

Deep Learning

*A Programmer's Guide for
Classification, Regression, and Clustering
of Big Labelled Datasets*

Dr Chris Willcocks

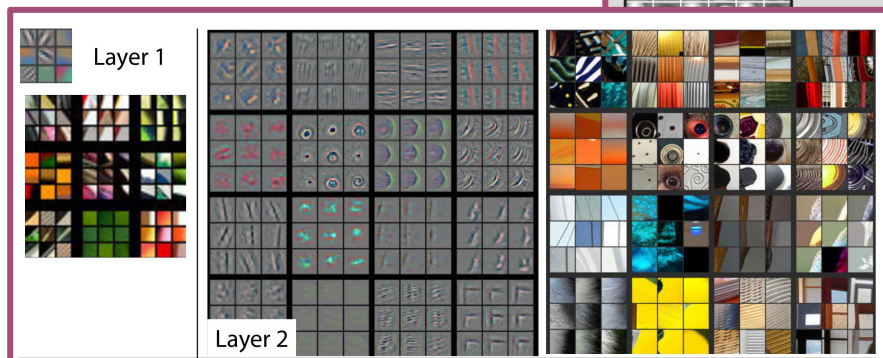
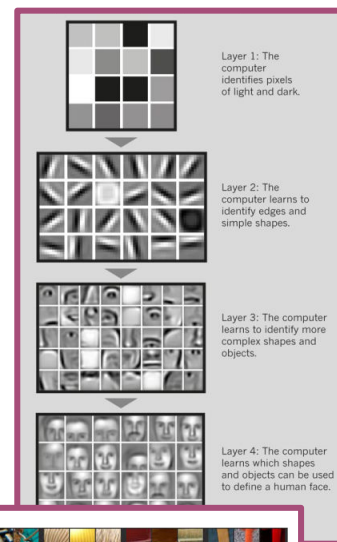


Durham
University

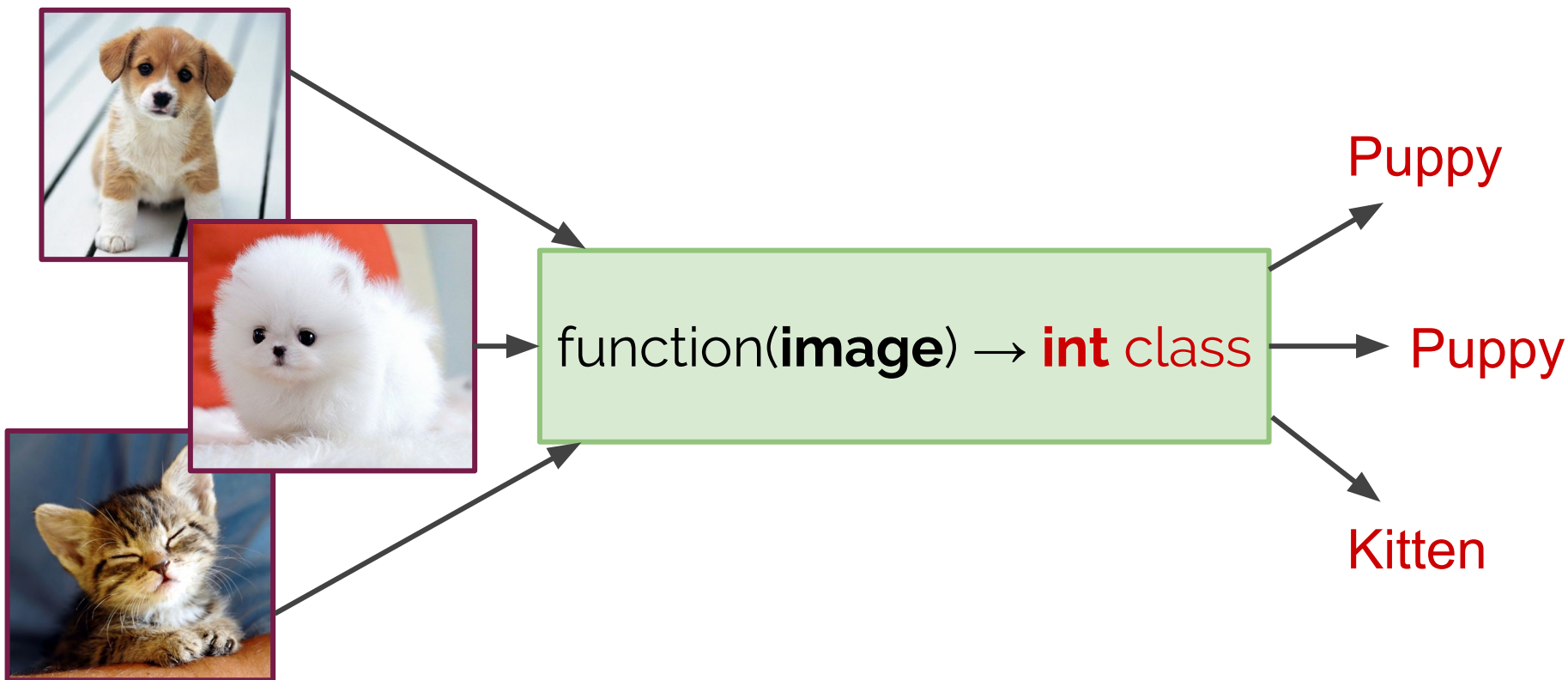
into \int gral[®]
LIMITED

In this talk

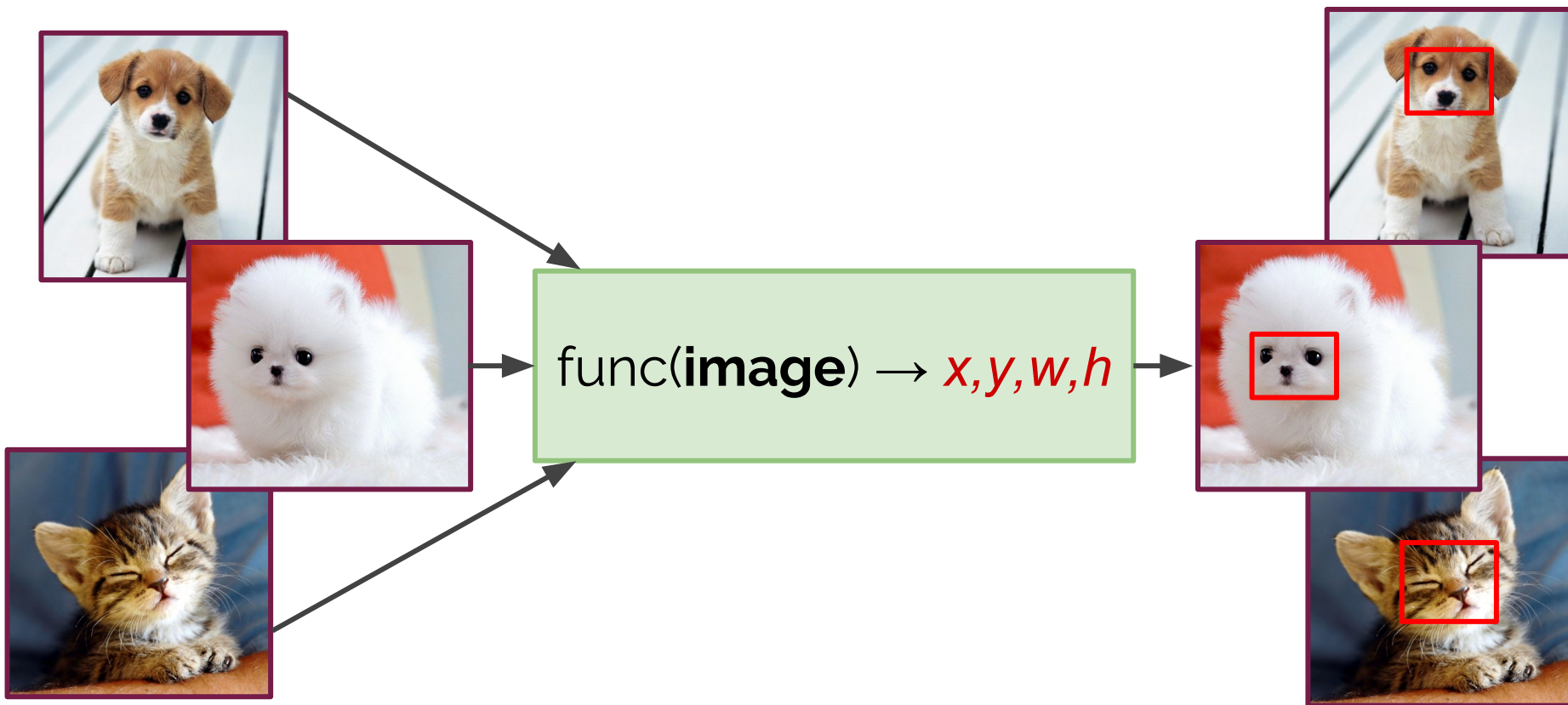
1. Focus on the **intuition of concepts** and **programming** solutions
2. Basic concepts (classification, regression, clustering)
3. Programming directly on the server
4. Reshaping and thinking of **problems in tensors**
5. **Building & programming** the dataset
6. ... the data loader
7. ... loading models with transfer learning
8. ... visdom
9. ... training
10. ... validation
11. **Deployment** of models
 - o Programming client-server
12. Challenges



Classification Example

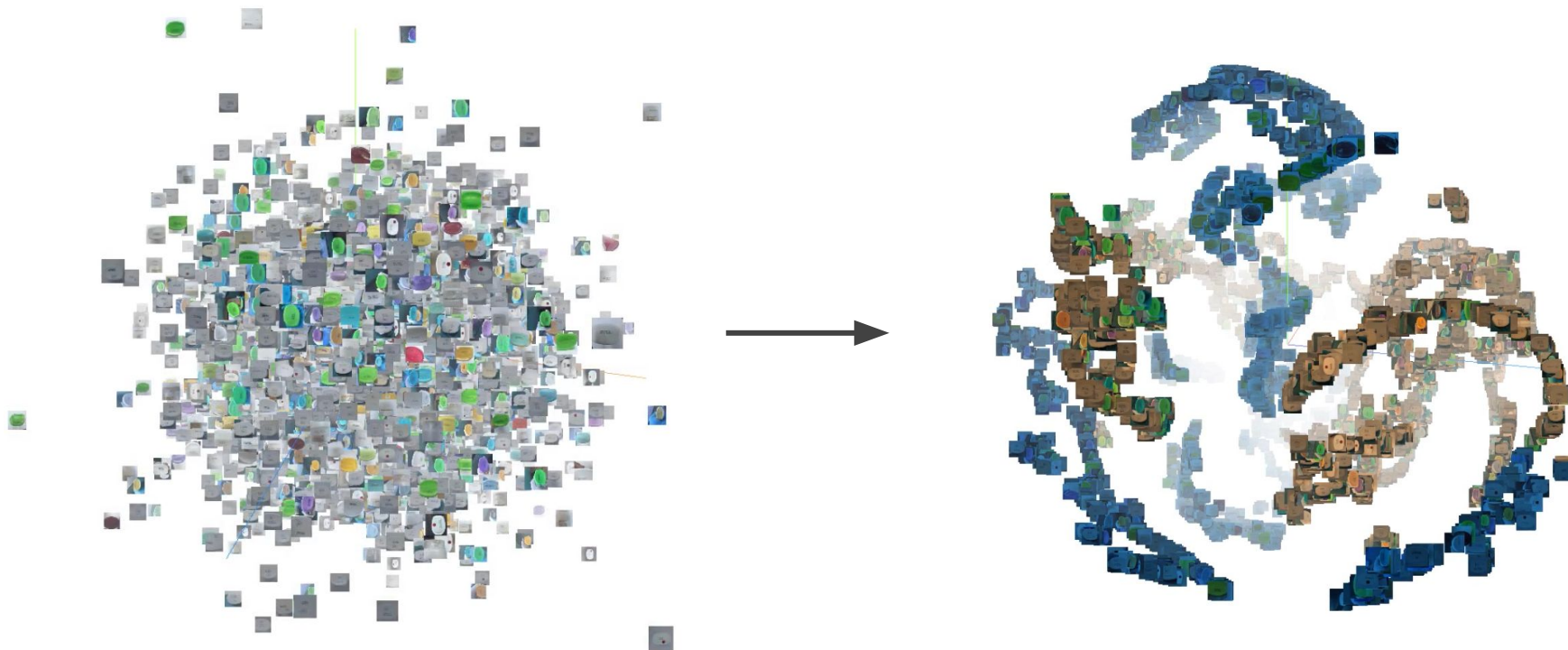


Regression Example



Clustering Example

- Can we get some meaningful story and new insight from the dataset?



Clustering Example

1 tensor found
res34june

Label by
Prediction

Color by
Prediction

0 2295
1 1320

☒ Sphereize data

Load data Publish

Checkpoint: Demo datasets
Metadata: oss_data/res34june_labels.tsv

T-SNE PCA CUSTOM

Dimension 2D 3D

Perplexity 16

Learning rate 10

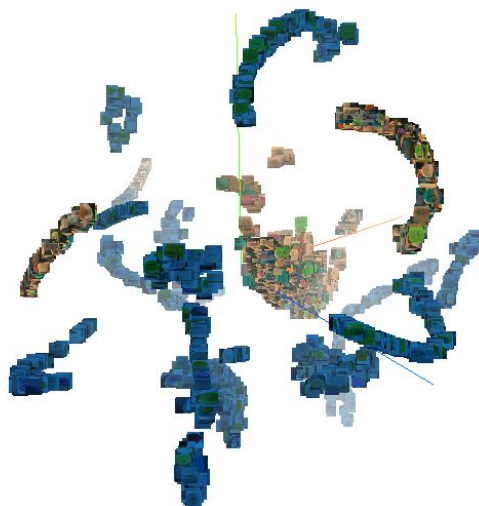
Re-run Stop

Iteration: 1629

[How to use t-SNE effectively.](#)

?

Predictions



Groundtruth Labels



Clustering Example



Programming on the Server

```
chris@chris-lab ~ | master • ssh chris@50.232.78.63
```

```
master • sshfs chris@50.232.78.63:/home/chris/deep-learning /tmp/gcp
```

Can be local on on server, use Github for code

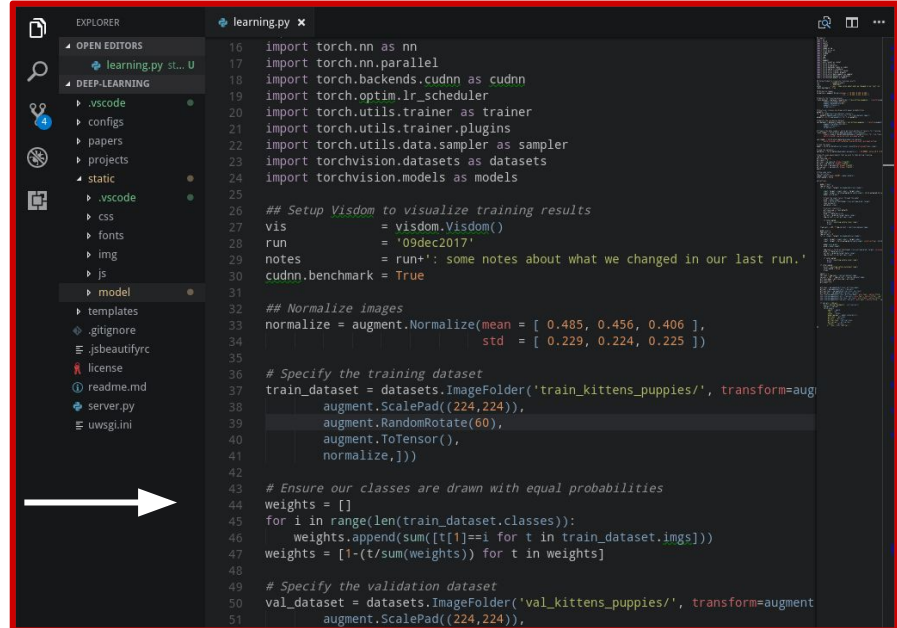
```
chris@chris-lab ~/repos/miniconda3 | master • source bin/activate
(root) chris@chris-lab ~/repos/miniconda3 | master • ../deep-learning
(root) chris@chris-lab ~/repos/deep-learning | master • ipython
Python 3.6.2 |Continuum Analytics, Inc.| (default, Jul 20 2017, 13:51:32)
Type 'copyright', 'credits' or 'license' for more information
IPython 6.1.0 -- An enhanced Interactive Python. Type '?' for help.

In [1]:
```

- Google Cloud Platform
- AWS
- Microsoft Azure
- Your home machine (if you have a good GPU)



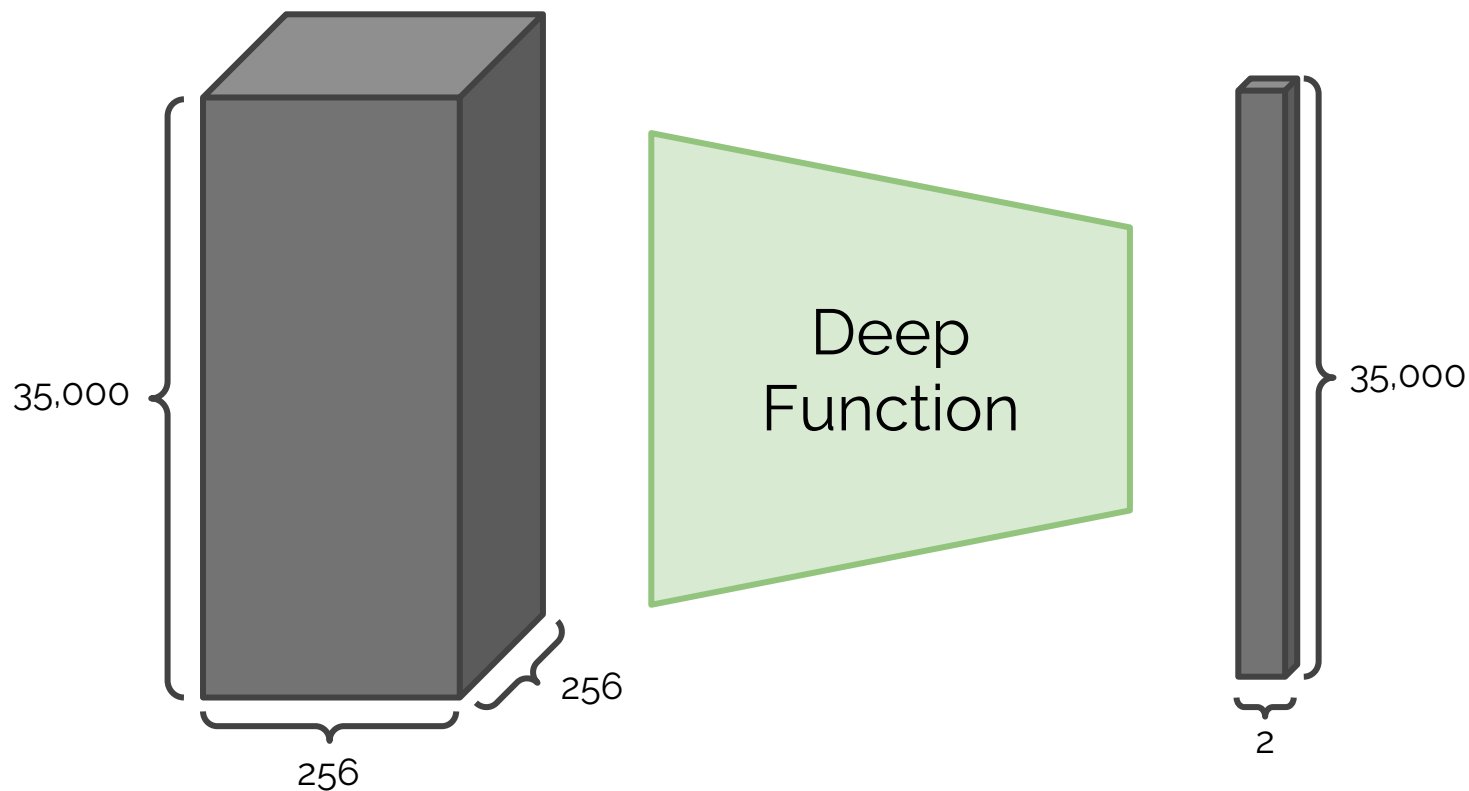
ssh, ipython



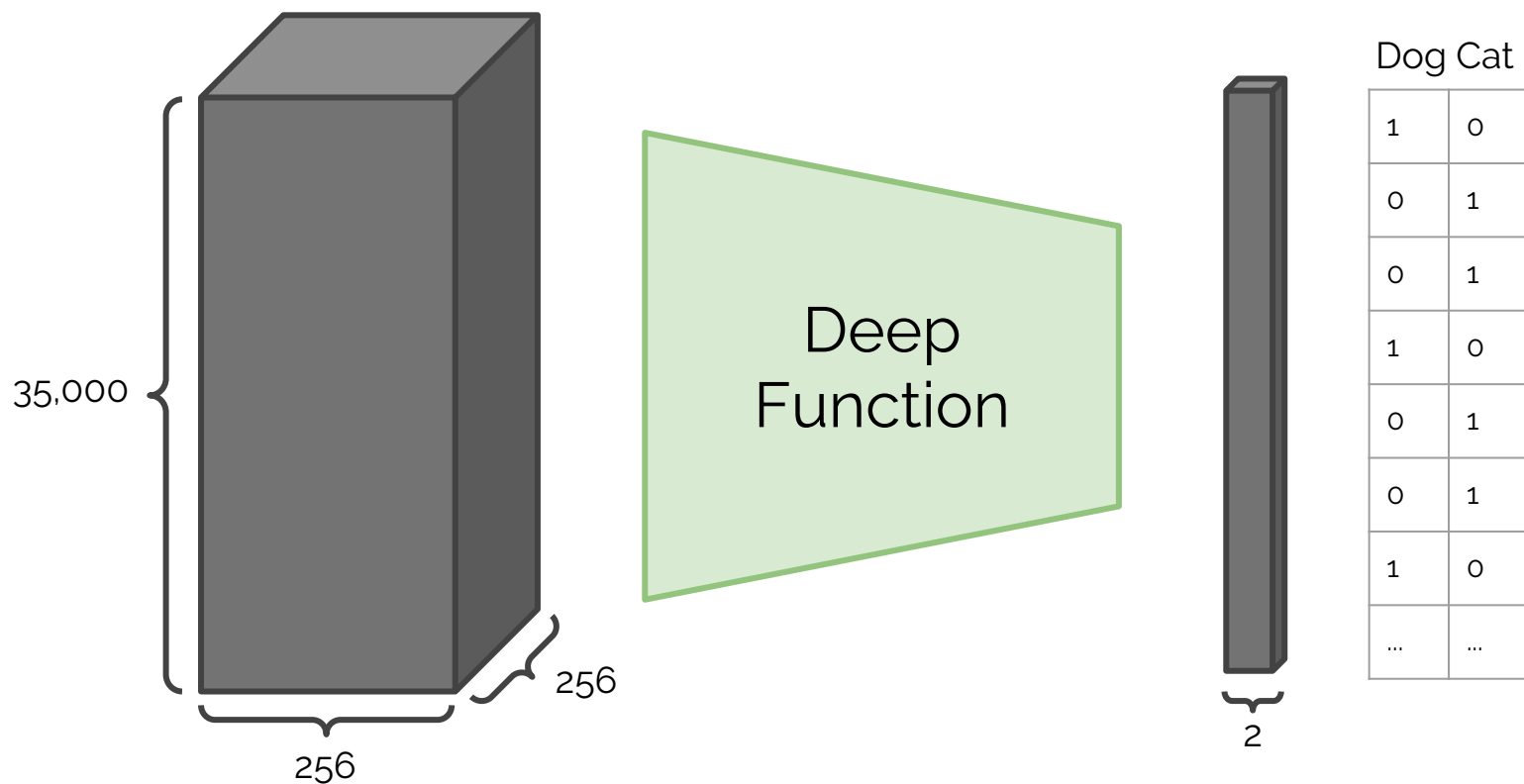
```
learning.py
16 import torch.nn as nn
17 import torch.nn.parallel
18 import torch.backends.cudnn as cudnn
19 import torch.optim.lr_scheduler
20 import torch.utils.trainer as trainer
21 import torch.utils.trainer.plugins
22 import torch.utils.data.sampler as sampler
23 import torchvision.datasets as datasets
24 import torchvision.models as models
25
26 ## Setup Visdom to visualize training results
27 vis = visdom.Visdom()
28 run = '09dec2017'
29 notes = run + ': some notes about what we changed in our last run.'
30 cudnn.benchmark = True
31
32 ## Normalize images
33 normalize = augment.Normalize(mean = [ 0.485, 0.456, 0.406 ],
34                               std = [ 0.229, 0.224, 0.225 ])
35
36 # Specify the training dataset
37 train_dataset = datasets.ImageFolder('train_kittens_puppies/', transform=aug
38                                     augment.ScalePad((224,224)),
39                                     augment.RandomRotate(60),
40                                     augment.ToTensor(),
41                                     normalize,))
42
43 # Ensure our classes are drawn with equal probabilities
44 weights = []
45 for i in range(len(train_dataset.classes)):
46     weights.append(sum([t[i]=i for t in train_dataset.imgs]))
47 weights = [1-(t/sum(weights)) for t in weights]
48
49 # Specify the validation dataset
50 val_dataset = datasets.ImageFolder('val_kittens_puppies/', transform=augment
51                                   augment.ScalePad((224,224)),
```

sshfs, visual studio code, pycharm, vim.

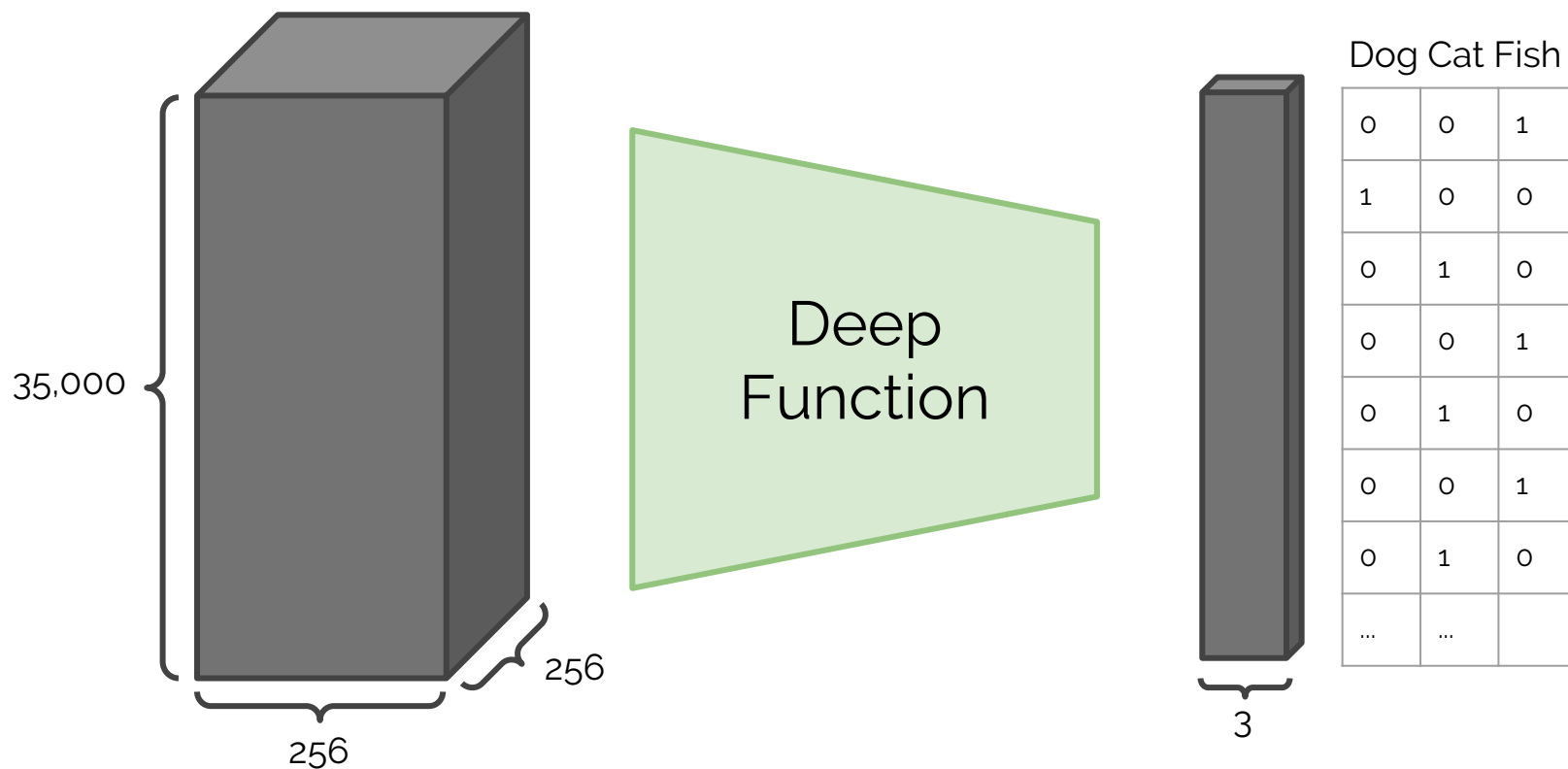
Tensors: Images \rightarrow Classes



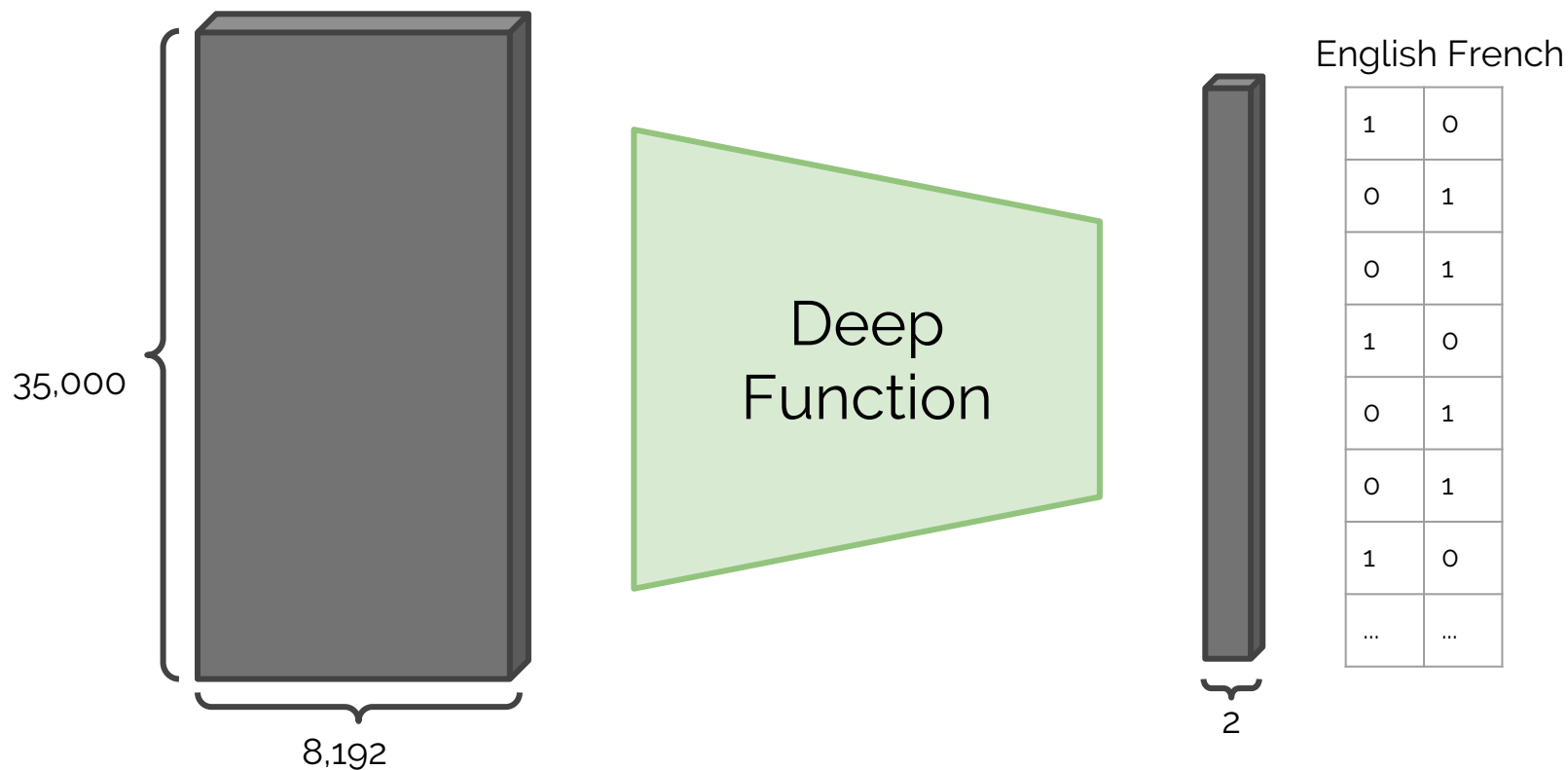
Tensors: Images \rightarrow Classes



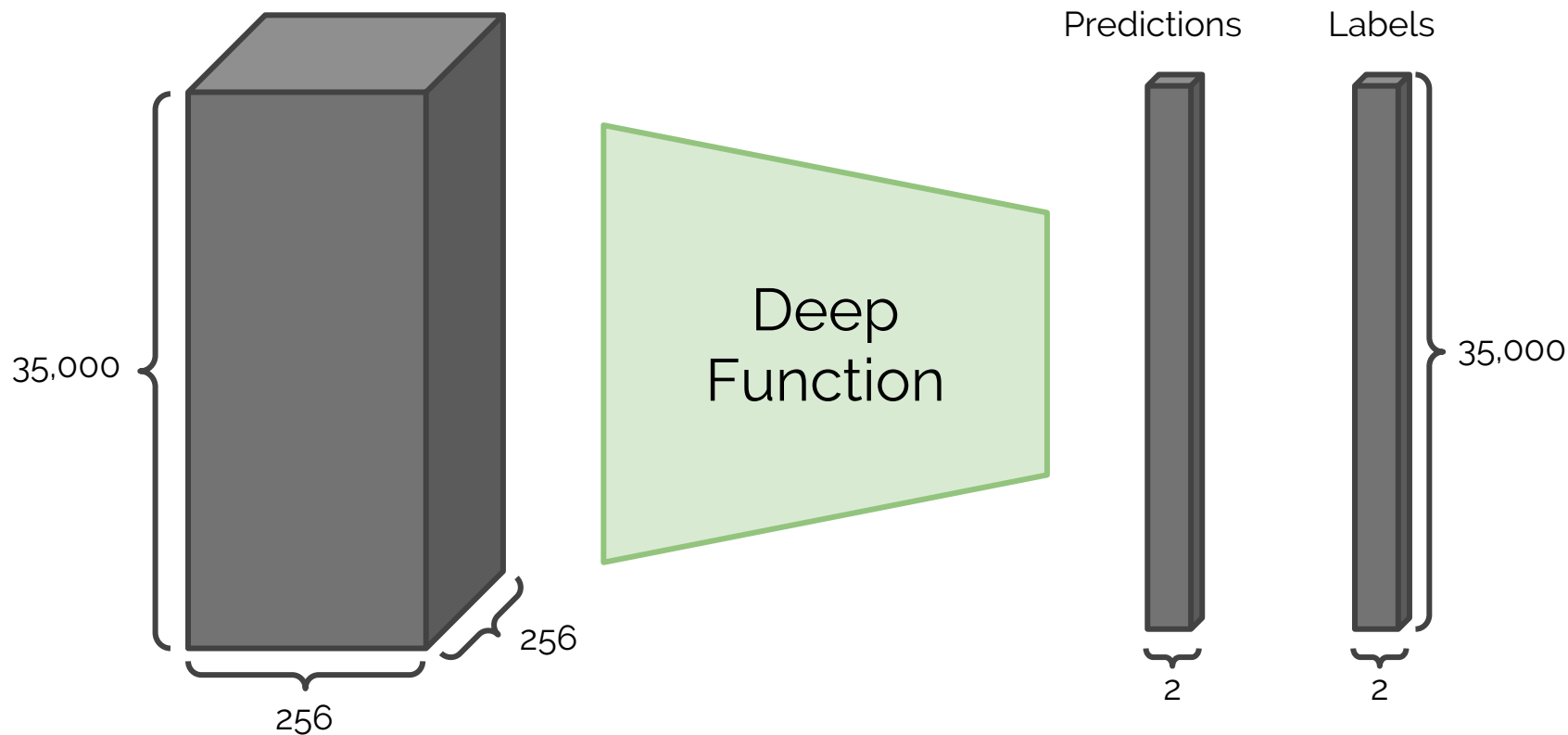
Tensors: Images \rightarrow Classes



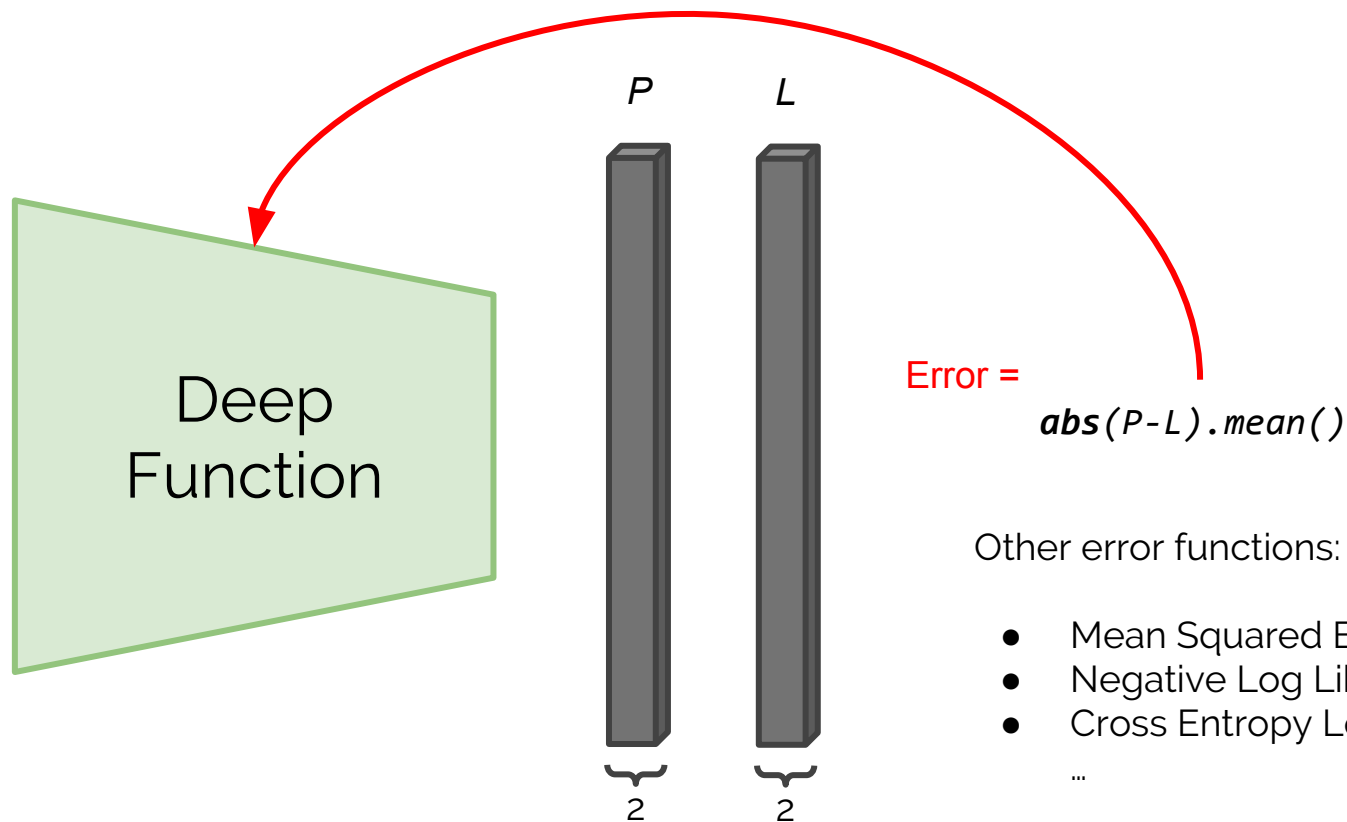
Tensors: Audio \rightarrow Classes



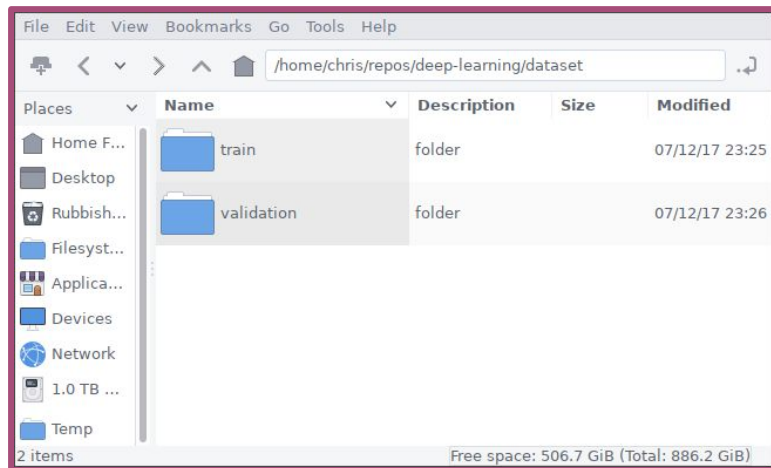
Predictions and Labels



Error Functions

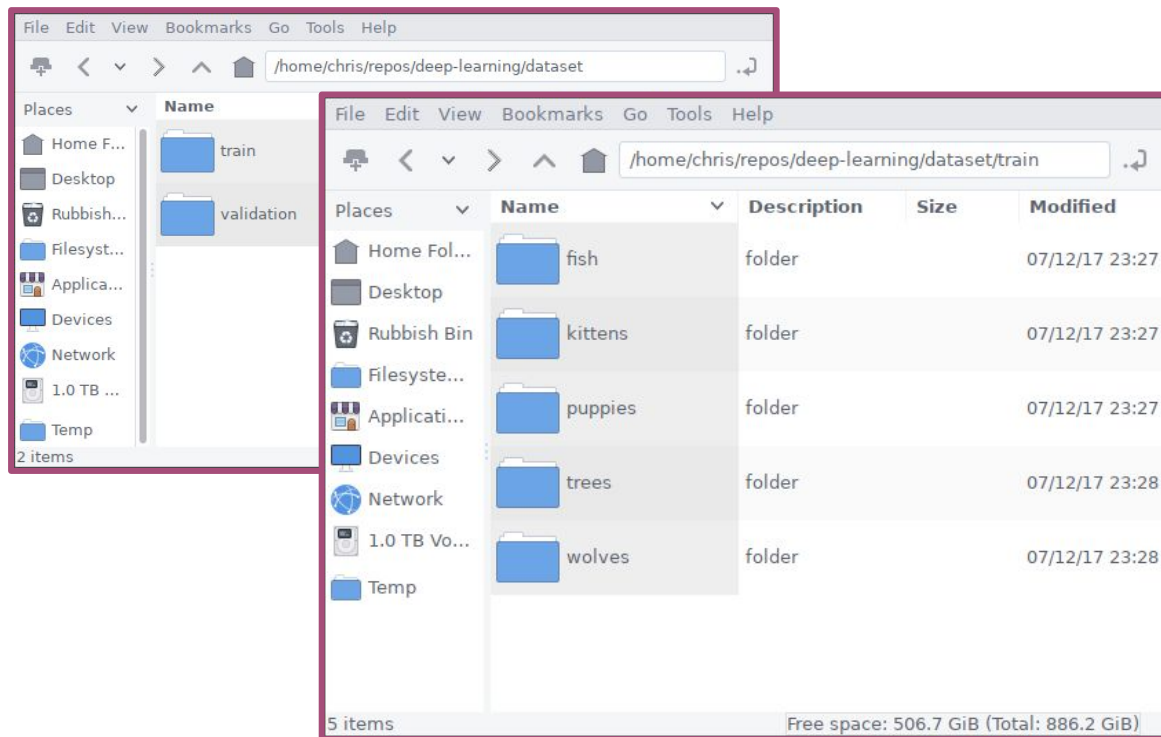


The Dataset



- Two folders
 - Train
 - Validation
- Validation contains about 10-20% of the train data
 - Don't randomly select, try to capture **harder** ones that represent different distributions, e.g:
 - Different weather conditions
 - Different cameras
 - Different geographical locations
 - Different poses

The Dataset



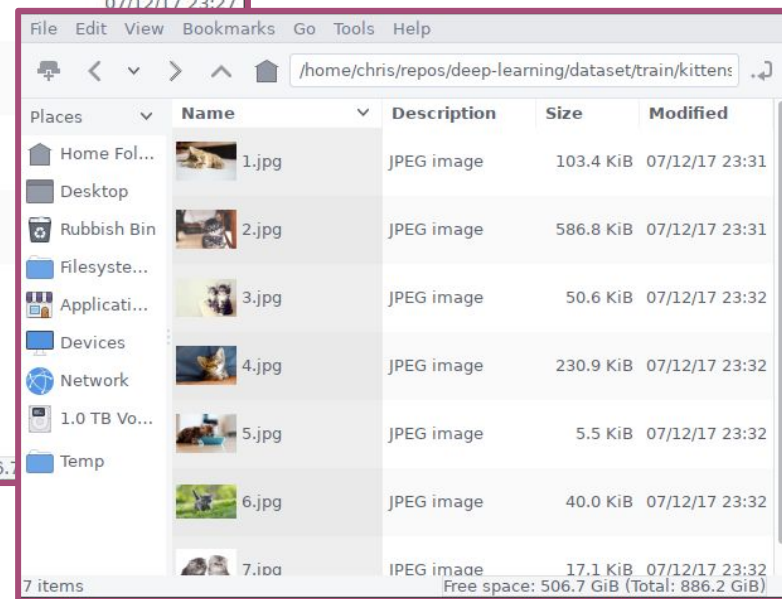
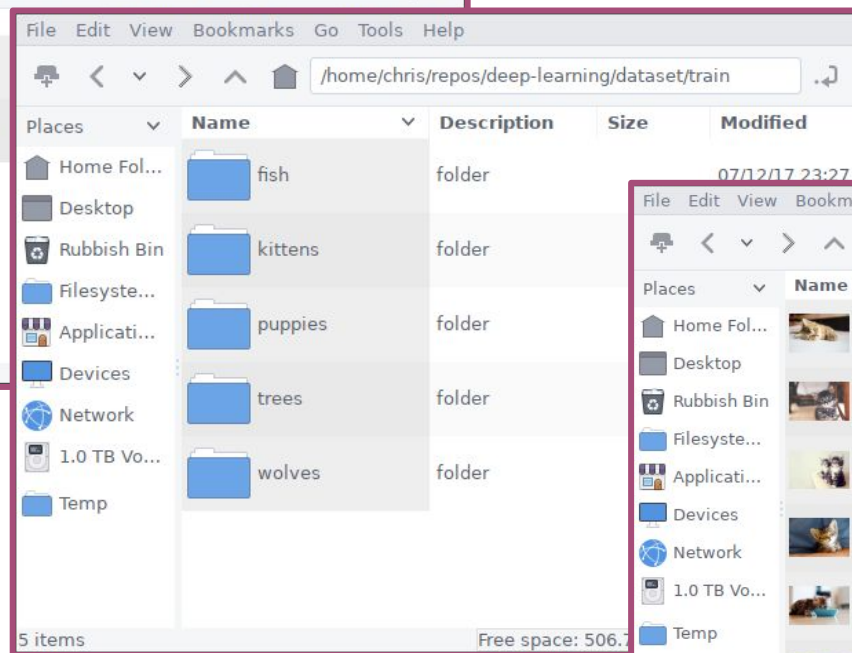
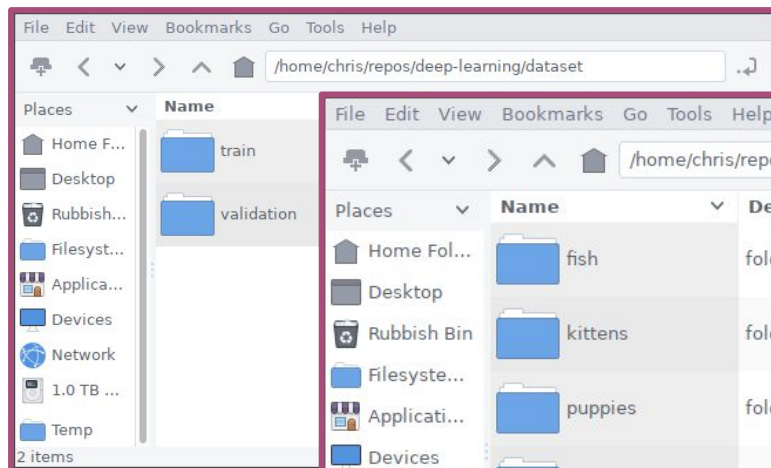
Classification:

- Put each class a separate folder inside train/validation
- Here we have 5-way classification

Regression:

Specify a CSV file with the target parameters, you will need to write your own code to parse this.

The Dataset



**~2,000 - 20,000 images
with transfer learning**

**try and get equal
images per class**

~100,000+ images without transfer learning
(approximations depend heavily on task complexity)

The Dataset

Just a list of
filenames and
mappings to
class indices (no
images in
memory)

```
...: import nets.resnet as resnet
...: import torch.nn as nn
...: import torch.nn.parallel
...: import torch.backends.cudnn as cudnn
...: import torch.optim.lr_scheduler
...: import torch.utils.trainer as trainer
...: import torch.utils.trainer.plugins
...: import torch.utils.data.sampler as sampler
...: import torchvision.datasets as datasets
...: import torchvision.models as models
...:

In [2]: vis = visdom.Visdom()
...: run = '09dec2017'
...: notes = run+' : some notes about what we changed in our last run.'
...: cudnn.benchmark = True
...:

In [3]: ## Normalize images
...: normalize = augment.Normalize(mean = [ 0.485, 0.456, 0.406 ],
...:                                std = [ 0.229, 0.224, 0.225 ])
...:

In [4]: # Specify the training dataset
...: train_dataset = datasets.ImageFolder('../..../dataset/train', transform=augment.Compose([
...:     augment.ScalePad((224,224)),
...:     augment.RandomRotate(60),
...:     augment.ToTensor(),
...:     normalize,]))
...:

In [5]: train_dataset.class_to_idx[
class_to_idx loader() transform
classes root
imgs target_transform
instance
```

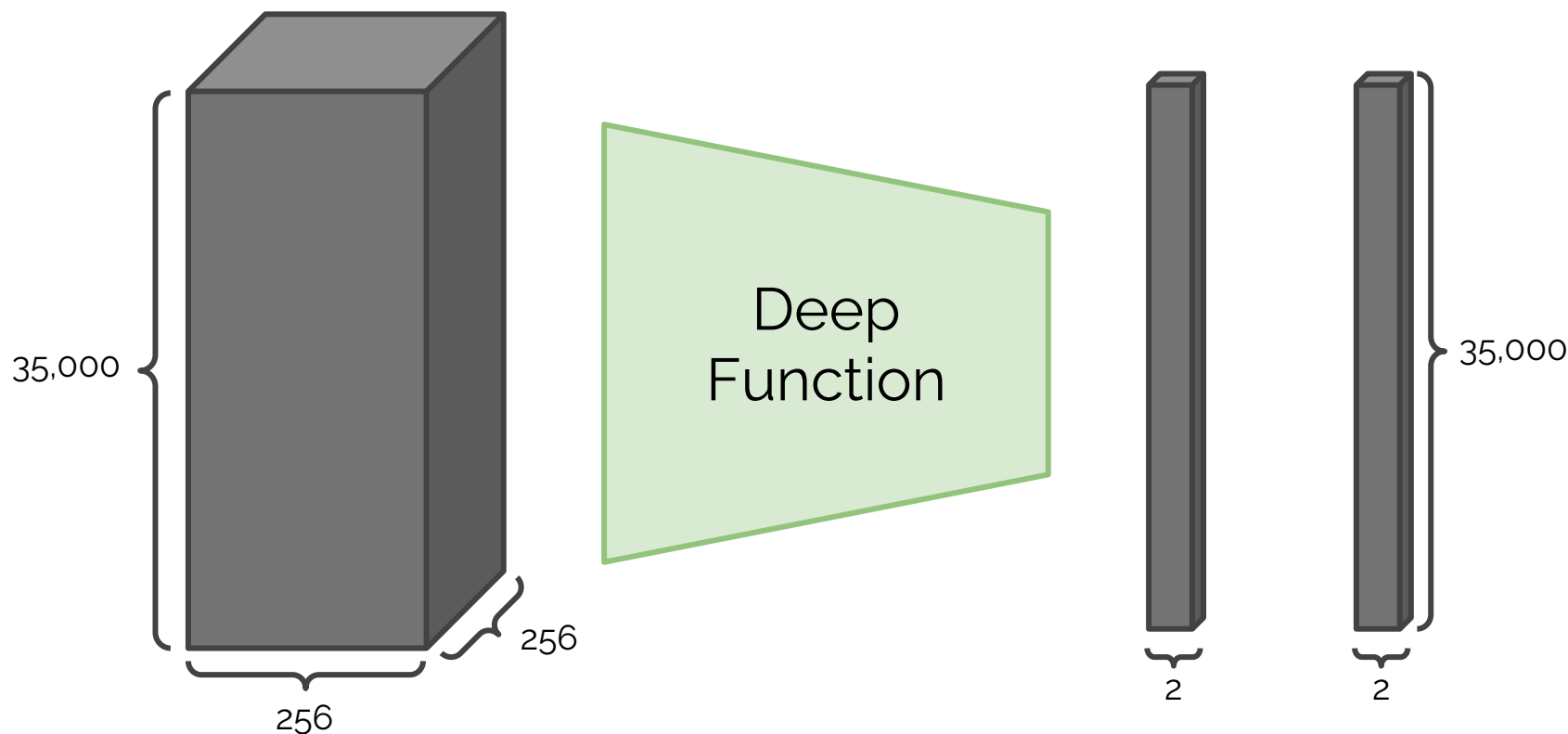
The Dataset

```
...: import nets.resnet as resnet
...: import torch.nn as nn
...: import torch.nn.parallel
...: import torch.backends.cudnn as cudnn
...: import torch.optim.lr_scheduler
...: import torch.utils.trainer as trainer
...: import torch.utils.trainer.plugins
...: import torch.utils.data.sampler as sampler
...: import torchvision.datasets as datasets
...: import torchvision.models as models
...:
In [2]: vis = visdom.Visdom()
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...: notes = run+' : some notes about what we changed in our last run.'
...: cudnn.benchmark = True
...:
In [3]: ## Normalize images
...: normalize = augment.Normalize(mean = [ 0.485, 0.456, 0.406 ],
...:                               std = [ 0.229, 0.224, 0.225 ])
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In [4]: # Specify the training dataset
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...:     augment.ScalePad((224,224)),
...:     augment.RandomRotate(60),
...:     augment.ToTensor(),
...:     normalize,]))
...:
In [5]: train_dataset.class_to_idx
Out[5]: {'fish': 0, 'kittens': 1, 'puppies': 2, 'trees': 3, 'wolves': 4}
In [6]: []
```

Classes and
their indices

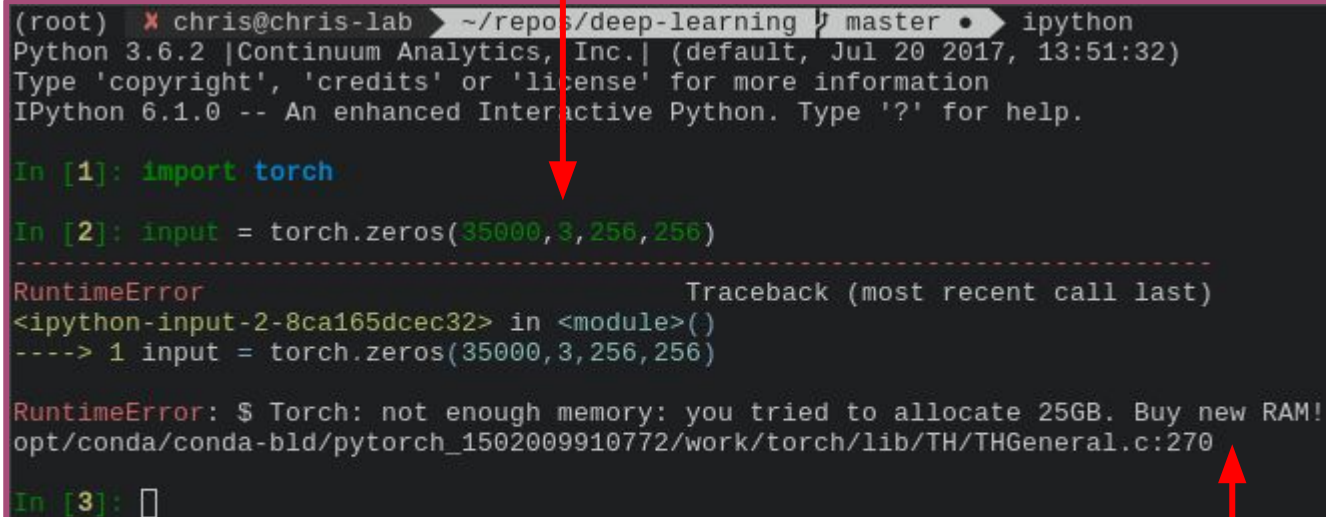
We run out of memory...

$35,000 * 3 * 256 * 256 * (32 \text{ bits}) = \mathbf{27.52 \text{ gigabytes}}$ *not including the model!*



We run out of memory...

Try and create the tensor



```
(root) ✖ chris@chris-lab > ~/repos/deep-learning master • ipython
Python 3.6.2 |Continuum Analytics, Inc.| (default, Jul 20 2017, 13:51:32)
Type 'copyright', 'credits' or 'license' for more information
IPython 6.1.0 -- An enhanced Interactive Python. Type '?' for help.

In [1]: import torch

In [2]: input = torch.zeros(35000, 3, 256, 256)
-----
RuntimeError                                Traceback (most recent call last)
<ipython-input-2-8ca165dcec32> in <module>()
----> 1 input = torch.zeros(35000, 3, 256, 256)

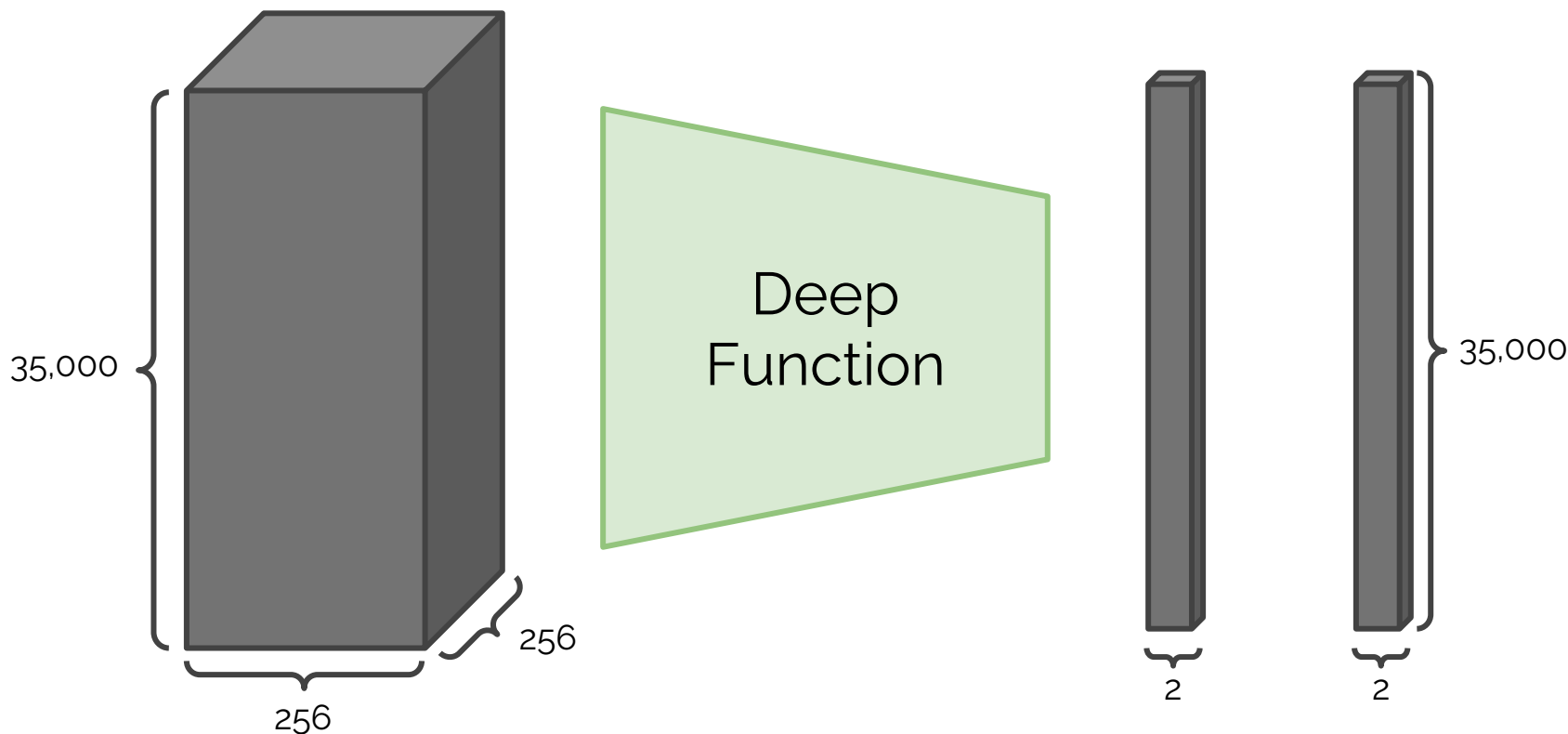
RuntimeError: $ Torch: not enough memory: you tried to allocate 25GB. Buy new RAM!
opt/conda/conda-bld/pytorch_1502009910772/work/torch/lib/TH/THGeneral.c:270

In [3]: □
```

Nope!

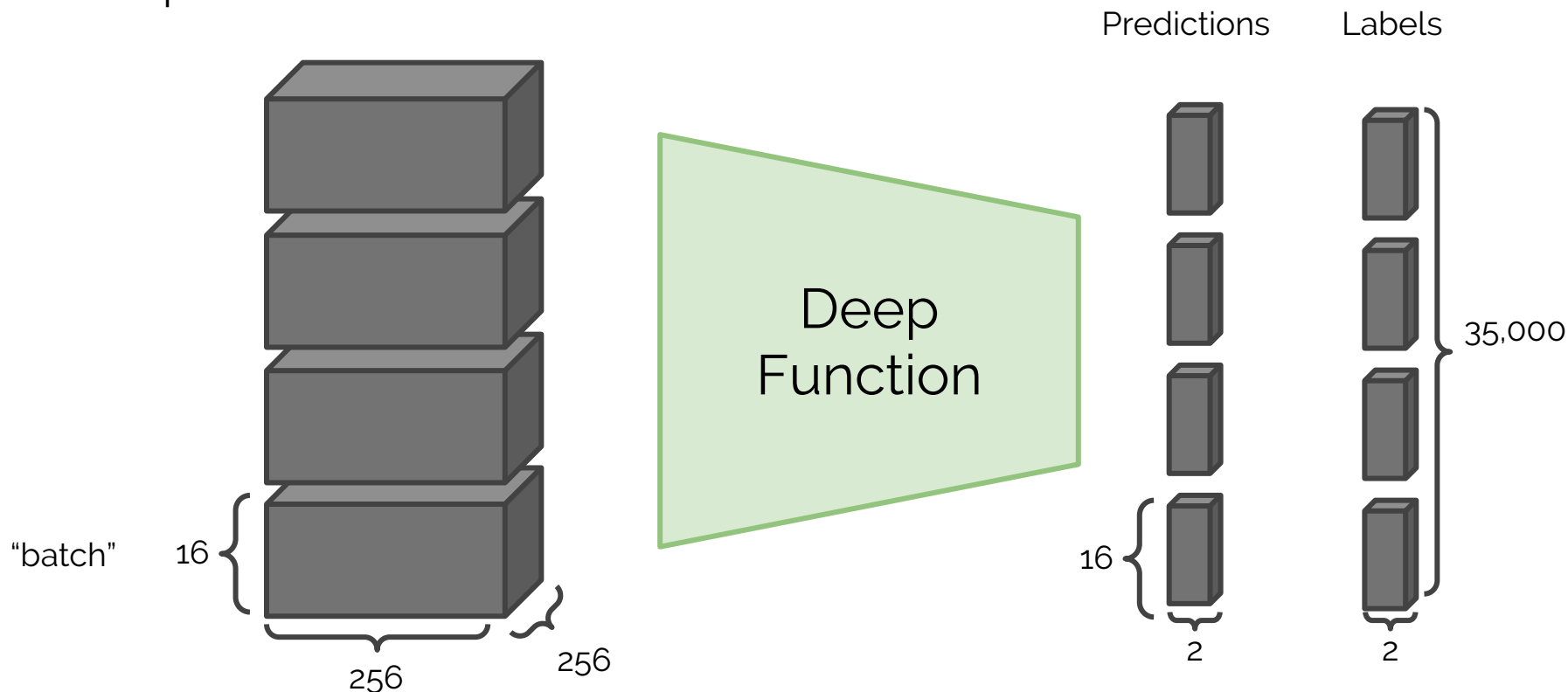
We run out of memory...

$35,000 * 256 * 256 * 3 * (32 \text{ bits}) = \mathbf{27.52 \text{ gigabytes}}$ *not including the model!*



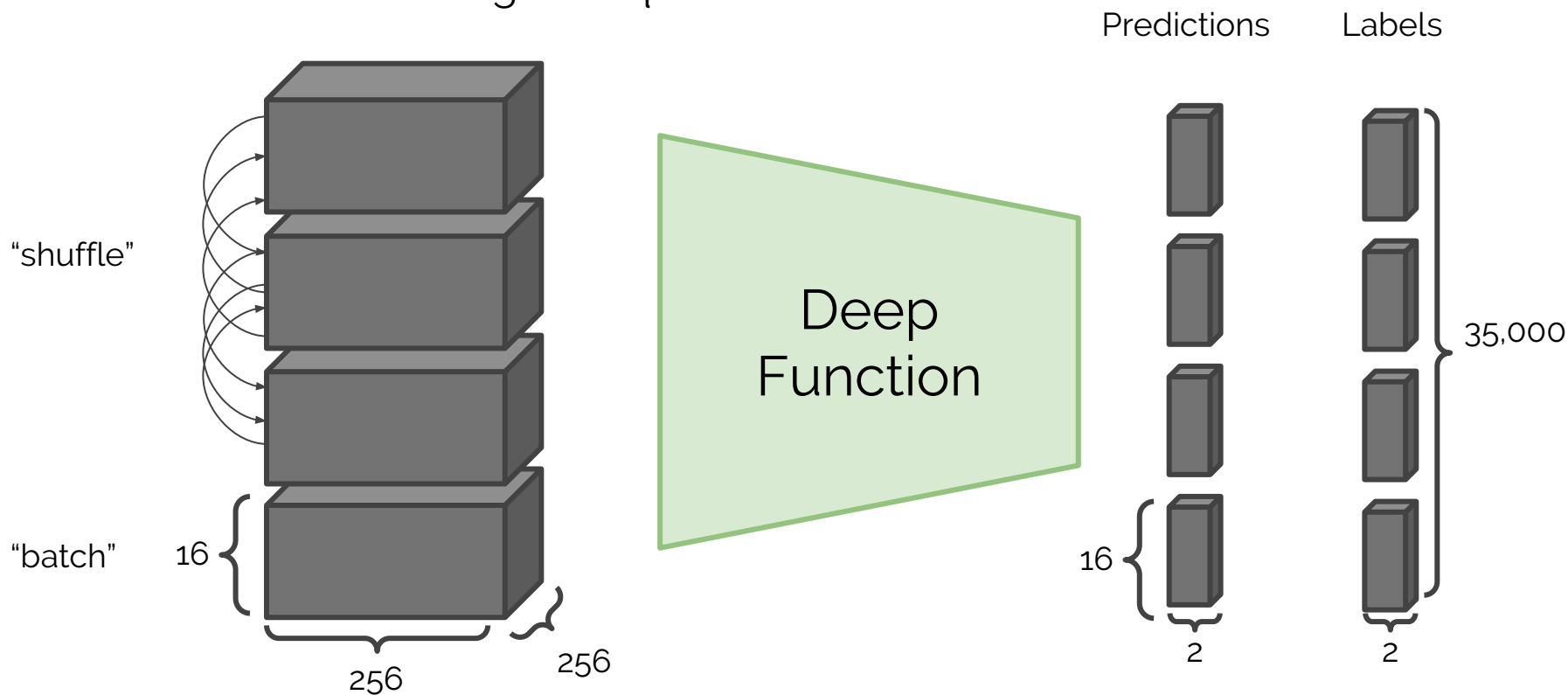
The Data Loader

- Split dataset into mini batches each iteration



The Data Loader

- Shuffle dataset to get unique batches



Mini batches in memory

```
(root) chris@chris-lab > ~/repos/deep-learning / master • ipython
Python 3.6.2 |Continuum Analytics, Inc.| (default, Jul 20 2017, 13:51:32)
Type 'copyright', 'credits' or 'license' for more information
IPython 6.1.0 -- An enhanced Interactive Python. Type '?' for help.
```

```
In [1]: import torch
```

```
In [2]: images = torch.zeros(16,3,256,256)
```

```
In [3]: output = torch.zeros(16,2,1,1)
```

```
In [4]: images.size()
```

```
Out[4]: torch.Size([16, 3, 256, 256])
```

```
In [5]: output.size()
```

```
Out[5]: torch.Size([16, 2, 1, 1])
```

```
In [6]: []
```

12.58 megabytes
much better!

The Data Loader

Recap, the dataset is not “in memory” we just load a list of filenames and mappings to their class indices

```
import imp
import util
import augment
import nets.resnet as resnet
import torch.nn as nn
import torch.nn.parallel
import torch.backends.cudnn as cudnn
import torch.optim.lr_scheduler
import torch.utils.trainer as trainer
import torch.utils.trainer.plugins
import torch.utils.data.sampler as sampler
import torchvision.datasets as datasets
import torchvision.models as models

## Setup Visdom to visualize training results
vis = visdom.Visdom()
run = '09dec2017'
notes = run + ': some notes about what we changed in our last run.'
cudnn.benchmark = True

## Normalize images
normalize = augment.Normalize(mean = [ 0.485, 0.456, 0.406 ],
                              std = [ 0.229, 0.224, 0.225 ])

# Specify the training dataset
train_dataset = datasets.ImageFolder('../dataset/train/', transform=augment.Compose([
    augment.ScalePad((224,224)),
    augment.RandomRotate(60),
    augment.ToTensor(),
    normalize,]))

# Specify the validation dataset
val_dataset = datasets.ImageFolder('../dataset/validation/', transform=augment.Compose([
    augment.ScalePad((224,224)),
    augment.ToTensor(),
    normalize,]))

In [2]:
```


The Data Loader

Create a data loader for the train dataset, with a **batch_size** of 16 and **shuffle=True**

```
import torch.nn.parallel
import torch.backends.cudnn as cudnn
import torch.optim.lr_scheduler
import torch.utils.trainer as trainer
import torch.utils.trainer.plugins
import torch.utils.data.sampler as sampler
import torchvision.datasets as datasets
import torchvision.models as models

## Setup Visdom to visualize training results
vis = visdom.Visdom()
run = '09dec2017'
notes = run + ': some notes about what we changed in our last run.'
cudnn.benchmark = True

## Normalize images
normalize = augment.Normalize(mean = [ 0.485, 0.456, 0.406 ],
                              std  = [ 0.229, 0.224, 0.225 ])

# Specify the training dataset
train_dataset = datasets.ImageFolder('.../dataset/train/', transform=augment.Compose([
    augment.ScalePad((224,224)),
    augment.RandomRotate(60),
    augment.ToTensor(),
    normalize,]))

# Specify the validation dataset
val_dataset = datasets.ImageFolder('.../dataset/validation/', transform=augment.Compose([
    augment.ScalePad((224,224)),
    augment.ToTensor(),
    normalize,]))


In [ ]: # Prepare the data loaders, which get mini-batches of tensors for training
train_loader = torch.utils.data.DataLoader(train_dataset,
    batch_size=16, shuffle=True, num_workers=12, pin_memory=True)

In [3]:
```

The Data Loader

```
...: import torch.utils.trainer.plugins
...: import torch.utils.data.sampler as sampler
...: import torchvision.datasets as datasets
...: import torchvision.models as models
...:
...: ## Setup Visdom to visualize training results
...: vis = visdom.Visdom()
...: run = '09dec2017'
...: notes = run + ': some notes about what we changed in our last run.'
...: cudnn.benchmark = True
...:
...: ## Normalize images
...: normalize = augment.Normalize(mean = [ 0.485, 0.456, 0.406 ],
...:                               std = [ 0.229, 0.224, 0.225 ])
...:
...: # Specify the training dataset
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...:     augment.ScalePad((224,224)),
...:     augment.RandomRotate(60),
...:     augment.ToTensor(),
...:     normalize,]))
...:
...: # Specify the validation dataset
...: val_dataset = datasets.ImageFolder('../..../dataset/validation/', transform=augment.Compose([
...:     augment.ScalePad((224,224)),
...:     augment.ToTensor(),
...:     normalize,]))
...:
In [2]: # Prepare the data loaders, which get mini-batches of tensors for training
...: train_loader = torch.utils.data.DataLoader(train_dataset,
...:     batch_size=16, shuffle=True, num_workers=12, pin_memory=True)
...:
In [3]: val_loader = torch.utils.data.DataLoader(val_dataset,
...:     batch_size=16, shuffle=False, num_workers=12, pin_memory=True)
...:
In [4]: []
```

The validation data
loader doesn't
need to shuffle

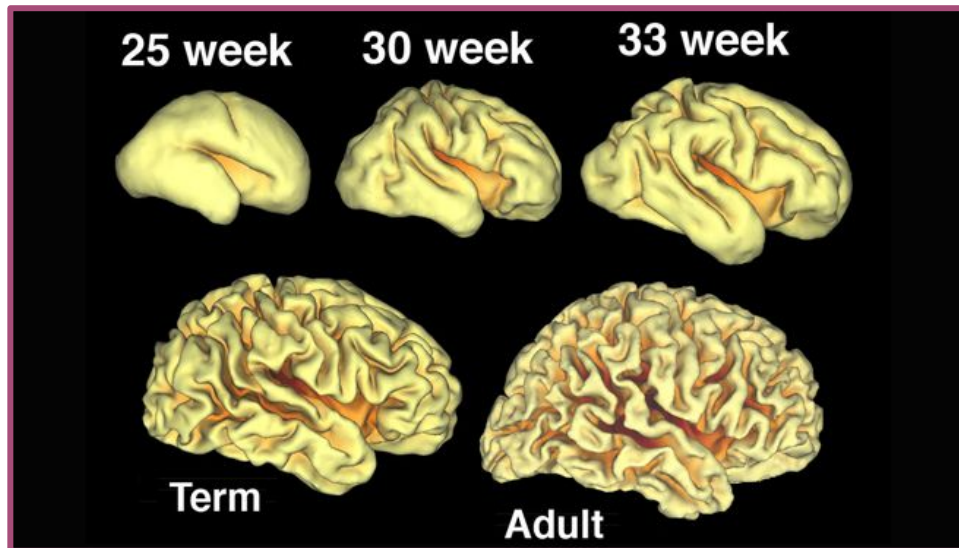


Load Model with Transfer Learning

```
63 # Load the model
64 model = torch.nn.DataParallel(resnet.resnet34(pretrained=True)).cuda()
```

Nice!

- Is it easier to train a **baby** to detect cancer or an **adult** to detect cancer?
- We train networks on complex tasks with lots of public data (even until they outperform humans)
- We then change the data to our tasks, and continue training




Architectures Available








- **Official** architectures (networks) with pre-trained weights:
- Also lots of **unofficial** ones on Github

Branch: master vision / torchvision / models /

Create new file Upload files Find file History

 alykhantejani committed with fmassa add stride=1 for average pooling in models to have consistent printin... 3 Latest commit d#7524# on Oct 22

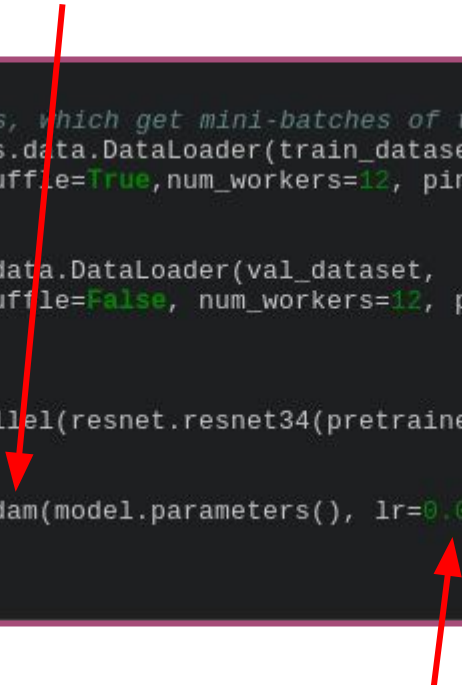
..

 __init__.py	Fix models documentation	2 months ago
 alexnet.py	move pre-trained models URL to download.pytorch.org	9 months ago
 densenet.py	add stride=1 for average pooling in models to have consistent printin...	2 months ago
 inception.py	fix unbroadcastable UserWarning in inception.py (#231)	4 months ago
 resnet.py	add stride=1 for average pooling in models to have consistent printin...	2 months ago
 squeezenet.py	add stride=1 for average pooling in models to have consistent printin...	2 months ago
 vgg.py	Update vgg.py (#233)	3 months ago

Specify the Optimizer algorithm

- Currently, for now, use Adam (most of the time)

```
....  
In [2]: # Prepare the data loaders, which get mini-batches of tensors for training  
....: train_loader = torch.utils.data.DataLoader(train_dataset,  
....:      batch_size=16, shuffle=True, num_workers=12, pin_memory=True)  
....:  
In [3]: val_loader = torch.utils.data.DataLoader(val_dataset,  
....:      batch_size=16, shuffle=False, num_workers=12, pin_memory=True)  
....:  
In [4]: # Load the model  
....: model = torch.nn.DataParallel(resnet.resnet34(pretrained=True)).cuda()  
  
In [5]: # Load the optimizer  
....: optimizer = torch.optim.Adam(model.parameters(), lr=0.00005, betas=(0.5, 0.999), weight_decay  
....:      =0.0002)  
  
In [6]: □
```



Set your **learning rate** carefully! (usually first thing you need to adjust)

Train and Collect Metrics

```
(root) X chris@chris-lab ~/repos/deep-learning master • python -m visdom.server  
It's Alive!  
█
```

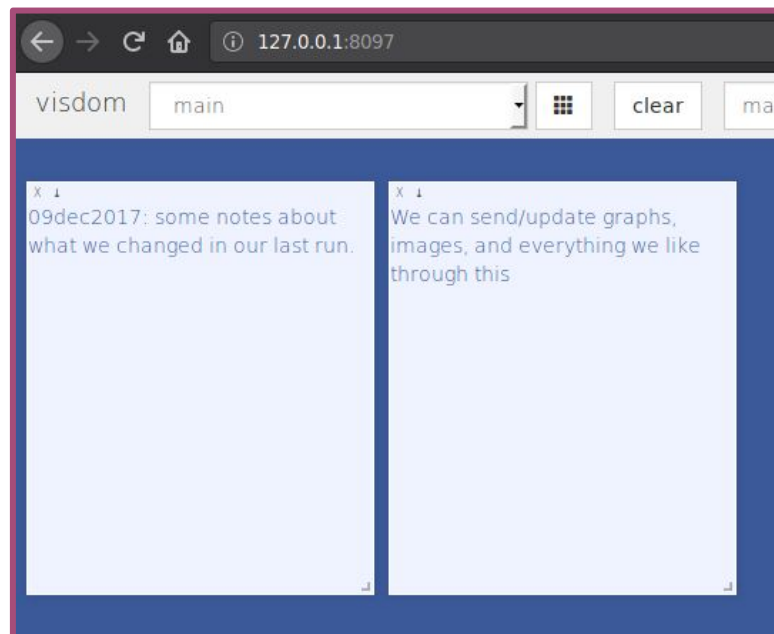
```
batch_size=16, shuffle=False, num_workers=12, pin_memory=True)
# Load the model
model = torch.nn.DataParallel(resnet.resnet34(pretrained=True)).cuda()
# Load the optimizer
optimizer = torch.optim.Adam(model.parameters(), lr=0.00005, betas=(0.5, 0.999), weight_decay=0.000
2)
# Specify some measurements that we wish to take during training
chk_acc = 0
plt_loss_sum = 0
plt_count = 0
plt_loss = np.empty(0, dtype='float32')
plt_acc = np.empty(0, dtype='float32')
plt_val_loss = np.empty(0, dtype='float32')
plt_val_acc = np.empty(0, dtype='float32')
epoch = 0
# Function for cleanly exiting
def signal_handler(signal, frame):
    global interrupted
    interrupted = True
# Show some notes
vis.text(notes)
signal.signal(signal.SIGINT, signal_handler)
interrupted = False
```

```
In [2]: vis.text("We can send/update graphs, images, and everything we like through this")
Out[2]: 'pane_35be5596041be6'
```

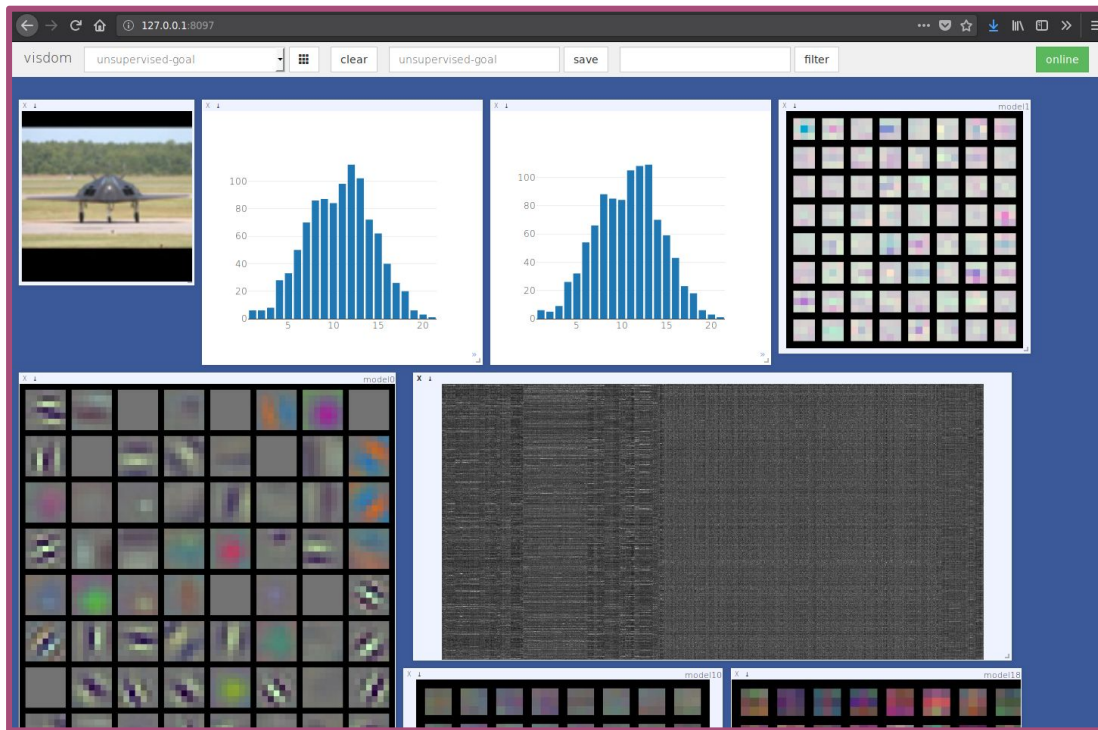
```
In [3]: vis.

|           |             |          |        |           |        |               |
|-----------|-------------|----------|--------|-----------|--------|---------------|
| bar()     | endpoint    | image()  | mesh() | quiver()  | stem() | updateTrace() |
| boxplot() | env         | images() | pie()  | save()    | surf() | video()       |
| close()   | heatmap()   | ipynb    | port   | scatter() | svg()  |               |
| contour() | histogram() | line()   | proxy  | server    | text() |               |

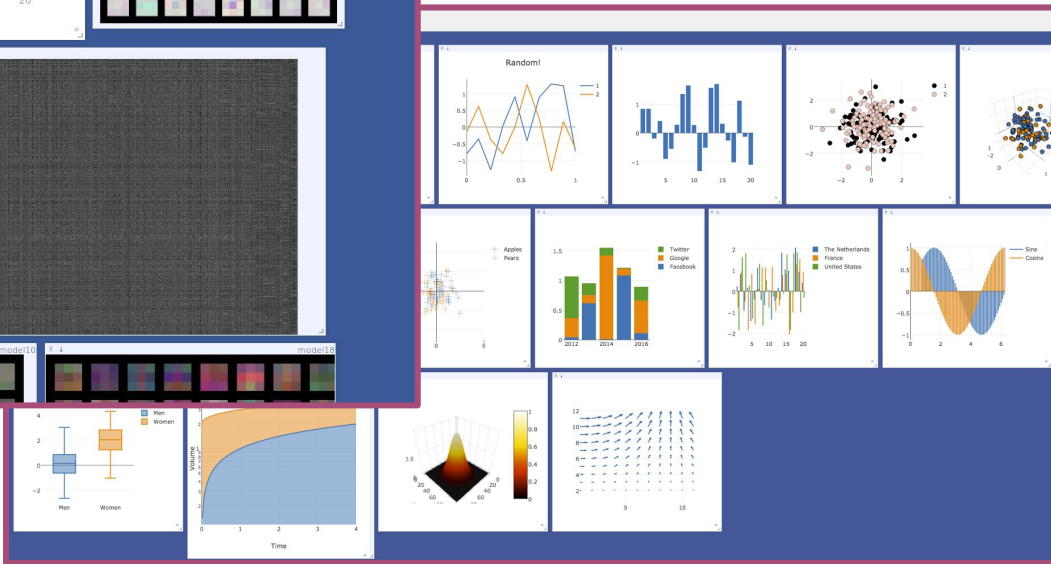

```



Visdom

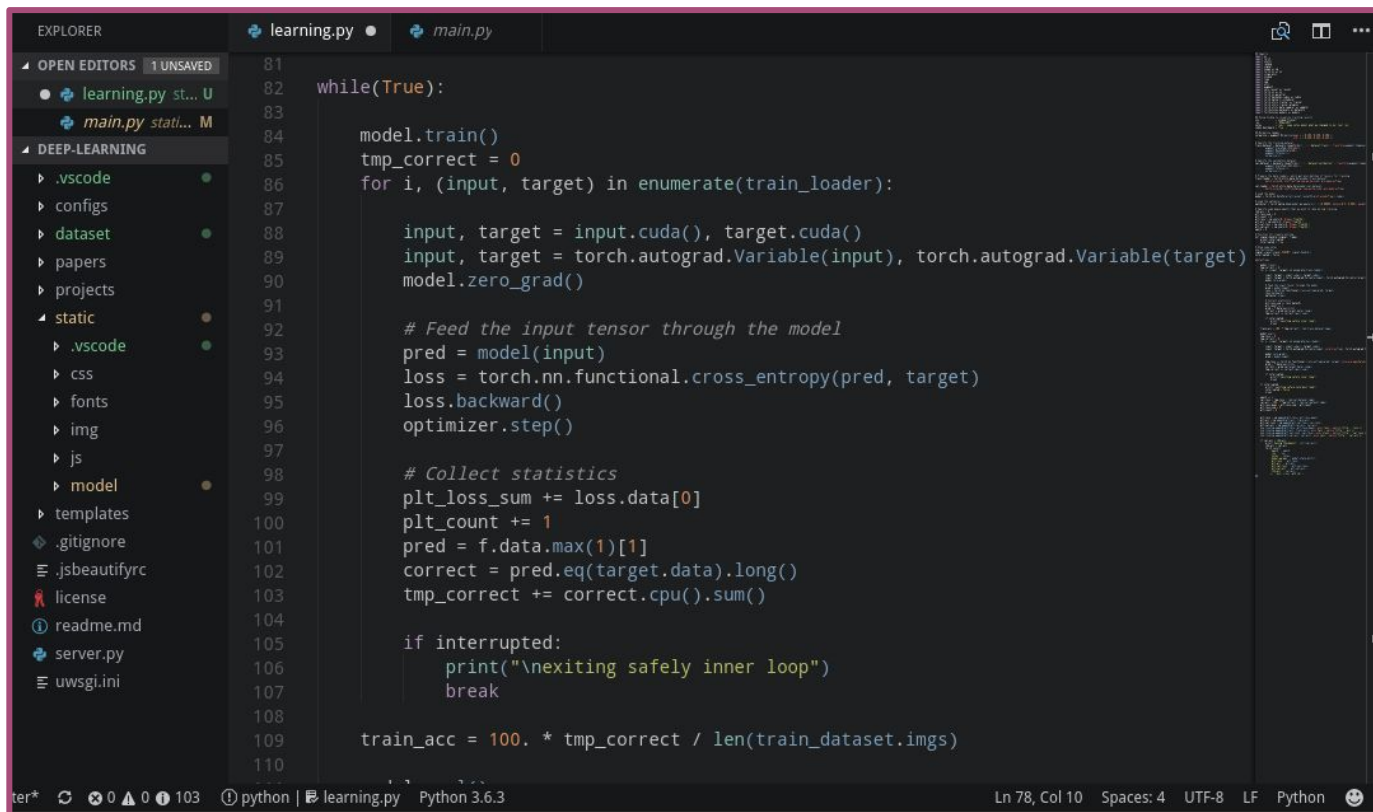


- Visualize accuracy/loss
- Visualize parameters



Lots of graph options

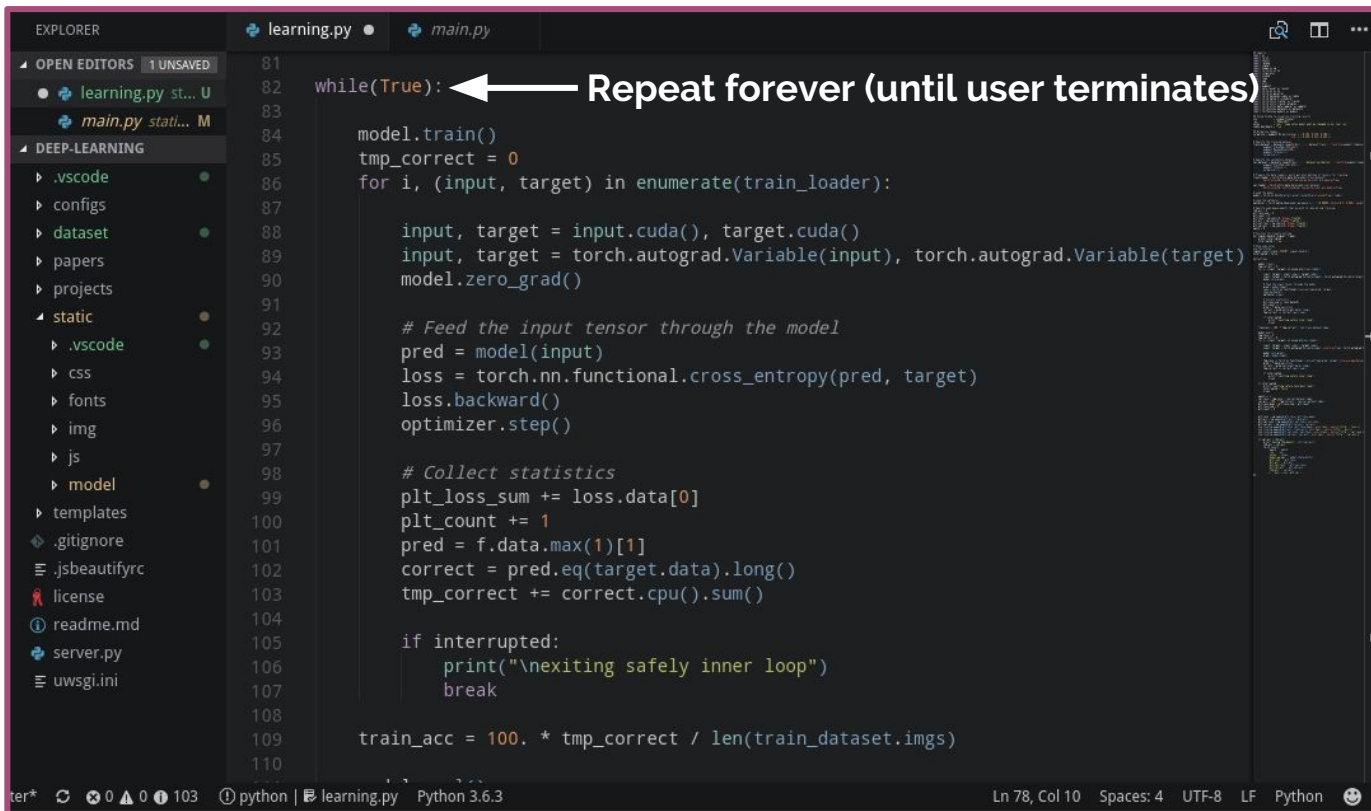
Training



The screenshot shows a VS Code editor window with a dark theme. The Explorer sidebar on the left shows a project structure for 'DEEP-LEARNING' with folders like '.vscode', 'configs', 'dataset', 'papers', 'projects', 'static', and 'model'. The main editor area displays a Python script named 'learning.py' with a 'while(True):' loop for training a model. The script includes comments for feeding input, collecting statistics, and handling interrupts. The status bar at the bottom indicates the file is 'learning.py' in Python 3.6.3, with 78 lines and 10 columns selected.

```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105        if interrupted:
106            print("\nexiting safely inner loop")
107            break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

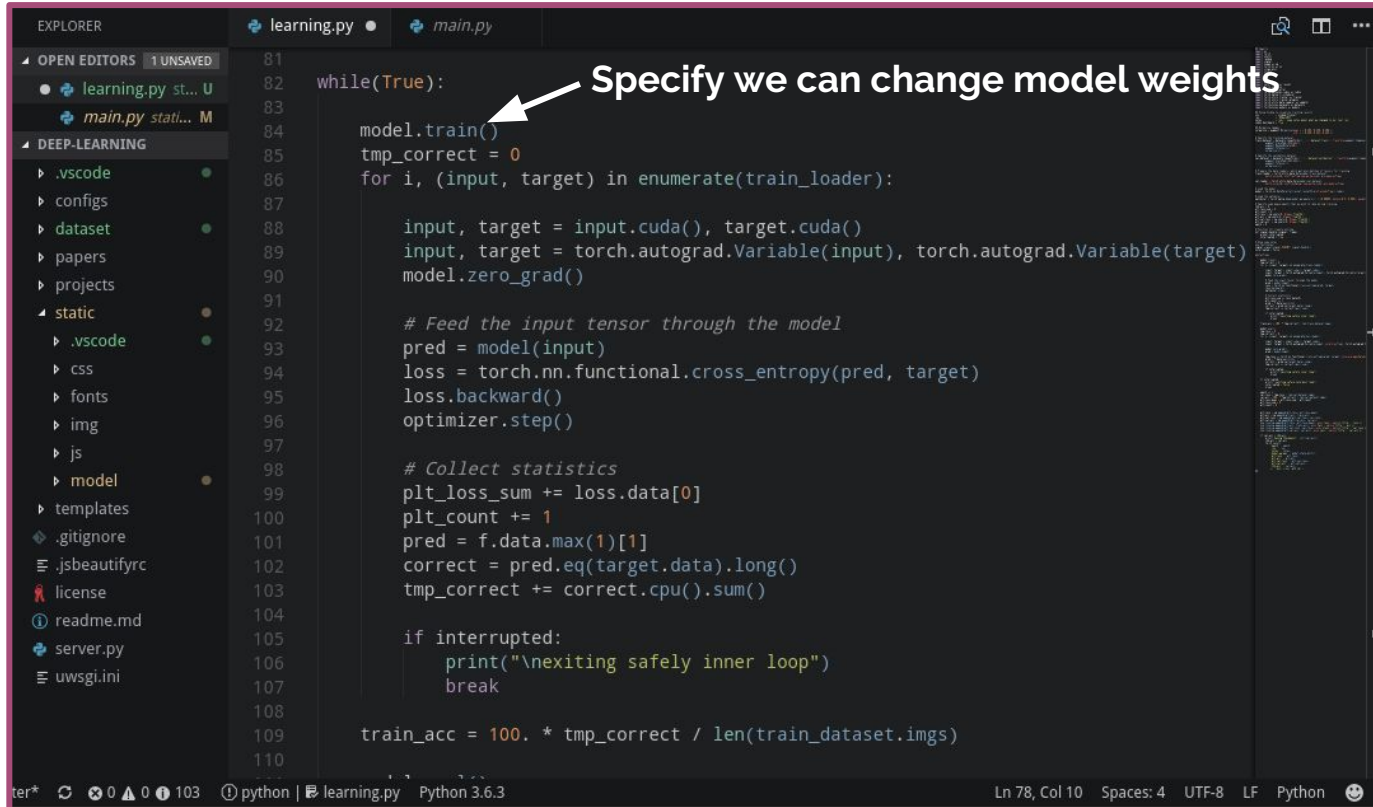
Training



```
81
82 while(True): ← Repeat forever (until user terminates)
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105        if KeyboardInterrupt:
106            print("\nexiting safely inner loop")
107            break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

ter* 0 0 103 python | learning.py Python 3.6.3 Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

Training



```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105        if interrupted:
106            print("\nexiting safely inner loop")
107            break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

Specify we can change model weights

EXPLORER

learning.py • main.py

OPEN EDITORS 1 UNSAVED

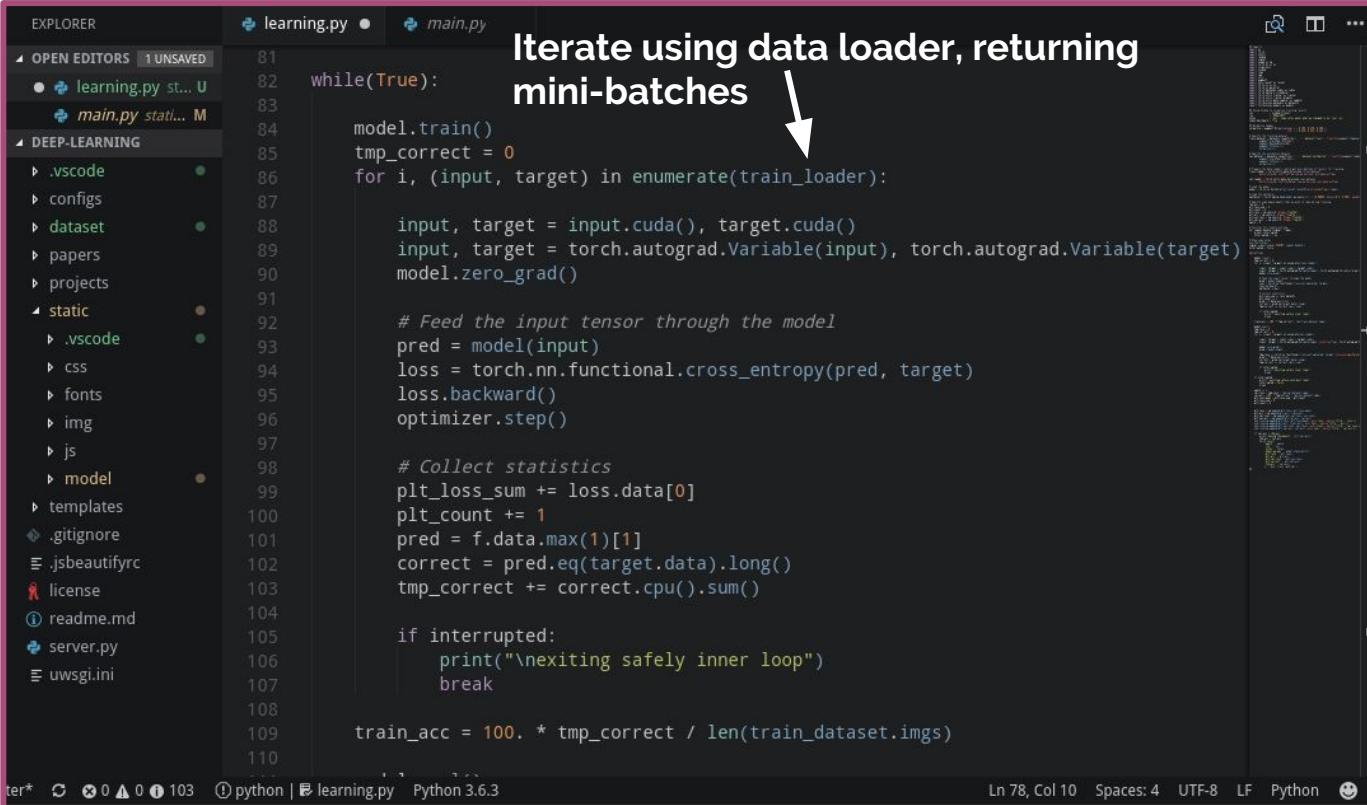
- learning.py st... U
- main.py stati... M

DEEP-LEARNING

- .vscode
- configs
- dataset
- papers
- projects
- static
 - .vscode
 - css
 - fonts
 - img
 - js
 - model
- templates
- .gitignore
- .jsbeautifyrc
- license
- readme.md
- server.py
- uwsgi.ini

Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

Training

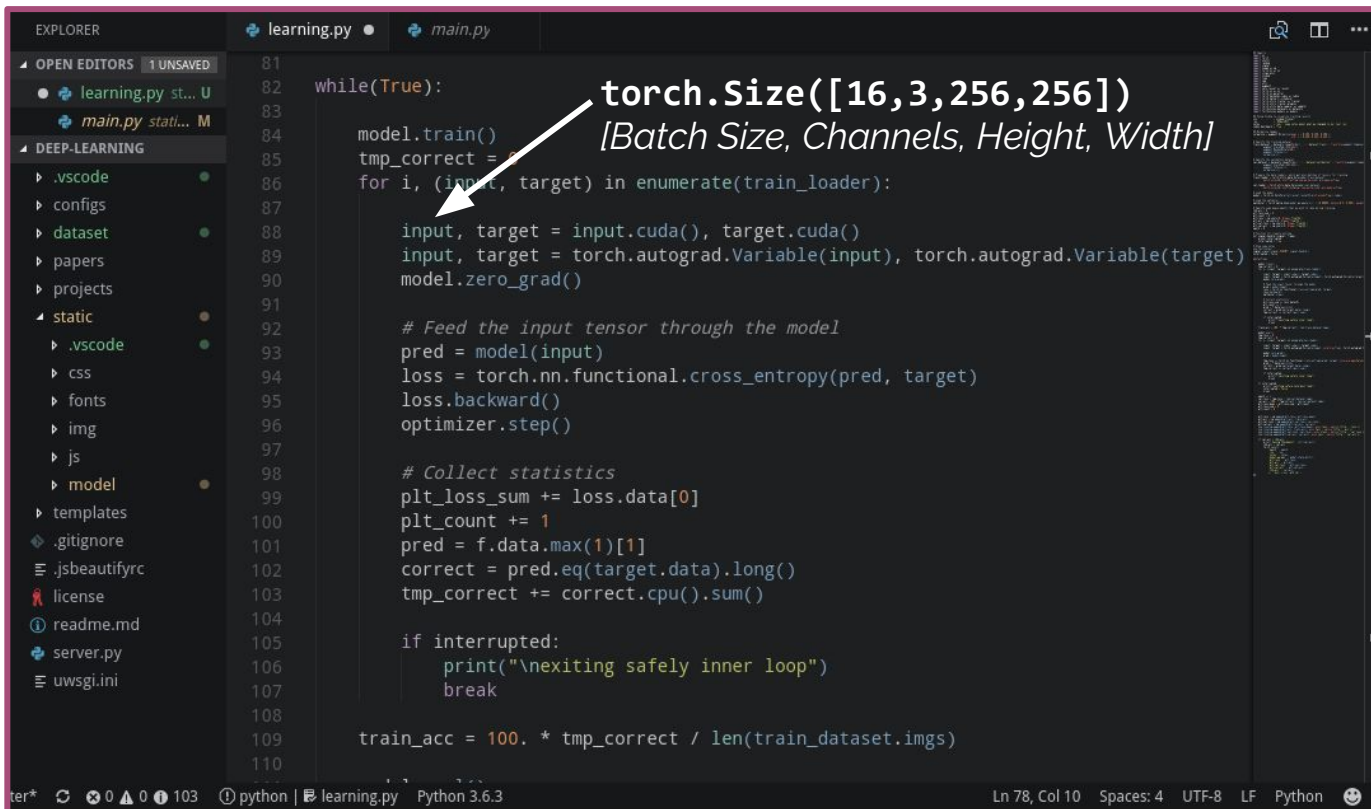


Iterate using data loader, returning mini-batches

```
81 while(True):
82
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105        if interrupted:
106            print("\nexiting safely inner loop")
107            break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

Training

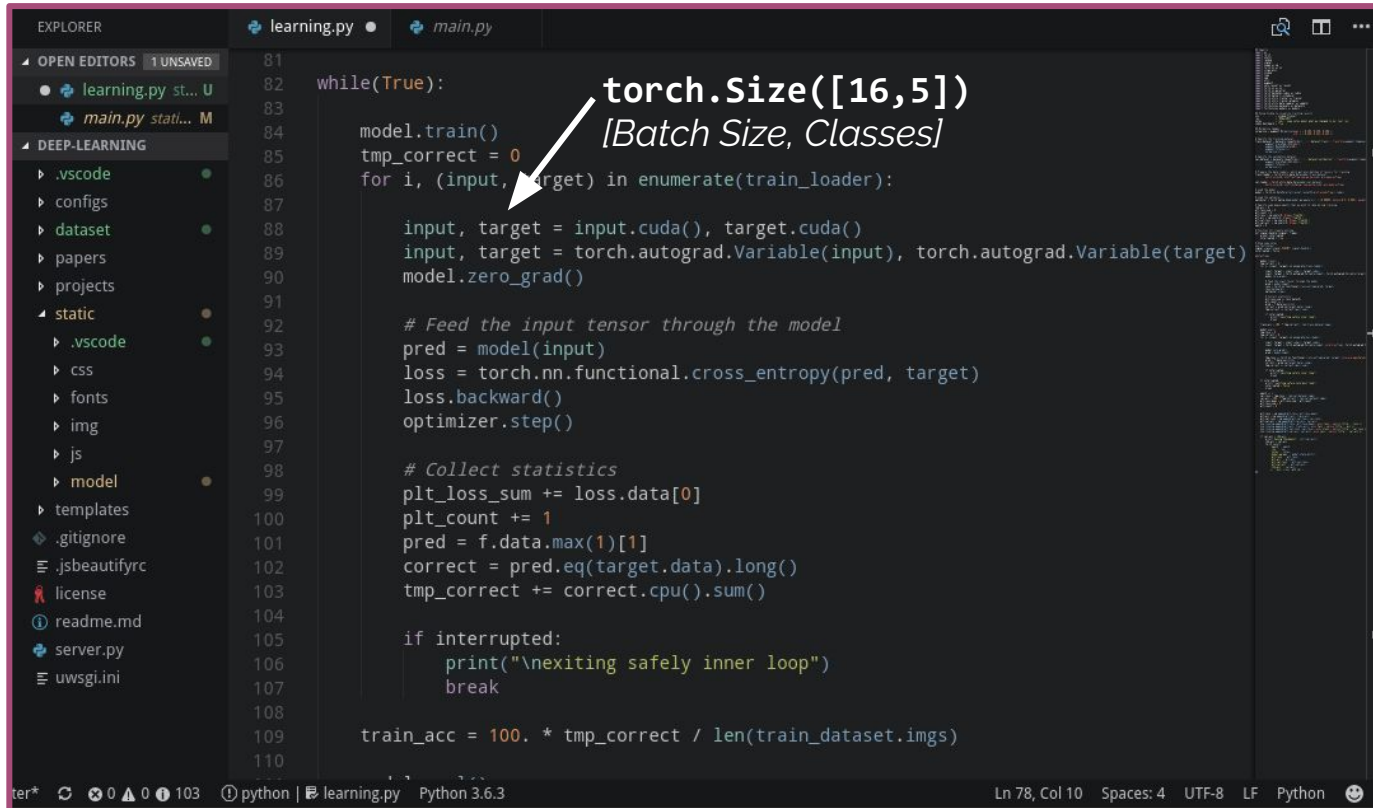


```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105        if interrupted:
106            print("\nexiting safely inner loop")
107            break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

torch.Size([16,3,256,256])
[Batch Size, Channels, Height, Width]

python | learning.py Python 3.6.3 Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

Training

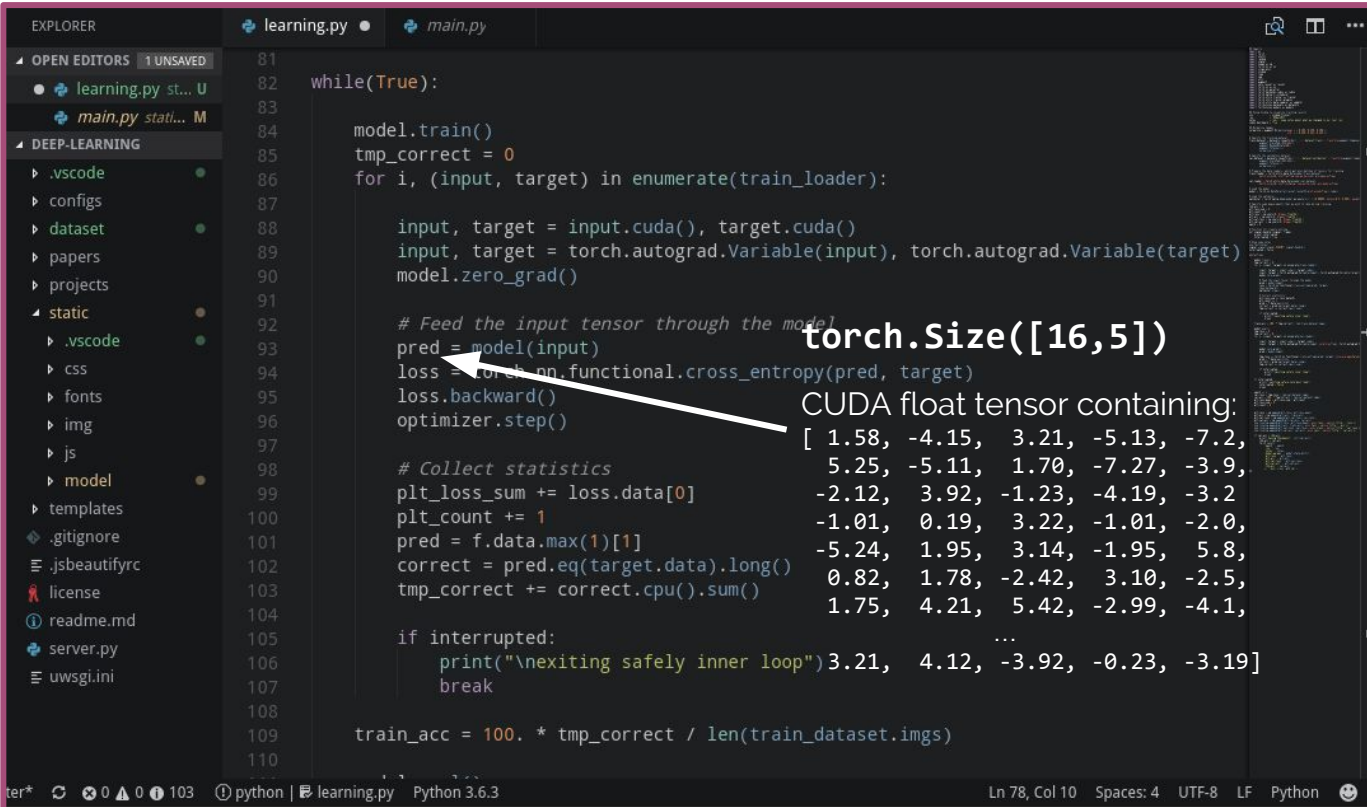


```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105        if interrupted:
106            print("\nexiting safely inner loop")
107            break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

torch.Size([16,5])
[Batch Size, Classes]

Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

Training



```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105    if interrupted:
106        print("\nexiting safely inner loop")
107        break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

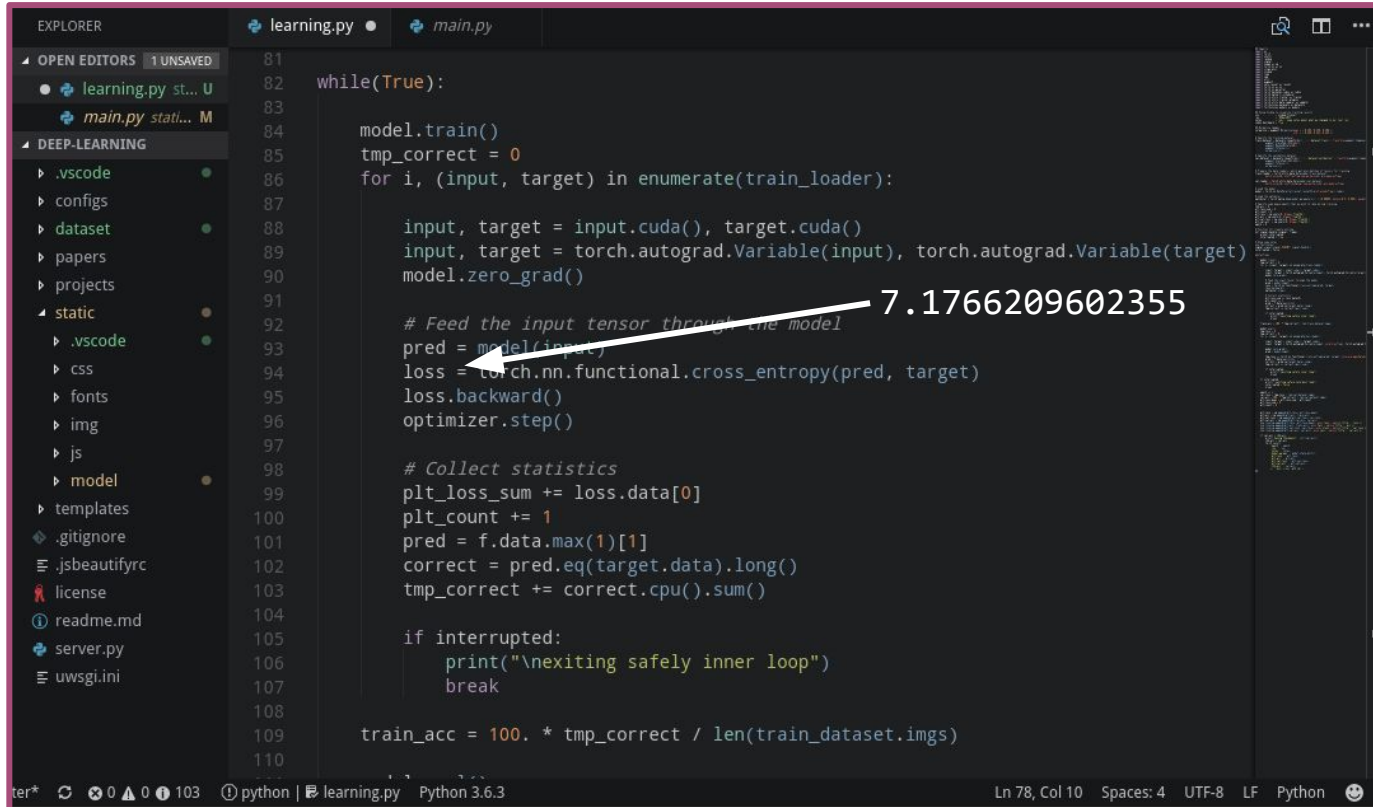
torch.Size([16,5])

CUDA float tensor containing:

1.58	-4.15	3.21	-5.13	-7.2
5.25	-5.11	1.70	-7.27	-3.9
-2.12	3.92	-1.23	-4.19	-3.2
-1.01	0.19	3.22	-1.01	-2.0
-5.24	1.95	3.14	-1.95	5.8
0.82	1.78	-2.42	3.10	-2.5
1.75	4.21	5.42	-2.99	-4.1
...
3.21	4.12	-3.92	-0.23	-3.19

Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

Training

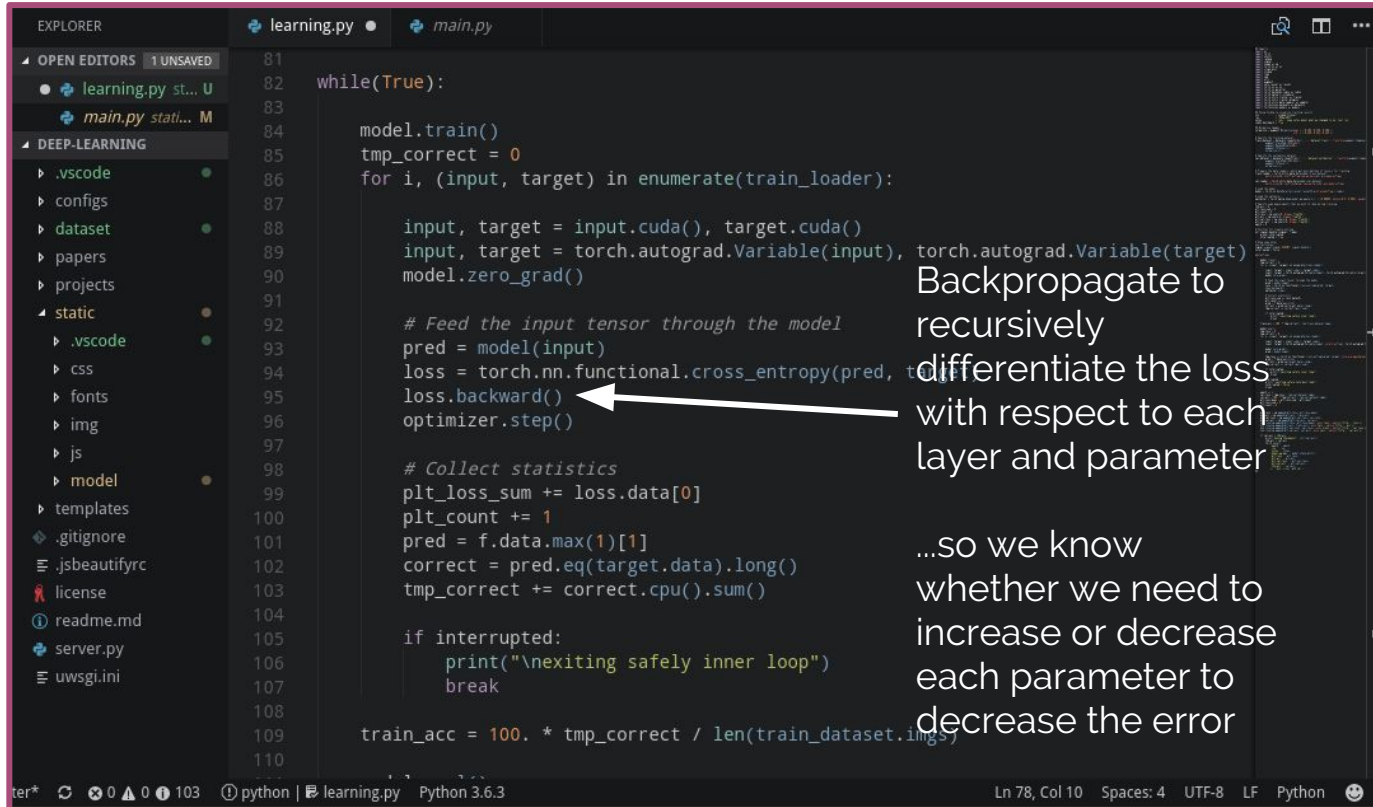


```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
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92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105        if interrupted:
106            print("\nexiting safely inner loop")
107            break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

7.1766209602355

Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

Training



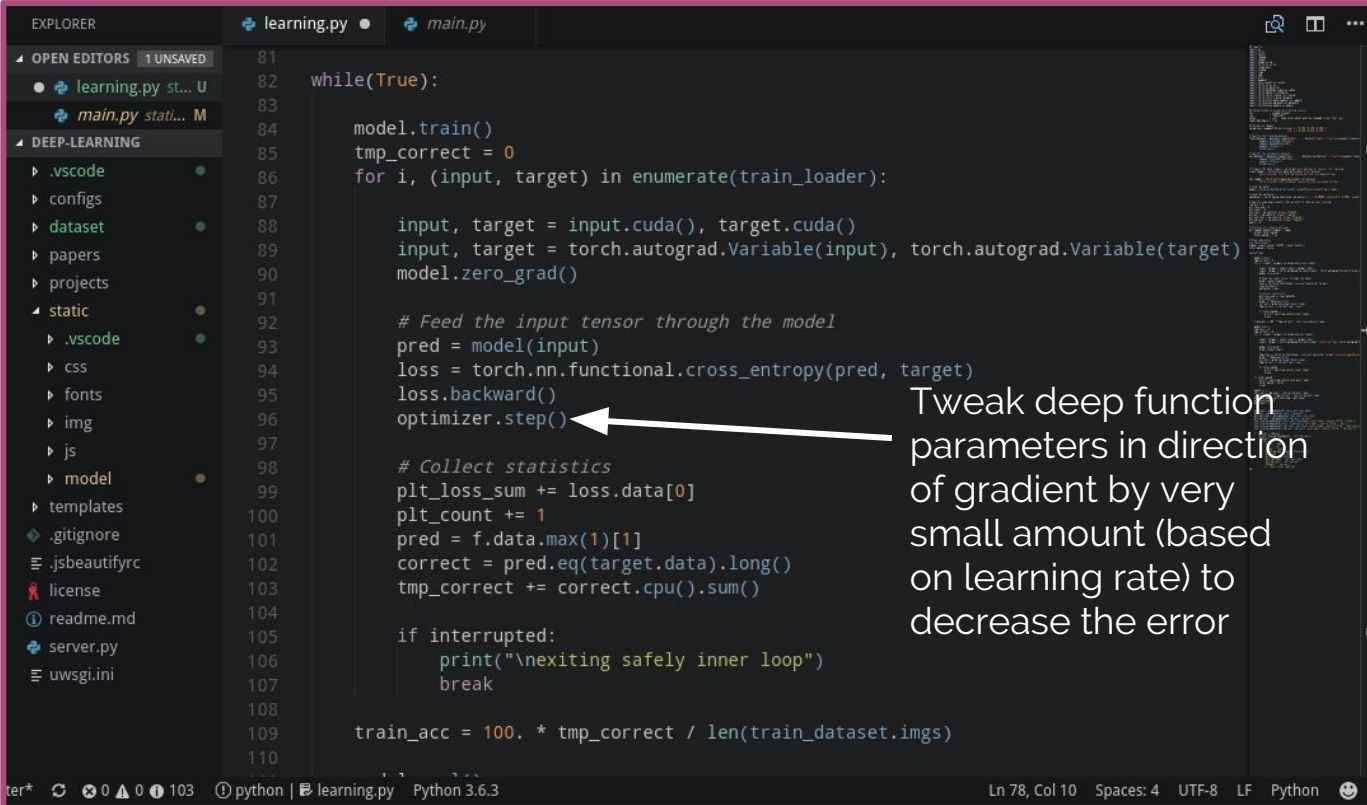
```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
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99         plt_loss_sum += loss.data[0]
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101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105    if interrupted:
106        print("\nexiting safely inner loop")
107        break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.images)
110
```

Backpropagate to recursively differentiate the loss with respect to each layer and parameter

...so we know whether we need to increase or decrease each parameter to decrease the error

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Training

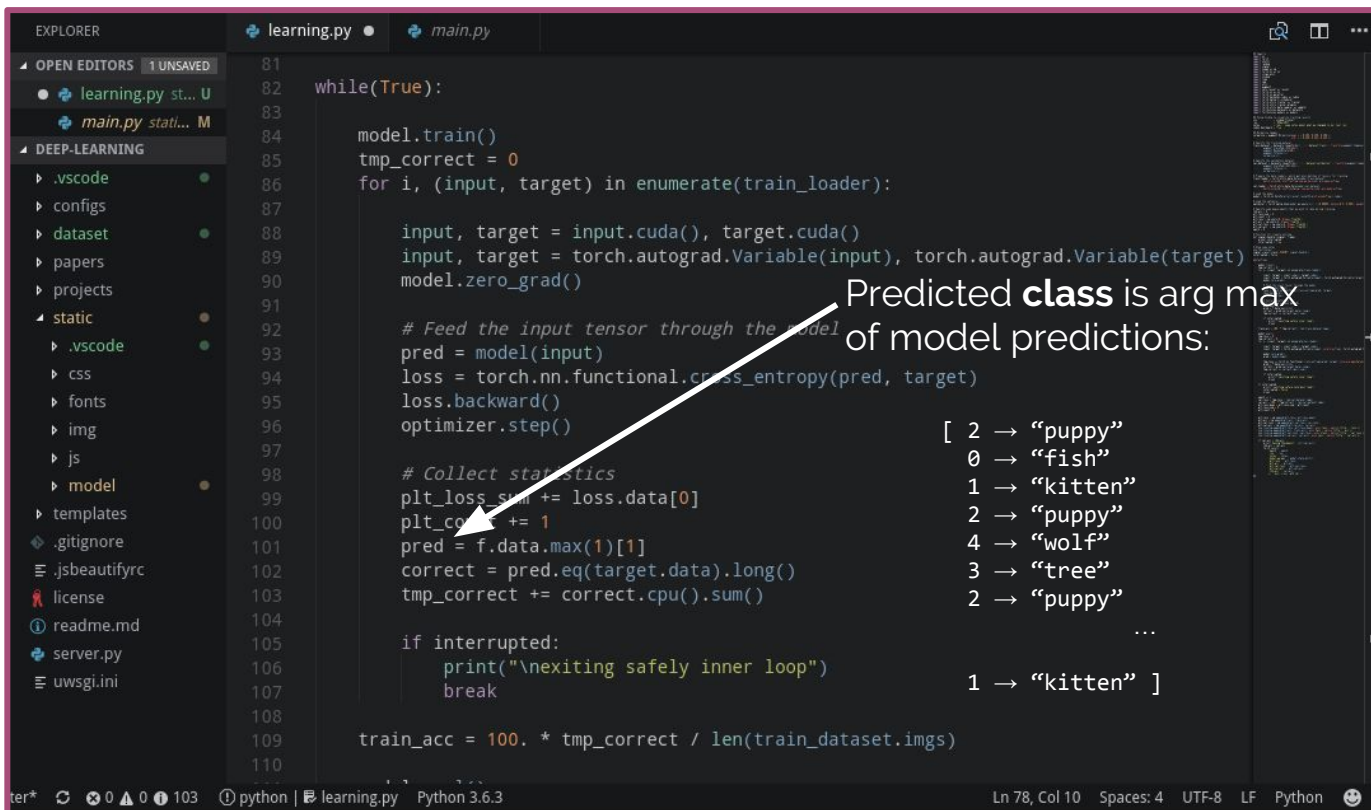


```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_count += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105    if interrupted:
106        print("\nexiting safely inner loop")
107        break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

Tweak deep function parameters in direction of gradient by very small amount (based on learning rate) to decrease the error

Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

Training



```
81
82 while(True):
83
84     model.train()
85     tmp_correct = 0
86     for i, (input, target) in enumerate(train_loader):
87
88         input, target = input.cuda(), target.cuda()
89         input, target = torch.autograd.Variable(input), torch.autograd.Variable(target)
90         model.zero_grad()
91
92         # Feed the input tensor through the model
93         pred = model(input)
94         loss = torch.nn.functional.cross_entropy(pred, target)
95         loss.backward()
96         optimizer.step()
97
98         # Collect statistics
99         plt_loss_sum += loss.data[0]
100        plt_correct += 1
101        pred = f.data.max(1)[1]
102        correct = pred.eq(target.data).long()
103        tmp_correct += correct.cpu().sum()
104
105    if interrupted:
106        print("\nexiting safely inner loop")
107        break
108
109    train_acc = 100. * tmp_correct / len(train_dataset.imgs)
110
```

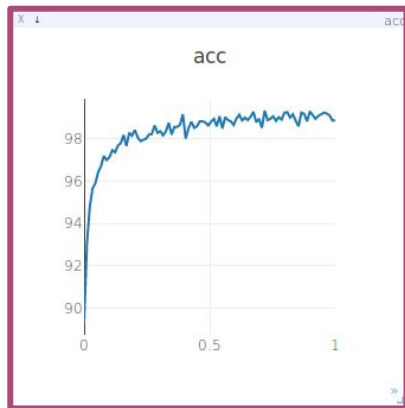
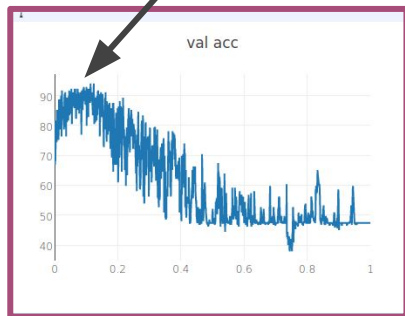
Predicted **class** is arg max
of model predictions:

- 2 → "puppy"
- 0 → "fish"
- 1 → "kitten"
- 2 → "puppy"
- 4 → "wolf"
- 3 → "tree"
- 2 → "puppy"
- ...
- 1 → "kitten"]

Ln 78, Col 10 Spaces: 4 UTF-8 LF Python

...eval

Checkpoint!



```
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learning.py

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model.eval()
tmp_loss = 0
tmp_correct = 0
for i, (input, target) in enumerate(val_loader):

    input, target = input.cuda(), target.cuda()
    input, target = torch.autograd.Variable(input, volatile=True), torch.autograd.Variable(target)

    model.zero_grad()
    pred = model(input)

    tmp_loss += torch.nn.functional.cross_entropy(pred, target, size_average=False).data[0]
    pred = f.data.max(1)[1]
    correct = pred.eq(target.data).long()
    tmp_correct += correct.cpu().sum()

    if interrupted:
        print("\nexiting safely inner loop")
        break

if interrupted:
    print("\nexiting safely outermost loop")
    interrupted = False
    break

epoch += 1
val_loss = tmp_loss / len(val_dataset.imgs)
val_acc = 100. * tmp_correct / len(val_dataset.imgs)
plt_loss_mean = plt_loss_sum / plt_count
plt_loss_sum = 0
plt_count = 0

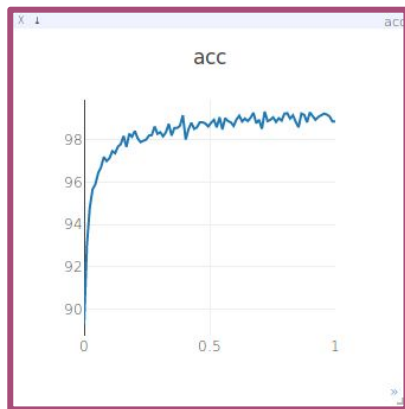
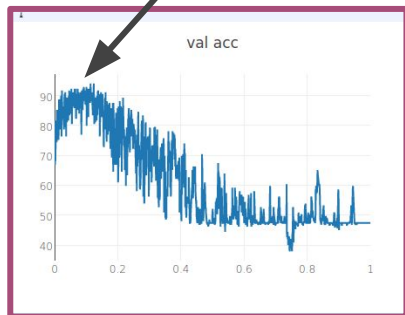
plt_loss = np.append(plt_loss, plt_loss_mean)
plt_acc = np.append(plt_acc, train_acc)
plt_val_loss = np.append(plt_val_loss, val_loss)
plt_val_acc = np.append(plt_val_acc, val_acc)
vis.line(np.append(plt_loss, plt_loss_mean), win='loss', opts={'title': 'loss'})
vis.line(np.append(plt_acc, train_acc), win='tacc', opts={'title': 'acc'})
vis.line(np.append(plt_val_loss, val_loss), win='vloss', opts={'title': 'val loss'})
vis.line(np.append(plt_val_acc, val_acc), win='vacc', opts={'title': 'val acc'})

if val_acc > chk_acc:
    print('Saving Checkpoint: '+str(val_acc))
    chk_acc = val_acc
    torch.save({
        'epoch' : epoch,
        'run' : run,
        'notes' : notes,
        'model_params' : model.state_dict(),
        'plt_loss' : plt_loss,
        'plt_acc' : plt_acc,
```

Parameters are locked

...eval

Checkpoint!



```
EXPLORER
main.py
learning.py

OPEN EDITORS 1 UNSAVED
main.py stati... M
learning.py st... U

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model.eval()
tmp_loss = 0
tmp_correct = 0
for i, (input, target) in enumerate(val_loader):

    input, target = input.cuda(), target.cuda()
    input, target = torch.autograd.Variable(input, volatile=True), torch.autograd.Variable(target)

    model.zero_grad()
    pred = model(input)

    tmp_loss += torch.nn.functional.cross_entropy(pred, target, size_average=False).data[0]
    pred = f.data.max(1)[1]
    correct = pred.eq(target.data).long()
    tmp_correct += correct.cpu().sum()

    if interrupted:
        print("\nexiting safely inner loop")
        break

if interrupted:
    print("\nexiting safely outermost loop")
    interrupted = False
    break

epoch += 1
val_loss = tmp_loss / len(val_dataset.imgs)
val_acc = 100. * tmp_correct / len(val_dataset.imgs)
plt_loss_mean = plt_loss_sum / plt_count
plt_loss_sum = 0
plt_count = 0

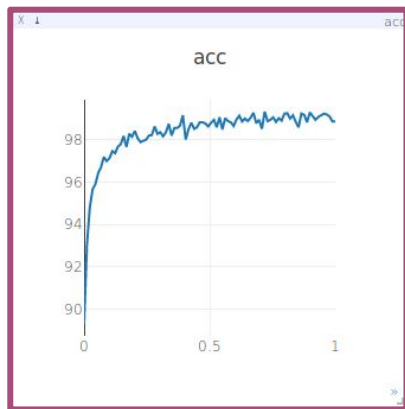
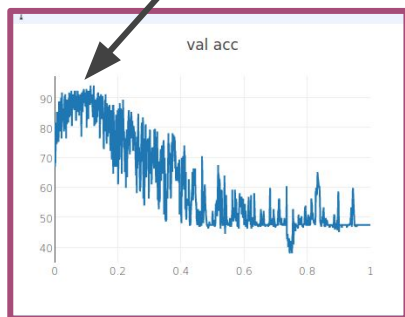
plt_loss = np.append(plt_loss, plt_loss_mean)
plt_acc = np.append(plt_acc, train_acc)
plt_val_loss = np.append(plt_val_loss, val_loss)
plt_val_acc = np.append(plt_val_acc, val_acc)
vis.line(np.append(plt_loss, plt_loss_mean), win='loss', opts={'title': 'loss'})
vis.line(np.append(plt_acc, train_acc), win='tacc', opts={'title': 'acc'})
vis.line(np.append(plt_val_loss, val_loss), win='vloss', opts={'title': 'val loss'})
vis.line(np.append(plt_val_acc, val_acc), win='vacc', opts={'title': 'val acc'})

if val_acc > chk_acc:
    print('Saving Checkpoint: '+str(val_acc))
    chk_acc = val_acc
    torch.save({
        'epoch' : epoch,
        'run' : run,
        'notes' : notes,
        'model_params' : model.state_dict(),
        'plt_loss' : plt_loss,
        'plt_acc' : plt_acc,
```

Validation dataset

...eval

Checkpoint!



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EXPLORER main.py learning.py
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model.eval()
tmp_loss = 0
tmp_correct = 0
for i, (input, target) in enumerate(val_loader):

    input, target = input.cuda(), target.cuda()
    input, target = torch.autograd.Variable(input, volatile=True), torch.autograd.Variable(target)

    model.zero_grad()
    pred = model(input)

    tmp_loss += torch.nn.functional.cross_entropy(pred, target, size_average=False).data[0]
    pred = f.data.max(1)[1]
    correct = pred.eq(target.data).long()
    tmp_correct += correct.cpu().sum()

    if interrupted:
        print("\nexiting safely inner loop")
        break

if interrupted:
    print("\nexiting safely outermost loop")
    interrupted = False
    break

epoch += 1
val_loss = tmp_loss / len(val_dataset.imgs)
val_acc = 100. * tmp_correct / len(val_dataset.imgs)
plt_loss_mean = plt_loss_sum / plt_count
plt_loss_sum = 0
plt_count = 0

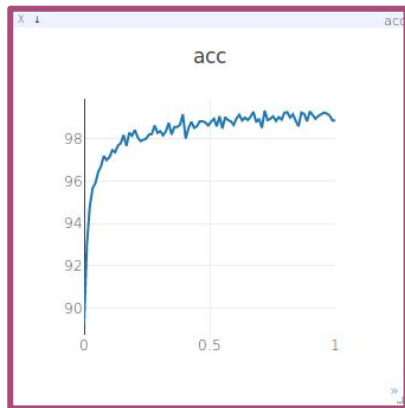
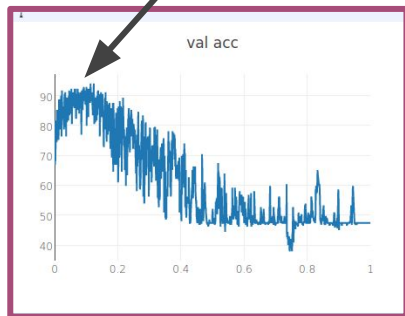
plt_loss = np.append(plt_loss, plt_loss_mean)
plt_acc = np.append(plt_acc, train_acc)
plt_val_loss = np.append(plt_val_loss, val_loss)
plt_val_acc = np.append(plt_val_acc, val_acc)
vis.line(np.append(plt_loss, plt_loss_mean), win='loss', opts={'title': 'loss'})
vis.line(np.append(plt_acc, train_acc), win='tacc', opts={'title': 'acc'})
vis.line(np.append(plt_val_loss, val_loss), win='vloss', opts={'title': 'val loss'})
vis.line(np.append(plt_val_acc, val_acc), win='vacc', opts={'title': 'val acc'})

if val_acc > chk_acc:
    print('Saving Checkpoint: '+str(val_acc))
    chk_acc = val_acc
    torch.save({
        'epoch' : epoch,
        'run' : run,
        'notes' : notes,
        'model_params' : model.state_dict(),
        'plt_loss' : plt_loss,
        'plt_acc' : plt_acc,
```

Same again, but no
backpropagation or
optimization needed

...eval

Checkpoint!



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EXPLORER
main.py
learning.py

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DEEP-LEARNING
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papers
projects
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  .vscode
  css
  fonts
  img
  js
model
templates
.gitignore
.jsbeautifyrc
license
readme.md
server.py
uwsgi.ini

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model.eval()
tmp_loss = 0
tmp_correct = 0
for i, (input, target) in enumerate(val_loader):

    input, target = input.cuda(), target.cuda()
    input, target = torch.autograd.Variable(input, volatile=True), torch.autograd.Variable(target)

    model.zero_grad()
    pred = model(input)

    tmp_loss += torch.nn.functional.cross_entropy(pred, target, size_average=False).data[0]
    pred = f.data.max(1)[1]
    correct = pred.eq(target.data).long()
    tmp_correct += correct.cpu().sum()

    if interrupted:
        print("\nexiting safely inner loop")
        break

if interrupted:
    print("\nexiting safely outermost loop")
    interrupted = False
    break

epoch += 1
val_loss = tmp_loss / len(val_dataset.imgs)
val_acc = 100. * tmp_correct / len(val_dataset.imgs)
plt_loss_mean = plt_loss_sum / plt_count
plt_loss_sum = 0
plt_count = 0

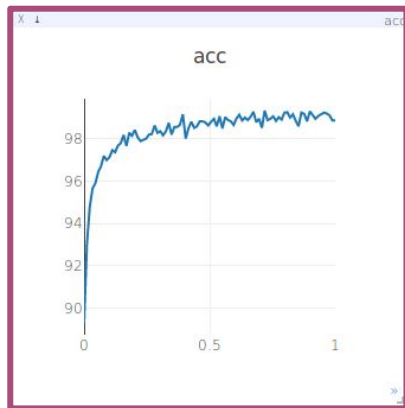
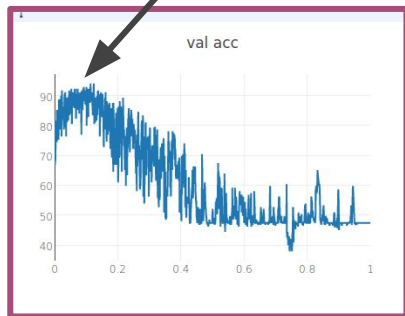
plt_loss = np.append(plt_loss, plt_loss_mean)
plt_acc = np.append(plt_acc, train_acc)
plt_val_loss = np.append(plt_val_loss, val_loss)
plt_val_acc = np.append(plt_val_acc, val_acc)
vis.line(np.append(plt_loss, plt_loss_mean), win='loss', opts={'title': 'loss'})
vis.line(np.append(plt_acc, train_acc), win='tacc', opts={'title': 'acc'})
vis.line(np.append(plt_val_loss, val_loss), win='vloss', opts={'title': 'val loss'})
vis.line(np.append(plt_val_acc, val_acc), win='vacc', opts={'title': 'val acc'})

if val_acc > chk_acc:
    print('Saving Checkpoint: '+str(val_acc))
    chk_acc = val_acc
    torch.save({
        'epoch' : epoch,
        'run' : run,
        'notes' : notes,
        'model_params' : model.state_dict(),
        'plt_loss' : plt_loss,
        'plt_acc' : plt_acc,
```

Plot loss, accuracy and validation accuracy in visdom

...eval

Checkpoint!



```
EXPLORER
main.py
learning.py

model.eval()
tmp_loss = 0
tmp_correct = 0
for i, (input, target) in enumerate(val_loader):

    input, target = input.cuda(), target.cuda()
    input, target = torch.autograd.Variable(input, volatile=True), torch.autograd.Variable(target)

    model.zero_grad()
    pred = model(input)

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    pred = f.data.max(1)[1]
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epoch += 1
val_loss = tmp_loss / len(val_dataset.imgs)
val_acc = 100. * tmp_correct / len(val_dataset.imgs)
plt_loss_mean = plt_loss_sum / plt_count
plt_loss_sum = 0
plt_count = 0

plt_loss = np.append(plt_loss, plt_loss_mean)
plt_acc = np.append(plt_acc, train_acc)
plt_val_loss = np.append(plt_val_loss, val_loss)
plt_val_acc = np.append(plt_val_acc, val_acc)
vis.line(np.append(plt_loss, plt_loss_mean), win='loss', opts={'title': 'loss'})
vis.line(np.append(plt_acc, train_acc), win='tacc', opts={'title': 'acc'})
vis.line(np.append(plt_val_loss, val_loss), win='vloss', opts={'title': 'val loss'})
vis.line(np.append(plt_val_acc, val_acc), win='vacc', opts={'title': 'val acc'})

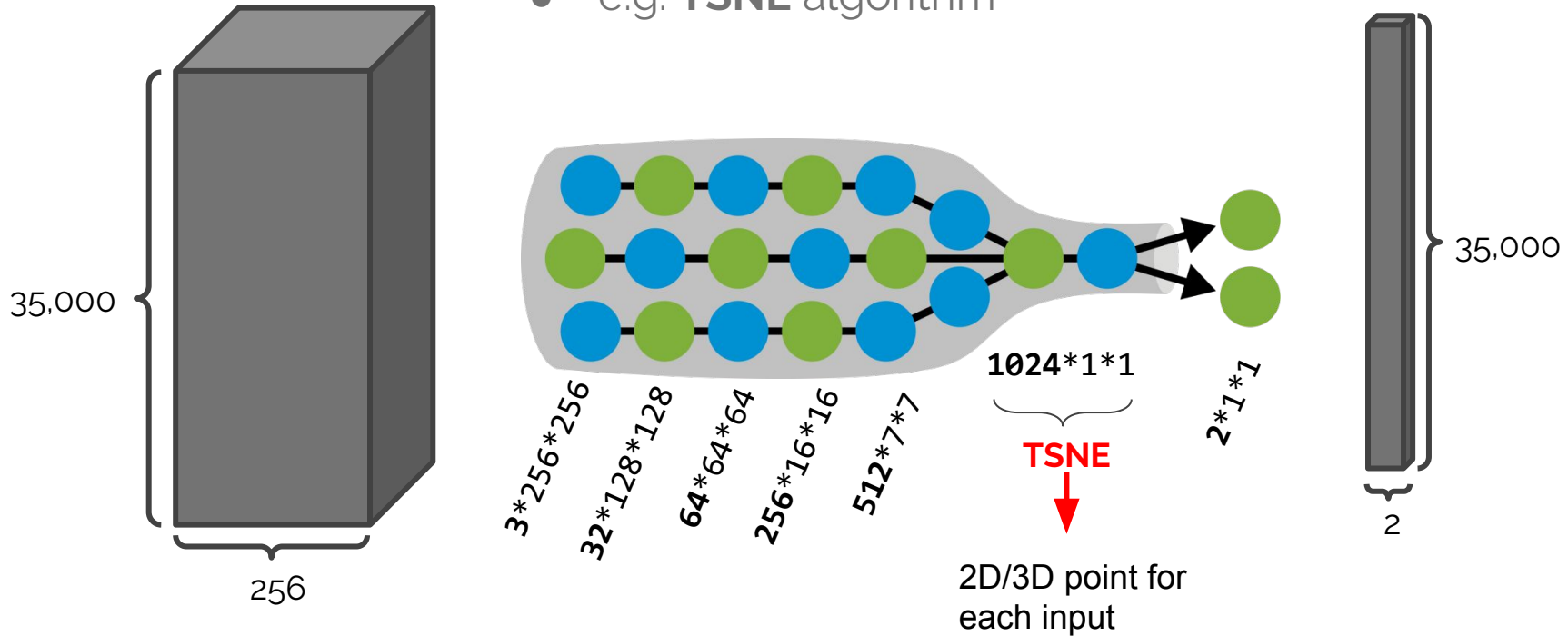
if val_acc > chk_acc:
    print('Saving Checkpoint: ' + str(val_acc))
    chk_acc = val_acc
    torch.save({
        'epoch': epoch,
        'run': run,
        'notes': notes,
        'model_params': model.state_dict(),
        'plt_loss': plt_loss,
        'plt_acc': plt_acc,
```

Save checkpoint if you get a new best validation accuracy

Dimensionality Reduction & Clustering

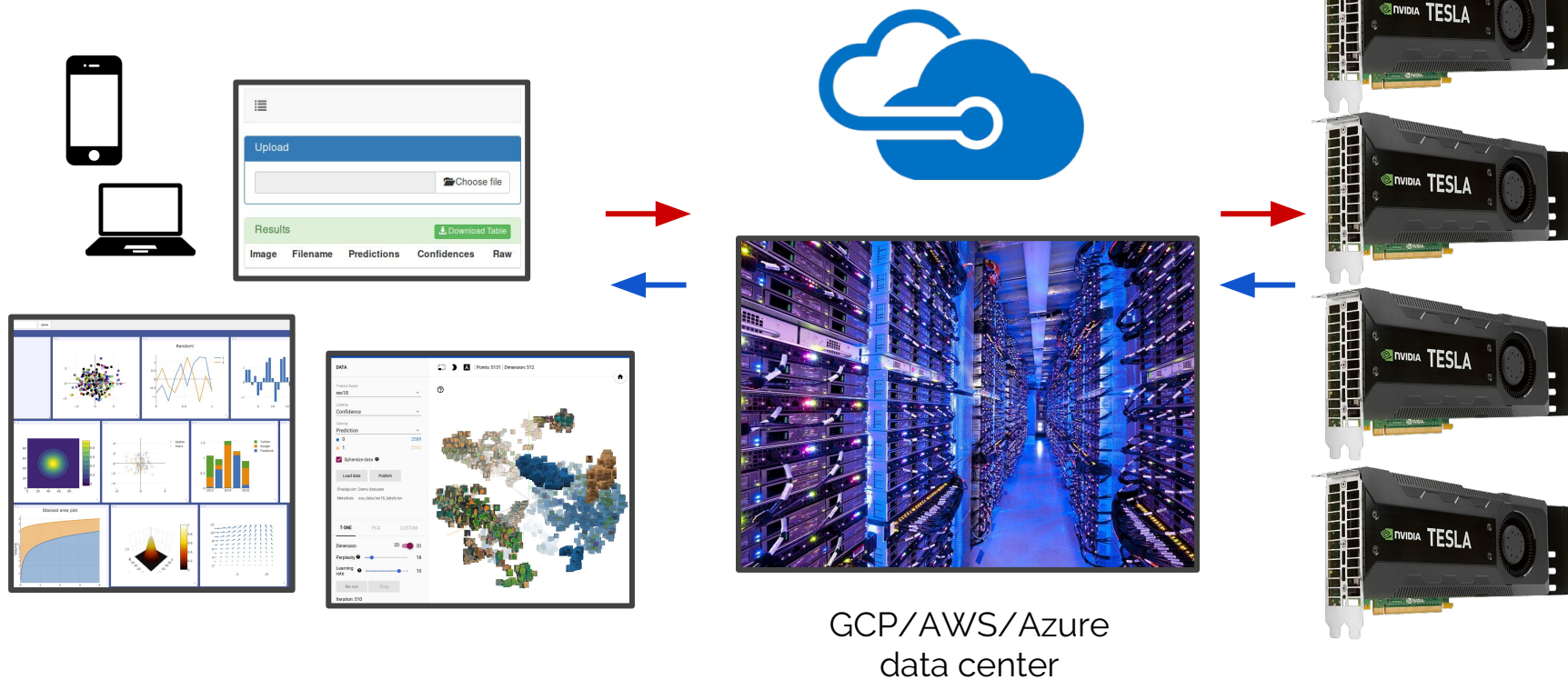
We reduce the dimensionality of the bottleneck to a 2D or 3D space

- e.g. **TSNE** algorithm



Deployment

Deployment of models is something easy to do badly and difficult to do properly



Proposed Stack

- Cross-platform
 - Runs on phone/browser
 - Upload entire folders at once
 - Download CSV results
- HTML5/CSS3
 - Javascript
 - AJAX
 - Flask
 - PyTorch
- Security
 - Password protected
 - No files needlessly stored on disk
 - Audit logs



- Simple architecture
 - **No PHP** server code, **no files stored on disk**, very simple codebase, all asynchronous responsive, no loops checking for signals etc
 - **very easy** to extend to handle new project requirements:
 - GPS, heatmap, d3 visualisations of model...

Server in 60 Lines

Load model at start

Queue access from different threads to GPU

Serve website

Client

```
1 $(document).ready(function() {  
2  
3     function setupReader(file) {  
4         var name = file.name;  
5         var reader = new FileReader();  
6         reader.onload = function(e) {  
7             var fileName = file.name;  
8             $.post('/upload-image', { data: reader.result, name: fileName }, function(data) {  
9                 if (data.success) {  
10                     var html = '<tr> <td><img src='+reader.result+' height="48" width="48" data-bbox="15 536 563 884" data-label="Text">  
11                         $('#resultsTableBody tr').last().after(html);  
12                 }  
13             });  
14         }  
15         reader.readAsDataURL(file);  
16     }  
17 }
```

Upload

Convert downloaded
model outputs to HTML

Server

```
1 from flask import Flask, jsonify, render_template, request, g  
2 from celery import Celery  
3 from PIL import Image  
4 from io import BytesIO  
5 import traceback  
6  
7  
8 app = Flask(__name__)  
9 celery = Celery(__name__)  
10 celery.config_from_object(app.config)  
11 inference = None  
12  
13 @app.before_request  
14 def modelLoad():  
15     global inference  
16     if inference is None:  
17         from static.model.inference import Inference  
18         inference = Inference()  
19  
20 @celery.task()  
21 def runModel(im):  
22     with app.test_request_context() as request:  
23         return inference.run(im)  
24  
25 @app.route('/')  
26 def home():  
27     return render_template('index.html')  
28  
29 @app.route('/upload-image', methods=['post'])  
30 def uploadImage():  
31     try:  
32         dat = re.sub('^data:image/.+;base64,', '', request.form['data'])  
33         im = Image.open(BytesIO(base64.b64decode(dat))).convert('RGB')  
34         outputs = runModel(im)  
35         return jsonify(success=True, outputs=outputs)  
36     except IOError as e:  
37         errno, strerror = e.args  
38         err = "I/O error({0}): {1}".format(errno, strerror)  
39         print(err)  
40         return jsonify(success=False, err=err)  
41     except ValueError:  
42         err = "Could not parse image data."  
43         print(err)  
44         return jsonify(success=False, err=err)  
45     except Exception as err:  
46         err = "Could not parse image data."  
47         print(err)  
48         # traceback.print_tb(err.__traceback__)  
49         return jsonify(success=False)  
50         raise  
51  
52 if __name__ == '__main__':  
53     app.run(  
54         threaded=True,  
55         debug=True,
```

Challenges in Deep Learning

1. Getting a good dataset to begin with
 - **This is the main thing and it's not straightforward**
 - Roll up your sleeves and get involved, don't rely on others as you will know best!
 - Look out for data bias and come up with solutions
2. **Wrangling tensors** to fit task at hand
 - Initially one of the hardest parts, later with experience this is one of the easiest
3. **Designing** architectures
 - Keep it simple, stupid! Trying to utilize transfer learning.
4. Dealing with **overfitting** and **underfitting**
 - Lots of tricks, the challenge is knowing which to try and not doing too many at once
 - Experience helps here
5. **Waiting** for your model to test your adjustments
6. Deployment
 - Easy to do badly
 - Very hard to do properly (multiple users, stable in production environments, keeping the human in the loop, updating with new data and changing project requirements)

Thank you

- Questions? Feel free to find me afterwards, also in **E289**

Some popular ones:

Can I do X? How would you do Y? How long would it take to do Z?

Why PyTorch and not Tensorflow, Torch, Keras, Caffe, Neon, Theano, ...?

Why Python and not C++, CUDA, C#, Java, C, Haxe, Javascript, Blah ...

What Tutorials, best place to start? What books? What maths do I need?

Any Ethical or Security issues with this topic?



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<https://github.com/cwkx>



<https://twitter.com/cwkx>

Live demo if time or catch me afterwards for live demo