

CS 378 Lecture

Classification 4:

Multiclass

Announcements

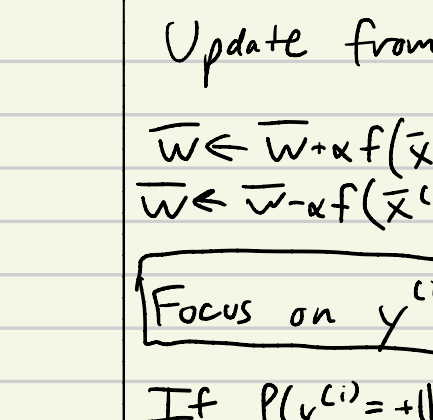
- Pronouns on Zoom
- AI due in a week
- Videos

Recap: Logistic regression

$$P(y=+1|\bar{x}) = \frac{e^{\bar{w}^T f(\bar{x})}}{1 + e^{\bar{w}^T f(\bar{x})}}$$

Train to maximize likelihood of data:

$$\max_{\bar{w}} \prod_{i=1}^D P(y=y^{(i)}|\bar{x}^{(i)}) \Rightarrow \max_{\bar{w}} \sum_{i=1}^D \log P(y=y^{(i)}|\bar{x}^{(i)})$$



Update from SGD:

$$\bar{w} \leftarrow \bar{w} + \alpha f(\bar{x}^{(i)}) (1 - P(y=+1|\bar{x}^{(i)})) \text{ if } y^{(i)}=+1$$

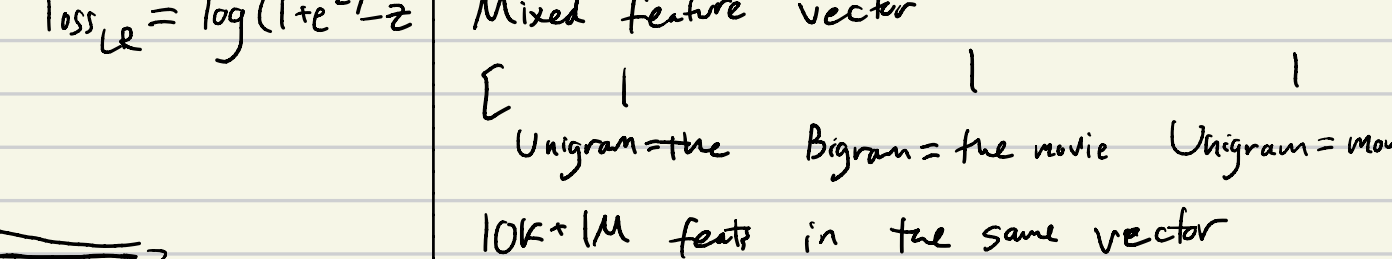
$$\bar{w} \leftarrow \bar{w} - \alpha f(\bar{x}^{(i)}) (1 - P(y=-1|\bar{x}^{(i)})) \text{ if } y^{(i)}=-1$$

Focus on $y^{(i)}=+1$

If $P(y^{(i)}=+1|\bar{x}^{(i)}) \approx 1$, prediction is correct
 $\Rightarrow \bar{w} \leftarrow \bar{w} + \alpha \cdot 0$

If $P(\text{---}) \approx 0$, wrong
 $\Rightarrow \bar{w} \leftarrow \bar{w} + \alpha f(\bar{x}^{(i)})$ ← perception

Define $z = \bar{w}^T f(\bar{x})$ $\text{loss}_{\text{LR}} = \log(1 + e^z) - z$



Today Finish sentiment

Multiclass classification

Perc, LR

Sentiment Features

Unigrams: [1 0 0 1 ... 0] 10K long

Bigrams: [1 0 ...] 1M long

How to combine?

"Mixed" feature vector

[Unigram=the Bigram=the movie Unigram=movie ...]

10K+1M feats in the same vector

Maintain one feature index

the movie was

Unigram=the

Unigram=movie

Unigram=was

Bigram=the m

Bigram=m was

Multiclass

label space output space $y = \{1, 2, 3\}$

one-vs-all

one-vs-all

one-vs-all

one-vs-all

one-vs-all

one-vs-all

one-vs-all

key idea Two ways to do multiclass:

one weight vector per class (different weights DW)

different feature vector per class, single weight vector (DF)

DW $\bar{w}_1, \bar{w}_2, \bar{w}_3$ for each class

predicted label = $\arg\max_{y \in Y} \bar{w}_y^T f(\bar{x})$

$f(\bar{x}) = [1, 1, 0]$

$\bar{w}_1 = [2, 5.6, -3]$ $\bar{w}_2 = [1.2, -3.1, 5.7]$

score for class 1 = 7.6 class 2 = -1.9

$\Rightarrow$ class 1 is highest $\Rightarrow$ return 1

DF One $\bar{w}$, features differ per class

predicted label = $\arg\max_{y \in Y} \bar{w}^T f(\bar{x}, y)$

Ex $\bar{x}$ = too many drug trials, too few patients

$y = \{\text{health, sports, science}\}$

$y = \text{health}$

$f(\bar{x}) = [\text{Unigram}=\text{drug}, \text{Unigram}=\text{patients}, \text{Unigram}=\text{baseball}]$

$f(\bar{x}) = [1, 1, 0]$ copy-pasted $f(\bar{x})$ 3 times

$f(\bar{x}, y) = [\text{---} \text{---} \text{---}]$

$f(\bar{x}, y = \text{health}) = [1, 1, 0, 0, 0, 0, 0, 0, 0, 0]$

Multiclass Perceptron

for t in epochs

for i in data:

$y_{\text{pred}} = \arg\max_{y \in Y} \bar{w}_y^T f(\bar{x})$

if $y_{\text{pred}} \neq y^{(i)}$:

$\bar{w}_{y_{\text{pred}}} \leftarrow \bar{w}_{y_{\text{pred}}} - \alpha f(\bar{x})$

$\bar{w}_{y^{(i)}} \leftarrow \bar{w}_{y^{(i)}} + \alpha f(\bar{x})$

Why? DW: neural nets

$\bar{w}_y^T f(\bar{x})$ our NN

DF: Eisenstein book

Structured prediction: POS tagging

Example 3 classes

[1, 1, 0] class 1

[1, 0, 1] class 2

default pred = 3

$\bar{w}_1 = \bar{0}$ $\bar{w}_2 = \bar{0}$ $\bar{w}_3 = \bar{0}$

after ex 1: $\bar{w}_1 = 1 \ 1 \ 0$

$\bar{w}_2 = 0 \ 0 \ 0$

$\bar{w}_3 = -1 \ -1 \ 0$

ex 2: $y_{\text{pred}} = 1$

Answer $\bar{w}_1 = 0 \ 1 \ -1$

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Multiclass Perc w/different features

for ...

for ...

$y_{\text{pred}} = \arg\max_{y \in Y} \bar{w}^T f(\bar{x}, y)$

if $y_{\text{pred}} \neq y^{(i)}$:

$\bar{w} \leftarrow \bar{w} + \alpha f(\bar{x}, y^{(i)}) - \alpha f(\bar{x}, y_{\text{pred}})$

Multiclass Logistic Regression

$P(y = \hat{y}|\bar{x}) = \frac{e^{\bar{w}_{\hat{y}}^T f(\bar{x})}}{\sum_{y \in Y} e^{\bar{w}_y^T f(\bar{x})}}$

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