HW03_linear_kulikov

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1 Linear models – Amazon Fine Food Reviews

1.1 Kulikov Alex, gr. 397

В данном домашнем задании вы будете решать задачу классификации отзывов.

Шаги решения:

1. Извлечение признаков: напишите код для создания TF-IDF матрицы из представленного корпуса отзывов
2. Обучение моделей: напишите код для обучения SVM и логистической регрессии
3. Кросс-валидация для подбора гиперпараметров: напишите код для оптимизации метрик обучения
4. Участие в контесте на kaggle.com

In [1]:
```
import pandas
import random
import numpy
from matplotlib import pyplot as plt
from matplotlib import pyplot

%matplotlib inline
pyplot.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
pyplot.rcParams['image.interpolation'] = 'nearest'
pyplot.rcParams['image.cmap'] = 'gray'

# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

pandas.options.display.max_colwidth = 0

from IPython.core.display import HTML
HTML("<style>.container { width:90% !important; }</style>")
```

Out[1]:
```
<IPython.core.display.HTML object>
```

1.2 A super-cool trick for multithreading + visualization

1.2.1 https://habrahabr.ru/post/277919/

In [3]:
```
def log_progress(sequence, every=None, size=None):
    from ipywidgets import IntProgress, HTML, VBox
    from IPython.display import display
```

```
        is_iterator = False
        if size is None:
            try:
                size = len(sequence)
            except TypeError:
                is_iterator = True
        if size is not None:
            if every is None:
                if size <= 200:
                    every = 1
                else:
                    every = size / 200     # every 0.5%
        else:
            assert every is not None, 'sequence is iterator, set every'

        if is_iterator:
            progress = IntProgress(min=0, max=1, value=1)
            progress.bar_style = 'info'
        else:
            progress = IntProgress(min=0, max=size, value=0)
        label = HTML()
        box = VBox(children=[label, progress])
        display(box)

        index = 0
        try:
            for index, record in enumerate(sequence, 1):
                if index == 1 or index % every == 0:
                    if is_iterator:
                        label.value = '{index} / ?'.format(index=index)
                    else:
                        progress.value = index
                        label.value = u'{index} / {size}'.format(
                            index=index,
                            size=size
                        )
                yield record
        except:
            progress.bar_style = 'danger'
            raise
        else:
            progress.bar_style = 'success'
            progress.value = index
            label.value = str(index or '?')
```

```
In [4]: def jobs_manager():
        from IPython.lib.backgroundjobs import BackgroundJobManager
        from IPython.core.magic import register_line_magic
        from IPython import get_ipython

        jobs = BackgroundJobManager()

        @register_line_magic
        def job(line):
```

```
        ip = get_ipython()
        jobs.new(line, ip.user_global_ns)

    return jobs
```

```
In [5]: def kill_thread(thread):
            import ctypes

            id = thread.ident
            code = ctypes.pythonapi.PyThreadState_SetAsyncExc(
                ctypes.c_long(id),
                ctypes.py_object(SystemError)
            )
            if code == 0:
                raise ValueError('invalid thread id')
            elif code != 1:
                ctypes.pythonapi.PyThreadState_SetAsyncExc(
                    ctypes.c_long(id),
                    ctypes.c_long(0)
                )
                raise SystemError('PyThreadState_SetAsyncExc failed')
```

```
In [6]: def get_chunks(sequence, count):
            count = min(count, len(sequence))
            chunks = [[] for _ in range(count)]
            for index, item in enumerate(sequence):
                chunks[index % count].append(item)
            return chunks
```

1.2.2 Demo

Just look at that!

```
In [7]: jobs = jobs_manager()
```

```
In [8]: from time import sleep
        from random import random

        def fetch_url(url):
            sleep(random())
            return url

        urls = range(100)
        urls2 = range(100)
```

```
In [9]: %job [fetch_url(_) for _ in log_progress(urls, every=1)]
```

```
Starting job # 0 in a separate thread.
```

```
In [10]: kill_thread(jobs.running[0])
```

```
In [11]: for chunk in get_chunks(urls, 3):
             %job [fetch_url(_) for _ in log_progress(chunk, every=1)]
```

```
Starting job # 2 in a separate thread.
Starting job # 3 in a separate thread.
Starting job # 4 in a separate thread.
```

```
In [12]: for job in jobs.running:
             kill_thread(job)
```

1.3 But tqdm is still better and simpler to use

In [13]:
```
from tqdm import tqdm
from time import sleep
```

In [14]:
```
for i in tqdm(range(10)):
    sleep(1)
```

```
100%|| 10/10 [00:10<00:00,  1.00s/it]
```

1.4 Знакомство с данными

In [15]:
```
data = pandas.read_csv("kaggle_data/train.csv", index_col=0, na_values="NaN")

print(data.shape)
print(data.head())
print(data.tail())
```

```
(352278, 2)
                                                  Reviews_Summary  Prediction
ID
230872  Babies love these                                            3
344823  Salmon Trout                                                 0
211754  disappointment                                               1
259421  Doesn't taste like Cinnabon; tastes like Waffle Crisp        2
253418  Delicious San Daniele prosciutto and good customer service   3
                              Reviews_Summary  Prediction
ID
110273  We enjoy this coffee                 3
259187  Satisfied                            2
365859  quite good                           3
131937  Great yummy treat for my little ones 3
121963  Disappointed                         1
```

1.4.1 Seems that there aren't any missing values..

In [16]:
```
print(data.Reviews_Summary.value_counts()) # no NaN
# print(data.Reviews_Summary.value_counts()["NaN"]) # -- KeyError
print(data.Prediction.value_counts()) # no NaN
# print(data.Prediction.value_counts()["NaN"]) # -- KeyError
```

```
Delicious!                                                      1627
Delicious                                                       1529
Yummy!                                                          1039
Yummy                                                           826
Yum!                                                            733
Great product                                                   703
Excellent                                                       637
Great Product                                                   622
Love it!                                                        605
Great!                                                          527
Great                                                           486
Tasty                                                           422
Yum                                                             412
Excellent!                                                      376
```

```
Great Coffee                                                   372
Awesome                                                        362
Good stuff                                                     360
Disappointed                                                   349
Awesome!                                                       347
yummy                                                          337
Great product!                                                 325
Good Stuff                                                     317
Great coffee                                                   302
YUM!                                                           300
great product                                                  299
Love it                                                        297
delicious                                                      288
Very good                                                      288
The Best                                                       261
Amazing                                                        250
                                                              ...
Don't use for Tiramisu Recipe                                   1
good texture and good taste                                     1
not great ... but good for the price                            1
Benecol - works for me!                                         1
A great alternative to coffee                                   1
Perfect grain-free treats                                       1
10 stars!                                                       1
LOVE it, great for toddlers too                                 1
Super filling!                                                  1
Disappointing, low quality                                      1
False statement and inflated price!!!                           1
Get some!                                                       1
A sample got us hooked!                                         1
very low quality Tea                                            1
These saved my relationship with my cat!                        1
The Flames of Hell in a Bottle                                  1
Perfect healthy sugar replacement                               1
Got the wheat and the rye                                       1
Fantastic flavor and value!                                     1
It May Be Low Acid, but it Still Gave Me Heartburn              1
Horrid!=( Actually...zero stars.                               1
Incredible Mango flavor                                         1
AMAZING COFFEE!!                                                1
Remember biting the top and pretending to drink the cola out?   1
Disappointed, not the classic flavor                            1
simply addicting delicous.                                      1
THE best gluten-free cookie!                                    1
Gritty and Gross                                                1
i like it ICED!!!!                                              1
ST. DALFOUR Golden Peach is Delicious                           1
Name: Reviews_Summary, dtype: int64
3    243136
2     53979
0     35097
1     20066
Name: Prediction, dtype: int64
```

```
In [17]: corpus = data["Reviews_Summary"].values[:1000]
         score = data["Prediction"].values[:1000]
```

```
In [18]: print(score[:10])
         print(corpus[:10])
```

```
[3 0 1 2 3 2 3 2 2 3]
['Babies love these' 'Salmon Trout' 'disappointment'
 "Doesn't taste like Cinnabon; tastes like Waffle Crisp"
 'Delicious San Daniele prosciutto and good customer service'
 'My Dog Loves Them' "My husband's new favorite coffee."
 'Good Job, Betty Crocker' 'Good chips, more cheese'
 "Nature's Hallow Sugar Free Jam"]
```

Как видите, каждый объект представляет собой отзыв о продукте и оценку по шкале от 0 до 3. Выдвинем гипотезу, что слова, используемые в написании отзыва коррелируют с оценкой, которая была поставлена. Поставим задачу - предсказать оценку, по тексту отзыва.

1.5 1. Извлечение признаков - 10 Баллов

1. Для решения задачи классификации необходимо преобразовать каждый отзыв (документ) в вектор. Размерность данного вектора будет равна количеству слов используемых в корпусе (все документы). Каждая координата соответствует слову, значение в координает равно количеству раз, слово используется в документе.

Для решения данной задачи вам необходимо написать код, который преобразовывает матрицу документов в численную матрицу.

Дополнительная информация для решения задачи:

- Подробнее про векторное представление документов: http://scikit-learn.org/stable/modules/feature_extraction.html#text-feature-extraction
- Используйте данный трансформер: http://scikit-learn.org/stable/modules/feature_extraction.html#common-vectorizer-usage
- Подробнее про разреженные матрицы: http://docs.scipy.org/doc/scipy-0.14.0/reference/sparse.html
- Hashing trick: https://en.wikipedia.org/wiki/Feature_hashing

Используйте n_features = 3000

```
In [19]: from sklearn.feature_extraction.text import CountVectorizer

         vectorizer = CountVectorizer(min_df=1)

         corpus_vect = vectorizer.fit_transform(corpus)

         print(corpus_vect)

         mean_matrix_vect = corpus_vect.mean(axis = 1)

         # print(vectorizer.get_feature_names())
         # print(corpus_vect.toarray())
```

```
(0, 79)        1
  (0, 666)       1
  (0, 1115)      1
  (1, 938)       1
  (1, 1150)      1
```

```
  (2, 318)	1
  (3, 330)	1
  (3, 1094)	1
  (3, 648)	2
  (3, 220)	1
  (3, 1096)	1
  (3, 1196)	1
  (3, 269)	1
  (4, 301)	1
  (4, 943)	1
  (4, 288)	1
  (4, 880)	1
  (4, 50)	1
  (4, 489)	1
  (4, 282)	1
  (4, 969)	1
  (5, 744)	1
  (5, 331)	1
  (5, 672)	1
  (5, 1114)	1
  :	:
  (995, 437)	1
  (996, 672)	1
  (996, 153)	1
  (996, 440)	1
  (996, 1075)	1
  (996, 471)	1
  (996, 1225)	1
  (996, 458)	1
  (996, 1033)	1
  (996, 1021)	1
  (996, 486)	1
  (997, 744)	1
  (997, 331)	1
  (997, 592)	1
  (997, 1118)	1
  (997, 788)	1
  (997, 1215)	1
  (997, 626)	1
  (997, 649)	1
  (998, 503)	1
  (998, 1133)	1
  (998, 41)	1
  (998, 450)	1
  (999, 489)	1
  (999, 232)	1
```

In [20]:
```
from sklearn.feature_extraction.text import HashingVectorizer

hash_vectorizer = HashingVectorizer(n_features=3000)
print(type(corpus))

corpus_hashed = hash_vectorizer.transform(corpus)
```

```python
print(corpus_hashed)

mean_matrix_hash = corpus_hashed.mean(axis = 1)
```

```
<type 'numpy.ndarray'>
  (0, 1134)	0.57735026919
  (0, 2170)	0.57735026919
  (0, 2201)	-0.57735026919
  (1, 1353)	-0.707106781187
  (1, 1857)	-0.707106781187
  (2, 1544)	1.0
  (3, 1465)	-0.316227766017
  (3, 1473)	-0.316227766017
  (3, 1480)	-0.316227766017
  (3, 1534)	-0.316227766017
  (3, 1706)	0.316227766017
  (3, 1855)	-0.632455532034
  (3, 2437)	0.316227766017
  (4, 72)	0.353553390593
  (4, 442)	-0.353553390593
  (4, 448)	-0.353553390593
  (4, 845)	-0.353553390593
  (4, 1729)	0.353553390593
  (4, 2369)	0.353553390593
  (4, 2381)	-0.353553390593
  (4, 2860)	-0.353553390593
  (5, 93)	-0.5
  (5, 719)	-0.5
  (5, 1490)	0.5
  (5, 1591)	0.5
  :	:
  (995, 2704)	-0.4472135955
  (996, 49)	-0.316227766017
  (996, 275)	0.316227766017
  (996, 861)	0.316227766017
  (996, 985)	-0.316227766017
  (996, 1092)	-0.316227766017
  (996, 1212)	0.316227766017
  (996, 1563)	-0.316227766017
  (996, 1591)	0.316227766017
  (996, 2344)	0.316227766017
  (996, 2462)	0.316227766017
  (997, 93)	-0.353553390593
  (997, 897)	-0.353553390593
  (997, 918)	0.353553390593
  (997, 1124)	-0.353553390593
  (997, 1490)	0.353553390593
  (997, 2201)	0.353553390593
  (997, 2531)	-0.353553390593
  (997, 2763)	-0.353553390593
  (998, 691)	0.5
  (998, 1000)	-0.5
  (998, 2027)	0.5
  (998, 2388)	0.5
```

```
  (999, 1729)        0.707106781187
  (999, 2704)        -0.707106781187
```

```
In [21]: mean_matrix_hash[:10]
```

```
Out[21]: matrix([[ 0.00019245],
                 [-0.0004714 ],
                 [ 0.00033333],
                 [-0.00042164],
                 [-0.0002357 ],
                 [ 0.        ],
                 [-0.00014907],
                 [ 0.00066667],
                 [ 0.        ],
                 [ 0.00044721]])
```

Для учета важности редких, но показательных слов (термов), используется схема взвешивания TF-IDF. Напишите код, принимающий на вход разреженную матрицу векторного представления документов и возвращающий разреженную матрицу документов, частоты термов которых взвешенны по TF-IDF.

Дополнительная информация для решения задачи:

- Подробнее про TF-IDF: https://en.wikipedia.org/wiki/Tf%E2%80%93idf
- Используйте трансформер: http://scikit-learn.org/stable/modules/feature_extraction.html#tfidf-term-weighting

```
In [22]: from sklearn.feature_extraction.text import TfidfTransformer

         TFIDFtransformer = TfidfTransformer()

         corpus_TFIDF = TFIDFtransformer.fit_transform(corpus_hashed)

         print(corpus_TFIDF)
         corpus_TFIDF


         mean_matrix_TFIDF = corpus_TFIDF.mean(axis = 1)
```

```
(0, 2201)        -0.390666501164
  (0, 2170)        0.779067464351
  (0, 1134)        0.490340260287
  (1, 1857)        -0.707106781187
  (1, 1353)        -0.707106781187
  (2, 1544)        1.0
  (3, 2437)        0.400179329608
  (3, 1855)        -0.511667069701
  (3, 1706)        0.251870403554
  (3, 1534)        -0.281490746435
  (3, 1480)        -0.400179329608
  (3, 1473)        -0.400179329608
  (3, 1465)        -0.339250028345
  (4, 2860)        -0.398862124748
  (4, 2381)        -0.42260974453
  (4, 2369)        0.241570983252
  (4, 1729)        0.196491295799
```

```
  (4, 845)        -0.221485108061
  (4, 448)        -0.398862124748
  (4, 442)        -0.42260974453
  (4, 72)        0.42260974453
  (5, 1591)        0.561683898009
  (5, 1490)        0.41152000634
  (5, 719)        -0.523493979178
  (5, 93)        -0.491036186919
  :        :
  (995, 179)        -0.436247113522
  (996, 2462)        0.223607164312
  (996, 2344)        0.37541247004
  (996, 1591)        0.286718110855
  (996, 1563)        -0.184805274749
  (996, 1212)        0.327739843415
  (996, 1092)        -0.327739843415
  (996, 985)        -0.339349520165
  (996, 861)        0.354316996698
  (996, 275)        0.310233920079
  (996, 49)        -0.37541247004
  (997, 2763)        -0.420486443733
  (997, 2531)        -0.378820253791
  (997, 2201)        0.248724097697
  (997, 1490)        0.277544209108
  (997, 1124)        -0.367336841689
  (997, 918)        0.277544209108
  (997, 897)        -0.468133855274
  (997, 93)        -0.33117284225
  (998, 2388)        0.28699434447
  (998, 2027)        0.629513686819
  (998, 1000)        -0.602921027075
  (998, 691)        0.397282015024
  (999, 2704)        -0.765929143778
  (999, 1729)        0.642924993067
```

In [23]:
```
print(mean_matrix_vect[:10])
print(mean_matrix_hash[:10])
print(mean_matrix_TFIDF[:10])
```

```
[[ 0.00236035]
 [ 0.00157356]
 [ 0.00078678]
 [ 0.00629426]
 [ 0.00629426]
 [ 0.00314713]
 [ 0.00393391]
 [ 0.00314713]
 [ 0.00314713]
 [ 0.00393391]]
[[ 0.00019245]
 [-0.0004714 ]
 [ 0.00033333]
 [-0.00042164]
 [-0.0002357 ]
 [ 0.        ]
```

```
 [-0.00014907]
 [ 0.00066667]
 [ 0.        ]
 [ 0.00044721]]
[[  2.92913741e-04]
 [ -4.71404521e-04]
 [  3.33333333e-04]
 [ -4.26905590e-04]
 [ -3.34585608e-04]
 [ -1.37754206e-05]
 [ -1.31798867e-04]
 [  6.44775804e-04]
 [ -7.92367694e-05]
 [  4.08042424e-04]]
```

Преобразуем csc матрицу в numpy array

```
In [24]: corpus_np = corpus_TFIDF.toarray()

         print(corpus_np)
         print(corpus_np.shape)
```

```
[[ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 ...,
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]]
(1000, 3000)
```

1.6 2. Код для SVM и логистической регресии - 40 Баллов

После того, как вы получили матрицу признаков, вам необходимо реализовать алгоритм обучения SVM и логистической регрессии. Обе модели являются линейными и отличаются функциями потерь. Для решения оптимизационных задач в обеих моделей будет использоваться стохастический градиентный спуск.

Дополнительная информация для решения задачи:

- Линейные модели: http://cs231n.github.io/linear-classify/
- SGD: http://cs231n.github.io/optimization-1

Начнем с SVM стартовый код находится в файле cs231n/classifiers/linear_svm.py вашей задачей является реализация подсчета функции потерь для SVM

Разбейте обучающую выборку на 2 части train и test

Дополнительная информация для решения задачи: - Используйте трансформер: http://scikit-learn.org/stable/modules/generated/sklearn.cross_validation.train_test_split.html#sklearn.cross_validation.train_test_sp

```
In [25]: from sklearn import cross_validation

         X_train, X_test, y_train, y_test = cross_validation.train_test_split(corpus_np, score)

In [26]: print(X_train.shape)
         print(X_test.shape)
         print(y_train.shape)
         print(y_test.shape)
```

```
(750, 3000)
(250, 3000)
(750,)
(250,)
```

Транспонируем матрицы с данными, т.к. так будет проще реализовать код SVM

```
In [27]: X_train = X_train.transpose()
         X_test = X_test.transpose()
```

Возьмем подвыборки из обучающей выборки, для быстрой проверки кода.

```
In [28]: X_train_sample = X_train[:, 0:1000]
         y_train_sample = y_train[0:1000]

In [29]: print(X_train_sample.shape)
         print(y_train_sample.shape)
```

```
(3000, 750)
(750,)
```

Найдем чему равен градиент:

```
In [30]: from cs231n.classifiers.linear_svm import svm_loss_naive
         import time

         # generate a random SVM weight matrix of small numbers
         W = numpy.random.randn(4, X_train_sample.shape[0]) * 0.01
         loss, grad = svm_loss_naive(W, X_train_sample, y_train_sample, 0.00001)
         print 'loss: %f' % (loss, )
```

```
loss: 3.000200
```

Градиент равен 0, т.к. код который должен его считать отсутствует. Реализуйте наивную версию и проверьте результат с помощью численного метода расчета. Градиенты должны почти совпадать.

```
In [31]: # Once you've implemented the gradient, recompute it with the code below
         # and gradient check it with the function we provided for you

         # Compute the loss and its gradient at W.
         loss, grad = svm_loss_naive(W, X_train_sample, y_train_sample, 0.0)

         # Numerically compute the gradient along several randomly chosen dimensions, and
         # compare them with your analytically computed gradient. The numbers should match
         # almost exactly along all dimensions.
         from cs231n.gradient_check import grad_check_sparse
         f = lambda w: svm_loss_naive(w, X_train_sample, y_train_sample, 0.0)[0]
         grad_numerical = grad_check_sparse(f, W, grad, 5)
```

```
numerical: 0.000000 analytic: 0.000000, relative error: nan
numerical: 0.000000 analytic: 0.000000, relative error: nan
numerical: 0.000000 analytic: 0.000000, relative error: nan
numerical: 0.000000 analytic: 0.000000, relative error: nan
numerical: 0.000800 analytic: 0.000800, relative error: 7.134922e-09
```

Теперь реализуйте векторизованную версию расчета фунции потерь - svm_loss_vectorized

```
In [32]: tic = time.time()
         loss_naive, grad_naive = svm_loss_naive(W, X_train_sample, y_train_sample, 0.00001)
         toc = time.time()
         print 'Naive loss: %e computed in %fs' % (loss_naive, toc - tic)

         from cs231n.classifiers.linear_svm import svm_loss_vectorized
         tic = time.time()
         loss_vectorized, _ = svm_loss_vectorized(W, X_train_sample, y_train_sample, 0.00001)
         toc = time.time()
         print 'Vectorized loss: %e computed in %fs' % (loss_vectorized, toc - tic)

         # The losses should match but your vectorized implementation should be much faster.
         print 'difference: %f' % (loss_naive - loss_vectorized)
```

```
Naive loss: 3.000200e+00 computed in 0.039408s
Vectorized loss: 3.000200e+00 computed in 0.022170s
difference: -0.000000
```

Завершите реализацию SVM, реализуйте векторизированную версию расчета градиента.

```
In [33]: tic = time.time()
         _, grad_naive = svm_loss_naive(W, X_train_sample, y_train_sample, 0.00001)
         toc = time.time()
         print 'Naive loss and gradient: computed in %fs' % (toc - tic)

         tic = time.time()
         _, grad_vectorized = svm_loss_vectorized(W, X_train_sample, y_train_sample, 0.00001)
         toc = time.time()
         print 'Vectorized loss and gradient: computed in %fs' % (toc - tic)

         # The loss is a single number, so it is easy to compare the values computed
         # by the two implementations. The gradient on the other hand is a matrix, so
         # we use the Frobenius norm to compare them.
         difference = numpy.linalg.norm(grad_naive - grad_vectorized, ord='fro')
         print 'difference: %f' % difference
```

```
Naive loss and gradient: computed in 0.034995s
Vectorized loss and gradient: computed in 0.022172s
difference: 0.000011
```

1.7 Stochastic Gradient Descent

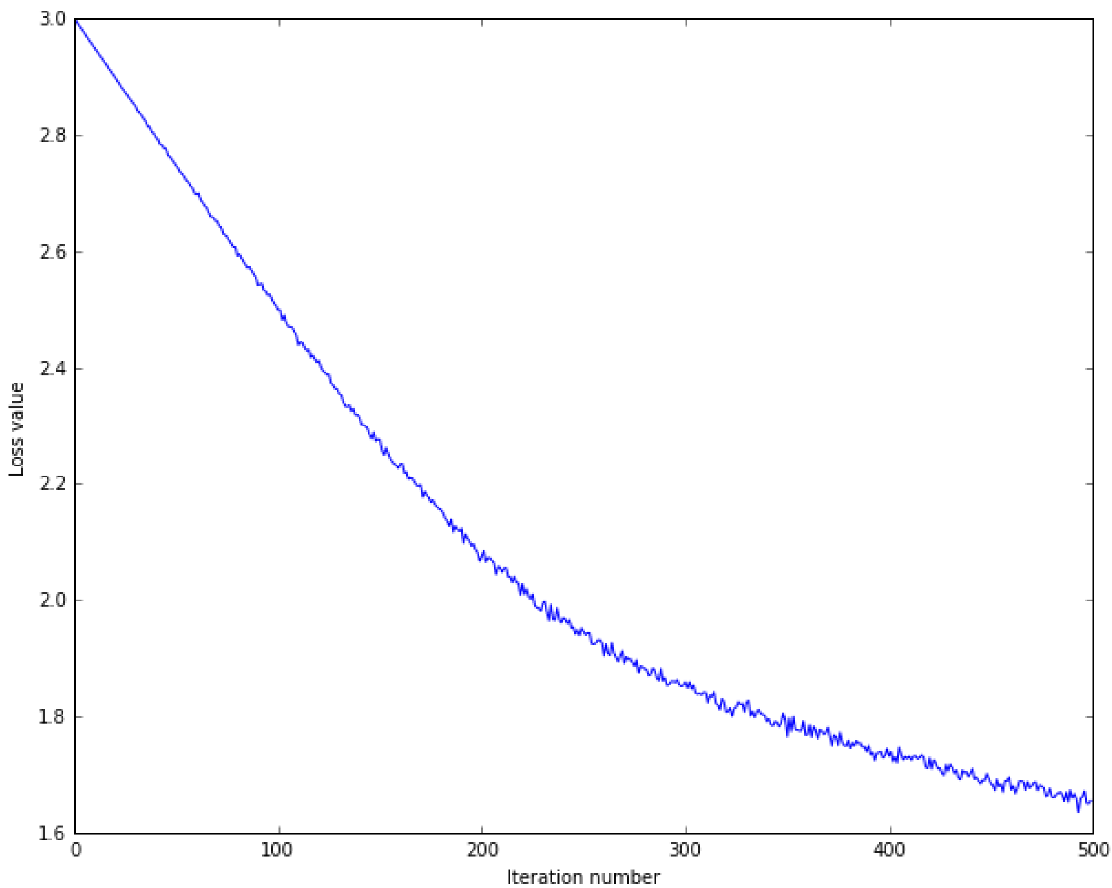
```
In [36]: # Now implement SGD in LinearSVM.train() function and run it with the code below
         from cs231n.classifiers import LinearSVM
         svm = LinearSVM()
         tic = time.time()
         loss_hist = svm.train(X_train, y_train, learning_rate=5e-2, reg=0.01,
                               num_iters=500, verbose=True, batch_size=20000)

         toc = time.time()
         print 'That took %fs' % (toc - tic)
         print 'Current loss is %f' % loss_hist[-1]
```

```
iteration 0 / 500: loss 2.999926
iteration 100 / 500: loss 2.498815
```

```
iteration 200 / 500: loss 2.075648
iteration 300 / 500: loss 1.858928
iteration 400 / 500: loss 1.731245
That took 410.631081s
Current loss is 1.654567
```

In [37]:
```python
# A useful debugging strategy is to plot the loss as a function of
# iteration number:
plt.plot(loss_hist)
plt.xlabel('Iteration number')
plt.ylabel('Loss value')
```

Out[37]: <matplotlib.text.Text at 0x7f1bc9c10750>



In [38]:
```python
# Write the LinearSVM.predict function
y_train_pred = svm.predict(X_train)
y_test_pred = svm.predict(X_test)
```

In [39]:
```python
#and evaluate the performance on both the test set
from sklearn.metrics import classification_report
```

In [40]:
```python
print classification_report(y_test, y_test_pred)
```

```
precision    recall  f1-score   support

          0       0.40      0.24      0.30        25
          1       0.14      0.07      0.10        14
          2       0.13      0.07      0.09        30
          3       0.76      0.89      0.82       181

avg / total       0.61      0.68      0.64       250
```

In [41]:
```
# compare result with the most common dummy classifier
print classification_report(y_test, [3]*len(y_test))
```

```
precision    recall  f1-score   support

          0       0.00      0.00      0.00        25
          1       0.00      0.00      0.00        14
          2       0.00      0.00      0.00        30
          3       0.72      1.00      0.84       181

avg / total       0.52      0.72      0.61       250

/usr/lib/python2.7/site-packages/sklearn/metrics/classification.py:1074: UndefinedMetricWarning: Precisi
  'precision', 'predicted', average, warn_for)
```

1.8 Softmax Classifier

In [42]:
```
# First implement the naive softmax loss function with nested loops.
# Open the file cs231n/classifiers/softmax.py and implement the
# softmax_loss_naive function.

from cs231n.classifiers.softmax import softmax_loss_naive
import time

# Generate a random softmax weight matrix and use it to compute the loss.
W = numpy.random.randn(4, X_train_sample.shape[0]) * 0.01
loss, grad = softmax_loss_naive(W, X_train_sample, y_train_sample, 0.0)

# As a rough sanity check, our loss should be something close to -log(0.1).
print 'loss: %f' % loss
print 'sanity check: %f' % (-numpy.log(0.1))
```

```
loss: 1.386475
sanity check: 2.302585
```

In [43]:
```
# Complete the implementation of softmax_loss_naive and implement a (naive)
# version of the gradient that uses nested loops.
loss, grad = softmax_loss_naive(W, X_train_sample, y_train_sample, 0.0)

# As we did for the SVM, use numeric gradient checking as a debugging tool.
# The numeric gradient should be close to the analytic gradient.
from cs231n.gradient_check import grad_check_sparse
f = lambda w: softmax_loss_naive(w, X_train_sample, y_train_sample, 0.0)[0]
grad_numerical = grad_check_sparse(f, W, grad, 5)
```

```
numerical: -0.000327 analytic: -0.000327, relative error: 8.012937e-09
numerical: 0.000000 analytic: 0.000000, relative error: nan
```

```
numerical: 0.000621 analytic: 0.000621, relative error: 9.943626e-10
numerical: 0.000000 analytic: 0.000000, relative error: nan
numerical: 0.000000 analytic: 0.000000, relative error: nan
```

In [45]:
```
# Now that we have a naive implementation of the softmax loss function and its gradient,
# implement a vectorized version in softmax_loss_vectorized.
# The two versions should compute the same results, but the vectorized version should be
# much faster.
tic = time.time()
loss_naive, grad_naive = softmax_loss_naive(W, X_train_sample, y_train_sample, 0.00001)
toc = time.time()
print 'naive loss: %e computed in %fs' % (loss_naive, toc - tic)

from cs231n.classifiers.softmax import softmax_loss_vectorized
tic = time.time()
loss_vectorized, grad_vectorized = softmax_loss_vectorized(W, X_train_sample, y_train_sample, (
toc = time.time()
print 'vectorized loss: %e computed in %fs' % (loss_vectorized, toc - tic)

# As we did for the SVM, we use the Frobenius norm to compare the two versions
# of the gradient.
grad_difference = numpy.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print 'Loss difference: %f' % numpy.abs(loss_naive - loss_vectorized)
print 'Gradient difference: %f' % grad_difference
```

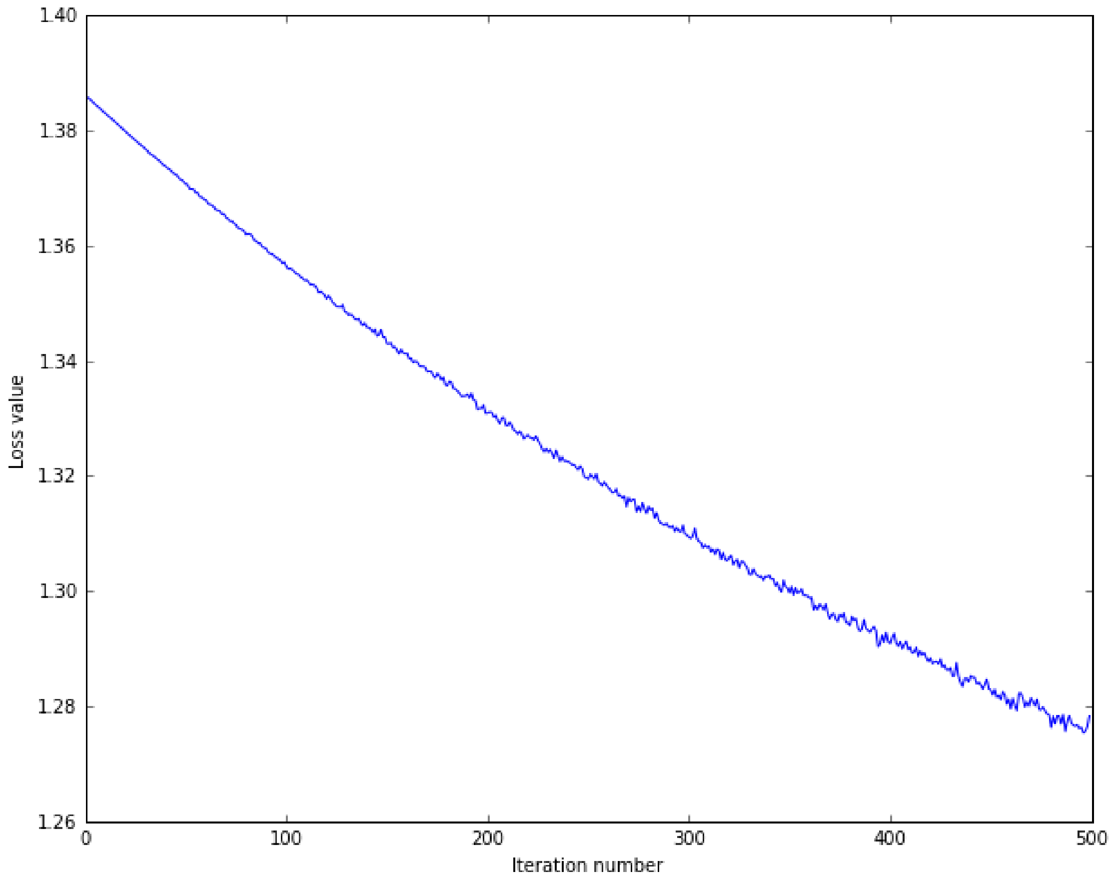
```
naive loss: 1.386481e+00 computed in 0.054284s
vectorized loss: 1.386481e+00 computed in 0.033899s
Loss difference: 0.000000
Gradient difference: 0.000000
```

In [46]:
```
from cs231n.classifiers import Softmax
sm = Softmax()
tic = time.time()
loss_hist = sm.train(X_train, y_train, learning_rate=5e-2, reg=0.01,
                      num_iters=500, verbose=True, batch_size=20000)

toc = time.time()
print 'That took %fs' % (toc - tic)
print 'Current loss is %f' % loss_hist[-1]
```

```
iteration 0 / 500: loss 1.386206
iteration 100 / 500: loss 1.356404
iteration 200 / 500: loss 1.330890
iteration 300 / 500: loss 1.309366
iteration 400 / 500: loss 1.290849
That took 515.802718s
Current loss is 1.278269
```

In [47]:
```
# A useful debugging strategy is to plot the loss as a function of
# iteration number:
plt.plot(loss_hist)
plt.xlabel('Iteration number')
plt.ylabel('Loss value')
```

Out[47]:
```
<matplotlib.text.Text at 0x7f1bc9ac3750>
```




```
In [48]: # Write the LinearSVM.predict function
         y_train_pred = sm.predict(X_train)
         y_test_pred = sm.predict(X_test)
```

```
In [49]: print classification_report(y_test, y_test_pred)
```

```
precision    recall  f1-score   support

          0       0.38      0.20      0.26        25
          1       0.14      0.07      0.10        14
          2       0.07      0.03      0.05        30
          3       0.75      0.90      0.82       181

avg / total       0.60      0.68      0.63       250
```

```
In [50]: # compare result with the most common dummy classifier
         print classification_report(y_test, [3]*len(y_test))
```

```
precision    recall  f1-score   support

          0       0.00      0.00      0.00        25
          1       0.00      0.00      0.00        14
          2       0.00      0.00      0.00        30
```

```
          3       0.72      1.00      0.84       181

avg / total       0.52      0.72      0.61       250
```

1.9 Cross-validation

In [51]:
```
data = pandas.read_csv("kaggle_data/train.csv", index_col=0, na_values="NaN")

print(data.shape)
print(data.head())
print(data.tail())
```

```
(352278, 2)
                                           Reviews_Summary  Prediction
ID
230872  Babies love these                                    3
344823  Salmon Trout                                         0
211754  disappointment                                       1
259421  Doesn't taste like Cinnabon; tastes like Waffle Crisp      2
253418  Delicious San Daniele prosciutto and good customer service  3
                      Reviews_Summary  Prediction
ID
110273  We enjoy this coffee                   3
259187  Satisfied                              2
365859  quite good                             3
131937  Great yummy treat for my little ones   3
121963  Disappointed                           1
```

In [52]:
```
corpus = data["Reviews_Summary"].values[:1000]
score = data["Prediction"].values[:1000]
```

In [53]:
```
from sklearn.feature_extraction.text import HashingVectorizer

hash_vectorizer = HashingVectorizer(n_features=3000)

corpus_hashed = hash_vectorizer.transform(corpus)

# print(corpus_hashed)

mean_matrix_hash = corpus_hashed.mean(axis = 1)
```

In [54]:
```
from sklearn.feature_extraction.text import TfidfTransformer

TFIDFtransformer = TfidfTransformer()

corpus_TFIDF = TFIDFtransformer.fit_transform(corpus_hashed)

print(corpus_TFIDF)
corpus_TFIDF


mean_matrix_TFIDF = corpus_TFIDF.mean(axis = 1)
```

```
(0, 2201)        -0.390666501164
  (0, 2170)        0.779067464351
```

```
  (0, 1134)	0.490340260287
  (1, 1857)	-0.707106781187
  (1, 1353)	-0.707106781187
  (2, 1544)	1.0
  (3, 2437)	0.400179329608
  (3, 1855)	-0.511667069701
  (3, 1706)	0.251870403554
  (3, 1534)	-0.281490746435
  (3, 1480)	-0.400179329608
  (3, 1473)	-0.400179329608
  (3, 1465)	-0.339250028345
  (4, 2860)	-0.398862124748
  (4, 2381)	-0.42260974453
  (4, 2369)	0.241570983252
  (4, 1729)	0.196491295799
  (4, 845)	-0.221485108061
  (4, 448)	-0.398862124748
  (4, 442)	-0.42260974453
  (4, 72)	0.42260974453
  (5, 1591)	0.561683898009
  (5, 1490)	0.41152000634
  (5, 719)	-0.523493979178
  (5, 93)	-0.491036186919
  :	:
  (995, 179)	-0.436247113522
  (996, 2462)	0.223607164312
  (996, 2344)	0.37541247004
  (996, 1591)	0.286718110855
  (996, 1563)	-0.184805274749
  (996, 1212)	0.327739843415
  (996, 1092)	-0.327739843415
  (996, 985)	-0.339349520165
  (996, 861)	0.354316996698
  (996, 275)	0.310233920079
  (996, 49)	-0.37541247004
  (997, 2763)	-0.420486443733
  (997, 2531)	-0.378820253791
  (997, 2201)	0.248724097697
  (997, 1490)	0.277544209108
  (997, 1124)	-0.367336841689
  (997, 918)	0.277544209108
  (997, 897)	-0.468133855274
  (997, 93)	-0.33117284225
  (998, 2388)	0.28699434447
  (998, 2027)	0.629513686819
  (998, 1000)	-0.602921027075
  (998, 691)	0.397282015024
  (999, 2704)	-0.765929143778
  (999, 1729)	0.642924993067
```

In [55]:
```
corpus_np = corpus_TFIDF.toarray()

print(corpus_np)
print(corpus_np.shape)
```

```
[[ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 ...,
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]]
(1000, 3000)
```

```
In [56]: CVX_train = corpus_np
         CVy_train = score
```

```
In [57]: CVX_train = CVX_train.transpose()
         CVy_train = CVy_train.transpose()
```

```
In [58]: from sklearn import metrics

         def accuracy(y_true, y_predict):
             return metrics.accuracy_score(y_true, y_predict)
```

```
In [62]: # Cross validation
         from sklearn import cross_validation
         from datetime import datetime

         def my_cross_validation(X, y, predictor, batch_size, q_fold = 5, r_fold = 5):

             scores = []

             total_size = X.shape[1]

             seed = datetime.now().microsecond + datetime.now().second * 1000000

             shuffled_split = cross_validation.ShuffleSplit(total_size, n_iter=r_fold, test_size=1.0/q_f

             for train_index, test_index in shuffled_split:
         #         print(train_index, test_index)
         #         print(X.shape)
                 X_train = X[:, train_index]
                 y_train = y[train_index]
                 X_test = X[:, test_index]
                 y_test = y[test_index]

                 predictor.train(X_train, y_train, learning_rate=5e-2, reg=0.01,
                               num_iters=500, verbose=True, batch_size=20000)

                 y_predicted = predictor.predict(X_test)

         #         predictor = predictor.fit(X_train, y_train)
         #         predictor = predictor.calc_dist(X_test, metric)
         #         y_predicted = predictor.predict_labels(X_test)

                 scores.append(accuracy(y_test, y_predicted))

             return np.mean(scores)
```

```
In [66]: from cs231n.classifiers import Softmax

         my_cross_validation(CVX_train, CVy_train, Softmax(), 2500)
```

```
0.74
```

```
In [67]: # for chunk in get_chunks(urls, 3):
         #     %job [fetch_url(_) for _ in log_progress(chunk, every=1)]

         import sys

         for batch_size in [10, 15, 20, 25]:#[10000, 15000, 20000, 25000]:
             %job [sys.stderr.print(my_cross_validation(CVX_train, CVy_train, Softmax(), _)) for _ in lo
```

```
Starting job # 5 in a separate thread.
Starting job # 6 in a separate thread.
Starting job # 7 in a separate thread.
Starting job # 8 in a separate thread.
```

```
In [68]: for job in jobs.running:
             kill_thread(job)
```

1.10 3. Kaggle In Class - 50 Баллов

Используйте полученные модели для решения контеста. Выберете одну из моделей, реализуйте настройку гиперпараметров и пайплайн для предсказания классов тестовой выборки для сабмита в систему.

1.11 Disclaimer

Финальные результаты для контеста я получал на другом, более мощном компе (здесь датасет не влезал в оперативку, начинался лютый swap, трешинг и оно могло продолжаться вечно).

Поэтому в этом ноутбуке эта часть не исполнялась.

Однако, в архиве лежит та самая посылка, кажется.

```
In [3]: corpus = data["Reviews_Summary"].values[:150000]
        score = data["Prediction"].values[:150000]
```

```
In [4]: from sklearn.feature_extraction.text import HashingVectorizer

        hash_vectorizer = HashingVectorizer(n_features=3000)

        corpus_hashed = hash_vectorizer.transform(corpus)

        # print(corpus_hashed)

        mean_matrix_hash = corpus_hashed.mean(axis = 1)
```

```
In [5]: from sklearn.feature_extraction.text import TfidfTransformer

        TFIDFtransformer = TfidfTransformer()

        corpus_TFIDF = TFIDFtransformer.fit_transform(corpus_hashed)

        print(corpus_TFIDF)
```

```
corpus_TFIDF
```

```
mean_matrix_TFIDF = corpus_TFIDF.mean(axis = 1)
```

```
(0, 2201)        -0.388087041871
  (0, 2170)        0.797261449037
  (0, 1134)        0.46234470886
  (1, 1857)        -0.585449721059
  (1, 1353)        -0.810708717181
  (2, 1544)        1.0
  (3, 2437)        0.406636837688
  (3, 1855)        -0.472879818054
  (3, 1706)        0.223009443256
  (3, 1534)        -0.276326371382
  (3, 1480)        -0.427133236033
  (3, 1473)        -0.429236822175
  (3, 1465)        -0.343881714801
  (4, 2860)        -0.415063911996
  (4, 2381)        -0.479051022982
  (4, 2369)        0.208293833248
  (4, 1729)        0.166347090244
  (4, 845)        -0.181486200877
  (4, 442)        -0.315606706645
  (4, 442)        -0.35157973944
  (4, 72)        0.520597006681
  (5, 1591)        0.528041718732
  (5, 1490)        0.405698776136
  (5, 719)        -0.567388184332
  (5, 93)        -0.484407983627
  :        :
  (149994, 811)        0.36106911323
  (149994, 582)        0.246338063177
  (149994, 522)        -0.257311653332
  (149994, 312)        0.514746539396
  (149995, 2294)        1.0
  (149996, 2388)        0.341739803231
  (149996, 1801)        0.778369270629
  (149996, 972)        0.526645217797
  (149997, 2958)        -0.338519179805
  (149997, 1298)        -0.494010033191
  (149997, 735)        0.666610424603
  (149997, 277)        0.443834872246
  (149998, 2729)        0.750388410987
  (149998, 1209)        0.660997150264
  (149999, 2996)        0.301877382692
  (149999, 2958)        -0.166352860126
  (149999, 2284)        -0.276875393828
  (149999, 1682)        0.315189493813
  (149999, 1568)        0.335193964914
  (149999, 1298)        -0.242763148605
  (149999, 1209)        0.271153695427
  (149999, 1118)        -0.406101180722
  (149999, 869)        0.316097711125
```

```
  (149999, 534)        -0.384672288263
  (149999, 277)        0.218106402315
```

In [6]:
```
corpus_np = corpus_TFIDF.toarray()

print(corpus_np)
print(corpus_np.shape)
```

```
[[ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 ...,
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]]
(150000, 3000)
```

In [70]:
```
KX_train = corpus_np[:10]
Ky_train = score[:10]
```

In [71]:
```
KX_train = KX_train.transpose()
Ky_train = Ky_train.transpose()
```

In [ ]:
```
from cs231n.classifiers import Softmax
import time
sm = Softmax()
tic = time.time()
loss_hist = sm.train(KX_train, Ky_train, learning_rate=5e-2, reg=0.01,
                      num_iters=500, verbose=True, batch_size=20000)

toc = time.time()
print 'That took %fs' % (toc - tic)
print 'Current loss is %f' % loss_hist[-1]
```

```
iteration 0 / 500: loss 1.386600
```

In [ ]:
```
data_test = pandas.read_csv("kaggle_data/test.csv", na_values="NaN")

print(data_test.shape)
print(data_test.head())
print(data_test.tail())
```

In [ ]:
```
KX_test = data_test["Reviews_Summary"]
KIDs = data_test["ID"]
```

In [ ]:
```
from sklearn.feature_extraction.text import HashingVectorizer

hash_vectorizer = HashingVectorizer(n_features=3000)

KX_test_hashed = hash_vectorizer.transform(KX_test)

# print(corpus_hashed)

mean_matrix_hash = KX_test_hashed.mean(axis = 1)
```

In [ ]:
```
from sklearn.feature_extraction.text import TfidfTransformer
```

```
TFIDFtransformer = TfidfTransformer()

KX_test_TFIDF = TFIDFtransformer.fit_transform(KX_test_hashed)

print(KX_test_TFIDF)
KX_test_TFIDF


mean_matrix_TFIDF = KX_test_TFIDF.mean(axis = 1)
```

In [ ]:
```
KX_test = KX_test_TFIDF.toarray()

print(KX_test)
print(KX_test.shape)
```

In [ ]:
```
KX_test = KX_test.transpose()

print(KX_test.shape)
```

In [ ]:
```
Ky_test_pred = sm.predict(KX_test)
```

In [ ]:
```
print(Ky_test_pred)
print(Ky_test_pred.shape)
```

In [ ]:
```
print(numpy.unique(Ky_test_pred, return_counts = True)) # no NaN
```

In [ ]:
```
import sys

ans = open("kaggle_prediction.csv", "w")

ans.write("ID,class_0,class_1,class_2,class_3\n")

for index in range(KIDs.size):
    ID = KIDs[index]
    class_0 = float(Ky_test_pred[index] == 0)
    class_1 = float(Ky_test_pred[index] == 1)
    class_2 = float(Ky_test_pred[index] == 2)
    class_3 = float(Ky_test_pred[index] == 3)
    ans.write("%d,%.1f,%.1f,%.1f,%.1f\n" % (ID, class_0, class_1, class_2, class_3))

ans.close()
```

1.12 Fin