summer-2019-csc131-assignment7

August 11, 2019

```
In [211]: import numpy as np
          import math
          import pandas as pd
          import string
          import matplotlib.pyplot as plt
          import re
          import operator
          %cd '/Users/xiaoyingliu/desktop'
```

```
/Users/xiaoyingliu/Desktop
```

```
In [279]: #1.What is the entropy over words in English?
          words=pd.read_csv('WordFrequencies.csv', header=None, index_col=0, squeeze=True).to_c
          words= {str(k):float(v) for k,v in words.items()}

In [280]: def compute_entropy(words):
              entropy=0
              for i in words:
                  prob=words[i] #get the probability
                  entropy+=prob*np.log2(1./prob)
              return entropy


In [214]: def normalization(words):
              factor=1.0/sum(words.values())
              for k in words:
                  words[k] = words[k]*factor
              return words

In [282]: normalized_words=normalization(words)

In [284]: compute_entropy(normalized_words)

Out[284]: 11.488297514501706

In [285]: #2.Using your answer from Q1, decide whether the game 20 questions1 is a fair gameca
          #you win more than half the timeassuming (a) if the word being guessed is chosen acc
```

```
#frequency, and (b) if the word is chosen uniformly
#(a) if the word is chosen according to frequency, we already get the entropy of the
#question game is fair under such circumstances, since we will only need 12 bits of
#12 questions). And we can actually ask 20 questions and obtain 20 bits of informtio
#(b)
word_count=len(words.keys())
for k in words:
    words[k]=1/word_count
uniform_words=words
```

In [286]:
```
compute_entropy(uniform_words)
#similarly, 20 questions is still a fair game, since we need to obtain 16 bits of in
#of questions we can ask.
```

Out[286]: 15.080984034059139

In [290]:
```
words=pd.read_csv('WordFrequencies.csv', header=None, index_col=0, squeeze=True).to_d
words= {str(k):float(v) for k,v in words.items()}
normalized_words=normalization(words)
```

In [291]:
```
#3.Make a plot of the conditional entropy over words in English, conditioning on the
#character (e.g. one bar for a, one for b, one for c, etc.).
#construct dics
chars=list(string.ascii_lowercase)
all_fl_dics=[]  #all 26 dictionaries generated.will append in order of a,b,c.....
def fl_generator(words):
    for i in chars:
        new={}
        for j in list(words.keys()):
            if i==j[0]:
                new.update({j:words[j]}) #takes in a dic
        all_fl_dics.append(new)
    return all_fl_dics
```

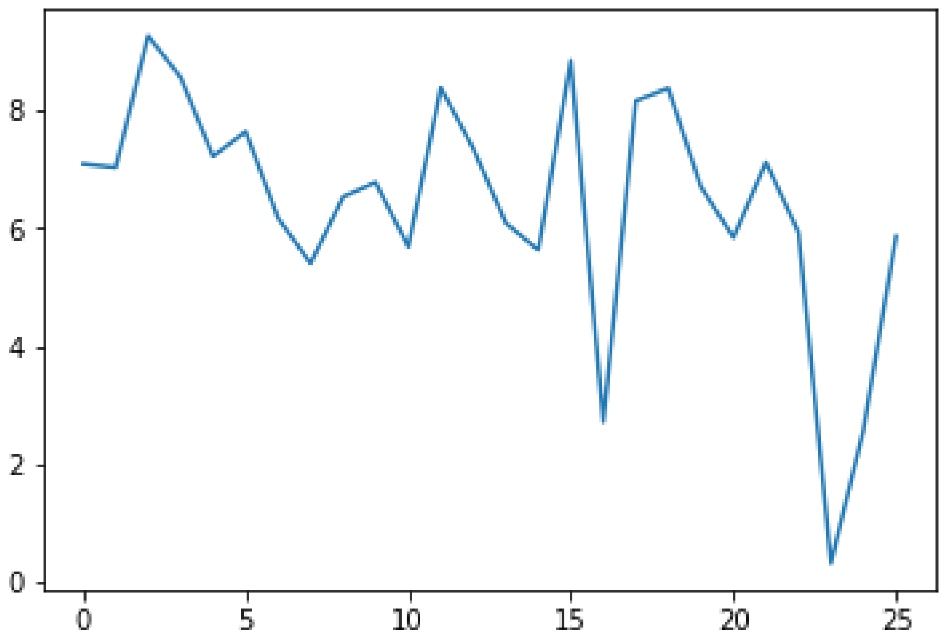
In [292]:
```
all_fl_dics=fl_generator(normalized_words)
```

In [293]:
```
#compute conditional entropy
def compute_conditional_entropy(all_fl_dics):
    p_list=[]
    y=[]
    for i in all_fl_dics:
        p_list.append(sum(i.values()))
    for i in all_fl_dics:
        i=normalization(i)
    condi_e=0
    for i in range(0,len(all_fl_dics)):
        y.append(compute_entropy(all_fl_dics[i])*p_list[i])
        condi_e+=compute_entropy(all_fl_dics[i])*p_list[i]
    return condi_e,y
```

In [294]:
```
fl_entropy=compute_conditional_entropy(all_fl_dics)[0]
```

In [295]:
```
x=range(0,26)
y=compute_conditional_entropy(all_fl_dics)[1]
plt.plot(x,y)
```

Out[295]: [<matplotlib.lines.Line2D at 0x11e7ab630>]



In [296]:
```
#4.Plot the information about word identity that is conveyed by (1) the first charac
#last character, or (3) the first vowel (aeiou). Which of these would you predict th
#for word recognition?
H_words=compute_entropy(normalized_words)
#(a)
fl_info=H_words-fl_entropy
```

In [297]:
```
fl_info
```

Out[297]: 4.338063902281873

In [298]:
```
#(b)
#ll_generator, get all_ll_dics, and get ll_infor=ll_entropy-ll_conditional_entropy
all_ll_dics=[]
def ll_generator(words):
    for i in chars:
        new={}
        for j in list(words.keys()):
```

```
                if i==j[len(j)-1]:
                    new.update({j:words[j]}) #takes in a dic
            all_ll_dics.append(new)
        return all_ll_dics
```

In [299]:
```
all_ll_dics=ll_generator(normalized_words)
```

In [263]:
```
ll_entropy=compute_conditional_entropy(all_ll_dics)[0]
```

In [300]:
```
ll_info=H_words-ll_entropy
```

In [301]:
```
ll_info
```

Out[301]:
```
0.1288473243195245
```

In [302]:
```
#(c)
#fv_generator, get all_fv_dics, and get fv_info=fv_entropy-fv_conditional_entropy
all_fv_dics=[]
vowels=['a','e','i','o','u']
def fv_generator(words):
    for each in vowels:
        new={}
        for k in list(words.keys()):
            fv_pos = [ i for i,v in enumerate(k) if v.lower() in vowels ]
            if not fv_pos ==[]:
                if k[fv_pos[0]]==each:
                    new.update({k:words[k]}) #takes in a dic
        all_fv_dics.append(new)
    return all_fv_dics
```

In [303]:
```
all_fv_dics=fv_generator(normalized_words)
```

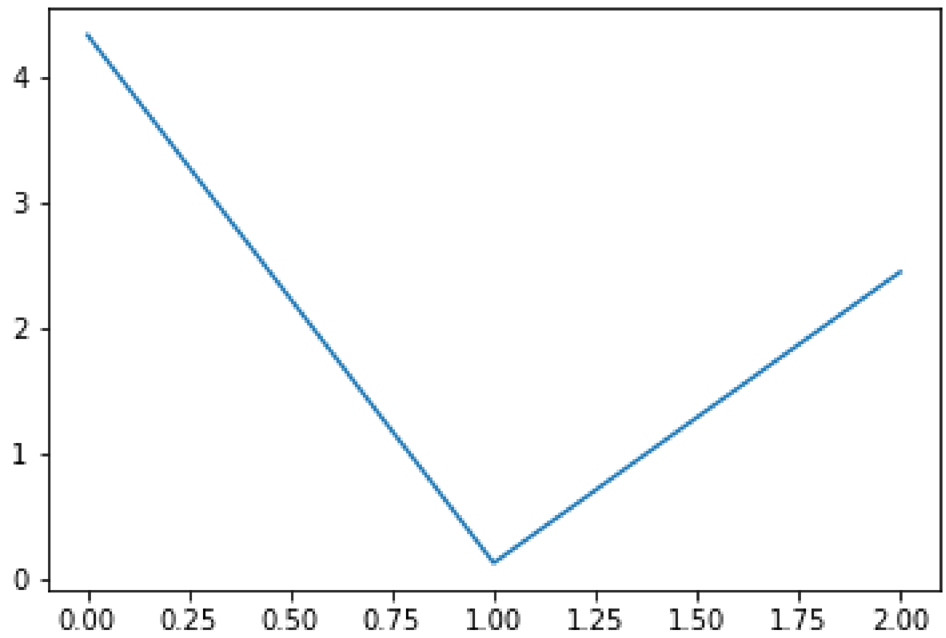
In [304]:
```
fv_entropy=compute_conditional_entropy(all_fv_dics)[0]
```

In [305]:
```
fv_info=H_words-fv_entropy
```

In [306]:
```
fv_info
```

Out[306]:
```
2.4492926945595723
```

In [307]:
```
info_list=[fl_info,ll_info,fv_info]
x=range(0,3)
plt.plot(x,info_list)
plt.show()
#According to the plot, the most important indicator for words is the last letter. S
#out of the three.
```



In [308]:
```
#5.For each word length (1, 2, 3, ) plot the average surprisal of words that are tha
#plot the averages, not a point for each word). Generally, what would this plot look
#an efficient code in Shannon's sense? Qualitatively describe in 1-2 sentences place
#does or does not agree with an efficient code.
def average_surprisal(words):
    sum_of_surprisal=0
    for i in words:
        sum_of_surprisal+=np.log(1./words[i])
    return sum_of_surprisal/len(words)


all_eq_dics=[]
def equal_len_generator(words): #tested that max length is 37
    for i in range(0,37):
        new={}
        for j in list(words.keys()):
            if len(j)==i:
                new.update({j:words[j]})
        all_eq_dics.append(new)
    return all_eq_dics
```

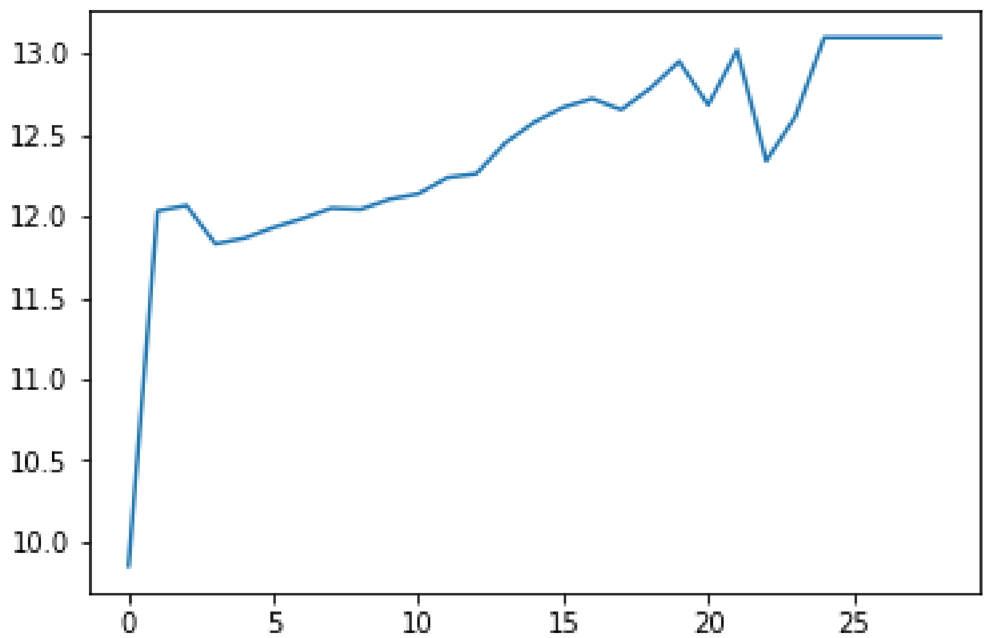
In [309]:
```
all_eq_dics=equal_len_generator(normalized_words)
while {} in all_eq_dics:
    all_eq_dics.remove({}) # remove the lengths where there are no words
```

In [310]:
```
avgs=[]
```

```
    for i in all_eq_dics:
        avgs.append(average_surprisal(i))
```

In [311]:
```
#make plots for average surprisal and explanation
plt.plot(range(0,29),avgs)
```

Out[311]: [<matplotlib.lines.Line2D at 0x118f987b8>]



In [ ]:
```
# In shannon's sense, according to ppt, higher probability events have shorter codewor
#For instance, words starting with first letter as z are relatively fewer, this is a l
#perfect sense. English is an efficient code.
```

In [241]:
```
#6. Perhaps the most frequent words are more optimized to be like an efficient
#code. Come up with a measure of how well word length agrees with surprisal (as in Q
#measure for the most frequent N words, N=10, 20, 30, ... for the entire lexicon (ea
#should be cumulative, including words 1 through N). What does your plot indicate ab
#possibility?

#Measurement. I will rearrange the dictionary with descending frequency of words. Th
#(N=10,20,30...cumulative). I will be getting the average length for the most freque
#follow a linear pattern.
```

In [242]:
```
words=pd.read_csv('WordFrequencies.csv', header=None, index_col=0, squeeze=True).to_
words= {str(k):float(v) for k,v in words.items()}
normalized_words=normalization(words)
```

In [200]:
```
sorted_words = sorted(words.items(), key=lambda x: x[1])
```

In [243]:
```
sorted_words=sorted_words[::-1]
```

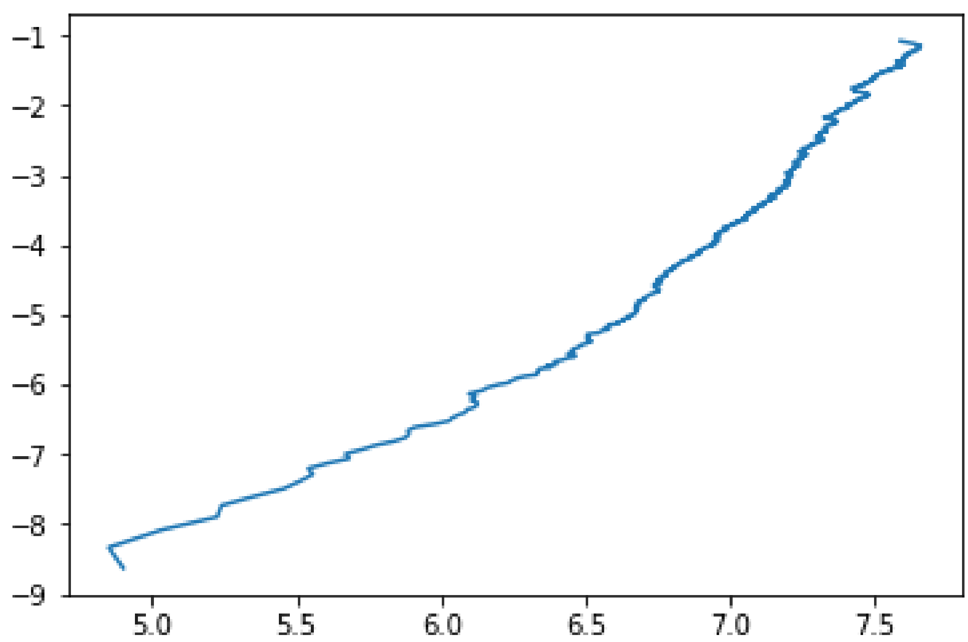
In [244]:
```
#compute avg surprisal on sorted dic
def compute_avg_surp(sorted_words):
    i=10
    avg_surp=[]
    while i< len(sorted_words):
        avg_surp.append(average_surprisal(dict(sorted_words[0:i])))
        i+=10
    return avg_surp
```

In [206]:
```
avg_surp=compute_avg_surp(sorted_words)
```

In [208]:
```
#compute avg word length on sorted dic
def compute_avg_len(sorted_words):
    avg_len=[]
    i=10
    while i<len(sorted_words):
        sum=0
        for j in dict(sorted_words[0:i]).keys():
            sum+=len(j)
        avg_len.append(sum/i)
        i+=10
    return avg_len
```

In [209]:
```
avg_len=compute_avg_len(sorted_words)
```

In [210]:
```
plt.plot(avg_len,avg_surp)
plt.show()
```



```
In [ ]: #conclusion: the codelength and actual length of the most frequent words in English ar
        #most frequent words are more optimized to be like an efficient code makes sense.
```