

# Machine Learning

## Lecture 2

Yang Yuan

# Review of the last lecture

- History of AI
  - AI Boom + AI winter, multiple times
  - People started to study many difficult problems long time ago
    - (still unsolved yet...)



# Review of the last lecture

## Supervised learning: step by step

1. Identify the task you want to solve (e.g., MNIST)
2. Create a dataset, containing thousands, or millions of examples
  - Input  $X = (x_1, x_2, \dots, x_N)$
  - Output  $Y = (y_1, y_2, \dots, y_N)$
3. Define a loss function  $L$  to evaluate  $f(X)$
4. Learn a function  $f$  to minimize  $L$  (optimization)
5. **Minimizing  $L$  is not enough!** (generalization)
  - We need to ensure  $f$  that generalizes well
  - We could use a validation set in practice
  - But in theory, we will see some guarantees

# Today's plan

- Create dataset
- Overfit vs underfit
- Unsupervised & semi-supervised learning framework
- Instruction on using pycharm + pytorch

# How to create a dataset?

- **Attention:** high quality big data is more important than everything you will learn in this class
  - Everyone can learn how to train a network in 1 hour
    - Easy steps, 10 lines of code
  - Not everyone can build a good dataset!
  - Unfortunately we will not cover it
- How do you build a dataset of millions of data points?



# How to create a dataset?

- Create the input  $X$  (from internet or other source)
- How to get the correct label  $Y$ ?
  - Crowd sourcing is the right way to go!
  - <https://www.mturk.com/>
  - Split the task into millions of micro-tasks
- This is **highly nontrivial**, but super important in practice
  - There will be hundreds or thousands of workers
    - Get paid by their performance
  - How do you know the labels are correct?
    - Usually for any  $x_i$ , multiple workers will label it, then take majority voting
    - But sometimes the label is not a simple number!





# MS COCO dataset

- You need to draw the whole region, which is even harder
- Moreover, how to minimize the cost of labeling?
  - Split the task into multiple small, easy steps
  - Every worker only works on one step (**assembly line**)

## Dataset examples





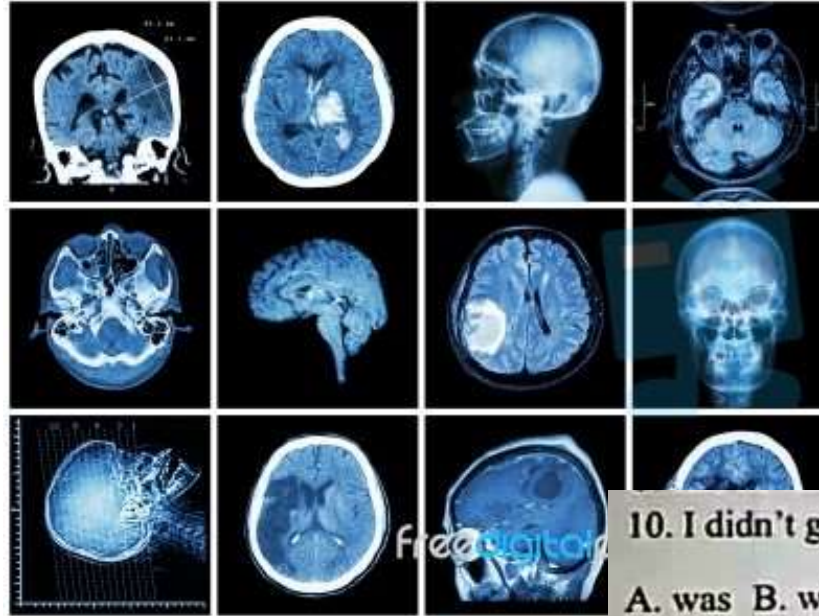


# ReCAPTCHA: a smart idea



# What if labeling tasks are harder?

- For example:
  - Health care
  - Law suits
  - Education
  - ....
- What if some workers are strategic?
  - Spend least time to make most money
  - Use AI to generate label
- Main bottleneck in practice

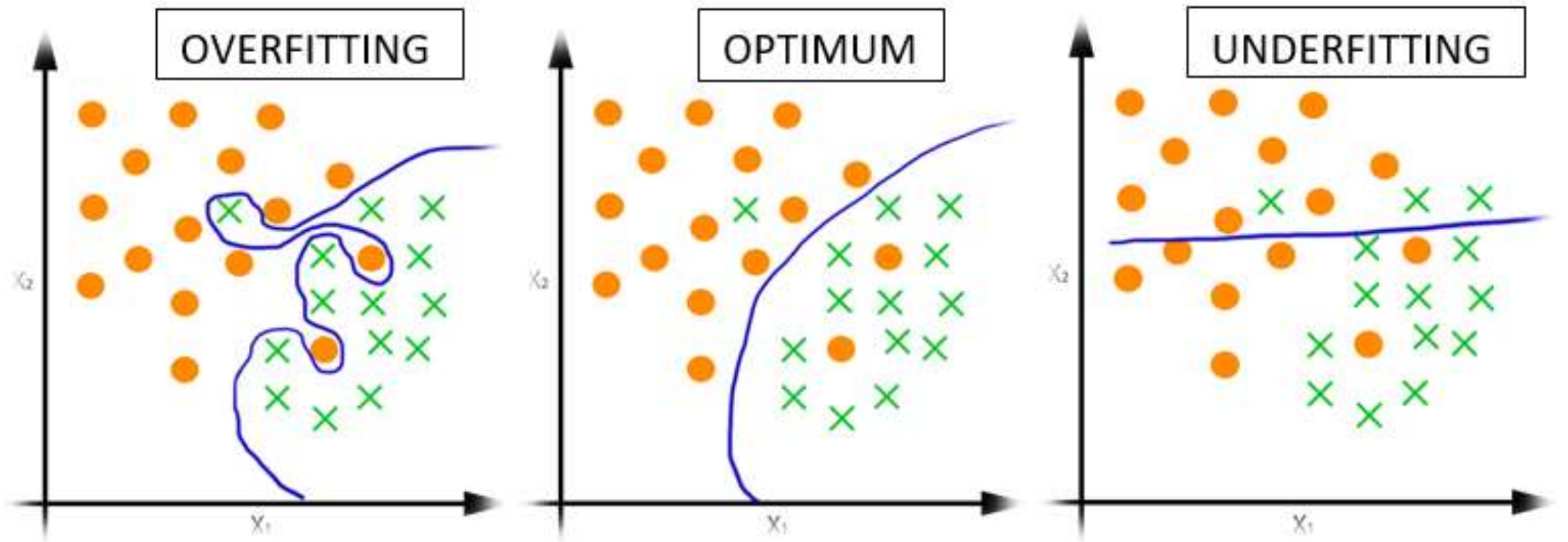


10. I didn't go to our class get-together last weekend, but I do wish \_\_\_\_\_  
A. was B. will be  
C. were D. had been  
11. His visit to London last spring is \_\_\_\_\_ as a great success.  
A. looked into B. looked to  
C. looked over D. looked upon  
12. You will complete your project more easily if you take \_\_\_\_\_  
A. privilege B. advantage

# From now on, always assume we have data

- **Training loss**:  $L_{\text{train}} = L(f, X_{\text{train}}, Y_{\text{train}})$ 
  - $X_{\text{train}}, Y_{\text{train}}$  is training set
  - They define the **empirical distribution**  $\Pr((x_i, y_i)) = \frac{1}{N}$
- **Test loss**:  $L_{\text{test}} = L(f, X_{\text{test}}, Y_{\text{test}})$
- **Validation loss**:  $L_{\text{valid}} = L(f, X_{\text{valid}}, Y_{\text{valid}})$ 
  - Practical trick for estimating test loss
- $(X_{\text{test}}, Y_{\text{test}}), (X_{\text{train}}, Y_{\text{train}}), (X_{\text{valid}}, Y_{\text{valid}})$  are all sampled from **population distribution**  $D_X, D_Y$
- **Population loss**:  $L_{\text{population}} = E_{X, Y \sim D_X, D_Y} L(f, X, Y)$
- We want to minimize  $L_{\text{population}}$ 
  - In practice, we estimate  $L_{\text{population}}$  using  $L_{\text{test}}$
  - The **ultimate goal** in supervised learning

# Classical view: overfit vs underfit



# Classical view

- Underfit:
  - Your function does not have enough representation power
    - E.g., use a straight line to fit this complicated world
  - Underfit gives you bad  $L_{train}$
  - Usually no generalization problem, because  $L_{test}$  is equally bad
- Overfit:
  - Your function had too much representation power
    - E.g., neural network, which can represent everything (we will see later)
  - Overfit easily gives you  $L_{train} = 0$
  - However, generalization problem:  $L_{test}$  could be very bad!



# Classical view

- Since overfitting **could** lead to bad  $L_{test}$ 
  - Classical view thinks we should avoid it
  - Therefore, we should restrict the representation power of  $f$ , so that it could not overfit!
    - This is called “regularization”
- Modern view:
  - Sometimes, explicit regularization is not necessary
  - For neural networks, there are implicit regularizations to prevent overfitting
    - Because of optimization process: SGD algorithm
    - We will cover it later
  - In other words, although overfitting could lead to bad  $L_{test}$ , it **almost never happens**
  - Researchers were afraid of overfitting for neural networks for decades!

# Regularization

- In order to avoid overfitting
  - We want to make sure  $f$  is “simple”
    - We will see a few examples later
  - Therefore, if there are two functions:
    - Simple function  $f$  with worse  $L_{train}$
    - Complex function  $f$  with better  $L_{train}$
  - Maybe we should pick the first one!
- A more fundamental fact:
  - The function that minimizes empirical loss (i.e.,  $L_{train}$ )
  - Is not necessarily the one that minimizes population loss (i.e.,  $L_{test}$ )
  - This is true even in convex case [stochastic convex optimization, SSSS09]

Is it clear? Do we need to go back?

- ☐ A It is clear
- ☐ B Let us go back

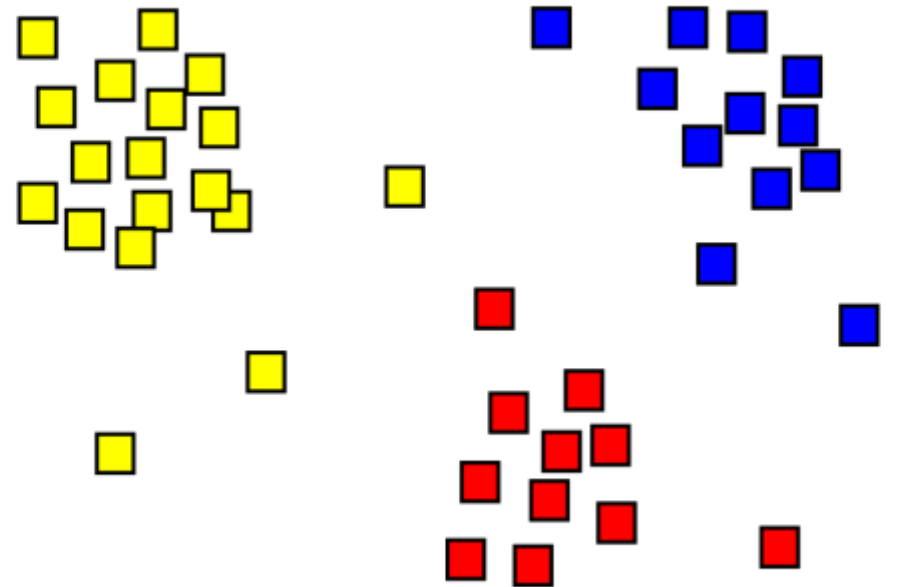
提交

# Unsupervised learning framework

- Supervised learning framework
  - Inputs  $X$
  - Labels  $Y$
- Unsupervised learning framework
  - Inputs  $X$
  - No labels  $Y$
- What can you do?
  - Learn the distribution of  $X$

# 1. Clustering

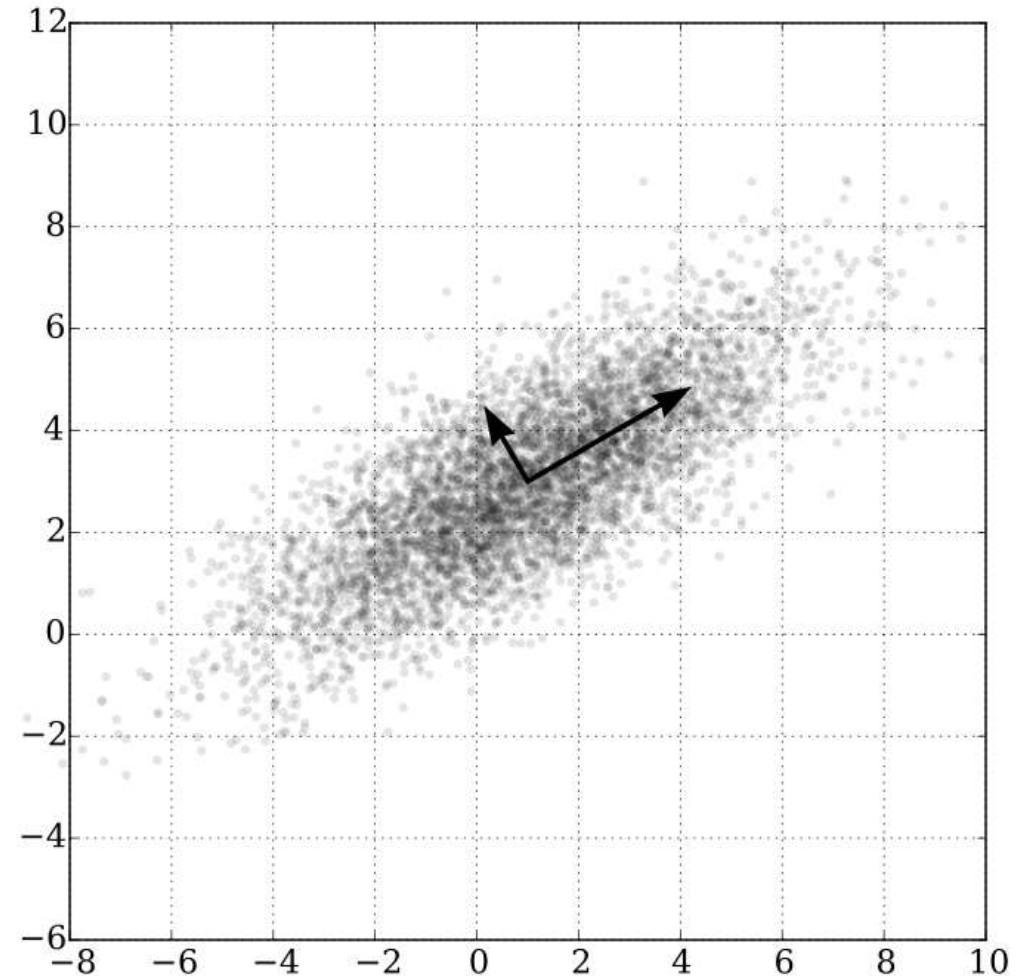
- Objects in the same group are similar to each other
- But no unique solution!
  - Depends on loss function
- Why is it useful?
  - Data mining
    - To see whether inside the same cluster they share something in common
  - Speed-up optimization process
  - Recommendation system





## 2. Principle component analysis

- Find most important components (directions)
- a best-fitting line is defined as one that minimizes the average squared distance from the points to the line.
- Or, the line with most “variance”



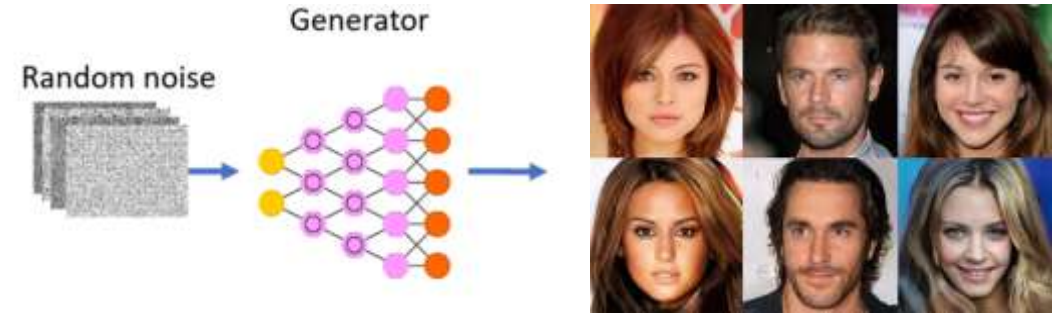
### 3. Generative model

- Generative model, is essentially what God has, what we really want
- Why do we want to describe the data distribution?
  - Once we have the (true) data distribution, we can sample it and get abundant data!



- Data distribution is hard to describe
  - Usually:  $X$  follows Gaussian?
  - Empirically:  $X$  follows a bizarre distribution

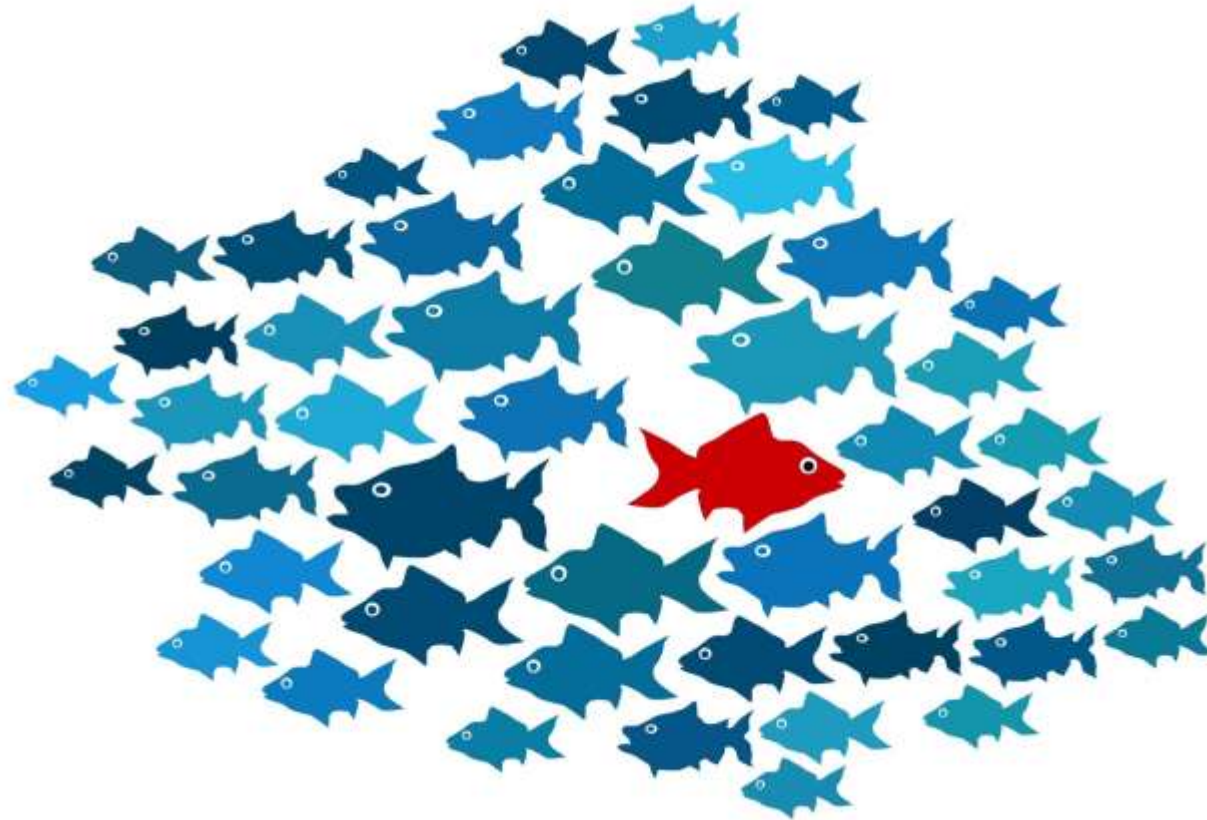
# Why generative model?



- How do we describe a bizarre distribution?
  - Generative model!
- Generative model did not directly answer the question of “describing a bizarre distribution”
- Instead, it maps a Gaussian to the target distribution
- Hope:
  - When sampling the Gaussian, after the transformation, we get a good sample from real data  $X$
- So we get “real” faces for free!
- Bonus: we also get to understand the hidden structure of  $X$ 
  - What does it mean?

## 4. Anomaly detection

- Find rare items/events, that are different from other data points



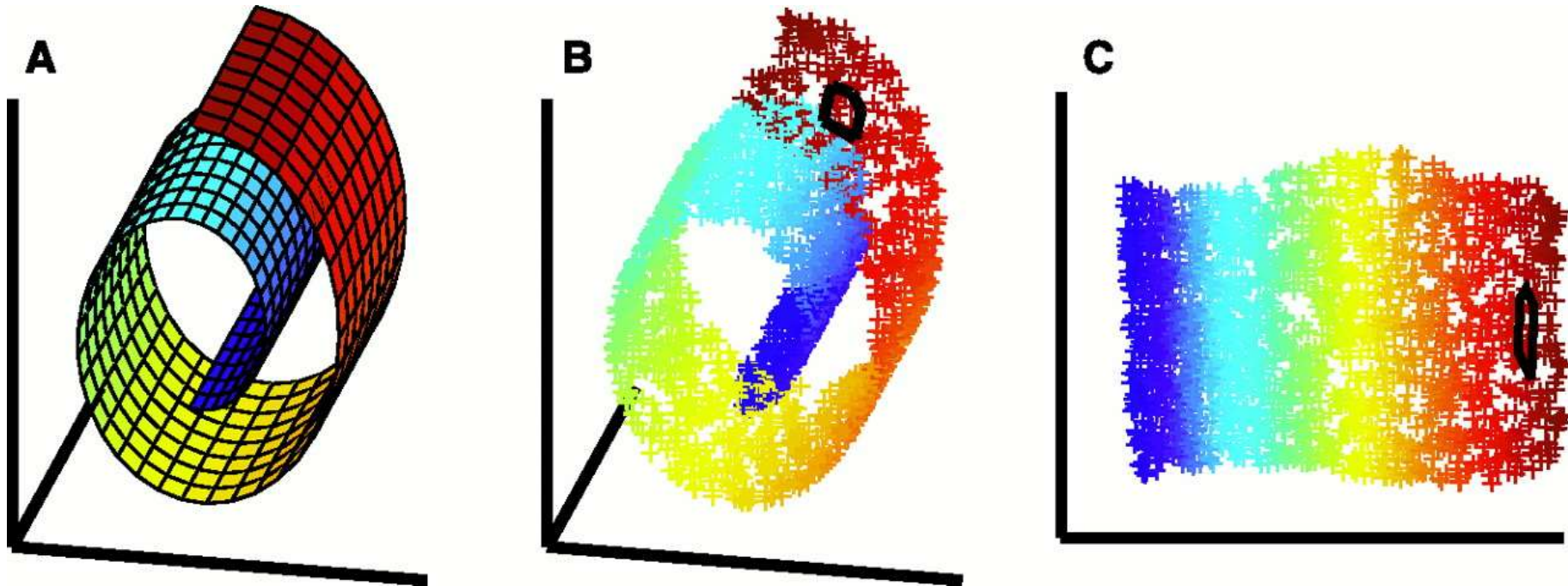
# 4. Anomaly detection

- Very important
  - COVID-19 auto detection
  - Weird online transactions
  - Computer virus monitoring
- However, how to detect anomalies?
  - Hard to give clear definitions...
  - Diverse solutions



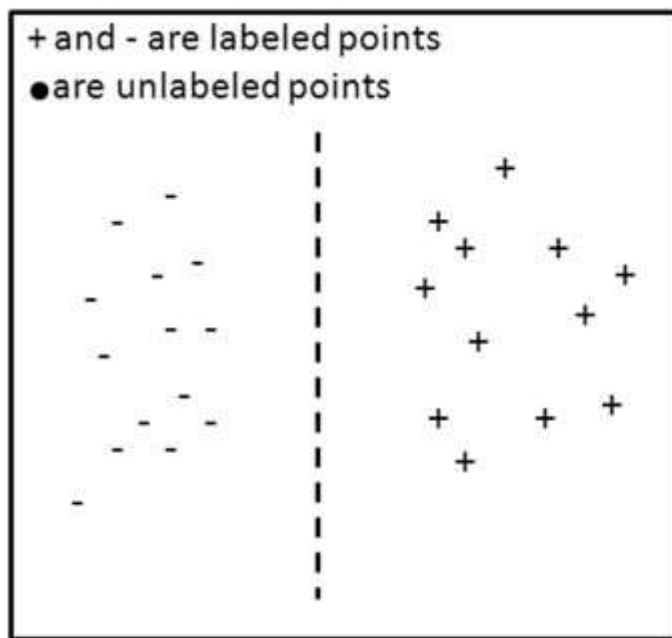
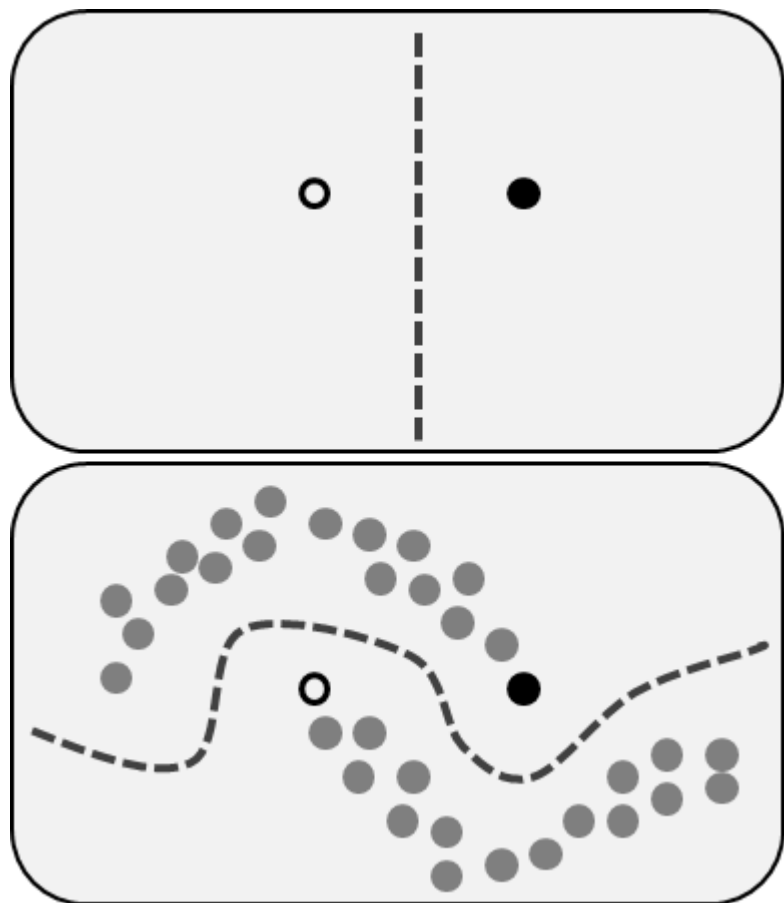
## 5. Dimension reduction

- Some data points live in high dim space, but are inherently low dim.
- How to map them into low dim? (E.g., PCA is one kind of dimension reduction)

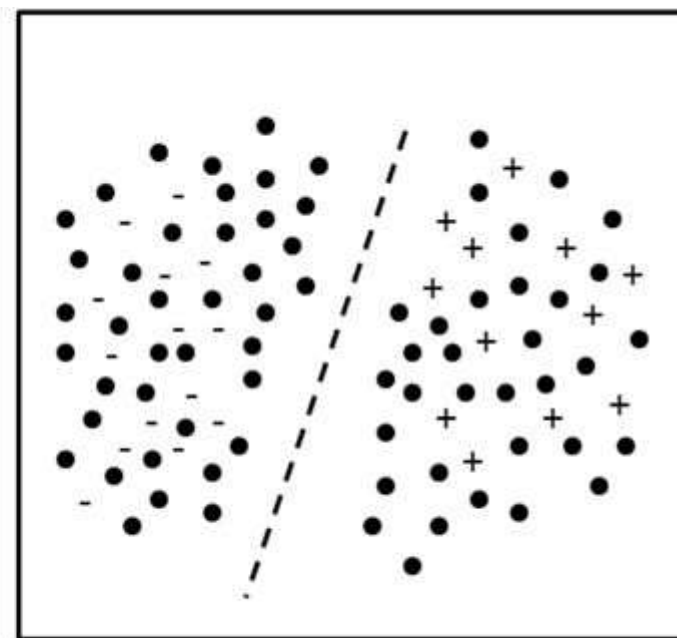


# Semi-supervised learning

- In practice, semi-supervised learning is common
  - Some data points (say 10%) have labels
  - Some data points (say 90%) do not have labels
- Can we always use the unlabeled data to improve prediction?
  - Not always! Why? (Y is pure noise)
- (Implicitly), we need some assumptions.
  - Continuity assumption
    - Points which are close to each other are more likely to share a label
    - Gives geometrically simple decision boundaries
  - Manifold assumption
    - The data lie approximately on a manifold of much lower dimension than the input space



(a)



(b)

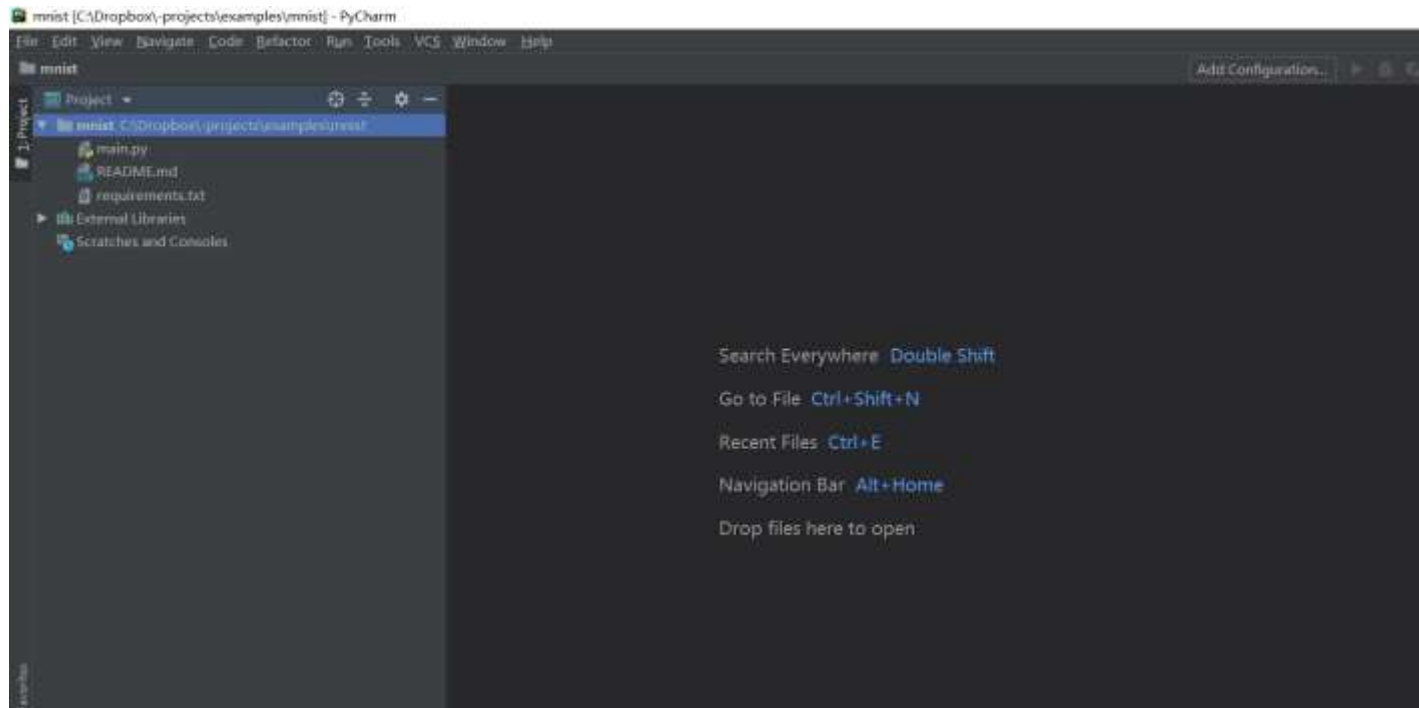
Is it clear? Do we need to go back?

- ☐ A It is clear
- ☐ B Let us go back

提交

# Use github

- git clone <https://github.com/pytorch/examples.git>
  - Download the source code for pytorch examples
- Open project using pycharm





mnist [C:\Dropbox\projects\examples\mnist] - PyCharm

File Edit View Navigate Code Refactor Run Tools VCS Window Help

mnist

Project

mnist C:\Dropbox\projects\examples\mnist

main.py

README.md

requirements.txt

External Libraries

Scratches and Consoles

Tasks & Contexts

IDE Scripting Console

Analyze Stack Trace...

Capture Memory Snapshot

Python Console...

Create setup.py

Show Code Coverage Data Ctrl+Alt+F6

✓ Vim Emulator Ctrl+Alt+V

R Console...

Refresh R Package Index

Deployment

Add new Bash console

HTTP Client

Start SSH session...

Vagrant

Open CProfile snapshot

Upload to Default Server

Upload to... Ctrl+Alt+Shift+X

Download from Default Server

Download from...

Compare Local File with Deployed Version

Compare with Deployed to ...

Sync Local Subtree with Deployed

Sync with Deployed to ...

Configuration...

Options...

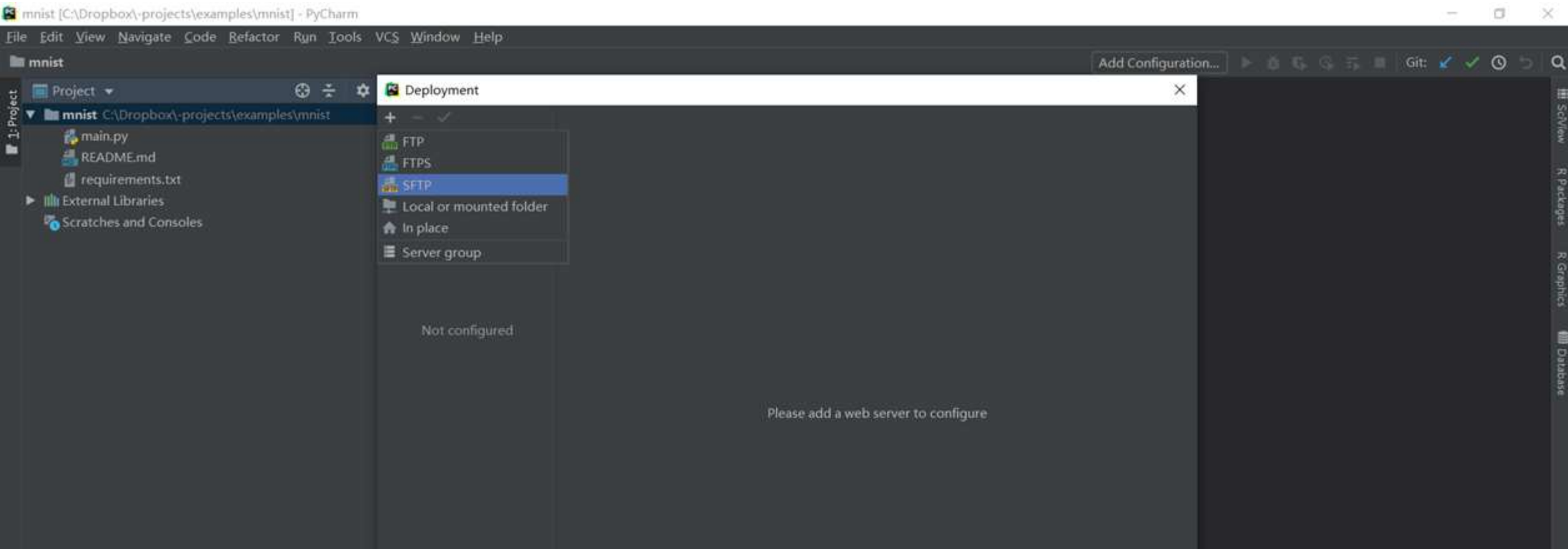
Automatic Upload

Browse Remote Host

Add Configuration...

Git: ✓

# Use pytorch



+ - ✓

SFTP

h1

Connection

Mappings

Excluded Paths

☒ Visible only for this project

Type: 

SFTP

Host: 

101.6.96.191

 Port: 

6201

User name: 

yuanyang

Authentication: 

Key pair OpenSSH or PuTTY

Private key path: 

C:\Dropbox\yy\zm\new\_high\_private

Passphrase: 

.....

☐ Save passphrase

Test Connection

Root path: 

/

Autodetect

Web server URL: 

http://101.6.96.191

▶ Advanced

?

OK

Cancel



# Deployment



h1

Connection

Mappings

Excluded Paths

Local path:

C:\Dropbox\~projects\examples\mnist



Deployment path:

/



Web path:

Local path is absolute. Deployment path is relative to the server root path (/home/yuanyang/git).  
Web path is relative to the web server URL (http://101.6.96.191).

Add New Mapping

mnist

Project

mnist C:\Dropbox\projects\examples\mnist

main.py

README.md

requirements.txt

External Libraries

Scratches and Consoles

- Tasks & Contexts
- IDE Scripting Console
- Analyze Stack Trace...
- Capture Memory Snapshot
- Python Console...
- Create setup.py
- Show Code Coverage Data Ctrl+Alt+F6
- ✓ Vim Emulator Ctrl+Alt+V
- R Console...
- Refresh R Package Index
- Deployment
- Add new Bash console
- HTTP Client
- Start SSH session...
- Vagrant
- Open CProfile snapshot

- Upload to h1
- Upload to... Ctrl+Alt+Shift+X
- Download from h1
- Download from...
- Compare Local File with Deployed Version
- Compare with Deployed to ...
- Sync with Deployed to h1...
- Sync with Deployed to ...
- Configuration...
- Options...
- Automatic Upload
- Browse Remote Host

Add Configuration...

Git: ✓ ✓

ScView  
R Packages  
R Graphics  
Database

mnist [C:\Dropbox\projects\examples\mnist] - ...main.py [mnist] - PyCharm

File Edit View Navigate Code Refactor Run Tools VCS Window Help

mnist main.py

Add Configuration...

Git:

Project  
mnist C:\Dropbox\projects\examples\mnist  
main.py  
README.md  
requirements.txt  
External Libraries  
Scratches and Consoles

Settings

Search

Appearance & Behavior

Appearance

Menus and Toolbars

System Settings

File Colors

Scopes

Notifications

Quick Lists

Keymap

Editor

Plugins

Version Control

Project: mnist

Project Interpreter

Project Structure

Build, Execution, Deployment

Languages & Frameworks

Tools

Project: mnist Project Interpreter

For current project

Project Interpreter: Python 3.7 C:\Program Files (x86)\Python37-32\python.exe

Package	Version	Latest version
Jinja2	2.10	▲ 2.10.1
MarkupSafe	1.1.0	▲ 1.1.1
Pillow	6.1.0	6.1.0
PyQt5	5.13.0	▲ 5.13.1
PyQt5-sip	4.19.18	▲ 4.19.19
PyYAML	5.1.2	5.1.2
Pygments	2.3.0	▲ 2.4.2
QDarkStyle	2.7	2.7
QtPy	1.9.0	1.9.0
Send2Trash	1.5.0	1.5.0
backcall	0.1.0	
bleach	3.0.2	▲ 3.1.0
certifi	2019.6.16	
chardet	3.0.4	
colorama	0.4.1	
cycler	0.10.0	
decorator	4.3.0	
defusedxml	0.5.0	
entrypoints	0.2.3	

ments ignore requirements



## ▼ Appearance

Appearance

Menus

## ► System

File Co

Scope

Notific

Quick

## Keymap

## ► Editor

## Plugins

## ► Version C

## ▼ Project: n

Project

Project

## ► Build, Exe

## ► Language

## ► Tools

## Add Python Interpreter



Virtualenv Environment



Conda Environment



System Interpreter



Pipenv Environment



SSH Interpreter



Vagrant



WSL



Docker



Docker Compose



New server configuration

Host:

Port:

22

Username:



Existing server configuration

Deployment configuration:



h1

Host URL:

ssh://yuanyang@101.6.96.191:7210

Remote SDK is saved in IDE settings, so it needs the deployment server to be saved there too. Which do you prefer?

[Create](#) copy of this deployment server in IDE settings[Move](#) this server to IDE settings

Previous

Next

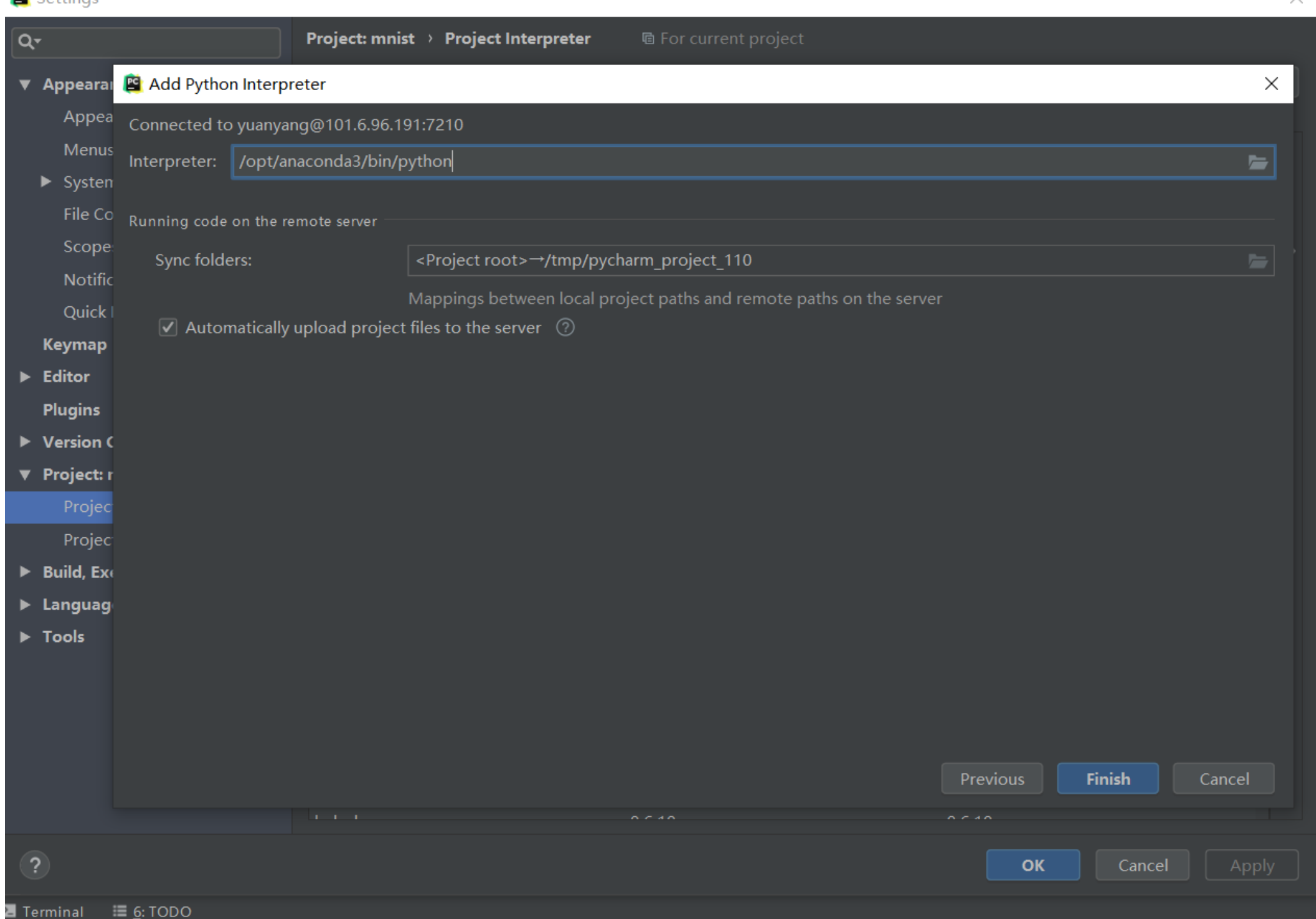
Cancel



OK

Cancel

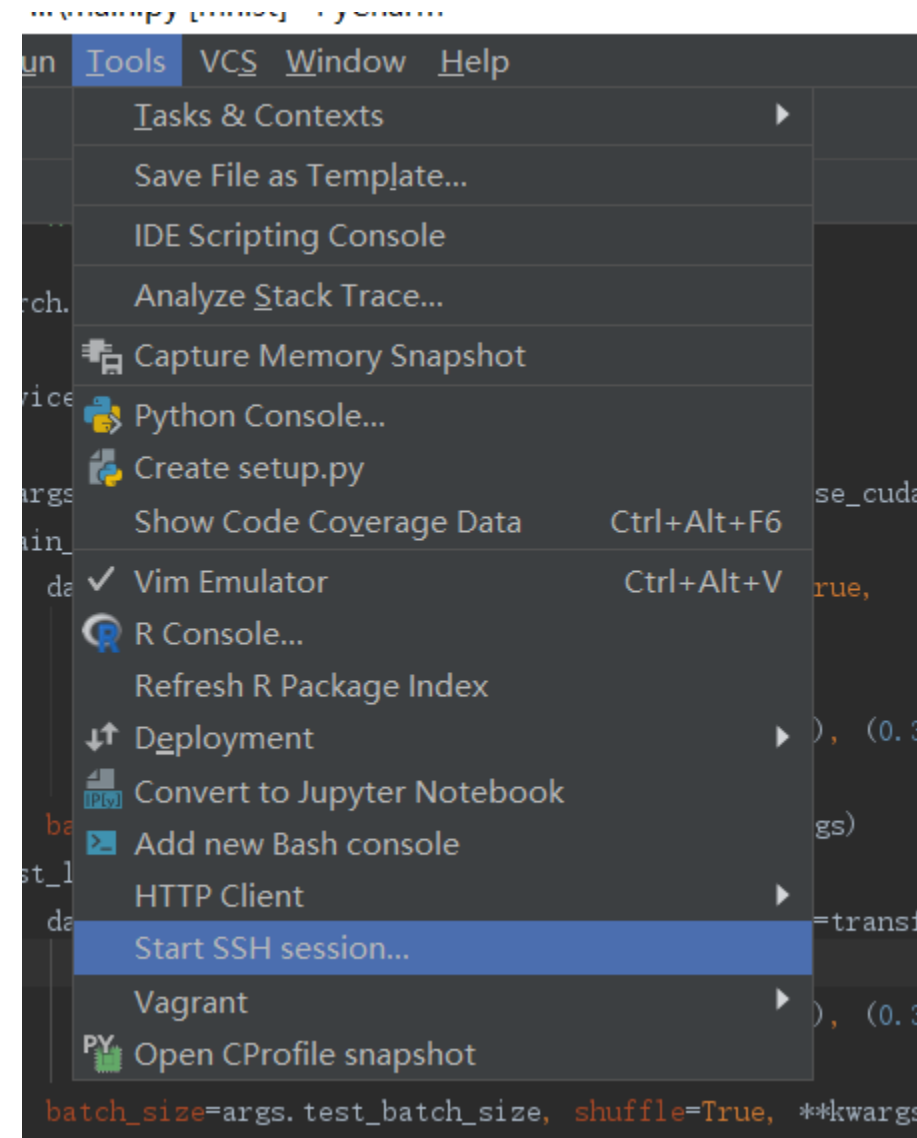
Apply





# Now you can run& update

- Run the code directly (suggested by Mingkuan Xu): shift+F10
- Run the code through SSH (most common way)
- Run the code using Pycharm SSH (convenient inside pycharm)



# Use jupyter to run code

```
Your Hardware Enablement Stack (HWE) is supported until April 2023.
Last login: Sat Sep 28 22:45:40 2019 from 123.114.52.117
(base) yuanyang@hl:~$ jupyter notebook
[I 22:46:38.025 NotebookApp] JupyterLab extension loaded from /opt/anaconda3/lib/python3.7/site-packages/jupyterlab
[I 22:46:38.025 NotebookApp] JupyterLab application directory is /opt/anaconda3/share/jupyter/lab
[I 22:46:38.026 NotebookApp] Serving notebooks from local directory: /home/yuanyang
[I 22:46:38.026 NotebookApp] The Jupyter Notebook is running at:
[I 22:46:38.026 NotebookApp] http://localhost:8888/?token=d1fafa4340eac9cc6211a7d966dde504f471637a91d24ba4
[I 22:46:38.026 NotebookApp] or http://127.0.0.1:8888/?token=d1fafa4340eac9cc6211a7d966dde504f471637a91d24ba4
[I 22:46:38.026 NotebookApp] Use Control-C to stop this server and shut down all kernels (twice to skip confirmation).
[C 22:46:46.479 NotebookApp]

To access the notebook, open this file in a browser:
    file:///home/yuanyang/.local/share/jupyter/runtime/nbserver-25142-open.html
Or copy and paste one of these URLs:
    http://localhost:8888/?token=d1fafa4340eac9cc6211a7d966dde504f471637a91d24ba4
    or http://127.0.0.1:8888/?token=d1fafa4340eac9cc6211a7d966dde504f471637a91d24ba4

[E 22:46:55.411 NotebookApp] Could not open static file ''
[W 22:46:55.457 NotebookApp] 404 GET /static/components/react/react-dom.production.min.js (127.0.0.1) 10.08ms referer=http://localhost:8888/tree?token=d1fafa4340eac9cc6211a7d966dde504f471637a91d24ba4
[W 22:46:55.468 NotebookApp] 404 GET /static/components/react/react-dom.production.min.js (127.0.0.1) 1.11ms referer=http://localhost:8888/tree?token=d1fafa4340eac9cc6211a7d966dde504f471637a91d24ba4
[I 22:47:03.495 NotebookApp] Creating new notebook in /git
[I 22:47:03.519 NotebookApp] Writing notebook-signing key to /home/yuanyang/.local/share/jupyter/notebook_secret
[W 22:47:04.097 NotebookApp] 404 GET /static/components/react/react-dom.production.min.js (127.0.0.1) 1.38ms referer=http://localhost:8888/notebooks/ipynb?kernel_name=python3
[W 22:47:04.283 NotebookApp] 404 GET /static/components/react/react-dom.production.min.js (127.0.0.1) 2.63ms referer=http://localhost:8888/notebooks/ipynb?kernel_name=python3
[I 22:47:05.046 NotebookApp] Kernel started: 1a6423b2-2a99-4ff1-ad5a-feeacb079268
[I 22:47:05.420 NotebookApp] Adapting from protocol version 5.1 (kernel 1a6423b2-2a99-4ff1-ad5a-feeacb079268) to 5.3 (client).
```



In [1]: `import torch`

In [2]: `print("Hellow world!")`

Hellow world!

In [3]: `a=torch.Tensor(5).cuda()`

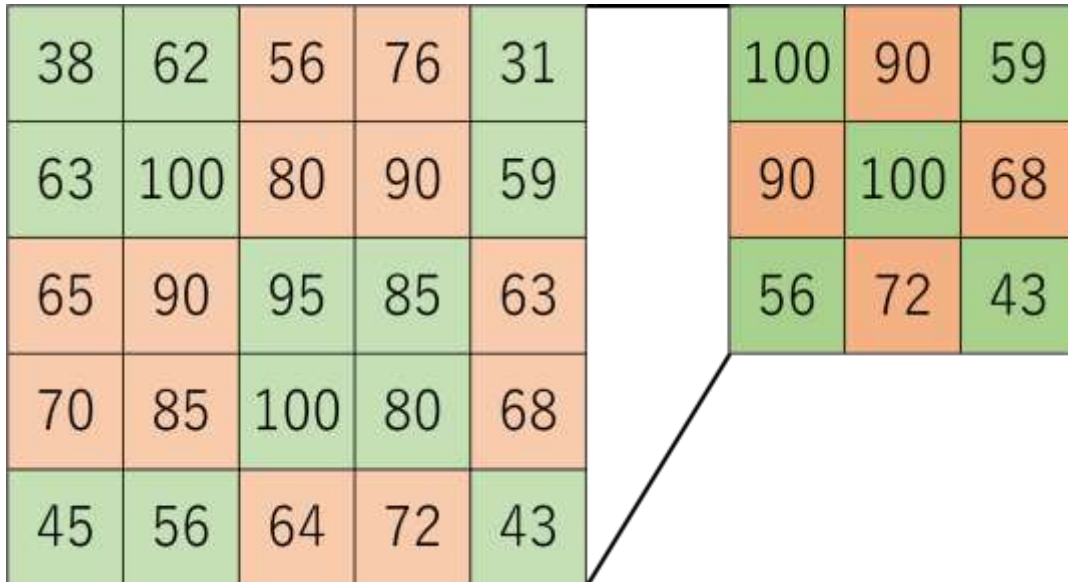
# Model

- Init:
  - **Define** the network components
  - `Super.__init__()`
  - Convolutional layers
  - Linear layers
- Forward:
  - **Run** the network
  - `x=F.relu(self.conv1(x))`
  - What is F?
  - What is `relu`, `max_pool2d`?
  - What is `view`, `log_softmax`?

```
class Net(nn.Module):  
    def __init__(self):  
        super(Net, self).__init__()  
        self.conv1 = nn.Conv2d(1, 20, 5, 1)  
        self.conv2 = nn.Conv2d(20, 50, 5, 1)  
        self.fc1 = nn.Linear(4*4*50, 500)  
        self.fc2 = nn.Linear(500, 10)  
  
    def forward(self, x):  
        x = F.relu(self.conv1(x))  
        x = F.max_pool2d(x, 2, 2)  
        x = F.relu(self.conv2(x))  
        x = F.max_pool2d(x, 2, 2)  
        x = x.view(-1, 4*4*50)  
        x = F.relu(self.fc1(x))  
        x = self.fc2(x)  
        return F.log_softmax(x, dim=1)
```

# Model

- Relu: activation calculation
  - $\text{Relu}(x)=0$  if  $x < 0$   
 $=x$  if  $x \geq 0$
- Max\_pool2d



38	62	56	76	31		100	90	59
63	100	80	90	59		90	100	68
65	90	95	85	63		56	72	43
70	85	100	80	68				
45	56	64	72	43				

- Relu: activation calculation
  - $\text{Relu}(x)=0$  if  $x < 0$   
 $=x$  if  $x \geq 0$
- Max\_pool2d

# Model

- view
  - Reshape the output
  - -1 means by calculation
  - E.g., A size=100\*100
  - A.view(-1,200)=50\*200
- Log\_softmax
  - Convert vectors into probabilities
  - Take log

```
class Net(nn.Module):  
    def __init__(self):  
        super(Net, self).__init__()  
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    def forward(self, x):  
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        x = F.max_pool2d(x, 2, 2)  
        x = F.relu(self.conv2(x))  
        x = F.max_pool2d(x, 2, 2)  
        x = x.view(-1, 4*4*50)  
        x = F.relu(self.fc1(x))  
        x = self.fc2(x)  
        return F.log_softmax(x, dim=1)
```



# Model

- More questions: check <https://pytorch.org/docs/stable/index.html>
- Also check the tutorial <https://pytorch.org/tutorials/>

Tensor Attributes

Type Info

torch.sparse

torch.cuda

torch.Storage

torch.nn

● torch.nn.functional

torch.nn.init

torch.optim

torch.autograd

torch.distributed

torch.distributions

torch.hub

torch.jit

torch.multiprocessing

torch.random

torch.utils.bottleneck

torch.utils.checkpoint

torch.utils.cpp\_extension

## log\_softmax

```
torch.nn.functional.log_softmax(input, dim=None, _stacklevel=3, dtype=None)
```

[SOURCE]

Applies a softmax followed by a logarithm.

While mathematically equivalent to  $\log(\text{softmax}(x))$ , doing these two operations separately is slower, and numerically unstable. This function uses an alternative formulation to compute the output and gradient correctly.

See [LogSoftmax](#) for more details.

### Parameters

- **input** (*Tensor*) – input
- **dim** (*int*) – A dimension along which log\_softmax will be computed.
- **dtype** (*torch.dtype*, optional) – the desired data type of returned tensor. If specified, the input tensor is casted to *dtype* before the operation is performed. This is useful for preventing data type overflows.  
Default: None.