

# Midterm 1 Review

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## Test format

- 1 hour test
- Multiple choice & short answer questions
- No calculator
- Closed book, closed notes

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## Supervised Learning

Regression  
(Output  $\in \mathbb{R}$ )

Classification  
(Output in a finite set)

Hypothesis:  $\theta^T x$ .

Learning: Identifying hypothesis

Computation: Find the hypothesis in our  
Objective: set that minimizes the cost on  
the training set.

Key: Identify cost function that is  
"continuous / differentiable"

Cost:  $J(\theta) = \frac{1}{2} \sum_{i=1}^n (y_i - \theta^T x_i)^2$

(Stochastic) Gradient Descent

Start with an initial  $\theta$

Repeat for some number of iterations

$$\theta \leftarrow \theta - \alpha \nabla_{\theta} J(\theta)$$

Linear Regression: (S)GD on least squares

Perceptron: SGD on a particular loss fn

Logistic: (S)GD on a particular cost fn.

Softmax: (S)GD on another cost fn.

→ Alternate Solution: Solve Normal eqns.

## Generalized Linear Models

-  $p(y | x; \theta) \sim$  Exponential Family

$$p(y | \eta) = b(y) e^{\eta^T T(y) - a(\eta)}$$

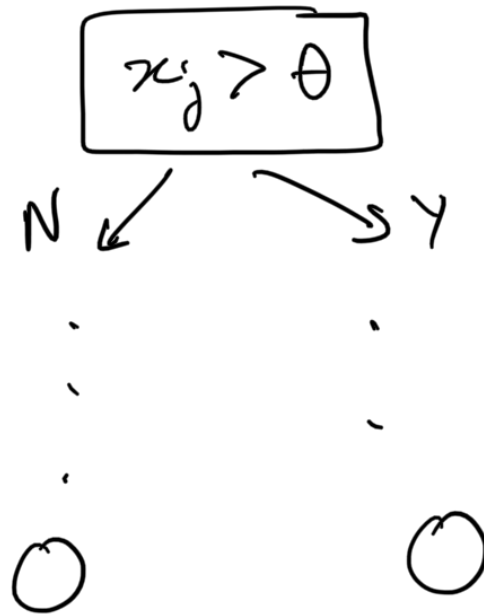
- Compute  $E[T(y)]$

- Finding  $\eta$  that maximizes the likelihood of the training set.

$$\theta_j \leftarrow \theta_j - \alpha \sum_{i=1}^n (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)}$$


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Decision Trees



Cons: Overfitting data.

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**k**-Nearest Neighbors

↳ k neighbors of test data in training set.

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$$h_{\theta}(x) = \begin{cases} -1 & \theta^T x \leq T \\ +1 & \theta^T x > T \end{cases}$$

$$J(\theta) = \frac{1}{n} \sum_{i=1}^n \mathbb{1} [h_{\theta}(x^{(i)}) \neq y^{(i)}]$$


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$$p(y; \eta) = b(y) e^{\eta^T T(y) - a(\eta)}$$

$$p(y; \lambda) = \frac{\lambda^y}{y!} e^{-\lambda}$$

Observation:  $\eta$  is same fun of  $\lambda$ .

Term  $\frac{\lambda^y}{y!}$  - depends on  $\lambda$  &  $y$

Let  $z = e^{\ln z}$

$$p(y; \lambda) = \frac{1}{y!} e^{y \ln \lambda - \lambda}$$

$$b(y) = \frac{1}{y!}$$

$$\eta^T T(y) = y \ln \lambda$$

$$\eta = \ln \lambda$$

$$T(y) = y$$

$$a(\eta) = \lambda = e^\eta$$

$$p(y; \phi) = \begin{cases} \phi & y=1 \\ 1-\phi & y=0 \end{cases}$$

$$p(y; \phi) = \phi^y (1-\phi)^{1-y}$$