

CS 360: Machine Learning

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Spring 2024



HAVERFORD
COLLEGE

Sit somewhere new!

Admin

- **EVERYONE:** Sign in again
- We will be making waitlist decisions and lab switches after looking at attendance today
- Sorelle office hours **TODAY: 3-4pm in H110**
- Sara office hours **Monday: 3-4pm in Zubrow**
- TA hour schedule hopefully up today on Piazza

Candidate lunch/talk today!

- **Talk:** “Routing our Way to Next-Generation Internet Services”
 - 4:15 p.m. with a tea reception at 4:00 p.m.
 - H109
- **Student lunch**
 - 12:30-1:30pm
 - Swarthmore Room of the DC

Class notes and materials

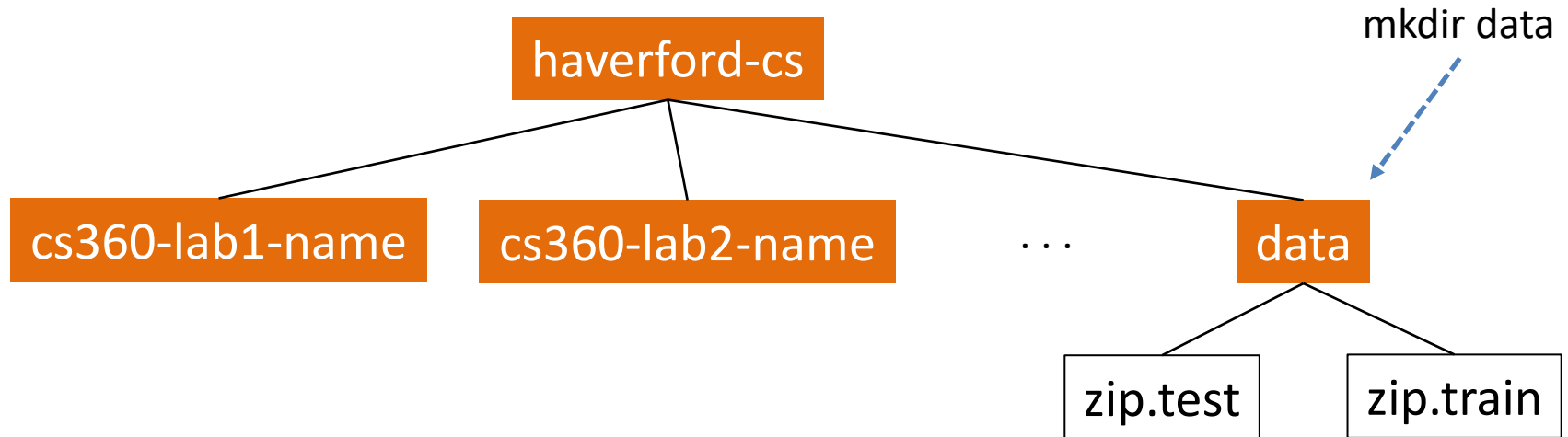
- Sorelle is taking **notes** and we will post these along with **slides, board photos, and handouts**
- Opportunity for extra credit (rare!) for creating **video solutions for handouts**
 - I will post details on Piazza and you can sign up for one handout
 - I will attempt to create video and/or written solutions for the rest

Reading for Week 1

- Geron Chap 3 through pg 119
(binary classification and evaluation metrics)
- Geron Chap 4 through pg 151
(linear regression and gradient descent)
- Geron Chap 4 pg 164-169 (logistic regression)

Unix/GitHub workflow issues

- Come to Sorelle's office hours today if:
 - You can't clone or push
 - You cannot get the zipcode data



```
python3 lab01.py -r ../data/zip.train -e ../data/zip.train -d 5
```

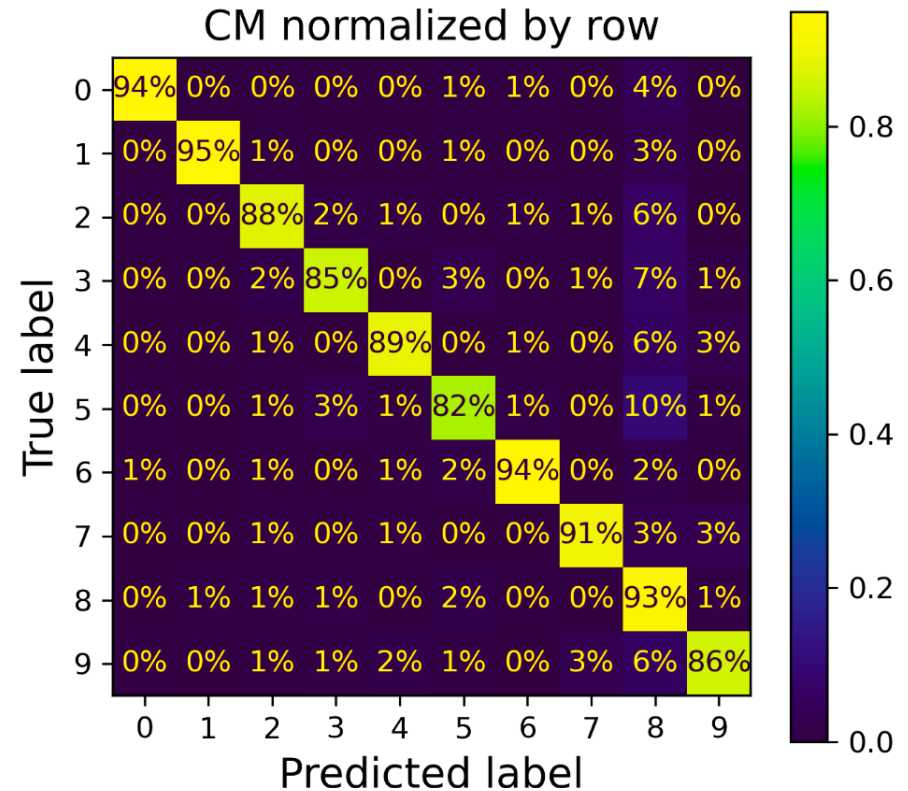
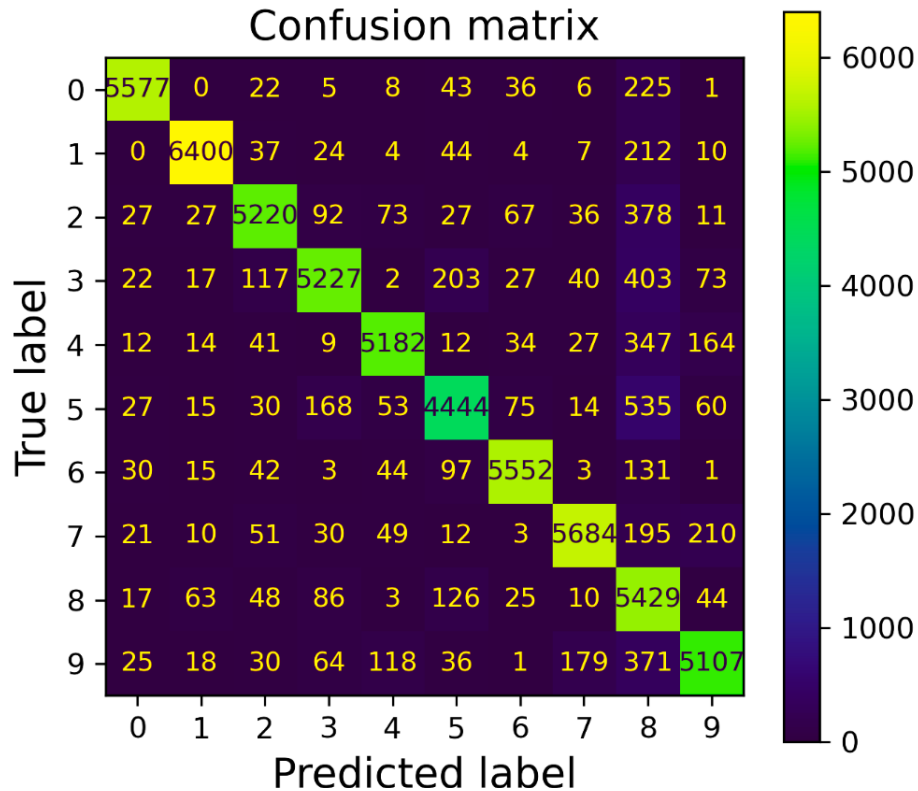
Unix/GitHub workflow issues

scp <source> <dest>

scp

~~smathieson~~@cook.cs.haverford.edu:/home/smathieson/Public/cs360/zip/zip.train
~~~/Desktop/~~zip.train

# Another example of confusion matrix normalization



# Outline for Jan 25

- Naïve Bayes review
- ROC curve review
- Logistic Regression review
- Gradient descent review

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# Informal quiz: discuss with a partner

- Naïve Bayes question from Handout 1

(a) If  $\vec{x}$  is a vector of *features* and  $y$  is the associated *label*, the components of a typical Bayesian model are  $p(\vec{x})$ ,  $p(y)$ ,  $p(y|\vec{x})$ ,  $p(\vec{x}|y)$ . What are the terms for each of these probabilities?

|                |            |
|----------------|------------|
| $p(\vec{x})$   | evidence   |
| $p(y)$         | prior      |
| $p(y \vec{x})$ | posterior  |
| $p(\vec{x} y)$ | likelihood |

(b) Using Bayes' rule, arrange these probabilities into an equation.

$$p(\vec{x}) p(y|\vec{x}) = p(y) p(\vec{x}|y) \quad \Rightarrow \text{valid form of Bayes' rule!}$$

$$p(y|\vec{x}) = p(y) p(\vec{x}|y) / p(\vec{x}) \quad \Rightarrow \text{more common}$$

(c) If  $\vec{x} = [x_1, x_2]^T$  (two features or  $p = 2$ ), how would you approximate  $p(\vec{x}|y)$  using our Naive Bayes assumption?

$$p(\vec{x}|y) = p(x_1|y) p(x_2|y)$$



$$P(A, B) = P(A)P(B|A)$$

Naive Bayes  $k \in \{1, 2, 3 \dots K\}$

$$P(y=k | \vec{x}) = \frac{P(y=k)P(\vec{x} | y=k)}{P(\vec{x})}$$

prediction

$$\hat{y} = \underset{k=1 \dots K}{\operatorname{argmax}} \frac{P(y=k)P(\vec{x} | y=k)}{P(\vec{x})}$$

likelihood

$$P(\vec{x} | y=k) = P(x_1, x_2, \dots, x_p | y=k) \\ \approx P(x_1 | y) P(x_2 | y) \dots P(x_p | y)$$

Naive Bayes assumption

$\Rightarrow$  features are conditionally independent given the label

$P(A, B) \neq P(A)P(B)$   
if independent  $\Rightarrow$  then equal

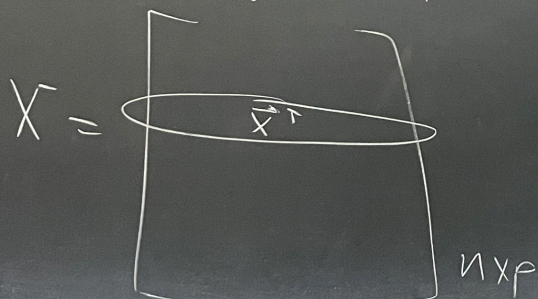


$$p(x_1|y=k) \dots p(x_p|y)$$

$x_1 = \text{four legs}$   
 $x_2 = \text{fur}$   
 $y = \text{cat}$

$$p(y=k|\vec{x}) \approx p(y=k) \prod_{j=1}^p p(x_j|y=k)$$

Single example  $\uparrow$   
 product  $\uparrow$   
 $p(\vec{x})$



$\sum$  (sum)

Prior

$$p(y=k) \approx \frac{N_k}{n} \Rightarrow \begin{matrix} \text{num train} \\ \text{with label } k \\ \text{total num} \\ \text{train} \end{matrix}$$

$$p(y=k) \approx \frac{N_k + 1}{n + K}$$

$$\Rightarrow \sum_k p(y=k) = 1$$

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



$k$  likelihood

$$p(x_j = v | y = k) = \frac{p(x_j = v, y = k)}{p(y = k)}$$

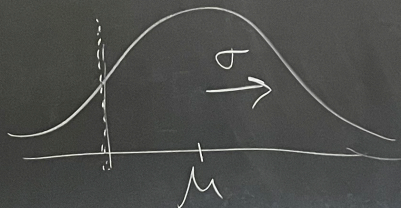
$$\approx \frac{N_{k,j,v} + 1}{N_k + |f_j|}$$

$j=5$

$\Rightarrow x_5$  or 5th feature

$\Rightarrow x_5 \in \{\text{red, green, blue}\}$

$v = \text{blue}$



In practice  $p=3$  features  
(binary)  $\Rightarrow X_{\text{test}} = [x_1^{=v}, x_2, x_3]^T$

$y=0$

$$\left( \frac{N_0 + 1}{n + 2} \right) \left( \frac{N_{0,1,v} + 1}{N_0 + 2} \right) \left( \frac{N_{0,2,v} + 1}{N_0 + 2} \right) \dots$$

prior      feature1      feature2

$y=1$



$$p(y=0|\vec{x}) \approx 0.015 \Rightarrow \frac{0.015}{0.015+0.0718}$$

$$p(y=1|\vec{x}) \approx 0.0718$$

$$\Rightarrow$$

$$p(y=0|\vec{x}) \approx 0.16$$

$$p(y=1|\vec{x}) \approx 0.84 \quad \star$$

$$\cancel{t=0.3} \quad t=0.5 \quad \cancel{t=0.7}$$

$$0.2 \quad \quad \quad 0.8$$

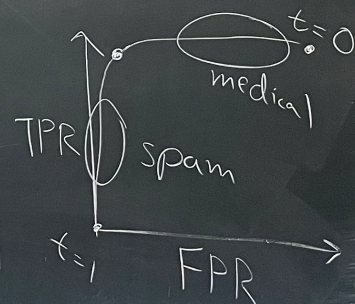
$$p(y=1|\vec{x}) \geq t \Rightarrow \text{predict } 1$$

$$\text{o.w.} \Rightarrow \text{predict } 0$$

$$t=0.5 \Rightarrow \hat{y}=1$$

$$t=0.9 \Rightarrow \hat{y}=0$$

$$t=0.1 \Rightarrow \hat{y}=1$$



# Handout 2

- Change  $t=0.3$  to  $t=0.2$
- Change  $t=0.7$  to  $t=0.8$



①

$y=1$

$t=0.2$

$t=0.5$

$t=0.8$

$y$

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②

$t=0.2$

$acc = \frac{6}{10}$

$t=0.5$

$acc = \frac{9}{10}$

$t=0.8$

$acc = \frac{8}{10}$

④

$total = n = 50$

$P(y=0) \approx \frac{35+1}{50+2}$

$P(y=1) \approx \frac{15+1}{50+2}$

$Q_2$



$$p(x_1 = \text{red} \mid y = 0) = \frac{N_{0,1,\text{red}} + 1}{N_0 + 3}$$
$$= \frac{19 + 1}{35 + 3}$$

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# ROC curve example

