Deep Learning

LM Computer Science, Data Science, Cybersecurity
2nd semester - 6 CFU

References:
Deep Learning Book (main book)
Mitchell (machine learining concepts)
Bishop (machine learning)

Practical Methodology (chapter 11),
i.e. How to use deep learning

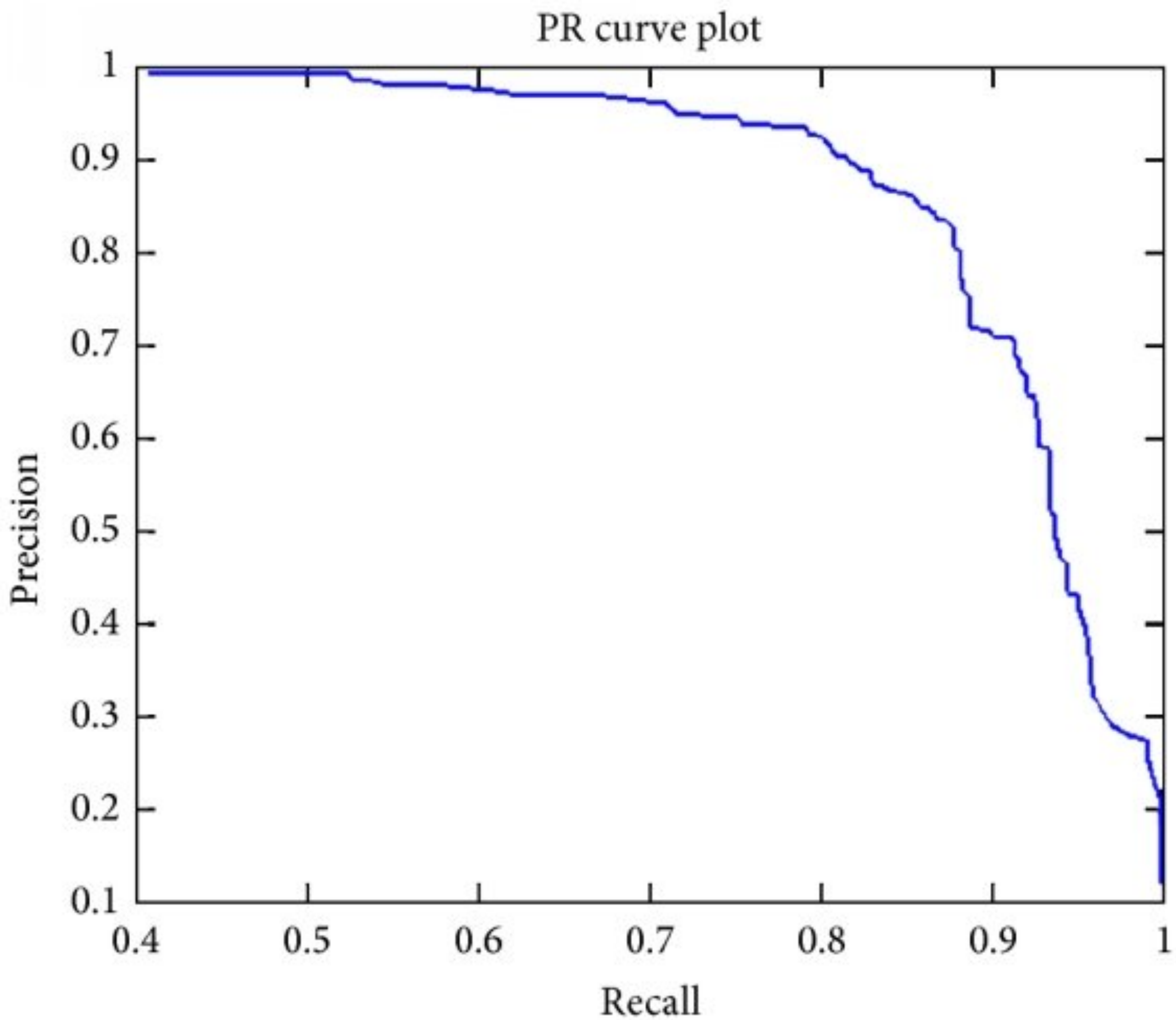
General methodology

- Determine your goals
  - error metrics, target value
- Build an end-to-end pipeline, including:
  - data ingestion, model training
  - and the estimation of the performance metrics
- Be prepared to analyse your system, to understand:
  - which component is performing worse than expected
  - if poor performance is due to underfitting, overfitting or a bug
- Repeatedly make incremental changes (one at a time!)
  - E.g. gathering new data, changing hyperparameters, changing algorithms based on specific observations
  - Understand the effect of each change

Performance metrics

- Decide which error metric to use
  - This metric will drive all future decisions
  - Different from loss: e.g. error rate
  - Often different errors should be weighted differently (e.g. spam classification)
- Detection of rare events:
  - Consider a disease that only one in 1M people have
  - 99.9999% accuracy simply predicting that nobody has the disease
  - Precision: fraction of detections that are correct
  - Recall: fraction of true events that are detected
  - If the classifier outputs a score, metrics depend on a threshold

Precision/Recall curve: varying the threshold



Ex. ID	Prediction	Target
5	0.99	1
10	0.97	1
7	0.96	0
1	0.86	1
	...	
42	0.1	1
9	005	0

- Single number summarising the performance (without fixing the threshold): Area under Precision/Recall curve
- If we fix the threshold:

$$Fscore = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

Desired level of performance

- Decide a desired level of performance
  - Based on the application (e.g. minimum accuracy for the system to be useful/trusted/safe in practice)
  - Previously published results
  - Zero error is often not possible!
    - Bayes error rate: lowest possible error rate for any classifier (seen in Machine Learning courses, or check it online)
  - May be limited by finite training data

Baseline models

- Baselines are simple Neural networks chosen to provide a first estimation of the achievable level of performance
- Depending on the complexity of the problem, you may start with machine learning (not deep learning) algorithms
- Define a baseline NN exploiting your knowledge:
  - if your data has a structure, exploit it (e.g. CNNs on images, RNNs on sequence data)
  - Use piecewise linear units (e.g. ReLU)
  - Chose e relatively simple architecture
  - Choose a standard learning algorithm: SGD with momentum and decaying learning rate, or Adam
  - Include regularisation (e.g. Dropout or weight decay)

Search for similar tasks

- If the task is similar to another task that has been studied:
  - Use the same model and algorithms that have been used for the other task
  - Use a pre-trained model

Determine whether to gather more data

- After training the first models, measure its performance and determine how to improve it
- Find out if the training performance is acceptable
  - Low training performance -> you are not exploiting the available data well. Increase model capacity: more layers or more units (Hyperparameters)
    - At the extreme, your data may be too noisy or not informative enough (or there are problems in data: check by yourself)
    - Re-collect the data measuring more variables or fixing the problems
- Measure test performance
  - If it is good, you are done
  - If it is not, try to decrease model capacity
    - Reduce the size of the model (Hyperparameters)
    - Add regularisation
  - If the generalisation gap is still high, gather more data if possible

Defects in data

- Can a human process it?

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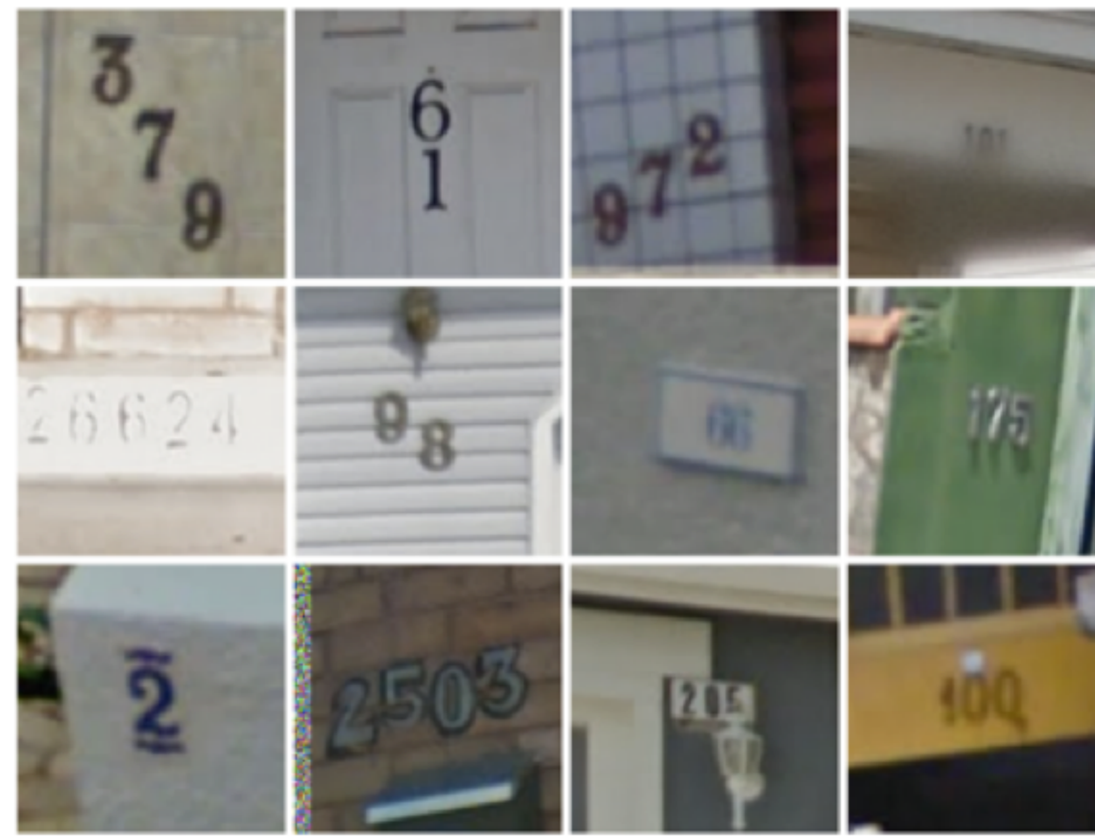
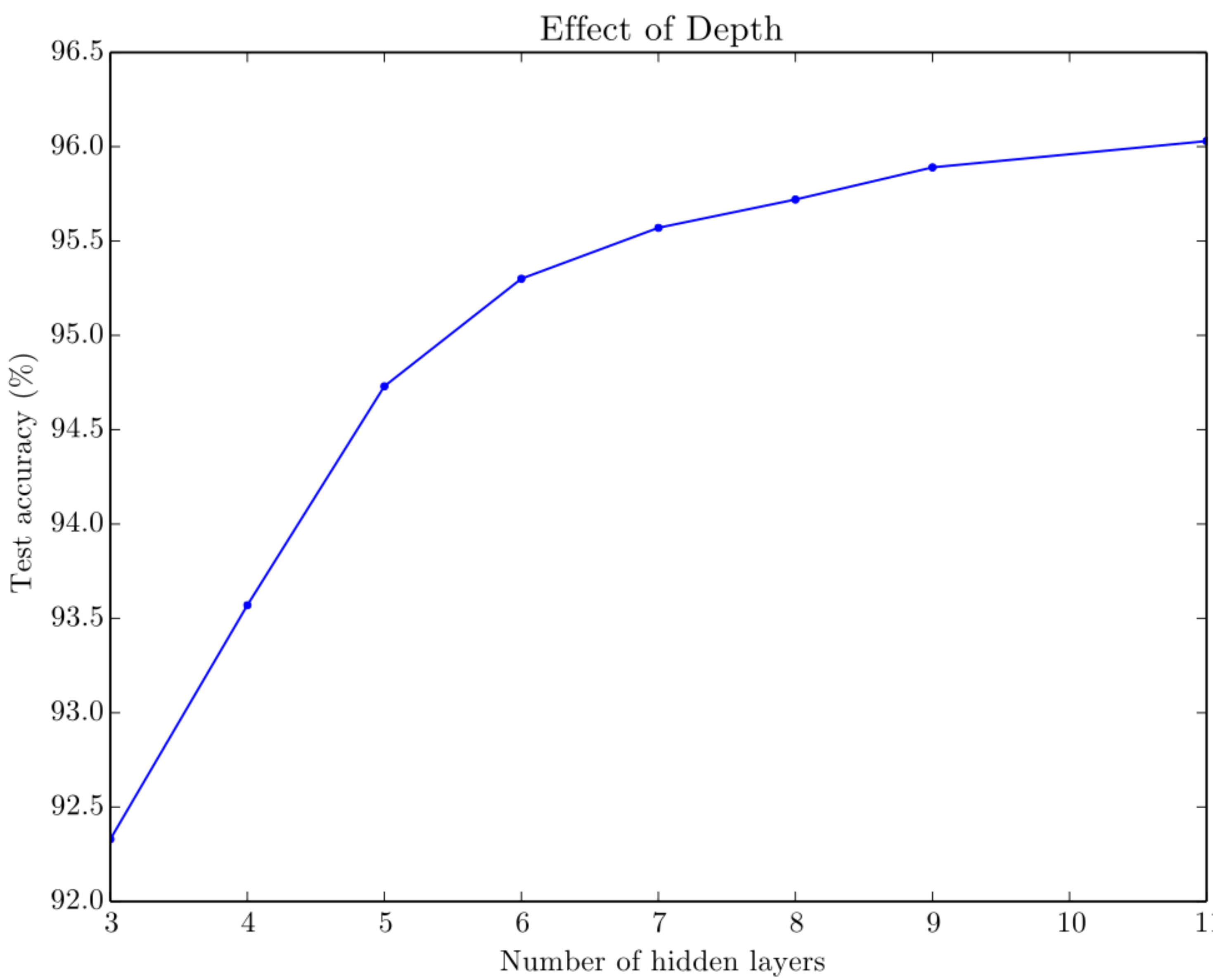
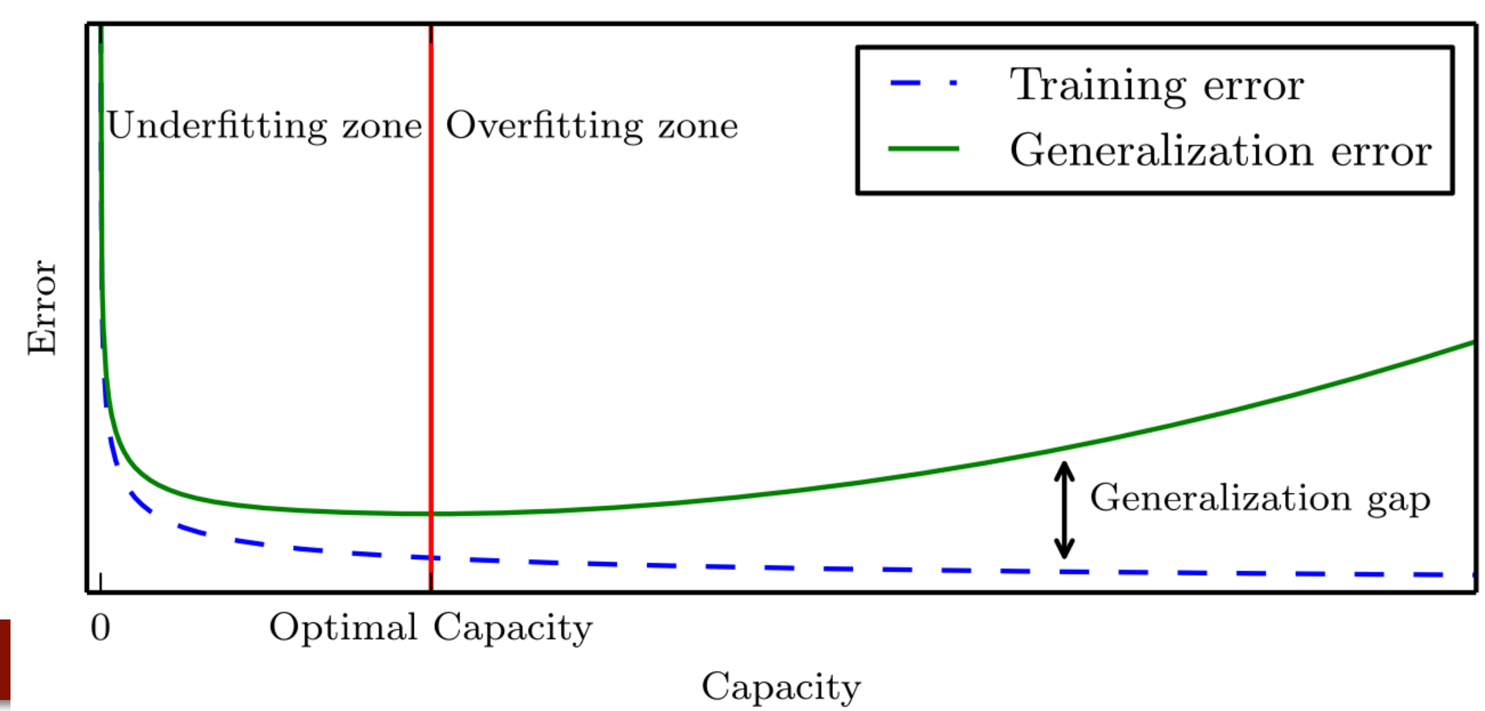


Model capacity

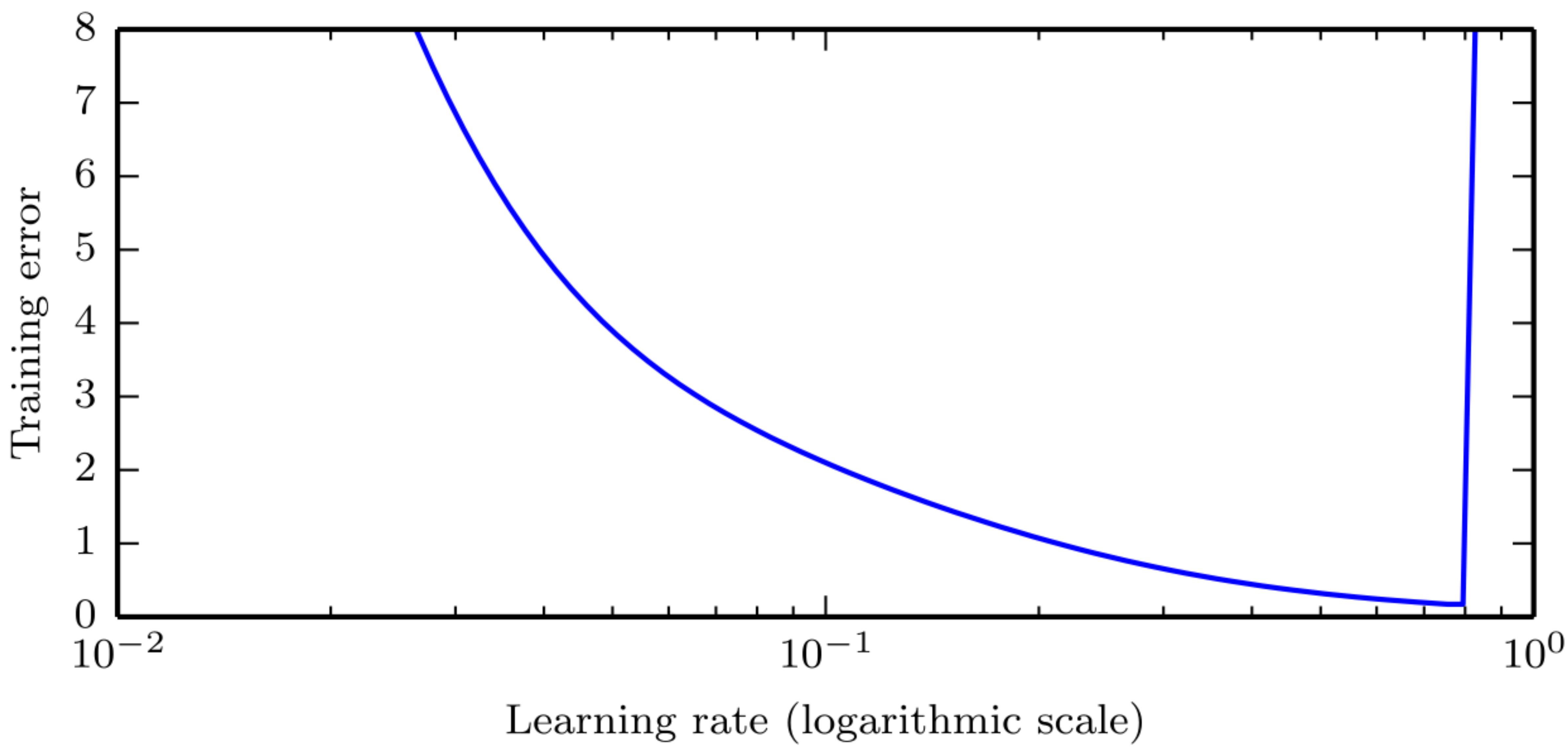


Hyperparameter selection

- Deep learning models are sensitive to hyperparameters
- Learning rate can be tuned on the training set
  - All the others on the validation set
- Usually the performance follows a U-shaped curve for each hyperparameter
  - Optimal model capacity lies between underfitting and overfitting zones
  - Usually, high-capacity models well regularized perform best
- Intuition should drive the search for hyperparameters

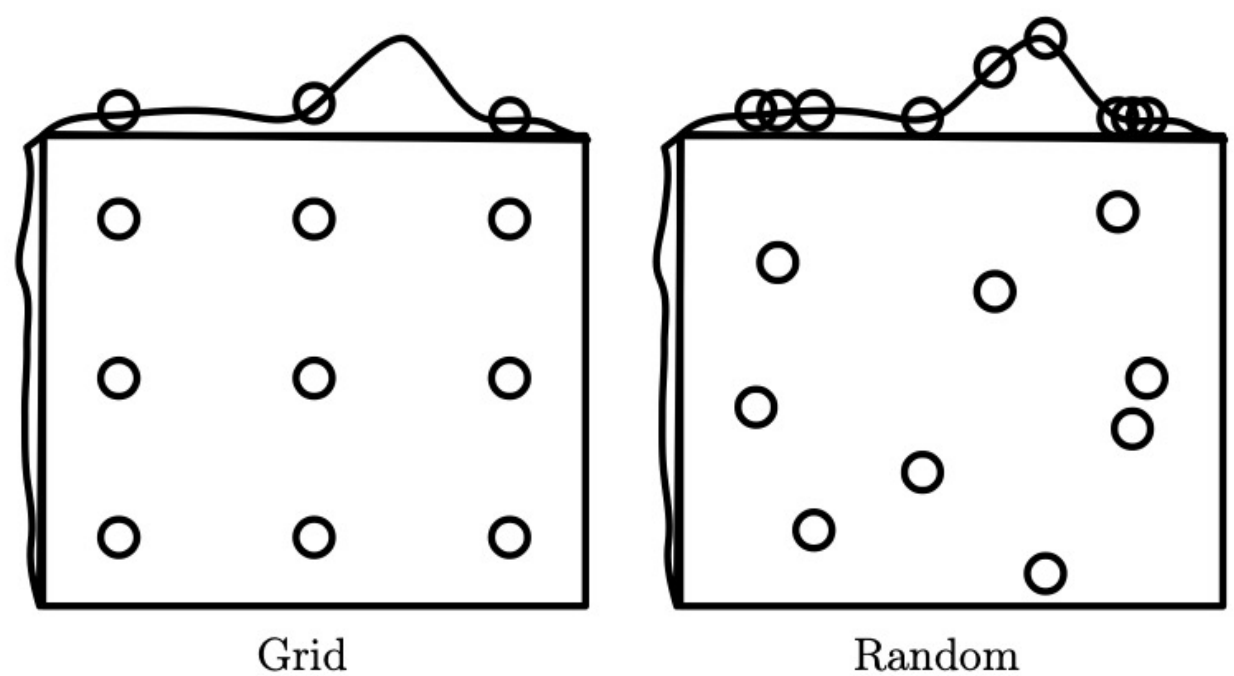


Learning rate



Automatic hyper-parameter selection

- You just select the range for each hyperparameter
- Grid search: Test many different pre-defined options
- Random search: usually just some of the hyperparameters have a significant impact in performance
  - It can be more efficient that grid search
- Other approaches: e.g. model-based (Bayesian)



Debug your network

- Visualise the outputs of the model
  - E.g. object detection/classification, speech synthesis
- Visualise the worst mistakes
- If training error is high, try to overfit a tiny dataset
- Check the gradient (exploding or vanishing)
  - If you implemented the derivatives, compare them with numerical derivatives
- Check the activations: how many neurons fire?
  - ReLU can induce “dead” neurons

Example

- In the book (chapter 11), an example of multi-digit number recognition (from Google) is described, check it out.