

# PRACTICAL DEEP LEARNING IN THEANO AND TENSORFLOW

## Previous course

- structure of a neural network
- softmax
- gradient of loss function, recursive / graphical structure
- a little about hyperparameters (learning rate, regularization)
- plug-and-play TensorFlow example

## What will this course cover?

- A very practical dataset: MNIST (handwritten digits benchmark)
- Different ways of doing gradient descent to improve speed:
  - full, batch, stochastic
- Momentum to improve speed
- Adaptive learning rate to improve speed
- Many new hyperparameters, how to choose them?
  - Grid search, random search
- Basics of Theano + Neural network in Theano
- Basics of TensorFlow + Neural network in TensorFlow
- GPU on Amazon Web Services to improve speed

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3134727121  
1742351244

Knowledge • 859 teams

## Digit Recognizer

Wed 25 Jul 2012

Sat 31 Dec 2016 (10 months to go)

Dashboard
Home
Data
Make a submission
Information
Description
Evaluation
Rules
Tutorial
Forum
Scripts
New Script
New Notebook
Leaderboard
Visualization
My Team

Competition Details » Get the Data » Make a submission

### Classify handwritten digits using the famous MNIST data

[Get started on this competition through Kaggle Scripts](#)

The goal in this competition is to take an image of a handwritten single digit, and determine what that digit is. As the competition progresses, we will release tutorials which explain different machine learning algorithms and help you to get started.

The data for this competition were taken from the MNIST dataset. The MNIST ("Modified National Institute of Standards and Technology") dataset is a classic within the Machine Learning community that has been extensively studied. More detail about the dataset, including Machine Learning algorithms that have been tried on it and their

# Full vs Batch vs Stochastic Gradient Descent

- We've been using full GD this whole time

$$J = \sum t(n) \log y(n) \text{ for } n=1\dots N$$

- Why?
- It makes sense to maximize the likelihood over the entire training set
- Disadvantage  $O(N)$
- Won't work on big data

## Stochastic

- One at a time

for  $n=1..N$ :

$$W \leftarrow W - \eta \nabla J(n)$$

- Depend on all samples being IID
- In the long run, error will improve
- But we have to do the update and calculate the gradient for every single sample, multiple times

## Batch GD

- happy medium, less erratic

batches = split data into batches

for batch in batches

$$W \leftarrow W - \eta \nabla J(\text{batch})$$

# Momentum

- speeds up training
- similar to physical momentum - moves you in the direction you were already going
- 2 flavors:
  - “regular”
  - “Nesterov momentum” - the math is hard, we won’t cover it

## Regular momentum

- Intuitively, we can let the “velocity” be the previous weight change

$$v(t-1) = \Delta w(t-1)$$

- Then we can update the weight as follows:

$$\Delta w(t) = \mu v(t-1) - \eta \nabla J(t)$$

- In “code” form:

`v = dw`

`dw = momentum * v - learning_rate * cost_gradient`

`w += dw`

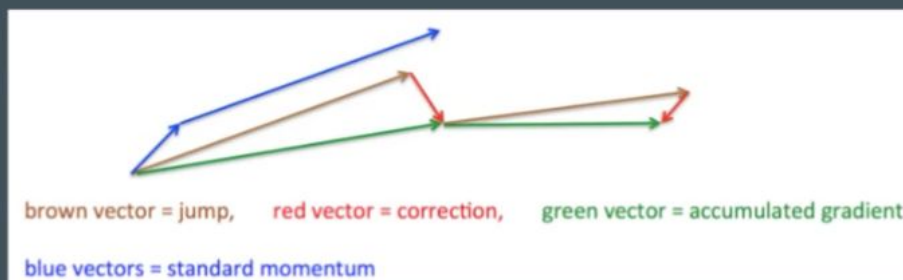
# Nesterov momentum

- Basic idea: look ahead, then correct yourself if you made a mistake
- Kinematics analogy:

$$w_{\text{ahead}} = w + \text{momentum} * v$$

$$dw = \text{momentum} * v - \text{learning\_rate} * \text{gradient\_at}(w_{\text{ahead}})$$

$$w += dw$$



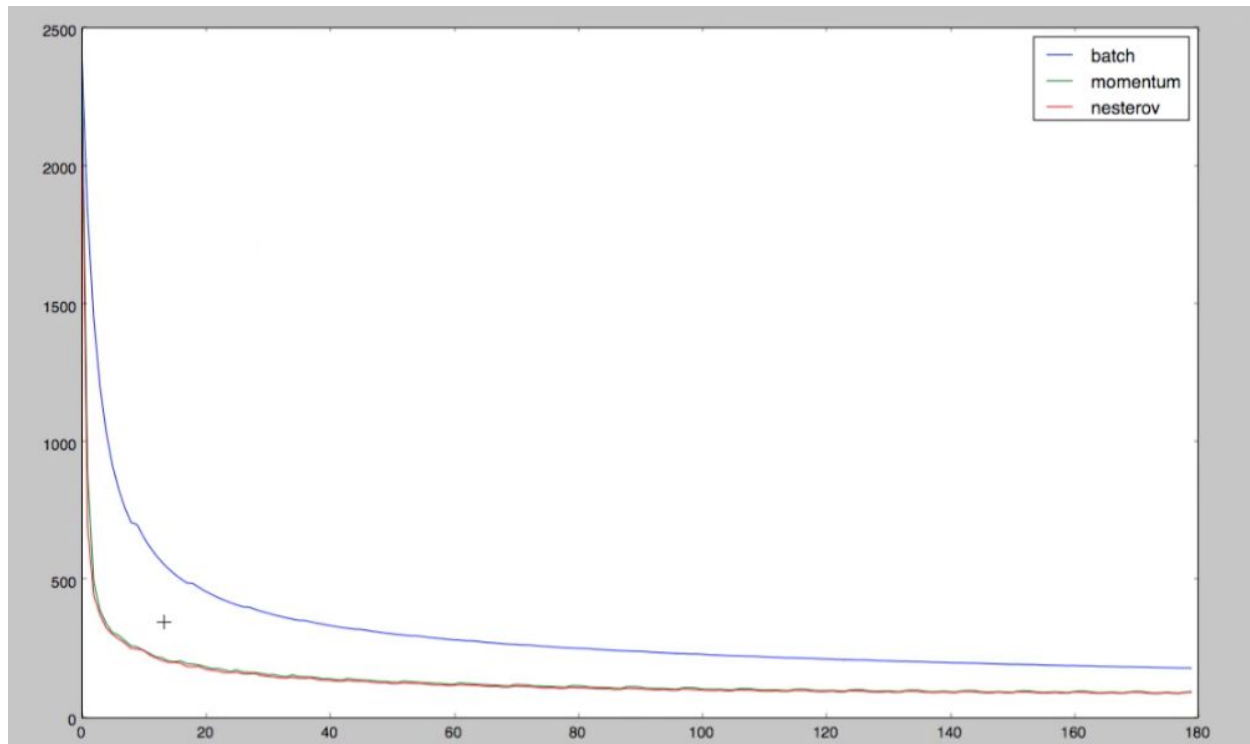
# Nesterov momentum

- Equivalent formulation:

$$v(t) = \mu v(t-1) - \eta \nabla J(t)$$

$$\Delta w(t) = -\mu v(t-1) + (1 + \mu)v(t)$$

- This is the one we'll use



# Learning rates

- What should we set it to?
- Might take a long time to choose it optimally
- Is there an automatic way? Sort of...
- Common theme: decreases over time

## Step decay

- Reduce every 5, 10, or 20 steps

Ex.

```
if iter % 10 == 0:
```

```
    learning_rate /= 2
```

## Exponential decay

$$\text{learning\_rate} = A \exp(-\lambda * t)$$

## 1/t decay

$$\text{learning\_rate} = A / (1 + kt)$$



## Newton's method

- no learning rate at all
- second order method (involves 2nd derivatives)

$$W \leftarrow W - H^{-1} \nabla J$$

- H is the “Hessian” matrix - 2nd derivative of J
- Not scalable (derivatives are hard, inverting matrices is hard)

## AdaGrad

- adaptive method (based on weight changes so far)

$$\text{cache} += \text{gradient}^2$$

$$w -= \text{learning\_rate} * \text{gradient} / (\sqrt{\text{cache}} + \text{epsilon})$$

- epsilon is a small number, i.e. 1E-10, so we don't divide by 0
- too aggressive

## RMSprop

- The cache itself also decays

$$\text{cache} = \text{decay\_rate} * \text{cache} + (1 - \text{decay\_rate}) * \text{gradient}^2$$

$$w -= \text{learning\_rate} * \text{gradient} / (\sqrt{\text{cache}} + \text{epsilon})$$



# Many hyperparameters to optimize

- We just introduced a lot of new hyperparameters
- Will only get worse
- We need to do hyperparameter optimization
  - learning rate / decay rate
  - momentum
  - regularization
  - hidden layer size
  - number of hidden layers

## Cross-validation

- split data into K parts, do K iterations - test on one part, train on the other K-1 parts

for k in xrange(K):

    training\_data = data[:k] + data[k+1:]

    model = train(training\_data)

    score = test(data[k])

- average the K scores, choose params with highest average score
- keep the test set out of here, “test” on the validation set
- `sklearn.cross_validation.KFold`

# Grid Search

- Exhaustive / try every combination
- `learning_rates = [0.1, 0.01, 0.001, 0.0001, 0.00001]`
- `momentums = [1, 0.1, 0.01, 0.001]`
- `regularizations = [1, 0.1, 0.01]`

```
for lr in learning_rates:  
    for mu in momentums:  
        for reg in regularizations:  
            score = cross_validation(lr, mu, reg, data)
```

## Grid search

- Very slow!
- But each is independent
- Good opportunity for parallelization
- Hadoop / Spark



## Random Search

- Instead of looking at every possibility, move in random directions until score is improved

```
theta = random position in hyperparameter space
score1 = cross_validation(theta, data)
for i in xrange(max_iterations):
    next_theta = sample from hypersphere around theta
    score2 = cross_validation(next_theta, data)
    if score2 is better than score1:
        theta = next_theta
```

## Art or science?

- What is the best combination to use?
- Nesterov momentum with RMSprop?
- Regular momentum with exponential decay?

## Ensembles

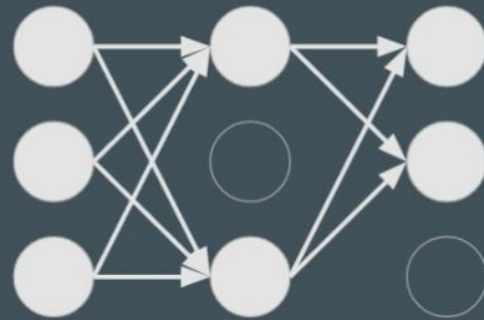
- Basic idea:
- Train a group of prediction models, then average their prediction or take the majority vote
- Result:
- Better accuracy than just one model
- Different how?
- Many possibilities
- Ex. Each model is trained on a subset of the data (also good if your algorithm can't scale)
- 1 million pts  $\rightarrow$  10 decision trees each trained on 100k pts

## Ensembles

- Another way to get different classifiers:
  - Train on different features
  - Ex. 100 features  $\rightarrow$  Each of 10 decision trees trains on 10 features
  - So if  $X.shape == (1 \text{ million}, 100)$
  - Each decision tree trains on  $x.shape == (100k, 10)$
  - (If we combined both these methods)
- 
- Dropout is more like the 2nd method

# Dropout

- Train on a subset of features
- Same as dropping nodes
- But not only at input layer
- Drop nodes at every layer!
- Use  $p(\text{drop})$  or  $p(\text{keep})$
- $p(\text{keep}) = 1 - p(\text{drop})$
- Typical values:
- $p(\text{keep}) = 0.8$  for input layer
- $p(\text{drop}) = 0.5$  for hidden layers



# Dropout

- We only drop layers during training
- Ensembles: 10 decision trees
- But only 1 neural network
- We also need to do prediction
- You'll see why we only need 1 neural network

## Dropout

- Prediction
- If we have 1 hidden layer:  $X \rightarrow Z \rightarrow Y$
- $X_{\text{drop}} = p(\text{keep}|\text{layer1}) * X$
- $Z = f(X_{\text{drop}} \cdot W + b)$
- $Z_{\text{drop}} = p(\text{keep}|\text{layer2}) * Z$
- $Y = \text{softmax}(Z_{\text{drop}} \cdot V + c)$
- We just multiply by the  $p(\text{keep})$  at that layer
- Shrinks the value
- (Think about L2 regularization - it encourages weights to be small, also leading to shrunken values)

## Dropout

- How is this an “ensemble”?
- If we have  $N$  nodes in a neural network ( $N = \# \text{ inputs} + \# \text{ hidden}$ )
- Each node can have 2 states: drop/keep
- Total # of possible neural networks:  $2^N$
- Suppose  $N=100$
- (For comparison, MNIST would have  $\sim 1000 = 700$  for input, 300 for hidden)
- But  $2^{100} \approx 1.3 \times 10^{30}$
- Training this many neural networks is infeasible
- So we can't do an actual ensemble
- Multiplying by  $p(\text{keep})$  approximates this ensemble

## Dropout Implementation

- Theano (requires understanding basic principles)
- TensorFlow (built-in)



## Dropout Theano

- You can't actually "drop nodes"
- That would result in a different computational graph
- Equivalent: multiply by 1 or 0
- Anything that comes after is still 0
- Input:  $N \times D$  matrix
- We need a "mask" of 0s and 1s of size  $N \times D$
- Familiar if you've done low-level C coding - bit-wise operations + bitmasks

## Dropout Theano

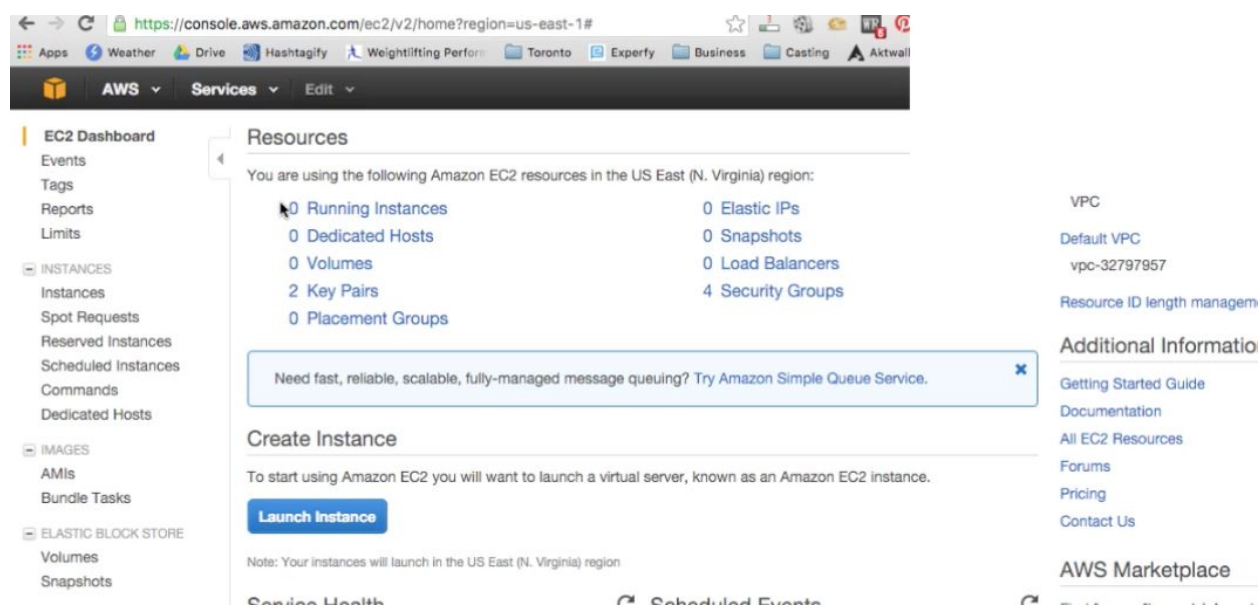
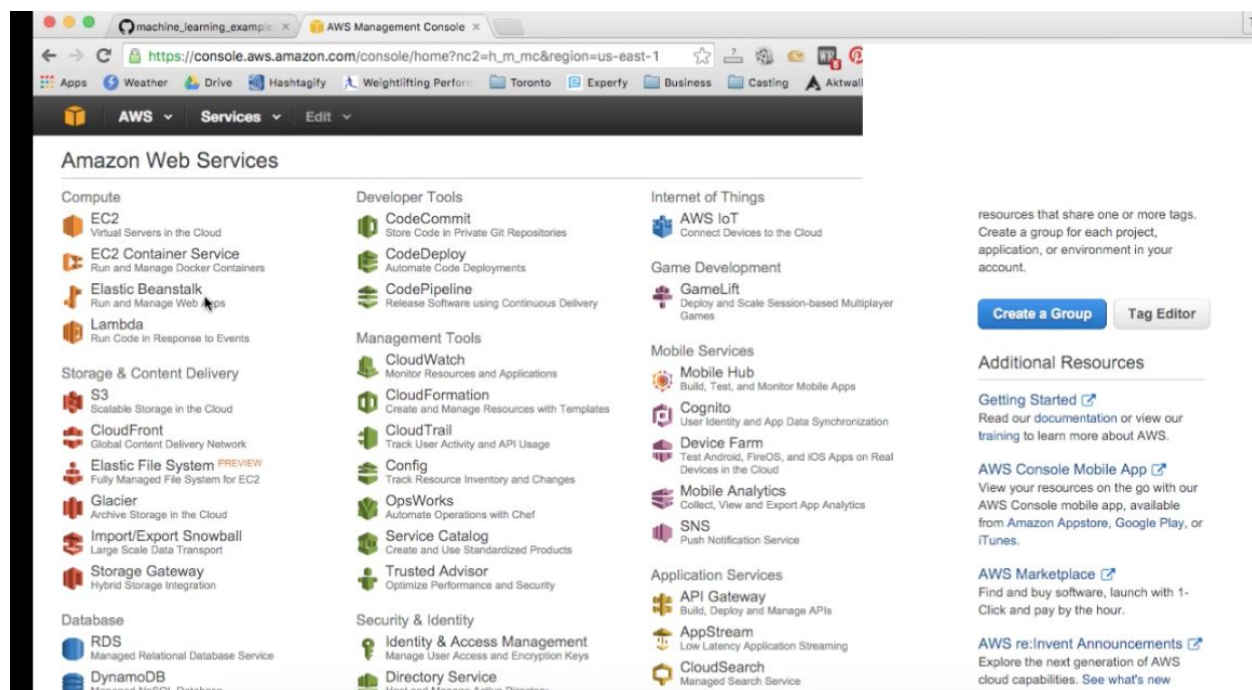
- Theano graph nodes don't have values
- Can't do this:
  - `mask = np.random.binomial(...)`
  - `Z = f((X*mask).dot(W) + b)`
- Because mask would only be calculated once
- Instead we want Theano to generate random values every time it's called
- `from theano.tensor.shared_randomstreams import RandomStreams`
- `rng = RandomStreams()`
- `mask = rng.binomial(n=1, p=p_keep, size=X.shape)`
- `X_drop = mask * X`

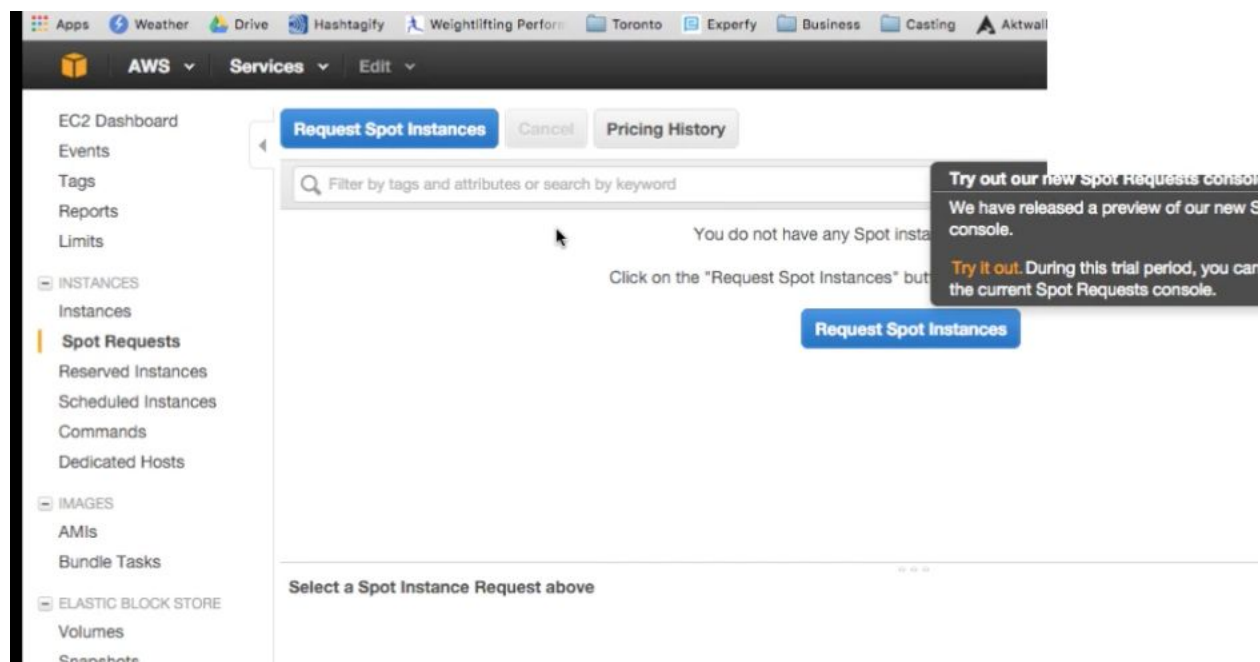
## Code

- `dropout_theano.py`
- `dropout_tensorflow.py`

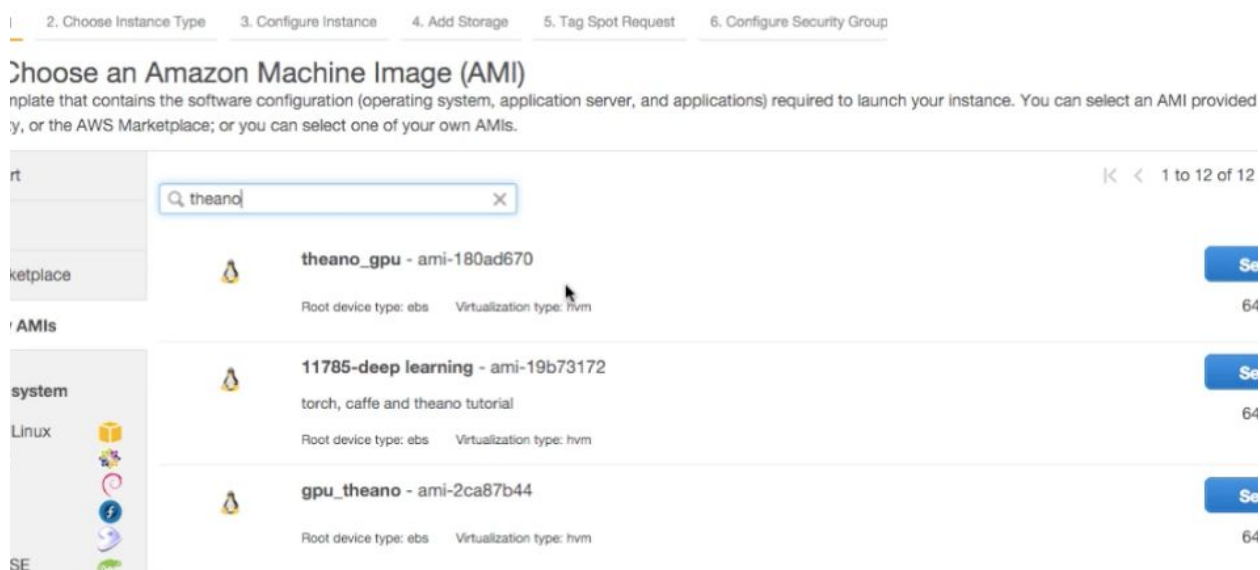


## SETTING UP THE GPU INSTANCES FOR THE AMAZON AWS (IN MAC OS)





Need to choose **gpu\_theano** for the community AMI.



Step 2: Choose an Instance Type

Instance Type	Instance Class	VCpus	Memory (GB)	Storage
<input type="radio"/> Compute optimized	c3.xlarge	4	15	2 x 40 (SSD)
<input type="radio"/> Compute optimized	c3.2xlarge	8	30	2 x 80 (SSD)
<input type="radio"/> Compute optimized	c3.4xlarge	16	60	2 x 160 (SSD)
<input type="radio"/> Compute optimized	c3.8xlarge	32	120	2 x 320 (SSD)
<input checked="" type="radio"/> GPU instances	<b>g2.2xlarge</b>	<b>8</b>	<b>15</b>	<b>1 x 60 (SSD)</b>
<input type="radio"/> GPU instances	g2.8xlarge	32	60	2 x 120 (SSD)
<input type="radio"/> Memory optimized	r3.large	2	15	1 x 32 (SSD)
<input type="radio"/> Memory optimized	r3.xlarge	4	30.5	1 x 80 (SSD)
<input type="radio"/> Memory optimized	r3.2xlarge	8	61	1 x 160 (SSD)

Step 3: Configure Instance Details

Purchasing option ☒ Request Spot instances

Current price

Maximum price  (e.g., 0.045 = 4.5 cents/hour)

Launch group

Request valid from  Edit

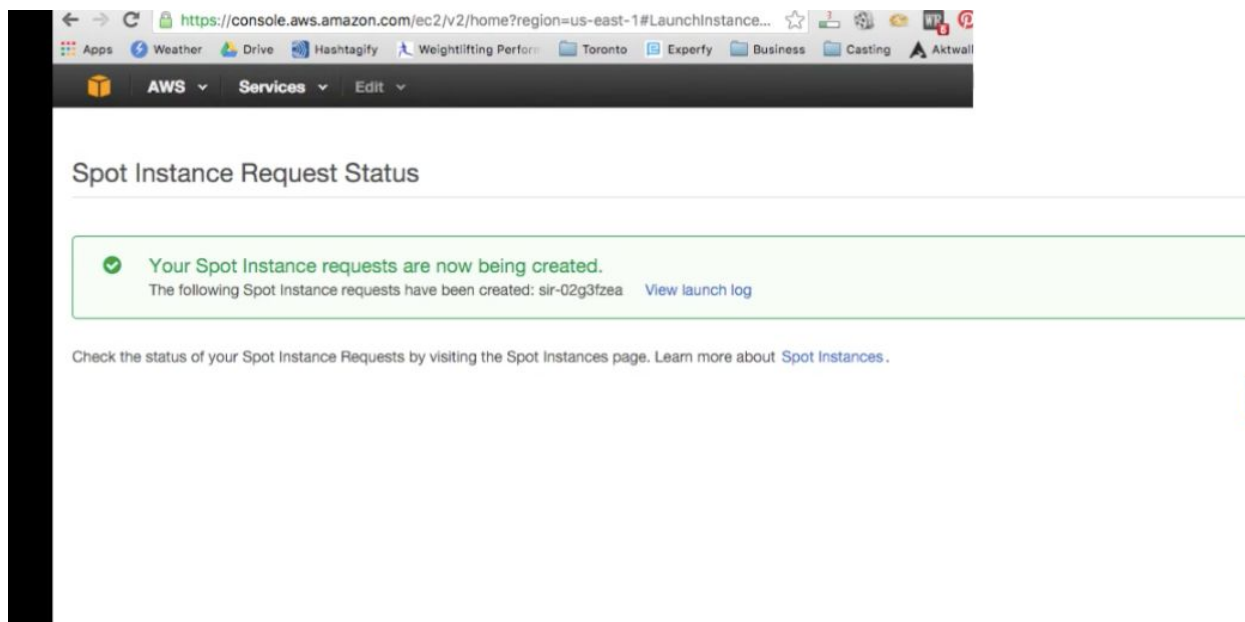
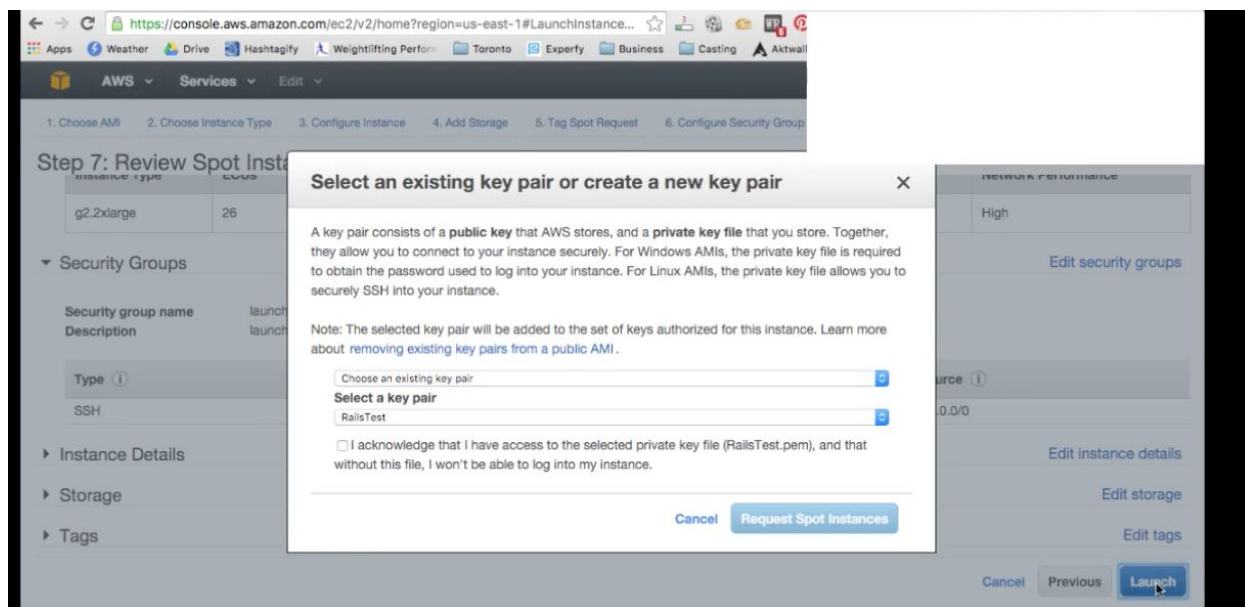
Request valid to  Edit

Persistent request ☐ Persistent request

Network

Subnet

Auto-assign Public IP



The top screenshot shows the AWS Management Console 'Request Spot Instances' page. The table below lists the spot requests:

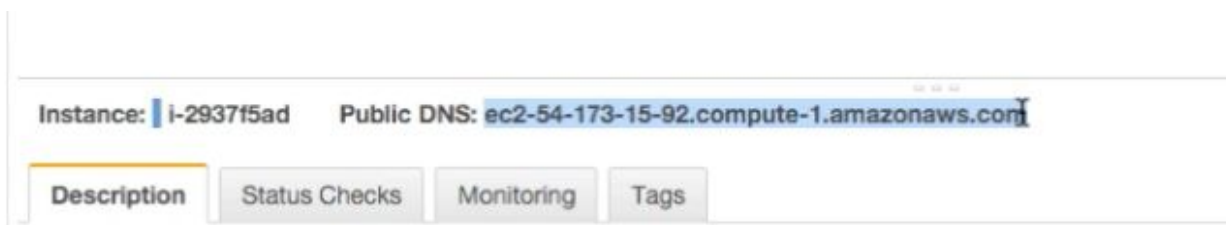
Name	Request ID	Max Price	AMI ID	Instance	Instance Type	State	Status
	sir-02g3fzea	\$0.1	ami-2ca87b44		g2.2xlarge	open	pending-evalu...

The bottom screenshot shows the AWS Management Console 'Launch Instance' page. The table below lists the instances:

Name	Instance ID	Instance Type	Availability Zone	Instance State	Status Checks	Alarm Status	Public DNS
	i-2937f5ad	g2.2xlarge	us-east-1a	running	Initializing	None	ec2-54-173-15-92.compute-1.amazonaws.com

Address to the machine is provided as the **Public DNS** and log in to the machine where name of the **operating system** needs to be selected while creating the stop instances. Enter in the folder where the `awstheano_name.pem` located, `cd` in the folder and type in the terminal,

```
> chmod 400 awstheano_name.pem
> ssh -i awstheano_name.pem
ubuntu@ec2-54-173-15-92.compute-1.amazonaws.com
```



After logged in the machine,

```
* Documentation: https://help.ubuntu.com/

System information as of Thu Feb 25 06:40:53 UTC 2016

System load: 0.83          Processes:            157
Usage of /:   51.8% of 7.74GB Users logged in:      0
Memory usage: 1%          IP address for eth0: 172.31.5.234
Swap usage:   0%

Graph this data and manage this system at:
https://landscape.canonical.com/

Get cloud support with Ubuntu Advantage Cloud Guest:
http://www.ubuntu.com/business/services/cloud

*** /dev/xvda1 should be checked for errors ***

Last login: Mon Aug 11 00:23:57 2014 from 209-6-206-91.c3-0.smr-ubr2.sbo-smr.ma.cable.rcn.com
ubuntu@ip-172-31-5-234:~$
```

```
Permission denied (publickey).
lost connection
MacBook-Pro:Code macuser$ scp -i TheanoClass.pem machine_learning_examples/large_files/train.csv ubuntu@ec2-54-173-15-92.compute-1.amazonaws.com:~
train.csv                                0% 0 0.0KB/s --:-- ETA
```

Copy the train data to the **EC2 AWS**,

```
> scp -i awstheano_name.pem machine_learning_examples/large_files/train.csv
ubuntu@ec2-54-173-15-92.compute-1.amazonaws.com
```

Install the **git** in the AWS cloud if necessary,

```
> sudo apt-get install git
```

Install the **pandas** in the AWS cloud if necessary,

```
> sudo easy_install pandas
```



Clone with the **SSH**

```
> git clone git@github.com:lazyprogrammer/machine_learning_examples.git
```

**ISSUE:** the GIT may take long time to install. So, it's better to copy over the file from the local sources. The following command will copy all the files from the **[ann\_class2]** folder to the **AWS cloud**. After **cd** in the **machine\_learning\_examples** folder, run the command in the terminal,

```
> scp -i awstheano_name.pem machine_learning_examples/ann_class2/*
ubuntu@ec2-54-173-15-92.compute-1.amazonaws.com
```

```
> ssh -i awstheano_name.pem
ubuntu@ec2-54-173-15-92.compute-1.amazonaws.com
```

# check what's in the folder

```
> ls
```

# make a new folder in the AWS cloud,

```
> mkdir ann_class2
```

Copy all the files that comes from the local machine to the [ann\_class2] folder in the AWS cloud.

# move all the .py files in the newly created **ann\_class2** folder,

```
> mv *.py ann_class2/
```

```
> cd ann_class2
```

Need to figure out how to open the files in the Ubuntu operating system in the AWS. Make sure all the data types in the **theano\_gpu.py** file are in 32 bytes,

```
Ytrain_ind = y2indicator(Ytrain).astype(np.float32)
```

```
Ytest_ind = y2indicator(Ytest).astype(np.float32)
```

Then, quit with the command **Q**

```
> vi theano2.py
```



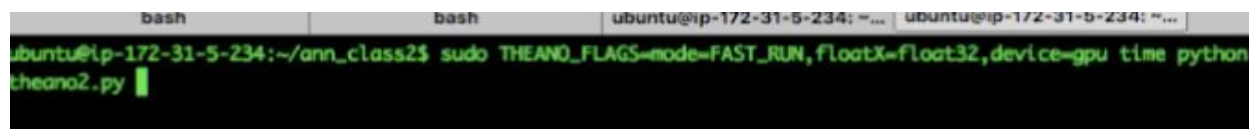
# run the command to execute the python file in the AWS cloud,

> **sudo python theano2.py**

# run the **theano2.py** file in the CPU AWS

> **sudo THEANO\_FLAGS=mode=FAST\_RUN,device=cpu,floatX=float32 time python theano2.py**

# Get rid of the matplotlib and run the **theano\_gpu.py** file in the CPU AWS



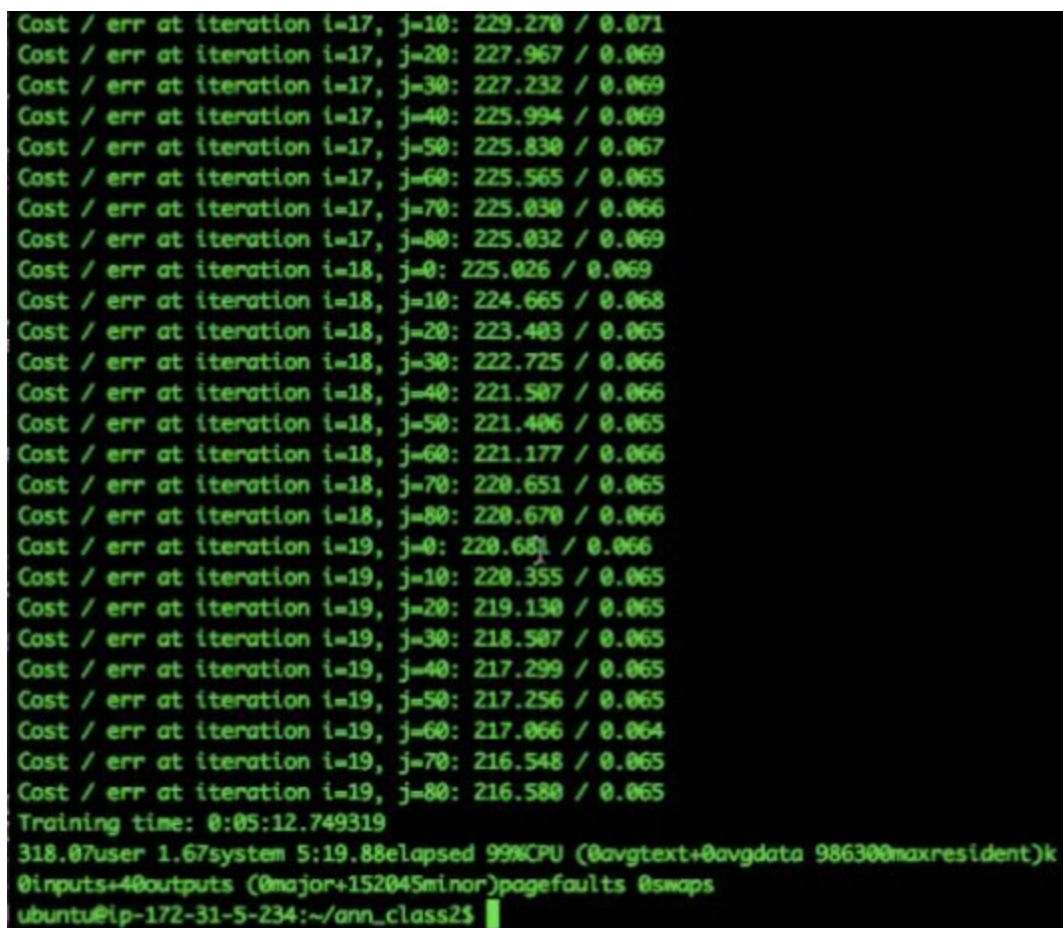
```

bash      bash      ubuntu@ip-172-31-5-234: ~...  ubuntu@ip-172-31-5-234: ~...
ubuntu@ip-172-31-5-234:~/ann_class2$ sudo THEANO_FLAGS=mode=FAST_RUN,floatX=float32,device=gpu time python theano2.py

```

> **sudo THEANO\_FLAGS=mode=FAST\_RUN,device=cpu,floatX=float32 time python theano\_gpu.py**

# with the CPU, the total time is about 5 minutes for the training time.



```

Cost / err at iteration i=17, j=10: 229.270 / 0.071
Cost / err at iteration i=17, j=20: 227.967 / 0.069
Cost / err at iteration i=17, j=30: 227.232 / 0.069
Cost / err at iteration i=17, j=40: 225.994 / 0.069
Cost / err at iteration i=17, j=50: 225.830 / 0.067
Cost / err at iteration i=17, j=60: 225.565 / 0.065
Cost / err at iteration i=17, j=70: 225.030 / 0.066
Cost / err at iteration i=17, j=80: 225.032 / 0.069
Cost / err at iteration i=18, j=0: 225.026 / 0.069
Cost / err at iteration i=18, j=10: 224.665 / 0.068
Cost / err at iteration i=18, j=20: 223.403 / 0.065
Cost / err at iteration i=18, j=30: 222.725 / 0.066
Cost / err at iteration i=18, j=40: 221.507 / 0.066
Cost / err at iteration i=18, j=50: 221.406 / 0.065
Cost / err at iteration i=18, j=60: 221.177 / 0.066
Cost / err at iteration i=18, j=70: 220.651 / 0.065
Cost / err at iteration i=18, j=80: 220.670 / 0.066
Cost / err at iteration i=19, j=0: 220.681 / 0.066
Cost / err at iteration i=19, j=10: 220.355 / 0.065
Cost / err at iteration i=19, j=20: 219.130 / 0.065
Cost / err at iteration i=19, j=30: 218.507 / 0.065
Cost / err at iteration i=19, j=40: 217.299 / 0.065
Cost / err at iteration i=19, j=50: 217.256 / 0.065
Cost / err at iteration i=19, j=60: 217.066 / 0.064
Cost / err at iteration i=19, j=70: 216.548 / 0.065
Cost / err at iteration i=19, j=80: 216.580 / 0.065
Training time: 0:05:12.749319
318.07user 1.67system 5:19.88elapsed 99%CPU (0avgtext+0avgdata 986300maxresident)k
0inputs+40outputs (0major+152045minor)pagefaults 0swaps
ubuntu@ip-172-31-5-234:~/ann_class2$

```

# now, run the **theano\_gpu.py** file in the GPU AWS

```

Training time: 0:05:11.745519
318.07user 1.67system 5:19.88elapsed 99%CPU (0avgtext+0avgdata 986300maxresident)k
0inputs+40outputs (0major+152045minor)pagefaults 0swaps
ubuntu@ip-172-31-5-234:~/ann_class2$ sudo THEANO_FLAGS=mode=FAST_RUN,floatX=float32,device=gpu time python
theano_gpu.py

```

> **sudo THEANO\_FLAGS=mode=FAST\_RUN,device=gpu,floatX=float32 time python theano\_gpu.py**

# with the GPU, the total training time is about 17 seconds which is much better than the CPU.

```

Cost / err at iteration i=19, j=70: 231.948 / 0.060
Cost / err at iteration i=19, j=80: 230.885 / 0.058
Training time: 0:00:17.883282
11.63user 13.79system 0:25.60elapsed 99%CPU (0avgtext+0avgdata 1080624maxresident)k
0inputs+40outputs (0major+184025minor)pagefaults 0swaps
ubuntu@ip-172-31-5-234:~/ann_class2$

```

## Theano vs. TensorFlow

- Ex. Recurrent neural network that can handle sequences of different lengths
- Simple example: representing a sentence
- Clearly our sentences will be of different lengths
- Possible in TensorFlow?
- Not really.
- Can pad every sequence so they're the same length, but functionality is not native

## Theano vs. TensorFlow

- Ex. Recursive Neural Networks (used for Deep NLP - representing sentences hierarchically)
  - Each sentence will be represented by a different tree
  - Neural networks have a static structure, graph must be compiled before using
  - TensorFlow can't do it
  - Clever trick in Theano makes it possible
- 
- BUT:
  - None of this will make intuitive sense to you, since you need to have a better idea of what these algorithms do, and what is required in the code

## Theano vs. TensorFlow

- I like Theano better for teaching and learning, it allows you to write lower-level code
- Deep learning is lots of math
- Theano allows you to write the equations directly (very little changes from theory → code)
- No need to translate your equation to something else
- No need to look up special library functions
- With TensorFlow, it becomes an exercise in reading documentation
- Theano lets you work from first principles

## Theano vs. TensorFlow

- Ex. Dropout (you've seen it)
- Theano: you have to think about the problem, come up with an equivalent solution in code
- We don't actually "drop" nodes (i.e. modify the graph, since as we discussed that's not possible), we just set them to 0
- TensorFlow: just call `tf.nn.dropout`
- Completely hides what's happening

## Theano vs. TensorFlow

- Another example: LSTM (recurrent neural unit)
- Very complicated structure
- We are used to one weight matrix  $W$  and one bias vector  $b$
- LSTM has 11  $W$ 's and 6  $b$ 's!
- Theano requires you to implement the equations directly
- TensorFlow: use the object LSTMCell
- Not really useful for studying LSTMs

## Theano vs. TensorFlow

- Advantages to using TensorFlow
- Huge team of people; lots of attention
- TensorFlow is industrial, Theano is academic
- Money, community
- Growing fast, changing/being updated all the time
- Parts of my courses have become out of date within months!
- Limitations of TensorFlow today may not be limitations tomorrow

## Theano vs. TensorFlow

- In the end, it's up to you to weight the unique factors of your own project
- Common sense solution:
- You want your team to develop fast and efficiently
- Use what they're familiar with
- But, if something can't be implemented in TensorFlow, you need a tool that can do it
- Use common sense!
- I hope you continue to study and practice both Theano and TensorFlow coding, so you can understand the points we brought up in this lecture



1. Choose AMI 2. Choose Instance Type 3. Configure Instance 4. Add Storage 5. Tag Spot Request 6. Configure Security Group

## Step 7: Review Spot Instance Request

Please review your instance launch details. You can go back to edit changes for each section. Click **Launch** to assign a key pair to your instance and complete the launch process.

**⚠ Improve your instances' security. Your security group, launch-wizard-4, is open to the world.**  
Your instances may be accessible from any IP address. We recommend that you update your security group rules to allow access from known IP addresses only. You can also open additional ports in your security group to facilitate access to the application or service you're running, e.g., HTTP (80) for web servers. [Edit security groups](#)

### AMI Details

[Edit AMI](#)


**gpu\_theano - ami-2ca87b44**

Root Device Type: ebs Virtualization type: hvm

### Instance Type

[Edit instance type](#)

Instance Type	ECUs	vCPUs	Memory (GiB)	Instance Storage (GB)	EBS-Optimized Available	Network Performance
g2.xlarge	26	8	15	1 x 60	Yes	High

[Cancel](#)
[Previous](#)
[Launch](#)

AWS

Services

Edit

EC2 Dashboard

Events

Tags

Reports

Limits

INSTANCES

Instances

**Spot Requests**

Reserved Instances

Scheduled Instances

Commands

Dedicated Hosts

IMAGES

AMIs

Request Spot Instances

Cancel

Pricing History

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Name	Request ID	Max Price	AMI ID	Instance	Instance Type	State	Status
	sr-02g3fzea	\$0.1	ami-2ca87b44		g2.xlarge	open	pending-evalu...



```

It is required that your private key files are NOT accessible by others.
This private key will be ignored.
Load key "TheanoClass.pem": bad permissions
Permission denied (publickey).
Macs-MacBook-Pro:Code macuser$ chmod 400 TheanoClass.pem
Macs-MacBook-Pro:Code macuser$ ssh -i TheanoClass.pem ubuntu@ec2-54-173-15-92.compute-1.amazonaws.com
Welcome to Ubuntu 14.04.1 LTS (GNU/Linux 3.13.0-32-generic x86_64)

 * Documentation:  https://help.ubuntu.com/

System information as of Thu Feb 25 06:40:53 UTC 2016

System load:  0.83           Processes:           157
Usage of /:   51.8% of 7.74GB Users logged in:      0
Memory usage: 1%            IP address for eth0: 172.31.5.234
Swap usage:   0%

Graph this data and manage this system at:
https://landscape.canonical.com/

Get cloud support with Ubuntu Advantage Cloud Guest:
http://www.ubuntu.com/business/services/cloud

*** /dev/xvda1 should be checked for errors ***

Last login: Mon Aug 11 00:23:57 2014 from 209-6-206-91.c3-0.smr-ubr2.sbo-smr.ma.cable.rcn.com
ubuntu@ip-172-31-5-234:~$
ubuntu@ip-172-31-5-234:~$
ubuntu@ip-172-31-5-234:~$

```

```

Cost / err at iteration i=17, j=50: 225.830 / 0.067
Cost / err at iteration i=17, j=60: 225.565 / 0.065
Cost / err at iteration i=17, j=70: 225.030 / 0.066
Cost / err at iteration i=17, j=80: 225.032 / 0.069
Cost / err at iteration i=18, j=0: 225.026 / 0.069
Cost / err at iteration i=18, j=10: 224.665 / 0.068
Cost / err at iteration i=18, j=20: 223.403 / 0.065
Cost / err at iteration i=18, j=30: 222.725 / 0.066
Cost / err at iteration i=18, j=40: 221.507 / 0.066
Cost / err at iteration i=18, j=50: 221.406 / 0.065
Cost / err at iteration i=18, j=60: 221.177 / 0.066
Cost / err at iteration i=18, j=70: 220.651 / 0.065
Cost / err at iteration i=18, j=80: 220.670 / 0.066
Cost / err at iteration i=19, j=0: 220.681 / 0.066
Cost / err at iteration i=19, j=10: 220.355 / 0.065
Cost / err at iteration i=19, j=20: 219.130 / 0.065
Cost / err at iteration i=19, j=30: 218.507 / 0.065
Cost / err at iteration i=19, j=40: 217.299 / 0.065
Cost / err at iteration i=19, j=50: 217.256 / 0.065
Cost / err at iteration i=19, j=60: 217.066 / 0.064
Cost / err at iteration i=19, j=70: 216.548 / 0.065
Cost / err at iteration i=19, j=80: 216.580 / 0.065
Training time: 0:05:12.749319
318.07user 1.67system 5:19.88elapsed 99%CPU (0avgtext+0avgdata 986300maxresident)k
0inputs+40outputs (0major+152045minor)pagefaults 0swaps
ubuntu@ip-172-31-5-234:~/ann_class2$ sudo THEANO_FLAGS=mode=FAST_RUN,floatX=float32,device=gpu time python
theano_gpu.py
Using gpu device 0: GRID K520
Reading in and transforming data...

```

CPU

Set up a GPU instance in the Amazon Web Service (AWS)

## Exercises

- 1) Implement logistic regression in Theano and TensorFlow.
- 2) Implement momentum in Theano.
- 3) Implement RMSprop in Theano.
- 4) Try them on GPU, compare with CPU.
- 5) How could you use a GPU-powered ANN in your own work? How would it fit into existing architecture? How would you save the weights learned by the model? When and how would it be updated?

## The data

- 48x48 grayscale images
- Faces are centered, approx same size
- 7 classes:
  - 0 = Angry
  - 1 = Disgust
  - 2 = Fear
  - 3 = Happy
  - 4 = Sad
  - 5 = Surprise
  - 6 = Neutral
- 3 column CSV: label, pixels (space-separated), train/test

# Hyperparameters

- Manually choosing the learning rate and regularization penalty
- It's a question I get often
- People are “uncomfortable” that there is a number you can't calculate, t just need to find
- Isn't this science? Doesn't science give direct and concrete answers?
- Get used to it!

## Learning rate

- We know so far: it's a “small number”
- You've seen some examples, so you have an idea of order of magnitude
- The right scale:
- If I've already tried 0.1, then I don't need to try 0.09, 0.08, 0.07, etc.
- (But you would have discovered that through experience!)
- Better to go down on log scale / factors of 10
- $10^{-1}$ ,  $10^{-2}$ ,  $10^{-3}$ , etc...
- I've used  $10^{-7}$  before

## Too high or too low

- Too high  $\rightarrow$  cost goes to infinity / NaN
- Neural network will continue to train as normal, multiplying NaNs as if they were actual numbers
- Cost converges too slowly  $\rightarrow$  learning rate is too low
- Try increasing by factor of 10
- Problems?
- Try to turn off all modifications except for regular gradient descent (no regularization or anything else you've learned)
- Learning rate that's too high will mess things up, but learning rate that's too low won't
- If things still don't work, could be a problem with your code

## Normalizing cost and regularization penalty

- In deep learning part 2 we discuss training a neural network in batches
  - Learning rate will be sensitive to number of training points / batch size
  - Because cost is sum of individual errors
  - Just divide by  $N$  (batch size) to normalize it
- 
- Same issue with number of parameters and regularization
  - To make regularization penalty independent of number of parameters, divide by number of parameters

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## Regularization too high

- In the past, I forgot to multiply my regularization penalty by the regularization parameter (effectively setting it to 1)
- For that particular problem, this was much too high
- So the error rate just hovered around random guessing
- Sometimes it's useful to just turn off regularization completely, and make learning rate very small
- Tells you if your model actually works or if there's a bug in your code