

AI6122 Text Data Management and Processing

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ABSTRACT

1 INTRODUCTION

2 DATASET ANALYSIS

In this project, we use *Amazon product data* from [1] to conduct all the following experiments. Specifically, we randomly select 200 product reviews from each of the two 5-core datasets with categories "Health and Personal Care" and "Video Games", respectively.

2.1 Writing Style

2.2 POS Tagging

2.3 Sentence Segmentation

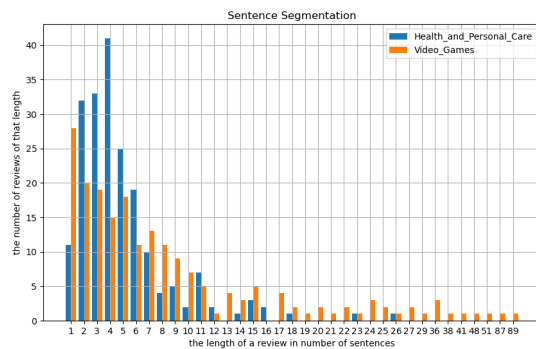


Figure 1: The distribution of the two datasets in terms of the number of sentences.

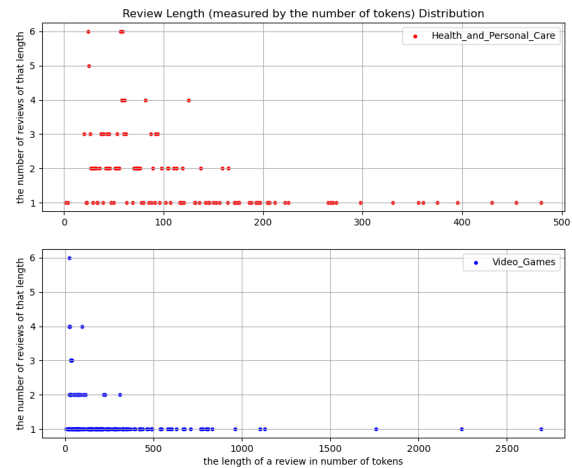


Figure 2: The distribution of the two datasets in terms of the number of tokens.

REFERENCES

- [1] Ruining He and Julian McAuley. 2016. Ups and Downs: Modeling the Visual Evolution of Fashion Trends with One-Class Collaborative Filtering. In *WWW*.

2.4 Tokenization and Stemming

2.5 Indicative Words

3 SEARCH ENGINE

4 REVIEW SUMMARIZER

5 SENTIMENT ANALYSIS

CONTRIBUTIONS

Junyu Yin: Dataset Analysis.

<i>It</i> PRP	<i>helped</i> VBD	<i>me</i> PRP	<i>take</i> VB	<i>off</i> RP	<i>those</i> DT	<i>extra</i> JJ	<i>pounds</i> NNS	<i>that</i> IN	<i>I</i> PRP	<i>had</i> VBD	<i>gained</i> VBN	<i>during</i> IN	<i>the</i> DT
<i>holidays</i> NNS	.												
<i>Everyone</i> NN	<i>should</i> MD	<i>read</i> VB	<i>this</i> DT	<i>article</i> NN	<i>and</i> CC	<i>use</i> VB	<i>this</i> DT	<i>formula</i> NN	.				
<i>Pretty</i> RB	<i>much</i> RB	<i>the</i> DT	<i>only</i> JJ	<i>way</i> NN	<i>to</i> TO	<i>shave</i> VB	<i>cheaper</i> JJR	<i>is</i> VBZ	<i>to</i> TO	<i>use</i> VB	<i>a</i> DT	<i>double</i> JJ	<i>edge</i> NN
<i>razor</i> NN	,	<i>and</i> CC	<i>even</i> RB	<i>then</i> RB	<i>you</i> PRP	<i>do</i> VBP	<i>n't</i> RB	<i>save</i> VB	<i>that</i> RB	<i>much</i> JJ	<i>more</i> RBR	.	
<i>Right</i> RB	<i>now</i> RB	<i>the</i> DT	<i>only</i> JJ	<i>things</i> NNS	<i>I</i> PRP	<i>'ve</i> VBP	<i>unlocked</i> VBN	<i>are</i> VBP	<i>Backpack</i> NNP	<i>option</i> NN	,	<i>Koga</i> NNP	,
<i>Kikyo</i> NNP	,	<i>Kagura</i> NNP	,	<i>and</i> CC	<i>you</i> PRP	<i>already</i> RB	<i>have</i> VBP	<i>Inuyasha</i> NNP	,	<i>Kagome</i> NNP	,	<i>Miroku</i> NNP	,
<i>Shippou</i> NNP	,	<i>and</i> CC	<i>Sango</i> NNP	<i>when</i> WRB	<i>the</i> DT	<i>game</i> NN	<i>starts</i> VBZ	<i>off</i> RP	.				
<i>My</i> PRP\$	<i>first</i> JJ	<i>xbox</i> NN	<i>since</i> IN	<i>2004</i> CD	.								

Table 1: The POS tagging results.

	w/o stemming	Porter stemming	Lancaster stemming	Snowball stemming
Health and Personal Care	3546	2591	2372	2559
Video Games	6582	4490	4049	4409

Table 2: The number of unqiue tokens with and without stemming.

Health and Personal Care	product	skin	smell	products	used	brand	bottle	taste	price	weight
Video Games	game	games	play	fun	graphics	playing	played	story	system	gameplay

Table 3: The top-10 most indicative words in each of the two datasets.

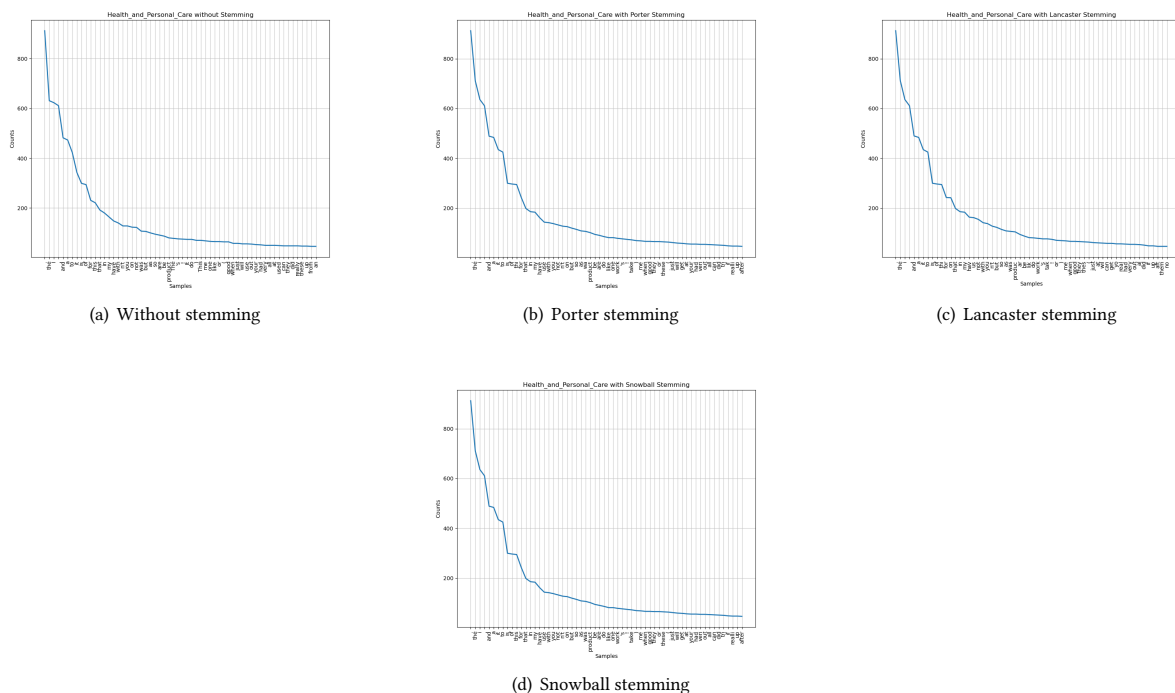


Figure 3: Word frequency distribution of *Health and Personal Care* with and without stemming.

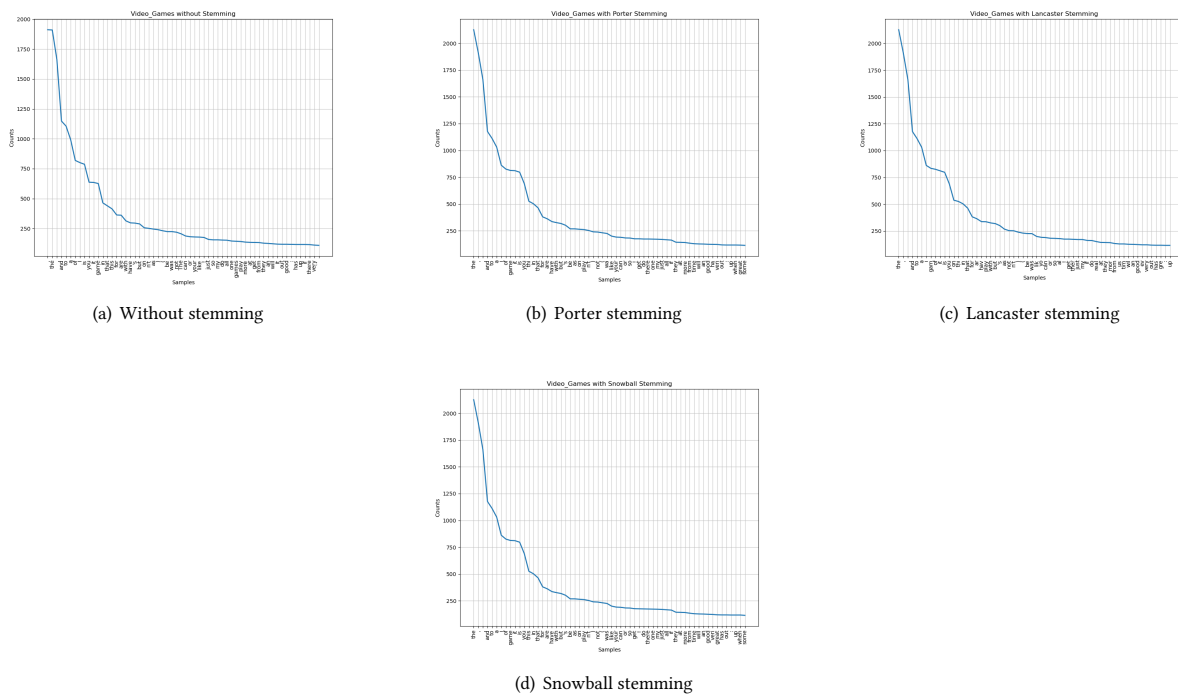


Figure 4: Word frequency distribution of *Video Games* with and without stemming.