

# CMPUT 367

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## Lecture 10 - Feb 13

### 1 Midterm Exam

3 questions; up to Feb 15 lecture

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#### 1.1 Exponential Family

(EXP)

(rev from last lecture)

$$p(x; \eta) = h(x) \exp\{\eta^\top T(x) - A(\eta)\}$$

$$A(\eta) = \ln \int h(x) \exp(\eta^\top T(x)) dx$$

$A(\eta)$  is convex

log likelihood is convex in  $\eta$

moment generating property

$$\frac{\partial A(\eta)}{\partial \eta} = \mathbb{E}_{x \sim p(x; \eta)} [T(x)] \quad \frac{\partial^2 A(\eta)}{\partial \eta \partial \eta^\top} = \text{Cov}_{x \sim p(x; \eta)} [T(x)]$$

MLE  $\iff$  Moment Matching

organize moment params - same as moment stat (?; 27 min feb 13 lec)

$$\hat{\mu} = \mathbb{E}_{x \sim p(x; \eta)} [T(x)]$$

##### 1.1.1 Linear Regression

$$\{(x^{(m)}, t^{(m)})\}_{m=1}^M$$

$$t^{(m)} | x^{(m)} \sim \text{EXP}(\eta^{(m)})$$

with canonical response function

$$\eta^{(m)} = w^\top x^{(m)}$$

GLM:

$$t^{(m)} | x^{(m)} \sim \text{EXP}(w^\top x^{(m)})$$

$w^\top x^{(m)}$  are the natural parameters

$$\ln p(t^{(1)} \dots t^{(m)} | x^{(1)} \dots x^{(m)}) = \sum_{m=1}^M \ln \cdot h(x^{(m)}) \exp(w^\top x^{(m)} t - A(\eta))$$

$$\begin{aligned} \frac{\partial}{\partial w} \ln p &= \sum_{m=1}^M \left[ t^{(m)} \cdot x_i^{(m)} - \frac{\partial A(\eta)}{\partial \eta} \cdot \frac{\partial \eta}{\partial w_i} \right] \\ &= \sum_{m=1}^M \left[ t^{(m)} \cdot x_i^{(m)} - \mathbb{E}_{t^{(m)} \sim \text{EXP}(t^{(m)} | x^{(m)}; \eta)} [t^{(m)}] \cdot x_i^{(m)} \right] \end{aligned}$$

### 1.1.2 Logistic Regression

$$\eta^{(m)} = w^\top x^{(m)}$$

mean param from natural param; need  $\psi$  inverse

$$\mu^{(m)} = \psi^{-1}(\eta^{(m)}) = \sigma(\eta^{(m)})$$

Linear poisson regression (see feb 13 notes)

(Canonical response func chosen bc gradient is nice; prediction uses mean params instead of natural)

## 2 Nonlinear Models

Design nonlinear features

Nonlinear kernels (68 min)

if model only depends on

$$[x^{(i)}]^\top [x^{(j)}]$$

we may extend the notion of inner product  $\langle x^{(i)}, x^{(j)} \rangle$

Neural networks - a stack of linear predictions (learnable)

Non linear problems exist