

MACHINE LEARNING DAY 2

DEEP LEARNING

Session III: Multi-Layer Perceptron



Isaac Ye, HPTC @ York University

Isaac@sharcnet.ca

Session III

- Binary classification
- Logistic model / cross entropy function
- Issue with linear regression
- XOR problem with Multi-Layer Perceptron (MLP)
- Lab 3A: Multivariable linear regression with MLP
- GPU on Graham / PyTorch + GPU
- Lab 3B: running a DL code on Graham using GPU

Supervised learning

Supervised

Classification

Regression

Supervised

Input Data (x, y) x: data, y: label

Goal learn a function to map x to y

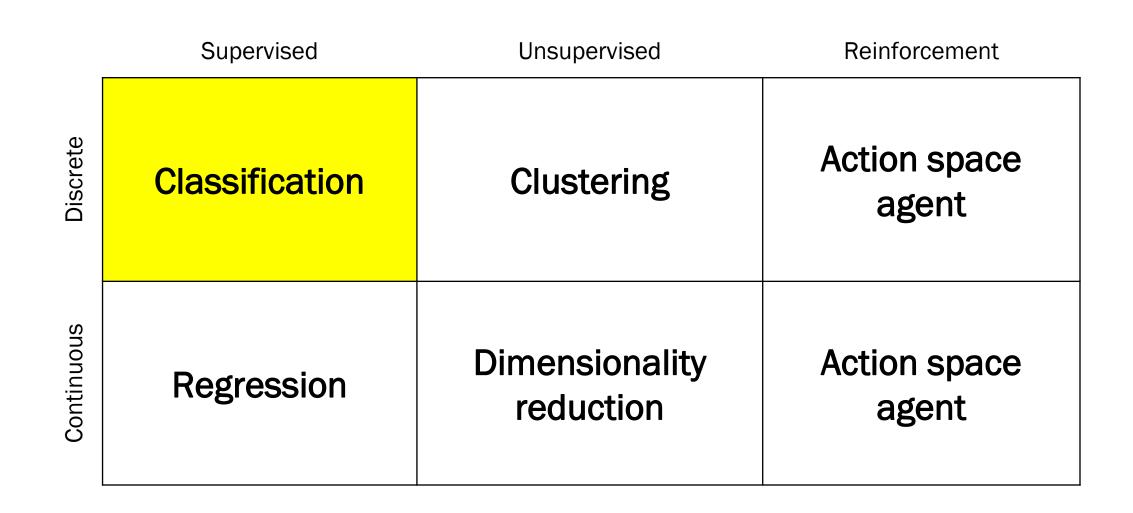
Examples classification, regression, object detection

semantic segmentation, image captioning

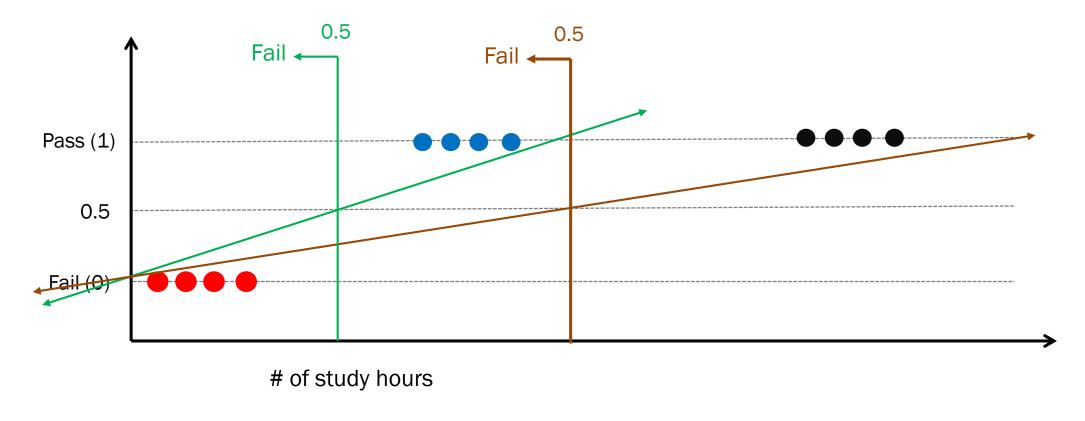
Discrete

Continuous

Categories of ML problems

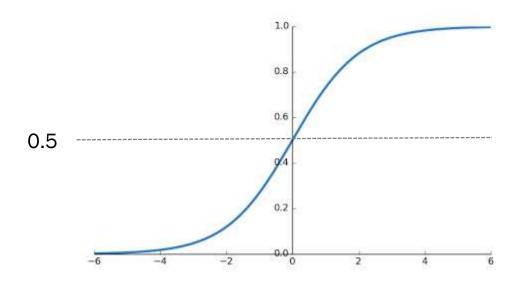


Binary classification



Linear regression is not good to solve binary problem!

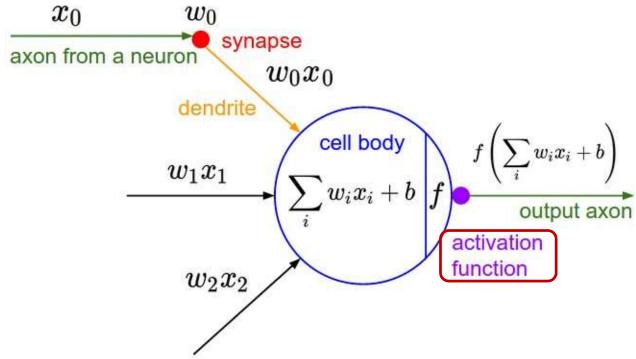
Model: Logistic (Sigmoid) hypothesis



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

$$H(x) = f(Wx + b)$$
$$z = Wx + b$$
$$H(z) = f(z)$$

Neural Network



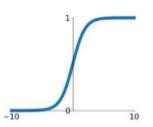
http://cs231n.github.io/neural-networks-1/

Mathematical model

Activation functions

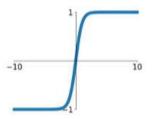
Sigmoid

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



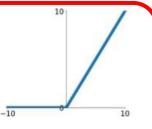
tanh

tanh(x)



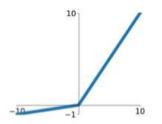
ReLU

 $\max(0, x)$



Leaky ReLU

 $\max(0.1x, x)$

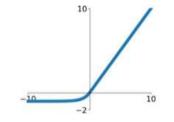


Maxout

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

ELU

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Most commonly used

Cost function: Cross Entropy

Cross entropy: difference between two probability distribution

$$H(P,Q) = -\sum P(x)\log Q(x)$$

P(x): actual probability

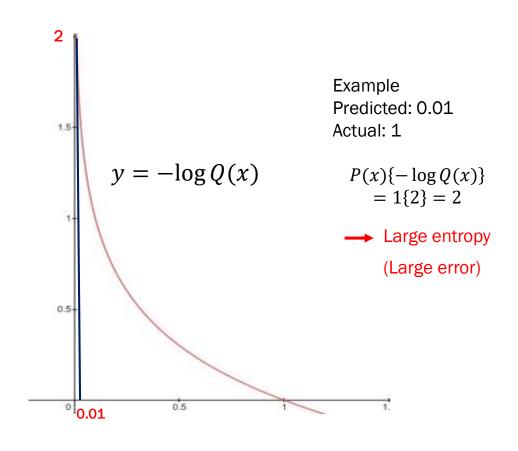
Q(x): predicted probability

CROSSENTROPYLOSS

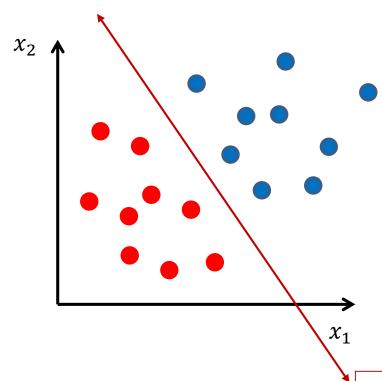
CLASS torch.nn.CrossEntropyLoss(weight=None, size_average=None, ignore_index=-100, reduce=None, reduction='mean') [SCURCE]

This criterion combines nn.LogSoftmax() and nn.NLLLoss() in one single class.

It is useful when training a classification problem with C classes. If provided, the optional argument weight should be a 1D Tensor assigning weight to each of the classes. This is particularly useful when you have an unbalanced training set.



Decision boundary



$$H(x) = G(Wx + b)$$

Sigmoid(wx + b) = 0.5

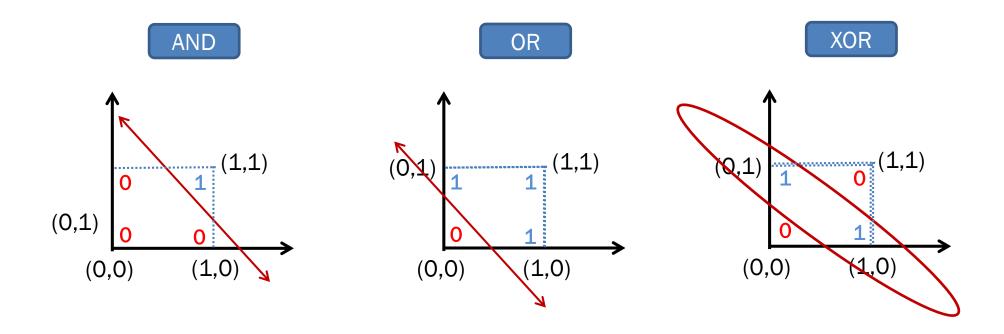
$$\rightarrow$$
 $wx + b = 0$

For two input feature problem, one can have

$$w_1 x_1 + w_2 x_2 + b = 0$$

→ Linear line!

Decision boundary line

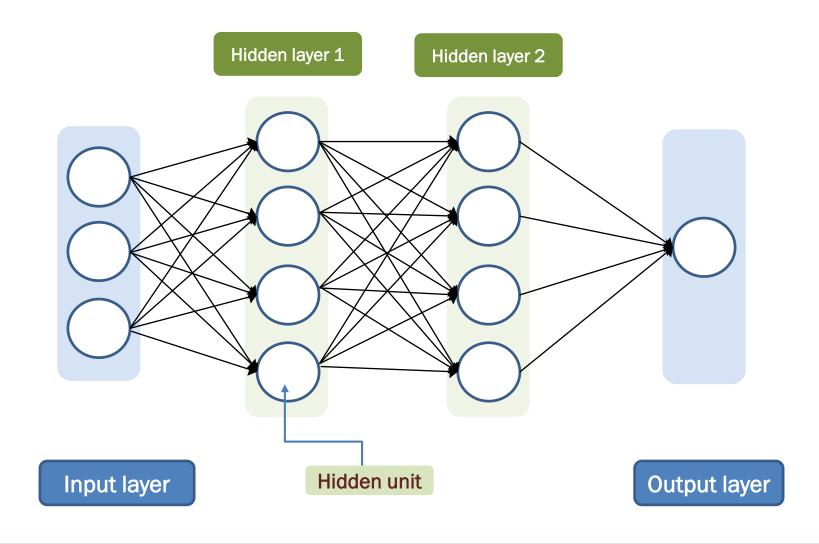


False: 0

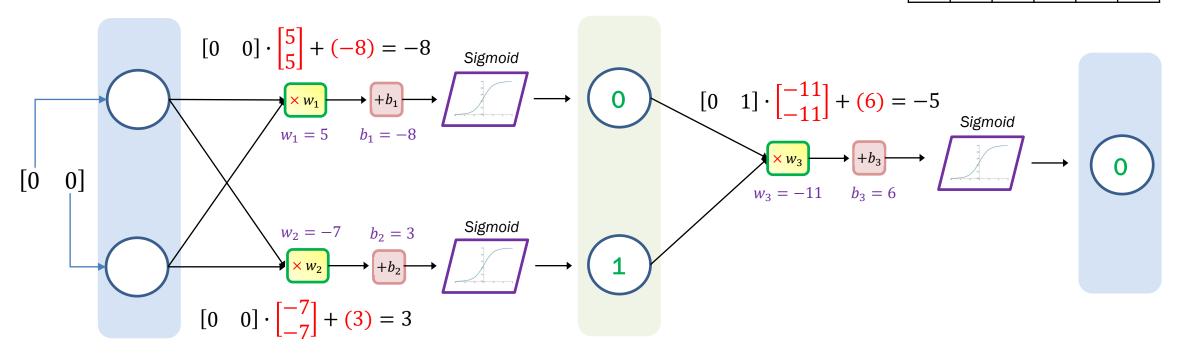
True: 1

Fail to find a decision line!

Multi-Layer Perceptron



x_1	x_2	y_1	y_2	ŷ	у
0	0	0	1	0	0
1	0				1
0	1				1
1	1				0



input features = 2 Output features = 2

Input layer

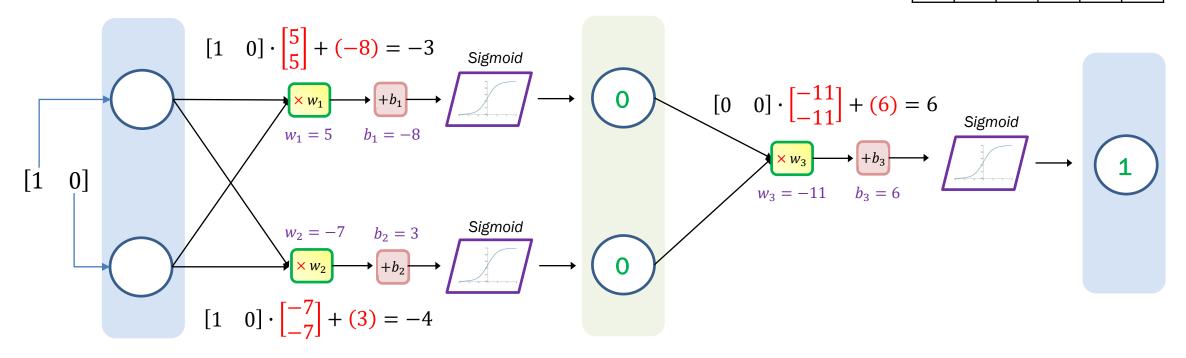
input features = 2 Output features = 1

Hidden layer

of feature = 1

Output layer

x_1	x_2	y_1	y_2	ŷ	у
0	0	0	1	0	0
1	0				1
0	1				1
1	1				0



input features = 2 Output features = 2

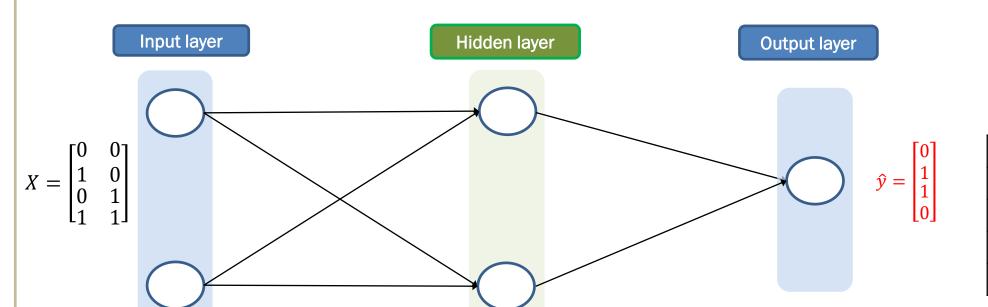
Input layer

input features = 2 Output features = 1

Hidden layer

of feature = 1

Output layer



x_1	x_2	y_1	y_2	ŷ	у
0	0	0	1	0	0
1	0	0	0	1	1
0	1	0	0	1	1
1	1	1	0	0	0

$$\begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} 5 & -7 \\ 5 & -7 \end{bmatrix} + \begin{bmatrix} -8 & 3 \\ -8 & 3 \\ -8 & 3 \end{bmatrix} = \begin{bmatrix} -8 & 3 \\ -3 & -4 \\ -3 & -4 \\ 2 & -11 \end{bmatrix} \xrightarrow{\text{Sigmoid}} \begin{bmatrix} 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \end{bmatrix}$$

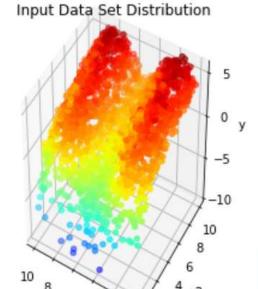
$$\begin{bmatrix} 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} -11 \\ -11 \end{bmatrix} + \begin{bmatrix} 6 \\ 6 \\ 6 \\ 6 \end{bmatrix} = \begin{bmatrix} -5 \\ 6 \\ 6 \\ -5 \end{bmatrix} \longrightarrow \begin{bmatrix} \text{Sigmoid} \\ 1 \\ 1 \\ 0 \end{bmatrix}$$

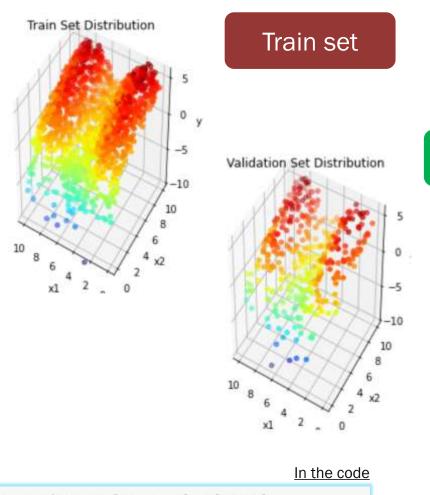
Data Preparation

Testing set

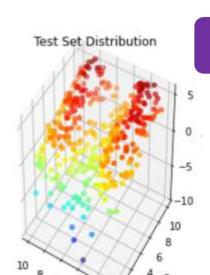
Data preparation

x ₁	x ₂	у
3.91870851	2.32626914	0.73817558
2.59194437	6.00656071	4.3940048
6.46991632	3.57514815	0.61488728
· ·	:	:
4.56486433	2.14296641	3.95964088
1.29483514	1.67730041	3.48018992





Validation set



train_X, train_y = X[:1600, :], y[:1600]
val_X, val_y = X[1600:2000, :], y[1600:2000]
test_X, test_y = X[2000:, :], y[2000:]

Model define

Model define

In the code

```
import torch
import torch.nn as nn
class MLPModel(nn.Module):
   def __init__(self):
        super(MLPModel, self).__init__()
       self.linear1 = nn.Linear(in_features=2, out_features=200)
        self.linear2 = nn.Linear(in_features=200, out_features=1)
       self.relu = nn.ReLU()
   def forward(self, x):
       x = self.linear1(x)
       x = self.relu(x)
       x = self.linear2(x)
        return x
```

Cost (loss) function + Optimizer



Loss function

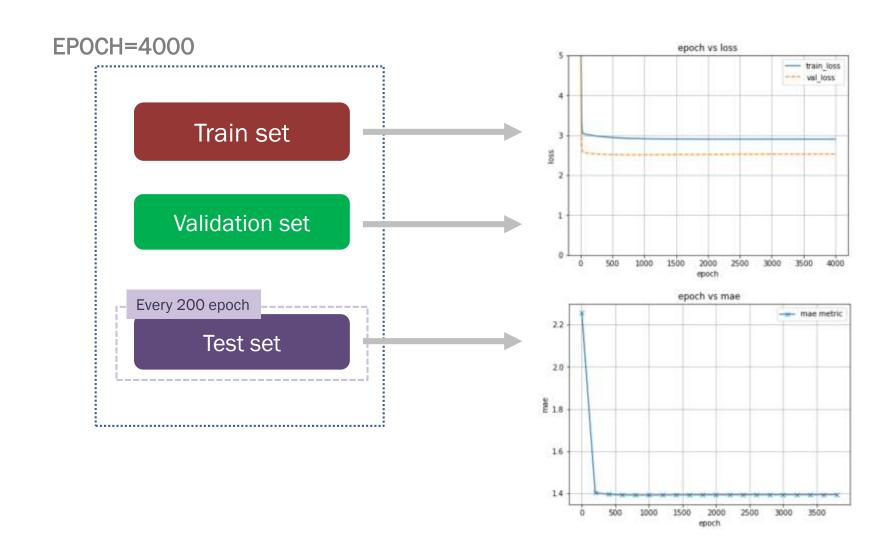
Optimizer

```
lr = 0.005
optimizer = optim.SGD(model.parameters(), lr =lr)
```

In the code

In the code

Model test



PyToch + GPU

Using GPU, one can reduce runtime!

Check if PyToch recognize 'GPU'

Put data to the detected device

Move data back to 'CPU'

```
# ===== GPU selection ====== #
device = 'cuda:0' if torch.cuda.is_available() else 'cpu'
model.to(device)

if device != 'cpu':
    input_x = input_x.to(device)
    true_y = true_y.to(device)

if device != 'cpu':
```

list train loss.append(loss.cpu().detach().numpy())

list train loss.append(loss.detach().numpy())

else:

Lab 3A: Linear regression – MLP

Exercise 1: CPU/GPU	cores
Run 1	CPU
Run 2	GPU

Exercise 2: more layers w/ 100 units	# of layers
Run 1	2
Run 2	4
Run 3	8

Exercise 3: more units w/ 2 layers	# of units
Run 1	100
Run 2	200

Exercise 4: different activation	Activation function
Run 1	relu
Run 2	sigmoid

https://pytorch.org/docs/stable/nn.html
#non-linear-activations-weighted-sum-nonlinearity

You may want to try

- 1. Increase size of data and re-run it
- 2. Use different optimizers

https://pytorch.org/docs/stable/optim.html?highlight=optimizer#torch.optim.Optimizer

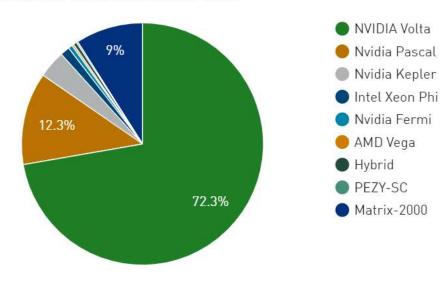


Running a DL code using GPU in Graham

DL and HPC architectures

NVIDIA GPUs are the main driving force for faster training DL models

Accelerator/CP Family Performance Share



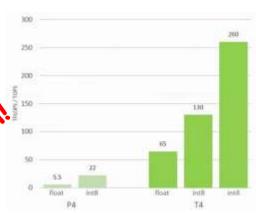
https://top500.org

NVIDIA T4 Turing GPU on Graham



Streaming Multiprocessor 8 Tensor cores

40 SM in T4 8.1 Tflops FP32 65 Tflops FP16



GPU resources in Compute Canada

As of Feb, 2020

	# of nodes	GPU type	Note
Graham	160	P100 Pascal	gres=gpu:1
	7	V100 Volta	CPU/GPU ≤ 3.5 gres=gpu:v100:1
	36	T4 Turing (for DL)	CPU/GPU ≤ 3.5 gres=gpu:t4:2
Cedar	146	P100 Pascal	-gres=gpu:1
Beluga	172	V100 Volta	CPU/GPU ≤ 3.5 gres=gpu:v100:1
Niagara	None		

Lab 3B - Running it on Graham (Interactive mode)

Running a DL code on CPU interactively in Graham

- cd /home/\$USER/scratch/\$USER/SS2020V2_ML_Day2/Session_3
- 2. Start interactive running mode

```
salloc --time=0:30:0 --ntasks=1 --cpus-per-task=3 --nodes=1 --mem=1000M --account=def-training-wa --reservation=snss20_wr_cpu
```

3. virtual environment (make sure you load python and scipy-stack module)

```
module load python
module load sci-py-stack
source ~/ENV/bin/activate
```

4. Run it

```
python SS20_lab3_LR_MLPg.py
```

5. File transfer plotting files to your local computer using WinScp or MobaXterm (Windows) / sftp (Linux, Mac) and check it out

Lab 3B - Running it on Graham (batch mode)

Running a DL code via scheduler in Graham

1. Write a submission script 'job_s.sh' like below using text editor

```
#!/bin/bash

# 
#SBATCH --nodes=1
#SBATCH --gres=gpu:t4:1
#SBATCH --mem=20000M
#SBATCH --time=0-30:00
#SBATCH --account=def-training-wa
#SBATCH --reservation=snss20_wr_gpu
#SBATCH --output=slurm.%x.%j.out

module load python scipy-stack
source ~/ENV/bin/activate
cd /home/$USER/scratch/$USER/SS2020V2_ML_Day2/Session_3
python /home/$USER/scratch/$USER/SS2020V2_ML_Day2/Session_3/SS20_lab3_LR_MLPg.py
```

2. Submit it

```
sbatch job_s.sh
```

3. Check the submitted job

```
squeue -u $USER
```

4. File transfer plotting files to your local computer using WinScp or MobaXterm (Windows) / sftp (Linux, Mac) and check it out

Session break:

Please come back by 3:30 PM