SEPHORA Project Final Report

BANA 295: Big Data Management

Professor:

Vagelis Hristidis

UCI Student Team:

Xiwen Li, Ye Xiao, Kun Zhang

June 10, 2018

Content

PREFACE	1
1. INTRODUCTION	1
1.1 Background	1
1.2 Project Objectives	1
2.DATA	2
2.1 Data Scraping	2
2.2 Data Description	2
2.3 Data Processing	3
2.3.1 Converting txt to csv	3
2.3.2 Processing data through Spark	4
3.NATURE LANGUAGE PROCESS	5
3.1 Word Frequency Analysis	5
3.2 Topic Extraction with LDA model	6
4. APPLICATION	7
4.1 Methodology	7
4.1.1 Query Records	7
4.1.2 Interactive Visualizations	8
4.1.3 Interactive Python File	8
4.2 Results	8
4.3 Limitations	11
5. CONCLUSION	11
APPENDICES	12
A: Collaboration Details	12
B: Data scraping detail	
C: Transforming TXT into CSV details	
D: PROCESSING DATA THROUGH SPARK	17
E: Word Frequency Analysis	18
F: LDA MODEL	

Preface

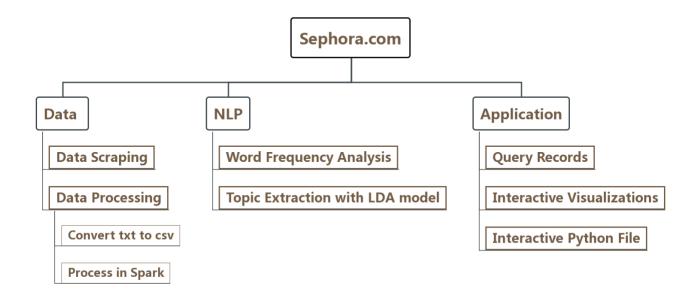


Figure.1 The overall figure of our project

1. Introduction

1.1 Background

Sephora is a global cosmetic retailer founded in 1970. Sephora carries more than 300 brands, and it operates approximately 2,300 stores in 33 countries worldwide, with over 430 stores across the Americas. Sephora provides an overall rating for every single product it carries as well as a brief specification, but it is important to read through the reviews to see other user's opinion in words before purchasing the products because a high rating does not suggest if the product is appropriate for you. Also, the product specification never mentions the negative side of the product. For example, a cleanser may have a high rating because it has a strong cleaning power, but you happen to have a sensitive skin and you need a gentle cleanser. In this case, if you only look at the overall rating of the product, it could be misleading.

1.2 Project Objectives

Our team thinks that customer reviews can be tremendously helpful since they contain first-hand experience from a wide range of people. However, a lot of products on Sephora.com have hundreds or even thousands of reviews. It is excruciating to read all of them. In order to extract valuable information from reviews, we summarize reviews using Natural Language Processing. At the end, we are able to provide customers with keywords generalized form genuine feedbacks from old customers. Moreover,

with the immense information we have, we are able to predict new customers' tastes based on their attributes like age, skin type, and so on. An easy application will be developed to expedite the process.

2.Data

2.1 Data Scraping

First, I went to Sephora's brands page (https://www.sephora.com/brand/list.jsp) and scraped all the brand names. Then I pasted each brand names after (www.sephora.com/), so I got all the links of each brand's homepage. Secondly, from each brands' homepage source codes, I got the unique brand-ID corresponding to each brand. Thirdly, after clicking on the "see all" from brand's homepage, I inspected the page and found out there were a JSON data file. Then I found out the API which could return all the product-ID from brand-ID, so I scraped all the product-IDs from all the brand-IDs. Finally, from the product page, I inspected out that an API which could return all the reviews along with reviewer information of a product, so I used the API by automatic adjusting parameters to acquire all the reviews of all the products from Sephora. In addition, in order to make a precise analysis, I export 2 csv files during data scraping. Brands_URL.csv contains mapping relationship between brand-ID and its url, and Products_info.csv contains each product's name product-ID along with the brand name and brand-ID.

Detailed information about codes for data scraping can be found in Appendix B.

2.2 Data Description

There are totally three data sets. Firstly, I scraped total of 235900 reviews from 312 brands' 9123 products. And Figure.2 is a screenshot of one review I scraped. Each record has a product-ID, a user-nickname, a rating, an age, an eye-color, a skin-tone, a skin-type, and the review. And if the reviewer left a section blank, it would show NA.

0.txt ~ P307803 LCD11 35-44 NA I'm a fan of gourmand 5 NA NA NA scents to a degree, such as Hanae Mori Butterfly, Prada Candy, Atelier Cologne Vanilla, etc. But this offering from ADP has won me over more than any other of the kind. When it's first sprayed it really does smell exactly like a root beer float, which I know might sound strange -- I certainly found it strange myself when I first applied it. I wasn't sure about it at that point ... but then it settles into this intoxicating scent that I can't get enough of! It has truly won me over. It's very unique yet comforting at the same time and doesn't have any fake, synthetic notes, which I hate. It's very sweet but not in a cloying or annoying way. It's just delicious. The scent lasts a good while on me but it could last longer. I wish this came in a stronger concentration.

Figure.2 The screenshot of an example review file

And the second and third are about the information of brands and products. Figrue.3 is the screenshots of these two csv files (foreign key: Brand_ID).

Α	В	С	D	E	Α	В	С	D	E
	Brand_URL				ProductID	Product_nan	Brand id	Brand_name	
	5847 https://www.sephora.com/acqua-di-parma				P307803	Blu Mediterr	_		
	https://www.sephora.com/aerin-perfume							Acqua Di Par	
	https://www.sephora.com/algenist				P163604	Colonia	5847	Acqua Di Pari	ma
5998	https://www	.sephora.co	m/alterna		P307804	Blu Mediterr	5847	Acqua Di Pari	ma
5723	https://www	.sephora.co	m/amazing-co	smetics	P307801	Blu Mediterr	5847	Acqua Di Pari	ma
6004	https://www	.sephora.co	m/amika					· ·	
5945	https://www	.sephora.co	m/amorepacit	fic	P409963	Colonia Quer		Acqua Di Pari	
5746	https://www	.sephora.co	m/anastasia-b	everly-hills	P375388	Blu Mediterr	5847	Acqua Di Pari	ma
4374	https://www	.sephora.co	m/anthony-lo	gistics-for-men	P269110	Colonia Esse	5847	Acqua Di Pari	ma
6212	https://www	.sephora.co	m/antonym		P388670	Rosa Nobile	5847	Acqua Di Pari	ma
6078	https://www	.sephora.co	m/apivita		P380568	Colonia Body	5847	Acqua Di Pari	ma
6173	https://www	.sephora.co	m/aquis		P252213	-		· ·	
5931	https://www	.sephora.co	m/the-art-of-s	shaving		Magnolia No		Acqua Di Par	
6241	https://www	.sephora.co	m/artis		P307802	Blu Mediterr	5847	Acqua Di Pari	ma
6242	https://www	.sephora.co	m/artist-cout	ıre	P413669	Peonia Nobil	5847	Acqua Di Pari	ma
6083	https://www	.sephora.co	m/atelier-colo	gne	P428073	Colonia Nom	5847	Acqua Di Pari	ma
6214	https://www	.sephora.co	m/axiology		P422289	Colonia Pura	5847	Acqua Di Pari	ma
7068	https://www	.sephora.co	m/besame-co	smetics	P380567	Colonia Talcu		Acqua Di Pari	
		•	m/balenciaga					<u> </u>	
E727	https://www.	canhara ca	m/haraminar	ala.	P200313	Colonia Inter	5847	Acqua Di Pari	ma

Figure.3 The screenshots of the data sets of brands and products

2.3 Data Processing

2.3.1 Converting txt to csv

In order to make the further analysis easier, I convert the txt reviews files to csv format. And Figure.4 is the screenshot of the csv generated.

Detailed information about how to convert the txt into csv is shown in Appendix C.

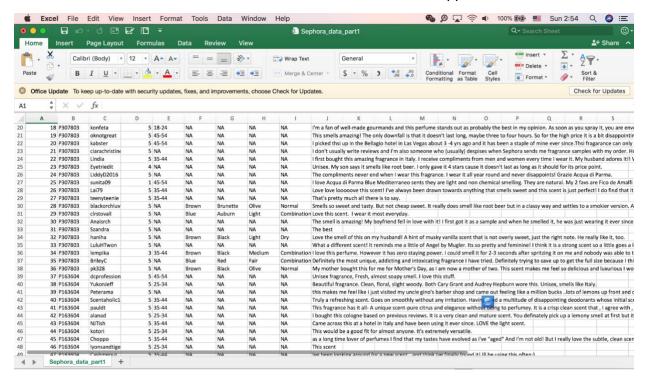


Figure.4 Screenshot of the csv file converted from txt

2.3.2 Processing data through Spark

After crawling data from Sephora website, we found that the size of data is around 10GB which meet the requirements for this project. Simultaneously, another problem is that the data is so large that it is hard to process it locally. So, we decided to upload it to AWS S3 and process it remotely using spark.

After uploading data to S3, we created a spark cluster and used Zeppelin as a notepad to write and execute code for big data processing purpose. Firstly, we used command "spark.read" to read data and create RDD "review" and "product". We could also use review.show() as an action command in spark to view top 20 rows in each RDD.

т					т
1	IDI	Product_name Br	rand_idl	Bran	d_name
+	+	+	+		+
1P30	7803 Blu	Mediterraneo	5847 I Acqu	a Di	Parmal
IP16	536041	Colonial	5847 I Acqu	a Di	Parmal
1P30	07804 Blu	Mediterraneo	5847 I Acqu	a Di	Parmal
1P30	07801 Blu	Mediterraneo	5847 I Acqu	a Di	Parmal
1P40	9963 Colo	onia Quercia EI	5847 I Acqu	a Di	Parmal

Figure.5 Sample data of "Product"

+-	+	+-	+	+	+-			+	+	+
1_	c0 file	eIndexip	productIDI	userNicknamelra	tingl	ageley	eColor Iha	irColorIsk	inTonelsk	reviewl reviewl
+-	+	+-	+	+	+-	+	+	+	+	+
1	01	01	P3078031	LCD111	51	35-441	nullI	nullI	nullI	nullII'm a fan of gourI
1	21	21	P3078031	EspritDuSoleill	51	nullI	nulli	nulli	nullI	nulliOh. My. Gosh. WhaI
1	31	31	P3078031	FrenchieBarbiel	51	nullI	nullI	nullI	nullI	null I recently got a
1	41	41	P3078031	kshersl	51	18-241	nullI	nullI	nullI	null This smells so go
1	51	51	P3078031	mdrajeskel	51	nullI	nullI	nullI	nullI	nullli just got a sampl

Figure.6 Sample data of "Review"

Like what the tables show here, from Figure 6 and Figure 7, we could know the demographic information of each customer like age, gender, skin type etc. Also, we could know customer reviews and which product they leave the review to.

In order to match the review data, customer information and product information together and do some processing work, we decided to use SparkSQL since the data is structured and a DataFrame provides more operations which are not available on RDDs like running SQL queries. So, we created 2 temp tables using "CreateOrReplaceTempView" command to execute SQL queries. By using the command below, we joined two tables together.

+			+	+	+-			+-	+	+		+	+
I IDI	Product_name Br	and_id Brand_	name l_	c0 file	IndexIp	roductIDI	userNicknamelra	tingl	ageley	eColorIha	irColorIsk	inTonelsk	reviewl reviewl
+	+	+	+	+	+-			+-	+			+	+
IP307803 Blu	Mediterraneo!	58471Acqua Di P	Parmal	01	01	P3078031	LCD111	51	35-441	nullI	nullI	nullI	null I'm a fan of gour
IP307803 Blu	Mediterraneo	5847 Acqua Di P	Parmal	21	21	P3078031E	spritDuSoleil	51	nullI	nulli	nullI	nullI	nullIOh. My. Gosh. WhaI
IP3078031Blu	MediterraneoI	5847 Acqua Di P	Parmal	31	31	P3078031Fr	renchieBarbiel	51	nullI	nullI	nullI	nullI	null I recently got a
IP307803 Blu	Mediterraneo	5847 Acqua Di P	Parmal	41	41	P3078031	kshersl	51	18-241	nullI	nullI	nullI	null This smells so go
IP3078031Blu	Mediterraneo	5847 Acqua Di P	Parmal	51	51	P3078031	mdrajeskel	51	nullI	nullI	nullI	nullI	nullli just got a samp!

Figure.7 The structure of the whole table

After joining data together, we used command like "group by", "Sort" etc. under sqlContext to select data under specific constraints and filter data for analysis purpose.

Detailed codes for Spark process are shown in Appendix D.

3. Nature Language Process

3.1 Word Frequency Analysis

After descriptive analysis, we found that the product "Naked Palette Collection" is very popular which has more than 20,000 reviews. So, in order to dig the reason why people give it positive reviews and negative reviews, we filtered reviews for this product and define reviews with rating=1 as negative reviews and reviews with rating = 5 as positive reviews. We create an RDD for review data and store it in S3. Then, we imported data into Python and did word frequency analysis and word cloud chart for both positive reviews and negative reviews.

From the word frequency chart for positive reviews, we could see that words like "palette", "brush", "skin" appear frequently. We may simply infer that people like this eye shadow because it's brush is easy to use, or the eye shadow looks great on skin.

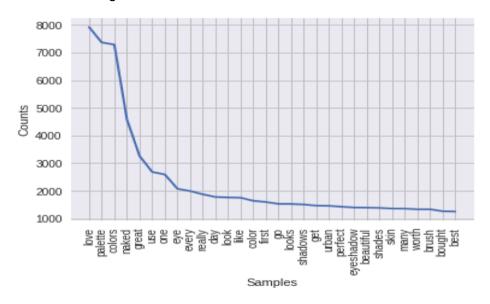


Figure.8 Word frequency for "positive reviews"

From the word frequency line chart for negative reviews, we could see that "colors" is the most frequent word so we may infer that people give it low rating because its color.

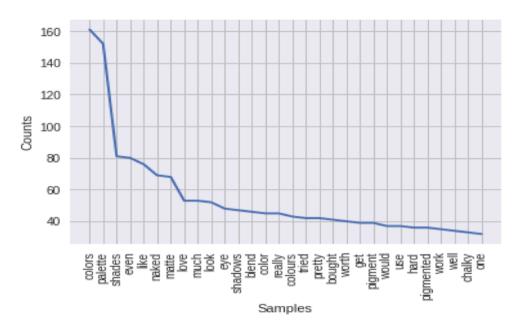


Figure.9 word frequency for "negative reviews" Detailed codes for word frequency analysis are shown in Appendix E.

3.2 Topic Extraction with LDA model

In order to know more about the reasons why people like or dislike the product, we decided to use LDA model to extract topics from reviews.

Firstly, we tokenized words from reviews with "RegexTokenizer" command. Then, since lots of words are stop words like "I", "are", "is" etc. which are meaningless for analysis purpose, we removed stop words from each review. Also, we changed all the words in to stem form since words always have different tense and will be recognized as different words if we didn't stem them (e.g like vs likes). After that, we changed each review into bags of words and then combine all those reviews into a matrix so that it can be used for LDA model analysis.

```
[(0,
    '0.142*"look" + 0.049*"shade" + 0.040*"eye" + 0.035*"creat" + 0.032*"matt"'),
(1,
    '0.261*"nake" + 0.092*"urban" + 0.090*"decay" + 0.071*"2" + 0.064*"first"'),
(2,
    '0.142*"skin" + 0.128*"tone" + 0.125*"best" + 0.089*"ever" + 0.053*"eye"'),
(3,
    '0.076*"color" + 0.075*"palett" + 0.069*"love" + 0.032*"use" + 0.028*"great"'),
(4, '0.042*"bought" + 0.035*"got" + 0.028*"get" + 0.026*"buy" + 0.023*"tri"')]
```

Figure.10 Positive Reviews with Rating=5

Consequently, based on the result, we could infer that people love this eyeshadow firstly because it's matt color; secondly, lots of people try it the first time and feels good so that they give it a high rating; additionally, some other people feel that the eye shadow matched greatly with their skin tone.

```
[(0,
    '0.044*"color" + 0.029*"palett" + 0.022*"nake" + 0.017*"use" + 0.016*"pigment"'),
(1,
    '0.039*"palett" + 0.036*"color" + 0.026*"look" + 0.018*"tri" + 0.016*"like"'),
(2,
    '0.036*"pigment" + 0.027*"palett" + 0.024*"money" + 0.023*"color" + 0.022*"worth"'),
(3,
    '0.041*"color" + 0.036*"palett" + 0.027*"like" + 0.021*"look" + 0.020*"get"'),
(4,
    '0.066*"shade" + 0.043*"matt" + 0.031*"pigment" + 0.028*"primer" + 0.026*"even"')]
```

Figure.11 Negative Reviews with Rating=1

As for the reasons why people give it negative reviews, some people don't like its pigment color; also, some other consumers feel that this product is not worth the money and kind of expensive.

Detailed codes for LDA model are shown in Appendix F.

4. Application

4.1 Methodology

We have two datasets scripted from Sephora.com, one for all information of reviews (including age, rating, skin-type of reviewers, and review texts), and another for product information. So according to the product ID, we left joined the product information into review datasets. And the following operations are performed on this joined dataset.

4.1.1 Query Records

For millions of records, it's time wasting to run filter function on local environment. So, we prefer to use Spark SQL to execute the filter process. We set six variables as customized inputs (Detailed introductions are shown in Table.1)

Symbol	Explanation	Choices
-k	Keywords	Enter any keywords you are interested in
-a	Age ranges	'35-44', '18-24', '45-54', 'over 54', '25-34', '13-17'
-e	Eye colors	'Brown', 'Blue', 'Hazel', 'Green', 'Gray'
-C	Hair colors	'Brunette', 'Auburn', 'Black', 'Red', 'Gray', 'Blonde'
-t	Skin tones	'Olive', 'Light', 'Medium', 'Fair', 'Porcelain', 'Deep', 'Tan', 'Dark', 'Ebony'

-s	Skin types	'Normal', 'Combination', 'Dry', 'Oily'

Table.1 The information of inputs

Based on the inputs, we can generate SQL syntaxes to select the fitted records. Below is a simple example in Figure.12.

```
result=sqlContext.sql('''SELECT *
FROM joined
WHERE review REGEXP 'dark circle'
AND age='35-44'
''')
```

Figure.12 Example for selecting fitted records by Spark SQL.

In this example, we can select the reviews that contain 'dark circle' and the reviewer's age is in 35-44.

4.1.2 Interactive Visualizations

Once we have selected the relevant records, we want to show some interesting interactive visualizations for business insights. The main package used in python is plotly, which generates interactive graphs in html format (refer to Ye_SparkSQL.ipynb for original codes). For each query, it will automatically generate two pie charts for top 20 brands and products, one box plot of ratings for each brand, and one scatter plot for review texts.

4.1.3 Interactive Python File

We allow users to input parameters to generate graphs with the help of 'argparse' package (refer to Ye_SparkSQL.py for complete codes). The information of parameters is listed in Table.1. And the example of command prompt is,

, where it searches the records that contain keywords 'dark circle', and that are written by the reviewers between 35 and 44 with brown eyes, brunette hairs, olive and normal skins.

4.2 Results

We use a simple example to better illustrate our works. When the command prompt is,

```
python3 Ye_SparkSQL.py -k dark\ circle -a 18-24
```

, the terminal interface is shown in Figure.13.

```
xiaoyedeMacBook-Pro:Project xy$ python3 Ye_SparkSQL.py -k dark\ circle -a 18-24

SELECT * FROM joined WHERE review REGEXP 'dark circle' AND age='18-24'
2018-06-10 00:33:52 WARN NativeCodeLoader:62 - Unable to load native-hadoop lib
rary for your platform... using builtin-java classes where applicable
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLeve
l(newLevel).
===== init finished =====
===== load finished =====
===== select finished =====
===== plot finished ======
```

Figure.13 The terminal interface after executing the example command prompt.

At the same time, it will output four graphs automatically (Shown in Figure.14, Figure.15, Figure.16, Figure.17. For integrated animations, refer to brands.html, products.html, boxplot of ratings.html, and scatter plot for reviews.html).

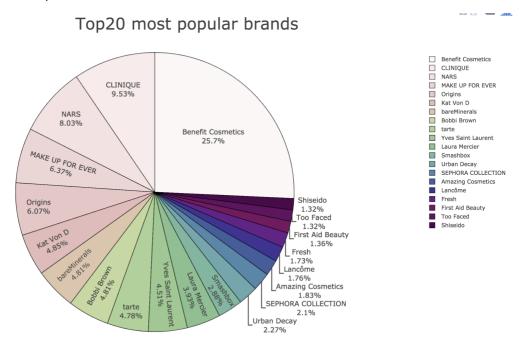


Figure 14 The top 20 most popular brands of the example command prompt

Top20 most popular products

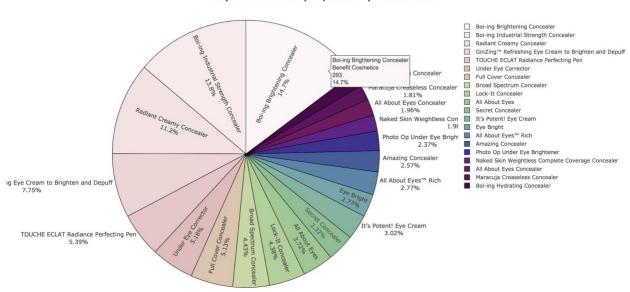


Figure.15 The top 20 most popular products of the example command prompt



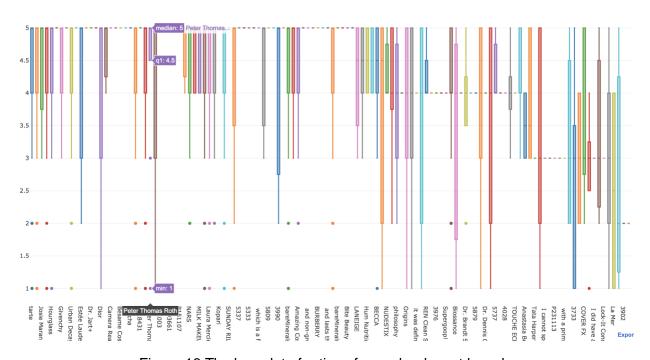


Figure.16 The box plot of ratings for each relevant brand

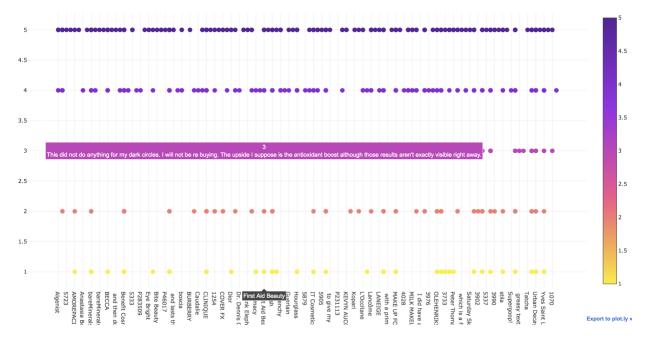


Figure.17 The scatter plot of relevant reviews

4.3 Limitations

The first obvious limitation is how to process the customized keywords. In general, people express the same meanings regardless of upper or lower case letters. But in our syntax, it simply uses regular expression to match the exact words. For example, we also input 'dark circle' as keywords, but it's impossible to select the reviews that contain 'Dark Circle' or 'Dark circle'. It is a distinct drawback and requires more considerations in the future.

5. Conclusion

regarding this project, we firstly crawled consumer and review data from Sephora website and processed it in Spark. After that, we did descriptive analysis for consumers' demographic distribution and popularity of brands and products. Then, we selected one product called "Naked Palette Collection" and analyzed its positive and negative reviews in detail with NLP model so that the company could optimize based the reason why consumers dislike it and treat those reasons why people like it as selling point to do promotion. Finally, based on NLP processing, we build a recommendation system which could recommend most relevant brands and products if you enter some keywords. Also, the relevant reviews could also be found so that consumers could select products based those relevant reviews.

Appendices

A: Collaboration Details

Our team collaborate well together, and we all agree that works distributes between three team members equally and fairly.

Xiwen Li: Data scraping, data processing, and PPT.

Ye Xiao: Application development, and PPT

Kun Zhang: Visualizations, Natural language processing, and PPT.

B: Data scraping detail

```
# get all the brands url
def get_brands_list(url, filedir):
    res = requests.get(url)
    soup = BeautifulSoup(res.text, "html.parser")
    brand_urls = []
    brand_ids = []
    base_url = "https://www.sephora.com"
    count = 0
    csvfile = open(os.path.join(filedir, "Brands_URL.csv"), "a+")
    writer = csv.writer(csvfile)
    writer.writerow([Frand_ID", "Brand_URL"])
    for href in soup.findAll("a", "class": "u-hoverRed u-db u-p1")):
        brand_url = base_url + href.get('href')
        print(brand_url)
        brandID = get_brandID(brand_url)
        print(count, "\t", brandID)

        writer.writerow([brandID, brand_url])

        brand_urls.append(brand_url)
        brand_urls.append(brand_url)
        count = 1
        csvfile.close()
        return brand_urls, brand_ids

# get the brandID

def get_brandID(url):
        res = requests.get(url)
        soup = BeautifutSoup(res.text, "html.parser")
        brand_Idg = soup.select("div!certona='BRAND']")
        # print(X)
        for item in brand_tag:
            brandID = soup.select("div!certona='BRAND']")
        # print(trandID)
        # print(trandID)
```

Figure 18. Code for grabbing brand URL and list of brandID from Web Source Page.

Figure 19. Code for acquiring all products ID of each brand through productID API.

```
# creater

# the apt of 1 ist https://psi.bazarocic com/data/reviews.json/Filters/roductIdN3A(M16375)65orteHelpfulnessAlAdescALimit=10000ffset=065includes/roductsACComments65tatsHerd IdNA share the Ion on be replaced and get the result as joon of get_reviews (araductly, lists, offset, filedir):

## the apt of 1 ist https://psi.bazarocic com/data/reviews.json/Filters/roductIdN3A" + str/productID) + "&SorteHelpfulnessAlAdescALimit=" + str/limit) + "&Offset=" + str/limit) + "&Offset=" + str/limit] + "&Offset=" + str/limit=" + str/l
```

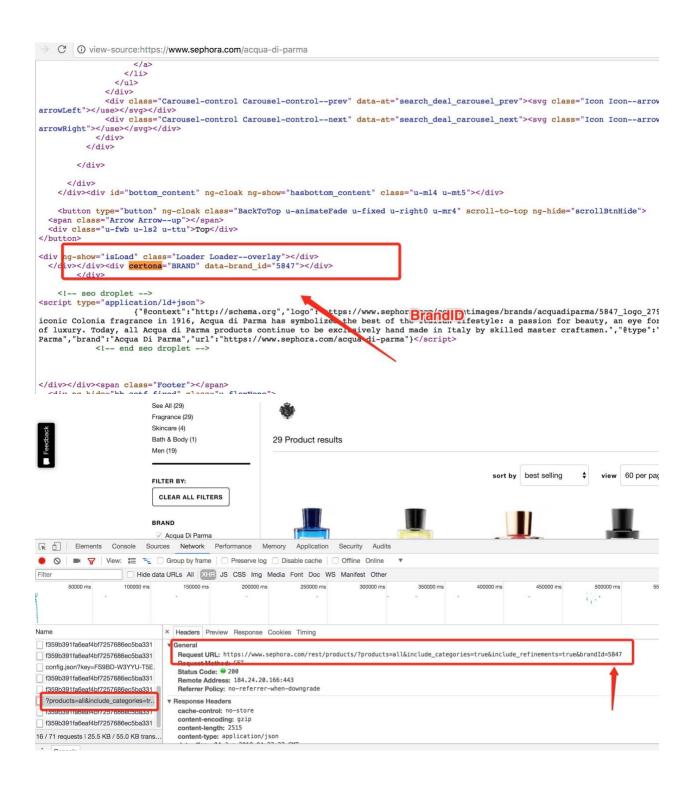
Figure 20. Code for acquiring reviews for all the product through its ID.

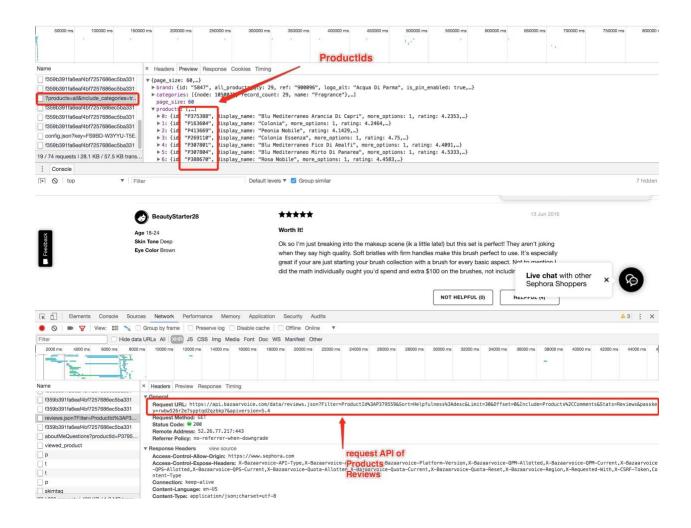
Figure 21. Code for information processing of reviews, placing NONE if the field information does not exist.

```
Version 1.0.1 — Python crawler_step_by_step_txt.py — 96×34
https://www.sephora.com/amazing-cosmetics
4 5723
https://www.sephora.com/amika
5 6004
https://www.sephora.com/amorepacific
https://www.sephora.com/anastasia-beverly-hills 7 5746
https://www.sephora.com/anthony-logistics-for-men
         4374
https://www.sephora.com/antonym
         6212
https://www.sephora.com/apivita
10 6078
https://www.sephora.com/aquis
         6173
https://www.sephora.com/the-art-of-shaving
         5931
https://www.sephora.com/artis
         6241
https://www.sephora.com/artist-couture
         6242
https://www.sephora.com/atelier-cologne
15 6083
https://www.sephora.com/axiology
         6214
https://www.sephora.com/besame-cosmetics
         7068
https://www.sephora.com/balenciaga
18 6053
https://www.sephora.com/bareminerals
https://www.sephora.com/the-beauty-chef
```

Figure 22. Run the crawler.

Command prompt: \$ python3 crawler_step_by_step_txt.py





C: Transforming TXT into CSV details

Figure 23. Reading all the reviews information from text file, and writing to CSV file.

```
{\sf Version\,1.0.1-Python\,csvConverter.py-96\times34}
global_count 38820
global_count 38821
global_count 38822
global_count 38823
global_count 38824
global_count 38825
global_count 38826
global_count 38827
global_count 38828
global_count 38829
global_count 38830
global_count 38831
global_count 38832
global_count 38833
global_count 38834
global_count 38835
global_count 38836
```

Figure 24. Run the csvConverter, which is used to read reviews from all the text file and store into CSV files.

Command prompt: \$ python3 csvConverter.py

D: Processing data through Spark

```
%pyspark
review=spark.read.csv("s3://295sephora/all_data.csv", header=True, mode="DROPMALFORMED")
product=spark.read.csv("s3://295sephora/Prducts_Info.csv", header=True, mode="DROPMALFORMED")
```

Figure.25 Spark code to create RDD

```
%pyspark
sqlContext
review.createOrReplaceTempView("review")
product.createOrReplaceTempView("product")
alldata=spark.sql("select * from product inner join review on product.ID= review.productID")
alldata.show()
```

Figure.26 Spark code to create temp table

E: Word Frequency Analysis

Figure.27 code to filter and save qualified data

```
pos=[]

for line in Naked_Palette_Collection['review'][Naked_Palette_Collection.rating == '5']:
    pos.append(line)

stop = set(stopwords.words('english'))
    new = [i for i in str(pos).lower().split() if i not in stop and i.isalpha() ]
    Freq_dist_nltk=nltk.FreqDist(new)
    Freq_dist_nltk.plot(30,cumulative = False)

neg=[]

for line in Naked_Palette_Collection['review'][Naked_Palette_Collection.rating == '1']:
    neg.append(line)

stop = set(stopwords.words('english'))
    new = [i for i in str(neg).lower().split() if i not in stop and i.isalpha() ]
    Freq_dist_nltk=nltk.FreqDist(new)
    Freq_dist_nltk.plot(30,cumulative = False)]
```

Figure.28 code for word frequency analysis

F: LDA model

```
num_reviews = df_pos.shape[0]
doc_set = [df_pos.review[i] for i in range(1, num_reviews)]
texts = []
for doc in doc_set:
    # putting our three steps together
    tokens = tokenizer.tokenize(doc.lower())
    stopped_tokens = [token for token in tokens if not token in merged_stopwords]
    stemmed_tokens = [sb_stemmer.stem(token) for token in stopped_tokens]

# add tokens to list
    texts.append(stemmed_tokens)
```

Figure.29 code for preprocessing natural language data

```
textsneg_dict = corpora.Dictionary(texts_neg)
textsneg_dict.save('negreview.dict')
corpus = [textsneg_dict.doc2bow(text) for text in texts_neg]
gensim.corpora.MmCorpus.serialize('review_neg.mm', corpus)
lda_model = gensim.models.LdaModel(corpuspos,alpha='auto', num_topics=5,id2word=texts_dict, passes=20)
lda_model.show_topics(num_topics=5,num_words=5)
```

Figure.30 code for LDA model