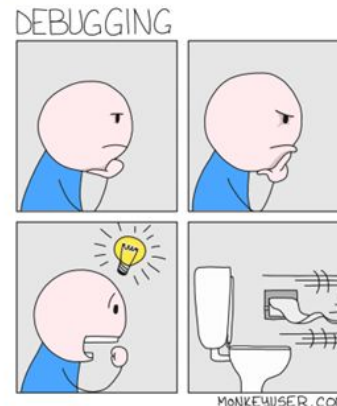
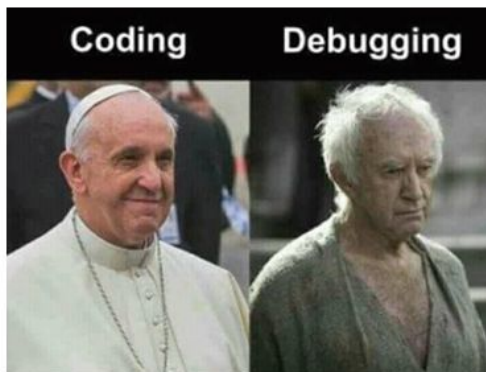
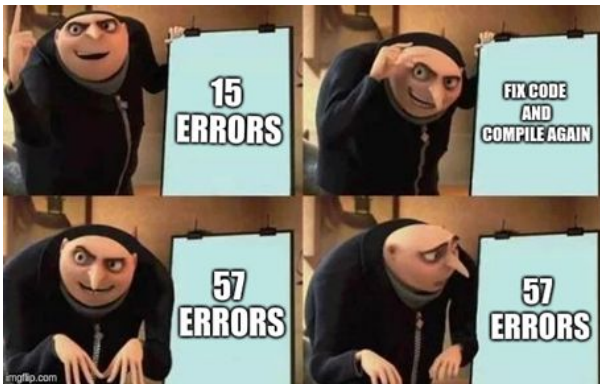

Debugging ML code

02476 Machine Learning Operations
Nicki Skafte Detlefsen

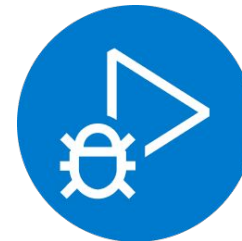
Debugging is a hard but necessary disziplin



Debugging ML code is even harder

Bugs in ML code can be classical and ML specific

- Classic bugs: Code does not run
 - Use traditional debugger to find these
- ML specific bugs: My model is not converging
 - Need the correct approach



Let's start with the classics..



First step: Get a good environment

Jupyter notebooks are great at what they are meant for: exploring ideas and combining code + text into a full standalone document. However, it can be a pain debugging code in notebooks...



Spyder



PyCharm



VS Code



Torchstudio

Python debugging in general

1. Print statements
2. Stop at an interesting point in your code and interact
3. Work in an actual debugger

Learn more here:

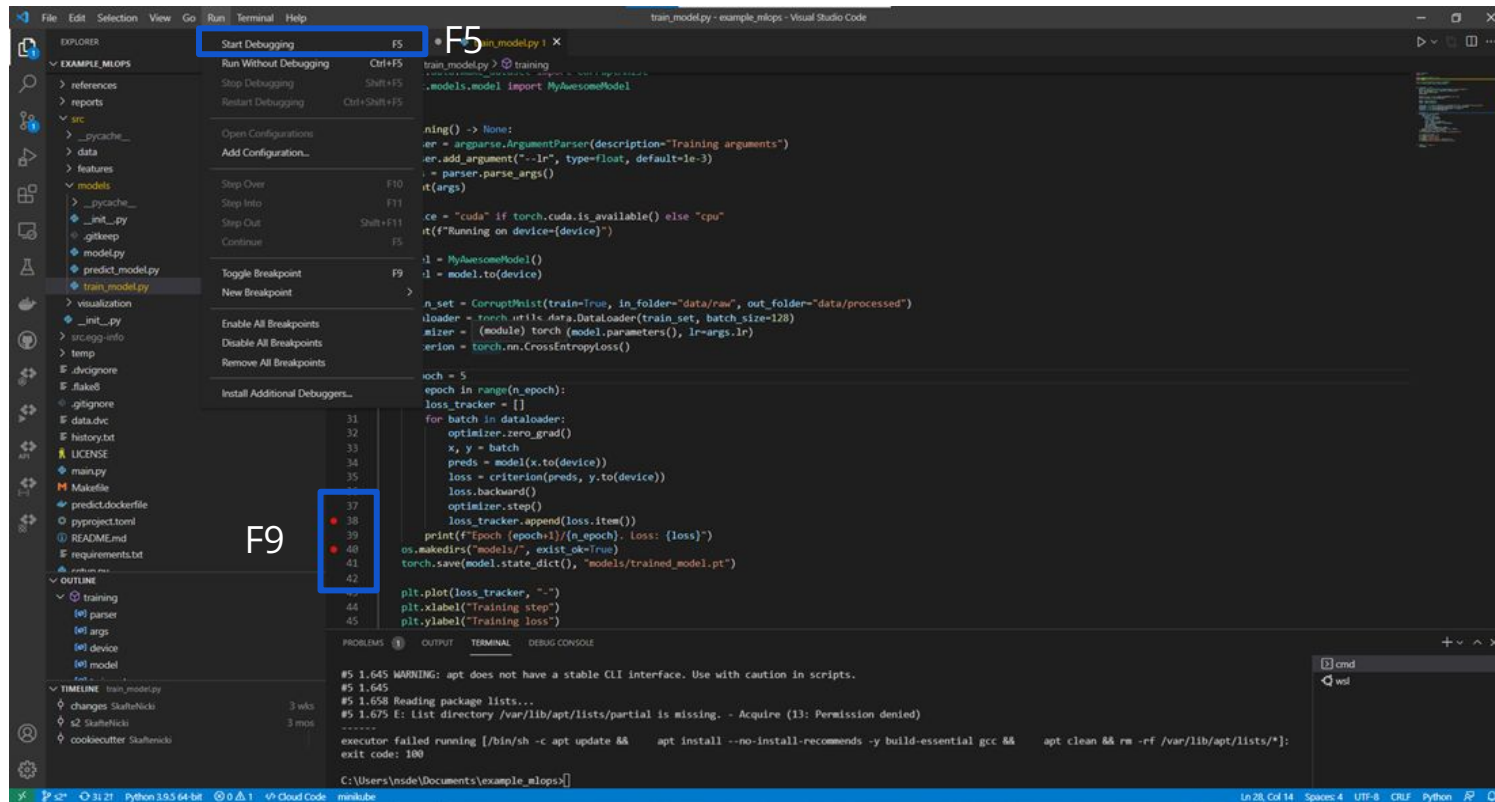
<https://switowski.com/blog/ipython-debugging>

```
print("x.shape = {}".format(x.shape))
```

```
from IPython import embed; embed()  
... # do your stuff interactively here  
exit() # exit ipython to let your code continue
```

```
import pdb; pdb.set_trace()
```

VS Code debugger



VS Code

File Edit Selection View Go Run Terminal Help

Run and Debug No Configurations Preview 56.md vae_mnist.py x

Local variables

- > Local
 - > special variables
 - > function variables
 - > class variables
 - > DEVICES: device(type='cuda')
 - batch_size: 100
 - cuda: True
 - dataset_path: './datasets'
 - epochs: 20
 - hidden_dim: 400
 - latent_dim: 20
 - lr: 0.001
 - nn: module 'torch.nn' from 'C:\Users\insde\Anaconda3\...
 - os: module 'os' from 'C:\Users\insde\Anaconda3\envs\...
 - torch: module 'torch' from 'C:\Users\insde\Anaconda3\...
 - transforms: module 'torchvision.transforms' from 'C:\VL...
 - x_dim: 784
 - > Globals

Where you are

WATCH

CALL STACK

BREAKPOINTS

TERMINAL

Step options

```
s3_reproducibility> exercise_files> vae_mnist.py> 90 mnist_transform
1  ***
2  Adapted from
3  https://github.com/Jackson-Kang/Pytorch-VAE-tutorial/blob/master/01_VAEs/VAE.ipynb
4
5  A simple implementation of Gaussian MLP Encoder and Decoder trained on MNIST
6  ***
7  import os
8  import torch
9  import torch.nn as nn
10 from torchvision.utils import save_image
11 from torchvision.datasets import MNIST
12 import torchvision.transforms as transforms
13 from torch.utils.data import DataLoader
14 from model import Encoder, Decoder, Model
15
16
17 # Model Hyperparameters
18 dataset_path = './datasets'
19 cuda = True
20 DEVICE = torch.device("cuda" if cuda else "cpu")
21 batch_size = 100
22 x_dim = 784
23 hidden_dim = 400
24 latent_dim = 20
25 lr = 1e-3
26 epochs = 20
27
28
29
30 Data loading
31 mnist_transform = transforms.Compose([transforms.ToTensor()])
32
33 train_dataset = MNIST(dataset_path, transform=mnist_transform, train=True, download=True)
34 test_dataset = MNIST(dataset_path, transform=mnist_transform, train=False, download=True)
35
36 train_loader = DataLoader(dataset=train_dataset, batch_size=batch_size, shuffle=True)
37 test_loader = DataLoader(dataset=test_dataset, batch_size=batch_size, shuffle=False)
38
39 encoder = Encoder(input_dim=x_dim, hidden_dim=hidden_dim, latent_dim=latent_dim)
40 decoder = Decoder(latent_dim=latent_dim, hidden_dim=hidden_dim, output_dim=x_dim)
41
42 model = Model(encoder=encoder, decoder=decoder).to(DEVICE)
43
44 from torch.optim import Adam
45
46 BCE_loss = nn.BCELoss()
47
48 def loss_function(x, x_hat, mean, log_var):
49     reproduction_loss = nn.functional.binary_cross_entropy(x_hat, x, reduction='sum')
50     KLD = - 0.5 * torch.sum(1+ log_var - mean.pow(2) - log_var.exp())
51     return reproduction_loss + KLD
52
53 optimizer = Adam(model.parameters(), lr=lr)
54
55
56 print("Start training VAE...")
57 model.train()
58 for epoch in range(epochs):
```



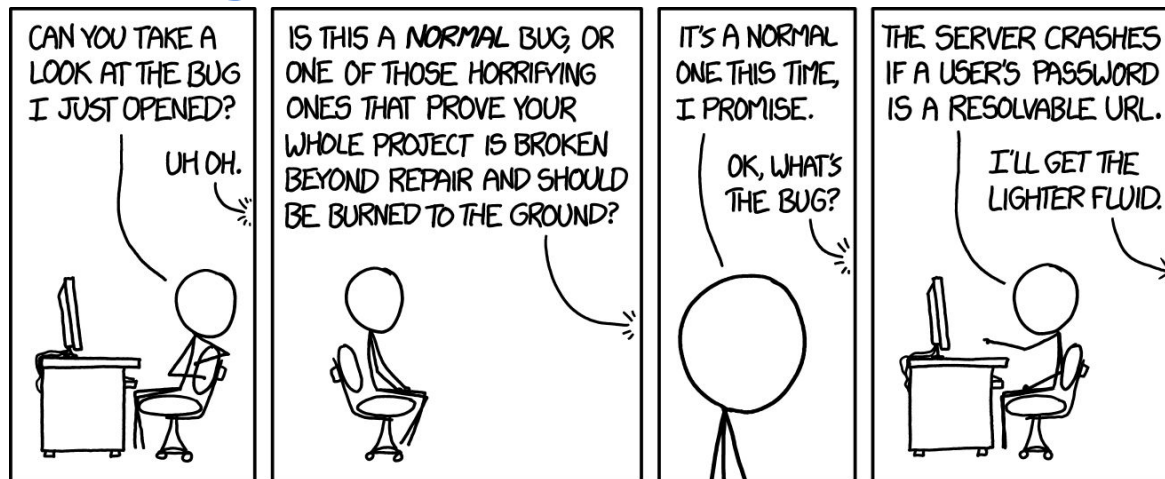
Step options:

- F5: next breakpoint
- F10: next line
- F11: step into
- Shift-F11: step out
- CTRL-Shift-F11: Restart
- Shift-F5: stop

Back to these ML specific bugs

Or better known as

When everything is running,
but results are wrong



Finding these buggers comes with experience

A potpourri of my findings over the last couple of years and others.

1. Check your data!

Your starting point should always be the data in ML!

Check

- Examine summary statistics (data normalized?)
- Look at label distributions (is it shuffled?)
- Visualize a few samples (are they as expected?)

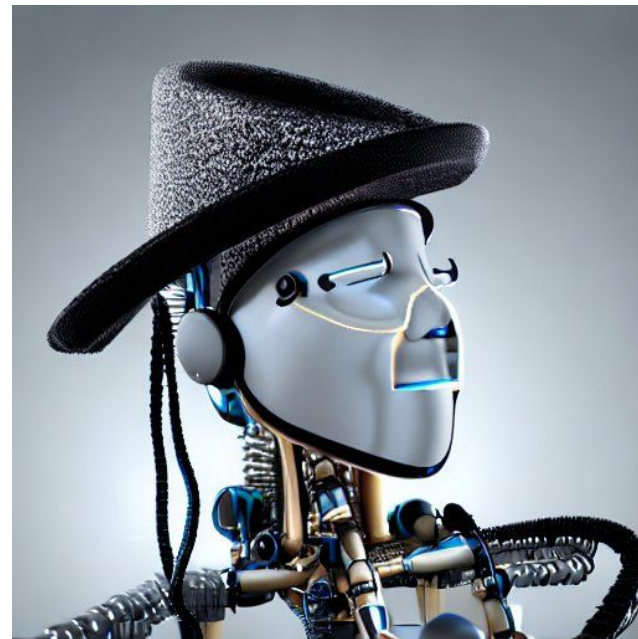
If you are working on dataset you know, you may skip these.

2. Start as simple as you can

Remove all fancy stuff.

- Mixed precision
- Regularization like dropout
- Early stopping
- Learning rate schedulers
- ...

This is often the case if you start from another codebase



"Machine learning bot with a fancy hat", [Stable diffusion](#)

3. Make everything deterministic

Every machine learning run is by default random. Try fixing

- Seed everything and use same seed everywhere
- Remove all data augmentation
- Use only a single batch of data where you have a feeling of the outcome

```
int getRandomNumber()  
{  
    return 4; // chosen by fair dice roll.  
              // guaranteed to be random.  
}
```

4. Investigate the math

Debug the math!

- Go through your code, line by line
- There should be a one-to-one match between equations and lines of code
- Refactor if it is not clear

Check dimensions and annotate if necessary or use [typing software](#)

```
# add shape comments
A = torch.randn(N, D)  # Nx D
x = torch.randn(D)     # D
Ax = A.mv(x)           # N
```

4. Investigate the math (continue)

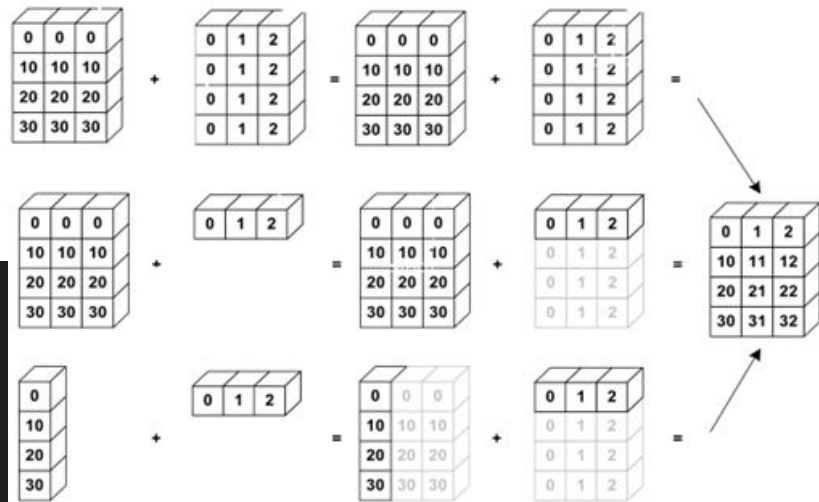
Lookout for broadcasting!

Broadcasting in python is both a blessing and a curse in python.

It can create problems (real life example)

```
import torch
preds = torch.randn(100,)
target = torch.randn(100,1)
loss = (preds - target).abs().pow(2.0).sum()
```

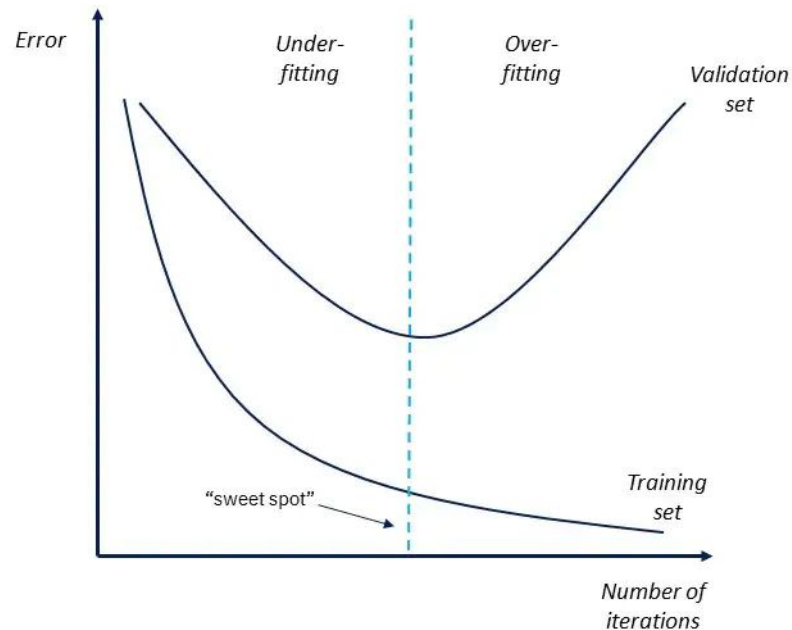
What is the problem here?



5. Overfitting is good?

Overfitting is usually seen as an bad thing but...

- Models should be able to memorize one batch
- Train on one batch, if loss is 0 move on to larger models else debug



6. Really look at your loss

Assuming your model is training without errors, but your loss is not behaving as it should.

- Are you printing/logging the results correctly?
- Did you remember `loss.backward`, `optimizer.step` and `optimizer.zero_grad` ?
- What about your learning rate and batch size?

For your loss, if possible calculate in log-space

```
a = 1
for x in data:
    a = a * x
```

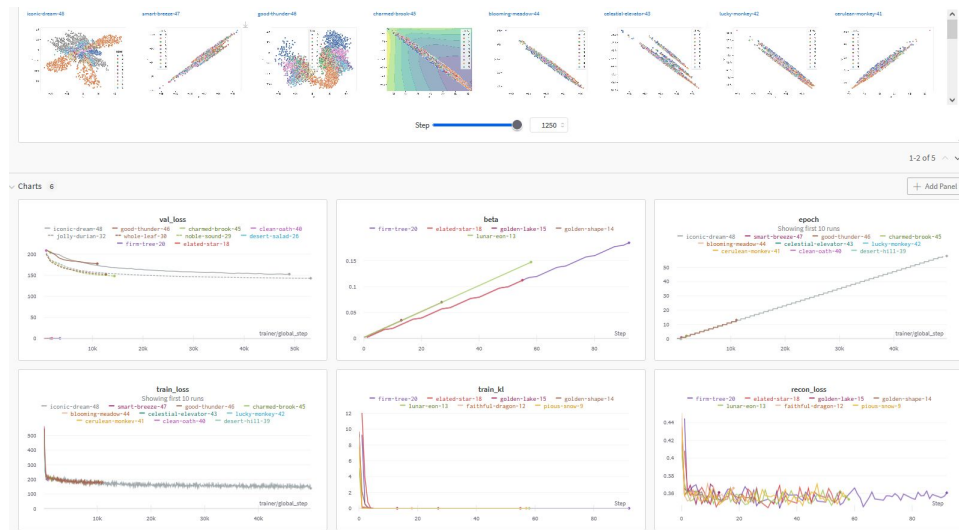
Trade-off between
precision and stability

```
log_a = 0
for x in data:
    log_a = log_a + log(x)
```


7. Visualizations are your friend

Log and visualize everything.

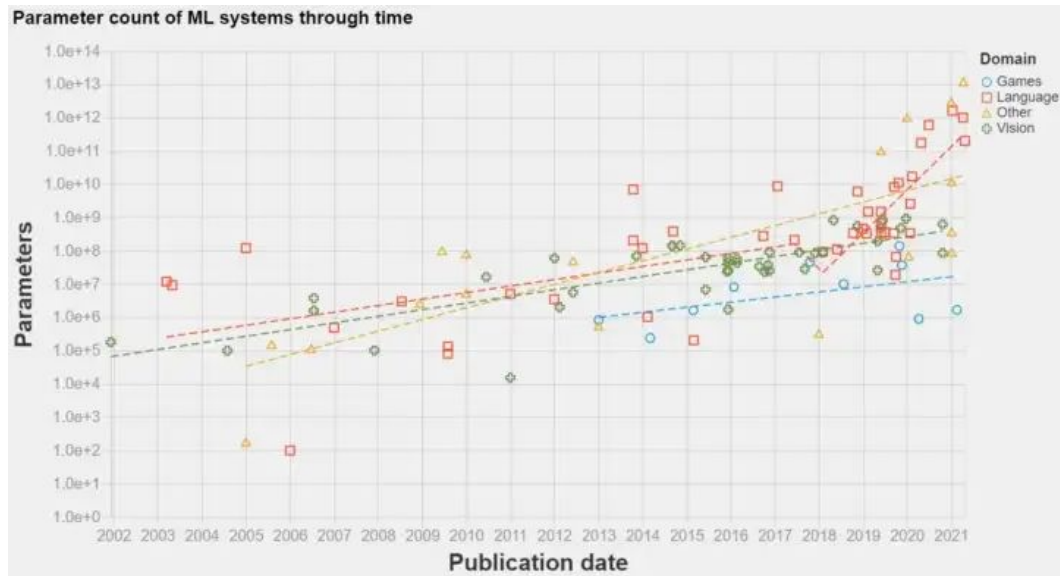
- Training loss is really decreasing right?
- Can you add additional metrics?
- Log dynamic changing hyperparameters (lr with lr schedulers)
- Plot data, predictions, reconstructions etc. over time



5. Add complexity in steps

If you are still good, then

- Get a baseline that just works (=train on more data data)
- Stop overfitting:
 - Add back regularization
 - Add back data augmentations
- Tune hyper parameters



Summary of ML debugging

1. Check your data
2. Start as simple as you can
3. Make everything deterministic
4. Investigate the math
5. Overfit to your data
6. Look at your loss
7. Add complexity in steps

Meme of the day

