Training Neural Nets: a Hacker's Perspective

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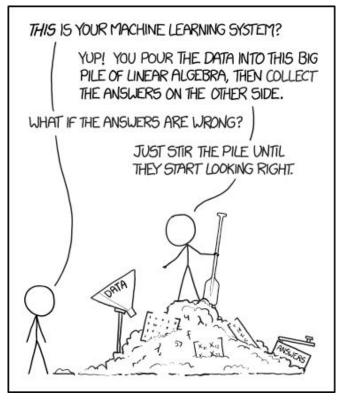
Launchpad Accelerator Program, October 14 - 18, 2019

Bengaluru, India



Agenda

- The motivation
- Being thorough about training neural nets
 - Training a neural network
 - Maintaining a healthy prototyping process
 - Gradually increasing model complexity
 - 0 ...
- Guiding lights



"Deep learning neural networks have become easy to define and fit, but are still hard to configure."

- Jason Brownlee, Machine Learning Mastery

2) Neural net training fails silently

When you break or misconfigure code you will often get some kind of an exception. You plugged in an integer where something expected a string. The function only expected 3 arguments. This import failed. That key does not exist. The number of elements in the two lists isn't equal. In addition, it's often possible to create unit tests for a certain functionality.

- Andrej Karpathy, Sr. Director of Al, Tesla

Implementation bugs



Implementation bugs

```
X_train = shuffle(X_train)
Y_train = shuffle(y_train)
```

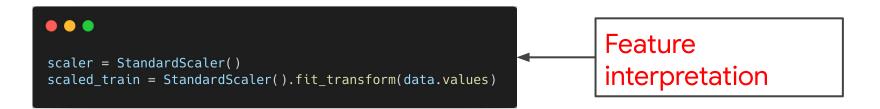
Wrong shuffling!

Implementation bugs

```
X train = shuffle(X train)
Y_train = shuffle(y_train)
                            X_train, y_train = shuffle(X_train, y_train)
```

Implementation bugs

Sex	Age	Has_Masters	Has_Bachelors	23451 98731	
0	23	1	1		
1	46	0	1		
0	21	0	1	12876	
1 53		0	1	100234	



Implementation bugs

Sex	Age	Has_Masters	Has_Bachelors	Bounties 23451	
0	23	1	1		
1	46	0	1	98731	
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scaled_train = StandardScaler().fit_transform(data[non_cat_feats].values)



- Implementation bugs
 - Wrong activation function & initialization

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 - tanh + He
 - ReLU + Xavier

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 - tanh + He -> tanh + Xavier
 - ReLU + Xavier -> ReLU + He

- Implementation bugs
 - Wrong activation function & initialization
 - Forgetting to zero out gradients (PyTorch)

```
for (...):
    ...
    log_ps = model(images)
    loss = criterion(log_ps, labels)
    loss.backward()
    optimizer.step()
    running_loss += loss.item()
```



- Implementation bugs
 - Wrong activation function & initialization
 - Forgetting to zero out gradients (PyTorch)

```
for (...):
    ...
    optimizer.zero_grad()

log_ps = model(images)
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running_loss += loss.item()
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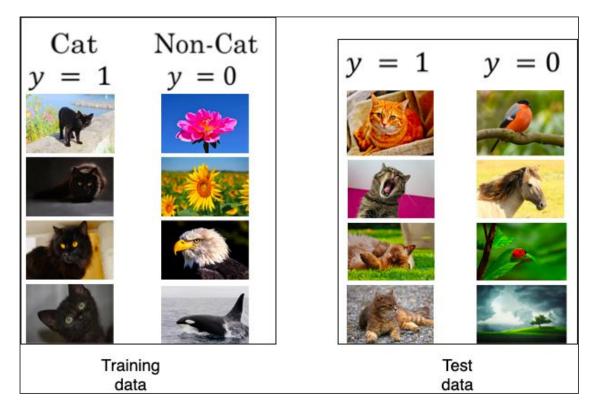
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- Model's sensitivity towards hyperparameter choices

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 - Too high learning rate leads to numerical instability
 - Loss quantity coming out as NaNs

- Implementation bugs
- Model's sensitivity towards hyperparameter choices
 - Too high learning rate leads to numerical instability
 - Too few epochs
 - Network not trained enough

- Implementation bugs
- Model's sensitivity towards hyperparameter choices
 - Too high learning rate leads to numerical instability
 - Too few epochs
 - Too large batch size for a small dataset

- Implementation bugs
- Model's sensitivity towards hyperparameter choices
- Dataset construction and others
 - Dataset distribution



... and just for fun



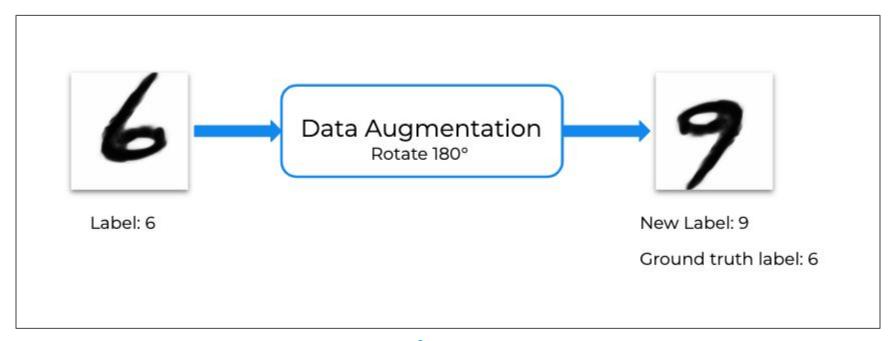
A sample image from the training set

... and just for fun



A corner case

- Implementation bugs
- Model's sensitivity towards hyperparameter choices
- Dataset construction and others
 - Dataset distribution
 - Effects of random data augmentation



Source

- Implementation bugs
- Model's sensitivity towards hyperparameter choices
- Dataset construction and others
 - Dataset distribution
 - Effects of random data augmentation
 - Wrong normalization statistics
 - Label noise
 - Class imbalance

- Write code quickly
 - Reuse existing codebases for quick baselines
 - But be very careful

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 - Reuse existing codebases for quick baselines
 - But be very careful

Writing code quickly - Use a framework!

- Don't start from scratch! Use someone else's components.

- Write code quickly
- Run experiments and keep track of what you tried

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- Run experiments and keep track of what you tried

Experimenter	git SHA	Background Search Method	Model	Dataset	Train Acc	Validation Acc	Notes
Pradeep	fc8d6ca3	Lucene	QAMNS (50d)	Intermediate	0.3114	0.3045	patience=20
Pradeep	fc8d6ca3	Lucene	QAMNS (300d)	Intermediate	0.8317	0.3864	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 50d	QAMNS (50d)	Intermediate	0.3008	0.35	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 50d	QAMNS (300d)	Intermediate	0.7466	0.4227	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 300d	QAMNS (50d)	Intermediate	0.3946	0.3591	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 300d	QAMNS (300d)	Intermediate	0.7311	0.4227	patience=20
Pradeep	fc8d6ca3	BOW-LSH+IDF question+answers Glove 300d	QAMNS (300d)	Intermediate	0.7446	0.4227	patience=20
Pradeep	fc8d6ca3	BOW-LSH+IDF question+answers Paragram 300d	QAMNS (300d)	Intermediate	0.7853	0.3955	patience=20
Pradeep	fc8d6ca3	Lucene	QAMNS (300d)	SciQ	0.5551	0.571	patience=6
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 300d	QAMNS (300d)	SciQ	0.5434	0.524	patience=6

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- Write code quickly
- Run experiments and keep track of what you tried
- Analyze model behavior. Did it do what you wanted?

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- The loss could go up instead of down
- The loss could go down for a while, then explode
- The loss could oscillate across a region
- The loss could get down to a fixed quantity (0.01, for example) and not get any better than that

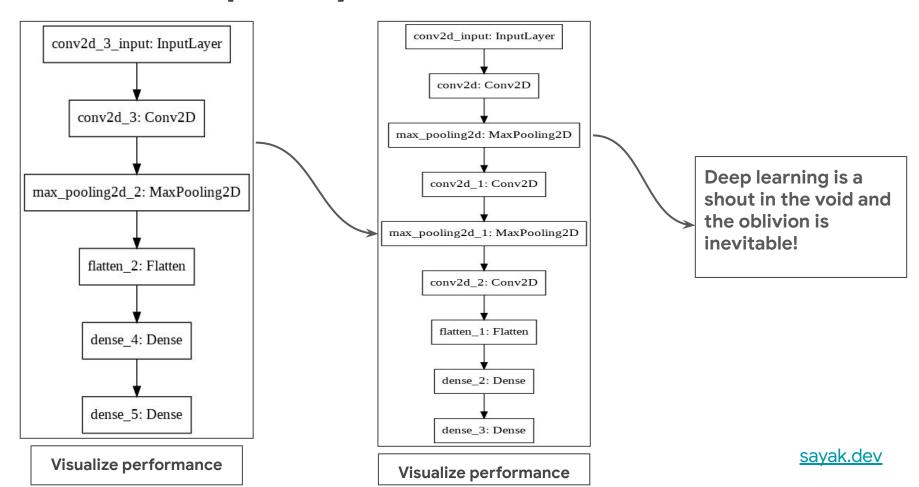
Deciding on a model architecture:

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- Time to train the network
- Size of the final network
- Inference speed
- Accuracy

Some points to remember here:

Ramping up the model complexity gradually

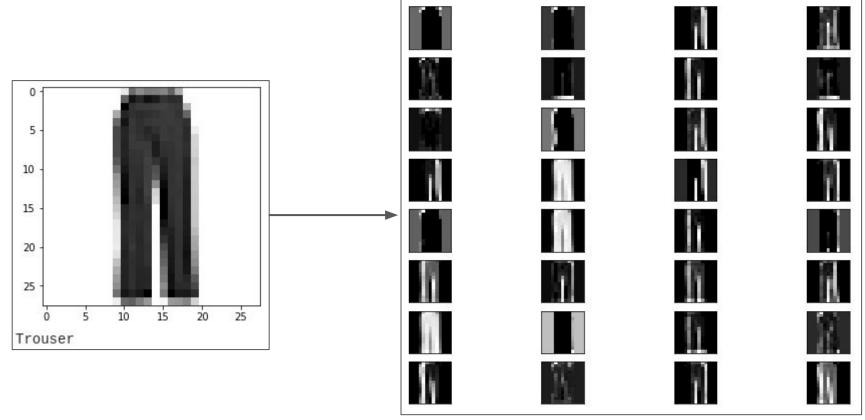


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Ramping up the model complexity gradually

Some points to remember here:

- Ramping up the model complexity gradually
- Experimentation with several random subsets
- Human evaluation
- Visualizing the intermediate activations of the model



Declarative configuration

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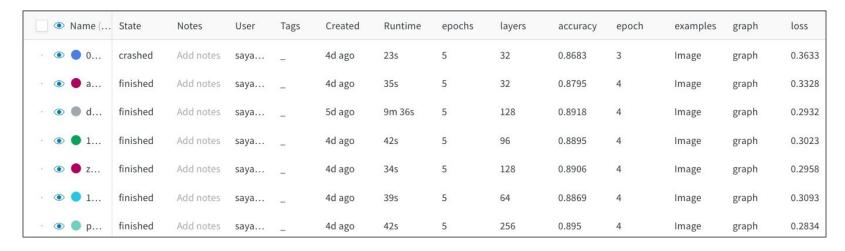
```
floyd run --task train
floyd run trainer.py \
                                                                    # floyd.yml
     -- gpu2 \
                                                                    env: tensorflow-1.14
     --env tensorflow-1.14 \
     --data sayak/datasets/imdb:imdb \
      'python trainer.py \
                                                                    task:
           --model=bert \
           --model type=bert-base-uncased \
                                                                      train:
           --problem=sentiment \
                                                                        machine: qpu2
           --data dir=/floyd/input/imdb \
                                                                        description: sentiment with bert-un
           --eval \
                                                                        input:
           --max seq length=128 \
                                                                          - source: sayak/datasets/imdb
           --batch size=256 \
           --learning rate 2e-5 \
                                                                            destination: imdb
            --num train epochs= 10 \
                                                                        command: trainer.py \
            --output dir ./output-bert-uncased
                                                                                 --model=bert \
                                                                                 --model type=bert-base-uncased \
```

- Declarative configuration
 - Use of Hyperparameter Sweeps with Weights & Biases

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```
program: train.py
method: bayes
metric:
  name: val loss
  goal: minimize
parameters:
  learning-rate:
   min: 0.001
   max: 0.1
  optimizer:
    values: ["adam", "sgd"]
```

- Declarative configuration
 - Use of Hyperparameter Sweeps with Weights & Biases (wandb)



Hyperparameter sweep results

- Declarative configuration
 - Use of Hyperparameter Sweeps with Weights & Biases (wandb)
 - The experiments are hosted by wandb as a cloud service
 - Can also be run locally via Python API

- Declarative configuration
- Organizing the hyperparameter tuning process

- Declarative configuration
- Organizing the hyperparameters' search process

Hyperparameter	Approximate sensitivity
Learning rate	High
Optimizer choice	Low
Other optimizer params (e.g., Adam beta1)	Low
Batch size	Low
Weight initialization	Medium
Loss function	High
Model depth	Medium
Layer size	High
Layer params (e.g., kernel size)	Medium
Weight of regularization	Medium
Nonlinearity	Low

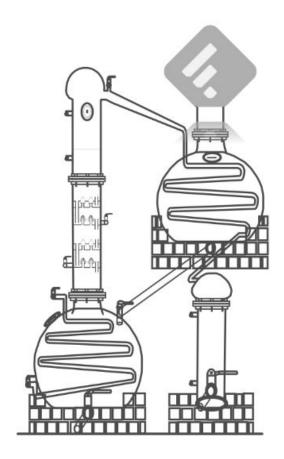
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Model ensembling

- Model ensembling
- Knowledge distillation

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- Lottery ticket hypothesis

- Model ensembling
- Knowledge distillation
- Lottery ticket hypothesis
- Model quantization



Summary

- Training (and debugging) neural nets
- Healthy model prototyping
- The idea of overfitting a single batch of data
- Practical hyperparameter tuning
- Squeezing the best out of a network

References

- Training Neural Nets: a Hacker's Perspective
- A Recipe for Training Neural Networks
- Troubleshooting Deep Neural Networks
- Deep Learning from the Foundations

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Slides are available here: http://bit.ly/LPA_3

See you next time



Find me here: sayak.dev

Thank you very much:)



