

#### **MACHINE LEARNING DAY 2**

## DEEP LEARNING

#### **Session II: Linear regression**



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#### Session II

- Categories of ML problems
- Linear regression (single variable)
- Cost function / gradient decent algorithm / learning rate
- Lab 2A: linear regression (single variable)
- Linear regression (multi-variables)
- PyTorch model/cost function/optimizer
- Lab 2B: linear regression

### Categories of ML problems

Supervised Unsupervised Reinforcement Discrete **Action space** Classification Clustering agent Continuous **Dimensionality Action space** Regression reduction agent

## Categories of ML problems

	Supervised	Unsupervised	Reinforcement
Discrete	Classification	Clustering	Action space agent
Continuous	Regression	Dimensionality reduction	Action space agent

### Reinforcement learning

Discrete

Action space agent

Continuous

Action space agent

#### Reinforcement

Goal Train an agent to achieve a goal through

state/action/reward

Examples Path finder, decision making problem

# Reinforcement learning

#### Reinforcement

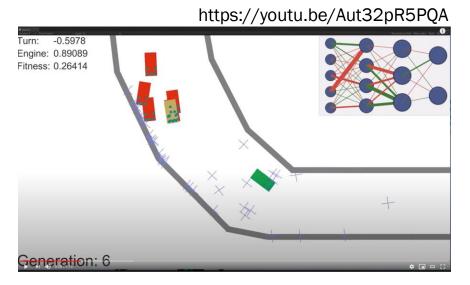
Goal Train an agent to achieve a

goal through

state/action/reward

Examples Path finder, decision making

problem





# Categories of ML problems

	Supervised	Unsupervised	Reinforcement
Discrete	Classification	Clustering	Action space agent
Continuous	Regression	Dimensionality reduction	Action space agent

### Unsupervised learning

Discrete

Continuous

Clustering

Dimensionality reduction

#### Unsupervised

Input Data x

Goal learn some underlying hidden structure of

the data

Examples Clustering, dimensionality reduction,

feature learning, density estimation

## **Unsupervised learning**

#### Unsupervised

Input Data x

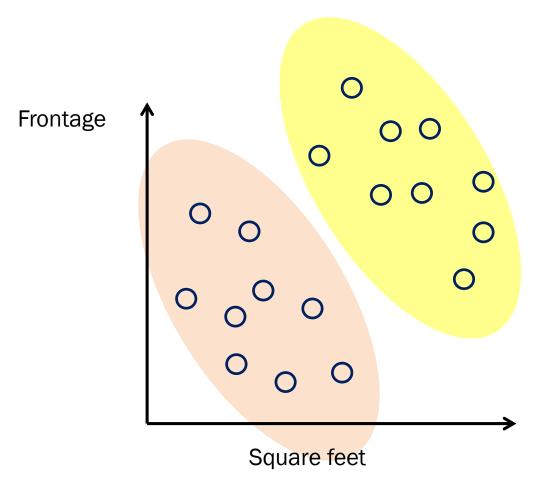
Goal learn some underlying hidden

structure of the data

Examples Clustering, dimensionality

reduction, feature learning,

density estimation



## Categories of ML problems

	Supervised	Unsupervised	Reinforcement
Discrete	Classification	Clustering	Action space agent
Continuous	Regression	Dimensionality reduction	Action space agent

# Supervised learning

Discrete

Continuous

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

# **Supervised learning**

Frontage

#### Supervised

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

Goal learn a function to map x to y

Examples classification, regression,

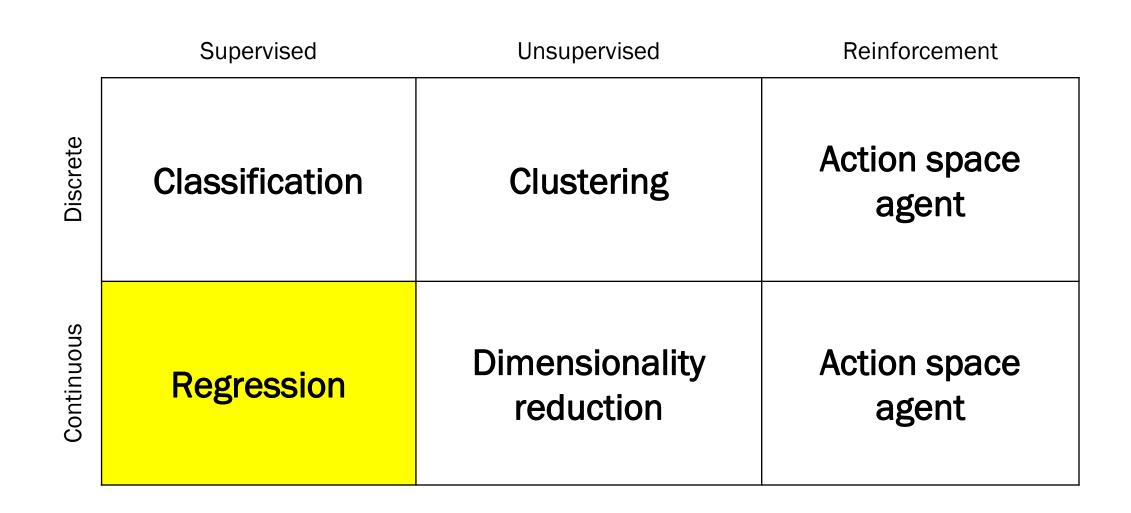
object detection

semantic segmentation, image

captioning

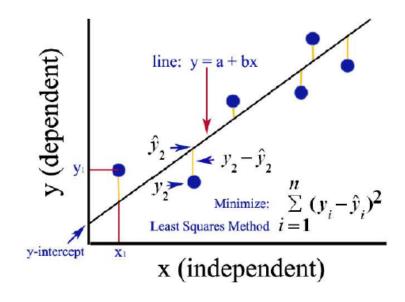
Label: Red(> \$1M), Blue(< \$1M) **Decision line** Square feet

### Categories of ML problems

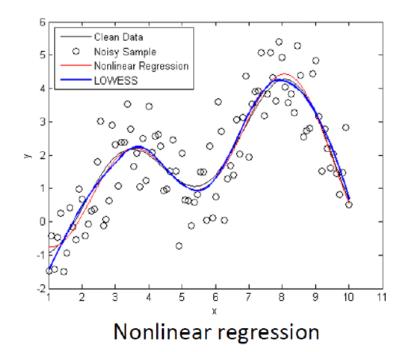


### Regression problem

Fit the prediction function f(x) to the training data to predict continuous real value

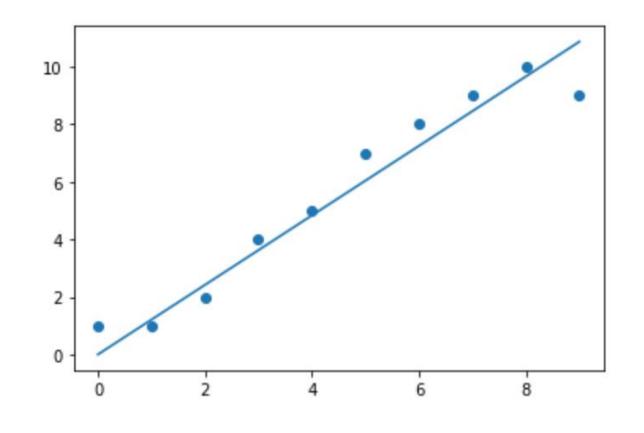


Linear regression



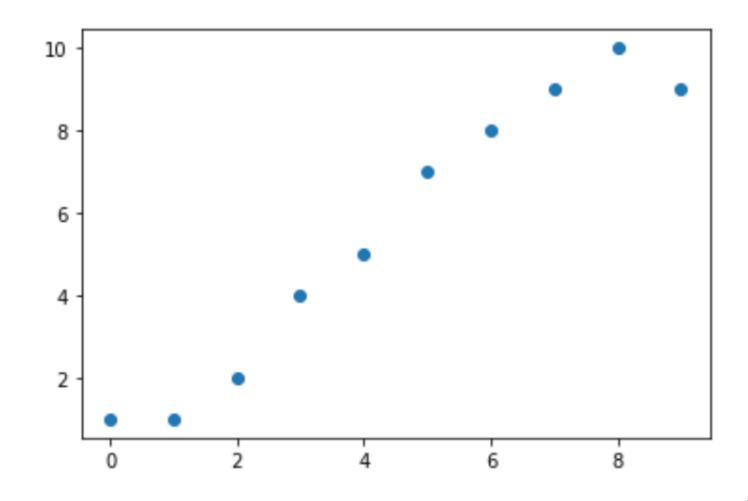
# Linear regression: single variable

X	у
0	1
1	1
2	2
3	4
4	5
5	7
6	8
7	9
8	10
9	9

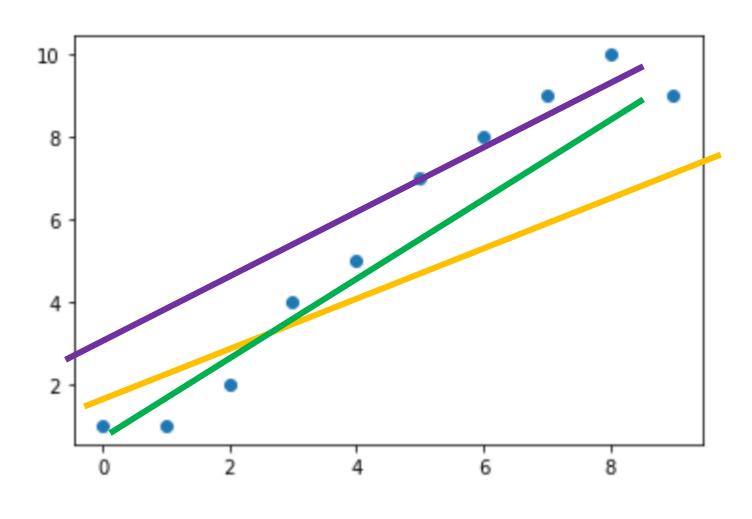


## Data preparation: Input (x, y)

Х	у
0	1
1	1
2	2
3	4
4	5
5	7
6	8
7	9
8	10
9	9

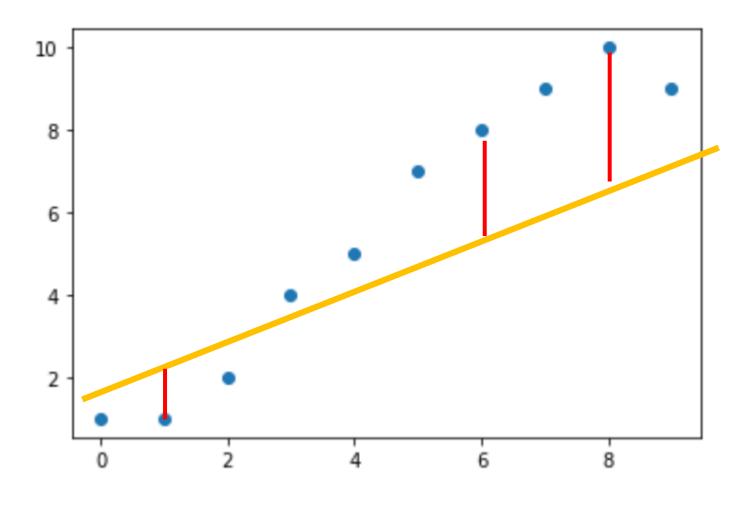


# Model (Hypothesis)



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

#### Which model is better?



How well fit the line to data?

$$H(x) - y$$
Predicted True

#### **Cost function**

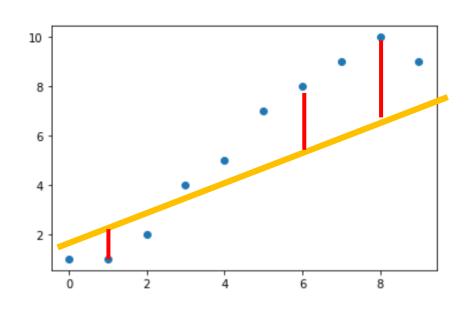
<u>Model</u>

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

Mean Square Error

$$cost = \frac{1}{m} \sum_{i=1}^{m} (H(x_i) - y_i)^2$$

m is the number of data.



Now we can see the <u>cost function</u> as a function of W and b.

$$cost(W, b) = \frac{1}{m} \sum_{i=1}^{m} ((Wx_i + b) - y_i)^2$$

#### Cost function: what we want?

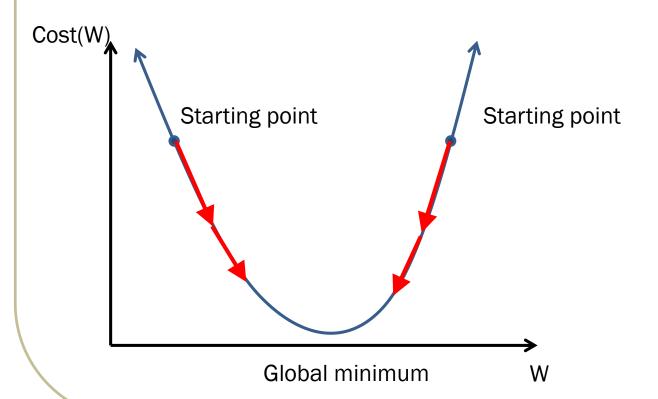
We want to minimize the cost!

$$cost(W,b) = \frac{1}{m} \sum_{i=1}^{m} ((Wx_i + b) - y_i)^2$$

### Gradient decent algorithm

Let's consider a simple case with W only.

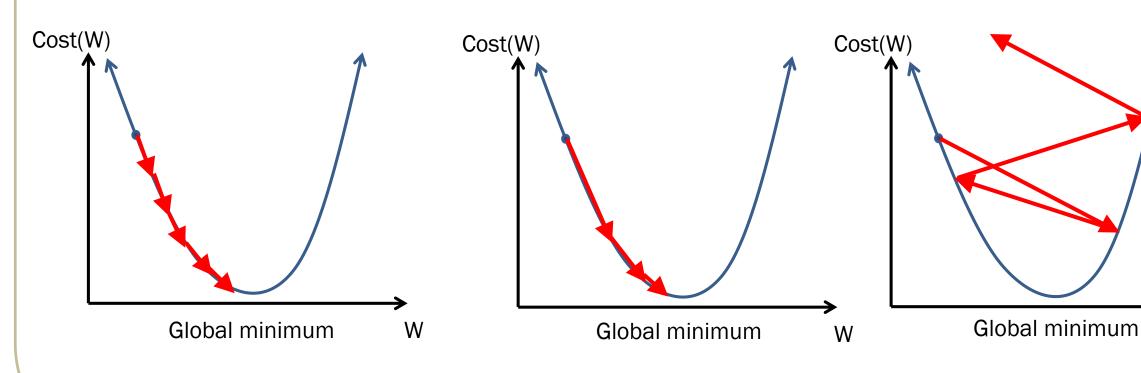
$$cost(W) = \frac{1}{2m} \sum_{i=1}^{m} (Wx_i - y_i)^2$$



$$\frac{d}{dW}cost(W) = \frac{1}{m} \sum_{i=1}^{m} (Wx_i - y_i)x_i$$

$$W \coloneqq W - \alpha \frac{d}{dW} cost(W)$$
Learning rate

Learning rate 
$$W := W - \omega \frac{d}{dW} cost(W)$$
Learning rate



The optimal learning rate (possibly adaptive value)

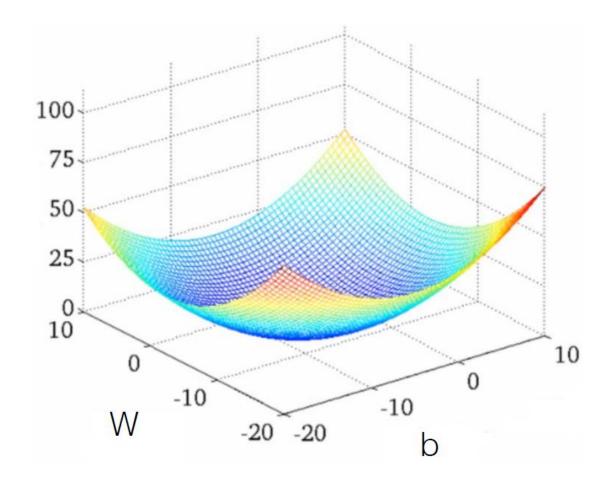
Too large learning rate causes divergence

W

A small learning rate requires many steps

### Cost (loss) function

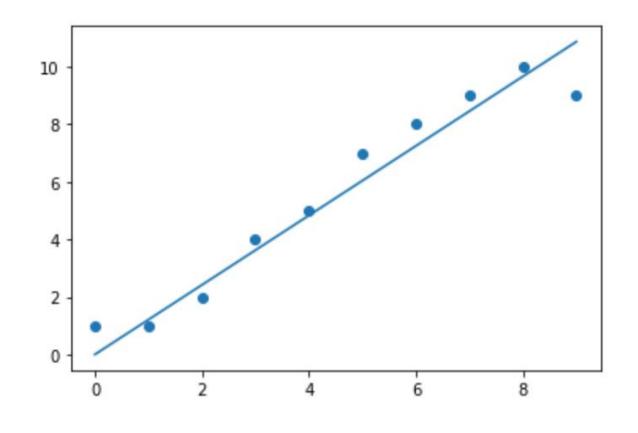
$$cost(W, b) = \frac{1}{m} \sum_{i=1}^{m} ((Wx_i + b) - y_i)^2$$



http://www.holehouse.org/mlclass

### Lab 2A: Linear regression (single variable)

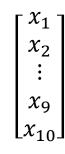
Х	у
0	1
1	1
2	2
3	4
4	5
5	7
6	8
7	9
8	10
9	9

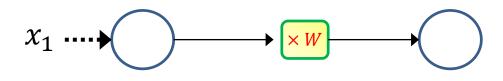


# Layout

Input features = 1
Output features = 1
# of feature = 1

Input layer
Output layer





$$H(x_i) = Wx_i$$

Let's consider a simple case with W only.

### Coding modules

Data Preparation Model define

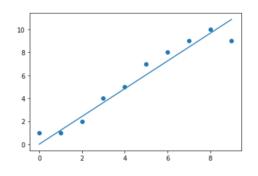
Cost function + optimizer

Model Test

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

$$cost(W) = \frac{1}{m} \sum_{i=1}^{m} (H(x_i) - y_i)^2$$

$$W \coloneqq W - \alpha \frac{d}{dW} cost(W)$$



## Lab 2A: Linear regression - vanilla

#### Github:

https://github.com/isaacye/SS2020 ML Day2

What you may want to try:

- 1. Check the model define
- 2. Check the result by changing the starting point
- 3. Check the result by changing learning rate

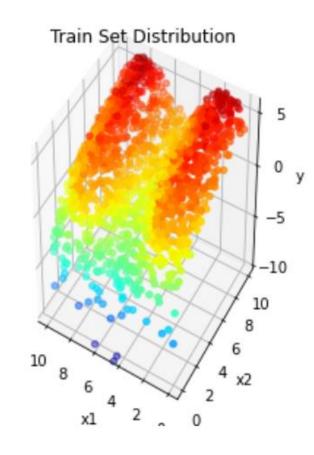


#### Linear regression: multivariable

#### Data preparation: Input $(x_1, x_2, y)$

x <sub>1</sub>	x <sub>2</sub>	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

```
num_data = 2400
x1 = np.random.rand(num_data) *10
x2 = np.random.rand(num_data) *10
e = np.random.normal(0, 0.5, num_data)
X= np.array([x1,x2]).T # T for transpose from (2, 2400) to (2400, 2)
y=2*np.sin(x1) + np.log(0.5*x2**2)+e
```



## Model (Hypothesis)

$$H(x_1, x_2) = w_1x_1 + w_2x_2 + b$$

For the data with n number of features, it is can be written as

$$H(x_1, x_2, x_3, \dots, x_n) = w_1 x_1 + w_2 x_2 + w_3 x_3 + \dots + w_n x_n + b$$

### **Expression in matrix**

$$H(x_{i1}, x_{i2}) = w_1 x_{i1} + w_2 x_{i2} + b$$
$$[x_1 \quad x_2] \cdot {w_1 \brack w_2} + b = w_1 x_1 + w_2 x_2 + b$$

$$\begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} + b = \begin{bmatrix} w_1 x_{11} + w_2 x_{12} + b \\ w_1 x_{21} + w_2 x_{22} + b \\ \vdots \\ w_1 x_{n1} + w_2 x_{n2} + b \end{bmatrix}$$

$$H(X) = XW + b$$

# Layout

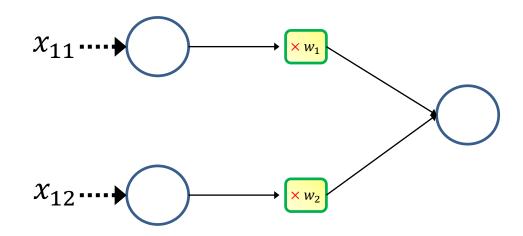
Input features = 2 Output features = 1

Input layer

# of feature = 1

Output layer

$$\begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \end{bmatrix}$$



 $H(x_{i1}, x_{i2}) = w_1 x_{i1} + w_2 x_{i2}$ 

Let's consider a simple case with W only.

#### **Cost function**

$$H(X) = XW + b$$

$$cost = \frac{1}{m} \sum_{i=1}^{m} (H(x_{i1}, x_{i2}) - y_i)^2$$

We want to minimize the cost as well!

# **Coding modules**

Data Preparation Model define

Cost function + optimizer

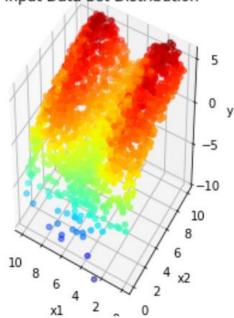
Model Test

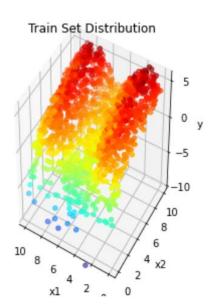
#### Data Preparation

#### **Data preparation**

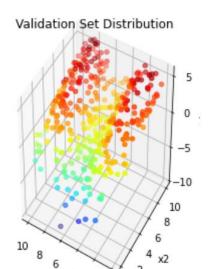
X <sub>1</sub>	X <sub>2</sub>	у
3.91870851	2.32626914	0.73817558
2.59194437	6.00656071	4.3940048
6.46991632	3.57514815	0.61488728
:	:	:
4.56486433	2.14296641	3.95964088
1.29483514	1.67730041	3.48018992

#### Input Data Set Distribution

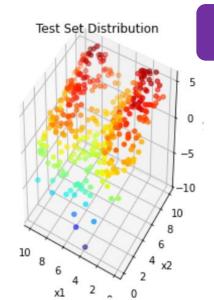




#### Train set



#### Validation set



#### In the code

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:]

Testing set

#### Model define

#### Model define

In the code

```
import torch
import torch.nn as nn

class LinearModel(nn.Module):
    def __init__(self):
        super(LinearModel, self).__init__()
        self.linear = nn.Linear(in_features=2, out_features=1, bias=True)

def forward(self, x):
    return self.linear(x)
```

### Linear model in PyTorch

#### Linear

CLASS torch.nn.Linear(in\_features, out\_features, bias=True)

[SOURCE]

Applies a linear transformation to the incoming data:  $y = xA^T + b$ 

#### **Parameters**

- in\_features size of each input sample
- out\_features size of each output sample
- bias If set to False, the layer will not learn an additive bias. Default: True

#### Shape:

- Input:  $(N,*,H_{in})$  where \* means any number of additional dimensions and  $H_{in}=$  in\_features
- ullet Output:  $(N,*,H_{out})$  where all but the last dimension are the same shape as the input and  $H_{out}={
  m out\_features}$  .

### Cost (loss) function + Optimizer



Loss function

In the code

reg\_loss = nn.MSELoss()

**MSELoss** 

CLASS torch.nn.MSELoss(size\_average=None, reduce=None, reduction='mean')

[SOURCE]

Creates a criterion that measures the mean squared error (squared L2 norm) between each element in the input x and target y.

In the code

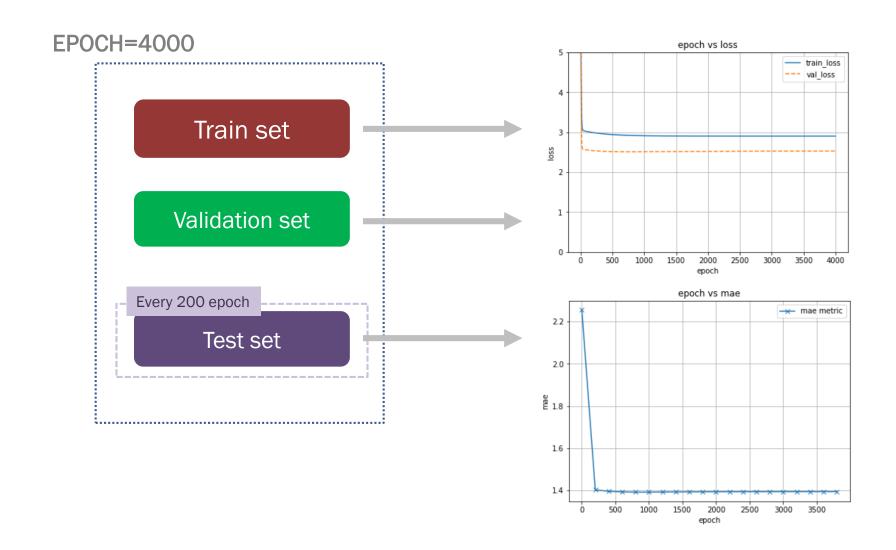
Optimizer

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

[SOURCE]

Implements stochastic gradient descent (optionally with momentum).

#### **Model test**



## Lab 2B: Linear regression – Linear model

- 1. Check the model define (linear model)
- 2. Check the result by varying learning rate
- 3. Check the result w/ w/o bias
- 4. Check the result with different number of Epoch



## Lab 2B: Linear regression – Linear model

#### Github:

https://github.com/isaacye/SS2020 ML Day2

What you may want to try:

- 1. Check the model define
- 2. Check the result by changing learning rate
- 3. Increase size of data and re-run it



**Session break:** 

### Please come back by 2 PM