## 1 MLE is illuminating (continued)

Let $D=\left\{x_{n}\right\}_{n=1}^{N}$

$$
\begin{aligned}
\log p\left(x_{1: N} \mid \eta\right) & =\sum_{n=1}^{N} \log p\left(x_{n} \mid \eta\right) \\
& =\sum_{n=1}^{N}\left(\log h\left(x_{n}\right)+\eta^{T} t\left(x_{n}\right)-a(\eta)\right) \\
& =\sum_{n=1}^{N} \log h\left(x_{n}\right)+\eta^{T} \sum_{n=1}^{N} t\left(x_{n}\right)-N a(\eta) .
\end{aligned}
$$

### 1.1 Notes

Note that $\sum_{n=1}^{N} t\left(x_{n}\right)$ is sufficient for $\eta$.

$$
\begin{aligned}
\nabla_{\eta} L & =\sum_{n=1}^{N} t\left(x_{n}\right)-N \nabla_{\eta} a(\eta) \\
\nabla_{\eta} a(\eta) & =\frac{\sum_{n=1}^{N} t\left(x_{n}\right)}{N}=\mathrm{E}[t(\mathbf{x})]
\end{aligned}
$$

### 1.2 Back to Linear Models

The idea behind both linear and logistic regression is as the following:

$$
\mathrm{E}[\mathbf{y} \mid \mathbf{x}]=f\left(\beta^{T} \mathbf{x}\right) \triangleq \mu
$$

- At linear regression $f(a)=a$
- At logistic regression $f(a)=\operatorname{logistic}(a)$
y is endowed with a distribution that depends on $\mu$
- At linear regression $y \sim N\left(\mu, \sigma^{2}\right)$
- At logistic regression $y \sim \operatorname{Bernoulli}(\mu)$


Figure 1: Relation between variables

### 1.3 Generalized Linear Model

- Input enters the model via $\beta^{T} x \triangleq Q$
- Conditional mean, $\mathrm{E}[\mathbf{y} \mid \mathbf{x}] \triangleq \mu$, is a function of $Q$ called a response function or link function.
- Y comes from an exponential family with parameter $\mu$.

Now let us model the diversity of response variables.

## Choices:

- We need to decide which exponential distribution family to use for the response. (this is determined by the data type of $y$.
- We need to specify the response function $f$ which is constrained but offers more freedom.

We will consider the canonical response function.

