# **Advanced techniques**

Lecture 6

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# Hyperparameter search and cross validation

#### **Outline**

1. Hyperparameter search

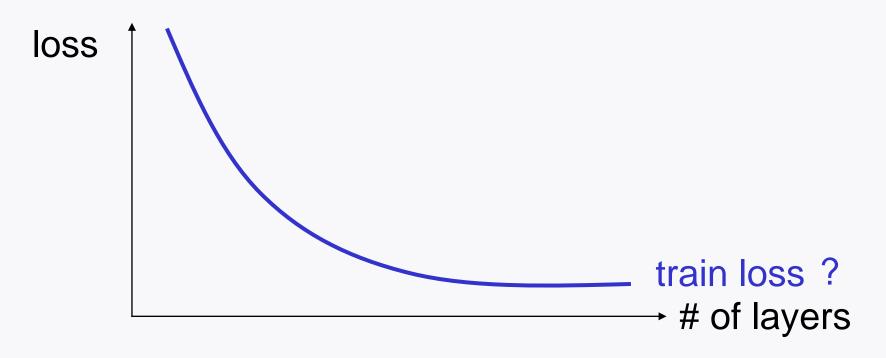
# L of layers, #  $n^{[\ell]}$  of hidden neurons, activation learning rate, betas, batch size, # T of epochs, regularization factor, dropout rate, ...

2. Cross validation

## # of layers

Just begin with a **single hidden** layer: L=1

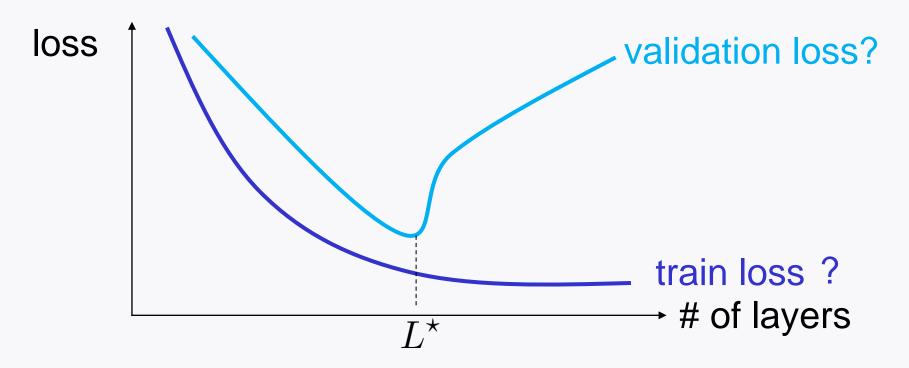
Gradually (linearly) ramp up # of hidden layers.



## # of layers

Just begin with a **single hidden** layer: L=1

Gradually (linearly) ramp up # of hidden layers.



Stop when overfitting starts.

## # of layers

### When increasing *L*:

How to set the number of hidden neurons for all hidden layers?

## For the time being:

Set that number around one half of the number of input neurons:

$$n^{[\ell]} = \frac{n}{2}$$

#### # of hidden neurons

Two approaches:

1. Fewer neurons for deeper layers

2. Same size for all hidden layers:

Linearly increase the size until not overfitting.

#### **Activation functions**

A default setup:

Hidden layers: ReLU

Output layer: Softmax for classification

No activation for regression

## **Optimizer**

A default use: Adam

Default parameters:  $(\beta_1, \beta_2) = (0.9, 0.999)$ 

Two approaches for a choice of the learning rate:

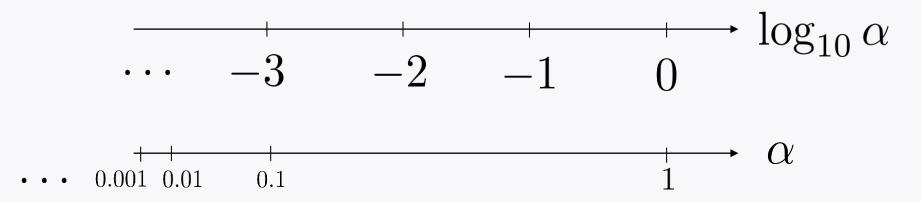
- 1. Learning rate decaying
- 2. Fixed (e.g.,  $\alpha = 0.001$ )

#### How to choose a fixed value of $\alpha$

Do not use a linear-scale grid search.

Try random values and then do a fine search around the good choices.

Grid scale for the fine search: Log scale



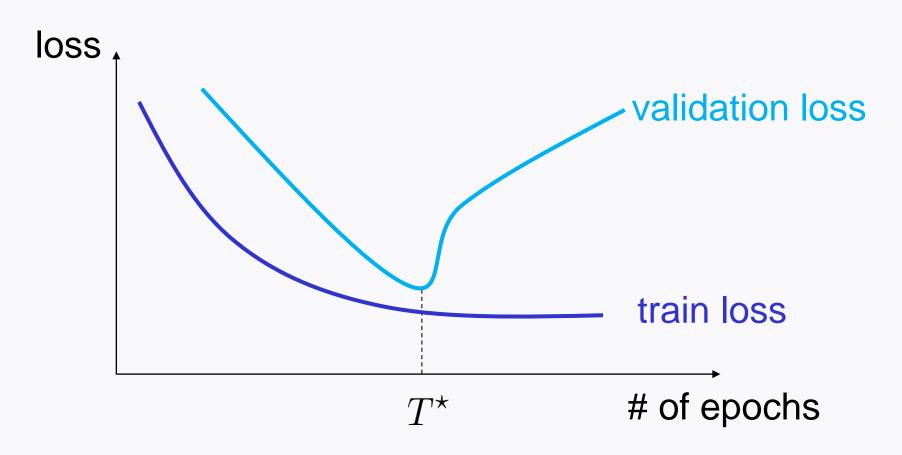
#### **Batch size**

A common choice: Power of two.

4, 8, 16, 32, 64, 128, 256

## # of epochs

## Choose according to early stopping:



## Regularization factor

#### **Log-scale** search:



## **Dropout rate**

A typical choice: p = 0.5

A good range:  $0.2 \le p \le 0.8$ 

#### **Cross validation**

Purpose: Obtain reliable validation loss via averaging.

→ Helps avoid overfitting

Example: 4-fold cross validation

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→ Compute a validation loss, say val<sub>1</sub>

Take the 2<sup>nd</sup> partition for val:

train	val	train	train	test
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→ Compute a corresponding loss: val<sub>2</sub>

#### **Cross validation**

val	train	train	train	test	$igc $ val $_1$
train	val	train	train	test	$val_2$
train	train	val	train	test	$val_3$
train	train	train	val	test	$ig $ val $_4$

Take the average over the 4 losses:

$$val loss = \frac{val_1 + val_2 + val_3 + val_4}{4}$$

Choose a hyperparameter that minimizes the average loss.

# A final model w.r.t. the best hyperparameter?

val	train	train	train	test	$model_1$
train	val	train	train	test	$model_2$
train	train	val	train	test	$model_3$
train	train	train	val	test	$model_4$

Which one to take among the four models?

A final model is the one trained based on:

train train train test	
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#### What is next?

One important question:

Can DNNs be specialized?

CNNs: Image data

RNNs: Text/audio data (language) and any sequential data

## **Outline of Day 3 lectures**

Focus on CNNs.

Specifically we will:

- 1. Investigate how CNNs were developed;
- 2. Study the two key building blocks:

Conv layer Pooling layer

3. Discuss popular CNN architectures.