

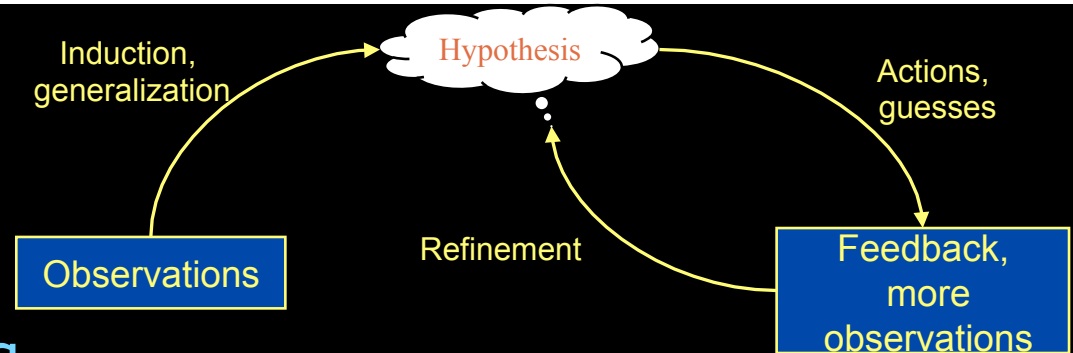
# CS 461: Machine Learning Lecture 2

Dr. Kiri Wagstaff  
wkiri@wkiri.com

# Today's Topics

- Review and Reading Questions
- Homework 1
- Data Representation (Features)
- Decision Trees
- Evaluation
- Weka

# Review



- Machine Learning
  - Computers learn from their past experience
- Inductive Learning
  - Generalize to new data
- Supervised Learning
  - Training data:  $\langle x, g(x) \rangle$  pairs
  - Known label or output value for training data
  - Classification and regression
- Instance-Based Learning
  - 1-Nearest Neighbor
  - k-Nearest Neighbors

# Reading Questions

- Introduction / Machine Learning (Ch. 1)
  - Classification: What is a discriminant?
  - Regression: to train an autonomous car to predict what angle to turn the steering wheel, where could the training data come from?
- Supervised Learning (Ch. 2.1, 2.4-2.9)
  - Is the most specific hypothesis  $S$  a member of the version space? Why or why not?
  - What happens if the true concept  $C$  is not in the version space?
  - What is Occam's Razor?

# Homework 1

- Solution/Discussion



# Data Representation: Which Features?

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# Decision Trees

## Chapter 9

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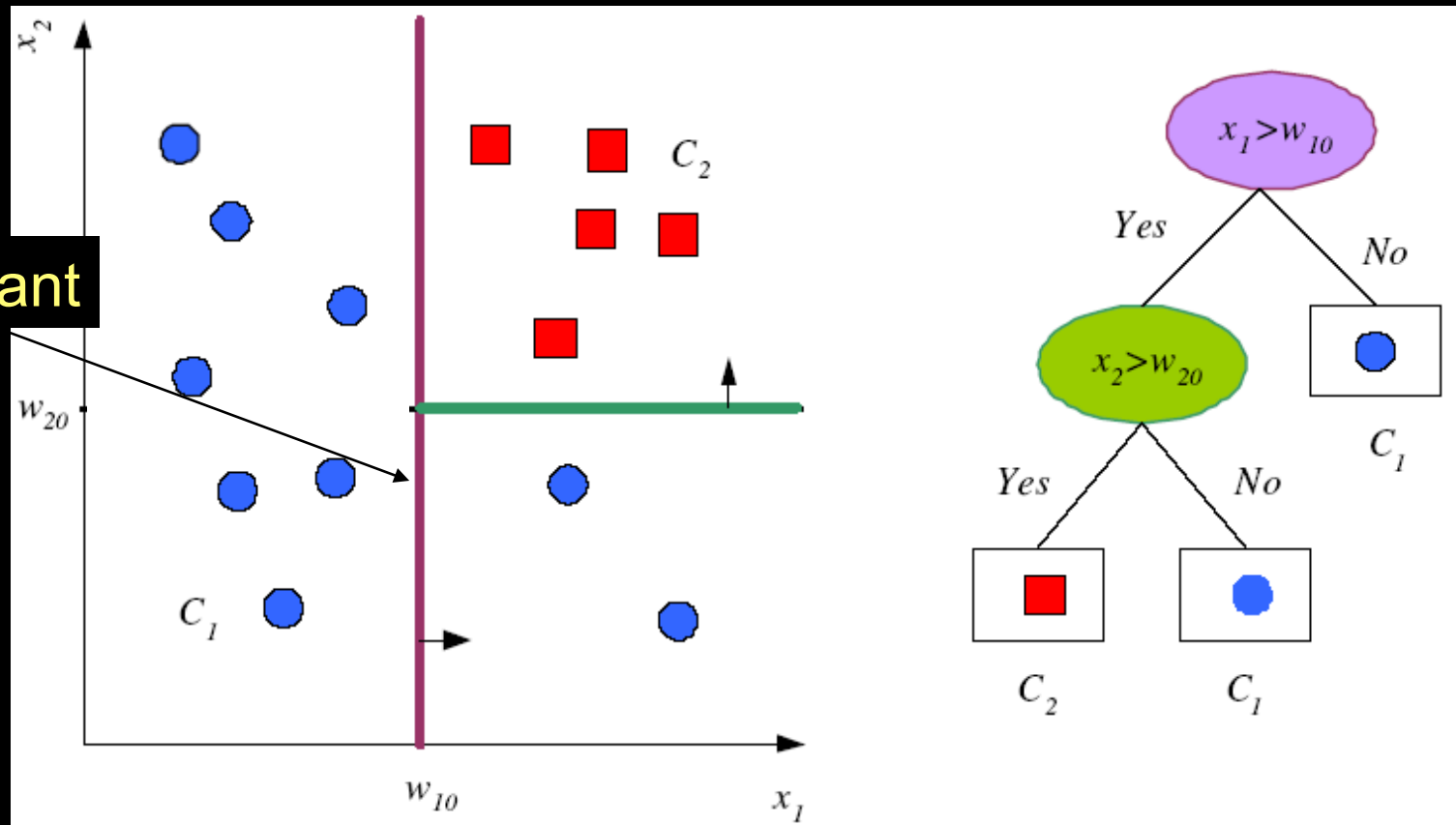
# Decision Trees

- Parametric method
- PredictionWorks
  - “Increasing customer loyalty through targeted marketing”
- Decision Tree Interactive Demo



# (Hyper-)Rectangles == Decision Tree

discriminant



# Measuring Impurity

$$\hat{P}(C_i | \mathbf{x}, m) \equiv p_m^i = \frac{N_m^i}{N_m}$$

## 1. Impurity = error using majority label

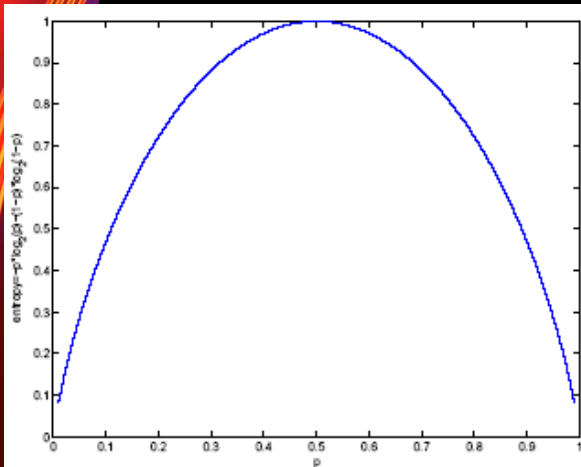
$$\mathcal{I}_m = 1 - \max_i(p_m^i)$$

- After a split

$$\mathcal{I}'_m = \sum_{j=1}^n \frac{N_{mj}}{N_m} 1 - \max_i(p_{mj}^i)$$

## 2. More sensitive: use entropy

- For node  $m$ ,  $N_m$  instances reach  $m$ ,  $N_m^i$  belong to  $C_i$



- Node  $m$  is **pure** if  $p_m^i$  is 0 or 1

- Entropy:

$$\mathcal{I}_m = - \sum_{i=1}^K p_m^i \log_2 p_m^i$$

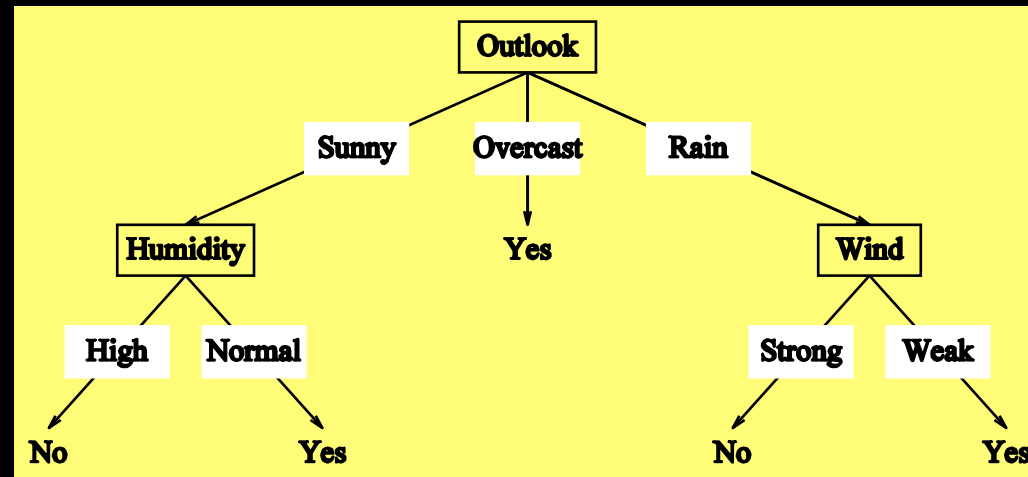
- After a split:

$$\mathcal{I}'_m = - \sum_{j=1}^n \frac{N_{mj}}{N_m} \sum_{i=1}^K p_{mj}^i \log_2 p_{mj}^i$$

# Should we play tennis?

Outlook	Temperature	Humidity	Wind	PlayTennis
<i>Training Sets</i>				
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Strong	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Weak	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

# How well does it generalize?



Outlook	Temperature	Humidity	Wind	PlayTennis
<i>Testing Examples</i>				
Sunny	Mild	Normal	Weak	Yes
Overcast	Hot	High	Strong	Yes
Sunny	Mild	High	Strong	No
Rain	Hot	High	Weak	Yes
Rain	Mild	Normal	Weak	Yes
Sunny	Mild	High	Strong	Yes

# Decision Tree Construction Algorithm

GenerateTree( $\mathcal{X}$ )

If NodeEntropy( $\mathcal{X}$ ) <  $\theta_I$  /\* eq. 9.3

    Create leaf labelled by majority class in  $\mathcal{X}$

    Return

$i \leftarrow$  SplitAttribute( $\mathcal{X}$ )

For each branch of  $\mathbf{x}_i$

    Find  $\mathcal{X}_i$  falling in branch

    GenerateTree( $\mathcal{X}_i$ )

SplitAttribute( $\mathcal{X}$ )

MinEnt  $\leftarrow$  MAX

For all attributes  $i = 1, \dots, d$

    If  $\mathbf{x}_i$  is discrete with  $n$  values

        Split  $\mathcal{X}$  into  $\mathcal{X}_1, \dots, \mathcal{X}_n$  by  $\mathbf{x}_i$

$e \leftarrow$  SplitEntropy( $\mathcal{X}_1, \dots, \mathcal{X}_n$ ) /\* eq. 9.8 \*/

        If  $e <$  MinEnt MinEnt  $\leftarrow$   $e$ ; bestf  $\leftarrow$   $i$

    Else /\*  $\mathbf{x}_i$  is numeric \*/

        For all possible splits

            Split  $\mathcal{X}$  into  $\mathcal{X}_1, \mathcal{X}_2$  on  $\mathbf{x}_i$

$e \leftarrow$  SplitEntropy( $\mathcal{X}_1, \mathcal{X}_2$ )

            If  $e <$  MinEnt MinEnt  $\leftarrow$   $e$ ; bestf  $\leftarrow$   $i$

Return bestf

# Evaluating a Single Algorithm

## Chapter 14

# Measuring Error

	Predicted class	
True Class	Yes	No
Yes	TP: True Positive	FN: False Negative
No	FP: False Positive	TN: True Negative

## Breast Cancer

	Survived	Died
Survived	9	3
Died	4	4

## Iris

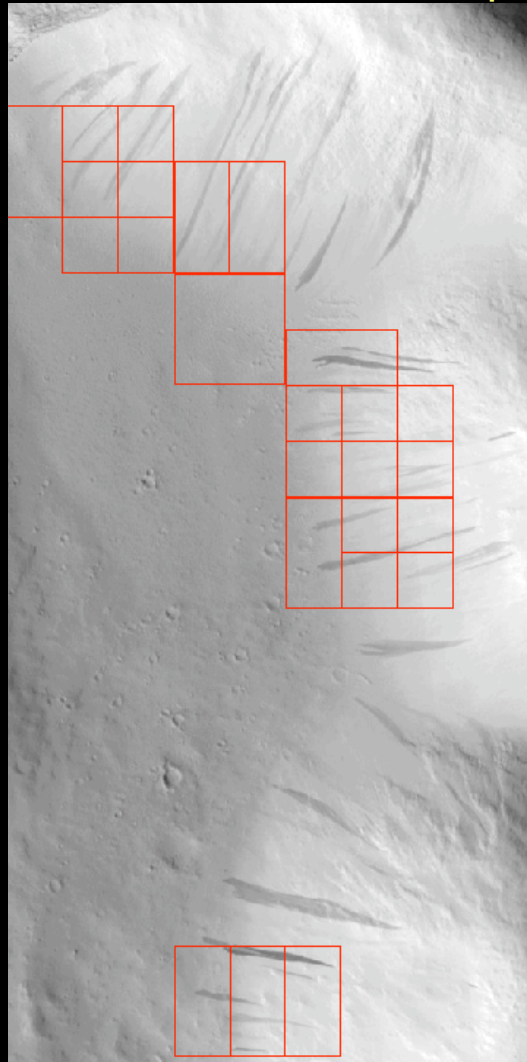
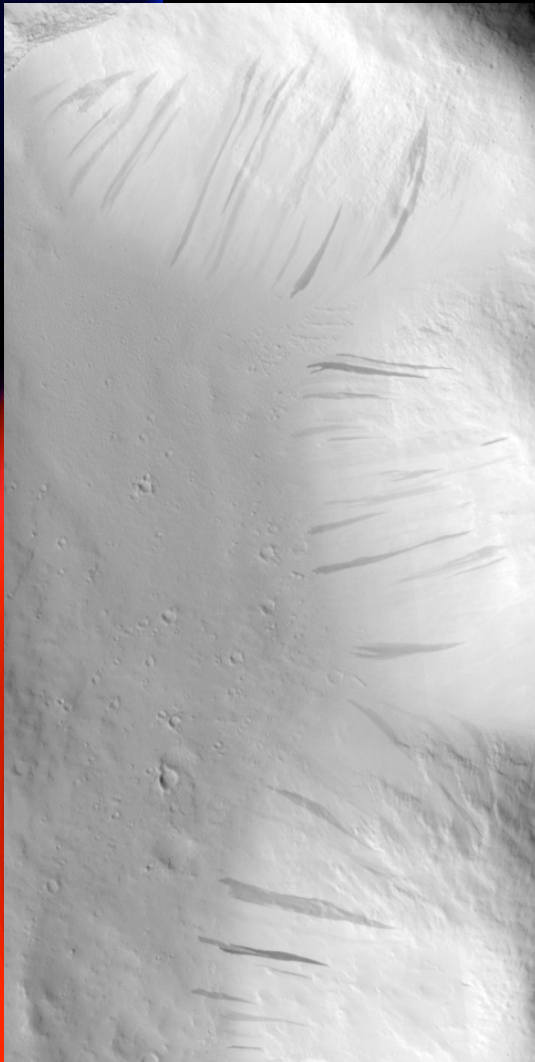
	Setosa	Versicolor	Virginica
Setosa	10	0	0
Versicolor	0	10	0
Virginica	0	1	9



# Example: Finding Dark Slope Streaks on Mars

Marte Vallis,  
HiRISE on MRO

Output of statistical  
landmark detector: top 10%



## Results

TP: 13

FP: 1

FN: 16

Recall =  $13/29 = 45\%$

Precision =  $13/14 = 93\%$



# Evaluation Methodology

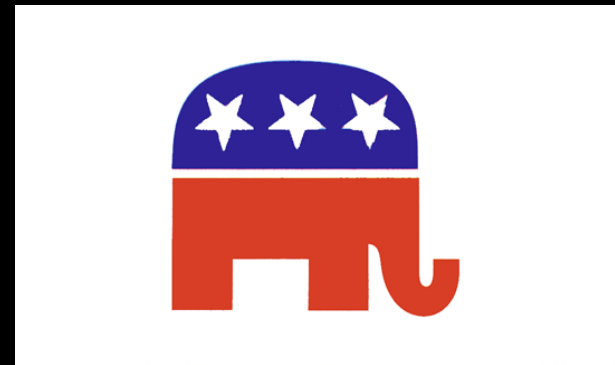
- Metrics: What will you measure?
  - Accuracy / error rate
  - TP/FP, recall, precision...
- What train and test sets?
  - Cross-validation
  - LOOCV
- What baselines (or competing methods)?
- Are the results significant?

# Baselines

- Simple rule
- “Straw man”
- If you can’t beat this... don’t bother!
- Imagine:



vs.



# Weka Machine Learning Library

## Weka Explorer's Guide



# Homework 2

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# Summary: What You Should Know

- Supervised Learning
  - Representation: features available
- Decision Trees
  - Hierarchical, non-parametric, greedy
    - Nodes: test a feature value
    - Leaves: classify items (or predict values)
  - Minimize impurity (%error or entropy)
- Evaluation
  - (10-fold) Cross-Validation
  - Confusion Matrix

# Next Time

- Reading:
  - Decision Trees  
(read Ch. 9.1-9.4)
  - Evaluation  
(read Ch. 14.1-14.4)
  - Weka Manual  
(read p. 25-27, 33-35, 39-42, 48-49)
- Questions to answer from the reading:
  - Posted on the website (calendar)
  - Three volunteers: Lewis, Natalia, and T.K.