Assignment 3

November 29, 2019

This set of assingments will teach you the differences between various fairness measures. Note that this is not a programming assingment.

Assume we have a Binary classifier to promote employees in an organization. The following table presents the Confusion Matrix for female and male employees:

Female	Actual positive	Actual negative
Predicted positve	30	70
Predicted negative	20	105

Male	Actual positive	Actual negative
Predicted positve	100	15
Predicted negative	90	20

1- Calculate the overall accuracy of the promotion classifier.

2- Calculate the accuracy of the promotion system for female and male employees.

3- Evaluate the pormotion system based on three fairness measures: Demographic parity, Equialized odds, and Equiality of opportunity.

4- Is this promotion model fair? if not, suggest an approach to make it fair. Justify your answer.

Answer

Please note that I expressed all probability calculations in up to 4 decimal places. The exact values shall be the fraction.

1. Overall Accuracy

$$\frac{\sum_G TP + TN}{\sum_G TP + FP + TN + FN} = \frac{30 + 105 + 100 + 20}{30 + 70 + 105 + 20 + 100 + 15 + 20 + 90} = \frac{255}{450} = 0.5667$$

2. Accuracies

Female:

$$\frac{TP + TN}{TP + FP + TN + FN} = \frac{30 + 105}{30 + 70 + 105 + 20} = \frac{135}{225} = 0.6$$

Male:

$$\frac{TP+TN}{TP+FP+TN+FN} = \frac{100+20}{100+15+20+90} = \frac{135}{225} = 0.5333$$

Female have a higher prediction accuracy than male

3.

Demographic Parity:

Female:

$$P(d=1|G=f) = \frac{30+70}{30+70+105+20} = \frac{100}{225} = 0.4444$$

Male:

$$P(d=1|G=m) = \frac{100+15}{100+15+20+90} = \frac{115}{225} = 0.5111$$

Male's is predicted positive is higher than female's

Equalized Odds:

Female:

$$P(d=1|Y=0,G=f) = \frac{70}{70+105} = \frac{70}{175} = 0.4$$

$$P(d=1|Y=1,G=f) = \frac{30}{30+20} = \frac{30}{50} = 0.6$$

Male:

$$P(d=1|Y=0,G=m) = \frac{15}{15+20} = \frac{15}{35} = 0.4286$$

$$P(d=1|Y=1,G=m) = \frac{100}{100+90} = \frac{100}{190} = 0.5263$$

When given it's actually negative, male's predicted positive is higher, so that's as if male were given false presumptions; when given it's actually positive, female's predicted positive is higher.

Equality of Opportunity:

Female:

$$P(d=0|Y=1,G=f) = \frac{20}{30+20} = \frac{20}{50} = 0.4$$

$$P(d=1|Y=1,G=f) = \frac{30}{20+30} = \frac{30}{50} = 0.6$$

Male:

$$P(d=0|Y=1,G=m) = \frac{90}{100+90} = \frac{90}{190} = 0.4737$$

$$P(d=1|Y=1,G=m) = \frac{100}{100+90} = \frac{100}{190} = 0.5263$$

When it's actually positive, we see male's predicted negative is higher, and female's predicted positive is higher.

4. Answer

In a general sense this system is not 100% fair, justified sufficiently by evaluation metrics we calculated above, as none of the metrics provide equal results as it shuold have been. Although there is no significant one-sided preference/bias towards one gender, male could get more favoured pre-judgement from, for instance, equalized odds.

We can improvise on a system level. One approach could be adding fairness constraints and to make it easy to solve for, making it a regularization parameter. For the problem concerned, when minimizing the loss function, we shall do so such that it's subjected to a certain metric, say demographic parity. Define a small constant (say smaller than 0.01), θ, and have

$$\theta >= |P(d=1|G=f) - P(d=1|G=m)|$$

And minimize the new, regularized loss function:

$$f_\theta(x, y; \theta) + \lambda \times \theta$$

And we can impose other regularization terms accordingly using the same technique, and in a way such that we achieve balance between being reasonably easy to solve the problem and ensure all the metrics are represented

Natural Language Processing

This set of assignments will give you experience with a text corpus, Python programming, part-of-speech (PoS) tags, sentiment analysis, and machine learning with scikit-learn.

This assignment shows how you can perform sentiment analysis on reviews using Python and [Natural Language Toolkit (NLTK) (https://www.nltk.org/)](https://www.nltk.org/).

Sentiment Analysis means analyzing the sentiment of a given text or document and categorizing the text/document into a specific class or category (like positive and negative). In other words, building a sentiment analysis model classifies any particular text or document as positive or negative. In the simplest form, the classification is done for two classes: positive and negative. However, we can add more classes like neutral, highly positive, highly negative, etc.

Sentiment analysis is an important topic in computational linguistics in which we quantify subjective aspects of language. These aspects can range from biases in social media for marketing, to a spectrum of cognitive behaviours for disease diagnosis.

In this assignment, you learn about labeling data, extracting features, training classifier, and testing the accuracy of the classifier.

For this assignment, we use a reviews dataset as our labeled data which is collected from Yelp, Amazon, and IMDB. We attempted to select sentences that have a clearly positive or negative connotaton, the goal was for no neutral sentences to be selected. The review corpus contains reviews with sentiment polarity classification, where score is either 1 (for positive) or 0 (for negative). You can find the assignment data on the [website (https://github.com/ift6758/ift6758.github.io/blob/master/assignments/assignment_3(data)](https://github.com/ift6758/ift6758.github.io/blob/master/assignments/assignment_3(data)).zip).

a) (Data processing): First create a list of all reviews and their categories. You can create a list of tuples where the first item is the review and the second item is the sentiment, i.e., '0' or '1'.

```python
In [0]: train_path = './assignment_3(data)/reviews/train.txt'
        test_path = './assignment_3(data)/reviews/test.txt'
        # create a list of all reviews and their categories
        def createlist(path):
            with open(path,'r') as fp:
                data = fp.read()
            data = data.split('\n')
            ret = []
            for i,review_label in enumerate(data):
                if len(review_label)==0:
                    print(i+1,':Blank line')
                    continue
                label = int(review_label[-1])
                review = ' '.join(review_label[:-1].split(' ')).replace('\t',
        '')
                ret.append((review,label),)
            return ret
        train_original  = createlist(train_path)
        test_original = createlist(test_path)
```

```
669 :Blank line
1418 :Blank line
225 :Blank line
```

b) (Tokenization): Extract all the words from the reviews. You can either use the string *split()* method directly or use the following method from NLTK.

```python
In [0]: from nltk.tokenize import word_tokenize
        # Extract all the words from the reviews
        def extract_words(original):
            ret = []
            for review,label in original:
                tokens = []
                for token in word_tokenize(review):
                    if token.lower() not in ['.',',','?','!']:
                        tokens.append(token.lower())
                ret.append((tokens,label),)
            return ret
        train_token = extract_words(train_original)
        test_token = extract_words(test_original)
```

Calculate the number of occurence of each word in the entire corpus and report the 10 most common tokens. You can use the following method from NLTK.

In [0]:
```python
from nltk.probability import FreqDist

fdist = FreqDist()
# Count the number of words
for review,_ in train_token+test_token:
    for word in review:
        fdist[word.lower()] += 1
print('the 10 most common tokens:')
for token,n in fdist.most_common(10):
    print(token,'\t',n)
```

```
the 10 most common tokens:
the      1941
and      1134
i        1027
a        886
it       784
is       760
to       667
this     642
of       622
was      594
```

c) (Stop words removal): Remove all the stop words from the reviews and re-calculate the number of occurence of each word in the entire corpus.

In [0]:

```
from nltk.corpus import stopwords

stopwords_english = stopwords.words('english')

# Extract all the words from the reviews(Not included stopwords)
def extract_words_remove_stop_words(original):
    ret = []
    for review,label in original:
        tokens = []
        for token in word_tokenize(review):
            if token.lower() not in stopwords_english:
                tokens.append(token.lower())
        ret.append((tokens,label),)
    return ret

train_token_remove_stopwords = extract_words_remove_stop_words(train_
original)
test_token_remove_stopwords = extract_words_remove_stop_words(test_or
iginal)

fdist = FreqDist()
# Count the number of words
for tokens,_ in train_token_remove_stopwords+test_token_remove_stopwo
rds:
    for token in tokens:
        fdist[token] += 1
print('the 10 most common tokens:')
for token,n in fdist.most_common(10):
    print(token,'\t',n)
```

```
the 10 most common tokens:
. 	 2639
, 	 1306
! 	 503
n't 	 276
's 	 244
good 	 225
great 	 209
movie 	 180
phone 	 165
film 	 159
```

d) (Stemmization): Normalize the reviews by stemming and re-calculate the number of occurence of each word in the entire corpus. You can use the following function from NLTK.

In [0]:
```python
from nltk.stem import SnowballStemmer

stemmer_spanish = SnowballStemmer('english')

# Extract all the words from the reviews and stemmization
def extract_words_remove_stop_words(original):
    ret = []
    for review,label in original:
        tokens = []
        for token in word_tokenize(review):
            if token.lower() not in stopwords_english:
                tokens.append(stemmer_spanish.stem(token.lower()))
        ret.append((tokens,label),)
    return ret

train_stemmization = extract_words_remove_stop_words(train_original)
test_stemmization = extract_words_remove_stop_words(test_original)

fdist = FreqDist()
for tokens,_ in train_stemmization+test_stemmization:
    for token in tokens:
        fdist[token] += 1
print('the 10 most common tokens:')
for token,n in fdist.most_common(10):
    print(token,'\t',n)
```

```
the 10 most common tokens:
.	 2639
,	 1306
!	 503
n't	 276
's	 244
good	 225
great	 210
movi	 210
film	 186
phone	 174
```

e) (BOW): Create 1-hot encoding and represent each review as Bag of Words (BOW).

In [0]:
```python
# Build vocabulary and generate vectors
bow = {}
index = 0
for word in fdist:
    bow[word] = index
    bow[index] = word
    index+=1
print('number of words:',index)

# get one-hot
def get_one_hot(stemization):
    ret = []
    for review,label in stemization:
        one_hot = [0]*(len(bow)//2)
        for token in review:
            one_hot[bow[token]]+=1
        ret.append((one_hot,label),)
    return ret

train_one_hot = get_one_hot(train_stemmization)
test_one_hot = get_one_hot(test_stemmization)
```

```
number of words: 4140
```

f) (Train a Classifier): Use reviews in the train folder as "train-set" and use reviews in the test folder as "test-set". Use Naive Bayes Classifer to train your sentiment predictor. You can use the following code for this purpose.

In [0]:
```python
from nltk import NaiveBayesClassifier,classify
import collections
# create unigram dataset
def getset(stemmization):
    ret = []
    for tokens,label in stemmization:
        features = collections.defaultdict(int)
        for feature in tokens:
            features[feature] += 1
        ret.append((features,label),)
    return ret

train_unigram_set = getset(train_stemmization)
test_unigram_set = getset(test_stemmization)

classifier = NaiveBayesClassifier.train(train_unigram_set)

accuracy = classify.accuracy(classifier, test_unigram_set)
print(accuracy)
```

```
0.8
```

g) (N-gram): There are different n-grams like unigram, bigram, trigram, etc. For example, Bigram = Item having two words, such as, very good. BOW and unigram representation as the same.

Extract Bigram features from the reviews and re-train the model with Naive Bayes classifier on the train-set and report accuracy on the test-set. You can use the following method from NLTK to extract bigrams.

In [0]:

```
from nltk.util import ngrams
import collections

fdisk_bigram = FreqDist()
# create bigram dataset
def get_bigram_set(stemmization):
    ret = []
    for tokens,label in stemmization:
        features = collections.defaultdict(int)
        for feature in ngrams(tokens,2):
            features[feature[0]+' '+feature[1]] += 1
            fdisk_bigram[feature[0]+' '+feature[1]] += 1
        ret.append((features,label),)
    return ret

train_bigram_set = get_bigram_set(train_stemmization)
test_bigram_set = get_bigram_set(test_stemmization)


classifier = NaiveBayesClassifier.train(train_bigram_set)

accuracy = classify.accuracy(classifier, test_bigram_set)
print(accuracy)
```

```
0.696
```

h) (Combined features): Represent each review based on the combination of 2000 most frequent unigram and bi-grams. Re-train the Naive Bayes Classifier and report the accuracy.

In [0]:

```
most_frequent_unigram = set(map(lambda x:x[0],fdist.most_common(2000
)))
most_frequent_bigram = set(map(lambda x:x[0],fdisk_bigram.most_common
(2000)))

# Combined features from unigram and bigram
def get_combined(uni_grams,bi_grams):
    ret = []
    for f1,f2 in zip(uni_grams,bi_grams):
        featuredict = collections.defaultdict(int)
        for feature in f1[0]:
            if feature in most_frequent_unigram:
                featuredict[feature] += 1
        for feature in f2[0]:
            if feature in most_frequent_bigram:
                featuredict[feature] += 1
        ret.append((featuredict,f1[1]),)
    return ret


train_com = get_combined(train_unigram_set,train_bigram_set)
test_com = get_combined(test_unigram_set,test_bigram_set)

classifier = NaiveBayesClassifier.train(train_com)

accuracy = classify.accuracy(classifier, test_com)
print(accuracy)
```

```
0.802
```

Dense representation with SVD

i) Generate a co-occurance matrix with window size = 2. Represent each revew with a dense vector extracted from SVD where dimention = 300. Re-train the model and report the accuracy on the test-set.

In [0]:
```
import numpy as np
import pandas as pd
def get_co_occurrence(stemmization, window_size):
    d = collections.defaultdict(int)
    vocab = set()
    for tokens,_ in stemmization:
        for i in range(len(tokens)):
            token = tokens[i]
            vocab.add(token)
            next_token = tokens[i+1 : i+1+window_size]
            for t in next_token:
                key = tuple(sorted([t, token]))
                d[key] += 1
    vocab = sorted(vocab)
    df = pd.DataFrame(data=np.zeros((len(vocab), len(vocab))),index=v
ocab,columns=vocab)
    for key, value in d.items():
        df.at[key[0], key[1]] = value
        df.at[key[1], key[0]] = value
    return df
df = get_co_occurrence(train_stemmization+test_stemmization,2)
```

In [0]:
```
from numpy.linalg import svd
X = df.to_numpy()
u, s, vh = np.linalg.svd(X, full_matrices=True)
vh
svd_model = {}
for i,word in enumerate(df.index):
    svd_model[word] = vh[i,:300]
```

In [0]:
```
data = []
for one_hot,_ in (train_one_hot+test_one_hot):
    data.append(one_hot)
data = np.array(data).T
u, s ,vh = np.linalg.svd(data, full_matrices=True)
```

In [0]:
```
data = vh.T[:,:300]
def get_set(data,one_hot):
    ret = []
    for features,o in zip(data,one_hot):
        featuresdict = {}
        for i,feature in enumerate(features):
            featuresdict['feature'+str(i)] = feature
        label = o[1]
        ret.append((featuresdict,label),)
    return ret
train_set = get_set(data[:len(train_one_hot)],train_one_hot)
test_set = get_set(data[len(train_one_hot):],test_one_hot)
```

In [0]:
```
svd_classifier = NaiveBayesClassifier.train(train_set)

accuracy = classify.accuracy(svd_classifier, test_set)
print(accuracy)
```

```
0.542
```

Word Embeddings

Download pretrained word embeddings from Google News dataset. The model includes embeddings for 3 million words and phrases. Words with frequency below 5 were discarded. Download the model from the link below: [https://code.google.com/archive/p/word2vec/ (https://code.google.com/archive/p/word2vec/)](https://code.google.com/archive/p/word2vec/)

You can load the model using gensim:

In [0]:
```
import gensim.models
model = gensim.models.KeyedVectors.load_word2vec_format('./GoogleNews.bin', binary=True)
```

j) Represent the 5 most positive informative words with word2vec (dimention = 300) and SVD.

k) Represent the 5 most negative informative words with word2vec (dimention = 300) and SVD.

You can use the following code to determine which features are most effective in sentiment analysis.

In [0]:
```
classifier.show_most_informative_features(20)
# positive excel,perfect,great,hippy,love
# negative bad,terribl,worst,money,aw
```

```
Most Informative Features
                   excel = 1                   1 : 0      =     34.3
: 1.0
                     bad = 1                   0 : 1      =     21.5
: 1.0
                 terribl = 1                   0 : 1      =     20.6
: 1.0
                   worst = 1                   0 : 1      =     20.6
: 1.0
                 perfect = 1                   1 : 0      =     19.4
: 1.0
                   great = 1                   1 : 0      =     18.6
: 1.0
                   money = 1                   0 : 1      =     17.3
: 1.0
                   happi = 1                   1 : 0      =     16.0
: 1.0
                    love = 1                   1 : 0      =     16.0
: 1.0
                      aw = 1                   0 : 1      =     13.4
: 1.0
              work great = 1                   1 : 0      =     13.2
: 1.0
                    fine = 1                   1 : 0      =     13.2
: 1.0
                 great . = 1                   1 : 0      =     12.6
: 1.0
                    nice = 1                   1 : 0      =     12.1
: 1.0
                   start = 1                   0 : 1      =     11.5
: 1.0
                  famili = 1                   1 : 0      =     11.2
: 1.0
                    bore = 1                   0 : 1      =      9.5
: 1.0
                 comfort = 1                   1 : 0      =      8.8
: 1.0
                    amaz = 1                   1 : 0      =      8.6
: 1.0
                   write = 1                   0 : 1      =      8.2
: 1.0
```

Answer

positive: excel, perfect, great, hippy, love

negative: bad, terribl, worst, money, aw

In [0]:

```
# positive excel,perfect,great,happi,love
positive_words = ['excel','perfect','great','happi','love']
for word in positive_words:
    print('word2vec: ',word)
    print(model[word])
    print('SVD: ' + word)
    print(svd_model[word])
```

```
word2vec:  excel
[-1.86523438e-01  1.02050781e-01 -1.83593750e-01 -5.44433594e-02
  6.93359375e-02  9.66796875e-02  1.79687500e-01  2.18200684e-03
 -2.32421875e-01  1.58691406e-02  1.26953125e-01 -4.15802002e-04
  1.20605469e-01  3.95507812e-02 -3.14941406e-02  1.57226562e-01
 -5.46875000e-02  3.53515625e-01  9.13085938e-02 -1.02539062e-01
 -2.84423828e-02  3.02734375e-02 -1.08886719e-01  1.71875000e-01
  7.22656250e-02 -1.66015625e-01  5.07812500e-02 -2.91015625e-01
 -7.91015625e-02 -4.80957031e-02  4.02832031e-02  1.25122070e-02
  1.27929688e-01 -3.07617188e-02  1.72851562e-01  1.04492188e-01
  5.98144531e-02  3.85742188e-02  9.42382812e-02 -5.07812500e-02
  4.37500000e-01  2.33398438e-01 -4.61425781e-02  1.69921875e-01
 -1.31835938e-01  6.20117188e-02 -2.98828125e-01 -1.30859375e-01
 -1.31835938e-01  1.53320312e-01 -2.07031250e-01  6.34765625e-02
 -4.63867188e-02 -6.39648438e-02 -5.98144531e-02 -1.66992188e-01
  2.16796875e-01 -2.45117188e-01 -1.07910156e-01 -9.76562500e-02
 -5.17578125e-02 -8.00781250e-02 -1.63085938e-01 -1.22070312e-01
 -2.55126953e-02  2.80761719e-02 -8.93554688e-02  5.54199219e-02
  2.80761719e-02  3.47656250e-01 -9.03320312e-03 -1.84570312e-01
  1.75781250e-01  5.83496094e-02 -1.36718750e-01 -3.12500000e-01
 -1.49414062e-01 -1.24023438e-01  8.25195312e-02  9.52148438e-03
 -9.52148438e-02  2.44140625e-01 -5.56640625e-02  1.96289062e-01
  1.58203125e-01  1.23046875e-01  5.44433594e-02  1.31835938e-01
  2.84423828e-02  2.94189453e-02  4.76074219e-02 -2.16796875e-01
  1.90429688e-02 -2.53906250e-01  3.39843750e-01  1.91497803e-03
  4.78515625e-01  3.80859375e-01  1.06811523e-02 -2.22656250e-01
 -3.86718750e-01 -6.71386719e-03  3.61328125e-02  3.75976562e-02
 -2.69531250e-01 -1.40625000e-01 -2.30468750e-01 -5.67626953e-03
  3.32031250e-01  4.39453125e-03 -9.37500000e-02  8.25195312e-02
 -2.85156250e-01  1.12792969e-01  2.83203125e-01  2.67333984e-02
  2.24609375e-02 -3.90625000e-01  7.86132812e-02 -2.04101562e-01
 -1.69921875e-01 -1.11816406e-01  1.26953125e-01  1.82617188e-01
 -2.85644531e-02 -2.37304688e-01 -3.63769531e-02 -4.66308594e-02
 -2.12890625e-01  3.06640625e-01 -8.88671875e-02  4.88281250e-02
  5.15136719e-02 -1.08398438e-01  2.48046875e-01  7.95898438e-02
  2.09960938e-01 -5.05371094e-02 -2.00195312e-01  1.12304688e-01
 -1.54296875e-01 -3.26171875e-01  5.15136719e-02 -1.34765625e-01
 -2.24609375e-01 -1.04980469e-01  1.99218750e-01  2.29492188e-02
  1.12792969e-01 -1.53320312e-01  7.17773438e-02  3.75000000e-01
 -1.43554688e-01  2.08007812e-01 -4.47265625e-01  2.34375000e-01
 -1.93786621e-03 -1.92382812e-01  3.66210938e-02 -2.51953125e-01
  9.86328125e-02  6.73828125e-02 -1.54296875e-01 -1.00097656e-01
  1.13769531e-01 -1.20117188e-01  9.66796875e-02 -1.52343750e-01
 -1.99218750e-01 -1.44042969e-02 -2.59765625e-01 -1.88476562e-01
 -1.03027344e-01 -1.93359375e-01  3.61328125e-02  2.55859375e-01
  1.72851562e-01 -2.73437500e-01 -1.10351562e-01 -1.56250000e-01
 -2.22656250e-01 -1.26953125e-01 -2.30712891e-02 -5.54199219e-02
 -2.83203125e-01 -2.63671875e-02  4.49218750e-02 -5.39550781e-02
 -9.13085938e-02 -5.66406250e-02  1.65039062e-01 -3.32031250e-02
  6.34765625e-02 -1.25976562e-01  9.66796875e-02 -5.71289062e-02
  3.39843750e-01 -2.05078125e-01 -1.57226562e-01 -8.20312500e-02
 -8.20312500e-02 -5.20019531e-02 -2.52685547e-02 -1.98242188e-01
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 -5.83331581e-03 -8.26898665e-03  3.62650777e-03 -1.63410606e-02]
```

In [0]:

```
# negative bad,terribl,worst,money,aw
negative_words = ['bad','terribl','worst','money','aw']
for word in positive_words:
    print('word2vec: ',word)
    print(model[word])
    print('SVD: ' + word)
    print(svd_model[word])
```

```
word2vec:  excel
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  6.93359375e-02  9.66796875e-02  1.79687500e-01  2.18200684e-03
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 -5.83331581e-03 -8.26898665e-03  3.62650777e-03 -1.63410606e-02]
```

l) Calculate the dot product between the most frequent positve word and the most frequent negative word represented with SVD and word2Vec. Compare the results.

m) Can one use word2vec for sentiment analysis on the review dataset? Justify your answer.

In [0]:
```
# 'excel','bad'
print((svd_model['excel']*svd_model['bad']).sum())

print((model['excel']*model['bad']).sum())
```

```
0.003902033146915265
0.67587197
```

Answer

l) Dot product: SVD: 0.003902033146915265 word2vec: 0.67587197

m) Theoretically, we could take a mean of words to get embeddings for a sentence and conduct the analysis. So this is feasible. But, in practice, sentiment information in word2vec represent only the relationship between words, and could be lacking of emotional information, which might pose some limitations.

Computer Vision

This assignment will give you experience with an image corpus. For most of the questions in this assingment, you need to write a python script.

1- *Read image*: Write a python code to read the image. You can find the image of this assingment on the [webpage (https://github.com/ift6758/ift6758.github.io/blob/master/assignments/assignment_3(data)](https://github.com/ift6758/ift6758.github.io/blob/master/assignments/assignment_3(data)).zip).

Answer

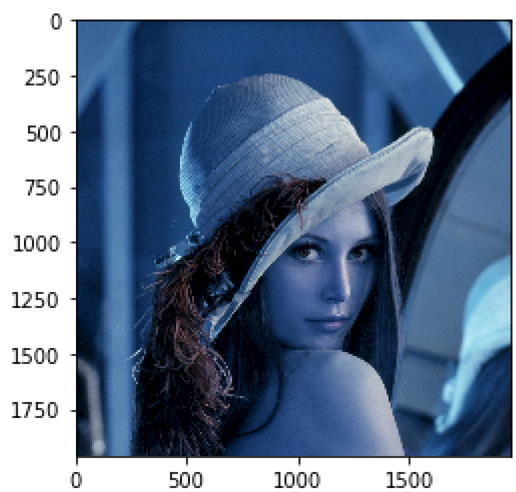
In [3]:
```python
import cv2
import matplotlib.pyplot as plt
import numpy as np


#write a function to read an image
img = cv2.imread('lena.jpg', -1)

# This line is just a proof that I've read the image
print("This is the BGR version of the image, for the RGB version, ple
ase refer to part 3: \n")
plt.imshow(img)
```

```
This is the BGR version of the image, for the RGB version, please ref
er to part 3:
```

Out[3]:
```
<matplotlib.image.AxesImage at 0x7f298d827ac8>
```



2- *Pre-processing*: data augmentation: Write a python code to resize the image and make it 20% smaller, and save the image as greyscale image.

Answer

Here I interpreted this as having the image's 2D area to be 80% of that of the original image. So the width and height shall shrink accordingly. That means either of them will shrink to sqrt(0.8) of the original.

Of course, we could alternatively shrink both width and height by 20% respectively, and that way the area of image would be 64% of the original.

In [4]:

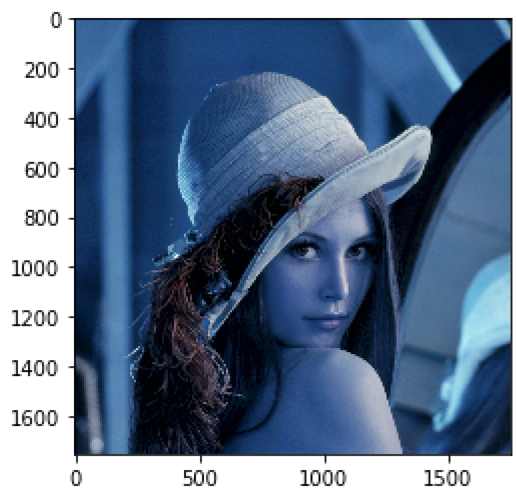
```
# re-size an image
scale = 0.8 # of original size area
# shrink the sides accordingly and define new dimension
width = int(img.shape[1] * (scale ** 0.5))
height = int(img.shape[0] * (scale ** 0.5))
dim = (width, height)
# resizing
img_resized = cv2.resize(img, dim, interpolation = cv2.INTER_AREA) #
 resized image

# This line is just a proof that I've resized the image
print("Here is the resized BGR image: \n")
plt.imshow(img_resized)
```

```
Here is the resized BGR image:
```

Out[4]:

```
<matplotlib.image.AxesImage at 0x7f298b2f1470>
```

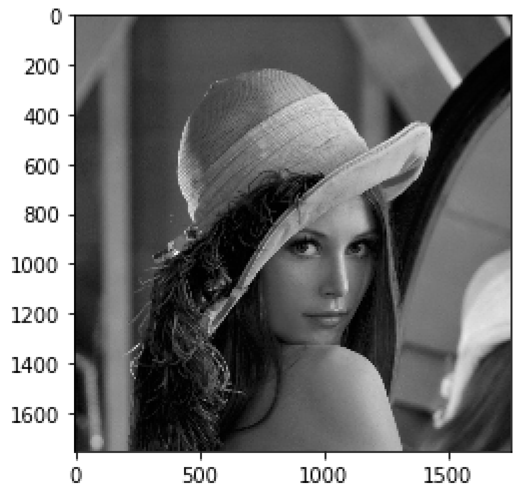


In [5]:
```
# save the processed image in grayscale
img_resized_gray = cv2.cvtColor(img_resized, cv2.COLOR_BGR2GRAY)

# This line is just a proof that I've converted the resized image
print("Here is the resized BGR image in gray scale: \n")
plt.imshow(img_resized_gray,cmap='gray')
```

```
Here is the resized BGR image in gray scale:
```

Out[5]:
```
<matplotlib.image.AxesImage at 0x7f298b2d2978>
```



3- *Filter*: Write a python code that load the image in RGB and generate three images where in each one the colors of one channel is inversed. Show the generated images.

In [6]:

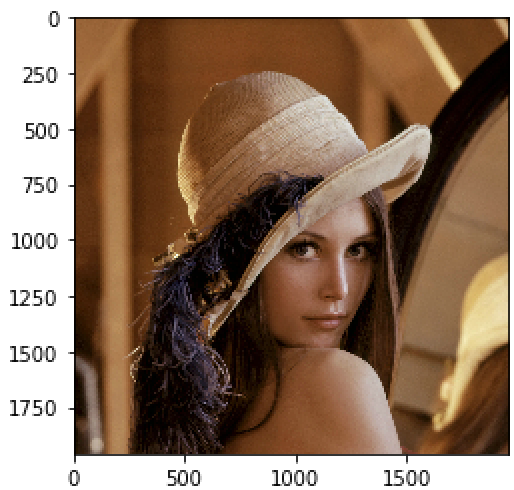
```python
# load image in RGB
img_rgb = cv2.cvtColor(cv2.imread('lena.jpg', -1) , cv2.COLOR_BGR2RGB
)

# This line is just a proof that I've load the image in RGB format
print("This is the RGB version of the image: \n")
plt.imshow(img_rgb)
```

```
This is the RGB version of the image:
```

Out[6]:

```
<matplotlib.image.AxesImage at 0x7f298b23a0b8>
```



In [0]:

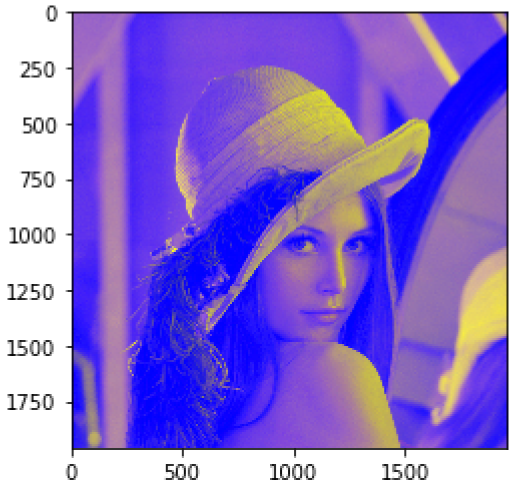
```python
# Generate 3 images where each the color of one channel in each image
is inverted
# Reverse B/G/R separately
r,g,b = cv2.split(img_rgb)

def inverse(img):
    height, width = img.shape
    dst = np.zeros((height,width), np.uint8)
    for i in range(0, height):
        for j in range(0, width):
            dst[i, j] = 255-img[i,j]
    return dst

inversed_r = inverse(r)
inversed_g = inverse(g)
inversed_b = inverse(b)
```

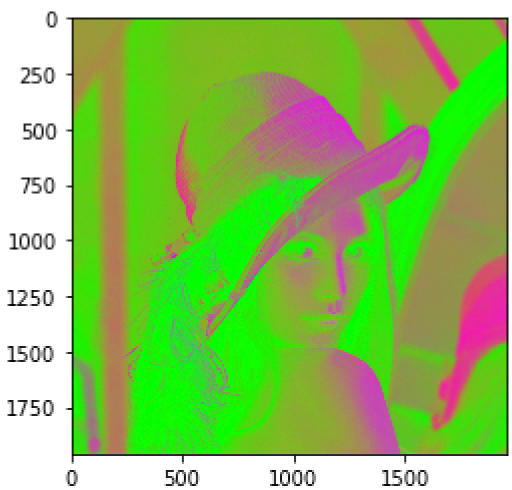
In [8]:
```
# show the processed images
plt.imshow(cv2.merge([r,g,inversed_b]))
```

Out[8]: <matplotlib.image.AxesImage at 0x7f298b21a0b8>



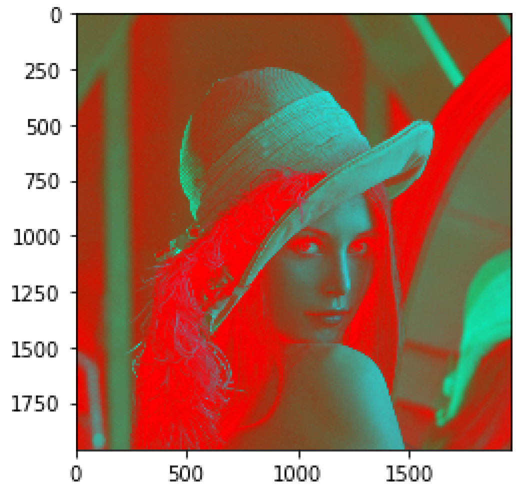
In [9]:
```
plt.imshow(cv2.merge([r,inversed_g,b]))
```

Out[9]: <matplotlib.image.AxesImage at 0x7f298b174208>



In [10]:
```
plt.imshow(cv2.merge([inversed_r,g,b]))
```

Out[10]: <matplotlib.image.AxesImage at 0x7f298b152358>

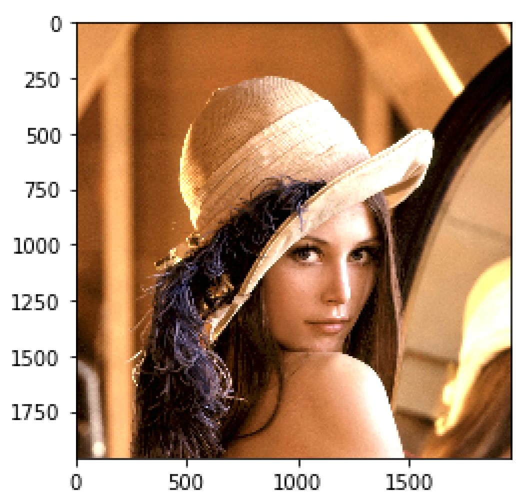


4- Suggest a filter that make the image 50% lighter and 50% darker. Write a python function that applies the filter on the image.

In [11]:
```
def lightening_filter(img):
    # make the image 50% lighter
    height, width, deep = img.shape
    dst = np.zeros((height,width,deep), np.uint8)
    for i in range(0, height):
        for j in range(0, width):
            for d in range(0,deep):
                dst[i, j, d] = int(img[i,j,d]*1.5) if img[i,j,d]*1.5 <
256 else 255
    return dst

lighter_img = lightening_filter(img)
plt.imshow(cv2.cvtColor(lighter_img, cv2.COLOR_BGR2RGB))
```

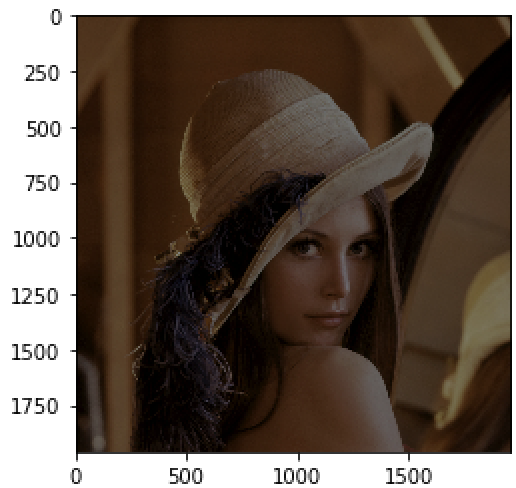
Out[11]: <matplotlib.image.AxesImage at 0x7f298b0b3630>



In [12]:
```
def darkening_filter(img):
    height, width, deep = img.shape
    dst = np.zeros((height,width,deep), np.uint8)
    for i in range(0, height):
        for j in range(0, width):
            for d in range(0,deep):
                dst[i, j, d] = int(img[i,j,d]*0.5)
    return dst

darker_img = darkening_filter(img)
plt.imshow(cv2.cvtColor(darker_img, cv2.COLOR_BGR2RGB))
```

Out[12]: <matplotlib.image.AxesImage at 0x7f298b091518>



5- Write two python functions that apply a 3 x 3 median and 3 x 3 mean filter on the image. Mean filter is a simple sliding window that replace the center value with the average of all pixel values in the window. While median filter is a simple sliding window that replace the center value with the Median of all pixel values in the window. Note that the border pixels remain unchanged.

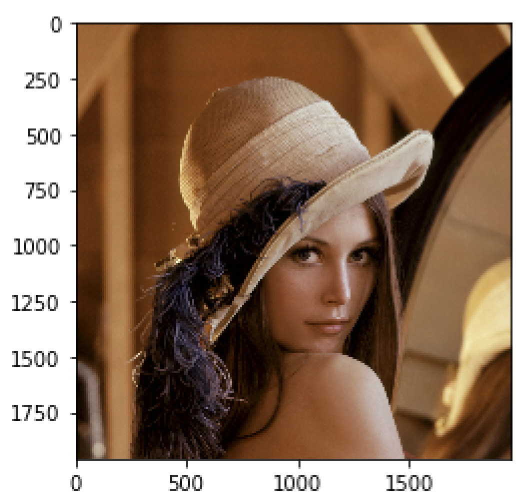
In [13]:
```
def mean_filter(img):
    # apply 3 x  3 mean filter
    def get_mean(height, width, single_c):
        dst = np.zeros((height,width,1), np.uint8)
        for i in range(height):
            for j in range(width):
                if i<1 or i>height-2 or j<1 or j>width-2:
                    dst[i,j] = single_c[i,j]
                    continue
                sum = 0
                for m in [-1,0,1]:
                    for n in [-1,0,1]:
                        sum+=single_c[i+m,j+n]
                dst[i,j] = sum/9
        return dst

    height, width, deep = img.shape
    b,g,r = cv2.split(img)

    mean_b = get_mean(height, width,b)
    mean_g = get_mean(height, width,g)
    mean_r = get_mean(height, width,r)
    res = cv2.merge([mean_b,mean_g,mean_r])
    return res

img_mean = mean_filter(img)
plt.imshow(cv2.cvtColor(img_mean, cv2.COLOR_BGR2RGB))
```

Out[13]: <matplotlib.image.AxesImage at 0x7f298aff3b70>



In [14]:

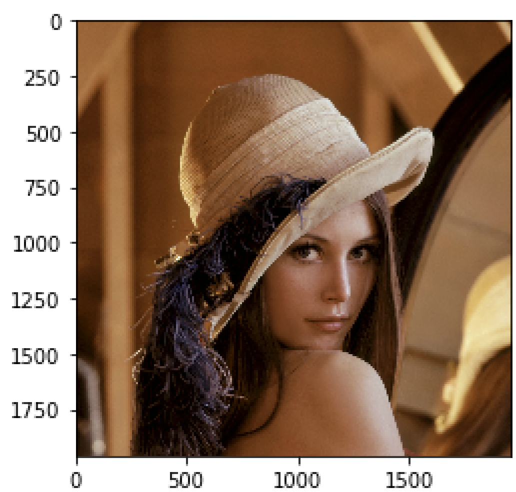
```python
def median_filter(img):
    # apply 3 x  3 median filter
    def get_median(height, width, single_c):
        dst = np.zeros((height,width,1), np.uint8)
        for i in range(height):
            for j in range(width):
                if i<1 or i>height-2 or j<1 or j>width-2:
                    dst[i,j] = single_c[i,j]
                    continue
                temp = []
                for m in [-1,0,1]:
                    for n in [-1,0,1]:
                        temp.append(single_c[i+m,j+n])
                dst[i,j] = np.median(temp)
        return dst

    height, width, deep = img.shape
    b,g,r = cv2.split(img)

    median_b = get_median(height, width,b)
    median_g = get_median(height, width,g)
    median_r = get_median(height, width,r)
    res = cv2.merge([median_b,median_g,median_r])
    return res

img_median = median_filter(img)
plt.imshow(cv2.cvtColor(img_median, cv2.COLOR_BGR2RGB))
```

Out[14]: <matplotlib.image.AxesImage at 0x7f298afd6dd8>



6- A mean filter is a linear filter, but a median filter is not. Why?

In order to be linear, a function must satisfy the following condition:

$$f(x_1 + x_2) = f(x_1) + f(x_2)$$

Which is called the Additivity. Together with Homogenity, the two forms principle of superposition. Linear funciton must satisfy this principle.

For mean filter, say we are filtering using a sliding window of size ***n***, and that the sum of the window is ***X***. For instance, in the code we did for the previous question, the filtering matrix is (n = 9):

$$X = \frac{1}{n}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Whereby the mean is then:

$$mean(X) = \frac{X}{n} = \frac{\sum x_{i,j}}{n}$$

And we can say that for the function ***mean***:

$$mean(F_n) = \frac{F_n}{n}$$

So when applied, the part of the original photo being filtered has a sum of ***Y***, then:

$$mean(X) + mean(Y) = \frac{X}{n} + \frac{Y}{n} = \frac{X+Y}{n} = mean(X+Y)$$

Which is exactly the Additivity we defined at the beginning. Therefore mean filter is linear.

For median filter, the median of each sequence cannot be computed with a definitive arithmetic formulation, as we do for the mean. Since it is just the 'middle' value, there is no guarantee that the sum of two medians DOES NOT equal to the median of the sum, formally,

$$median(X+Y) \neq median(X) + median(Y)$$

For example: Say we have 2 sequences X = [1, 2, 3], Y = [1, 3, 0]. The medians are 2 and 4 respectively. X + Y = [2, 5, 3], and the median is now 3. This obviously does not equal to the sum of the two medians.