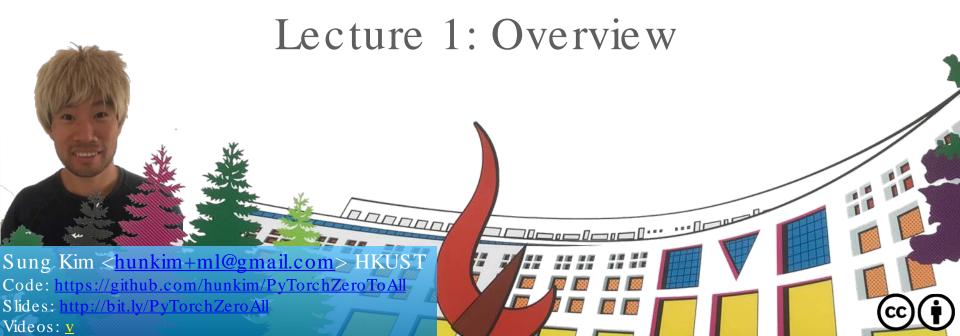
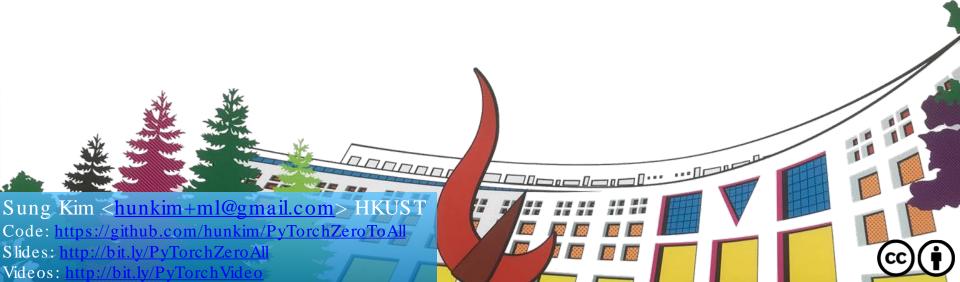
ML/DL for Everyone with PYTERCH



ML/DL for Everyone with PYTORCH

Lecture 1: Overview

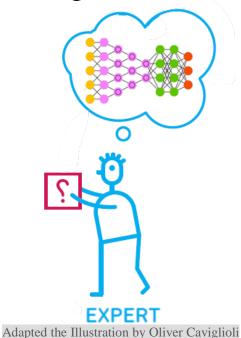


Goals

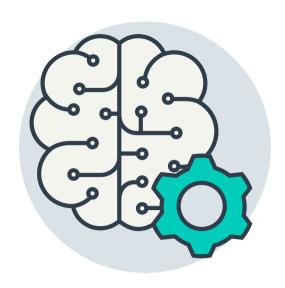
- Basic understanding of machine learning/deep learning
- PyTorch implementation skills

- Zero to All!
- Basic algebra + probability
- Basic python





What is ML?



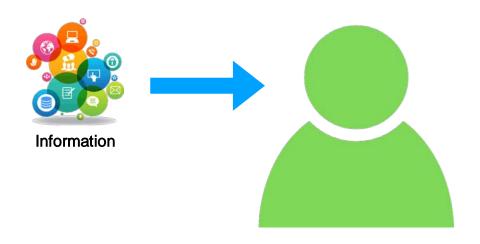
What is Human Intelligence?



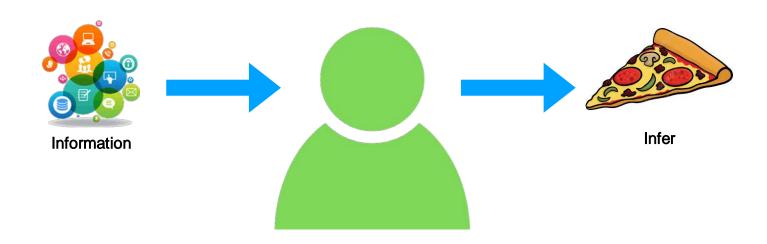
What is Human Intelligence? What to eat for lunch?



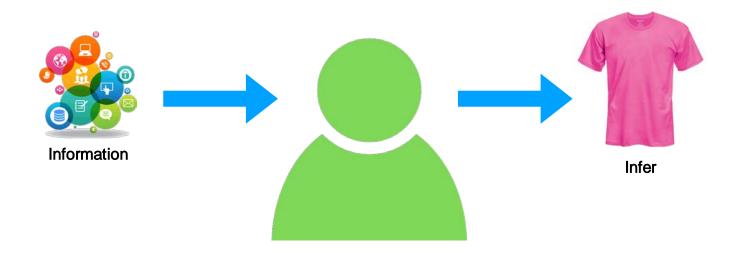
What is Human Intelligence? What to eat for Junch?



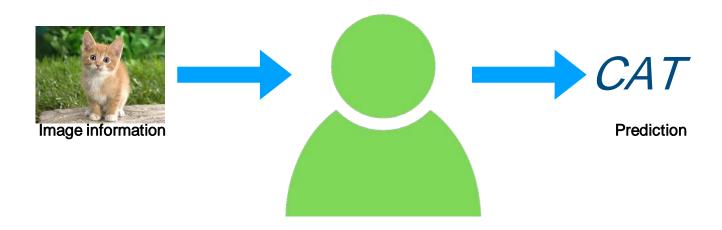
What is Human Intelligence? What to eat for Junch?



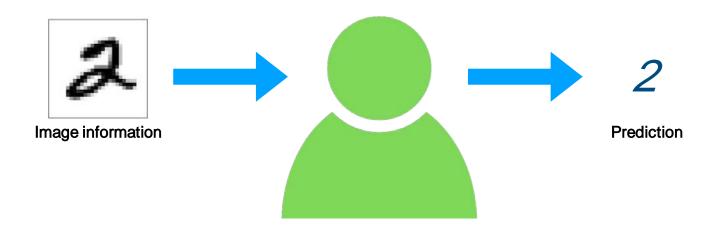
What is Human Intelligence? What to dress?



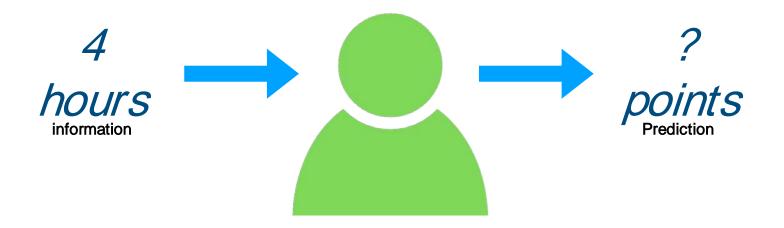
What is Human Intelligence? What is this picture?



What is Human Intelligence? What is this number?



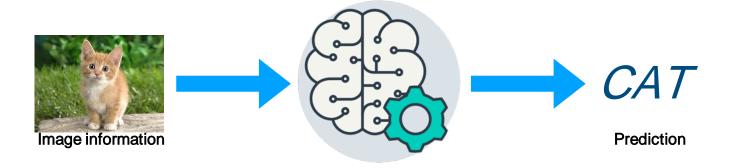
What is Human Intelligence? What would be the grade if I study 4 hours?



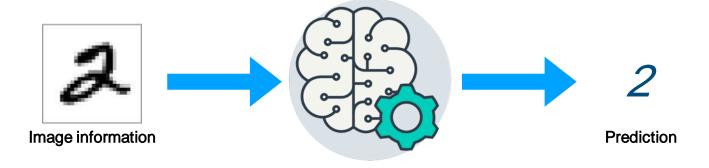
Machine Learning What to dress?



Machine Learning What is this picture?



Machine Learning What is this number?



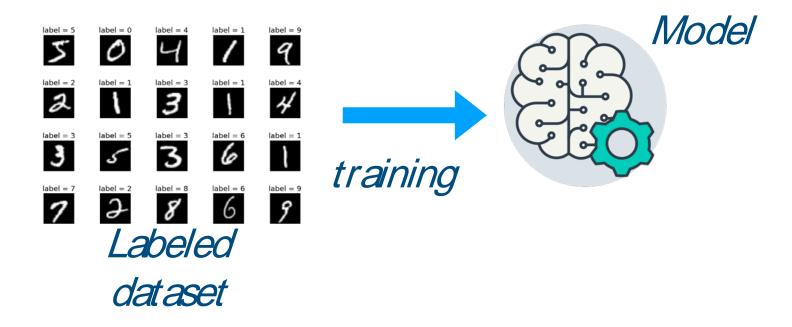
Machine Learning What would be the grade if I study 4 hours?



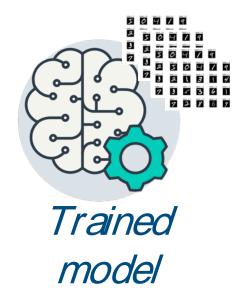
Machine Learning Machine needs lots of training



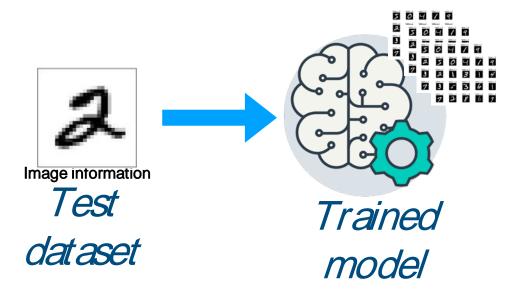
Machine Learning Machine needs lots of training



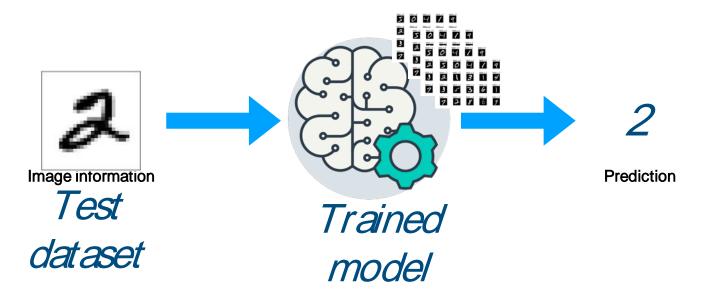
Machine Learning Predict (test) with trained model



Machine Learning Predict (test) with trained model



Machine Learning Predict (test) with trained model



Machine Learning

What would be the grade if I study 4 hours?



Hours (x)	Points (y)
1	2
2	4
3	6
4	?

Training dataset

Test dataset

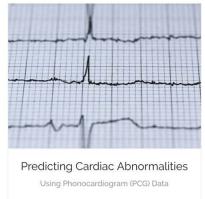
Deep Learning? Deep learning Example: Shallow Example: Example: Example: autoencoders Knowledge Logistic MLPsregression bases Representation learning Machine learning ΑI

Why We Care?

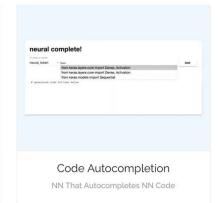






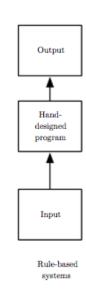




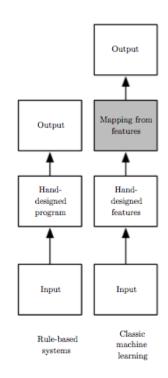


More demos at https://ml-showcase.com/

Why We Care as Developer?

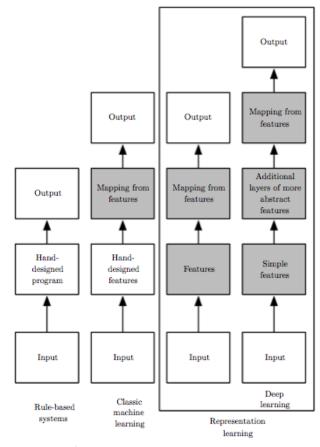


Why We Care as Developer?



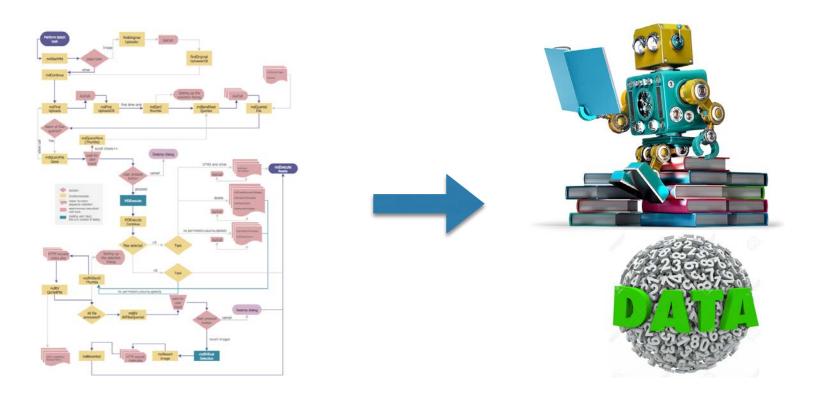
Deep Learning by Ian Goodfellow, Yoshua Bengio, Aaron Courville

Why We Care as Developer?



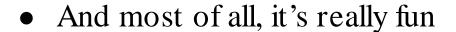
Deep Learning by Ian Goodfellow, Yoshua Bengio, Aaron Courville

Rule based VS representation learning



Good News

- Deep Learning is not too difficult (yet)
 - Basic algebra + probability + python
 - Less than one year study
- Many frameworks
- Unlimited study resources











PyTorch is a python package that provides two high-level features:

- Tensor computation (like numpy) with strong GPU acceleration
- Deep Neural Networks built on a tape-based autograd system

Why PYTÖRCH

- More Pythonic (imperative)
 - o Flexible
 - Intuitive and cleaner code
 - Easy to debug
- More Neural Networkic
 - Write code as the network works
 - o forward/backward

Install PYTORCH



Get Started.

Select your preferences, then run the PyTorch install command.

Please ensure that you are on the latest pip and numpy packages.

Anaconda is our recommended package manager



Run this command:

 $pip 3 in stall \ http://download.pytorch.org/whl/torch-0.2.0.post 3-cp 36-cp 36m-macosx_10_7_x86_64.whl pip 3 in stall \ torchvision$

OSX Binaries dont support CUDA, install from source if CUDA is needed



Google Colab is a platform helping machine learning education and research: https://colab.research.google.com/

- Notebook based on Jupyter/iPython
- Free TPU (Tensor Processing Unit) supported
- Python 2.7 and Python 3.6 supported
- Tensorflow, Scikit-learn, Matplotlib, PyTorch, etc. installed
- Bash command supported
- Google Drive, GitHub Repo, GitHub Gist, etc. interlocked

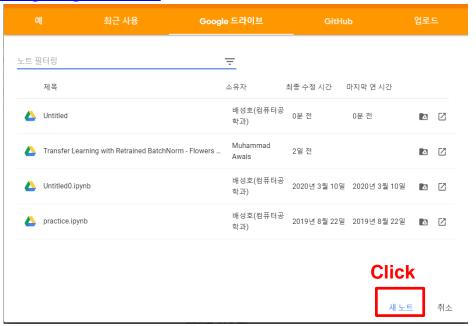
Google Colab Jupyter





How to use:

- 1. Enter https://colab.research.google.com/
- 2. Click (New Note)
- Note: 12 hours duration



Google Colab Jupyter



How to use:

TPUs in Colab - 3. Change the runtile-type \circ File Edit View Insert Runtime Tools Help Run all Ctrl+F9 Copy to Drive Table of contents Run before Ctrl+F8 **TPUs in Colab** Ctrl+Shift+Enter ab Run selection License Run after Ctrl+F10 Enabling and testing the 'll work through training Input data Ctrl+M | TPUs. Our model will ta Notebook settings Model ion, rose, sunflower, or to Training Hardware accelerator ramework, new to TPUs None Predictions Factory reset runtime None tput when saving this notebook Save and re-loading our Change runtime type GPU Next steps CANCEL SAVE TPU Manage sessions Section

Google Colab



A Pytorch Tensor is conceptually identical to an n-dimensional numpy array.

- Unlike numpy, PyTorch Tensor can utilize GPUs to accelerate their numeric computations
- First, import PyTorch library that pre-installed

```
[24] import torch import numpy as np import matplotlib.pyplot as plt
```



The default tensor type in PyTorch is a float defined as torch.FloatTensor

- We can create tensors:

```
# creating a tensor of 3 rows and 2 columns consisting of ones
x = torch.ones(3, 2)
print(x)

# creating a tensor of 3 rows and 2 columns consisting of zeros
x = torch.zeros(3, 2)
print(x)
```

```
tensor([[1., 1.],

[1., 1.],

[1., 1.]])

tensor([[0., 0.],

[0., 0.],

[0., 0.]])
```



Creating a tensor by random initialization

```
[9] # To increase the reproducibility, we often set the random seed
  # to a specific value first
  torch.manual_seed(2)
  #generating tensor randomly
  x = torch.rand(3, 2)
  print(x)

# generating tensor randomly from normal distribution
  x = torch.randn(3, 3)
  print(x)
```



Slicing of Tensors (same as slicing ndarrays in Numpy)

```
tensor([2, 4, 6])
tensor([1, 2])
tensor(4)
```



Reshape Tensor

- .view reshapes the tensor to a shape with input dimensions
- -1: indicates that the shape will be inferred from previous dimensions



Mathematical operations

- (_) as postfix: in-place operation

```
[19] # create two tensors
     x = torch.ones([3, 2])
     y = torch.ones([3, 2])
     # add two tensros
     z = x + y \# method 1
     z = torch.add(x,y) # method 2
     print(z)
     # subtract two tensors
     z = x - v \# method 1
     torch.sub(x,y) # method 2
     print(z)
     y.add_(x) # tensor y added with x and result will be stored in y
     print(y)
```



PyTorch to Numpy bridge

- .numpy: converting method from tensor to numpy

```
[22] x = torch.linspace(0, 1, steps = 5) # creating a tensor using linspace
x_np = x.numpy() # convert tensor to numpy
print(x)
print(type(x), type(x_np)) # check the types

tensor([0.0000, 0.2500, 0.5000, 0.7500, 1.0000])
<class 'torch.Tensor'> <class 'numpy.ndarray'>
```



PyTorch to Numpy bridge

- .from_numpy: converting method from tensor to numpy

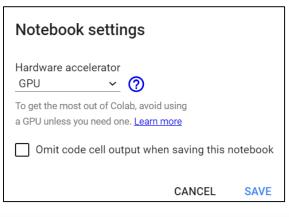
```
[33] a = np.random.randn(5) # generate a random numpy array
a_pt = torch.from_numpy(a) # convert numpy array to a tensor
print(a)
print(type(a), type(a_pt))

[-0.4078755  0.12263927 -0.62535906  2.04968161  0.74182697]
<class 'numpy.ndarray'> <class 'torch.Tensor'>
```

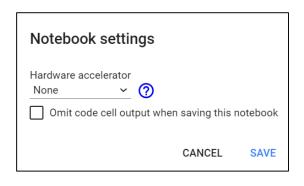


CUDA Support

- .from_numpy: converting method from tensor to numpy







```
[10] print(torch.cuda.device_count())
```

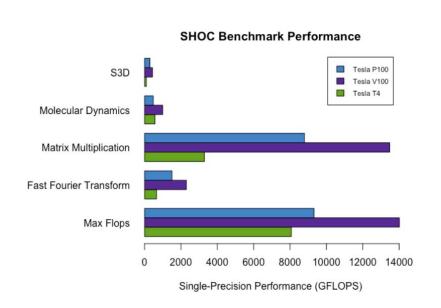


CUDA Support

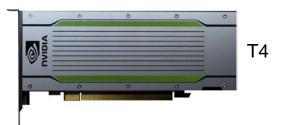
- You may get P100 or T4

[46] print(torch.cuda.get_device_name(0))

Tesla P100-PCIE-16GB









CUDA Support

- the selected GPU device can be changed with torch.cuda.device context manager

```
[47] # Assign cuda GPU located at location 'O' to a variable
     cuda0 = torch.device('cuda:0')
     #performing the addition on GPU
     a = torch.ones(3, 2, device=cuda0) # creating a tensor 'a' on GPU
     b = torch.ones(3, 2, device=cuda0) # create a tensor 'b' on GPU
     c = a + b
     print(c)
     tensor([[2., 2.],
             [2., 2.],
             [2., 2.]], device='cuda:0')
```



CUDA Support

- .cpu(): moves the results from GPU RAM to CPU RAM

```
[48] # move the result to CPU
c = c.cpu()
print(c)

tensor([[2., 2.],
[2., 2.]])
```



Automatic Differentiation (with autograd package)

- First, we create a tensor with requires_grad parameter set to True because we want to track all the operations performing on that tensor



Automatic Differentiation (with autograd package)

- grad_fn: a tensor type supporting to take derivative automatically

```
[51] y = x + 5 # tensor addition
    print(y) # check the result

z = y*y + 1
    print(z)
    t = torch.sum(z) # add all the values in z
    print(t)
```



Automatic Differentiation (with autograd package)

- .backward(): performs a back-propagation (a way of updating the parameters in deep neural networks)
- param.grad : the value of partial derivative of output with respect to param



Conclusion in Google Colab Section

- Google Colab & PyTorch is easy, powerful and for free
- PyTorch is based on tensor which has similar usage to narray in Numpy
- Autograd in PyTorch is one of the most powerful tool that allows to take derivative of variables automatically

Next Topics

- Linear, Logistic, softmax models
- DNN: Deep Neural Net
- CNN: Convolutional Neural Net
- Write everything in PyTorch



Lecture 2: Linear Model