hw2nguyen

October 2, 2020

1 INFO-4604/5604 HW2: Linear Classification

1.1 Deadline: Friday, October 2, 11:59pm MT

1.1.1 Solution by: Kevin Nguyen

1.2 Assignment overview

In this assignment, you will build a classifier that tries to infer whether tweets from [@realDonaldTrump](https://twitter.com/realDonaldTrump) were written by Trump himself or by a staff person. This is an example of binary classification on a text dataset.

It is known that Donald Trump uses an Android phone, and it has been observed that some of his tweets come from Android while others come from other devices (most commonly iPhone). It is widely believed that Android tweets are written by Trump himself, while iPhone tweets are written by other staff. For more information, you can read this blog post by David Robinson, written prior to the election, which finds a number of differences in the style and timing of tweets published under these two devices. (Some tweets are written from other devices, but for simplicity the dataset for this assignment is restricted to these two.)

This is a classification task known as "authorship attribution", which is the task of inferring the author of a document when the authorship is unknown. We will see how accurately this can be done with linear classifiers using word features.

You will need `sklearn` version 0.23 for this assignment.

1.2.1 What to hand in

You will submit the assignment on Canvas. Submit a single Jupyter notebook named `hw2lastname.ipynb`, where lastname is replaced with your last name.

If you have any output that is not part of your notebook, you may submit that as a separate document, in a single PDF named `hw2lastname.pdf`. For example, this assignment requires you to create plots. You could do it directly with python using matplotlib, but if you wanted to create them using other software, that's acceptable as long as you put all of the figures in a single document and you clearly label them with the corresponding deliverable number.

When writing code in this notebook, you are encouraged to create additional cells in whatever way makes the presentation more organized and easy to follow. You are allowed to import additional Python libraries, but mostly you need sklearn and matplotlib.

1.2.2 Submission policies

- **Collaboration:** You are allowed to work with one partner. You are still expected to write up your own solution. Each individual must turn in their own submission, and list your collaborator after your name.
- **Late submissions:** We allow each student to use up to 5 late days over the semester. You have late days, not late hours. This means that if your submission is late by any amount of time past the deadline, then this will use up a late day. If it is late by any amount beyond 24 hours past the deadline, then this will use a second late, and so on. Once you have used up all late days, late assignments will only be given credit in special circumstances.

1.3 Getting started

In this assignment, you will experiment with perceptron and logistic regression in `sklearn`. Much of the code has already been written for you. We will use a class called `SGDClassifier` (which you should read about in the sklearn documentation), which implements stochastic gradient descent (SGD) for a variety of loss functions, including both perceptron and logistic regression, so this will be a way to easily move between the two classifiers.

The code below will load the datasets. There are two data collections: the "training" data, which contains the tweets that you will use for training the classifiers, and the "testing" data, which are tweets that you will use to measure the classifier accuracy. The test tweets are instances the classifier has never seen before, so they are a good way to see how the classifier will behave on data it hasn't seen before. However, we still know the labels of the test tweets, so we can measure the accuracy.

For this problem, we will use what are called "bag of words" features, which are commonly used when doing classification with text. Each feature is a word, and the value of a feature for a particular tweet is number of times the word appears in the tweet (with value 0 if the word does not appear in the tweet).

Run the block of code below to load the data. You don't need to do anything yet. Move on to "Problem 1" next.

[1]:
```
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer

df_train = pd.read_csv('http://cmci.colorado.edu/classes/INFO-4604/data/tweets.
 ↪train.tsv', sep='\t', header=None)

Y_train = df_train.iloc[0:, 0].values
text_train = df_train.iloc[0:, 1].values

vec = CountVectorizer()
X_train = vec.fit_transform(text_train)
feature_names = np.asarray(vec.get_feature_names())

df_test = pd.read_csv('http://cmci.colorado.edu/classes/INFO-4604/data/tweets.
 ↪test.tsv', sep='\t', header=None)
```

```
Y_test = df_test.iloc[0:, 0].values
text_test = df_test.iloc[0:, 1].values

X_test = vec.transform(text_test)
```

[71]:
```
print("Number of training instances: " + str(len(df_train)))
print("Number of test instances: " + str(len(df_test)))
print("Number of features: " + str(len(feature_names)))

android = (Y_train == "Android")
iphone = (Y_train == "iPhone")

android_pct = sum(android) / len(df_train)
iphone_pct = sum(iphone) / len(df_train)

print(android_pct, iphone_pct)
```

```
Number of training instances: 2593
Number of test instances: 185
Number of features: 4829
0.5163902815271886 0.4836097184728114
```

1.4 Problem 1: Understand the data [6 points]

Before doing anything else, take time to understand the code above.

The variables `df_train` and `df_test` are dataframes that store the training (and testing) datasets, which are contained in tab-separated files where the first column is the label and the second column is the text of the tweet.

The `CountVectorizer` class converts the raw text into a bag-of-words into a feature vector representation that `sklearn` can use.

You should print out the values of the variables and write any other code needed to answer the following questions.

Deliverable 1.1: How many training instances are in the dataset? How many test instances? There are 2593 instances in the trainning dataset and 185 instances in the testing dataset.

Deliverable 1.2: How many features are in the training data? There are 4829 features in the training dataset.

Deliverable 1.3: What is the distribution of labels in the training data? That is, what percentage of instances are 'Android' versus 'iPhone'? Approximately 51.64% of the labels in the training data are 'Android' and 48.36% of the labels are 'iPhone'.

1.5 Problem 2: Perceptron [6 points]

The code below trains an `SGDClassifier` using the perceptron loss, then it measures the accuracy of the classifier on the test data, using `sklearn`'s `accuracy_score` function.

The `fit` function trains the classifier. The feature weights are stored in the `coef_` variable after training. The `predict` function of the trained `SGDClassifier` outputs the predicted label for a given instance or list of instances.

Additionally, this code displays the features and their weights in sorted order, which you may want to examine to understand what the classifier is learning. In this dataset, the Android class is considered the "negative" class because it comes first in the data.

There are 3 keyword arguments that have been added to the code below. It is important you keep the same values of these arguments whenever you create an `SGDClassifier` instance in this assignment so that you get consistent results. They are:

- `max_iter` is one of the stopping criteria, which is the maximum number of iterations/epochs the algorithm will run for.
- `tol` is the other stopping criterion, which is how small the difference between the current loss and previous loss should be before stopping.
- `random_state` is a seed for pseudorandom number generation. The algorithm uses randomness in the way the training data are sorted, which will affect the solution that is learned, and even the accuracy of that solution.

Wait a minute − in class we learned that the loss function is convex, so the algorithm will find the same minimum regardless of how it is trained. Why is there random variation in the output? The reason is that even though there is only one minimum value of the loss, there may be different weights that result in the same loss, so randomness is a matter of tie-breaking. What's more, while different weights may have the same loss, they could lead to different classification accuracies, because the loss function is not the same as accuracy. (Unless accuracy was your loss function… which is possible, but uncommon because it turns out to be a difficult function to optimize.)

Note that different computers may still give different answers, despite keeping these settings the same, because of how pseudorandom numbers are generated with different operating systems and Python environments.

To begin, run the code in the cell below without modification.

Deliverable 2.1: Based on the training accuracy, do you conclude that the data are linearly separable? Why or why not? If the data were linearly separable, the training accuracy would eventually reach 100% after SGD. Since the training accuracy is not 100%, the training data is not linearly separable.

Deliverable 2.2: Which feature most increases the likelihood that the class is 'Android' and which feature most increases the likelihood that the class is 'iPhone'? "00" most increases the likleihood that the class is 'Android'. "imwithyou" most increases the likelihood that the class is 'iPhone'

One technique for improving the resulting model with perceptron (or stochastic gradient descent learning in general) is to take an average of the weight vectors learned at different iterations of the algorithm, rather than only using the final weights that minimize the loss. That is, calculate $\bar{\mathbf{w}} = \sum_{t=1}^{T} \mathbf{w}^{(t)}$ where $\mathbf{w}^{(t)}$ is the weight vector at iteration t of the algorithm and T is the number of iterations, and then use $\bar{\mathbf{w}}$ when making classifications on new data.

To use this technique in your classifier, add the keyword argument `average=True` to the `SGDClassifier` function. Try it now.

Deliverable 2.3: Compare the initial training/test accuracies to the training/test accuracies after doing averaging. What happens? Why do you think averaging the weights from different iterations has this effect? The training accuracy goes down but the testing accuracy increases. We can decrease the noise effect from single observations by looking a the average of the each update. The average is a good approximation of the true gradient.

[3]:
```
from sklearn.linear_model import SGDClassifier
from sklearn.metrics import accuracy_score, precision_score

classifier = SGDClassifier(loss='perceptron', max_iter=1000, tol=1.0e-12,␣
↪random_state=123, eta0=100)
classifier.fit(X_train, Y_train)


print("Number of SGD iterations: %d" % classifier.n_iter_)
print("Training accuracy: %0.6f" % accuracy_score(Y_train, classifier.
↪predict(X_train)))
print("Testing accuracy: %0.6f" % accuracy_score(Y_test, classifier.
↪predict(X_test)))

print("\nFeature weights:")
args = np.argsort(classifier.coef_[0])
for a in args:
    print(" %s: %0.4f" % (feature_names[a], classifier.coef_[0][a]))
```

```
Number of SGD iterations: 38
Training accuracy: 0.997300
Testing accuracy: 0.864865

Feature weights:
 00: -1.5070
 veterans: -1.2056
 wow: -1.2056
 talking: -1.1052
 called: -1.1052
 badly: -1.0047
 into: -1.0047
 stay: -0.9042
 actually: -0.9042
 hillaryclinton: -0.9042
 woman: -0.9042
```

talks: -0.9042
look: -0.9042
weak: -0.8038
mails: -0.8038
illegals: -0.8038
standing: -0.8038
allowed: -0.8038
care: -0.8038
making: -0.8038
spent: -0.8038
donaldtrump: -0.8038
sources: -0.8038
wrong: -0.8038
cruz: -0.7033
reported: -0.7033
scared: -0.7033
frontrunner: -0.7033
expensive: -0.7033
four: -0.7033
game: -0.7033
old: -0.7033
oregon: -0.7033
use: -0.7033
mr: -0.7033
order: -0.7033
texas: -0.7033
charge: -0.7033
reviews: -0.7033
statement: -0.7033
username: -0.7033
taking: -0.6028
fake: -0.6028
presumptive: -0.6028
turned: -0.6028
sigh: -0.6028
read: -0.6028
teleprompter: -0.6028
tim: -0.6028
doesn: -0.6028
isn: -0.6028
many: -0.6028
senator: -0.6028
bush: -0.6028
circuited: -0.6028
coming: -0.6028
election: -0.6028
eric: -0.6028
call: -0.6028

broke: -0.6028
votetrump2016: -0.6028
crooked: -0.6028
poor: -0.6028
policy: -0.6028
such: -0.6028
being: -0.6028
january: -0.6028
night: -0.6028
big: -0.6028
taken: -0.5023
high: -0.5023
nyprimary: -0.5023
take: -0.5023
happening: -0.5023
would: -0.5023
facts: -0.5023
focus: -0.5023
landed: -0.5023
15: -0.5023
running: -0.5023
abc: -0.5023
happily: -0.5023
lived: -0.5023
megyn: -0.5023
intelligence: -0.5023
leader: -0.5023
created: -0.5023
brain: -0.5023
gee: -0.5023
complaining: -0.5023
trump: -0.5023
minutes: -0.5023
highlight: -0.5023
happy: -0.5023
returned: -0.5023
candidates: -0.5023
polls: -0.5023
eastern: -0.5023
results: -0.5023
voted: -0.5023
praised: -0.5023
likes: -0.5023
mind: -0.5023
mic: -0.5023
another: -0.5023
evil: -0.5023
mess: -0.5023

playing: -0.5023
themselves: -0.5023
politics: -0.5023
dead: -0.5023
price: -0.5023
thursday: -0.5023
thunder: -0.5023
rolling: -0.5023
said: -0.5023
set: -0.5023
than: -0.5023
happen: -0.5023
wonder: -0.5023
others: -0.5023
dumb: -0.5023
super: -0.5023
own: -0.5023
strong: -0.5023
republican: -0.5023
2016: -0.4019
knew: -0.4019
forward: -0.4019
do: -0.4019
pocahontas: -0.4019
finally: -0.4019
rubio: -0.4019
attack: -0.4019
women: -0.4019
used: -0.4019
able: -0.4019
mayor: -0.4019
could: -0.4019
crimea: -0.4019
ted: -0.4019
unite: -0.4019
continues: -0.4019
team: -0.4019
solve: -0.4019
tiffany: -0.4019
nominee: -0.4019
forget: -0.4019
bigger: -0.4019
overrated: -0.4019
except: -0.4019
brave: -0.4019
arena: -0.4019
racist: -0.4019
advance: -0.4019

hotel: -0.4019
stolen: -0.4019
military: -0.4019
rights: -0.4019
sold: -0.4019
cannot: -0.4019
opposite: -0.4019
chris: -0.4019
calls: -0.4019
deal: -0.4019
mistakes: -0.4019
fast: -0.4019
pathetic: -0.4019
khan: -0.4019
university: -0.4019
rather: -0.4019
convention: -0.4019
supporters: -0.4019
women4ttump: -0.4019
tweeted: -0.4019
carrier: -0.4019
turnberry: -0.4019
etc: -0.4019
dear: -0.4019
presidenttrump: -0.4019
disqualifying: -0.4019
rumsfeld: -0.4019
conduct: -0.4019
unity: -0.4019
kids: -0.4019
paid: -0.4019
leads: -0.4019
stage: -0.4019
turning: -0.4019
endlessly: -0.4019
2nd: -0.4019
children: -0.4019
year: -0.4019
hitting: -0.4019
yes: -0.4019
certainly: -0.4019
got: -0.4019
answer: -0.4019
lemon: -0.4019
crowd: -0.4019
bongino: -0.4019
bullied: -0.4019
amendment: -0.4019

heated: -0.4019
killing: -0.4019
point: -0.4019
anyone: -0.4019
annual: -0.4019
gathering: -0.4019
productive: -0.4019
cabinet: -0.4019
building: -0.4019
head: -0.4019
divided: -0.4019
focused: -0.4019
beat: -0.4019
may: -0.4019
chuck: -0.4019
that: -0.4019
special: -0.4019
had: -0.4019
won: -0.3014
makeamericagreatagain: -0.3014
ratings: -0.3014
30: -0.3014
please: -0.3014
wiprimary: -0.3014
were: -0.3014
proper: -0.3014
trouble: -0.3014
sanders: -0.3014
info: -0.3014
instead: -0.3014
unanimous: -0.3014
within: -0.3014
kaine: -0.3014
representation: -0.3014
dtmag: -0.3014
gives: -0.3014
referred: -0.3014
neverhillary: -0.3014
appreciate: -0.3014
democratic: -0.3014
picture: -0.3014
begins: -0.3014
spoken: -0.3014
signed: -0.3014
bob: -0.3014
announce: -0.3014
laughing: -0.3014
additional: -0.3014

losses: -0.3014
picked: -0.3014
are: -0.3014
hair: -0.3014
michael: -0.3014
thedonald: -0.3014
treatment: -0.3014
jimmyfallon: -0.3014
thetonightshow: -0.3014
supportstrump: -0.3014
billygraham: -0.3014
slaughter: -0.3014
cissy: -0.3014
lynch: -0.3014
chemistry: -0.3014
released: -0.3014
was: -0.3014
conditions: -0.3014
wage: -0.3014
twenty: -0.3014
army: -0.3014
cancelled: -0.3014
terms: -0.3014
shootings: -0.3014
best: -0.3014
wi: -0.3014
gun: -0.3014
bosses: -0.3014
challenge: -0.3014
moment: -0.3014
absolute: -0.3014
owners: -0.3014
despite: -0.3014
few: -0.3014
thanksgiving: -0.3014
boeing: -0.3014
company: -0.3014
imagine: -0.3014
announcement: -0.3014
somali: -0.3014
stabbing: -0.3014
lyingted: -0.3014
without: -0.3014
sided: -0.3014
down: -0.3014
move: -0.3014
trip: -0.3014
notice: -0.3014

tweeting: -0.3014
quality: -0.3014
greater: -0.3014
ready: -0.3014
mar: -0.3014
donald: -0.3014
lago: -0.3014
also: -0.3014
representatives: -0.3014
enemies: -0.3014
dems: -0.3014
angry: -0.3014
saw: -0.3014
john: -0.3014
immigrants: -0.3014
southern: -0.3014
pushed: -0.3014
saturday: -0.3014
rust: -0.3014
unlike: -0.3014
belt: -0.3014
cuban: -0.3014
former: -0.3014
agreed: -0.3014
inaccurately: -0.3014
temperament: -0.3014
mission: -0.3014
favorable: -0.3014
chooses: -0.3014
empire: -0.3014
25mil: -0.3014
66: -0.3014
agent: -0.3014
thiel: -0.3014
correct: -0.3014
19pts: -0.3014
remain: -0.3014
rating: -0.3014
holds: -0.3014
peter: -0.3014
bloomberg: -0.3014
inauguration: -0.3014
pass: -0.3014
maryland: -0.3014
contrary: -0.3014
wages: -0.3014
during: -0.3014
along: -0.3014

stated: -0.3014
november: -0.3014
prove: -0.3014
38: -0.3014
cleveland: -0.3014
recently: -0.3014
interview: -0.3014
network: -0.3014
blames: -0.3014
seriously: -0.3014
primary: -0.3014
statements: -0.3014
guns: -0.3014
word: -0.3014
among: -0.3014
bean: -0.3014
because: -0.3014
light: -0.3014
serious: -0.3014
200: -0.3014
protesters: -0.3014
belief: -0.3014
decisions: -0.3014
rough: -0.3014
intentions: -0.3014
arguing: -0.3014
sheldon: -0.3014
pledges: -0.3014
breitbart: -0.3014
paris: -0.3014
adelson: -0.3014
keeping: -0.3014
viciously: -0.3014
freedom: -0.3014
go: -0.3014
116: -0.3014
rich: -0.3014
horrible: -0.3014
points: -0.3014
flag: -0.3014
memorial: -0.3014
talkers: -0.3014
poorly: -0.3014
spirit: -0.3014
warm: -0.3014
asheville: -0.3014
delay: -0.3014
doers: -0.3014

ago: -0.3014
week: -0.3014
april: -0.3014
47: -0.3014
study: -0.3014
joke: -0.3014
35: -0.3014
businessman: -0.3014
political: -0.3014
against: -0.3014
records: -0.3014
cut: -0.3014
topics: -0.3014
bringing: -0.3014
comes: -0.3014
indie: -0.3014
lightweights: -0.3014
akron: -0.3014
biggest: -0.3014
revealed: -0.3014
cyberattack: -0.3014
continue: -0.3014
mccain: -0.3014
fortune: -0.3014
responsible: -0.3014
eleventh: -0.3014
upset: -0.3014
mrs: -0.3014
subscribers: -0.3014
state: -0.3014
heel: -0.3014
brought: -0.3014
total: -0.3014
referring: -0.3014
blacks: -0.3014
decision: -0.3014
germany: -0.3014
city: -0.3014
economy: -0.3014
media: -0.3014
budget: -0.3014
this: -0.3014
president: -0.3014
their: -0.3014
they: -0.3014
opponents: -0.3014
am: -0.3014
is: -0.3014

real: -0.2009
system: -0.2009
pay: -0.2009
times: -0.2009
comments: -0.2009
looking: -0.2009
shows: -0.2009
far: -0.2009
which: -0.2009
having: -0.2009
russia: -0.2009
security: -0.2009
office: -0.2009
chief: -0.2009
believe: -0.2009
states: -0.2009
inner: -0.2009
family: -0.2009
financial: -0.2009
swearing: -0.2009
plane: -0.2009
speak: -0.2009
naming: -0.2009
wall: -0.2009
lot: -0.2009
wanted: -0.2009
catching: -0.2009
flow: -0.2009
destruction: -0.2009
muslims: -0.2009
transfer: -0.2009
dignified: -0.2009
re: -0.2009
false: -0.2009
owens: -0.2009
legacy: -0.2009
partnership: -0.2009
danger: -0.2009
horrors: -0.2009
and: -0.2009
grand: -0.2009
received: -0.2009
innocent: -0.2009
praising: -0.2009
postcards: -0.2009
flood: -0.2009
devastated: -0.2009
inappropriately: -0.2009

trans: -0.2009
federal: -0.2009
approved: -0.2009
lie: -0.2009
killer: -0.2009
secretly: -0.2009
pacific: -0.2009
thoroughly: -0.2009
ultimate: -0.2009
historic: -0.2009
90: -0.2009
killings: -0.2009
knowing: -0.2009
feds: -0.2009
precluded: -0.2009
228: -0.2009
straight: -0.2009
neither: -0.2009
carnage: -0.2009
watching: -0.2009
idea: -0.2009
afternoon: -0.2009
start: -0.2009
rebuilding: -0.2009
ailsa: -0.2009
johnkasich: -0.2009
course: -0.2009
board: -0.2009
indicted: -0.2009
clock: -0.2009
knocking: -0.2009
eliminated: -0.2009
charleston: -0.2009
hundreds: -0.2009
folks: -0.2009
congress: -0.2009
awake: -0.2009
holding: -0.2009
mathematically: -0.2009
misrepresent: -0.2009
marco: -0.2009
dismiss: -0.2009
data: -0.2009
gifts: -0.2009
lied: -0.2009
disrespect: -0.2009
winner: -0.2009
burning: -0.2009

write: -0.2009
thousand: -0.2009
scrapping: -0.2009
stupidity: -0.2009
700: -0.2009
ranking: -0.2009
progress: -0.2009
nevercruz: -0.2009
benghazi: -0.2009
india: -0.2009
korea: -0.2009
disaster: -0.2009
nice: -0.2009
misinformed: -0.2009
surprise: -0.2009
administration: -0.2009
fantastic: -0.2009
wouldn: -0.2009
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everyone: 0.3014
miami: 0.3014
happened: 0.3014
from: 0.4019
government: 0.4019
place: 0.4019
obama: 0.4019
know: 0.4019
town: 0.4019
prior: 0.4019
say: 0.4019
things: 0.4019
tpp: 0.4019
victims: 0.4019
horribly: 0.4019
american: 0.4019
boring: 0.4019
stanleycup: 0.4019
champions: 0.4019

pittsburgh: 0.4019
otherwise: 0.4019
th: 0.4019
8pm: 0.4019
mexico: 0.4019
fleeing: 0.4019
thru: 0.4019
shoddy: 0.4019
opposition: 0.4019
tragic: 0.4019
initiated: 0.4019
demanded: 0.4019
philadelphia: 0.4019
probably: 0.4019
resign: 0.4019
pick: 0.4019
disgrace: 0.4019
right: 0.4019
street: 0.4019
legal: 0.4019
guarantee: 0.4019
explain: 0.4019
campaigning: 0.4019
class: 0.4019
11am: 0.4019
experts: 0.4019
fading: 0.4019
elected: 0.4019
cory: 0.4019
step: 0.4019
honored: 0.4019
repealobamacare: 0.4019
thirty: 0.4019
visiting: 0.4019
reach: 0.4019
simple: 0.4019
oil: 0.4019
fail: 0.4019
aberdeen: 0.4019
capital: 0.4019
maker: 0.4019
native: 0.4019
comprised: 0.4019
copies: 0.4019
abandon: 0.4019
pundits: 0.4019
open: 0.4019
local: 0.4019

find: 0.4019
harvard: 0.4019
offensive: 0.4019
sign: 0.4019
audience: 0.4019
thrown: 0.4019
fired: 0.4019
mass: 0.4019
dog: 0.4019
through: 0.4019
second: 0.4019
editorial: 0.4019
gov: 0.4019
kellogg: 0.4019
keith: 0.4019
bushy: 0.4019
shouldn: 0.4019
kellyanne: 0.4019
seat: 0.4019
listening: 0.4019
session: 0.4019
teacher: 0.4019
lies: 0.4019
extraordinary: 0.4019
name: 0.4019
receive: 0.4019
10pm: 0.4019
parent: 0.4019
meetthetrumps: 0.4019
fronting: 0.4019
ocean: 0.4019
featured: 0.4019
magnificent: 0.4019
icymi: 0.4019
nearly: 0.4019
365: 0.4019
mo: 0.4019
marchforlife: 0.4019
market: 0.4019
debatenight: 0.4019
marching: 0.4019
world: 0.4019
stamina: 0.4019
destroy: 0.4019
same: 0.4019
arriving: 0.4019
gang: 0.4019
complete: 0.4019

accept: 0.4019
ridiculous: 0.4019
forgiven: 0.4019
ditka: 0.4019
transferring: 0.4019
machine: 0.4019
affordable: 0.4019
vast: 0.4019
part: 0.4019
12: 0.4019
bernie: 0.5023
story: 0.5023
gop: 0.5023
him: 0.5023
americans: 0.5023
an: 0.5023
develop: 0.5023
makes: 0.5023
matters: 0.5023
endorsement: 0.5023
empty: 0.5023
outrage: 0.5023
event: 0.5023
days: 0.5023
iranians: 0.5023
once: 0.5023
indiana: 0.5023
scientist: 0.5023
helped: 0.5023
unfairly: 0.5023
support: 0.5023
shot: 0.5023
30pm: 0.5023
reports: 0.5023
bill: 0.5023
despair: 0.5023
hall: 0.5023
nbc: 0.5023
unpredictable: 0.5023
whole: 0.5023
disloyal: 0.5023
massively: 0.5023
teach: 0.5023
joining: 0.5023
entertaining: 0.5023
sides: 0.5023
low: 0.5023
7pme: 0.5023

journalistic: 0.5023
shoutout: 0.5023
expected: 0.5023
professional: 0.5023
msg: 0.5023
knight: 0.5023
music: 0.5023
nafta: 0.5023
2a: 0.5023
fiction: 0.5023
conversation: 0.5023
where: 0.5023
tv: 0.5023
proves: 0.5023
brazile: 0.5023
coal: 0.5023
shultz: 0.5023
americafirst: 0.5023
donna: 0.5023
borders: 0.5023
els: 0.5023
protect: 0.5023
inform: 0.5023
played: 0.5023
rates: 0.5023
represented: 0.5023
completely: 0.5023
ernie: 0.5023
management: 0.5023
greatly: 0.5023
style: 0.5023
christmas: 0.5023
trillion: 0.5023
platform: 0.5023
gloomy: 0.5023
prez: 0.5023
writer: 0.5023
resort: 0.5023
laws: 0.5023
deportation: 0.5023
land: 0.5023
show: 0.5023
paul: 0.5023
act: 0.5023
interventions: 0.5023
tank: 0.5023
catholics: 0.5023
emanated: 0.5023

action: 0.5023
wattersworld: 0.5023
gonna: 0.5023
realized: 0.5023
exact: 0.5023
endorsing: 0.5023
waterville: 0.5023
saying: 0.5023
liberal: 0.5023
vulgarian: 0.5023
8pme: 0.5023
washington: 0.5023
joined: 0.5023
electoral: 0.5023
press: 0.6028
radical: 0.6028
pushing: 0.6028
thoughts: 0.6028
crookedhillary: 0.6028
third: 0.6028
gopconvention: 0.6028
book: 0.6028
cnn: 0.6028
nieto: 0.6028
wacky: 0.6028
fortunately: 0.6028
online: 0.6028
congrats: 0.6028
reporter: 0.6028
refugees: 0.6028
violence: 0.6028
draintheswamp: 0.6028
june: 0.6028
podesta: 0.6028
details: 0.6028
nevada: 0.6028
loan: 0.6028
scheduled: 0.6028
pure: 0.6028
kind: 0.6028
ask: 0.6028
senate: 0.6028
japan: 0.6028
justice: 0.6028
email: 0.6028
ginsburg: 0.6028
enforce: 0.6028
announced: 0.6028

tragedy: 0.6028
employ: 0.6028
10pe: 0.6028
loves: 0.6028
power: 0.6028
drive: 0.6028
unleashed: 0.6028
valley: 0.6028
tune: 0.6028
elect: 0.6028
reilly: 0.6028
official: 0.6028
came: 0.6028
franklin: 0.6028
soon: 0.7033
front: 0.7033
ny: 0.7033
debates: 0.7033
known: 0.7033
congratulations: 0.7033
priebus: 0.7033
wife: 0.7033
trump2016: 0.7033
instincts: 0.7033
forgotten: 0.7033
piece: 0.7033
apprentice: 0.7033
jeb: 0.7033
every: 0.7033
untrue: 0.7033
50: 0.7033
couldn: 0.7033
magical: 0.7033
obamacareinthreewords: 0.7033
off: 0.7033
pro: 0.7033
7pm: 0.7033
prayers: 0.8038
bring: 0.8038
failing: 0.8038
safe: 0.8038
page: 0.8038
party: 0.8038
everybody: 0.8038
mn: 0.8038
albany: 0.8038
israel: 0.8038
1237: 0.8038

```
louisiana: 0.8038
work: 0.9042
twitter: 0.9042
supports: 0.9042
us: 0.9042
shackles: 0.9042
bigleaguetruth: 0.9042
evening: 0.9042
fight: 0.9042
tonight: 1.0047
officers: 1.0047
emails: 1.0047
congressional: 1.0047
wikileaks: 1.1052
watched: 1.2056
behind: 1.2056
_url_: 1.4066
imwithyou: 1.5070
```

[4]:

```python
classifier2 = SGDClassifier(loss='perceptron', max_iter=1000, tol=1.0e-12,␣
↪random_state=123, eta0=100, average = True)
classifier2.fit(X_train, Y_train)

print("Number of SGD iterations: %d" % classifier2.n_iter_)
print("Training accuracy: %0.6f" % accuracy_score(Y_train, classifier2.
↪predict(X_train)))
print("Testing accuracy: %0.6f" % accuracy_score(Y_test, classifier2.
↪predict(X_test)))
```

```
Number of SGD iterations: 38
Training accuracy: 0.991901
Testing accuracy: 0.870270
```

1.6 Problem 3: Logistic regression [15 points]

For this problem, create a new `SGDClassifier`, this time setting the `loss` argument to `'log'`, which will train a logistic regression classifier. Set `average=False` for the remaining problems.

Once you have trained the classifier, you can use the `predict` function to get the classifications, as with perceptron. Additionally, logistic regression provides probabilities for the predictions. You can get the probabilities by calling the `predict_proba` function. This will give a list of two numbers; the first is the probability that the class is Android and the second is the probability that the class is iPhone.

For the first task, add the keyword argument `alpha` to the `SGDClassifier` function. This is the regularization strength, called λ in lecture. If you don't specify `alpha`, it defaults to 0.0001. Experiment with other values and see how this affects the outcome.

Deliverable 3.1: Calculate the training and testing accuracy when `alpha` is one of $[0.0001, 0.001, 0.01, 0.1, 1.0, 10.0, 100.0]$. Create a plot where the x-axis is `alpha` and the y-axis is accuracy, with two lines (one for training and one for testing). You can borrow the code from HW1 for generating plots in Python. Use a log scale for the x-axis so that the `alpha` values are spaced evenly. See below.

Deliverable 3.2: Examine the classifier probabilities using the `predict_proba` function when training with different values of `alpha`. What do you observe? How does `alpha` affect the prediction probabilities, and why do you think this happens? The predicted probabilities generally moved closer to 50% (i.e. the weights moved closer to zero) as alpha increased. This is because we increased our regularization multipier which increases the penalty placed on large weights. We use regularization to prevent overfitting of our model.

Now remove the `alpha` argument so that it goes back to the default value. We'll now look at the effect of the learning rate. By default, `sklearn` uses an "optimal" learning rate based on some heuristics that work well for many problems. However, it can be good to see how the learning rate can affect the algorithm.

For this task, add the keyword argument `learning_rate` to the `SGDClassifier` function and set the value to `invscaling`. This defines the learning rate at iteration t as: $\eta_t = \frac{\eta_0}{t^a}$, where η_0 and a are both arguments you have to define in the `SGDClassifier` function, called `eta0` and `power_t`, respectively. Experiment with different values of `eta0` and `power_t` and see how they affect the number of iterations it takes the algorithm to converge. You will often find that it will not finish within the maximum of 1000 iterations.

`eta0`	`power_t`	# Iterations
10.0	0.5	96
10.0	1.0	1000
10.0	2.0	1000
100.0	0.5	15
100.0	1.0	1000
100.0	2.0	1000
1000.0	0.5	45
1000.0	1.0	1000
1000.0	2.0	1000
10000.0	0.5	40
10000.0	1.0	14
10000.0	2.0	1000

Deliverable 3.3: Fill in the table below with the number of iterations for values of `eta0` in $[10.0, 100.0, 1000.0, 10000.0]$ and values of `power_t` in $[0.5, 1.0, 2.0]$. You may find it easier to write python code that can output the markdown for the table, but if you do that place the output here. If it does not converge within the maximum number of iterations (set to 1000 by `max_iter`), record 1000 as the number of iterations. You will need to read the documentation for this class to learn how to recover the actual number of iterations before reaching the stopping criterion.

Deliverable 3.4: Describe how `eta0` and `power_t` affect the learning rate based on the formula (e.g., if you increase `power_t`, what will this do to the learning rate?), and connect this to what you observe in the table above. Eta0 and the learning rate are positively related that is, as eta0 increases, the learning rate increases. The learning rate and power_t are inversely related that is, as power_t increases, the learning rate decreases.

Now remove the `learning_rate`, `eta0`, and `power_t` arguments so that the learning rate returns to the default setting. For this final task, we will experiment with how high the probabiity must be before an instance is classified as positive.

The code below includes a function called `threshold` which takes as input the classification probabilities of the data (called `probs`, which is given by the function `predict_proba`) and a threshold (called `tau`, a scalar that should be a value between 0 and 1). It will classify each instance as Android if the probability of being Android is greater than `tau`, otherwise it will classify the instance as iPhone. Note that if you set `tau` to 0.5, the `threshold` function should give you exactly the same output as the classifier `predict` function.

You should find that increasing the threshold causes the accuracy to drop. This makes sense, because you are classifying some things as iPhone even though it's more probable that they are Android. So why do this? Suppose you care more about accurately identifying the Android tweets and you don't care as much about `iPhone` tweets. You want to be confident that when you classify a tweet as Android that it really is Android.

There is a metric called *precision* which measures something like accuracy but for one specific class. Whereas accuracy is the percentage of tweets that were correctly classified, the precision of Android would be the percentage of tweets classified as Android that were correctly classified. (In other words, the number of tweets classified as Android whose correct label was Android, divided by the number of tweets classified as Android.)

You can use the `precision_score` function from `sklearn` to calculate the precision. It works just like the `accuracy_score` function, except you have to add an additional keyword argument, `pos_label='Android'`, which tells it that Android is the class you want to calculate the precision of.

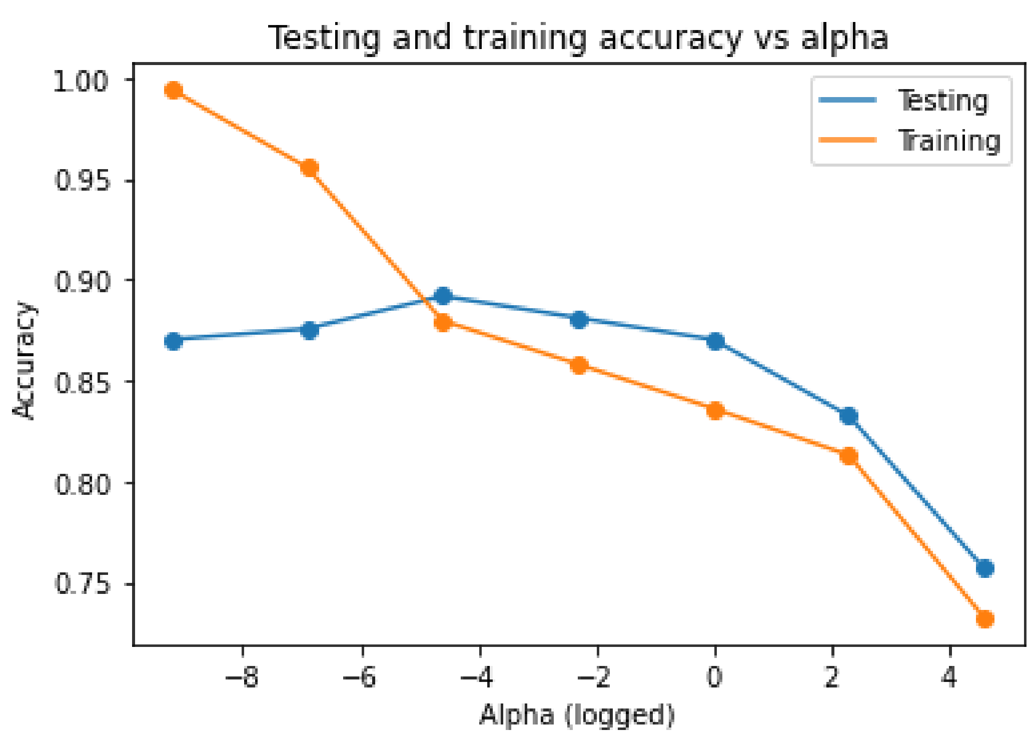
Deliverable 3.5: Calculate the testing precision when the value of `tau` for thresholding is one of $[0.5, 0.6, 0.7, 0.8, 0.9, 0.95, 0.99]$**. Create a plot where the x-axis is `tau` and the y-axis is precision.** See below.

Deliverable 3.6: Describe what you observe with thresholding (e.g., what happens to precision as the threshold increases?), and explain why you think this happens. As the threshold increases, the precision (generally) also increases. This is because a higher threshold means that we require a higher certainty that a tweet classified as 'Android' is actually 'Android'.

[162]:
```
# Deliverable 3.1
alpha = np.array([0.0001,0.001,0.01,0.1,1.0,10.0,100.0])

acc_test = np.array([])
acc_train = np.array([])
for i in alpha:
```

```
    classifier_log = SGDClassifier(loss='log', max_iter=1000, tol=1.0e-12,␣
↪random_state=123, eta0=100, average = False, alpha = i)
    classifier_log.fit(X_train, Y_train)

    test_accuracy = accuracy_score(Y_test, classifier_log.predict(X_test))
    train_accuracy = accuracy_score(Y_train, classifier_log.predict(X_train))


    acc_test = np.append(acc_test, test_accuracy)
    acc_train = np.append(acc_train, train_accuracy)


import matplotlib.pyplot as plt

plt.plot(np.log(alpha), acc_test, label = 'Testing')
plt.scatter(np.log(alpha), acc_test)
plt.plot(np.log(alpha), acc_train, label = 'Training')
plt.scatter(np.log(alpha), acc_train)
plt.title("Testing and training accuracy vs alpha")
plt.ylabel("Accuracy")

plt.xlabel("Alpha (logged)")
plt.legend()
```

[162]: <matplotlib.legend.Legend at 0x7f9e74ee0640>



[173]:
```
# Deliverable 3.2
import statistics as stats

mean_android = np.array([])
for i in alpha:
    classifier_log = SGDClassifier(loss='log', max_iter=1000, tol=1.0e-12,␣
 ↪random_state=123, eta0=100, average = False, alpha = i)
    classifier_log.fit(X_train, Y_train)

    mean_android = stats.mean(classifier_log.predict_proba(X_test)[:,0])
    print("alpha: " + str(i) + " --> " + str(mean_android))
```

```
alpha: 0.0001 --> 0.558736536555293
alpha: 0.001 --> 0.5198018531484025
alpha: 0.01 --> 0.5109166422748969
alpha: 0.1 --> 0.5228954516574309
alpha: 1.0 --> 0.5202971336274992
alpha: 10.0 --> 0.5040938155465652
alpha: 100.0 --> 0.50075937880869
```

[163]:
```
# Deliverable 3.3
eta0_array = np.array([10.0, 100.0, 1000.0, 10000.0])
power_t_array = np.array([0.5, 1.0, 2.0])

def three_three(eta_0 = 100, power_t = 0.5):
    classifier_log2 = SGDClassifier(loss='log', max_iter=1000, tol=1.0e-12,␣
 ↪random_state=123, eta0=eta_0,
                                    power_t = power_t, average = False,␣
 ↪learning_rate = 'invscaling')
    classifier_log2.fit(X_train, Y_train)
    return classifier_log2.n_iter_


for i in eta0_array:
    for j in power_t_array:
        print("eta0: " + str(i) + ", power_t: " + str(j) + " --> " +␣
 ↪str(three_three(eta_0 = i, power_t = j)))
```

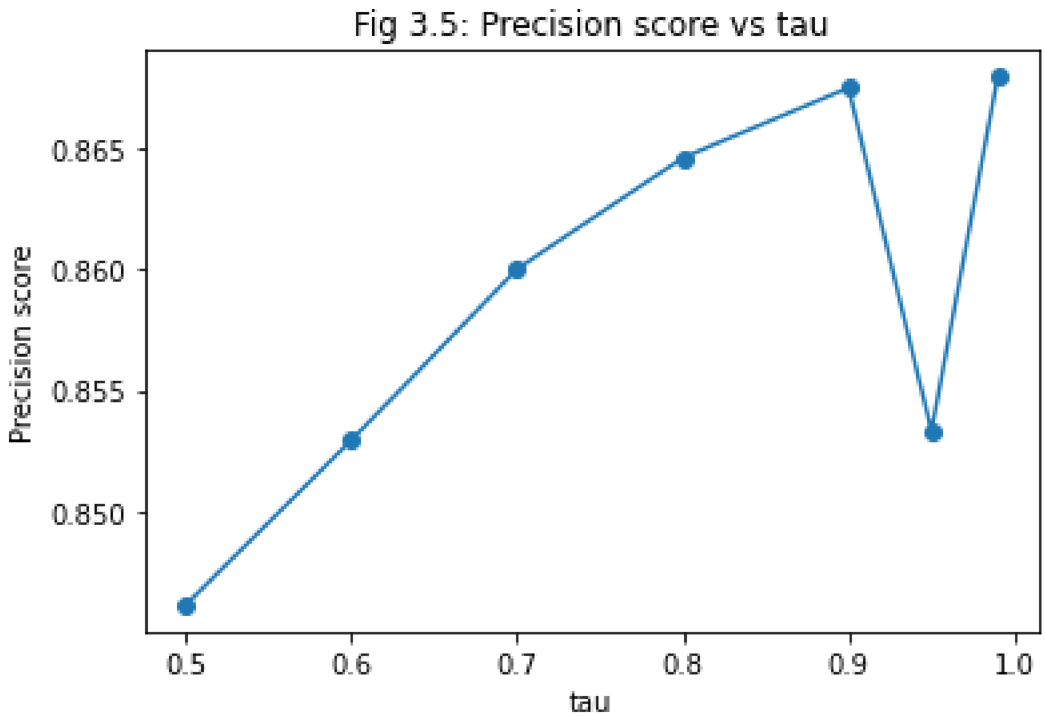
```
eta0: 10.0, power_t: 0.5 --> 96
```

```
/Users/nguyenkm13/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_stochastic_gradient.py:570: ConvergenceWarning:
Maximum number of iteration reached before convergence. Consider increasing
max_iter to improve the fit.
  warnings.warn("Maximum number of iteration reached before "
```

```
eta0: 10.0, power_t: 1.0 --> 1000
eta0: 10.0, power_t: 2.0 --> 1000
eta0: 100.0, power_t: 0.5 --> 15
eta0: 100.0, power_t: 1.0 --> 1000
eta0: 100.0, power_t: 2.0 --> 1000
eta0: 1000.0, power_t: 0.5 --> 45
eta0: 1000.0, power_t: 1.0 --> 1000
eta0: 1000.0, power_t: 2.0 --> 1000
eta0: 10000.0, power_t: 0.5 --> 40
eta0: 10000.0, power_t: 1.0 --> 14
eta0: 10000.0, power_t: 2.0 --> 1000
```

[164]:
```python
# use this function for deliverable 3.5
def threshold(probs, tau):
    return np.where(probs[:,0] > tau, 'Android', 'iPhone')

# your logistic regression code here

tau_array = np.array([0.5,0.6,0.7,0.8,0.9,0.95,0.99])

classifier = SGDClassifier(loss='log', max_iter=1000, tol=1.0e-12,␣
↪random_state=123)
classifier.fit(X_train, Y_train)

probs_ = classifier.predict_proba(X_test)

import sklearn.metrics as metrics

precision_array = np.array([])
for i in tau_array:
        thresh = threshold(probs = probs_, tau = i)
        precision_array = np.append(precision_array, metrics.
↪precision_score(Y_test, thresh, pos_label = 'Android'))


plt.plot(tau_array, precision_array)
plt.scatter(tau_array, precision_array)
plt.xlabel("tau")
plt.ylabel("Precision score")
plt.title("Fig 3.5: Precision score vs tau")
```

[164]: Text(0.5, 1.0, 'Fig 3.5: Precision score vs tau')



1.7 Problem 4: Sparse learning [5604: 5 points; 4604: +3 EC points]

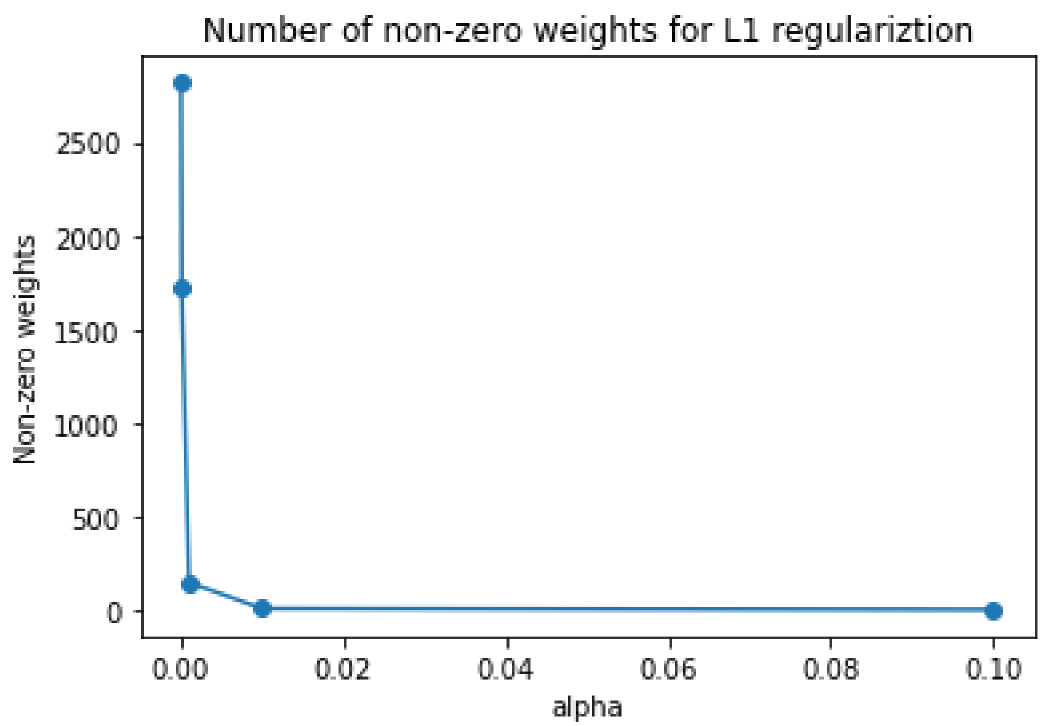
Add the `penalty` argument to `SGDClassifier` and set the value to `'l1'`, which tells the algorithm to use L1 regularization instead of the default L2. Recall from lecture that L1 regularization encourages weights to stay at exactly 0, resulting in a more "sparse" model than L2. You should see this effect if you examine the values of `classifier.coef_`.

Deliverable 4.1: Write a function to calculate the number of features whose weights are nonzero when using L1 regularization. Calculate the number of nonzero feature weights when `alpha` is one of $[0.00001, 0.0001, 0.001, 0.01, 0.1]$. Create a plot where the x-axis is `alpha` and the y-axis is the number of nonzero weights, using a log scale for the x-axis. See below.

[166]:
```
# your code here

alpha2 = np.array([0.00001,0.0001,0.001,0.01,0.1])

def problem4(alpha_ = 0.00001):
    classifier_sparse = SGDClassifier(loss='log', max_iter=1000, tol=1.0e-12,␣
 ↪random_state=123,
                                      penalty = 'l1', alpha = alpha_)
    classifier_sparse.fit(X_train, Y_train)
    non_zero = (classifier_sparse.coef_[0] != 0)
```

```
    return sum(non_zero)

non_zero_weights = np.array([])
for i in alpha2:
    non_zero_weights = np.append(non_zero_weights, problem4(i))

plt.plot(alpha2, non_zero_weights)
plt.scatter(alpha2, non_zero_weights)
plt.xlabel("alpha")
plt.ylabel("Non-zero weights")
plt.title("Number of non-zero weights for L1 regulariztion")
```

[166]: Text(0.5, 1.0, 'Number of non-zero weights for L1 regulariztion')



[ ]: