CS 383: Machine Learning

Prof Adam Poliak

Fall 2024

10/02/2024

Lecture 12

Updated schedule

No lecture on Thursday

No lecture Wednesday 10/09

HW03 polynomial regression due last night

HW04 naive Bayes due Wednesday 10/09 (it'll be a shorter assignment)

HW05 Logisitc Regression due Tuesday after Fall break

Midterm 1 on Thursday after fall break

Midterm - Format

Multiple Choice

Short Answer

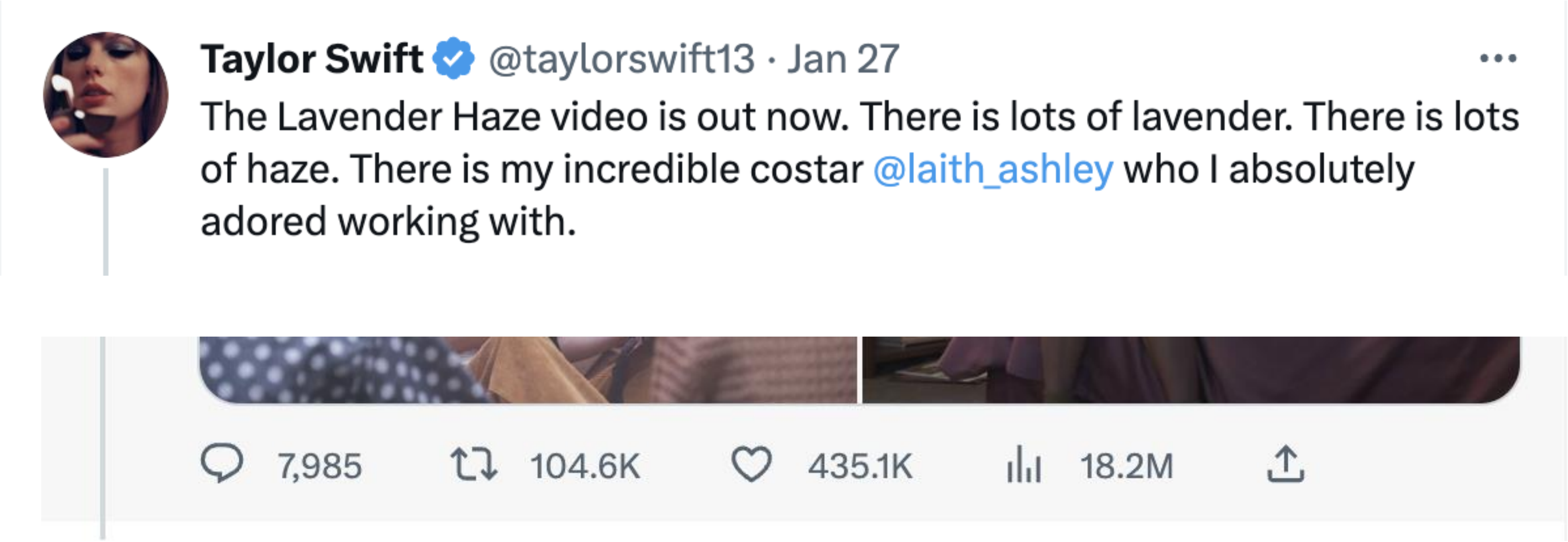
Problems to work out by hand

Outline

Evaluation Metrics

Logistic Regression

Classify a tweet as viral or not



Accuracy

- Model A performs 60% accuracy, would you say this is good, decent, or awful?
- Model B performs 80% accuracy, would you say this is good, decent, or awful
- Model C performs 98% accuracy, would you say this is good decent or awful?

Evaluation: Accuracy

- Imagine we saw 1 million tweets
  - 100 of them were viral
  - 999,900 were not
- We could build a dumb classifier that just labels every tweet "not viral"
  - It would get 99.99% accuracy!!! Wow!!!!
  - But useless! Cant find the viral tweets!
- When should we not we use **accuracy** as our metric?
  - When data isn’t balanced across labels/classes

The 2-by-2 confusion matrix

true positive	**false positive**
false negative	**true negative**

The 2-by-2 confusion matrix

		gold standard labels	
		gold positive	gold negative
system output labels	system positive	**true positive**	**false positive**
	system negative	**false negative**	**true negative**

The 2-by-2 confusion matrix

		gold standard labels		
		gold positive	gold negative	
system output labels	system positive	**true positive**	**false positive**	**precision** $= \frac{\text{tp}}{\text{tp+fp}}$
	system negative	**false negative**	**true negative**	
		recall $= \frac{\text{tp}}{\text{tp+fn}}$		**accuracy** $= \frac{\text{tp+tn}}{\text{tp+fp+tn+fn}}$

Evaluation: Precision

- % of items the system detected (i.e., items the system labeled as positive) that are in fact positive (according to the human gold labels)

$$\textbf{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

Evaluation: Recall

- % of items actually present in the input that were correctly identified by the system.

$$\textbf{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

Why Precision and recall

- Our dumb viral-classifier
  - label no tweets as ”viral"

Accuracy=99.99%

but

Recall = 0

- (it doesn't get any of the 100 viral tweets)

Precision and recall, unlike accuracy, emphasize true positives:

- finding the things that we are supposed to be looking for.

A combined measure: F

- F measure: a single number that combines P and R:

$$F_\beta = \frac{(\beta^2+1)PR}{\beta^2 P + R}$$

- We almost always use balanced F_1 (i.e., $\beta = 1$)

$$\mathrm{F}_1 = \frac{2PR}{P+R}$$

Confusion Matrix for 3-class classification

		gold labels urgent	normal	spam	
system output	urgent	8	10	1	**precision**$_u$=
	normal	5	60	50	**precision**$_n$=
	spam	3	30	200	**precision**$_s$=
		recall$_u$ =	**recall**$_n$ =	**recall**$_s$ =	

Confusion Matrix for 3-class classification

		gold labels urgent	normal	spam	
system output	urgent	8	10	1	**precision**$_u = \frac{8}{8+10+1}$
	normal	5	60	50	**precision**$_n = \frac{60}{5+60+50}$
	spam	3	30	200	**precision**$_s = \frac{200}{3+30+200}$
		recall$_u = \frac{8}{8+5+3}$	**recall**$_n = \frac{60}{10+60+30}$	**recall**$_s = \frac{200}{1+50+200}$	

How to combine Precision/Recall from 3 classes to get one metric

- **Macro**averaging:
  - compute the performance for each class, and then average over classes
- **Micro**averaging:
  - collect decisions for all classes into one confusion matrix
  - compute precision and recall from that table.

Macroaveraging and Microaveraging

Class 1: Urgent

	true urgent	true not
system urgent	8	11
system not	8	340

precision =

Class 2: Normal

	true normal	true not
system normal	60	55
system not	40	212

precision =

Class 3: Spam

	true spam	true not
system spam	200	33
system not	51	83

precision =

microaverage precision =

macroaverage precision =

Macroaveraging and Microaveraging

Class 1: Urgent

	true urgent	true not
system urgent	8	11
system not	8	340

$$\text{precision} = \frac{8}{8+11} = .42$$

Class 2: Normal

	true normal	true not
system normal	60	55
system not	40	212

$$\text{precision} = \frac{60}{60+55} = .52$$

Class 3: Spam

	true spam	true not
system spam	200	33
system not	51	83

$$\text{precision} = \frac{200}{200+33} = .86$$

microaverage precision =

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Pooled

	true yes	true no
system yes		
system no		

microaverage precision =

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Pooled

	true yes	true no
system yes	268	99
system no	99	635

microaverage precision =

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Pooled

	true yes	true no
system yes	268	99
system no	99	635

$$\text{microaverage precision} = \frac{268}{268+99} = \mathbf{.73}$$

$$\text{macroaverage precision} = \frac{.42+.52+.86}{3} = \mathbf{.60}$$

Outline

Evaluation Metrics

Logistic Regression

Linear regression for classification

Case Study: you need to identify the medical condition of a patient in the emergency room on the basis of their symptoms.

Possible conditions (*y*) are:
- Stroke
- Drug overdose
- Epileptic seizure

1) If you were forced to use linear regression for this problem, how could you encode *y* to make it real-valued?

2) What issues arise with making y real-valued?

3) What if you just had two outcomes (i.e. stroke and drug overdose) -- why is linear regression still not a good choice?

Linear regression for classification

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1) If you were forced to use linear regression for this problem, how could you encode *y* to make it real-valued?

You could choose stroke=0, drug overdose=1, epileptic seizure=2 (or some permutation)

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Assumes some *ordering* of the outcomes that is probably not there!

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The range of a linear function (i.e. y values) is $[-\infty, \infty]$, but we want $[0, 1]$