

Supervised Learning

Mapping from inputs to outputs

Need paired examples (x_i, y_i) to learn from

Examples are Regression, Text Classification, Image Classification, etc.

Double descent & COD

Double descent is the phenomenon when the test error increases while the training error is nearing zero and then decreases sharply and back to normal

The tendency of high-dimensional space to overwhelm the number of data points is called the curse of dimensionality

Double descent & COD (cont)

But distance from the origin of random samples is roughly constant and most of the volume of a high dimensional orange is in the peel not in the pulp

Volume of a diameter one hypersphere becomes zero and generate random points uniformly in hypercube, ratio of nearest to farthest becomes close to one

Loss/Cost function and Train/Test

Measurement of how bad a model performs

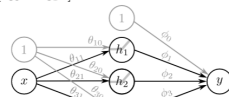
Trains on pair of data Find argmin of this loss function

Test on separate set of data Measure the loss there and see its generalizing power

Different loss functions are Squared Loss, log likelihood, ramp loss, etc

Counting number of parameters

$$\begin{aligned} h_1 &= a[\theta_{10} + \theta_{11}x] \\ h_2 &= a[\theta_{20} + \theta_{21}x] \\ h_3 &= a[\theta_{30} + \theta_{31}x] \end{aligned} \quad y = \phi_0 + \phi_1 h_1 + \phi_2 h_2 + \phi_3 h_3$$



Each parameter multiplies its source and adds to its target

Initialization

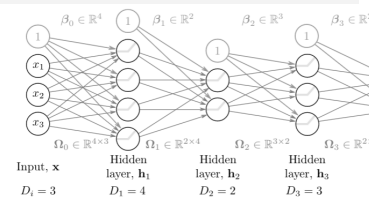
If on initialization the variance is small or big Then it can have floating point errors

Initialization (cont)

So, we want to set variance same in forward and backward pass

He Initialization does this by setting variance of k or $k+1$ is same at layer $k+1$ or k

Counting number of parameters



Regularization techniques

Explicit regularization is adding of a regularizing term to the loss function

This is also known as the prior in the probabilistic view. Normally L2 regularization is used where the square weights are added and controlled by a regularization term

Regularization techniques (cont)

Implicit regularization is the natural tendencies of optimization algorithms and other aspects of the training process

That even without explicitly adding regularization techniques, help improve the generalization performance of a model eg SGD due to batch sizes (cause of randomness)

Early stopping is the process of stopping training early to not overfit the weights since they start small

Ensembling is the collague of different models and is averaged then (by mean or median). Different subset of data resampled is bagging

Dropout is the technique of killing random units. Can eliminate kinks in function that are far from data and don't contribute to training loss

Regularization techniques (cont)		Momentum & Adam (cont)		Backpropagation (cont)		Deep neural networks (cont)	
Can also use bayesian inference to provide more information (to priors)	Transfer learning, multi-task learning, self-supervised learning, and data augmentation can be used too to improve generalization	Normalizing the gradients can lead to being stuck if we don't land on the optimal point exactly	Adam prevents that by computing mean and pointwise squared gradients with momentum and moderating near start of the sequence	We do not know gradients though so the loss cannot be modified (since units have a dependency chain at update)	Backward pass calculates the gradients then of the loss function but in reverse	Basically outputs from hidden units as inputs	Go into another hidden layer as inputs
Bias Variance Tradeoff		Stochastic Gradient Descent				Also obeys the universal approximation theorem	
Variance is the uncertainty in fitted model due to choice of training set	Bias is systematic deviation from the mean of the function we are modeling due to limitations in our model	Gradient descent might be slow	And not all gradients needed to find optimal point	This is very efficient but is memory hungry	Also the problem is trying to split the computation process apart (i.e. maybe parts exist in different computers)	The hyperparameters are K for width of network and D_i for number of units of the network at layer i	Difference from shallow network is more regions per parameters
Noise is inherent uncertainty in the true mapping from input to output	Can reduce variance by adding more datapoints	Compute gradient based on only a subset of points – a mini-batch	Work through dataset sampling without replacement	Gradient Descent		Convolutional networks	
Can reduce bias by making model more complex	But doing one or the other increases since model = overfitting = more variance	One pass though the data is called an epoch	This can escape from local minima, but adds noise. Uses all data equally but	Gradient descent finds optimal point (for convex function)	by step walking towards it, i.e., goes against the gradient calculated	Parameters only look at local image patches and so share parameters across image	The convolutional operation averages together the inputs
Momentum & Adam		Backpropagation		So derivative of loss function wrt to parameters is calculated		Stride = shift by k positions for each output, Kernel size = weight a different number of inputs for each output, Dilated or atrous convolutions = intersperse kernel values with zeros	
Momentum is the weighted sum of the current gradient and previous gradients	We can think of momentum as a prediction on where we are stepping	Two passes are done, forward pass, and backwards pass	Forward pass deals with knowing the activations at each layer and how it affects the loss and calculating inbetween values	Deep neural networks		Stride decreases output size, Kernel size combines info from larger area, while the last one uses few params while combine info	
				Simply neural networks with more than one hidden layer			
				Better than simply transposing the output of one shallow network to another (less params and regions)			

Convolutional networks (cont)		Reinforcement Learning (cont)		Shallow neural network (cont)		Unsupervised Learning	
But we want to lose information: done by apply several convolutions and stack them in channels (feature maps)	Receptive fields is the region in the input space that a particular CNN's feature is affected by	Flaws are that it is	Schocastic, temporal credit assignment, i.e., reward achieved by move or past moves, and Exploration-exploitation trade-off, i.e. when to explore and when to not	Called shallow since only one hidden layer	Universal approximation theorem states that enough hidden layers can approximate to any continuous function on a compact subset	Learning a dataset without any labels	So dataset is orgnaized in input only fashion
Benifit of CNN is better inductive bias, forcing the network to process each location similarly, share info, search from small family of input/-output maps, etc	Downsa-mping is the reducing of positions in data (max pooling most common ie take max), while upsampling is the increase	Shallow neural network		Maximum likelihood		Examples are	Clustering, Outlier Finding, Generating examples, fill missing data
		Use non convex (activation function)	to mold family of functions into dataset	Points in a database can be from an underlying distribution	The main idea of using likelihood function is to estimate this distribution	There are generative models	like generative adversal networks
		Common activation functions are	ReLU, sigmoid/s-oftmax (as final layer), tanh function (kinda like sigmoid), etc	Model predicts a conditional probability $\Pr(y x)=P-r(y \theta)=\Pr(y -f[x,\phi])$	Here the loss function aims to have correct outputs have high probability	Also probab-ilistic generative models	Who learn the dist over data. Examples are autoencoders, normalizing flows, and diffusion models
Reinforcement Learning		Pass a set of linear func normally and activation function transforms it (known as hidden layer)	So that a specific weight is activated or not depending on that function	So find argmax for ϕ (or argmin if we negative the objective function)	Product can be very small value so log is taken to make it a summation		
Create a set of states, actions, and rewards	Goal is to maximize reward by finding correct states						
No data involved	Is recieved by the world build and explored			Softmax is used in the case of multiclass categorization	It converts a vector of K real numbers into a probability distri-bution of K possible outcomes		
Examples are	Chess, Video games, etc						

