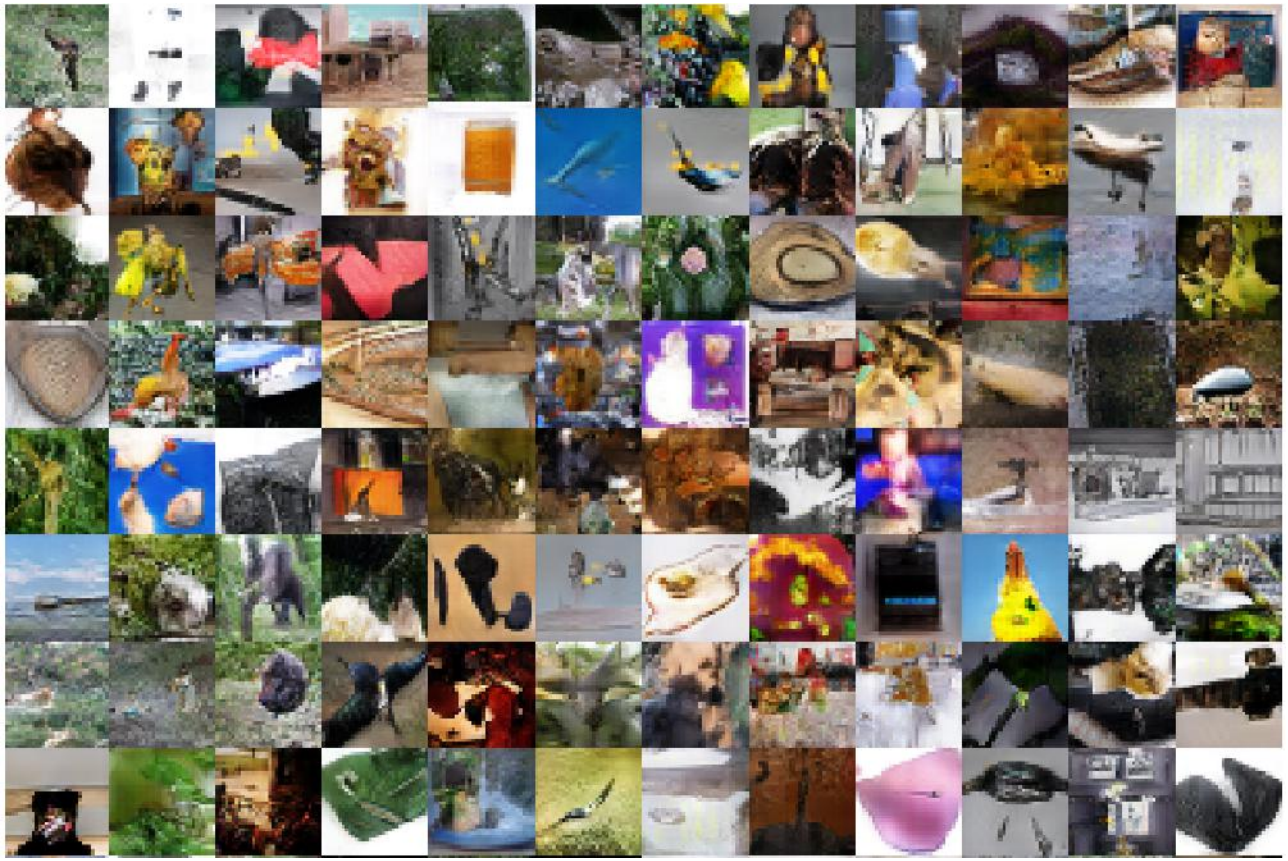


Deep Convolutional GAN (ICLR 2016)

- Generated Samples – Faces

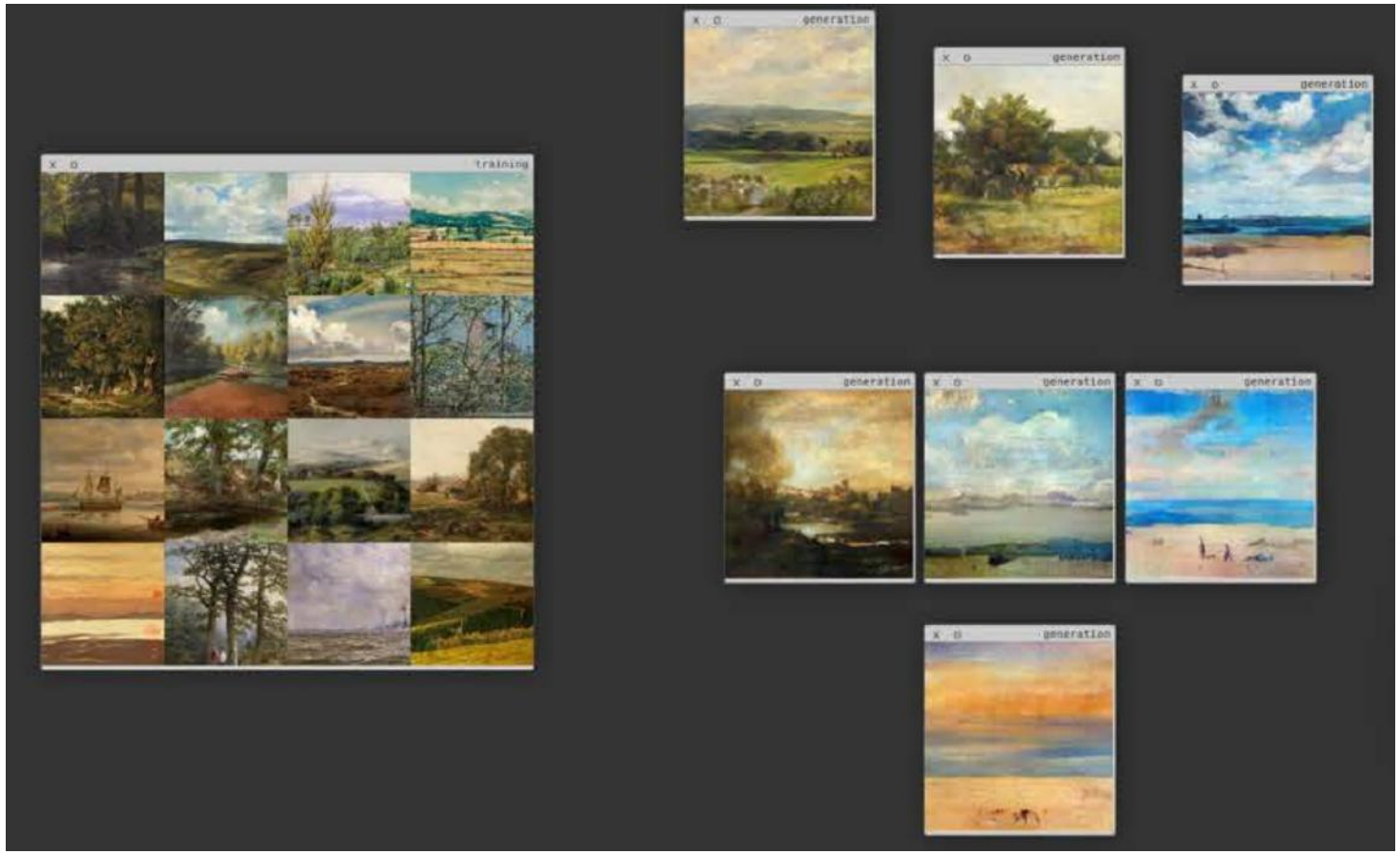
Deep Convolutional GAN (ICLR 2016)

- Generated Samples – ImageNet 1k(Trained with 32x32 center crop)



Deep Convolutional GAN (GTC 2016)

- Generated Samples – Natural Scene

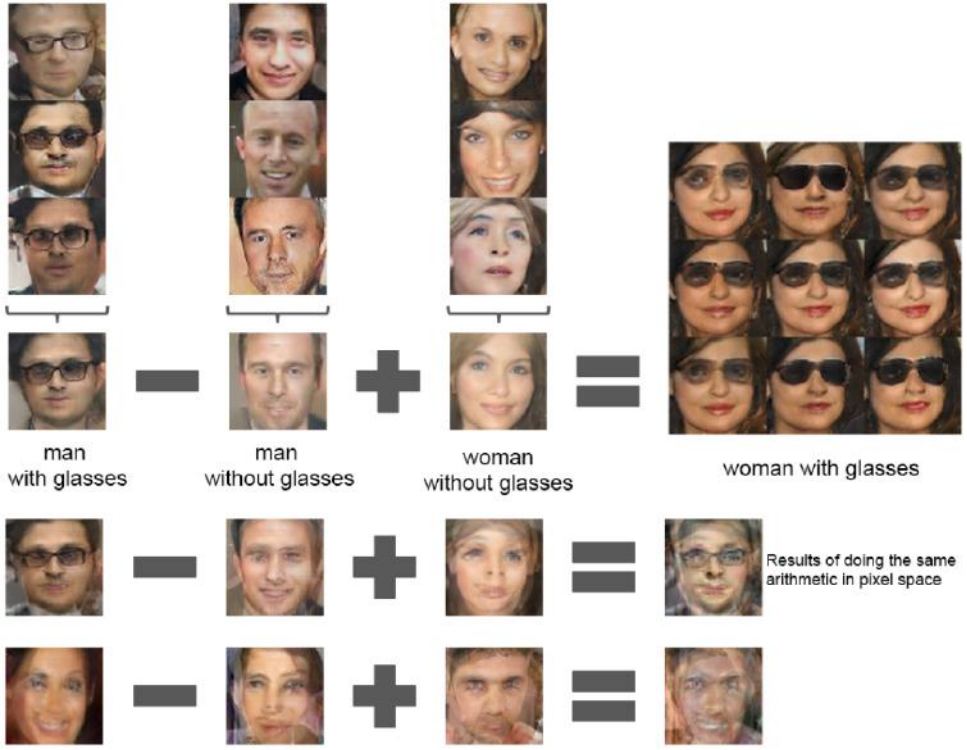


Deep Convolutional GAN (ICLR 2016)

- Walking in the Latent Space
  - If sharp transition is not observed and moving in the latent space result in semantic changes, it can be considered relevant representation has been learned.

Deep Convolutional GAN (ICLR 2016)

- Vector Arithmetic for Visual Concepts
  - Arithmetic on averaged Z representation of generator shows rich linear structure in the representation space.



Lab

Lab

- GANs for MNIST and CIFAR-10
  - https://github.com/KyuhwanJung/tensorflow_tutorial/tree/master/part3/notebook

Q&A Session

Thank You!

kyuhwanjung@gmail.com