Welcome and Introduction

Philip Schulz and Wilker Aziz

https://github.com/philschulz/VITutorial

About us . . .

Wilker Aziz

- Research associate at UvA
- Sampling, VI, Machine Translation

Philip Schulz

- PhD candidate at UvA
- Applied Scientist at Amazon
- VI, Machine Translation, Bayesian Models

Problems

Supervised problems: "learn a distribution over observed data"

- sentences in natural language, images, videos, . . .

Unsupervised problems: "learn a distribution over observed and unobserved data"

- sentences in natural language + parse trees, images + bounding boxes . . .

Maximum likelihood estimation

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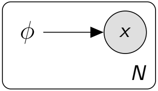
and proceed to estimate parameters that assign maximum likelihood to observations

Multiple problems, same language



(Conditional) Density estimation

	ϕ	x
Parsing	a sentence	its syntactic/semantic parse tree/graph
Translation	a sentence	its translation
Captioning	an image	caption in English
Entailment	a text and hypothesis	entailment relation

Where does deep learning kick in?

Let ϕ be all side information available
e.g. deterministic *inputs/features*

Have neural networks predict parameters of our probabilistic model

$$X|\phi \sim \text{Cat}(\pi_w(\phi)) \quad \text{or} \quad X|\phi \sim \mathcal{N}(\mu_w(\phi), \sigma_w(\phi)^2)$$

and proceed to estimate parameters w of the NNs

Task-driven feature extraction

Often our side information ϕ is itself some high dimensional data

- ϕ is a sentence and x a tree
- ϕ is the source sentence and x is the target
- ϕ is an image and x is a caption

and part of the job of the NNs that parametrise our models is to also deterministically encode that input in a low-dimensional space

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From the statistical point of view NNs do not generate data

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Prediction is done by a decision rule outside the statistical model

- e.g. beam search

MLE via gradient-based optimisation

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Given a dataset of i.i.d. observations, SGD gives us a local optimum of the log-likelihood

DL in NLP recipe

Maximum likelihood estimation

- tells you which loss to optimise
  (i.e. negative log-likelihood)

Automatic differentiation (*backprop*)

- "give me a tractable forward pass and I will give you gradients"

Stochastic optimisation powered by backprop

- general purpose gradient-based optimisers

Tractability is central

Likelihood gives us a differentiable objective to optimise for

- but we need to stick with tractable likelihood functions

When do we have intractable likelihood?

Latent variables: assessing the likelihood requires marginalisation

- too many forward passes

$$P_X(x) = \sum_{c=1}^{K} \mathrm{Cat}(c|\pi_1, \ldots, \pi_K) \underbrace{\mathcal{N}(x|\mu_w(c), \sigma_w(c)^2)}_{\text{forward pass}}$$

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- even infinitely many

$$P_X(x) = \int \mathcal{N}(z|0, I) \underbrace{\mathrm{Cat}(x|\pi_w(z))}_{\text{forward pass}} \mathrm{d}z$$

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Beam-search

- biased gradient estimates
  bye bye stochastic optimisation!

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Monte Carlo sampling

- breaks differentiability
  bye bye backprop!

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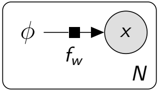

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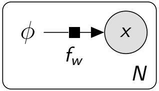

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But what if

- we want to learn clusters?
- or segmentation?
- or sparse models?
- or latent factors?
- or learn from incomplete supervision?
- or Bayesian NNs?

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Probabilistic models parametrised by neural networks

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  which is the reason why we are here today