#### CS 260: Foundations of Data Science

#### Prof. Sara Mathieson Fall 2023



# Write one midterm question or topic on your notecard

Will answer later in class today or on Piazza

#### Admin

- Exam due in class on Tuesday
  - Do not open the exam until you're ready to start
  - Time limit: **3 hours**
  - Resources: hand-written study sheet, calculator

- First candidate talk on Monday!
  - 4pm tea
  - 4:15pm talk (H109)

• Midterm 2 Review

- Entropy vs. classification error
- PCA
- Naïve Bayes
- Central Limit Theorem
- Logistic regression and cross entropy

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#### - Entropy vs. classification error

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## From the study guide

#### 4. Information Theory

- Conceptual idea of entropy as well as formal definition
- Shannon encoding (and decoding), plus how to use entropy to compute average number of bits needed to send one piece of information
- Use of conditional entropy and information gain to choose best features
- Comparison with classification accuracy as a way to choose best features
- How to transform continuous features into binary features? (see Handout 14)

#### Entropy vs. classification error



## One feature models (decision stumps): information gain vs. classification error



$$H(Y) = -\sum_{\substack{i=1 \\ i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}, f_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y(\xi_{i}) \\ -\sum_{\substack{i \in i}} P(y=i) \log_{2} \hat{p}(y=i) \quad y$$

# One feature models (decision stumps): information gain vs. classification error



H(Y) = 0.6136190195993708H(Y|age <= 55.5) = 0.5522480910534322H(Y|oldpeak <= 3.55) = 0.5568804630596093

=> Age feature produces more information gain!

## Decision trees from entropy (info gain) vs. classification error!

	[108 92]
	LIGG, 72]
	thai=lixed_delect [4, 6]
	ca<=0.5=False [0, 6]: 1
	ca<=0.5=True [4, 0]: -1
	thal=normal [84, 19]
	thalach<=110.0=False [84, 15]
	age <= 55, 5 = False [28, 11]
	sex=remaie [13, 3]
	cp=asympt [3, 3]
	age<=57.5=False [1, 3]
	chol<=337.5=False [1, 0]: -1
	chol<=337.5=True [0, 3]: 1
	ager=57 5=True [2 0]: -1
	cp-atyp_angina [2, 0]1
	cp=non_anginai[/, 0]: -1
	cp=typ_angina [1, 0]: -1
	sex=male [1, 7]
	age<=65.5=False [1, 2]
	age<=66.5=False [0, 2]: 1
	age66 5-True [1 0]: -1
	Cno1<=248.5=1fue [14, 1]
	oldpeak<=2.7=False [0, 1]: 1
	oldpeak<=2.7=True [14, 0]: -1
	age<=55.5=True [56, 4]
	trestbps<=113.5=False [47, 1]
	0]dpeak<=3.55=False [0, 1]: 1
	Oldbeak<=0.02=Haise [6, 0]: -1
	oldpeak<=0.05=True [3, 3]
	cp=asympt [0, 2]: 1
	cp=atyp_angina [2, 0]: -1
	cp=non anginal [1, 1]
	age<=41.5=False [0, 1]: 1
	thal=reversable_defect [20, 67]
	cp=asympt [5, 53]
	oldpeak<=0.55=False [0, 43]: 1
	chol<=237.5=False [0, 8]: 1
	chol<=237.5=True [5, 2]
	age<=59.5=False [1, 0]: -1
	age<=59.5=True [0, 2]: 1
	cp=atyp_angina [3, 3]
	age<=46.5=False [1, 3]
	trestbps<=109.0=False [0, 3]: 1
	trestbps<=109.0=True [1, 0]: -1
	$age < = 46.5 = True [2, 0] \cdot = 1$
	Cp-non_anginat [7, 10]
	I oropeak<=1.85=Irue [9, 5]
	trestbps<=121.0=False [3, 5]
	chol<=232.5=False [0, 4]: 1
J	chol<=232.5=True [3, 1]
	trestbps<=128.5=False [3, 0]: -1
	trestbps<=128.5=True [0. 1]: 1
	$\frac{1}{1} = \frac{1}{1} + \frac{1}$
J	olapeak<=0.3000000000000000404=False [3, 0]: -1
	01dpeak<=0.300000000000004=True [0, 1]: 1



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## From the study guide

#### 6. Data Visualization

- Best ways of visualizing discrete vs. continuous data
- How to choose colors; idea of sequential, diverging, or qualitative color schemes
- How to make color schemes color-blind and black/white printing friendly
- Idea of principal component analysis (PCA) as a way to accomplish dimensionality reduction
- Using dimensionality reduction to visualize high-dimensional data
- Details of the PCA algorithm (except computing eigenvalues and eigenvectors)
- Runtime of PCA
- Genealogical interpretation of PCA plots for genetic data

#### PCA creates linear combinations of features

0.03





#### PCA "classic" genetics example



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## From the study guide

#### 2. Naive Bayes

- Bayes rule in data science: identify and explain the evidence, prior, posterior, likelihood.
- Derivation of the Naive Bayes model for  $p(y = k | \vec{x})$  (via the Naive Bayes assumption).
- How do we estimate the probabilities of a Naive Bayes model?
- Laplace counts (motivation, application details)
- How can we predict the label of a new example after fitting a Naive Bayes model?
- What types of features/label do we currently require for Naive Bayes?
- How Naive Bayes can be implemented using dictionaries in Python

#### **Naïve Bayes assumption**

Bayes P(A,B) = P(A)P(B|A) independence P(A,B) = P(A)P(B) (Not alword) Conditional P(A|B,C) = P(A|C) Cindependence 1. kelhood  $P(x, x_2, x_3|y) = p(x, |y) p(x_2, x_3|y, y)$ P(x, |y) P(x, |y) P(x, |x, y) $\left( \left| p(x_{j}|y) \right| \right)$ 

#### Naïve Bayes Model

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$$p(y = k | \boldsymbol{x}) \propto p(y = k) \prod_{j=1}^{p} p(x_j | y = k).$$

#### **Naïve Bayes Prediction**

$$\hat{y} = \underset{k \in \{1, 2, \cdots, K\}}{\operatorname{arg\,max}} p(y = k) \prod_{j=1}^{p} p(x_j | y = k).$$

#### Estimating prior: p(y=k)

 $\theta_k = \frac{N_k + 1}{n + K}$ 

Estimating likelihood: p(x<sub>j</sub>=v | y=k)

$$\theta_{k,j,v} = \frac{N_{k,j,v} + 1}{N_k + |f_j|}$$

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#### 7. <u>Statistics</u>

- Motivation for studying statistics and hypothesis testing
- Probability distributions (discrete vs. continuous)
- Computing (theoretical) expected value and variance for discrete distributions
- Sample mean and sample variance
- Central limit theorem (CLT) and application in cases where the mean/variance are known
- Computation and interpretation of Z-scores and p-values
- Null vs. alternative hypotheses; when to reject the null hypothesis; significance level  $\alpha$
- Using randomized trials and permutation testing to obtain more precise p-values
- Idea of a t-test as a way to test differences in means (not details)
- Bootstrap: sampling from our data with replacement (usually keeping n the same)
- How to use bootstrapping to obtain confidence intervals
- Bagging (Bootstrap Aggregation): create a classifier for each bootstrapped training dataset
- Idea of using an ensemble of classifiers (ideally with low bias) to reduce variance
- To test, let each classifier in the ensemble "vote"

## <sup>See video tutorial on Piazza!</sup> Bootstrap demo

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#### 5. Logistic Regression

- Motivation for logistic regression; our model is a logistic function that takes in  $\vec{w} \cdot \vec{x}$
- Logistic regression creates a *linear* decision boundary (visualize for p = 1).
- In logistic regression our cost is the negative log likelihood (don't need to derive)
- Intuition/visualization of the cost function (and relationship to cross entropy)
- Idea of SGD for logistic regression, relationship to linear regression

For each method/approach, is X continuous or discrete? What about y?

- Linear regression
- Polynomial regression
- Decision trees/stumps
- ROC curve as an evaluation metric
- Naïve bayes
- Logistic regression
- Entropy and information gain
- PCA



Notecards: will post responses on Piazza!