

Exam Preparation Session

Lecture 1:

- important: multivariate gaussian
- know difference normal & gradient descent
 - ↳ question: if I swap these parameters can I still use?
 - ↳ when can you not use normal equation. If normal equations so good, why do we still look at Gradient Descent.
- regularization (not very important but know)
- softmax regression and how you use it!
 - ↳ when k-binary classifier, what's the difference
- recommender systems (!)
 - ↳ content based approach
 - know what's going on / algorithm and know the computations.
 - ↳ kurt will ask you something out of the box, e.g. apply the algorithm to classify you really need to know algorithm well.
- NNS
 - ↳ explainability

Lecture 2: Boltzmann + Deep learning

- KL-divergence and cost function
- Variational Autoencoders → Latent Space (!)
- know the algorithm
- vanishing gradient problem
 - ↳ what happens? what causes this? know it very well
 - ↳ what is the solution to this problem
- RNN is not ^{that} important, but know when to use this.
- check self-attention
- hopfield net not really in exam
- how to calc boltzmann, the energy is important, how you calculate the probabilities. Why is derivative simple?
- kurt is fan of hinton. Positive & Negative phase, understand this deeply. Slide 28 & 29

- log reg kernel
- should we regard the bias
- passing rate

Lecture 3: SVM

- won't ask to derive mathematics
- what if dataset is an image, how would you apply svm. Know the kernel trick
- slack variable, what does it control?
- kernel trick past exams very important
- SMO probably not asked, understand concept

Lecture 4: Gaussian Process

- watch the videos about it!
- why is good. How do we construct method?
- how do we derive it
- μ^* , σ^* MOST IMPORTANT know complexity

Lecture 5: Representation

- always first question on exam
- know difference between methods
- always explain why you use this method and not others
- boolean, AV, MI, RR rest less important
- kernels applied to multi instance

Lecture 7:

- design a specific kernel so you can solve this problem.
- no questions probably about graph kernels
- clustering medium chance of appearing
↳ set matching neither

Lecture 8: Quantum ML

- know the gates (mostly for assignments)
- slide 56: overview physical circuit
↳ could be asked to draw something like this and how they work
↳ know what each part does and means
↳ how does data pass between them
- Variational Quantum Classifier
- Feature maps
- Comparison quantum NN & normal NN. (!!!)

Q1: Representational Issues

We want to save ~~the~~ collisions in CERN with properties $\%$ and their label interesting / non-interesting.

ASSUMPTIONS: e.g. ^{how} ~~any~~ traj. snapshot is represented

I will use multi-Instance to represent this problem:

	particle	momentum	charge (v)	traj. snapshot	Label
e.e.	p1	4	3%	[0]	interesting
	p2	5	1%	[4]	
	p3	1050	0.5	[]	
	p4	1	0.5		
f.e.	p5	50	0.01		not interesting
	p6	0.01	50		

a learning example represents a collision here, where the rows represent 1 particle per collision.

BYC AV C MI C RR

Why use multi-Instance? In multi-instance I can represent multiple objects attached to one learning example. This means I can save a row per particle created in a collision. If we move one representation level down, to Attribute value we lose the ability

We are not using RR cause we gain information but not necessary + less solvers + less complex better

Q2: CAB'S

a) Explain why/how a shallower network can perform better in this learning setting.

A shallower network means there is less convolution/averaging, thus leaving the latent space bigger, \Rightarrow so we have more space to represent our data, thus this can perform better.

b) would you use this in the colorization task

No, as you want it to generalize over features. For colorization we don't want specific details of images. I or

c) how can we increase the reconstruction/colorization
more channels, smaller kernels.

Q3: Kernel Design

So our main issue is categorical data(?) so we can represent male/female like 0,1 and the hair colors on a numerical scale with 0 black and max white and scale on darkness.

We need to define a distance metric

1. transfer to numerical
2. transpose to 4×4 matrices as we have 4 features. So it against its transpose

Q4: Softmax & SSD

a) Do you think using an SSD loss for an NN with softmax final layer is possible?

Softmax outputs a probability for each class. SSD uses the ~~e~~ selected class. Without adaptations, this is not possible. So we compare a probability and a ground truth. We could argmax our softmax but then its not ~~if we can change~~ really softmax anymore.

c) Yes, you could but I'm not sure at all ~~if~~ you measure the probability error. You could, but its weird... But maybe not.