

## Problem 1

a) Discounted counts under GoodTuring discounting for the three bigrams are:

1. *beer drinker*:

$$\begin{aligned} N^*(w, h) &= [N(w, h) + 1] \frac{n_{N(w, h)+1}}{n_{N(w, h)}} \\ &= [1 + 1] \frac{1600}{5000} \\ &= 0.64 \end{aligned}$$

2. *beer lover*:

$$\begin{aligned} N^*(w, h) &= [N(w, h) + 1] \frac{n_{N(w, h)+1}}{n_{N(w, h)}} \\ &= [2 + 1] \frac{800}{1600} \\ &= 1.5 \end{aligned}$$

3. *beer glass*:

$$\begin{aligned} N^*(w, h) &= [N(w, h) + 1] \frac{n_{N(w, h)+1}}{n_{N(w, h)}} \\ &= [3 + 1] \frac{500}{800} \\ &= 2.5 \end{aligned}$$

b) By using a backing off model, the probabilities of the bigrams are:

1.  $p(\text{drinker}|\text{beer})$ :

$$\begin{aligned} P(w|h) &= \frac{N^*(w, h)}{N(h)} + \lambda(h)\beta(w|h) \\ \lambda(h) &= 1 - \frac{N^*(h)}{N(h)} \\ N(h) &= 6 \\ \text{therefore, } N^*(h) &= N(h) \\ \lambda(h) &= 0 \\ p(\text{drinker}|\text{beer}) &= \frac{0.64}{6} \\ &= 0.1067 \end{aligned}$$

2.  $p(\text{glass}|\text{beer})$ :

$$\begin{aligned} P(w|h) &= \frac{N^*(w, h)}{N(h)} + \lambda(h)\beta(w|h) \\ \lambda(h) &= 0 \\ p(\text{glass}|\text{beer}) &= \frac{2.5}{6} \\ &= 0.4167 \end{aligned}$$

3.  $p(\text{mug}|\text{beer})$ :

$$\begin{aligned} P(w|h) &= \frac{N^*(w, h)}{N(h)} + \lambda(h)\beta(w|h) \\ \lambda(h) &= 0 \\ N^*(\text{mug}|\text{mug beer}) &= [N(w, h) + 1] \frac{n_{N(w, h)+1}}{n_{N(w, h)}} \\ &= [0 + 1] \frac{N_1}{N_0 N} \\ N_1 &= 5000 \\ N_0 &= 1 \\ N &= \sum_{i=1}^5 N_i(w, h) n_{N_i(w, h)} \\ N &= 14100 \\ N^*(\text{mug}|\text{mug beer}) &= [0 + 1] \frac{5000}{14100} \\ &= 0.355 \\ p(\text{mug}|\text{beer}) &= [0 + 1] \frac{0.355}{6} \\ &= 0.059 \end{aligned}$$

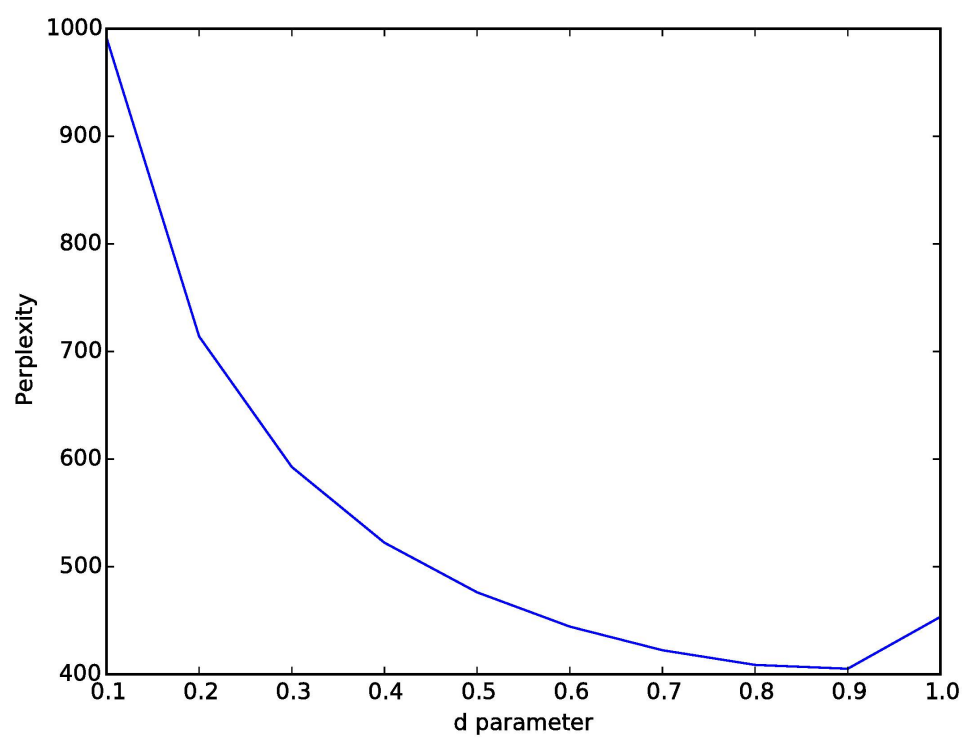
## Problem 2

**Instruction to run the the code** (for Linux):

```
$ python ex5.py
```

We got the following result:

Figure 1:



## Bonus

1) We have:

$$\begin{aligned}
 \frac{N(w, h) + \epsilon}{N(h) + \epsilon V} &= \frac{N(w, h)}{N(h) + \epsilon V} + \frac{\epsilon}{N(h) + \epsilon V} \\
 &= \frac{N(w, h)}{N(h) + \epsilon V} * \frac{N(h)}{N(h)} + \frac{\epsilon V}{(N(h) + \epsilon V)V} \\
 &= \frac{N(h)}{N(h) + \epsilon V} * \frac{N(w, h)}{N(h)} + \frac{N(h) - N(h) + \epsilon V}{N(h) + \epsilon V} * \frac{1}{V} \\
 &= \frac{N(h)}{N(h) + \epsilon V} * \frac{N(w, h)}{N(h)} + \left( \frac{N(h) + \epsilon V}{N(h) + \epsilon V} - \frac{N(h)}{N(h) + \epsilon V} \right) * \frac{1}{V} \\
 &= \frac{N(h)}{N(h) + \epsilon V} * \frac{N(w, h)}{N(h)} + \left( 1 - \frac{N(h)}{N(h) + \epsilon V} \right) * \frac{1}{V}
 \end{aligned}$$

With  $\mu = \frac{N(h)}{N(h) + \epsilon V}$ , then we have:

$$\frac{N(w, h) + \epsilon}{N(h) + \epsilon V} = \mu * \frac{N(w, h)}{N(h)} + (1 - \mu) * \frac{1}{V}$$

2) In case if the probability of a word estimated by a unigram model is 0, means that the word is an OOV word. Instead of using a zero-gram model probability value, we could improve it by adding the average probability value of the words similar to the current word. Hence metric will be:

$$\begin{aligned}
 P(w) &= \frac{N(w)}{N}, \text{ if } N(w) > 0 \\
 &= (1 - \lambda) \left( \sum_{v \in \text{Syn}(w)} \frac{N(v)}{N} \right) + \lambda c; N(w) = 0
 \end{aligned}$$

Syn(w) is a set of terms similar to w and c is the probability value obtained from zero gram model.