W207– Applied Machine Learning

Cornelia Ilin, PhD

School of Information
UC Berkeley

Network Architecture and ML debugging

Announcements

- Don’t worry about exact numbers for HMW10, Exercise 4. The idea is to do an ablation study.

Last week

- CNN for 1D data
- Application: Sentiment analysis based on drug reviews

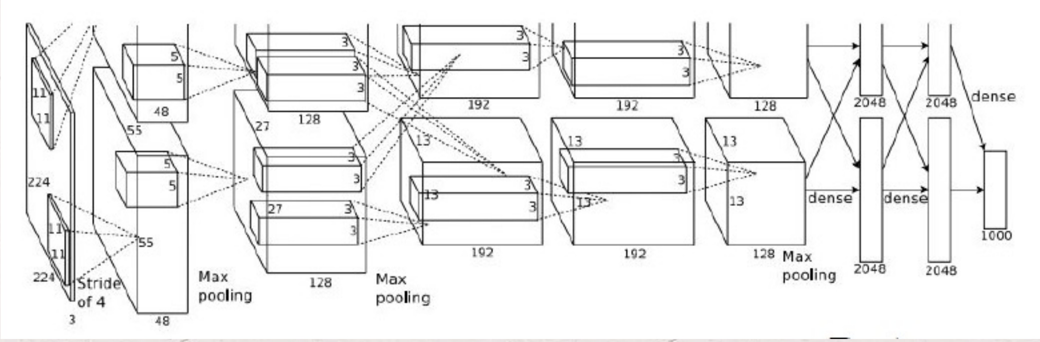
Today’s learning objectives

- Ingredients for ML/AI success
- How to debug learning curves
- End-to-end application: your final project. Ask me questions
- End-to-end application: my research + short intro to RNN/LSTM (RM, Ch 16; will come back here in week 13)

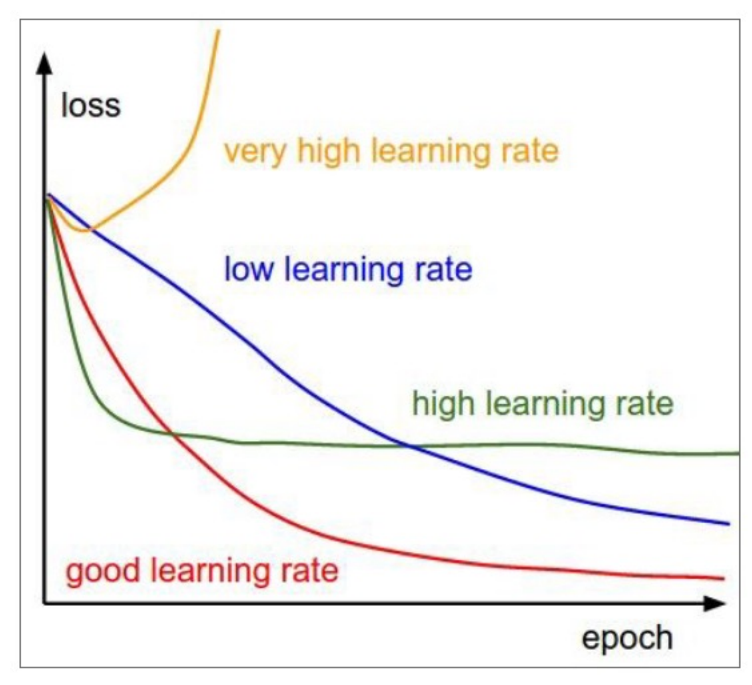
Ingredients for ML/AI success

Ingredients for ML/AI success

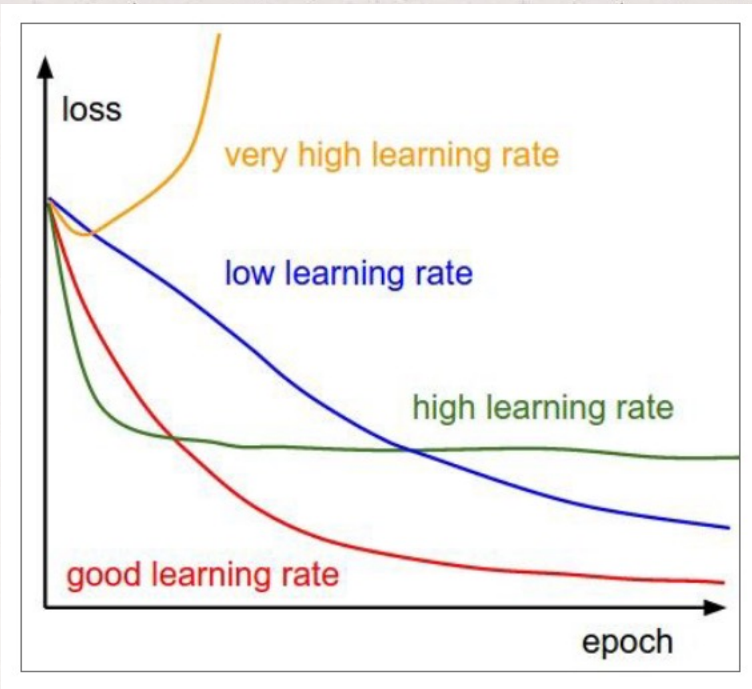
- Data
- Algorithms
- Compute



Best learning rate?



Best learning rate?



They are all good!

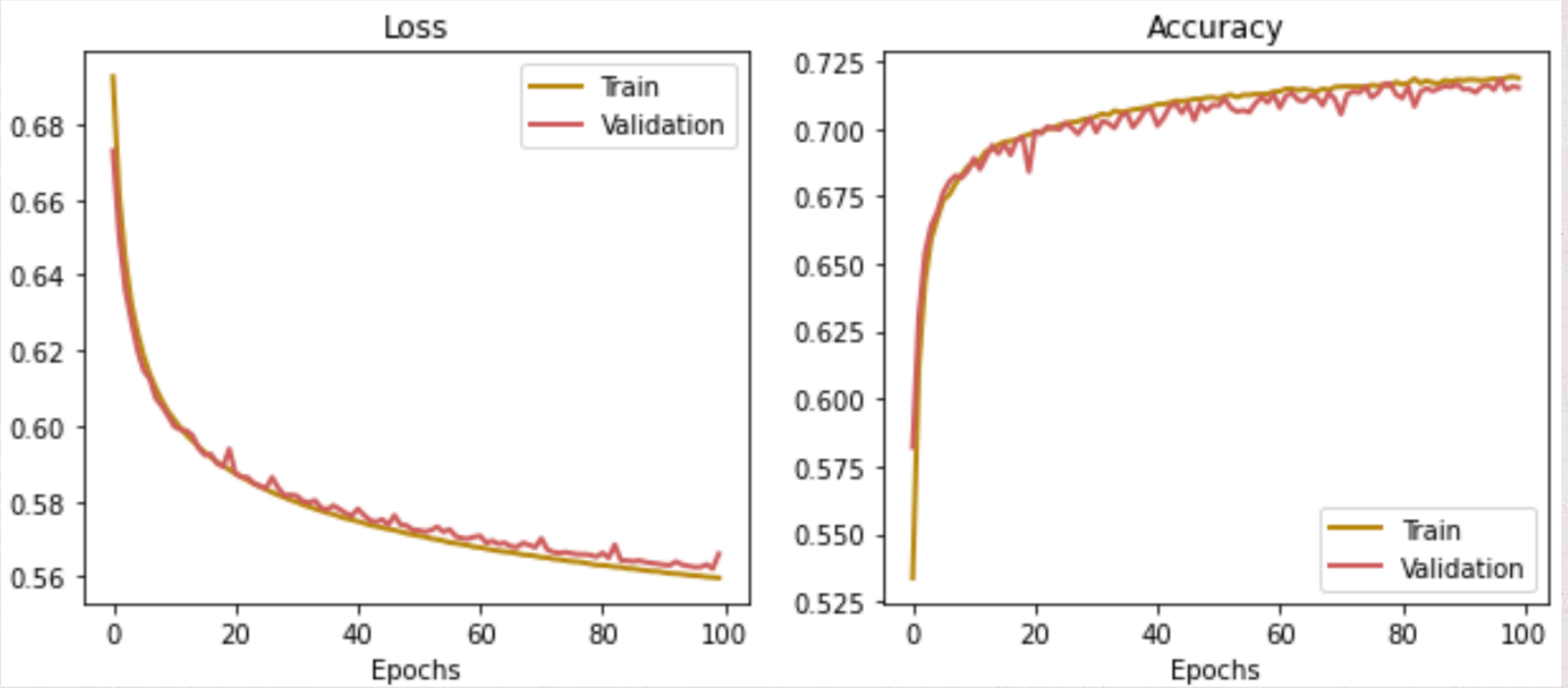
Start with large rate and decay over time

- at fixed points (20, 50, 80 epoch)
- cosine
- linear
- inverse sqrt

fancy schedules

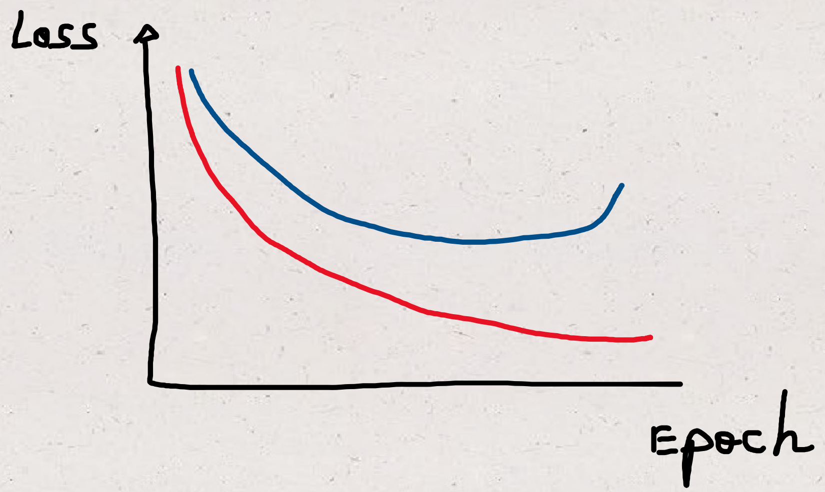
Monitor learning curves

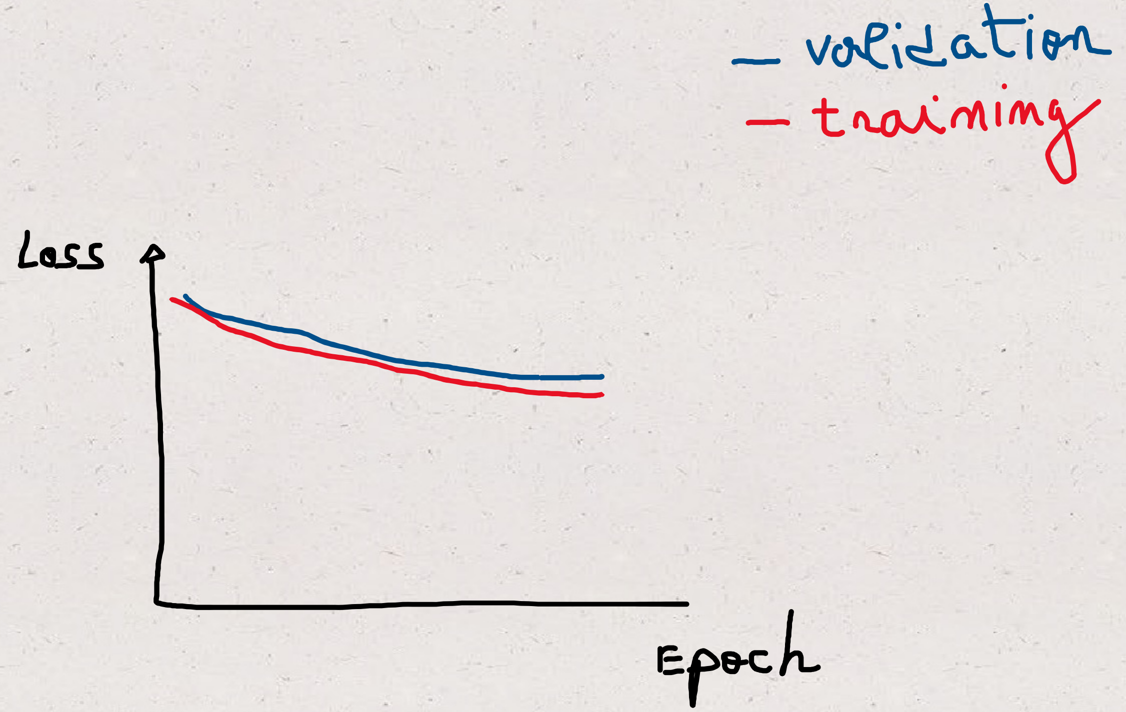
Important to monitor final validation metric as well!



Evaluate validation loss

Debugging learning curves

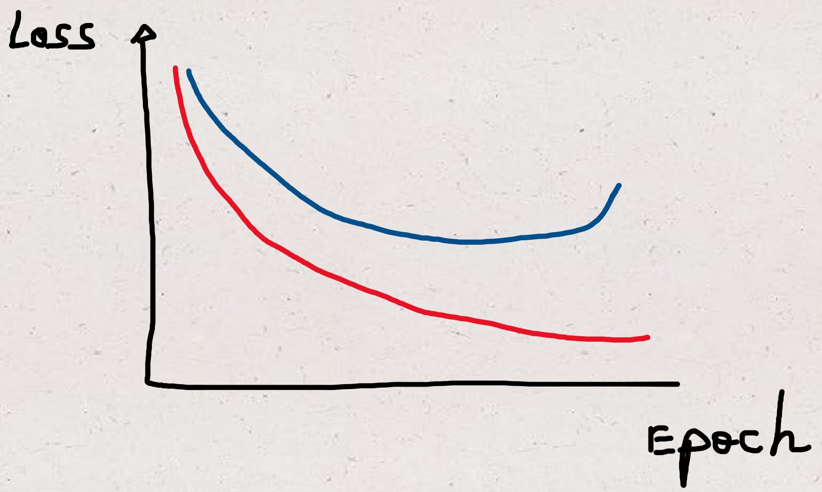




Debugging learning curves

— validation
— training

Overfitting

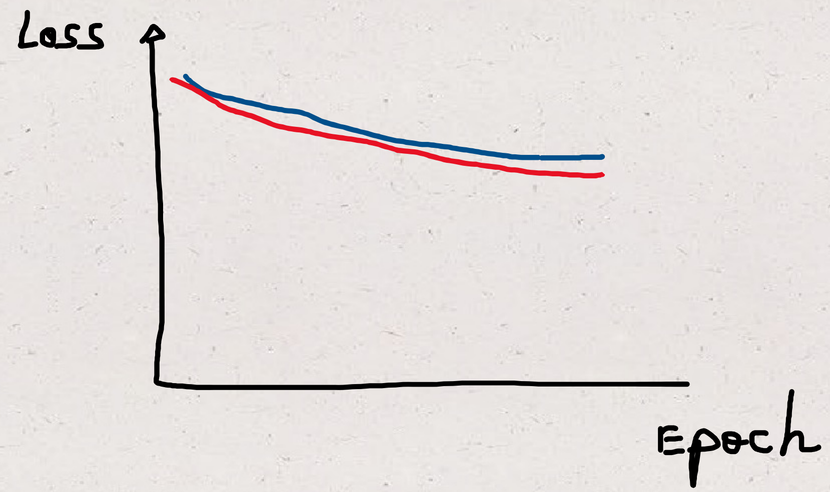


Training loss may continue to decrease but validation may get worse

How to improve:

- Increase data or regularize model, or
- decrease model capacity (make it simpler)

Underfitting



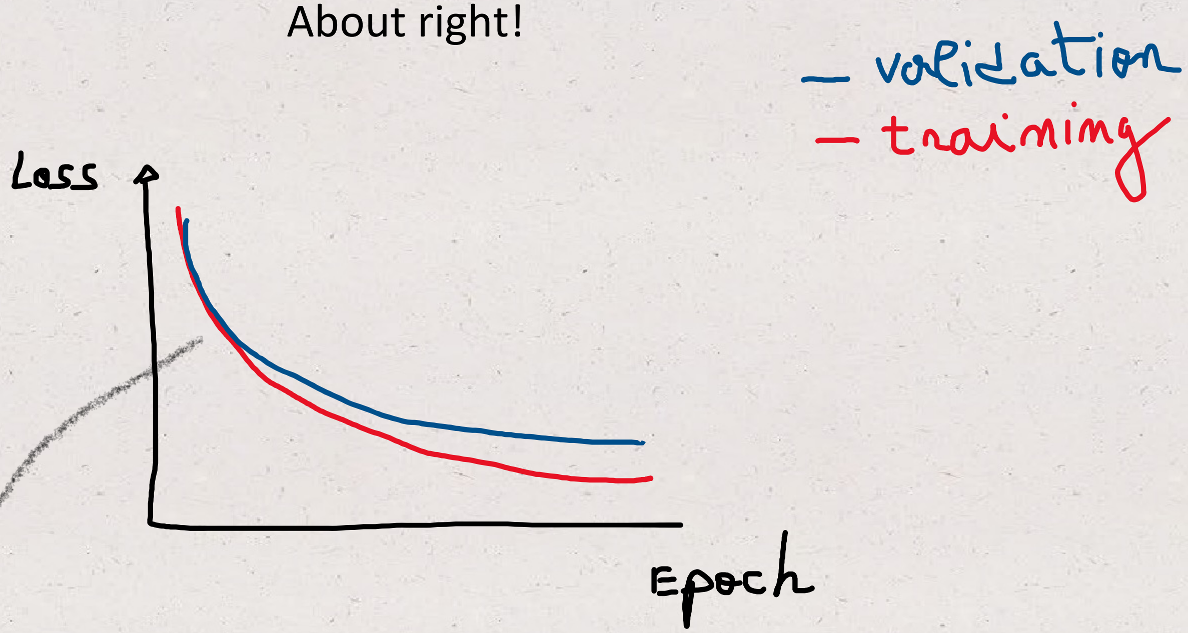
Small or no gap between training and validation loss. Model not learning sufficiently

How to improve:

- increase model complexity
- make task easier, clean data better

Debugging learning curves

About right!



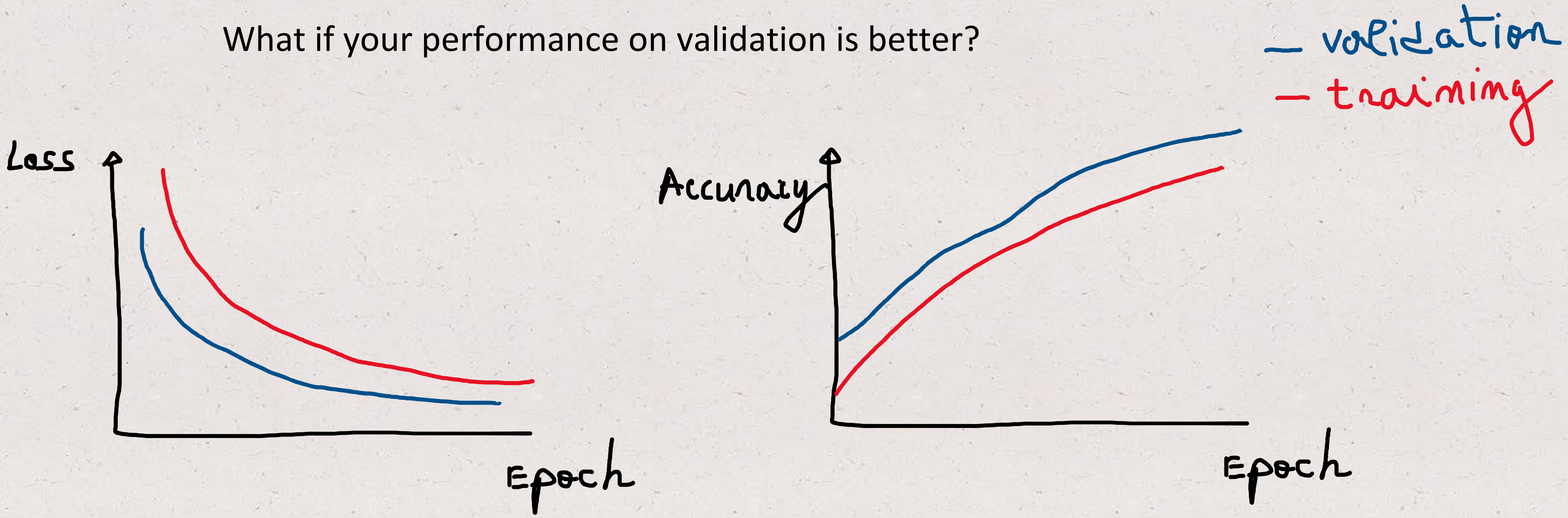
Best models often have small overfitting!

Push complexity of your model to the highest your data can handle!

Notice the steep improvement at the beginning

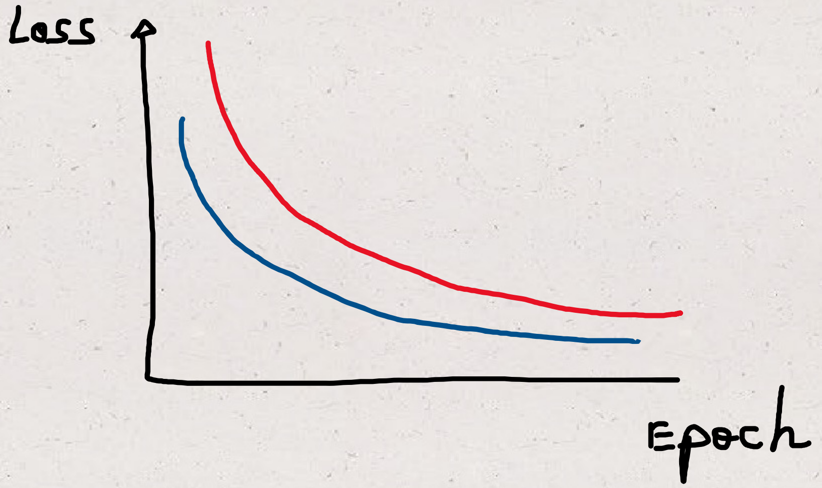
Debugging learning curves

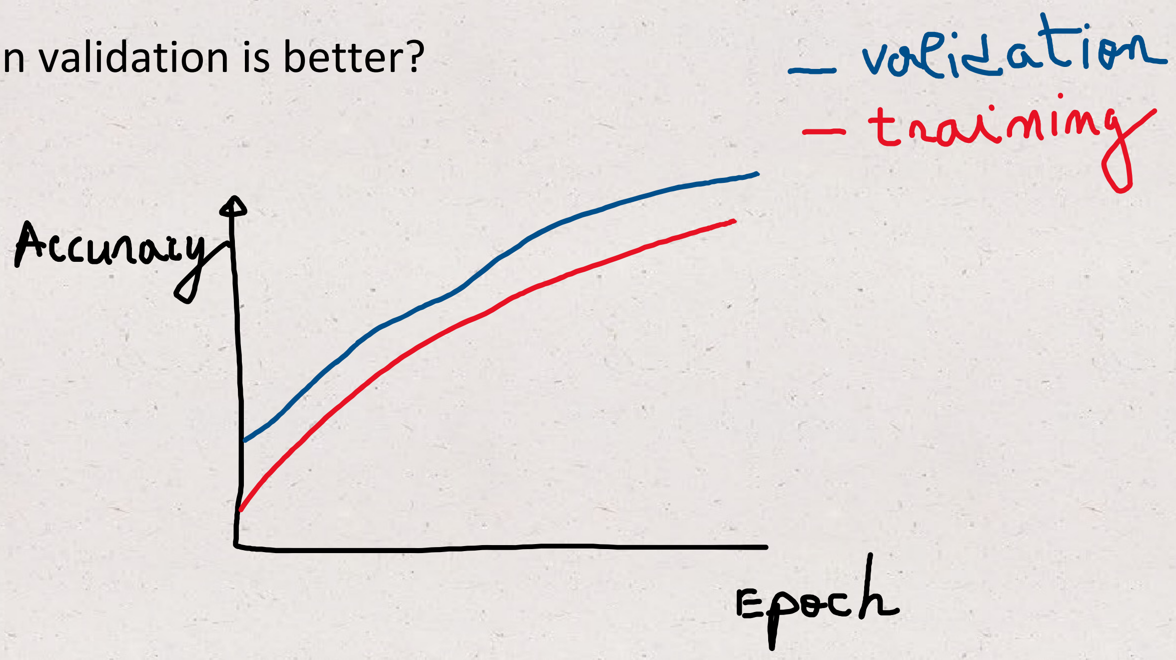
What if your performance on validation is better?



Debugging learning curves

What If your performance on validation is better?





Your training data is likely underfitting. Even though this happens, your validation data may perform well under the situation.

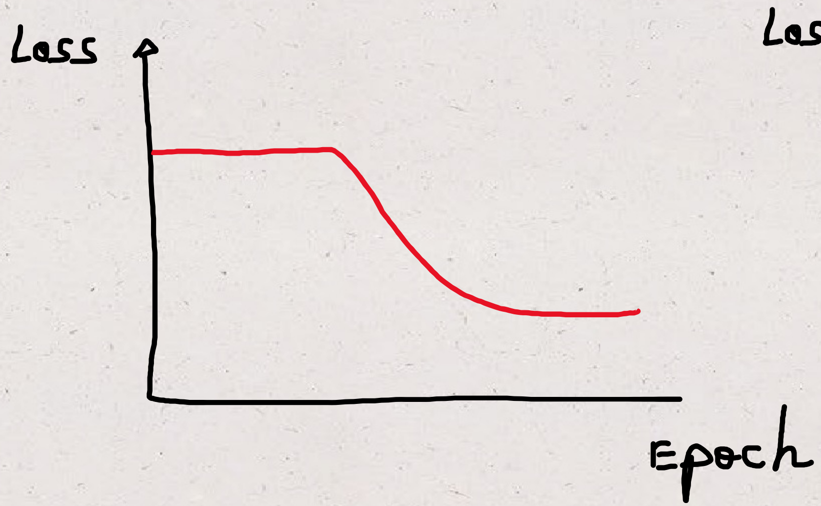
Maybe you have regularized too much? or

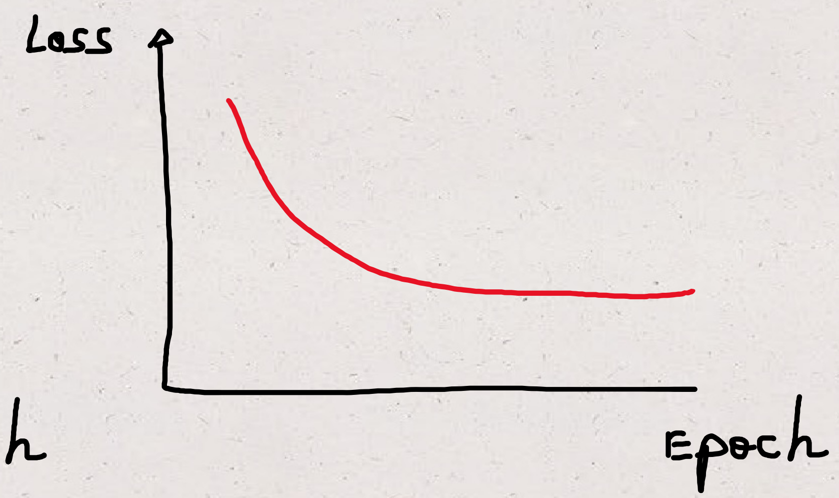
Maybe your validation examples are different/easier to predict?

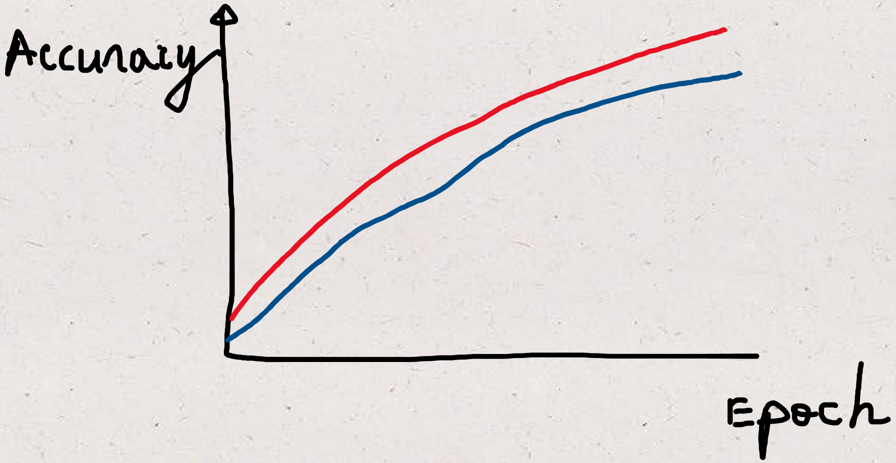
How to improve:

- Increase model capacity (add extra layers)
- decrease regularization (e.g., number of Dropout layers or percentage of units dropped out)
- K-fold cross validation exercise

Debugging learning curves

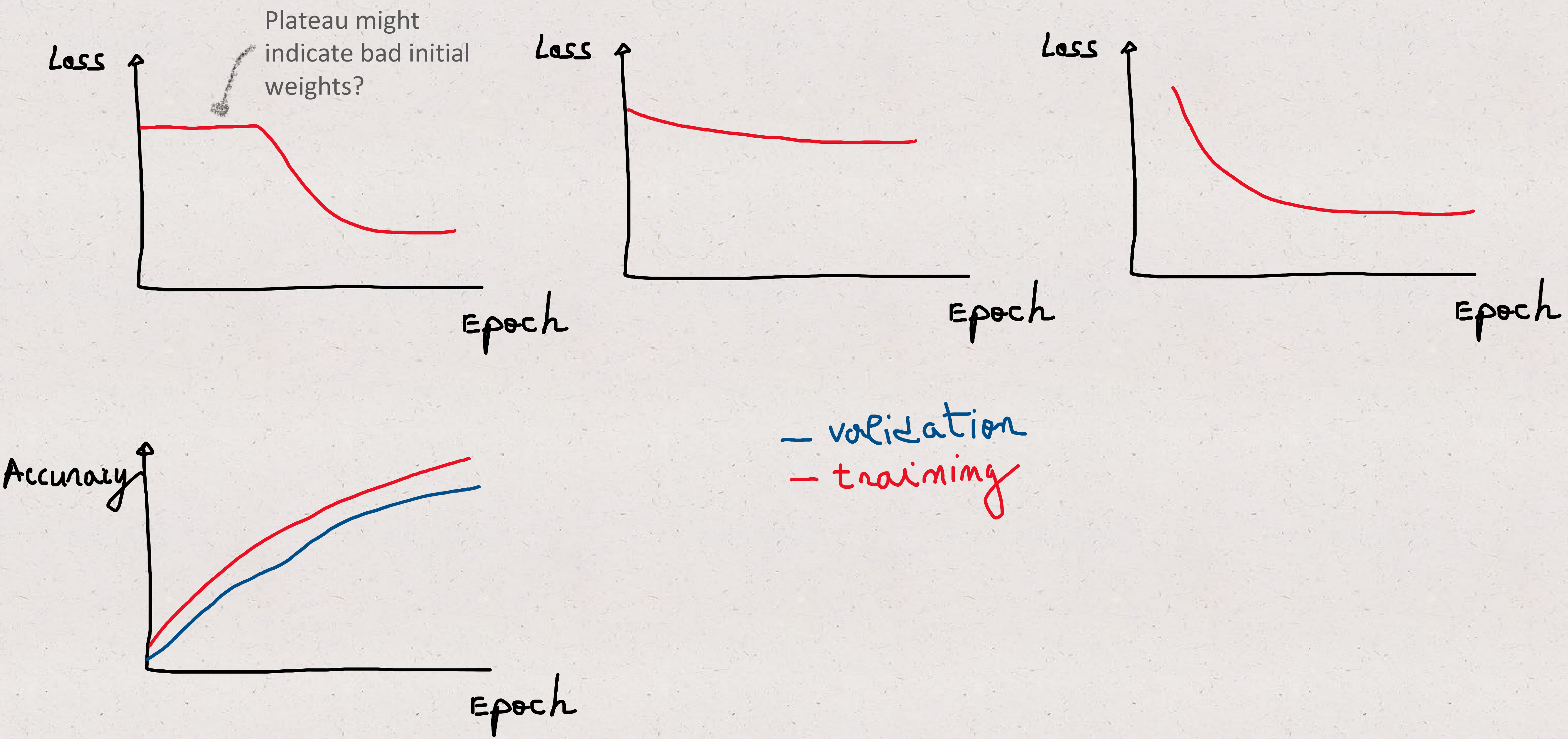






— validation
— training

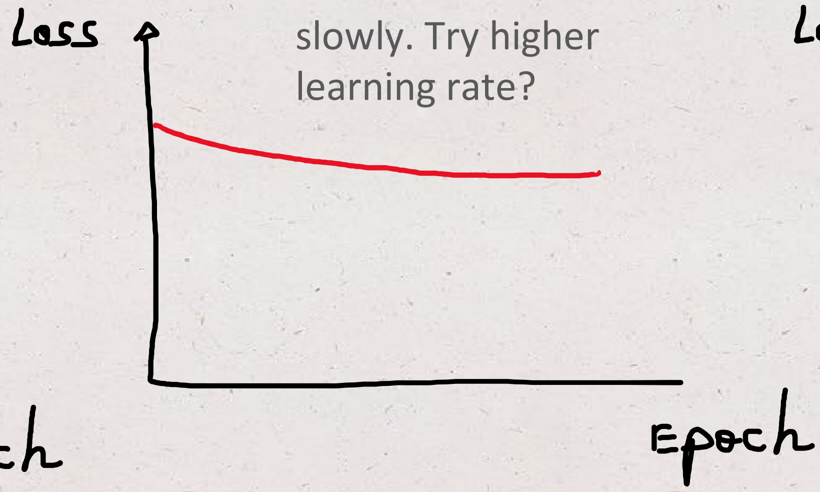
Debugging learning curves

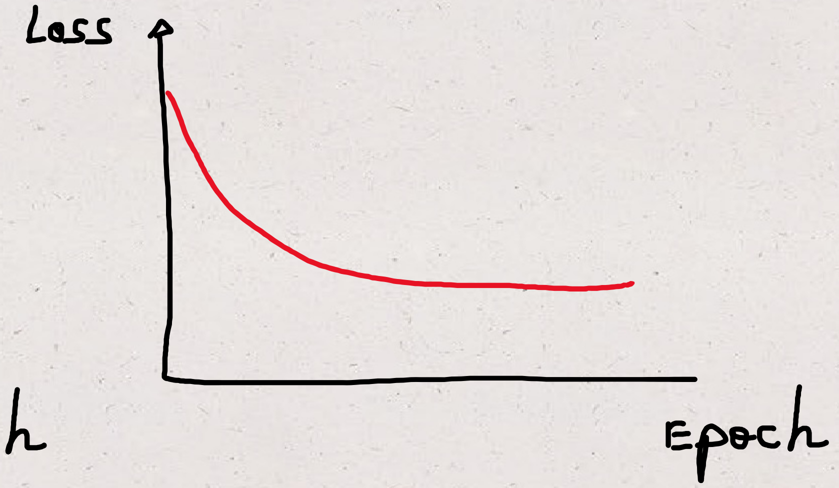


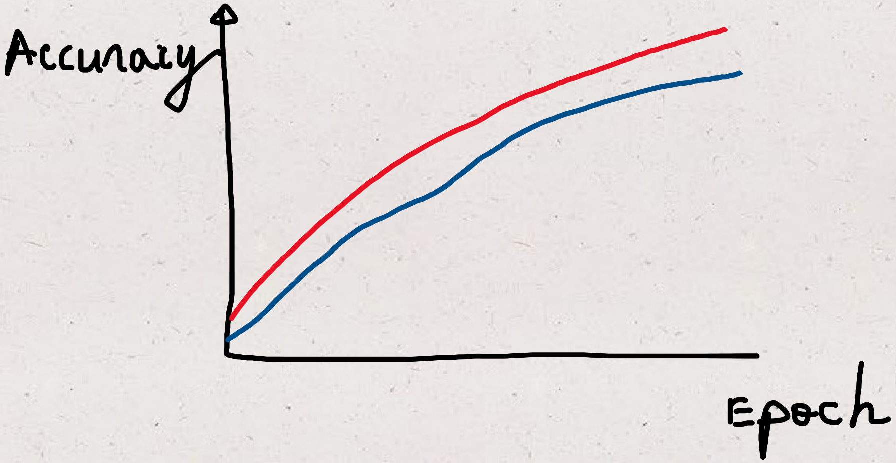
Debugging learning curves

Plateau might indicate bad initial weights?

Loss decreases slowly. Try higher learning rate?

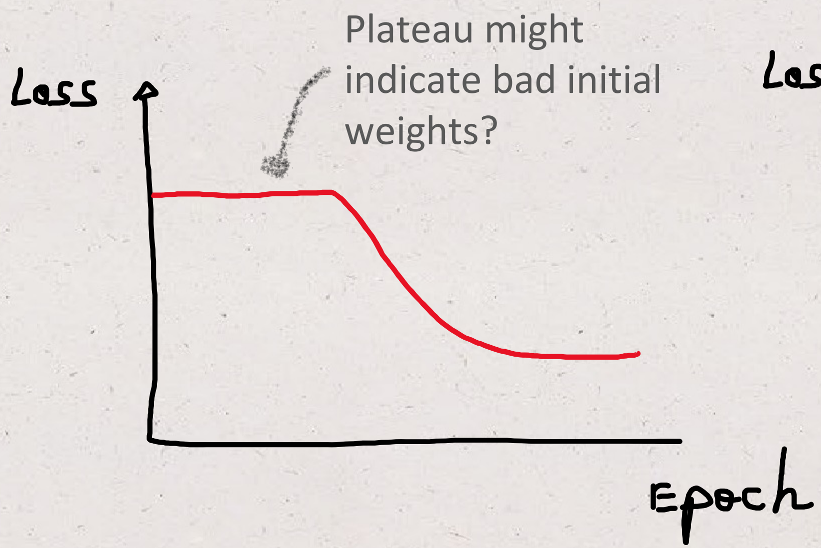


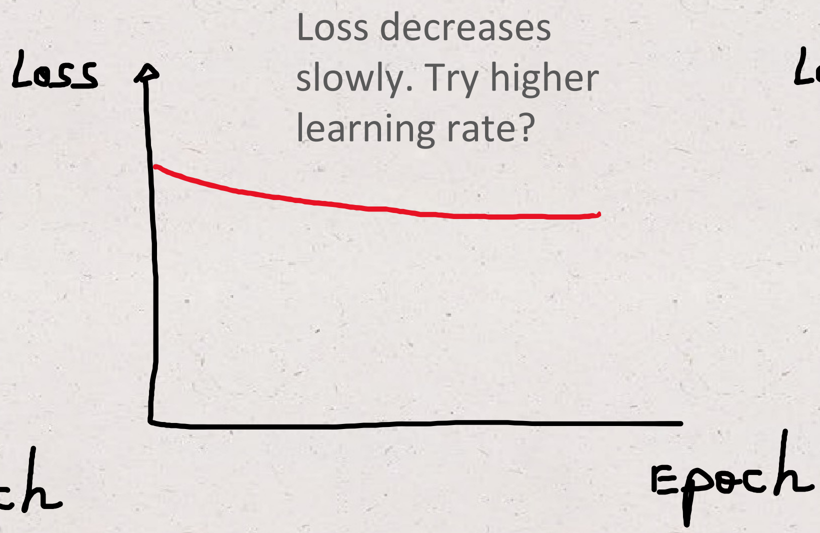


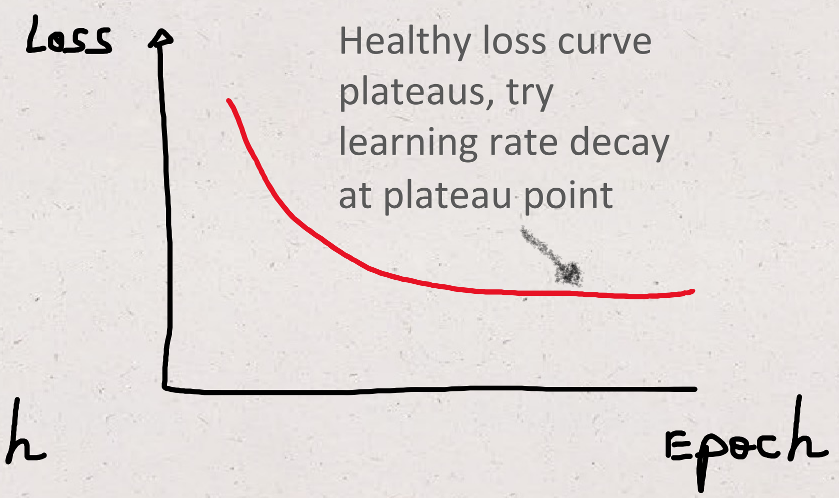


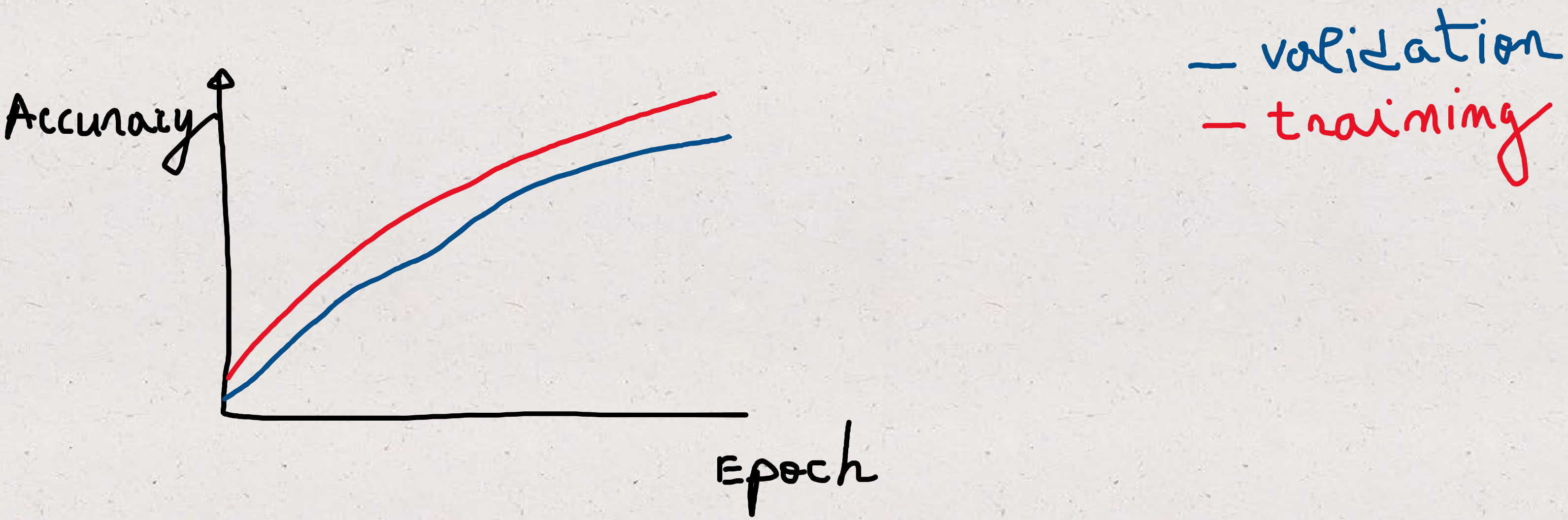
— validation
— training

Debugging learning curves



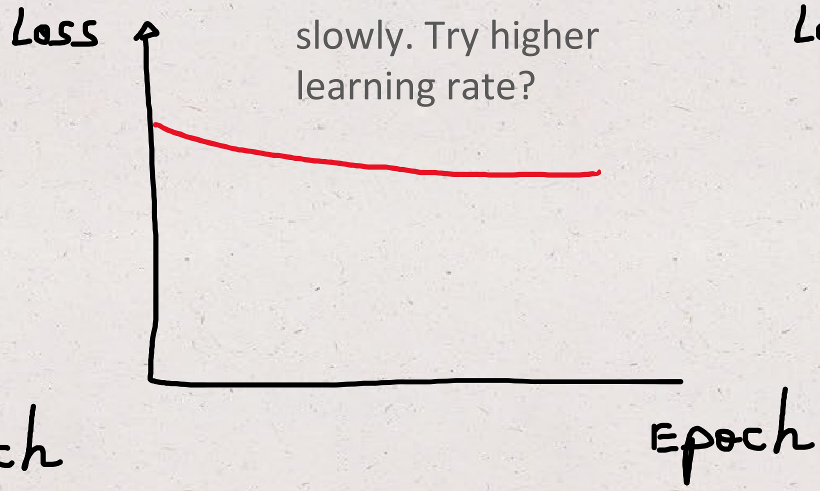




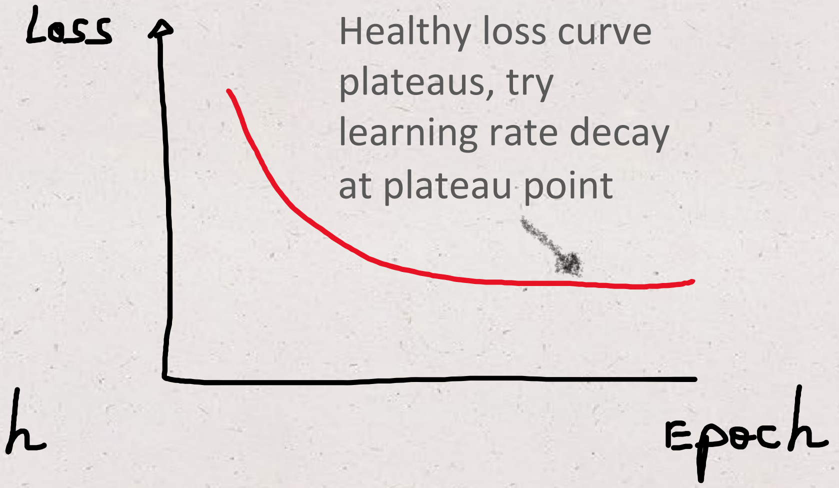


Debugging learning curves

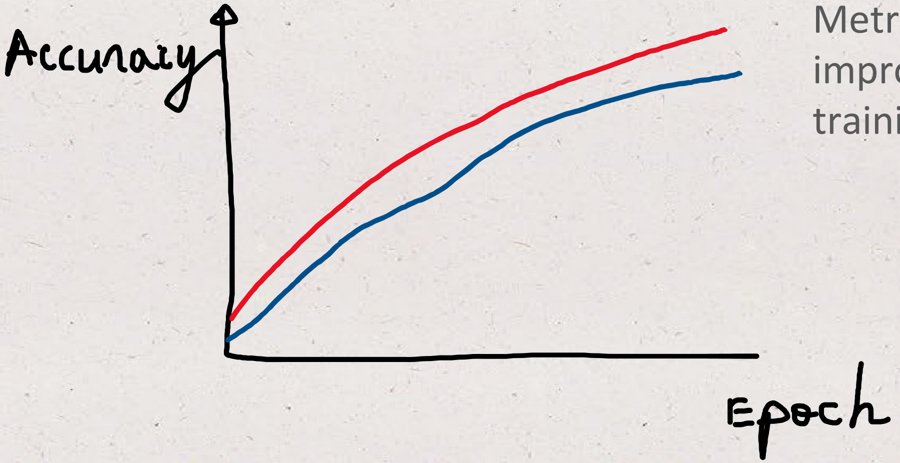
Plateau might indicate bad initial weights?



Loss decreases slowly. Try higher learning rate?



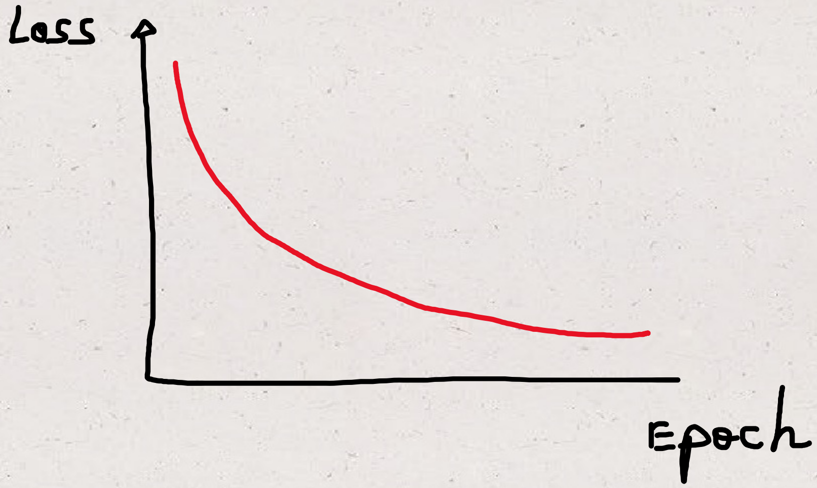
Healthy loss curve plateaus, try learning rate decay at plateau point

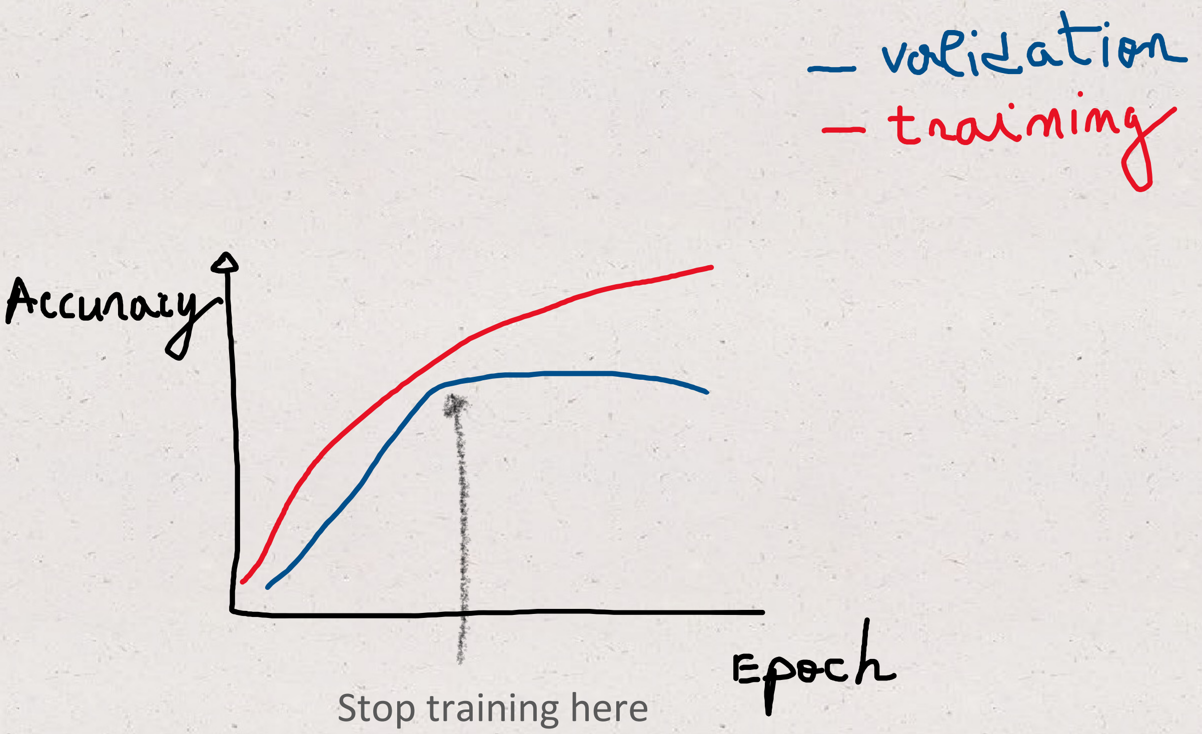


Metric still improving, keep training!

– validation
– training

Debugging learning curves



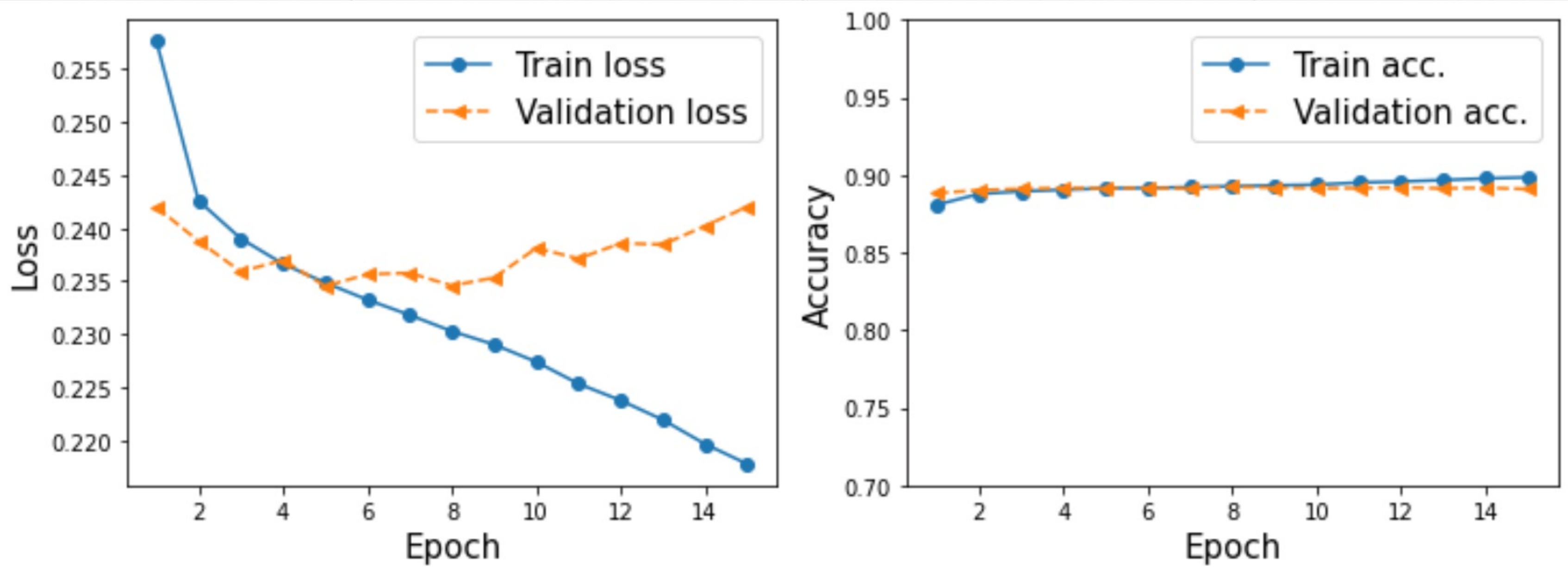


Early stopping:

stop training when accuracy on validation decreases.

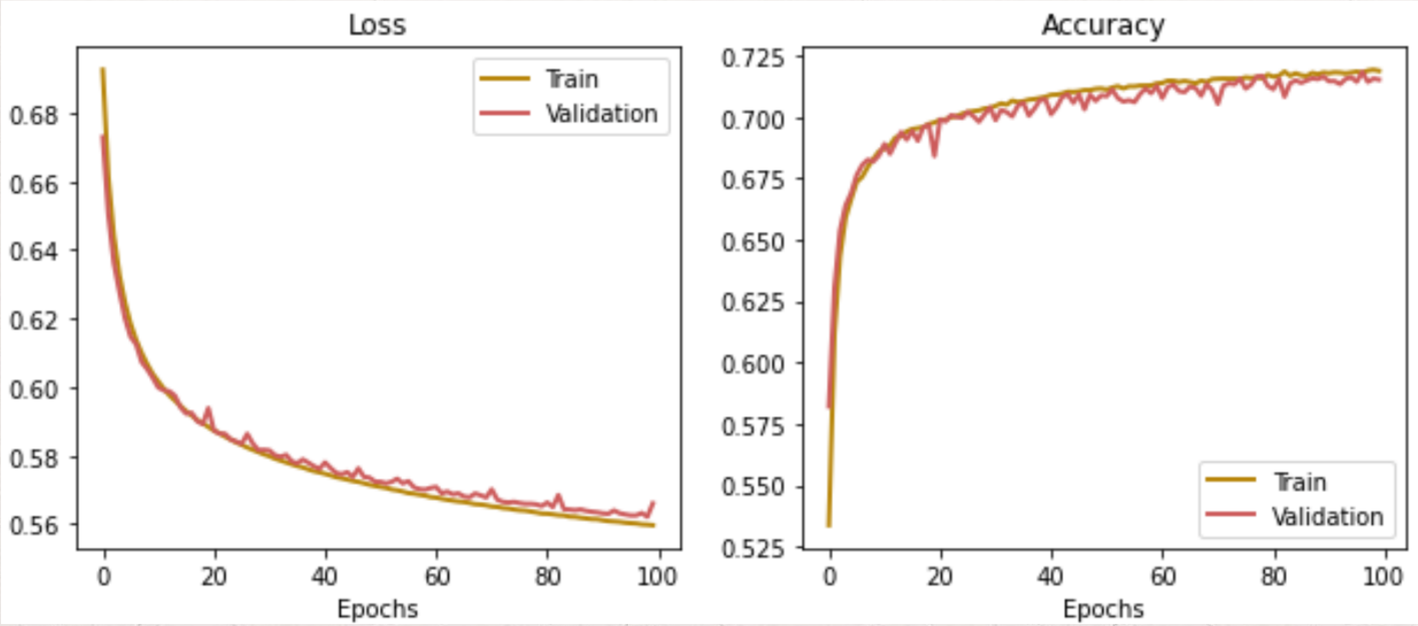
Debugging learning curves

What do you recommend?



Debugging learning curves

What do you recommend?



End-to-end application: your final project

Questions?

End-to-end application: my research

Time step t

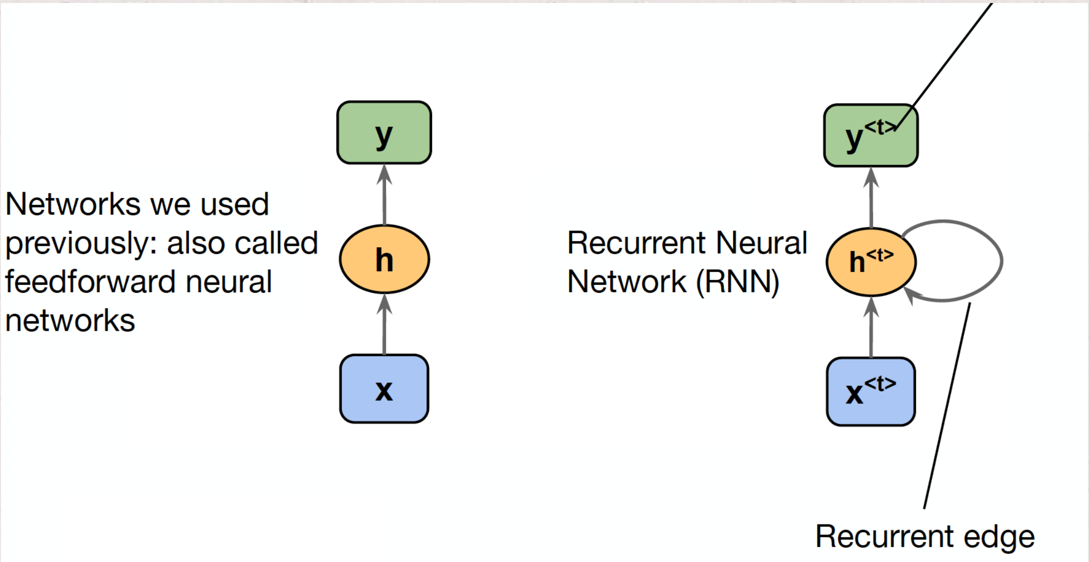
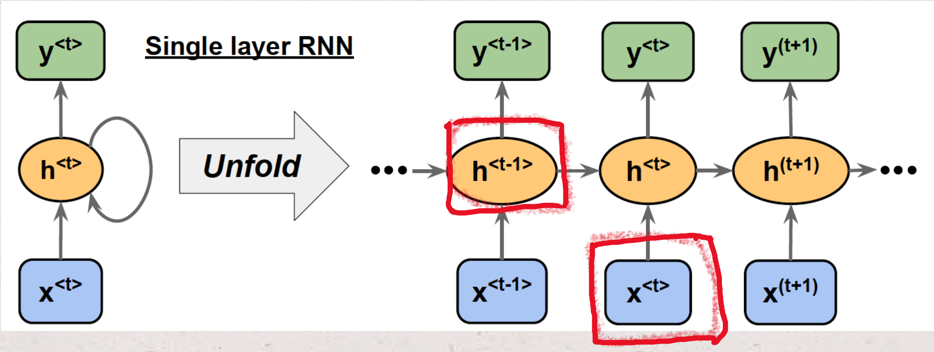


Image source: Sebastian Raschka, Vahid Mirjalili. *Python Machine Learning. 3rd Edition.* Packt, 2019

many-to-many architecture



Each hidden unit receives two inputs

Data: Electronic medical records (EMR)

Question: Predict diagnosis in the next hospital visit

Similar data: MIMIC II (https://archive.physionet.org/mimic2/)