

1.

Penn Treebank Tokenizer is used to tokenize words according to the Penn Treebank which is a corpus of annotated text data that has been used extensively in NLP. One of the big reasons to use this tokenizer is that almost all of our text is in English, so it contains contractions and punctuation that this tokenizer does well at handling. There are two big differences between the two tokenizers; the first is that the Treebank tokenizer splits words better compared to the GPT2 tokenizer since the GPT2 tokenizer splits words in two more commonly than the NLTK tokenizer; this also means that GPT2 has slightly more tokens for each set. The second difference is that the GPT2 tokenizer contains special characters such as the Ġ to indicate the beginning of a word and Ć for breaks. The first 200 tokens of the untokenized test set can be seen below.

= Robert <unk> =

Robert <unk> is an English film , television and theatre actor . He had a guest @-@ starring role on the television series The Bill in 2000 . This was followed by a starring role in the play Herons written by Simon Stephens , which was performed in 2001 at the Royal Court Theatre . He had a guest role in the television series Judge John <unk> in 2002 . In 2004 <unk> landed a role as " Craig " in the episode " Teddy 's Story " of the television series The Long Firm ; he starred alongside actors Mark Strong and Derek Jacobi . He was cast in the 2005 theatre productions of the Philip Ridley play Mercury Fur , which was performed at the Drum Theatre in Plymouth and the <unk> <unk> Factory in London . He was directed by John <unk> and starred alongside Ben <unk> , Shane <unk> , Harry Kent , Fraser <unk> , Sophie Stanton and Dominic Hall .

The 200 tokens from the GPT and NLTK tokenizers are at the bottom of this document.

2.

The results of applying uni-gram, bi-gram, tri-gram, and 7-gram models on the NLTK tokenized corpus and GPT tokenized corpus are shown below

	NLTK Tokenized	GPT Tokenized
Uni-gram	656.589	706.445
Bi-gram	NaN	NaN
Tri-gram	NaN	NaN
7-gram	NaN	NaN

The only model that produced a perplexity result was the uni-gram model with the rest of the models giving NaN because they had n-grams that resulted in  $\ln(0)$  which is undefined. One thing that we can determine is that all the words in the test set are in the training set as well otherwise the uni-gram would error out with NaN. It makes sense that as  $n$  increases even to 2 the perplexity likely becomes NaN since it becomes significantly less likely that there would be a  $n$ -gram in the training set that exactly matches the  $n$ -gram from the test set. Thus, it is more likely that there is a  $\ln(0)$  that results in a NaN.

3.

In an attempt to process text with unknown words or contexts, we first try ignoring n-grams that aren't present in the training set. The results are shown below.

	NLTK Tokenized	GPT Tokenized
Uni-gram	656.589	706.445
Bi-gram	41.428	35.257
Tri-gram	10.390	9.593
7-gram	2.600	2.666

The uni-gram matches the one from Q2 since there were no unknown words and calculates the same perplexity. While we now also have perplexity values for the other models, they are unrealistic measurements. A lower perplexity model typically means that the model can characterize the given test input well, but by excluding the unknown values it only calculates the perplexity of values that are known and does not factor in the large number of unknown n-grams in the test set. Thus, the perplexities are artificially low as the unlikeliness of unseen words is not factored in.

3a.

In another attempt to process text with unknown words or contexts, we try implementing Laplace smoothing. The results are shown below.

	NLTK Tokenized	GPT Tokenized
Uni-gram	658.951	707.652
Bi-gram	830.061	591.575
Tri-gram	4616.201	3186.890
7-gram	29022.051	21641.156

These models use a LaPlace smoothing function for unknown words or context. In this situation, the uni-gram gives a minimally higher perplexity; the difference most likely can be attributed to the smoothing function creating a more uniform distribution thus decreasing the probabilities across all the words, slightly increasing the uncertainty in the model. On the other hand, the other 3 models' perplexity now increases instead of decreasing with each n with the tri-gram and 7-gram models having high perplexity. This high perplexity is due to having extremely low probabilities because of the smoothing function. As the value of n increases linearly, the number of possible n-grams increases exponentially and the individual n-grams themselves become much sparser. Combined with the smoothing, the probability of known n-grams decreases to be closer to the probability of unknown n-grams. As the average n-gram likelihood drops, the perplexity increases.

In another sense, Laplace smoothing reserves too much of the probability space for unknown n-grams and leaves too little for known n-grams. This scales with the number of possible n-grams which itself scales exponentially with the value of n.

4.

The pre-trained GPT2 model gives 23.8789 for the Wikitext-2 test set. We can see that this model performs much better compared to the n-gram models; this can be due to two reasons. The first is that the GPT2 model is trained on a much bigger dataset so it has more information to better understand the test data and have a lower perplexity. The second reason is that the GPT2 model uses a transformer architecture, which has a larger and more flexible context window compared to n-grams which are stuck with a small, fixed context.

5.

The perplexity of the models was measured on a set of examples. The results are shown below.

Example	Uni-gram	Bi-gram	Tri-gram	7-gram	GPT2
1	1483.872	3370.214	16849.754	32164.916	18.371
2	3534.026	5235.325	22053.862	33271.000	96.344
3	2795.093	4526.919	19502.307	33271.000	12.528
4	8675.215	11672.437	25910.114	33271.000	139.320
5	8675.215	11672.436	25910.114	33271.000	36.378
6	2294.834	14015.742	29385.834	33271.000	19.555
7	227.231	54341.064	33271.000	NaN	151.078
8	4181.877	8751.601	21834.720	33271.000	18.244
9	4823.907	14843.932	28595.467	33271.000	137.231

10	1139.578	2265.001	14011.544	33271.000	20.022
11	2603.836	4273.913	18647.556	33271.000	14.564

Looking at the table, the GPT2 model performs consistently better than the n-gram models; the smoothed n-gram models perform as expected where the uni-gram has the lowest perplexity with the perplexity increasing with n. Some interesting points are examples 4 and 5, which when tokenized have the same perplexity since the extra spaces are removed, but the spaces greatly increase the perplexity for the GPT2 model. Also, example 7 only has 3 tokens so can not run the 7-gram model. Lastly, all the models at 7-gram give perplexity around 33271 (3-gram for example 7), which seems to be the perplexity that the smoothed models saturate at. If all n-grams in the example are unknown, then the probability for each n-gram is  $1/33271$  because it becomes  $1/|V|$  since the two count terms become 0. Then, since all the probabilities are the same, the perplexity becomes the  $\exp(-\ln(1/|V|))$  which equals to  $|V|$ .

## NLTK Tokenizer

=  
Robert  
<  
unk  
>  
=  
Robert  
<  
unk  
>  
is  
an  
English  
film  
,  
television  
and  
theatre  
actor  
.  
He  
had  
a  
guest  
@  
-  
@  
starring  
role  
on  
the  
television  
series  
The  
Bill  
in  
2000  
.  
This  
was  
followed  
by  
a  
starring  
role  
in  
the  
play  
Herons  
written  
by  
Simon  
Stephens  
,  
which  
was  
performed  
in  
2001  
at  
the  
Royal  
Court  
Theatre  
.  
He  
had  
a

guest  
role  
in  
the  
television  
series  
Judge  
John  
<  
unk  
>  
in  
2002  
.  
In  
2004  
<  
unk  
>  
landed  
a  
role  
as  
``  
Craig  
``  
in  
the  
episode  
``  
Teddy  
's  
Story  
``  
of  
the  
television  
series  
The  
Long  
Firm  
;  
he  
starred  
alongside  
actors  
Mark  
Strong  
and  
Derek  
Jacobi  
.  
He  
was  
cast  
in  
the  
2005  
theatre  
productions  
of  
the  
Philip  
Ridley  
play  
Mercury  
Fur  
,

which  
was  
performed  
at  
the  
Drum  
Theatre  
in  
Plymouth  
and  
the  
<  
unk  
>  
<  
unk  
>  
Factory  
in  
London  
.  
He  
was  
directed  
by  
John  
<  
unk  
>  
and  
starred  
alongside  
Ben  
<  
unk  
>  
,  
Shane  
<  
unk  
>  
,  
Harry  
Kent  
,  
Fraser  
<  
unk  
>  
,  
Sophie  
Stanton  
and  
Dominic  
Hall  
.  
In  
2006  
,  
<  
unk  
>  
starred  
alongside

## GPT Tokenizer

G  
C  
G=  
GRobert  
G<  
unk  
>  
G=  
G  
C  
G  
C  
GRobert  
G<  
unk  
>  
Gis  
Gan  
GEnglish  
Gfilm  
G,  
Gtelevision  
Gand  
Gtheatre  
Gactor  
G.  
GHe  
Ghad  
Ga  
Gguest  
G@  
-  
@  
Gstarring  
Grole  
Gon  
Gthe  
Gtelevision  
Gseries  
GThe  
GBill  
Gin  
G2000  
G.  
GThis  
Gwas  
Gfollowed  
Gby  
Ga  
Gstarring  
Grole  
Gin  
Gthe  
Gplay  
GHer  
ons  
Gwritten  
Gby  
GSimon  
GStephens  
G,  
Gwhich  
Gwas  
Gperformed  
Gin  
G2001  
Gat

Gthe  
GRoyal  
GCourt  
GTheatre  
G.  
GHe  
Ghad  
Ga  
Gguest  
Grole  
Gin  
Gthe  
Gtelevision  
Gseries  
GJudge  
GJohn  
G<  
unk  
>  
Gin  
G2002  
G.  
GIn  
G2004  
G<  
unk  
>  
Glanded  
Ga  
Grole  
Gas  
G"  
GCraig  
G"  
Gin  
Gthe  
Gepisode  
G"  
GTeddy  
G'  
s  
GStory  
G"  
Gof  
Gthe  
Gtelevision  
Gseries  
GThe  
GLong  
GFirm  
G;  
Ghe  
Gstarred  
Galongside  
Gactors  
GMark  
GStrong  
Gand  
GDerek  
GJacob  
i  
G.  
GHe  
Gwas  
Gcast  
Gin  
Gthe

G2005  
Gtheatre  
Gproductions  
Gof  
Gthe  
GPhilip  
GRidley  
Gplay  
GMercury  
GFur  
G,  
Gwhich  
Gwas  
Gperformed  
Gat  
Gthe  
GDrum  
GTheatre  
Gin  
GPlymouth  
Gand  
Gthe  
G<  
unk  
>  
G<  
unk  
>  
GFactory  
Gin  
GLondon  
G.  
GHe  
Gwas  
Gdirected  
Gby  
GJohn  
G<  
unk  
>  
Gand  
Gstarred  
Galongside  
GBen  
G<  
unk  
>  
G,  
GShane  
G<  
unk  
>  
G,  
GHarry  
GKent  
G,  
GFraser  
G<  
unk  
>  
G,  
GSophie  
GStanton  
Gand  
GDominic  
GHall