SHOPPING APP REVIEWS

Sim Yi Capstone

Content

- Introduction
- Problem Statement
- Data Gathering
- Data Cleaning
- EDA
- Models
- NN Model
- Limitations and further research
- Conclusions

Introduction

Users download apps for various purposes. Given that there is a rise in the usage of online shopping due to the Covid-19 pandemic, improvement of shopping experience has become more important than before. With that in mind, what are the important features we have to look out for to improve a shopping app?

Problem Statement

- How do the app ratings differ across different shopping apps?
- Is there any specific group of users we can look out for to improve the app?
- Are there any specific improvement we can work on to further improve user satisfaction of the app?

Data Gathering

```
app_infos_df['reviews']
```

```
0      20125
1      70213
2    2646815
3    3144111
4    1263982
5     415380
6     131789
7    4205170
Name: reviews, dtype: int64
```

```
app_reviews = []

for ap in tqdm(app_packages):
    for sort_order in [Sort.MOST_RELEVANT, Sort.NEWEST]:
        rvs, _ = reviews(ap,lang='en',
                         country='sg',
                         sort=sort_order,
                         count= 10000
                        )
    for r in rvs:
        r['sortOrder'] = 'most_relevant' if sort_order == Sort.MOST_RELEVANT else 'newest'
        r['appId'] = ap
    app_reviews.extend(rvs)
```

```
100%|██████████████████████████████████████████████████████████| 8/8 [05:38<00:00, 42.30s/it]
```

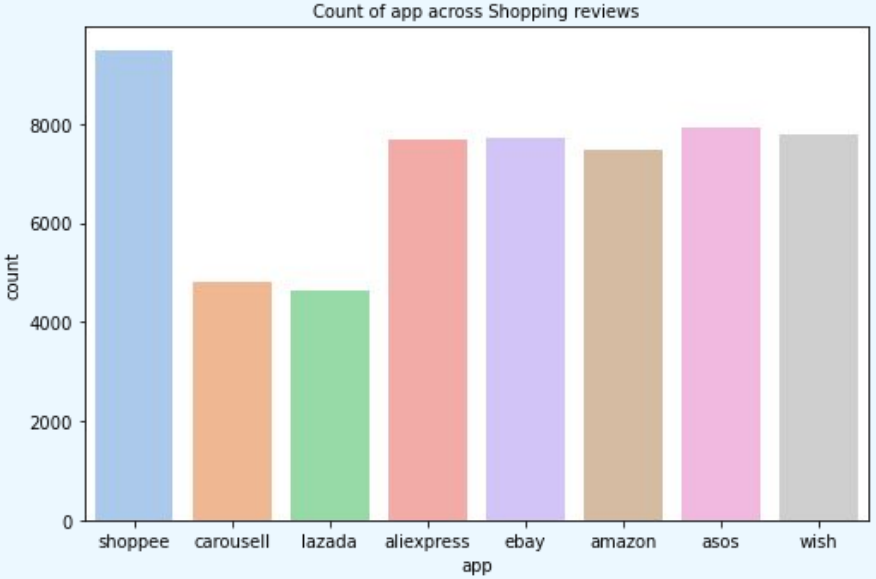
- Webscrap on 11th September 2020
- Google PlayStore (80,000 reviews)
- Apple Appstore (15,358 reviews)

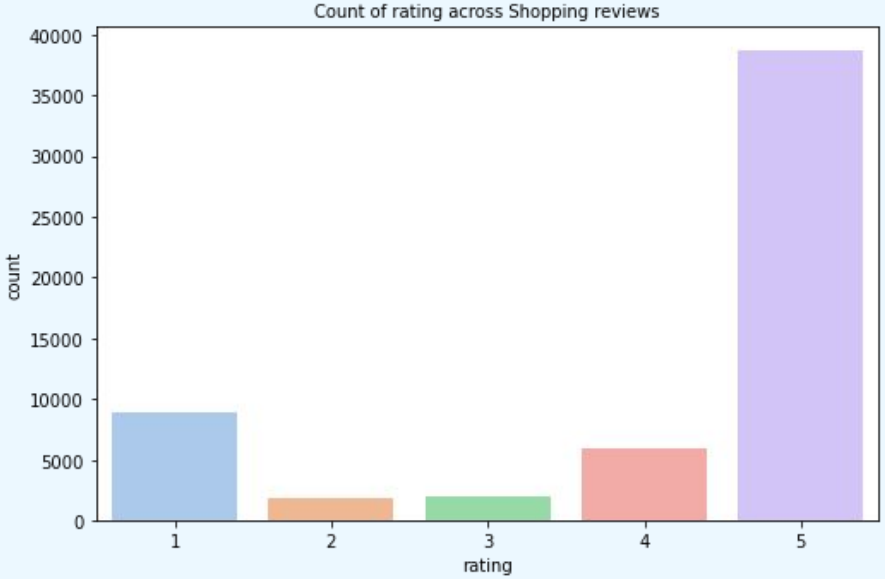
Data Cleaning

- Spacy
- Langdetect
- Spacy_Emoji
- Lemmatization
- VaderSentiments
- 57486 reviews left
- No. of keywords in reviews after cleaning: 24817

```
sp = spacy.load('en_core_web_sm')
emoji = Emoji(sp, merge_spans = False)
sp.add_pipe(emoji, first = True)
sp.add_pipe(LanguageDetector(), name='language_detector', last=True)
analyser = SentimentIntensityAnalyzer()
tokenizer = RegexpTokenizer(r'\w+')
lemma = WordNetLemmatizer()
app_titles = ['shopee' ,'amazon','wish','asos',
              'carousell','aliexpress','lazada','ebay']
def words_cleaning(text):

    #get score from raw text
    scores = analyser.polarity_scores(str(text))

    # use spacy to categorize words
    sen = sp(str(text))
    language = sen._.language['language']
    #creating list to store words
    adj_list = ''
    noun_list = ''
    verb_list = ''
    emoji_list = ''

    for word in sen:
        if word._.is_emoji:
            emoji_list += str(word)
        else:
            if word.pos_ == 'ADJ':
                adj_list += (str(word.lemma_).lower()) + ' '

            elif word.pos_ == 'NOUN':
                noun_list += (str(word.lemma_).lower()) + ' '

            elif word.pos_ == 'VERB':
                verb_list += (str(word.lemma_).lower()) + ' '

    string = []
    for word in sen:
        if word.is_stop == False:
            if word._.is_emoji == False:
                if word.pos_ != 'PUNCT':
                    if word.pos_ != 'NUM':
                        string.append(str(word.lemma_).lower())

    #removing non english words
    words = [w for w in string if w not in app_titles]

    #steming tokens
    words_lemma = [lemma.lemmatize(i) for i in words]

    #join words
    join_words = (" ".join(words_lemma))


    return(join_words, adj_list, noun_list, verb_list, emoji_list, scores, language)
```

EDA

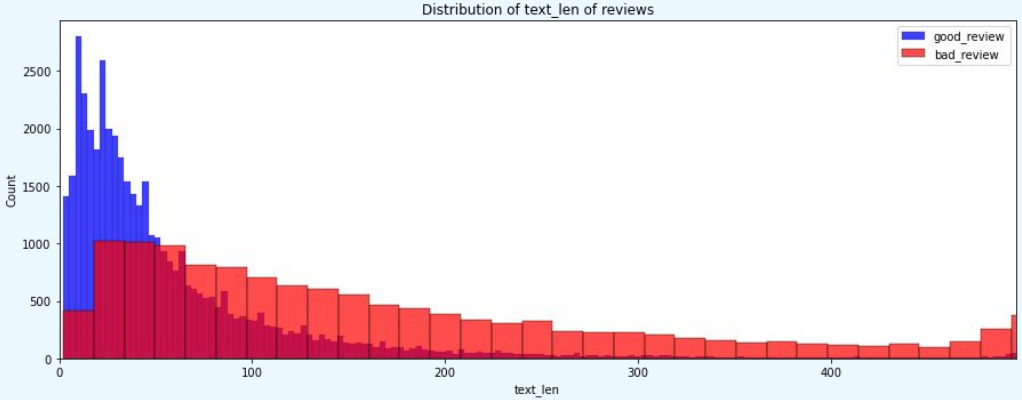

Count of app across Shopping reviews
count
app
shoppee
carousell
lazada
aliexpress
ebay
amazon
asos
wish
0
2000
4000
6000
8000

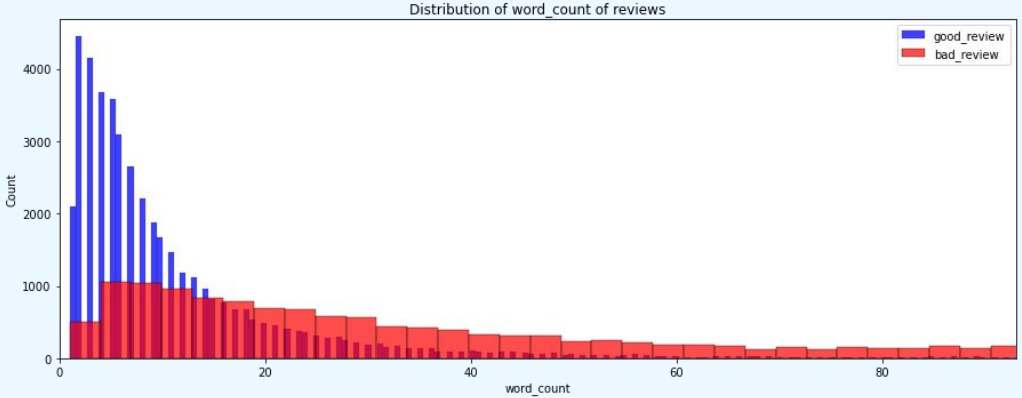

Count of rating across Shopping reviews
count
rating
1
2
3
4
5
0
5000
10000
15000
20000
25000
30000
35000
40000

EDA

- More negative reviews are seen in 9am - 3pm period

EDA





Text of bad reviews usually longer than good reviews

EDA

Removed wrongly rated reviews:

- Reviews with a low rating but high positive score
- Reviews with a high rating but high negative score

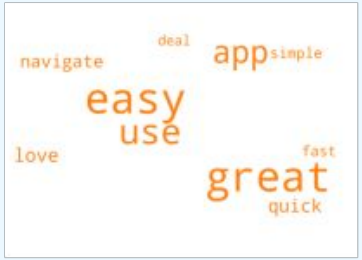
	rating	pos_score	review
1057	3	0.672	Great shopping experience
1518	2	0.534	great improvement no more freeze!!! but hope i...
1657	3	0.420	Slow,in receiving.but good in service.
1762	1	0.477	Candy game crash. Please fix. Thanks
2509	1	0.744	Good quality
2892	1	0.457	Price increase, have some nice games but poor ...
3193	3	0.608	Good to have fun online shopping.
3485	1	0.583	Love buy in shopee
3556	3	0.435	Thank u shopee i recieve the gift from you.
4158	3	0.744	Good experience

	rating	neg_score	review
1447	5	0.403	Sometime don't get free coin
2062	4	0.505	Returning the faulty products r very difficult...
3078	5	0.688	No issues.
4167	5	0.556	Lags sometimes though
4574	5	0.423	Fast and no hassle
5139	5	0.412	Low price. Fast delivery
5195	5	0.688	Lower price.
6111	4	0.608	Disappointed at time.
7440	5	0.423	Faster with lower prices
7746	4	0.655	Delivery delayed..

EDA

Convenient App

User Interface



Variety & Price

User Experience

Shopping Experience

Delivery

Consumer Satisfaction

In-App Actitives

Recommendations

Customer Service

EDA

Account Issues

Poor Seller Feedback

User Interface

Payment Issue

Poor Customer Service

Product Issue

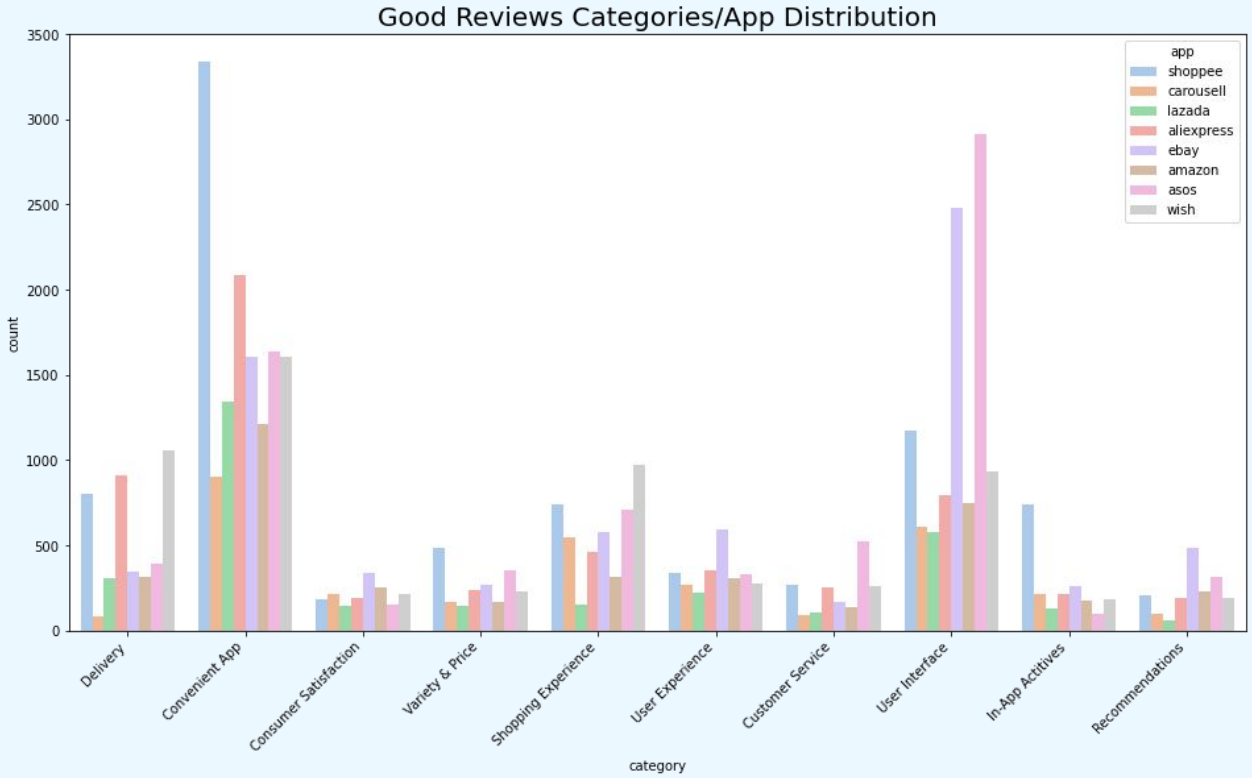
App Issues

Delivery Issue

Refund

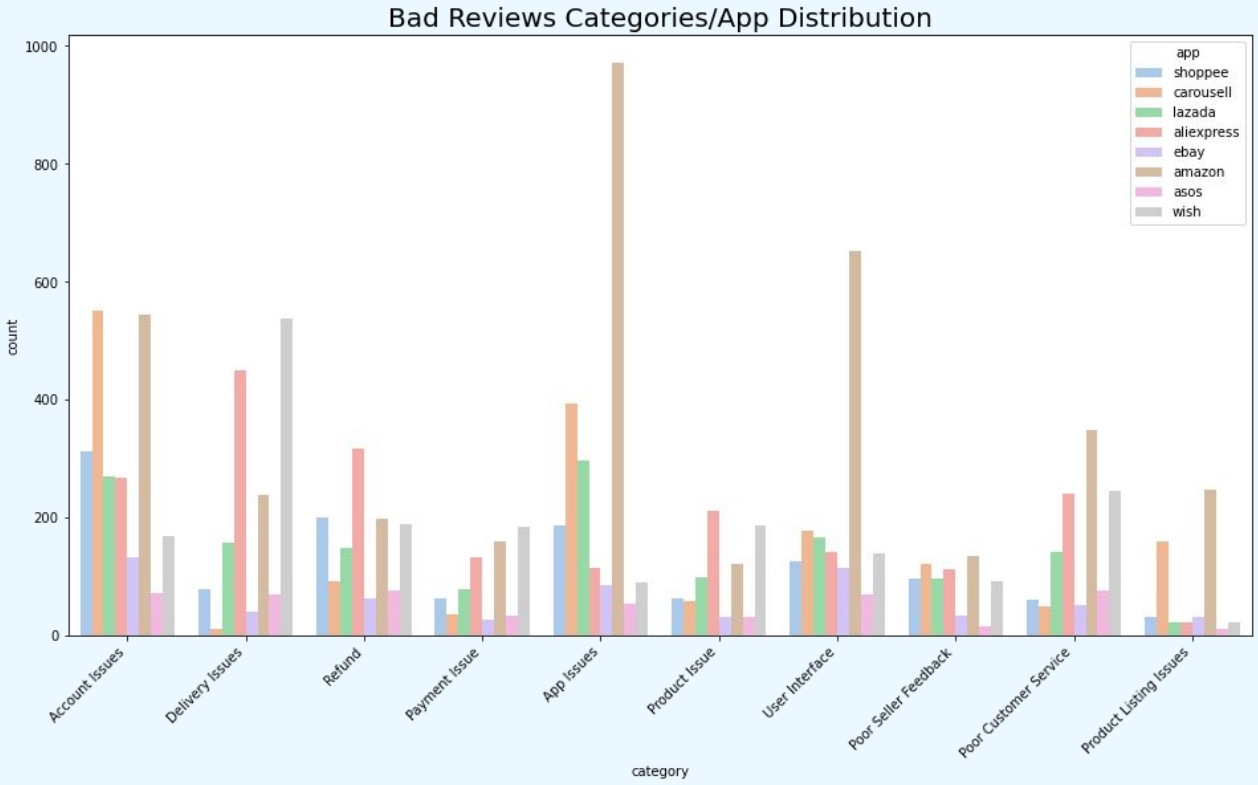
Product Listing Issues

EDA



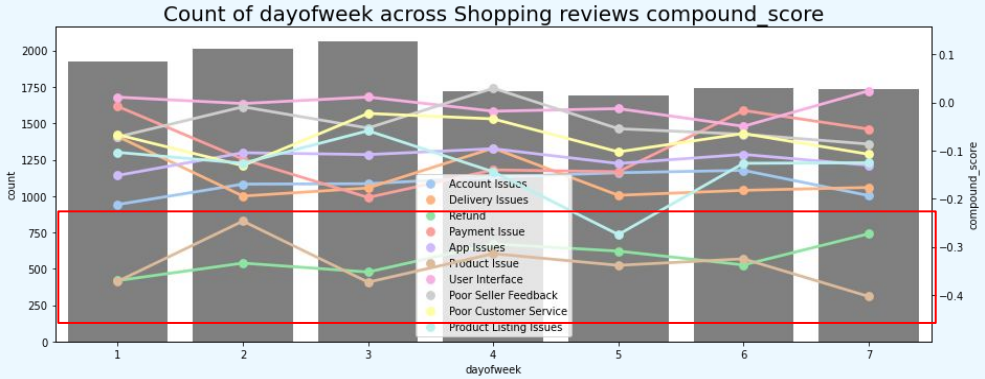
- Shoppee takes the lead in Convenient app while ASOS takes the lead for User Interface

EDA



- Amazon seems to take the lead in having more bad reviews as compared to the other apps, especially App Issues , User interface and Account issues
- Wish has slightly higher negative delivery issue reviews
- AliExpress has High Refund issues.

EDA



- Delivery, Consumer Satisfaction and Recommendations are scored lower in good reviews.
- Base on compound scores, Refund and Product tend to be very low as compared to other categories.
- Important categories:
  - Customer Service, Refund, Delivery and Recommendations
- It is important to put some focus on sellers that are doing bad on the platform.

Models

Classify Good or Bad review

- Logistic Regression
- AUC: 0.965
- MCC: 0.773

Multiclassification of Bad Reviews

- Logistic Regression
- MCC:0.705
- Kappa: 0.704

Multiclassification of Good Reviews

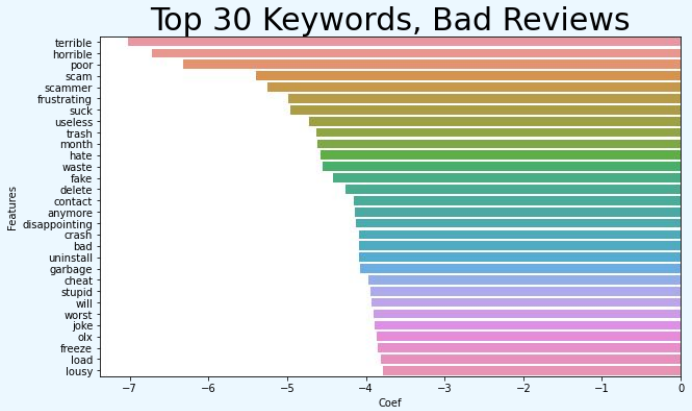
- Logistic Regression
- MCC: 0.851
- Kappa: 0.850

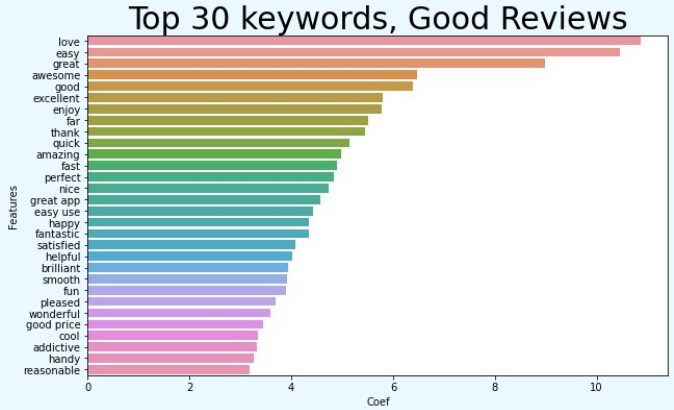
Model(Good & Bad)

	Train Score(AUC)	Test Score(AUC)	MCC	Time (s)
Logistic Regression	0.966	0.965	0.773	163
MultinomialNB	0.964	0.963	0.775	97
SGDClassifier	0.962	0.963	0.753	114
RandomForest	0.936	0.939	0.484	333
ADABoost	0.949	0.953	0.727	443

Model (Good or Bad reviews)

	predicted	actual	review	clean_content
47613	1	0	As soon as I got it I had the option to shop f...	soon get option shop man woman option filter r...
51472	1	0	Jewelry is cute well made but clothing is hit ...	jewelry cute clothing hit miss
30571	0	1	Not able to do all tasks, I find it frustratin...	able task find frustrating time use pc complet...
51635	1	0	We have a lot of stores like this in Florida d...	lot store like florida need order online buy
34561	1	0	The user interface needs to be improved otherw...	user interface need improve great app shopping
5028	0	1	Many Ads	ad
17895	1	0	I can't seem to access my account immediately ...	access account immediately finish place order ...
47289	1	0	Please make shipping available to Samoa	shipping available samoa
3533	0	1	Could be better if there was the option to cha...	well option change review long period time thi...
51804	1	0	My only issue is the fact that they give you a...	issue fact coupon code % % use code %



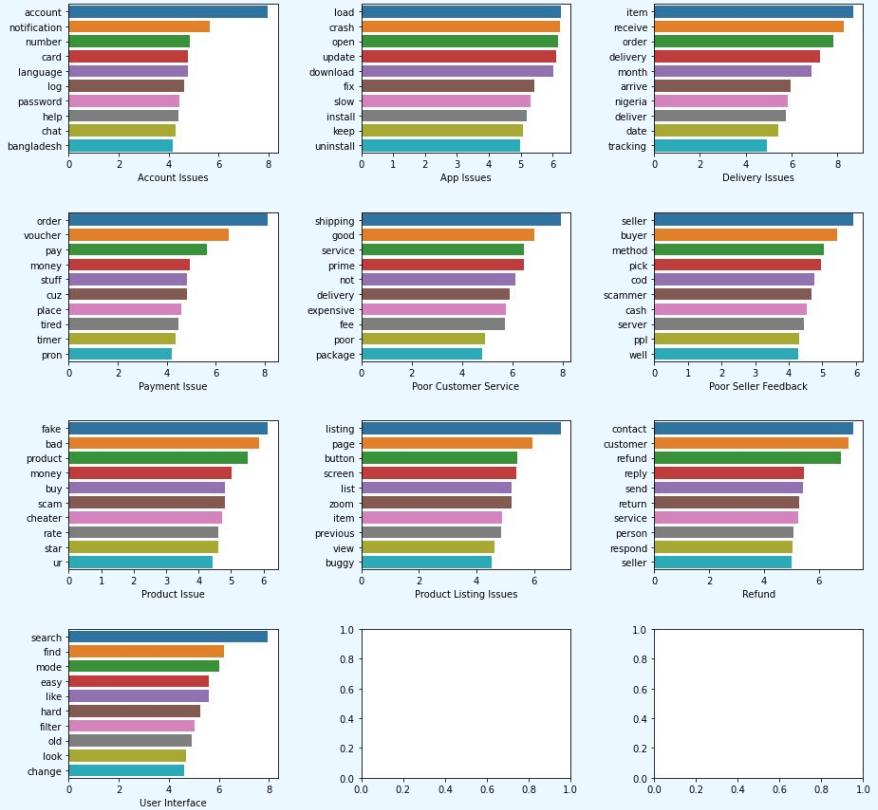


Model(Bad Reviews)

	Train Score(f1)	Test Score(f1)	MCC	Time (s)
Logistic Regression	0.731	0.741	0.705	512
MultinomialNB	0.691	0.708	0.678	68
SGDClassifier	0.703	0.702	0.661	105
RandomForest	0.545	0.550	0.509	216
ADABoost	0.454	0.463	0.380	405

Model (Bad Reviews)

	predicted	actual	review	clean_content
39141	Refund	Delivery Issues	I love asos...but I think it's wrong that when...	love think wrong wrong item send happen time p...
10749	App Issues	Product Listing Issues	Keep going back to previous page on its own ve...	go previous page irritating use nowadays.was w...
9780	Refund	Product Issue	Money grabbing policy will make this app usele...	money grab policy app useless soon seller caus...
23594	Account Issues	Poor Seller Feedback	So so difficult to fill in address and postal ...	difficult fill address postal code impossible ...
36522	User Interface	Account Issues	Freezes whenever I try to change my payment op...	freeze try change payment option shipping deta...
1944	Refund	Payment Issue	Not professional enough n very upset with prod...	professional n upset product deliver initiativ...
55260	User Interface	Product Issue	Generally good promo but bank promo always ful...	generally good promo bank promo fully redeem s...
37856	Product Listing Issues	User Interface	What is going on Amazon? Anything I search for...	go search bring page result option page check ...
32160	App Issues	User Interface	Unable to log in or use the app at all with my...	unable log use app vpn enable samsung galaxy s...
10778	User Interface	Account Issues	waste of time it won't show you what you want ...	waste time will want miss old olx aps

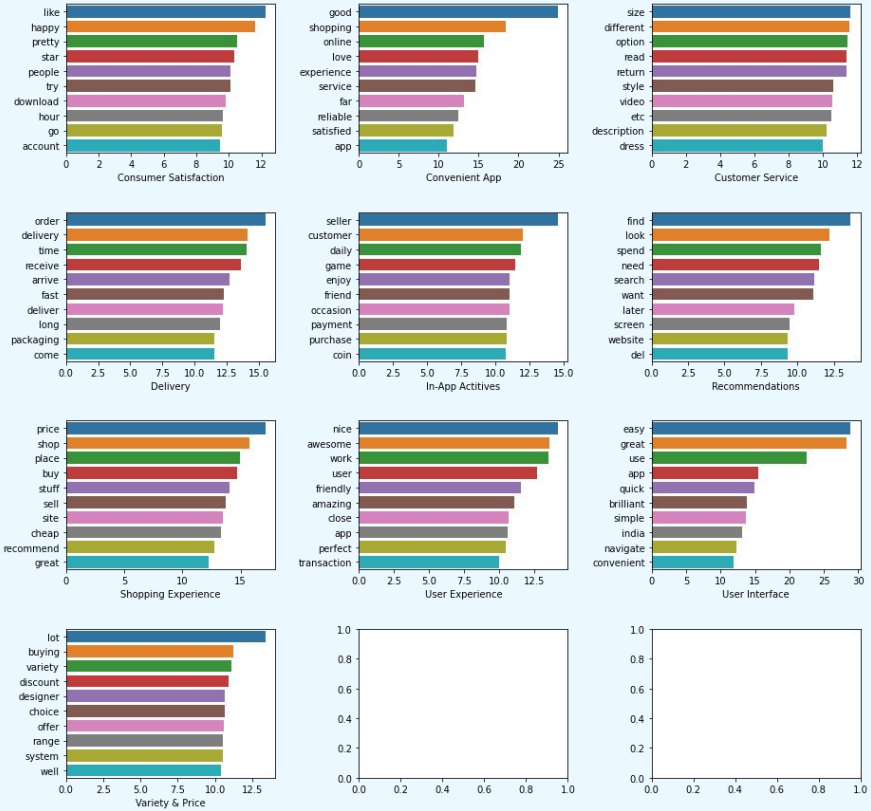


Model(Good Reviews)

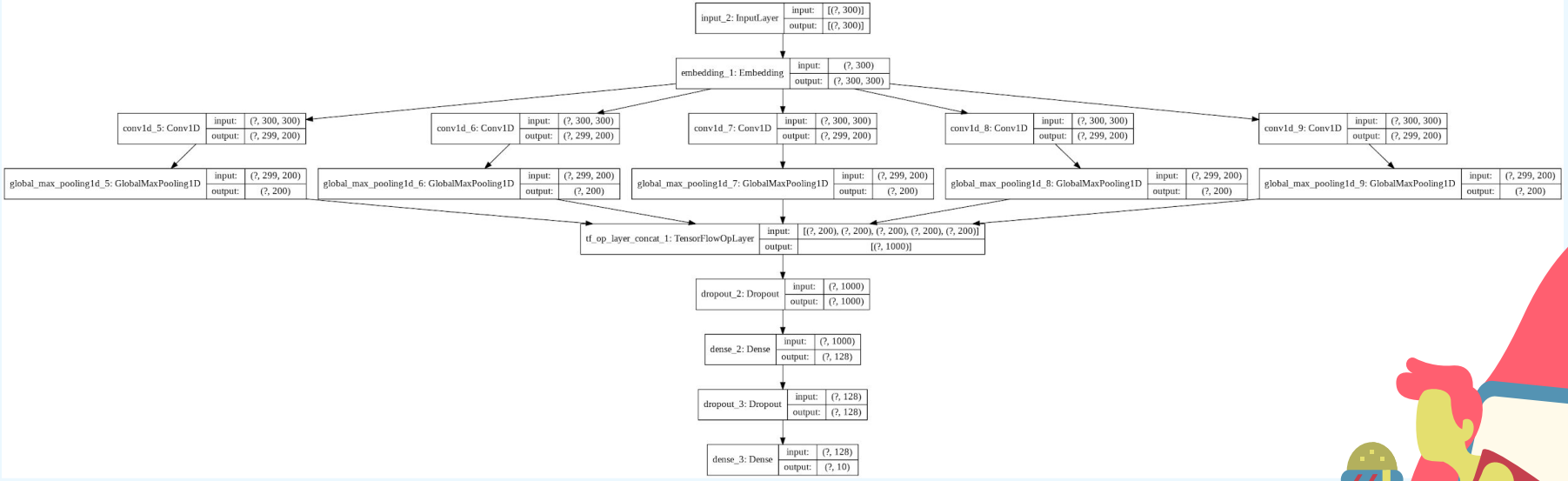
	Train Score(f1)	Test Score(f1)	MCC	Time (s)
Logistic Regression	0.868	0.878	0.851	2367
MultinomialNB	0.751	0.751	0.701	151
SGDClassifier	0.702	0.705	0.663	247
RandomForest	0.657	0.653	0.590	532
ADABoost	0.700	0.701	0.633	1337

Awards

	predicted	actual	review	clean_content
20226	Convenient App	Consumer Satisfaction	I really like that using this app is a holisti...	like app holistic experience right confirm rec...
38359	User Interface	Customer Service	Great app, sometimes the tracking for parcels ...	great app tracking parcel accurate mobile devi...
42027	User Interface	Convenient App	Seamless and great.	seamless great
53106	User Interface	Convenient App	Though, my first order is still pending but th...	order pende exceptional love
49638	Variety & Price	User Interface	Love it! Really easy to use with a ton of litt...	love easy use ton little reward saving
49118	Variety & Price	Consumer Satisfaction	never had a bad product. been with wish for ma...	bad product year
55662	Convenient App	Shopping Experience	items are good to buy and sellers quite reliable.	item good buy seller reliable
46923	Variety & Price	Delivery	Everything I've ordered has been exactly as I ...	order exactly except
7300	Convenient App	In-App Actitives	The most user friendly platform. Easy and simp...	user friendly platform easy simple reward syst...
20449	Delivery	Customer Service	Was a little dubious on using this to be hones...	little dubious honest buy item great read desc...



NN Models


input_2: InputLayer
input: [(?, 300)]
output: [(?, 300)]
embedding_1: Embedding
input: (?, 300)
output: (?, 300, 300)
conv1d_5: Conv1D
input: (?, 300, 300)
output: (?, 299, 200)
conv1d_6: Conv1D
input: (?, 300, 300)
output: (?, 299, 200)
conv1d_7: Conv1D
input: (?, 300, 300)
output: (?, 299, 200)
conv1d_8: Conv1D
input: (?, 300, 300)
output: (?, 299, 200)
conv1d_9: Conv1D
input: (?, 300, 300)
output: (?, 299, 200)
global_max_pooling1d_5: GlobalMaxPooling1D
input: (?, 299, 200)
output: (?, 200)
global_max_pooling1d_6: GlobalMaxPooling1D
input: (?, 299, 200)
output: (?, 200)
global_max_pooling1d_7: GlobalMaxPooling1D
input: (?, 299, 200)
output: (?, 200)
global_max_pooling1d_8: GlobalMaxPooling1D
input: (?, 299, 200)
output: (?, 200)
global_max_pooling1d_9: GlobalMaxPooling1D
input: (?, 299, 200)
output: (?, 200)
tf_op_layer_concat_1: TensorFlowOpLayer
input: [(?, 200), (?, 200), (?, 200), (?, 200), (?, 200)]
output: [(?, 1000)]
dropout_2: Dropout
input: (?, 1000)
output: (?, 1000)
dense_2: Dense
input: (?, 1000)
output: (?, 128)
dropout_3: Dropout
input: (?, 128)
output: (?, 128)
dense_3: Dense
input: (?, 128)
output: (?, 10)

NN Models

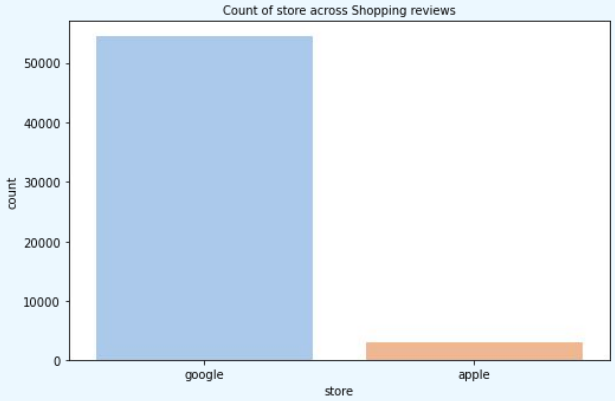
	Train Score	Test Score	MCC
Good & Bad	NN: 0.977 ML: 0.966	NN: 0.961 ML: 0.965	NN: 0.767 ML: 0.773
Good Reviews	NN: 0.914 ML: 0.731	NN: 0.717 ML: 0.741	NN: 0.679 ML: 0.705
Bad Reviews	NN: 0.941 ML: 0.868	NN: 0.841 ML: 0.878	NN: 0.805 ML: 0.851

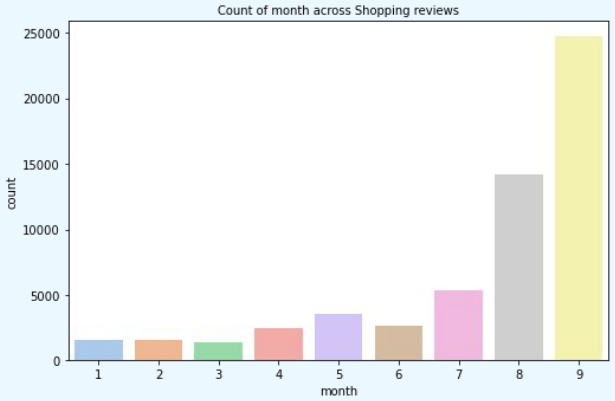
Scores are not better than machine learning models, which could be due to the size of the data is too small for a complicated model like NN to work well.

Limitations

- The data set is mostly collected in the month of August and September

- More data could be collected, as there is a major lack of Apple Appstore reviews compared to Google Play Store





Further Research

- Collect more Data to improve the model accuracy, as most of the data collected are in August and September

- Try different categories, not just shopping app category apps, do create a more complete review prediction model

- Try to work with different languages, as most of the population is multilinguistic.

Conclusion

- Using the model, Categories for the reviews will be predicted faster then the traditional way of figuring it out.
- The user that posted the review will be referred to the correct department according to the topic prediction, without time wasted from sorting out.

Thanks!

Do you have any questions?
https://github.com/SimYiSY

https://www.linkedin.com/in/simyi/

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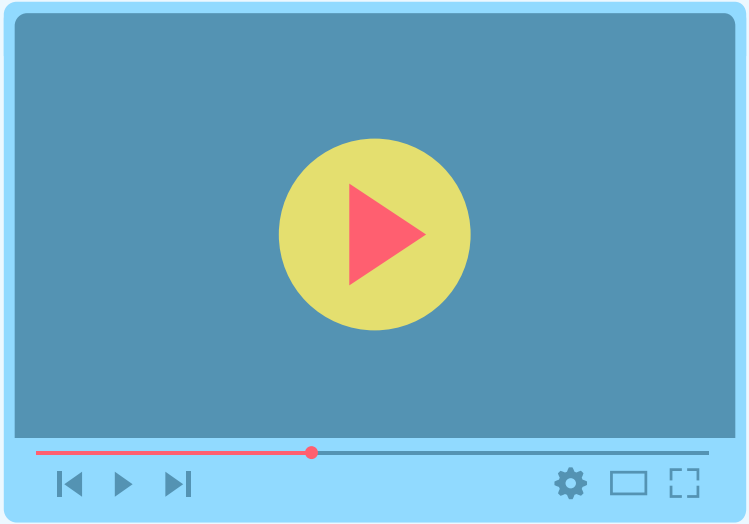
Product Demo



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