Homework 3: SVM and Sentiment Analysis

rj1407

1 Introduction

2 Calculating Subgradients

1. **Solution:**

$$\because g \in \partial f_k(x)$$
$$f(z) \geq f_k(z) \geq f_k(x) + g^T(z-x) = f(x) + g^T(z-x)$$
$$\therefore f(z) \geq f(x) + g^T(z-x), i.e. g \in \partial f(x)$$

2. [Subgradient of hinge loss for linear prediction] Give a subgradient of

$$J(w) = \max\left\{0, 1 - yw^T x\right\}.$$

Solution: a subgradient of $J(w)$ can be:

$$subgradient = \begin{cases} 0, 1 - yw^T x < 0 \\ \dfrac{-yx}{2}, else \end{cases} \quad (1)$$

3 Perceptron

1. **Solution:**
If $\left\{x \mid w^T x = 0\right\}$ is a separating hyperplane for a training set $\mathcal{D} = ((x_1, y_1), \ldots, (x_n, y_n))$, then we have

$$y_i w^T x_i > 0 \; \forall i \in \{1, \ldots, n\}.$$
$$-\hat{y}_i y_i = -w^T x_i y_i < 0.$$

And we know loss function is:

$$\ell(\hat{y}, y) = \max\{0, -\hat{y}y\}.$$
$$\therefore \ell(\hat{y}, y) = 0; \forall i \in \{1, \ldots, n\}$$

Therefore,the average perception loss on D is $\frac{1}{n}\sum_i^n 0 = 0$.

2. **Solution:**
From Problem 2 we know that a subgradient for perceptron loss can be:

$$subgradient = \begin{cases} 0, y_i w^T x_i > 0 \\ -y_i x_i^T, else \end{cases} \tag{2}$$

That is:

$$\begin{aligned} &if(y_i w^T x_i > 0): \\ &\quad w^{(k+1)} = w^{(k)} + 0 \\ &else: \\ &\quad w^{(k+1)} = w^{(k)} - 1 \cdot (-x_i y_i) \end{aligned}$$

So the whole algorithm is as following:

```
input: Training set (x_1, y_1), ..., (x_n, y_n) ∈ R^d × {-1, 1}
w^(0) = (0, ..., 0) ∈ R^d
k = 0 # step number
repeat
  all_correct = TRUE
  for i = 1, 2, ..., n # loop through data
    if (y_i x_i^T w^(k) ≤ 0)
      w^(k+1) = w^(k) + x_i y_i
      all_correct = FALSE
    else
      w^(k+1) = w^(k)
    end if
    k = k + 1
  end for
until (all_correct == TRUE)
return w^(k)
```

It's the exactly the same we are doing in the Perceptron Algorithm.

3. **Solution:**
In Perceptron algorithm, for each step, it either update with $w^{(k+1)} = w^{(k)} + y_i x_i$ or keep it unchanged, so we can write $w = \sum_{i=1}^{n} \alpha_i x_i$, where $\alpha_1, \ldots, \alpha_n = 0$(if $y_i x_i^T w^{(k)} \geq 0$) or else y_i Points(x_i, y_i) that are support vectors should satisfy: $y_i x_i^T w^{(k)} \leq 0$, which means they are misclassified.

4 The Data

5 Sparse Representations

6 Support Vector Machine via Pegasos

1. **Solution:**
   When $1 - y_i w^T x_i = 0, i.e. y_i w^T x_i = 1, J_i(w)$ is not differentiable, the gradient is not defined
   Else, it's defined,$\because \frac{\lambda}{2}\|w\|^2$ and $\max\left\{0, 1 - y_i w^T x_i\right\}$ are convex functions,
   $\therefore$ the gradient of $J_i(w) = \begin{cases} \lambda w, y_i w^T x_i > 1 \\ \lambda w - y_i x_i, else \end{cases}$

2. **Solution:**

   $\because \frac{\lambda}{2}\|w\|^2$ and $\max\left\{0, 1 - y_i w^T x_i\right\}$ are convex functions, and when $y_i w^T x_i \geq 1$, $J_i(w) = \frac{\lambda}{2}\|w\|^2$, when $y_i w^T x_i < 1$,$J_i(w) = \frac{\lambda}{2}\|w\|^2 + \max\left\{0, 1 - y_i w^T x_i\right\}$ $\therefore$ similar to previous questions,

   $$g = \begin{cases} \lambda w - y_i x_i & \text{for } y_i w^T x_i < 1 \\ \lambda w & \text{for} y_i w^T x_i \geq 1. \end{cases}$$

3. [Written] Show that if your step size rule is $\eta_t = 1/(\lambda t)$, then doing SGD with the subgradient direction from the previous problem is the same as given in the pseudocode.

   Solution:
   when step size rule is $\eta_t = 1/(\lambda t)$,w is updated as:

   $$w_{t+1} = \begin{cases} w_t - \eta_t(\lambda w_t - y_i x_i) & \text{for } y_i w^T x_i < 1 \\ w_t - \eta_t(\lambda w_t) & \text{for } y_i w^T x_i \geq 1. \end{cases}$$

   That is,

   $$w_{t+1} = \begin{cases} (1 - \eta_t \lambda) w_t + \eta_t y_i x_i & \text{for } y_i w^T x_i < 1 \\ (1 - \eta_t \lambda) w_t & \text{for } y_i w^T x_i \geq 1. \end{cases}$$

   So it's the same as given in pseudocode.

In [1]:
```
import os
import numpy as np
import pickle
import random
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
def folder_list(path,label):
    '''
    PARAMETER PATH IS THE PATH OF YOUR LOCAL FOLDER
    '''
    filelist = os.listdir(path)
    review = []
    for infile in filelist:
        file = os.path.join(path,infile)
        r = read_data(file)
        r.append(label)
        review.append(r)
    return review
def read_data(file):
    '''
    Read each file into a list of strings.
    Example:
    ["it's", 'a', 'curious', 'thing', "i've", 'found', 'that', 'when', 'willis', 'is', 'not', 'called', 'on',
    ...'to', 'carry', 'the', 'whole', 'movie', "he's", 'much', 'better', 'and', 'so', 'is', 'the', 'movie']
    '''
    f = open(file)
    lines = f.read().split(' ')
    symbols = '${}()[].,:;+-*/&|<>=~" '
    words = map(lambda Element: Element.translate(str.maketrans("", "", symbols)).strip(), lines)
    # For python 3 users: use the following instead
    words = list(filter(None, words))
#     words = filter(None, words)
    return words
```

4.1

- Load all the data and randomly split it into 1500 training examples and 500 validation exam- ples.

In [3]:
```
def shuffle_data():
    '''
    pos_path is where you save positive review data.
    neg_path is where you save negative review data.
    '''
    pos_path = "data/pos"
    neg_path = "data/neg"

    pos_review = folder_list(pos_path,1)
    neg_review = folder_list(neg_path,-1)

    review = pos_review + neg_review
    random.shuffle(review)
    train = review[:1500]
    val = review[-500:]
    return train, val
```

In [63]:
```
train,val = shuffle_data()
```

In [64]:
```
pickle.dump( train, open( "train.p", "wb" ) )
pickle.dump( val, open( "val.p", "wb" ) )
```

In [65]:
```
train = pickle.load(open( "train.p", "rb" ) )
val = pickle.load(open("val.p", "rb"))
```

5.1

- Write a function that converts an example (e.g. a list of words) into a sparse bag-of-words representation.

In [55]:
```
from collections import Counter
def convert_bag(review):
    cnt = Counter()
    for word in review:
        cnt[word] += 1
    return cnt
```

In [37]:
```python
def dotProduct(d1, d2):
    """
    @param dict d1: a feature vector represented by a mapping from a feature (string) to a weight (float).
    @param dict d2: same as d1
    @return float: the dot product between d1 and d2
    """
    if len(d1) < len(d2):
        return dotProduct(d2, d1)
    else:
        return sum(d1.get(f, 0) * v for f, v in d2.items())

def increment(d1, scale, d2):
    """
    Implements d1 += scale * d2 for sparse vectors.
    @param dict d1: the feature vector which is mutated.
    @param float scale
    @param dict d2: a feature vector.

    NOTE: This function does not return anything, but rather
    increments d1 in place. We do this because it is much faster to
    change elements of d1 in place than to build a new dictionary and
    return it.
    """
    for f, v in d2.items():
        d1[f] = d1.get(f, 0) + v * scale
```

6.4

In [281]:
```python
def pegasos(datalist,lambd,max_epoch):
    t = 0
    w = dict()
    epoch = 0
    while(epoch < max_epoch):
        epoch += 1
        for review in datalist:
            t +=1
            eta = 1/(t * lambd)
            y_i = review[-1]
            x_i = convert_bag(review[:-1])
            factor = y_i * dotProduct(w, x_i)
            if factor < 1:
                increment(w,(- eta * lambd),w)
                increment(w, eta*y_i,x_i)
            else:
                increment(w,(- eta * lambd),w)
    return w
```

6.5

$

$$
\begin{aligned}
w_{t+1} &= s_{t+1} W_{t+1} \\
&= (1 - \eta_t \lambda) s_t W_t + \eta_t y_j x_j \\
&= (1 - \eta_t \lambda) w_t + \eta_t y_j x_j
\end{aligned}
$$

- so it's equivalent

In [282]:
```
def scale(w, s):
    for k in w.keys():
        w[k] = w.get(k, 0) * s

def pegasos_faster(datalist,lambd, max_epoch):
    t = 0
    s = 1
    W = dict()

    epoch = 0
    while(epoch < max_epoch):
        epoch += 1
        for review in datalist:
            t += 1
            eta = 1/(t * lambd)
            y_i = review[-1]
            x_i = convert_bag(review[:-1])
            factor = y_i * s * dotProduct(W, x_i)
            s = (1 - eta *lambd) * s
            if s == 0:
                s = 1
                W = dict()

            if factor < 1:
                increment(W,(eta * y_i/s),x_i)
    scale(W, s)
    return W
```

6.6

- I choose epoch = 5 and run two functions, compare the time. The results are as follows, the time spent in the first approach is much more than using the second one.

In [286]:
```
%timeit w = pegasos(train, 0.1, 5)
```

```
50.5 s ± 852 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

In [287]:
```
%timeit w_faster = pegasos_faster(train,0.1, 5)
```

```
2.18 s ± 18.6 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

In [288]:
```
a = True
for k,v in w.items():
    if abs(w_faster[k] - w[k]) >1e-6:
        a = False
        print(k)
        break
print(a)
```

```
True
```

- From the above cell, we can verify that the two approaches give essentially the same result.

6.7

In [195]:
```
def loss(w,datalist):
    loss = 0
    for review in datalist:
        y_i = review[-1]
        x_i = convert_bag(review[:-1])
        if dotProduct(w,x_i) * y_i < 0:
            loss += 1
    return loss/len(datalist)
```

6.8

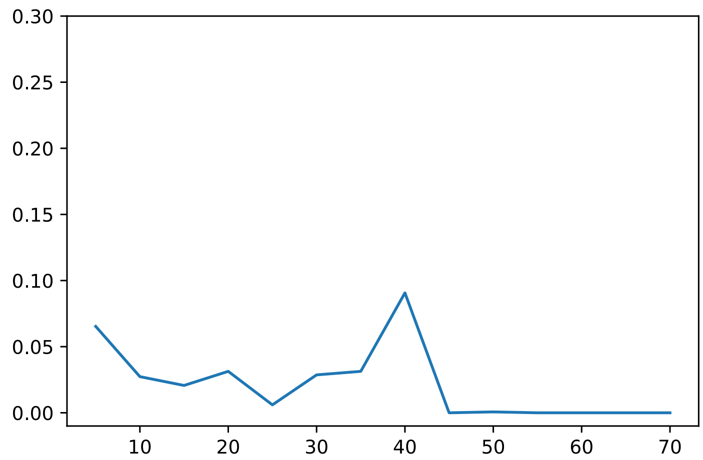
- First, we can observe the approximate number of epochs it need to converge.

In [439]:
```
epoch_list = np.arange(5,75,5)
w_list = []
for epoch in epoch_list:
    w = pegasos_faster(train,0.01, epoch)
    w_list.append(w)
```

In [440]:
```python
loss_train = []
for w in w_list:
    loss_train.append(loss(w,train))
```

In [441]:
```python
plt.plot(epoch_list,loss_train)
plt.ylim(-0.01,0.3)
```

Out[441]: (-0.01, 0.3)



- We can see from the plot that it will converge after around 45 epochs, so we can choose epoch=60 in the following searching for the optimum regularization parameter process. We first start with a set of regularization parameters spanning a broad range of orders of magnitude.

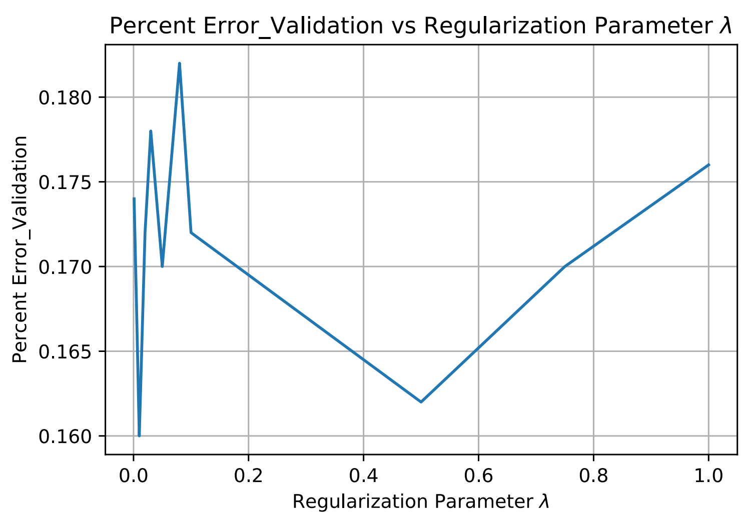
In [442]:
```python
lambd_list = [0.001,0.005,0.01,0.02,0.03,0.05,0.08,0.1,0.5,0.75,1]
loss_val = []

for lambd in lambd_list:
    w = pegasos_faster(train,lambd, 60)
    loss_val.append(loss(w,val))
#     print('When epoch={:f}, lambd={:f}, loss = {:f}'.format(epoch, lambd,loss(w, val)))
```

In [443]:
```python
%config InlineBackend.figure_format = 'svg'

fig, ax = plt.subplots()
ax.plot(lambd_list, loss_val)
ax.grid()
ax.set_title("Percent Error_Validation vs Regularization Parameter $\lambda$")
ax.set_xlabel("Regularization Parameter $\lambda$")
ax.set_ylabel("Percent Error_Validation")
fig.show()
```

```
/Users/jr/anaconda3/lib/python3.7/site-packages/matplotlib/figure.py:445: UserWarning: Matplotlib is currently using module://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot show the figure.
  % get_backend())
```

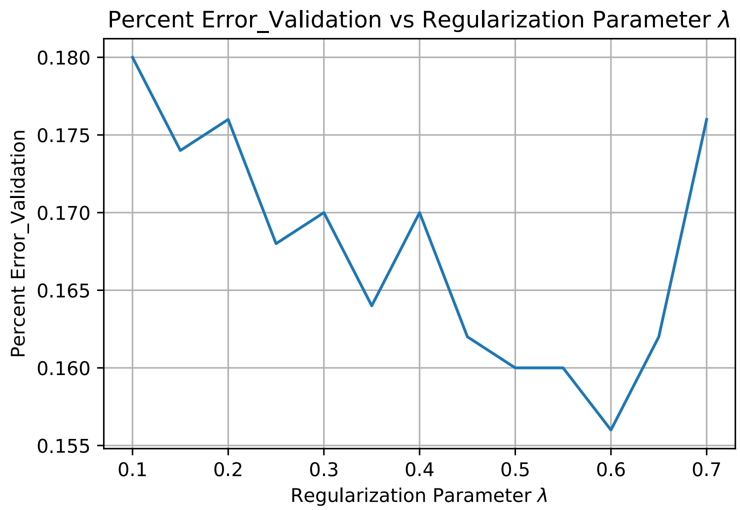


- Then we continue to zoom in, observe the percent error with parameter λ is within the range of (0.1, 0.75)

In [444]:
```
lambd_list = np.arange(0.1,0.75,0.05)
loss_val = []

for lambd in lambd_list:
    w = pegasos_faster(train,lambd, 50)
    loss_val.append(loss(w,val))
```

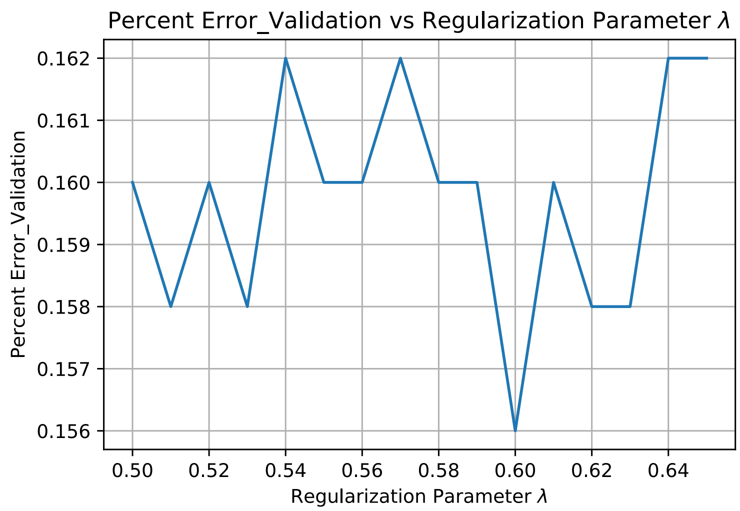
In [445]:
```
fig, ax = plt.subplots()
ax.plot(lambd_list, loss_val)
ax.grid()
ax.set_title("Percent Error_Validation vs Regularization Parameter $\lambda$")
ax.set_xlabel("Regularization Parameter $\lambda$")
ax.set_ylabel("Percent Error_Validation")
fig.show()
```



In [446]:
```
lambd_list = np.arange(0.5,0.65,0.01)
loss_val = []

for lambd in lambd_list:
    w = pegasos_faster(train,lambd, 50)
    loss_val.append(loss(w,val))
```

In [447]:
```
fig, ax = plt.subplots()
ax.plot(lambd_list, loss_val)
ax.grid()
ax.set_title("Percent Error_Validation vs Regularization Parameter $\lambda$")
ax.set_xlabel("Regularization Parameter $\lambda$")
ax.set_ylabel("Percent Error_Validation")
fig.show()
```



- So we can basically convince ourselves that $\lambda = 0.60$ is the optimum point.

7.1

7.1.1. choose two input examples that the model got wrong

In [448]:

```
#choose the optimum regularization parameter $\lambda$ in the above question then
lambd = 0.6
w = pegasos_faster(train,lambd, 50)
num = 0
wrong_egs = []
x_list = []
for review in val:
    y_i = review[-1]
    x_i = convert_bag(review[:-1])
    if dotProduct(w,x_i) * y_i < 0:
        num += 1
        wrong_egs.append(review)
        x_list.append(x_i)
    if num == 2:
        break
```

In [417]:

```
for count, eg in enumerate(wrong_egs,1):
    x_i = x_list[(count - 1)]
    print('example',count,"\n",' '.join(eg[:-1]))
    print(' ')
    print("The true y value is:",eg[-1], ", but we predict wx as",dotProduct(w,x_i))
    print(' ')
```

```
example 1
 girl 6 is in a word a mess i was never able to determine what spike lee was trying to accomplish with this fi
lm there was no sense of where the film was going or any kind of coherent narrative if there was a point to th
e film i missed it girl 6 by the way is the way theresa randle's character is addressed in the phone sex workp
lace all the girls are known by their numbers the plot such as it is theresa randle is a struggling n y actres
s and eventually takes a job as a phonesex operator she begins to lose contact with reality as her job consume
s her also she must deal with the advances of her exhusband isiah washington he is an ex con thief and she tri
es to keep him away while at the same time it's clear that she still harbors feelings for him her neighbor jim
my spike lee functions as the observer mediating between the ex husband and girl 6 he also functions as a poin
t of stability as he watches her become seduced by the lurid world of phone sex the soundtrack consisting of s
ongs by prince was jarring it kept taking my attention from the film not altogether a bad thing i'll grant you
as what was transpiring onscreen wasn't that riveting for parts of the middle of the film the music stayed bli
ssfully in the background in the opening sequence and one scene later in the film however the music was partic
ularly loud and distracting of course i've never really cared for prince's or tafkap if you like music prince
fans might love the soundtrack but it will probably be distracting even to diehard fans of the performances th
e only one that stood out was spike lee's buddy character jimmy he was excellent as the alwaysbroke neighbor o
f girl 6 he should have stuck to acting in this film there are several sequences that gave me the impression t
hat he'd like to be oliver stone when he grows up there are scenes shot with different types of film which are
purposely grainy and reminiscent of some of the scenes in oliver stone's natural born killers in that film the
y worked to propel the narrative in this film they just made me more confused there are some amusing moments a
nd a few insights into the lives of the women who use their voices to make the phonesex industry the multibill
ion dollar industry that it has become other than that though nothing much happens there are a few intense mom
ents as when one caller becomes frightening but even that is rather lackluster i'm not the biggest fan of spik
e lee though i'd agree that he has done some very good work in the past in girl 6 though he seems to be flound
ering he had an interesting idea a fairly good setup and seemed to wander aimlessly from there girl 6 earns a
grade of d

The true y value is: -1 , but we predict wx as 0.42546666666666794

example 2
 lengthy and lousy are two words to describe the boring drama the english patient great acting music and cinem
atography were nice but too many dull subplots and characters made the film hard to follow ralph fiennes stran
ge days schindler's list gives a gripping performance as count laszlo almasy a victim of amnesia and horrible
burns after world war ii in italy the story revolves around his past in flashback form making it even more con
fusing anyway he is taken in by hana juliette binoche the horseman on the roof a boring wartorn nurse she was
never really made into anything until she met an indian towards the end developing yet another subplot count a
lmasy begins to remember what happened to him as it is explained by a stranger willem dafoe basquiat his love
kirstin scott thomas mission impossible was severely injured in a plane crash and eventually died in a cave he
returned to find her dead and was heartbroken so he flew her dead body somewhere but was shot down from the gr
ound don't get the wrong idea it may sound good and the trailer may be tempting but good is the last thing thi
s film is maybe if it were an hour less it may have been tolerable but 2 hours and 40 minutes of talking is to
o much to handle the only redeeming qualities about this film are the fine acting of fiennes and dafoe and the
beautiful desert cinematography other than these the english patient is full of worthless scenes of boredom an
d wastes entirely too much film

The true y value is: -1 , but we predict wx as 0.15331111111111384
```

For this example, our model predicts it to be a positive one but it's indeed a negative review.

7.1.2. create a table of the most important features(sorted by $|w_i x_i|$)

In [420]:
```
import pandas as pd
df1 = pd.DataFrame(columns=['feature_name','feature_value','feature_weight','product'])
idx = 0
x_i = x_list[0]
for k,v in x_i.items():
    df1.loc[idx] = [k, v, w.get(k,0), abs(w.get(k, 0)* v)]
    idx+=1
df1.sort_values(by=['product'])
```

Out[420]:

	feature_name	feature_value	feature_weight	product
104	mediating	1	0.000000	0.000000
40	randle's	1	0.000000	0.000000
78	isiah	1	0.000000	0.000000
220	multibillion	1	0.000000	0.000000
172	alwaysbroke	1	0.000000	0.000000
45	workplace	1	0.000000	0.000000
154	tafkap	1	0.000000	0.000000
130	transpiring	1	0.000000	0.000000
64	phonesex	2	0.000000	0.000000
246	floundering	1	0.000000	0.000000
221	dollar	1	0.000178	0.000178
253	wander	1	-0.000200	0.000200
128	grant	1	-0.000244	0.000244
153	prince's	1	0.000289	0.000289
239	agree	1	-0.000378	0.000378
57	n	1	0.000422	0.000422
140	opening	1	0.000511	0.000511
167	stood	1	-0.000667	0.000667
238	i'd	1	-0.000711	0.000711
147	loud	1	-0.000756	0.000756
137	stayed	1	0.000756	0.000756
124	altogether	1	-0.000778	0.000778
98	feelings	1	-0.000778	0.000778
55	randle	1	0.000800	0.000800
110	seduced	1	-0.000867	0.000867
197	stone's	1	-0.000889	0.000889
182	he'd	1	-0.000911	0.000911
230	caller	1	0.000933	0.000933
114	consisting	1	-0.000978	0.000978
256	grade	1	-0.001000	0.001000
...	...	...	...	...
22	no	1	-0.061622	0.061622
52	plot	1	-0.061844	0.061844
0	girl	6	-0.010378	0.062267
1	6	6	0.010489	0.062933
109	become	2	0.031867	0.063733
4	a	12	0.005356	0.064267
196	some	3	-0.021644	0.064933
174	have	1	-0.069067	0.069067
37	by	4	0.017444	0.069778
95	that	10	0.007267	0.072667
163	even	2	-0.036511	0.073022
63	job	2	0.037067	0.074133
166	only	1	-0.075200	0.075200
71	her	5	-0.015111	0.075556
162	be	3	-0.026244	0.078733

	feature_name	feature_value	feature_weight	product
225	though	3	0.027422	0.082267
48	are	6	-0.016444	0.098667
73	also	2	0.052711	0.105422
129	you	2	0.055111	0.110222
33	if	2	-0.056378	0.112756
125	bad	1	-0.115622	0.115622
8	was	10	0.012044	0.120444
2	is	7	0.018467	0.129267
24	of	17	-0.008089	0.137511
60	and	8	0.026444	0.211556
21	there	7	-0.036622	0.256356
80	he	9	0.029156	0.262400
54	as	9	0.030867	0.277800
11	to	12	-0.023244	0.278933
26	the	34	0.011067	0.376267

258 rows × 4 columns

In [423]:
```
pd.set_option('display.max_rows', None)
df1.sort_values(by=['product'])
```

166	only	1	-0.075200	0.075200
71	her	5	-0.015111	0.075556
162	be	3	-0.026244	0.078733
225	though	3	0.027422	0.082267
48	are	6	-0.016444	0.098667
73	also	2	0.052711	0.105422
129	you	2	0.055111	0.110222
33	if	2	-0.056378	0.112756
125	bad	1	-0.115622	0.115622
8	was	10	0.012044	0.120444
2	is	7	0.018467	0.129267

In [438]:
```
df2 = pd.DataFrame(columns=['feature_name','feature_value','feature_weight','product'])
idx = 0
x_i = x_list[1]
for k,v in x_i.items():
    df2.loc[idx] = [k, v, w.get(k,0), abs(w.get(k, 0)* v)]
    idx+=1
df2.sort_values(by=['product'])
```

135	may	3	0.017810	0.053429
44	of	5	-0.011333	0.056667
141	last	1	-0.057143	0.057143
49	world	1	0.058476	0.058476
144	maybe	1	-0.059143	0.059143
163	beautiful	1	0.059143	0.059143
148	have	1	-0.060000	0.060000
39	as	2	0.033333	0.066667
154	minutes	1	-0.070952	0.070952
158	only	1	-0.076952	0.076952
92	yet	1	0.078762	0.078762
13	great	1	0.100095	0.100095
6	to	6	-0.020000	0.120000

- we can see for example in the first review, the words that set the tone for the whole review such as “mess”, “never able to”, “no sense” can not be shown in the weights or only played a trivial role in the weights, and some words like “loud” and “distracting” also show it’s an negative comment .

- However, positive words such as “excellent” (and also “interesting) appeared with relatively high feature value, but in the context, it appeared as “the only one that stood out was spike lee's buddy character jimmy he was excellent”, which is not a good sign to indicate it’s positive.
- Third, after observing the “feature importance”, we found that most features with high value are neutral. Even if their feature values are small, because of their high frequency, their products turned to be large and may dominate the result.
- One possible solution might be: we can exclude some of the neutral words from the feature list,decrease their impact to the result as possible as we can. And maybe take the negative word that appears before an adjective into consideration when creating features.

6.9

- generate absolute score for each review in validation set(to present magnitude)

In [453]:

```
df3 = pd.DataFrame(columns=['actual y','score','abs_score'])
idx = 0
for review in val:
    y_i = review[-1]
    x_i = convert_bag(review[:-1])
    score = dotProduct(w,x_i)
    abs_score = abs(score)
    df3.loc[idx] = [y_i, score,abs_score]
    idx+=1
df4 = df3.sort_values(by=['abs_score'])
df4
```

Out[453]:

	actual y	score	abs_score
406	-1.0	-0.001022	0.001022
141	1.0	0.002800	0.002800
317	1.0	0.003311	0.003311
435	-1.0	-0.010022	0.010022
409	-1.0	-0.010200	0.010200
96	1.0	-0.022178	0.022178
389	1.0	-0.022556	0.022556
471	-1.0	-0.026333	0.026333
91	1.0	0.033289	0.033289
251	1.0	-0.033956	0.033956
108	-1.0	0.035089	0.035089

- create a function to return a table for a given number of groups that the validation will be split into.

In [498]:

```
def table_percentage_error_group(group_num):
    df5 = pd.DataFrame(columns=['magnitude_score','percentage error'])
    idx = 0
    for group in np.array_split(df4, group_num):
        average_abs_score = group['abs_score'].sum(axis=0)/(500/group_num)
        loss = 0
        for i in group['score']:
            y = group.loc[group['score'] == i]['actual y'].values
            if y * i <0:
                loss +=1
        avg_loss = loss/50
        df5.loc[idx] = [average_abs_score, avg_loss]
        idx +=1
    return df5
```

- show the result as following:
- I found that there is a correlation between higher magnitude scores and accuracy (although there is some fluctuation)the overall trend is: the higher the magnitude scores , the lower the precentage error is, i.e. the higher the accuracy is.

In [499]:

```
table_percentage_error_group(5)
```

Out[499]:

	magnitude_score	percentage error
0	0.127975	0.70
1	0.318731	0.52
2	0.572055	0.22
3	0.945051	0.08
4	1.789378	0.04

In [500]:
```
table_percentage_error_group(10)
```

Out[500]:

	magnitude_score	percentage error
0	0.072798	0.28
1	0.183152	0.42
2	0.263439	0.22
3	0.374024	0.30
4	0.506593	0.18
5	0.637516	0.04
6	0.819903	0.04
7	1.070199	0.04
8	1.377315	0.02
9	2.201440	0.02

In [501]:
```
table_percentage_error_group(20)
```

Out[501]:

	magnitude_score	percentage error
0	0.039524	0.14
1	0.106072	0.14
2	0.162456	0.22
3	0.203849	0.20
4	0.241499	0.12
5	0.285379	0.10
6	0.340310	0.10
7	0.407737	0.20
8	0.480252	0.08
9	0.532935	0.10
10	0.598204	0.00
11	0.676828	0.04
12	0.763847	0.02
13	0.875959	0.02
14	1.003617	0.04
15	1.136780	0.00
16	1.264900	0.00
17	1.489730	0.02
18	1.804742	0.00
19	2.598139	0.02

6.10

In [502]:
```
def scale(w, s):
    for k in w.keys():
        w[k] = w.get(k, 0) * s

def pegasos_faster_count(datalist,lambd, max_epoch):
    t = 0
    s = 1
    W = dict()
    count = 0
    epoch = 0
    while(epoch < max_epoch):
        epoch += 1
        for review in datalist:
            t += 1
            eta = 1/(t * lambd)
            y_i = review[-1]
            x_i = convert_bag(review[:-1])
            factor = y_i * s * dotProduct(W, x_i)
            s = (1 - eta *lambd) * s
            if s == 0:
                s = 1
                W = dict()

            if factor < 1:
                increment(W,(eta * y_i/s),x_i)
            elif factor ==1:
                count += 1
#     scale(W, s)
    return count
```

In [505]:
```
pegasos_faster_count(train,0.6,50)
```

Out[505]: 0

we found $y_i w^T x_i = 1$ did not appear

In [513]:
```
def scale(w, s):
    for k in w.keys():
        w[k] = w.get(k, 0) * s

def pegasos_faster_count(datalist,lambd, max_epoch):
    t = 0
    s = 1
    W = dict()
    count = 0
    epoch = 0
    while(epoch < max_epoch):
        epoch += 1
        for review in datalist:
            t += 1
            eta = 1/(t * lambd)
            y_i = review[-1]
            x_i = convert_bag(review[:-1])
            factor = y_i * s * dotProduct(W, x_i)
            s = (1 - eta *lambd) * s
            if s == 0:
                s = 1
                W = dict()

            if factor < 1:
                increment(W,(eta * y_i/s),x_i)
            elif abs(factor - 1)<1e-4:
                count += 1
#     scale(W, s)
    return count
```

In [514]:
```
pegasos_faster_count(train,0.6,50)
```

Out[514]: 8

But when I set a small distance(0.0001) of $y_i w^T x_i$ from 1, I found that within 50 epochs, this appeared 8 times.

In [ ]: