Yelp Review

Web Scraping, Sentiment Analysis and ML prediction

Frank Wang 5/22/ 2016

Yelp review scrapy, Sentiment Analysis and NB Prediction

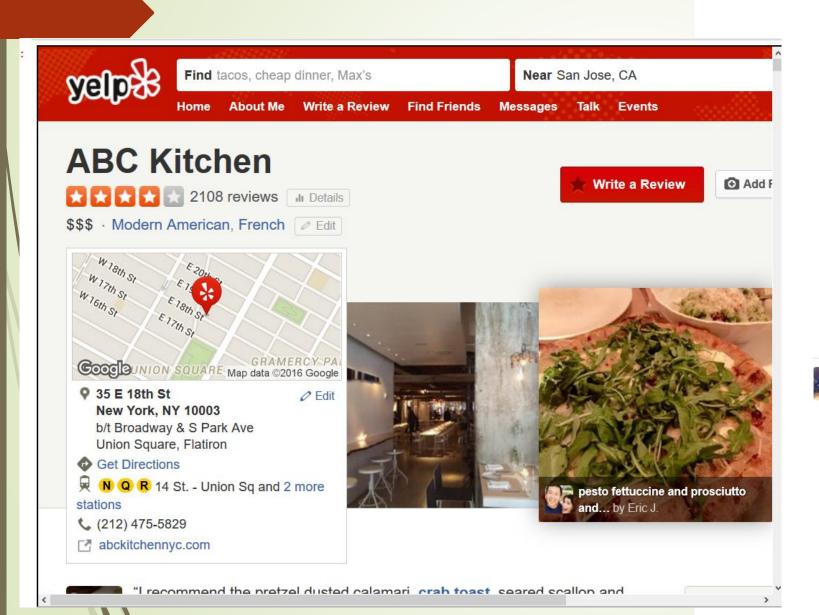
This Project first scrapy yelp review data, then we do Sentiment Analysis, prediction using Naive Bayes Frank Lanfa Wang, 5/2016, FrankWanglf@gmail.com

This section is app for Yelp review download

```
In [1]: ## Project 3 Web scraping
        %matplotlib inline
        import pandas as pd
                                                                             Tool: beautifulSuop
        from bs4 import BeautifulSoup
        from urllib.request import urlopen
        import re
        gueries = 0
        tot reviews=0
        tot authors=0
        tot ratings=0
        authors rev=[]
        ratings rev=[]
        Features=[]
        f=open("summary auth rating tmp.txt", encoding='utf-8', mode="w")
        f1=open("reviews tmp.txt", encoding='utf-8', mode="w")
        f2=open("author tmp.txt", encoding='utf-8', mode="w")
        f3=open("rating tmp.txt", "w")
        while queries <2020:
            stringQ = str(queries)
            page =urlopen('http://www.yelp.com/biz/abc-kitchen-new-york?start=' + stringQ)
            soup = BeautifulSoup(page,"lxml")
            reviews = soup.findAll('p', attrs={'itemprop':'description'})
            authors = soup.findAll('meta',attrs={'itemprop':'author'})
            ratings= soup.findAll('meta',attrs={'itemprop':'ratingValue'})
            flag = True
            indexOf = 1
            for it, review in enumerate (reviews):
                dirtyEntry = str(review)
                tot reviews+=1
```

example





But there's always room for dessert! We got the Basil and Mint Panna cotta with Meyer Lemon Sorbet! The Panna Cotta was soft and light. It came out looking like an egg because of the thinly sliced lemon on top. The lemon sorbet was a good palette cleanser and keep your mouth guessing. Will I get the tart sorbet or the creamy panna cotta this time.

P.S. They have a gender neutral bathroom!







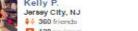
See all photos from Joanne K. for ABC Kitchen

Was this review ...?









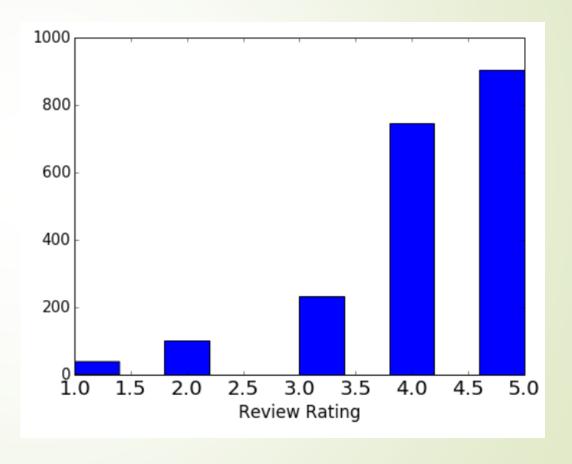


2 check-ins

The fresh closures of Telepan, Perilla, and Fishtail exhibit the caliber of New York's restaurant scene. It is not only over saturated but also dense with merciless critics. Even Michelin celebrity chefs are unable to persevere. Spaces are quickly transformed with new successors that share the same doomed fate... and eventually they become a Chase bank branch.

ABC Kitchen's business is booming. Jean Georges Vongerichten, the Michelin awarded chef pleases the eager palettes of his patrons at this establishment, located minutes away from Union Square. Like a speakeasy, there is a back entrance through a home furniture store. All décor is furnished courtesy of ABC Carpet and Home which expresses their passion for "green" through sustainable furnishings. Brick walls are painted with thick layers of milky white lacquer. Pillars of dark wood, untouched by varnish are piped throughout the dining room for a striking contrast. Simple metal pendant light fixtures, bare bulbs, and traditional Victorian chandeliers dot the ceiling. After sunset, flickering candles materialize on white table surfaces illuminating the dining room with a romantic dim luminescence. The environment compliments the restaurant's ingredients perfectly: strictly local and fair trade farm to table. Destinides antihisting and hermones

	Name	Rating
0	Joanne K.	5
1	Kelly P.	4
2	Jane R.	3
3	Qian H.	4
4	Serena A.	5
5	Eugenia L.	5
6	Sheila R.	5
7	Jason H.	3
8	Julia K.	4
9	Jenn P.	4

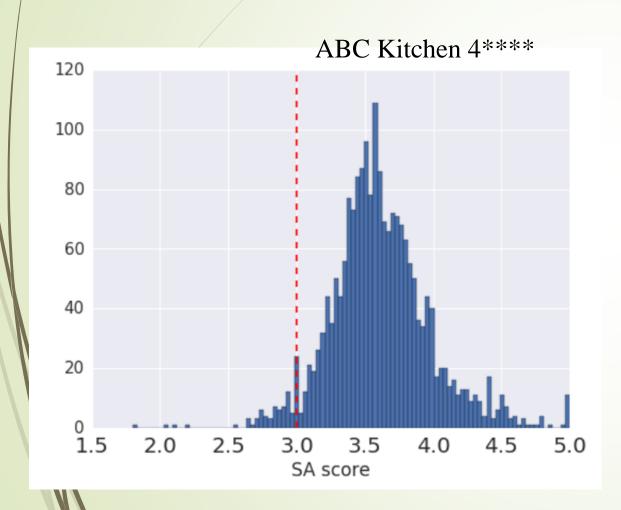


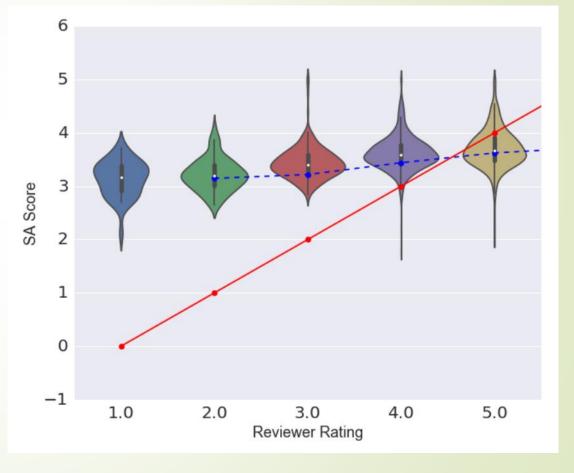
Sentiment Analysis

```
from textblob import TextBlob
from textblob.sentiments import NaiveBayesAnalyzer
sa score=[]
for ir in range(len(reviewers.Rating)):
        testimonial = TextBlob(Features[ir])
        sc=testimonial.sentiment.polarity
        \#sc=sc*2.5+2.5
        sc=sc*2+3
        sa score.append(sc)
reviewers['Sa_score']=sa_score
accuacy sa=[1 for x in sa score if x>3]
accuacy sa=sum(accuacy sa)/len(sa score)
print('The accuracy of SA prediction is : {}'.format(accuacy sa))
The accuracy of SA prediction is: 0.9589108910891089
```

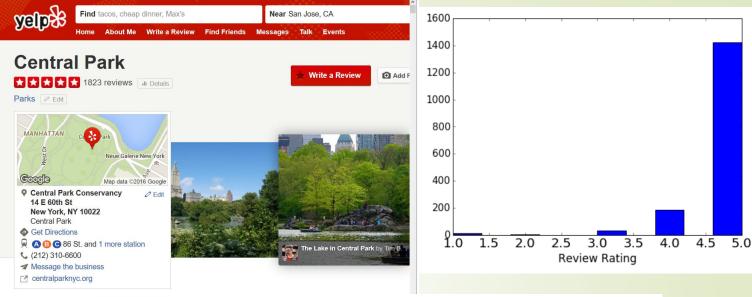
SA for restaurant review

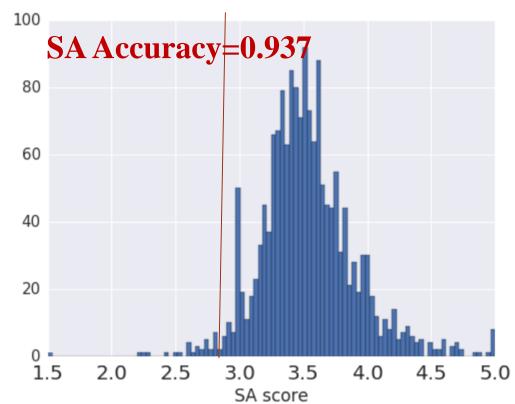
The accuracy of SA prediction is: 0.9589

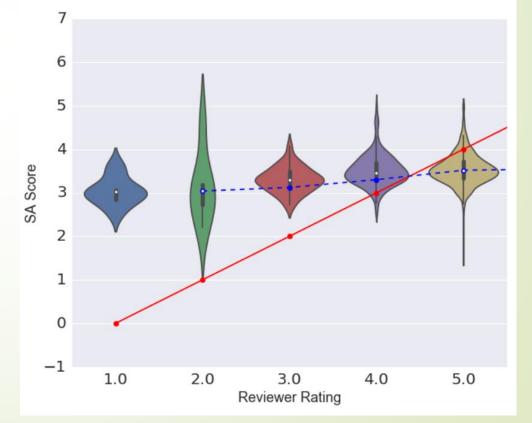




Example 2:







Prediction using Navie Baye

```
10]: def features extra(Features, reviewers):
         yelpFeatures=[]
         for ir, feature in enumerate(Features):
             Words = re.findall(r''[\w']+|[.,!?;]'', feature.rstrip())
             wordb=dict([(word.lower(), True) for word in Words])
             if (reviewers.Rating[ir]>=3):
                 Words = [wordb, 'pos']
             else:
                 Words = [wordb, 'neg']
             yelpFeatures.append(Words)
         return yelpFeatures
     ## test for greeting is treated as a negative word
     def features extra mod(Features, reviewers):
         yelpFeatures=[]
         postive words=['greeting','ultimately','politely']
         for ir,feature in enumerate(Features):
             Words = re.findall(r''[\w']+|[.,!?;]'', feature.rstrip())
             wordb=dict([(word.lower(), True) for word in Words])
             pol='neg'
             if (reviewers.Rating[ir]>=3):
                 pol='pos'
             for wor in wordb.keys():
                 if wor in postive words:
                     print('positiveword corrected={} in reviwer {}'.format(wor,ir))
                     pol='pos'
             Words = [wordb, pol]
             yelpFeatures.append(Words)
         return yelpFeatures
```

Prediction of yelp feature

dismissive = True

```
import re, math, collections, itertools, os
import nltk, nltk.classify.util, nltk.metrics
from nltk.classify import NaiveBayesClassifier
from nltk.metrics import BigramAssocMeasures
from nltk.probability import FreqDist, ConditionalFreqDist
import random
random.shuffle(yelpFeatures)
Cutoff = int(math.floor(len(yelpFeatures)*3/4))
trainFeatures = yelpFeatures[:Cutoff]
testFeatures = yelpFeatures[Cutoff:]
classifier = NaiveBayesClassifier.train(trainFeatures)
referenceSets = collections.defaultdict(set)
testSets = collections.defaultdict(set) *
for i, (features, label) in enumerate(testFeatures):
    referenceSets[label].add(i)
    predicted = classifier.classify(features)
    testSets[predicted].add(i)
print ('train on %d instances, test on %d instances' % (len(trainFeatures), len(testFeatures)))
print ('accuracy:', nltk.classify.util.accuracy(classifier, testFeatures))
classifier.show most informative features (20)
train on 4500 instances, test on 1500 instances
accuracy: 0.72
Most Informative Features
               apologies = True
                                          neq : pos
                                                               32.7 : 1.0
               horribly = True
                                                               27.7 : 1.0
                                           neq : pos =
                  ripped = True
                                            neg : pos
                                                               27.7 : 1.0
               mistakes = True
                                            neg : pos
                                                               27.7 : 1.0
                message = True
                                            neg : pos
                                                               27.7 : 1.0
                                                               22.6 : 1.0
              compensate = True
                                            neg : pos
```

nea: pos

22.6 : 1.0

Small number of dataset

```
train on 1515 instances, test on 505 instances
accuracy: 0.6237623762376238
Most Informative Features
                                                      = 38.4 : 1.0
              greeting = True
                                          neg : pos
                                                      = 38.4 : 1.0
             Ultimately = True
                                          neq : pos
                                                      = 29.8 : 1.0
              tasteless = True
                                          neg : pos
                    55 = True
                                          neg : pos
                                                           29.8 : 1.0
                 Sadly = True
                                                           29.8:1.0
                                          neg : pos
                                                      = 29.8 : 1.0
              politely = True
                                          neg : pos
                                                      = 21.3 : 1.0
                   WAY = True
                                          neq : pos
                                                      = 21.3 : 1.0
            photographs = True
                                          neg : pos
                                                      = 21.3 : 1.0
                  2016 = True
                                          neg : pos
                                                           21.3 : 1.0
                liquor = True
                                          neg : pos
                   act = True
                                                            21.3 : 1.0
                                          neg : pos
                  pity = True
                                                           21.3 : 1.0
                                          neg : pos
              Nougatine = True
                                                      = 21.3 : 1.0
                                          neg: pos
                they'd = True
                                                            21.3 : 1.0
                                          neg : pos
                  hell = True
                                                           21.3 : 1.0
                                          neg : pos
                 dirty = True
                                                            21.3 : 1.0
                                          neg : pos
                 acted = True
                                                            21.3 : 1.0
                                          neg: pos
               Walking = True
                                                           21.3 : 1.0
                                          neg : pos
               improved = True
                                                           21.3 : 1.0
                                          neg : pos
              redeeming = True
                                                            21.3:1.0
                                          neg : pos
```

Really disappointed to our dining experience tonight. Thursday night, 6:30PM for 2 people. We made reservation 1 month earlier for the birthday dinner.---Environment---Dining area: The decoration and ambiance of main area was beautiful and great, HOWEVER, they sat us in the back bar area, which was a passage between ABC Kitchen, ABC Cocina, and abcmkt. It had no decoration at all. While we ate, some people were walking on the stairs above us (we were eating under the edge of stairs. I felt some dust were falling into our dishes from it...). The customers of abcmkt also randomly walked to our area and peaked into our dishes. I felt really uncomfortable about it. I understand they didn't want to waste the space and put more tables to make money, but they should probably make it only for the bar guests, not the customers who have the full dinner.*-----.*Sundae: good idea to put salted caramel ice cream and popcorn together. It was tasty but it got very sweet at the end. The portion was big, so it's ideal to share it between 2-3 people.---Service---The staff were friendly. However, they were not attentive. It might be a busy night, so our waiter disappeared for a while time/to time when we needed him. We waited for 20 mins to order dessert and 30 mins to get the bill. Some of the serving ways were also odd. Most of our dishes were

dropped without any words. **No greeting** (we were still in the middle of conversation), no explaining, no "bon appetit". They just came and left like we were air...If you ask questions, they would answer politely. But it was really awkward. I've been to many high-end or Michelin starred restaurants. By the dining experience tonight, I don't think ABC Kitchen deserved Michelin 3 stars. Foods were good but not excellent, and the sorvice back bar group and bathroom were not on the lovel. Overall, it was a

train on 4500 instances, test on 1500 instances accuracy: 0.722 Most Informative Features = 32.8 : 1.0 message = True neq : pos neg : pos = 32.8 : 1.0poisoning = True neg : pos = 27.7 : 1.0mistakes = True neg : pos = 24.8 : 1.0apologize = True ripped = True neg : pos = 22.7 : 1.0neg : pos = 19.7 : 1.0horrible = True 19.7 : 1.0 snotty = True neq: pos = hater = True neg: pos = 17.6 : 1.0 neg : pos = 17.6 : 1.0rudely = True neg : pos = 17.6 : 1.0applies = True neg : pos = 17.6 : 1.0increasingly = True appalling = True neg : pos = 17.6 : 1.0neg : pos = 17.6 : 1.0remotely = True compensate = True 17.6 : 1.0 neq: pos = 17.6 : 1.0 sauna = True neg: pos = neg : pos = 17.6 : 1.0behavior = True 17.6 : 1.0 curt = True neg: pos = neg : pos = 17.6 : 1.0updated = True conservative = True neg : pos = 17.6 : 1.017.6 : 1.0 warmer = True neq : pos

The following run Yelp prediction with Movie review traning data!

The accuaracy is pretty high 0.811

```
Cutoff = int(math.floor(len(Features)*3/4))
trainFeatures1 = Features[:Cutoff]
testFeatures1 = Features[Cutoff:]
referenceSets = collections.defaultdict(set)
testSets = collections.defaultdict(set) *
for i, (features, label) in enumerate(testFeatures):
   referenceSets[label].add(i)
   predicted = classifier.classify(features)
   testSets[predicted].add(i)
print ('train on %d instances, test on %d instances' % (len(trainFeatures1), len(testFeatures1)))
print ('accuracy:', nltk.classify.util.accuracy(classifier, testFeatures1))
classifier.show most informative features (20)
train on 1515 instances, test on 505 instances
accuracy: 0.811881188119
Most Informative Features
            magnificent = True
                                                      = 15.0 : 1.0
                                         pos : neg
            outstanding = True
                                         pos : neg
                                                      = 13.6 : 1.0
              insulting = True
                                                      = 13.0 : 1.0
                                         neq : pos
             vulnerable = True
                                         pos : neg
                                                      = 12.3 : 1.0
              ludicrous = True
                                                      = 11.8 : 1.0
                                         neg : pos
                                                      = 11.7 : 1.0
                 avoids = True
                                         pos : neg
            uninvolving = True
                                         neg : pos
                                                      = 11.7 : 1.0
             astounding = True
                                                      = 10.3 : 1.0
                                         pos : neg
            fascination = True
                                                      = 10.3 : 1.0
                                         pos : neg
               idiotic = True
                                                      = 9.8 : 1.0
                                          neq : pos
                                                      = 9.7 : 1.0
              affecting = True
                                         pos : neg
                                                      = 9.7 : 1.0
                symbol = True
                                          pos : neg
                                                             0 0 - 1 0
              1---1----1
```

Summary

- The Yelp review text is downloaded.
- Sentiment Analysis for positive and negative prediction show good agreement with review rating.
- Supervised machine learning (Naive Bayes here) has a prediction accuracy is about 72% with 6000 features
- This is very preliminary study. Further improvements with bigram and other technics is planned.