

Introduction

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VI Tutorial @ Host
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Why are we here today?

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but they may struggle with

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- partial supervision
- lack of inductive bias

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- develop a shared vocabulary to talk about generative models powered by NNs
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Goal

- you should be able to navigate through fresh literature
- and start combining probabilistic models and NNs

Supervised problems

We have data $x^{(1)}, \dots, x^{(N)}$ e.g. sentences, images generated by some **unknown** procedure which we assume can be captured by a probabilistic model

- with **known** probability (mass/density) function e.g.

$$X \sim \text{Cat}(\theta_1, \dots, \theta_K) \quad \text{or} \quad X \sim \mathcal{N}(\theta_\mu, \theta_\sigma^2)$$

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and **estimate parameters** θ that assign maximum likelihood $p(x^{(1)}, \dots, x^{(N)} | \theta)$ to observations

Supervised NN models

Let y be all side information available

e.g. deterministic *inputs/features/predictors*

Have neural networks predict parameters of our probabilistic model

$$X|y \sim \text{Cat}(\pi_{\theta}(y)) \quad \text{or} \quad X|y \sim \mathcal{N}(\mu_{\theta}(y), \sigma_{\theta}(y)^2)$$

and proceed to **estimate parameters θ** of the NNs

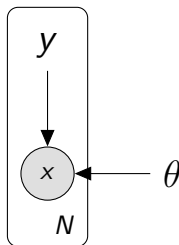
Graphical model

Random variables

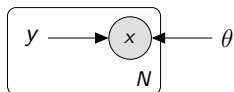
- observed data
 $x^{(1)}, \dots, x^{(N)}$

Deterministic variables

- inputs or predictors
 $y^{(1)}, \dots, y^{(N)}$
- model parameters θ



Multiple problems, same language



(Conditional) Density estimation

	Side information (y)	Observation (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

Task-driven feature extraction

Often our side information is itself some high dimensional data

- y is a sentence and x a tree
- y is the source sentence and x is the target
- y 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

NN as efficient parametrisation

From a statistical point of view, NNs do not generate data

- they parametrise distributions that *by assumption* govern data
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Prediction is done by a decision rule outside the statistical model

- e.g. argmax, beam search

Maximum likelihood estimation

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MLE via gradient-based optimisation

If the log-likelihood is **differentiable** and **tractable** then backpropagation gives us the gradient

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and we can update θ in the direction

$$\gamma \nabla_{\theta} \mathcal{L}(\theta | x^{(1:N)})$$

to attain a local maximum of the likelihood function

Big Data

For large N , computing the gradient is inconvenient

$$\nabla_{\theta} \mathcal{L}(\theta | x^{(1:N)}) = \underbrace{\sum_{s=1}^N \nabla_{\theta} \log p(x^{(s)} | \theta)}_{\text{too many terms}}$$

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S selects data points uniformly at random

Stochastic optimisation

For large N , we can use a gradient estimate

$$\nabla_{\theta} \mathcal{L}(\theta | x^{(1:N)}) = \underbrace{\mathbb{E}_{S \sim \mathcal{U}(1/N)} [N \nabla_{\theta} \log p(x^{(S)} | \theta)]}_{\text{expected gradient :)}}$$

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and take a step in the direction

$$\gamma \frac{N}{M} \underbrace{\nabla_{\theta} \mathcal{L}(\theta | x^{(s_1:s_M)})}_{\text{stochastic gradient}}$$

where $x^{(s_1:s_M)}$ is a random mini-batch of size M

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

Constraints

Differentiability

- intermediate representations must be continuous
- activations must be differentiable

Tractability

- the likelihood function must be evaluated exactly, thus it's required to be tractable

When do we have intractable likelihood?

Unsupervised problems contain unobserved random variables

$$p(x, z|\theta)$$

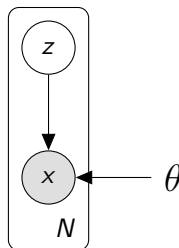
thus assessing the marginal likelihood requires
marginalisation of latent variables

$$p(x|\theta) = \int p(x, z|\theta) \mathrm{d}z$$

Latent variable model

Latent random variables

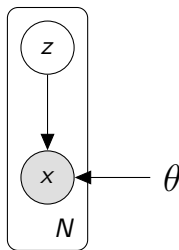
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A joint distribution over data and unknowns

$$p(x, z|\theta) = p(z)p(x|z, \theta)$$

Examples of latent variable models

Discrete latent variable, continuous observation

$$p(x|\theta) = \sum_{c=1}^K \underbrace{\text{Cat}(c|\pi_1, \dots, \pi_K)}_{\text{too many forward passes}} \underbrace{\mathcal{N}(x|\mu_\theta(c), \sigma_\theta(c)^2)}_{\text{forward pass}}$$

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Continuous latent variable, discrete observation

$$p(x|\theta) = \underbrace{\int \mathcal{N}(z|0, I) \text{Cat}(x|\pi_\theta(z)) \, dz}_{\text{infinitely many forward passes}}$$

Intractable gradient

$$\nabla_{\theta} \log p(x|\theta)$$

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- uncertainty quantification
e.g. Bayesian NNs

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a mixture model whose mixture components are labelled
by words marginalisation $O(|x||y|)$

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A factor model whose factors are labelled by words

marginalisation $O(2^{|y|})$

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- news: *recently hosted the world cup final*

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