

# CS540 Introduction to Artificial Intelligence

## Lecture 14

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Based on lecture slides by Jerry Zhu and Yingyu Liang

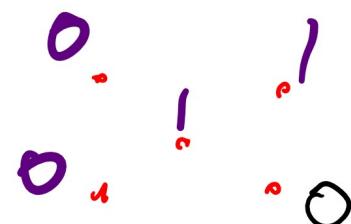
July 2, 2019

# Perceptron

## Review

- Perceptron update rule.
- Perceptron termination condition.

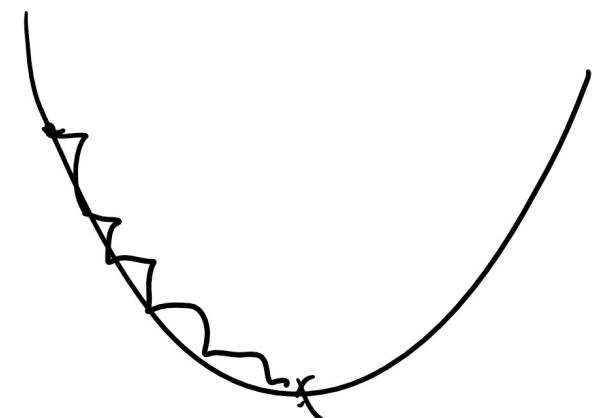
iff data points linearly separable



# Logistic Regression

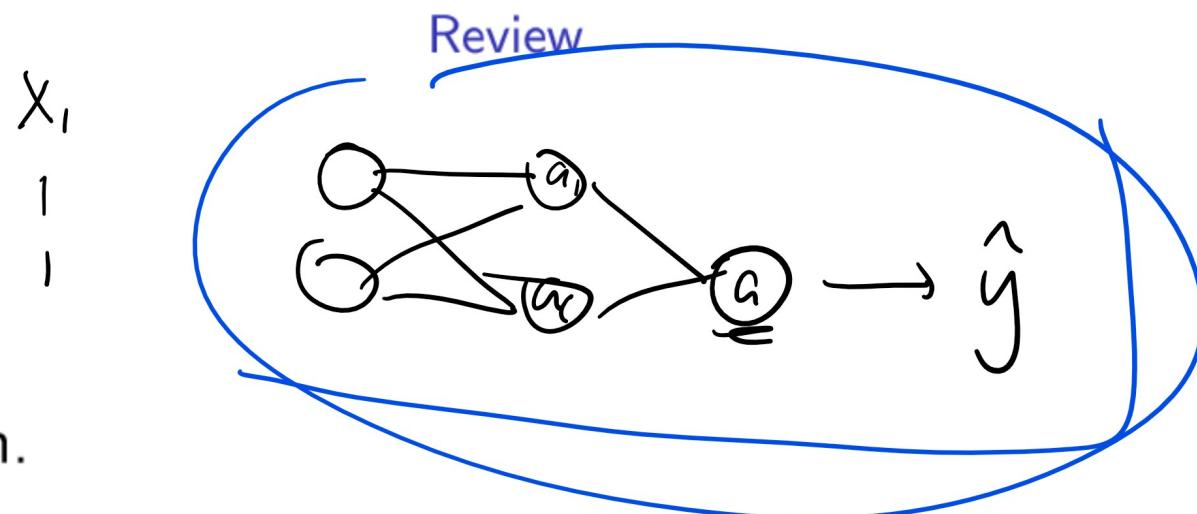
## Review

- Logistic update rule.
- Logistic cost function. ↗  
↳ log cost.
- Convexity. ↙
- Hessian, Laplacian, eigenvalue.  
↳ eigenvalue  $\geq 0$



$$\frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

# Neural Network



- Activation.
- Backpropagation.
- $L_1$  and  $L_2$  regularization.
- Cross validation.
- Multi class classification.

One vs One  
 one vs all  
softmax

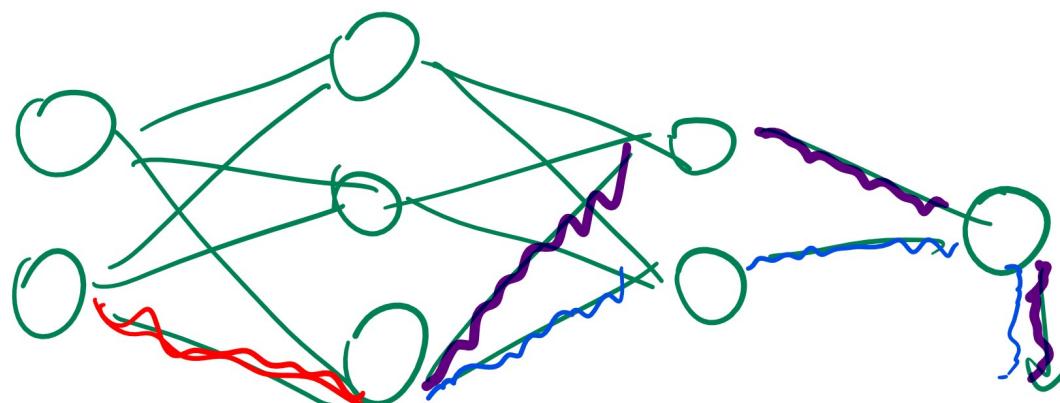
$$C = \sum_{i=1}^n (y_i - a_i^{(s)})^2$$

3 activation in last layer

$$y = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \Rightarrow \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

# Multi Layer Neural Network Example

Review



$$a_1^{(2)} \cdot (1 - a_1^{(1)}) w_{31}^{(2)}$$

$$a_1^{(2)} = g\left(\frac{w^T a^{(1)} + b}{z_1^{(2)}}\right)$$

$$\begin{aligned} \frac{\partial C}{\partial w_{23}} &= \frac{\partial C}{\partial a^{(3)}} \cdot \frac{\partial a^{(3)}}{\partial a^{(2)}} \cdot \frac{\partial a^{(2)}}{\partial a^{(1)}} \cdot \frac{\partial a^{(1)}}{\partial w_{23}} \\ &\rightarrow \frac{\partial C}{\partial a^{(3)}} \cdot \frac{\partial a^{(3)}}{\partial a^{(2)}} \cdot \frac{\partial a^{(2)}}{\partial a^{(1)}} \cdot \frac{\partial a^{(1)}}{\partial w_{23}} \end{aligned}$$

# LTU Activation Example

## Review

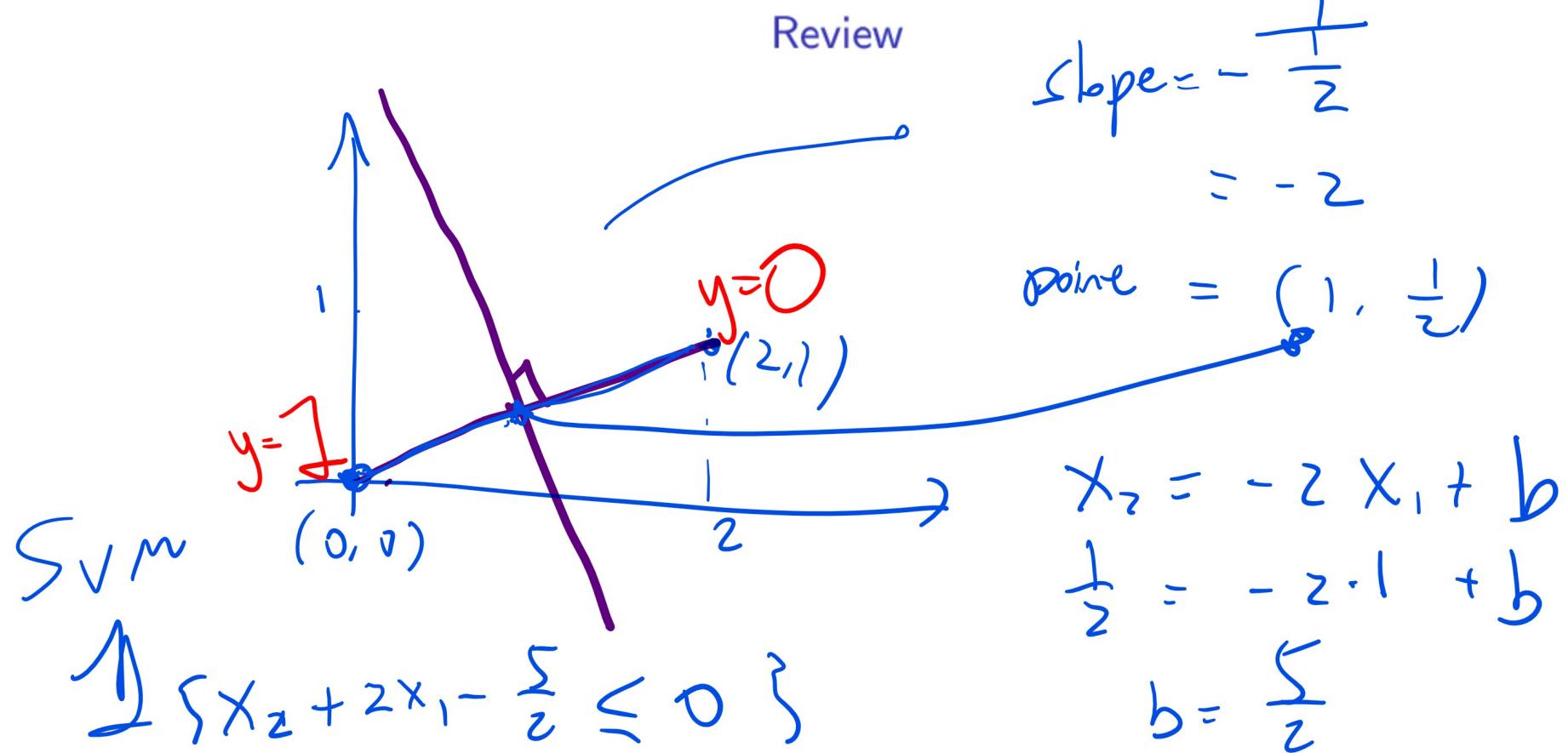
# Hw 2

# Support Vector Machine

## Review

- Hard margin support vector.
- Soft margin maximization.
- Subgradient descent.
- Kernel trick.

# Support Vector Margin Example



# Feature Vector to Kernel Example

Review

$$\phi(x_1, x_2) = (x_1^2, \sqrt{2}x_1x_2, x_2^2)$$

$$K = \phi^T(x_1, x_2) \phi(x'_1, x'_2) = (x_1^2, \sqrt{2}x_1x_2, x_2^2) \begin{pmatrix} x'_1 \\ \sqrt{2}x'_1x'_2 \\ x'_2 \end{pmatrix}$$

$$= (x_1 x'_1)^2 + 2(x_1 x'_1)(x_2 x'_2) + (x_2 x'_2)^2$$

$$x = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \quad x' = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

$$= (x_{i1} x'_{i1} + x_{i2} x'_{i2})^2$$

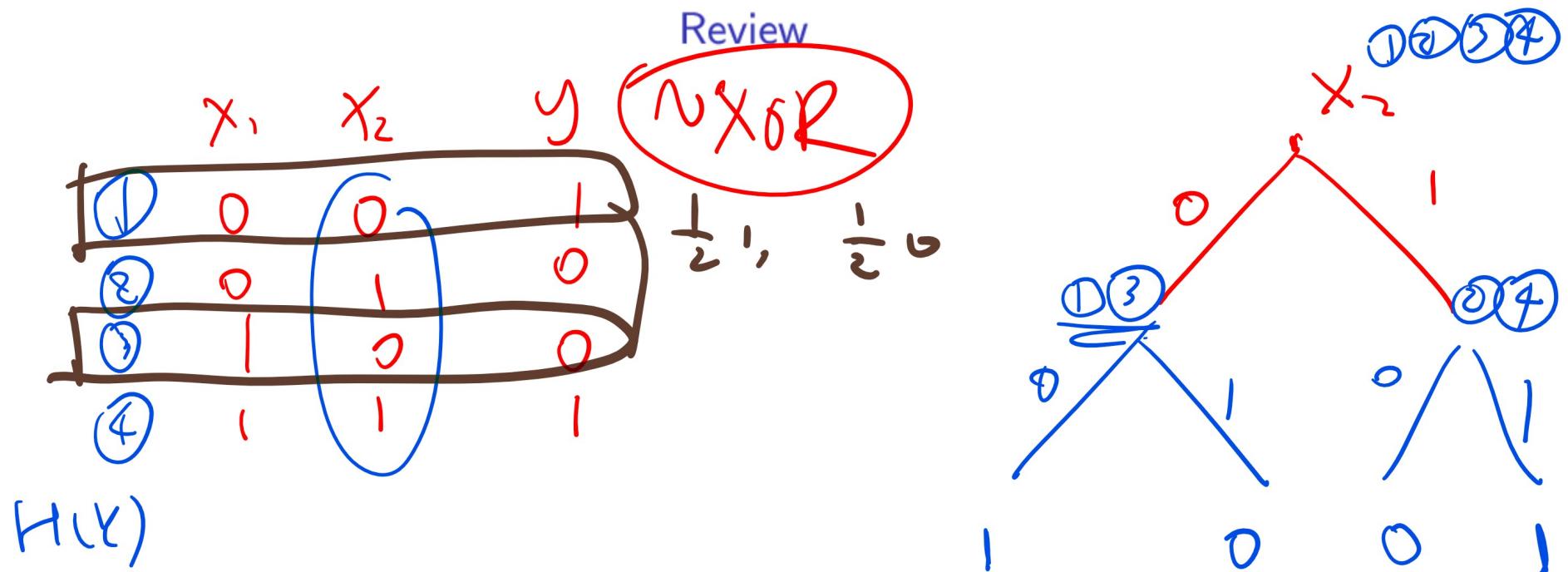
$$K(x, x') = 0$$

# Decision Tree

## Review

- Entropy. ↗
- Information gain.
- Bagging and boosting. ↗

# Decision Tree Example



$$\begin{aligned}
 H(Y|X_2) &= P\{X_2=0\} \cdot H(Y|X_2=0) + P\{X_2=1\} \cdot H(Y|X_2=1) \\
 &= \frac{1}{2} \left( \underbrace{-\frac{1}{2} \log \frac{1}{2}}_{Y=0} - \underbrace{\frac{1}{2} \log \frac{1}{2}}_{Y=1} \right) + \frac{1}{2} (-1) \\
 &\quad \left( \frac{1}{2} + \frac{1}{2} \right) = 1 = 1
 \end{aligned}$$

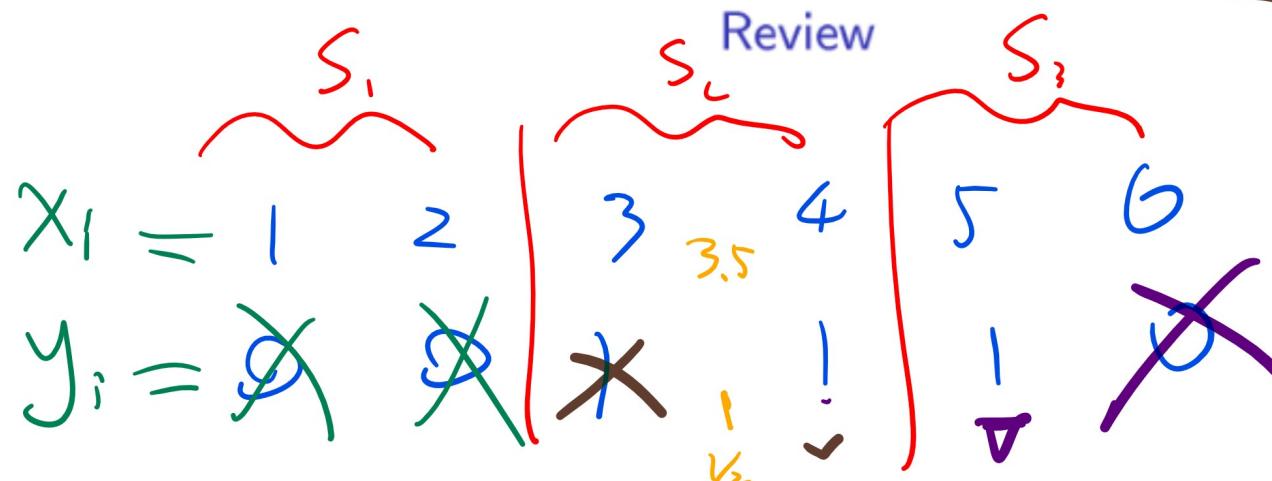
# K Nearest Neighbor

Review

$$L_1, L_2, L_\infty$$

- Distance functions.

# K Nearest Neighbor Cross Validation Example



1 - nn  
3 - fold CV

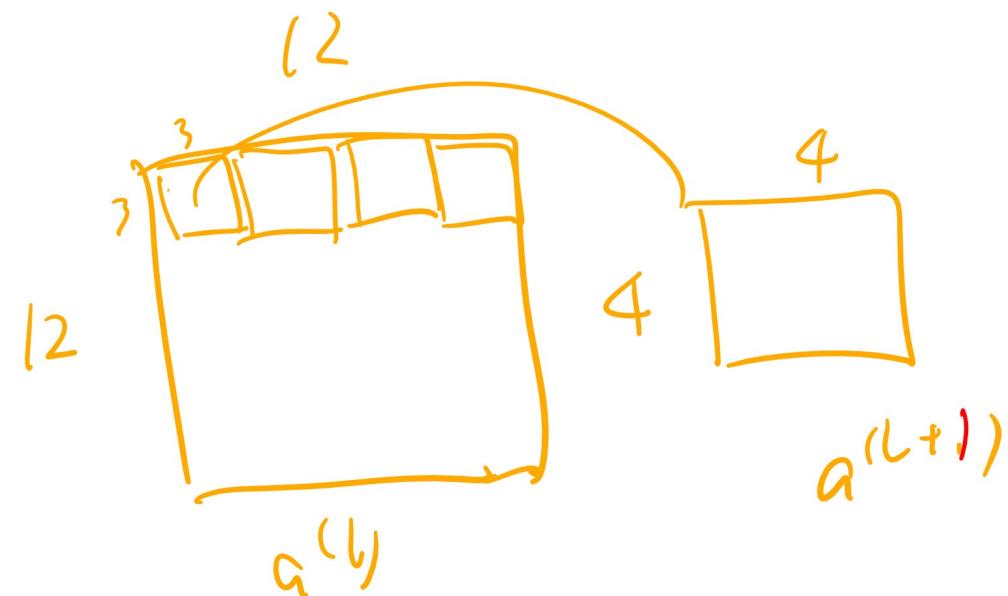
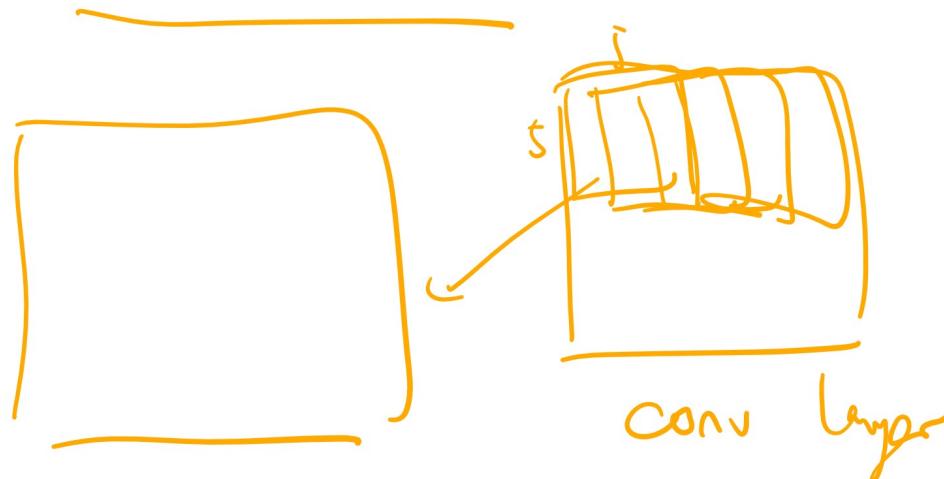
train on  $S_2, S_3$ , test on  $S_1 \Rightarrow$

$$\left. \begin{matrix} S_2 \\ S_3 \end{matrix} \right\} \text{accuracy} = \frac{2}{6} = \frac{2}{3}.$$

# Convolutional Neural Network

Review

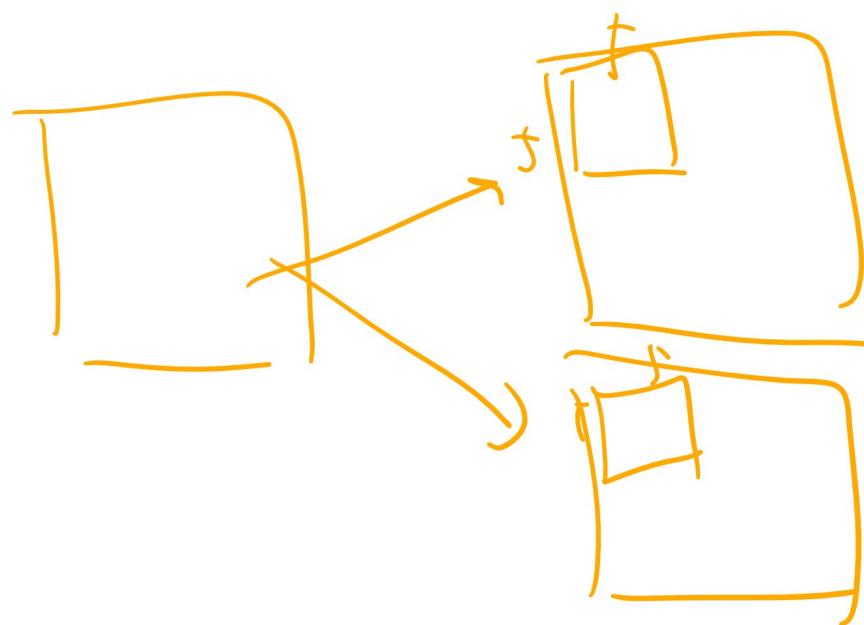
- Convolution.
- Pooling.
- Trained weights.



# trained weights in conv layer  
 = # elements of filters  
 = 25  
 # weights in pooling = 0

# Convolutional Weights Count Example

Review



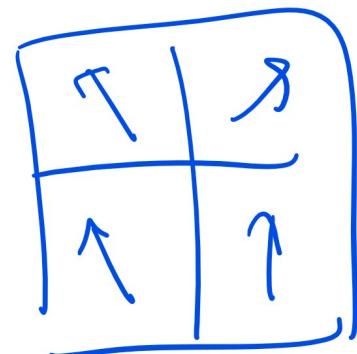
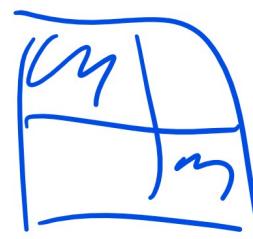
$$5 \times 5 \times 2 = 50$$

# Computer Vision

## Review

HW4

- Histogram of Gradients Features.
- Scale Invariant Feature Transform.
- Block normalization.
- Dominant orientation.
- Harr Features.



add up G

hot counting

# Histogram of Gradient Example

Review

# Natural Language Processing

## Review

HW5

- Bigram and trigram model.
- Transition matrix.
- Random word generation.
- Bayes rule.

$P(a | b)$

$$\frac{C_{ba} + 1}{C_b + |\text{vocabulary}|}$$

a b b b c → 3

# Document Bayes Rule Example

Review

A	70%	"the"	$\left. \begin{array}{c} \frac{1}{3} \\ \frac{1}{3} \\ \frac{1}{3} \end{array} \right\}$
B	20%	"the"	
C	10%	"the"	

$$\Pr \{ B \mid \text{"the"} \} = \frac{\Pr \{ B, \text{"the"} \}}{\Pr \{ \text{"the"} \}} \rightarrow \Pr \{ B \mid \text{"the"} \}$$

$$= \frac{\frac{1}{3} \cdot 0.2}{\frac{1}{3} \cdot 0.7 + \frac{1}{3} \cdot 0.2 + \frac{1}{3} \cdot 0.1} = \frac{0.2}{0.7 + 0.2 + 0.1} = \frac{0.2}{1.0} = 0.2$$

$\Pr \{ \text{"the"} \mid A \}$   
 $\Pr \{ \text{"the"} \mid B \}$   
 $\Pr \{ \text{"the"} \mid C \}$

# Bayesian Network

## Review

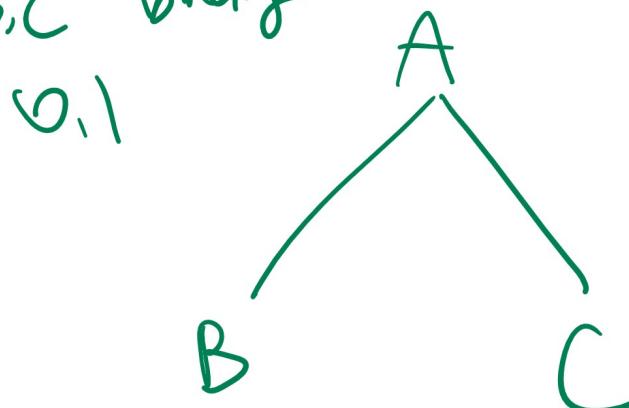
- Conditional probability table.
- Maximum likelihood estimation.
- Training vs inference.
- Chow Liu algorithm.

$$\frac{C_{AB}}{C_B}$$

Max Spanning tree.

# Common Cause Network Example

$A, B, C$  binary



$$\Pr\{B \mid \neg C\}$$

=

$$\frac{\Pr\{B, \neg C, A=?\}}{\Pr\{\neg C, A=?\}}$$

$$= \Pr\{B \mid A\} \cdot \Pr\{\neg C \mid A\} \cdot \Pr\{A\}$$

$$0.2 \cdot (1 - 0.4) \cdot 0.1$$

$$+ 0.3 \cdot (1 - 0.25) \cdot (1 - 0.1)$$

Review

CPT

$$\Pr\{A\} = 0.1$$

$$\Pr\{\neg B \mid A\} = 0.2, \Pr\{\neg B \mid \neg A\} = 0.8$$

$$\Pr\{\neg B \mid \neg A\} = 0.3$$

$$\Pr\{\neg C \mid A\} = 0.4$$

$$\Pr\{\neg C \mid \neg A\} = 0.5$$

$$\Pr\{B, \neg C, A\}$$

$$+ \Pr\{\neg B, \neg C, \neg A\}$$

$$+ \Pr\{\neg B \mid A\} \cdot \Pr\{\neg C \mid \neg A\} \cdot \Pr\{\neg A\}$$

$$\Pr\{\neg C, A\} + \Pr\{\neg C, \neg A\}$$

$$= (1 - 0.4) \cdot 0.1 + (1 - 0.5) \cdot (1 - 0.1)$$