
Analysis of TripAdvisor Data for Restaurants in Thessaloniki

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Introduction

- Web scraping and specifically Selenium were used for the extraction of the necessary data from the Tripadvisor site.
- Our team was tasked to analyse the reviews written for all the restaurants listed in Tripadvisor for the city of Thessaloniki.

The informations we decided to collect belong to the following categories.

- Username of the reviewer
- Name of the business
- Review Date
- Visit date
- Title of the review
- Text of the review
- Rating of the review
- Reviewer's Age
- Reviewer's Gender
- Reviewer's Location
- Reviews distribution

szndjuric wrote a review
Mar 2019

BEST BRUNCH EVER!!!!!

"Great place for brunch! Food is delicious, we had Carbonara , ravioli and they have winter wine promotion 50% off bottles of wine. We would definitely come back!"

Date of visit: March 2019

Olio e Piu
2,495 reviews
New York City, New York

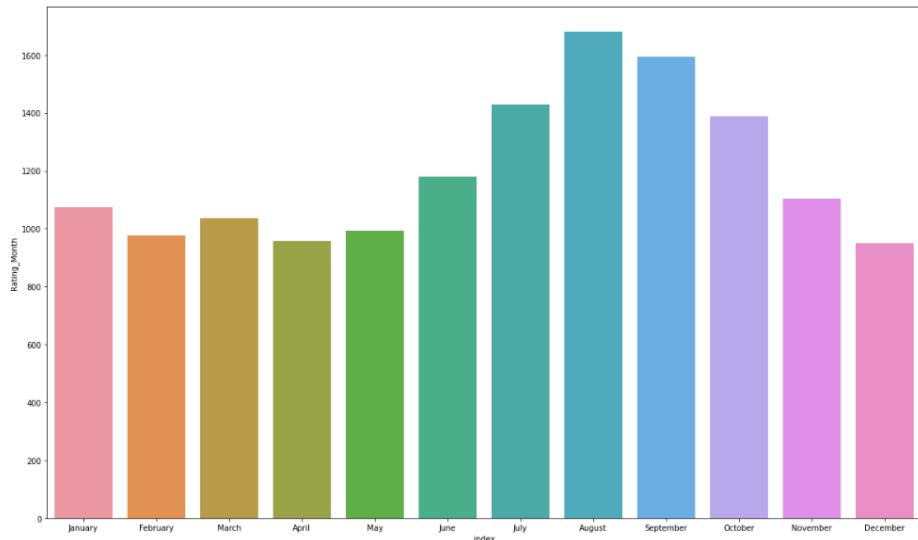
1 Helpful vote



Number of Monthly Reviews

Before analysing further the reviews, an interesting observation

- ★ Most of the reviews as seen, were made during the summer indicating that a lot of reviewers were probably tourists.

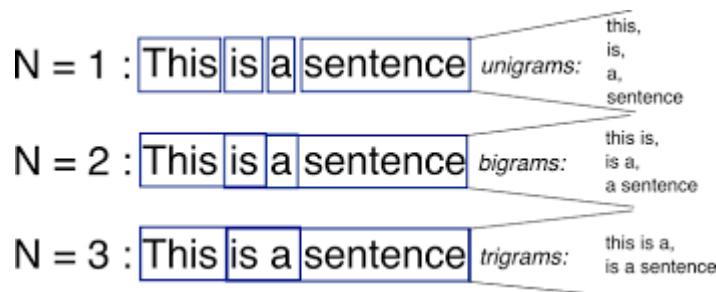


Most Common Words, Bi-grams, Tri-grams

- Bi-grams and Tri-grams are correspondingly series of 2 or 3 words.

Steps:

1. FreqDist function of NLTK was used. Takes as input the list of texts and the ngram type you are interested in.
2. Create a dictionary with the information concerning each type of n-grams.
3. Create a dataframe for each type of n-gram storing the word(s) and their frequencies.
4. Use word cloud for the presentation of the results.



Most Common uni-grams



- Food
 - Good
 - Great
 - Place
 - Servic
 - Restaur

Little amount of context.

Most Common bi-grams



- good_Food
 - one_best
 - service_good
 - staff_friendli
 - reason_price

More context. Generally giving a good feeling about the overall quality of the restaurant.

Most Common tri-grams



- food_great_servic
- one_best_restaur
- good_valu_money
- definit_come_back
- food_good_price

Even more context. Different topics are distinguishable. Price, overall experience, thoughts.

One-star Reviews

The same 3 wordclouds were created but this time only taking into consideration 1 star or 5 star reviews respectively.



- Bad_service , recommend_place_anyone (didn't quite catch the content right) , never_come_back

Five-Star Reviews



- friendly_staff , great_food , definetely_come_back , would_highly_recommend

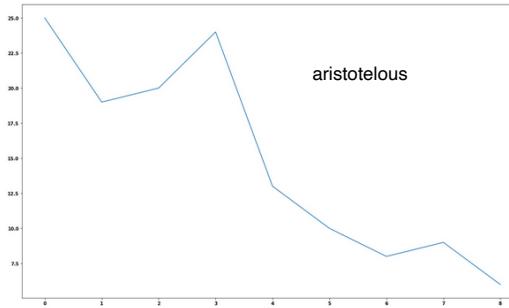
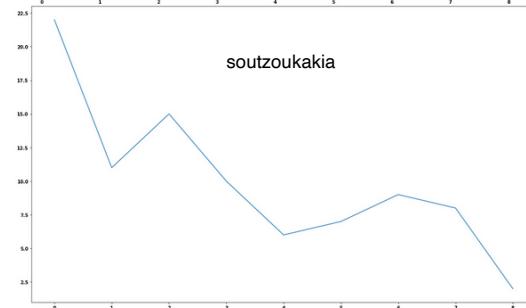
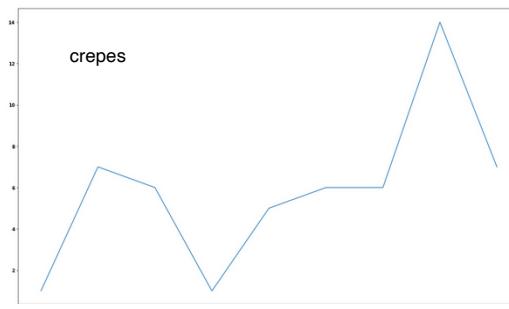
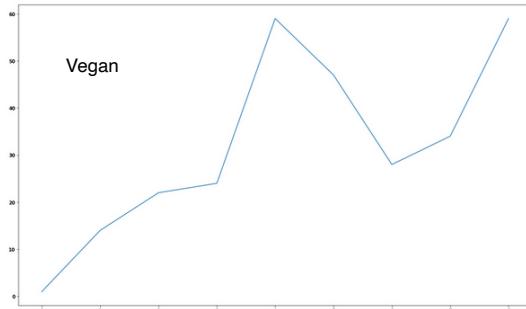
Fastest Growing and Shrinking Words

Top 10 growing and shrinking words based on the sum
of the percentage of differences

specialti	-0.978968	vegan	15.462606
aristotel	-1.032368	apolog	12.472222
meze	-1.037670	decad	11.555556
room	-1.061111	appetis	11.352453
famou	-1.067434	thin	11.242424
window	-1.084149	becam	10.955556
werent	-1.151007	warmli	10.750000
soutzoukakia	-1.278427	request	10.473485
youll	-1.520704	carpaccio	10.164502
histori	-1.865385	crepe	10.057143



Fastest Growing and Shrinking Words



Map of Locations

The world map where users
reviewed from





Map of Locations

Here we can see the europe region
and the distribution of the reviewers
in the said region



Sentiment Analysis

Sentiment analysis is important as it helps with the extraction, scoring, classification and visualization of the feelings and opinions the customers display for the business.

Simplest method to get the general feeling of the customers

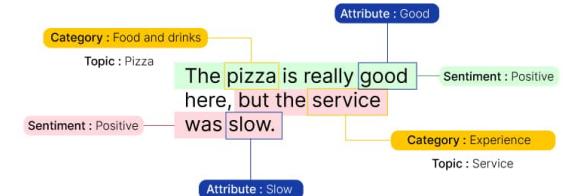
- Get a look at the total score of the restaurant! (Can be misleading)

Calculated the polarity score:

- Per review
- Per restaurant

Basic Visualizations using most common words

- Positive
- Negative

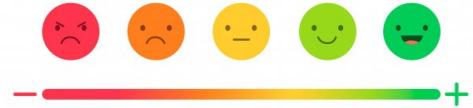


Business_Name	
MINIMAL ALL DAY COFFEE HOUSE	50.0
MIMIS	50.0
MILONGA MEZE CLUB	50.0
MIKRI MARMITA	50.0
MEZEDOPOLEIO ZAIR 79	50.0

Business_Name	
LOS HERMANOS	10.000000
ASIAN HOUSE TOUMPA	10.000000
MODIANO RETSINADIKO	10.000000
TAVERNA SOTIRIS	10.000000
TOMMY COFFEE HOUSE & EATERY	10.000000



Sentiment Analysis



The polarity score is a float within the range [-1.0, 1.0].

Per Review

Negative Polarity Score

654	eat worst thing vacat seafood frozen wait 15 h..
8715	rudenessaw servic treat u like anim credit car..
11432	eat hungri believ one worst place ever eat nev..
5011	dirti place terribl servic waiter behav improp..
12822	worst pizza ever eaten ask crispi pepperoni go..

654	-1.0
8715	-1.0
11432	-1.0
5011	-1.0
12822	-1.0

Positive Polarity Score

9771	visit takada even read tripadvisor review disa..
13562	that best gyro ever life visit soon mani choic..
890	realli best valu money steak hous town bavett ..
3076	restaur feel comfort eat perfect foodth person..
4508	impress qualiti food tri mani differ dish reco..

9771	1.0
13562	1.0
890	1.0
3076	1.0
4508	1.0

Sentiment Analysis



Per Restaurant

- No maximum or minimum polarity score
- Top restaurants could be described as very good according to the score
- Negative ~ 0 polarity score means the restaurants create a neutral to mildly negative emotion

Positive Polarity Score

Business_Name	
KAFENEION DIEFNES	0.700000
ANOPOLIS	0.700000
LARRY'S COFFEE-WINE-DRINKS	0.700000
CHICKEN BAR	0.700000
AVANTI PIZZA	0.716667
ATHENA BAKERY CAFE	0.750000
TO STEKI AFYTOS	0.750000
MER KA BA	0.800000
R2 STORE	0.800000
MUZIK BAR CAFE	1.000000

Negative Polarity Score

Business_Name	
MARMELADA	-0.291667
MYSTIKOS DIPNOS	-0.250000
MARCHE BISTRO	-0.250000
OVELISTIRIO TO PAGGAIO	-0.212727
PEINIRLADIKO "TO ROLOI"	-0.125000
OMBRELLO	-0.125000
10 TO KALO	-0.124444
RALENTATO	-0.100000
KOTOPARADOSI	-0.091667
DESKATI	-0.089315

Sentiment Analysis

But wait!

- We need to consider the number of reviews.
- One negative or positive review can greatly impact the outcome of the polarity score, if there is only a handful amount of reviews to analyze.
- Now we don't see that big of a difference!



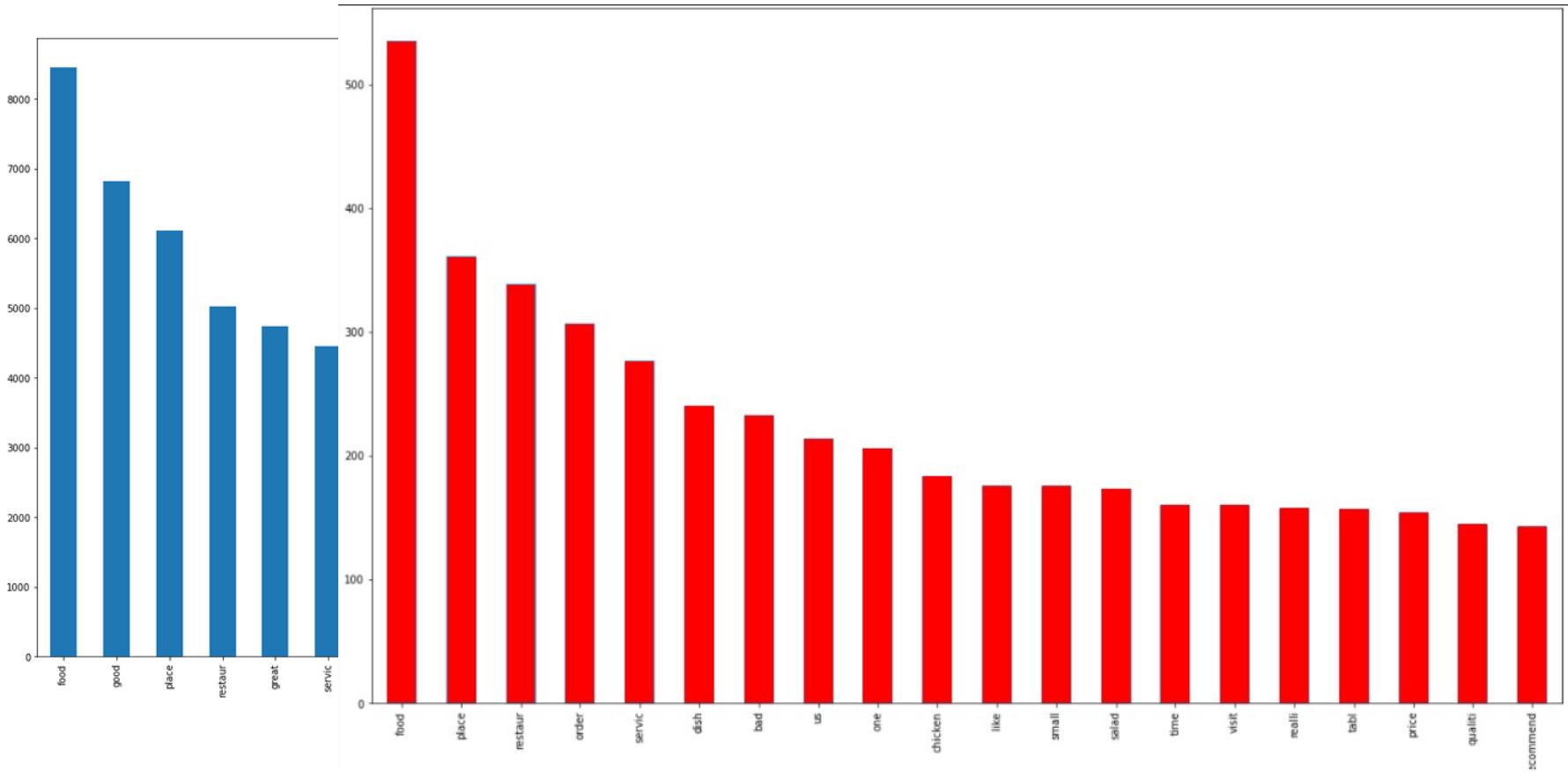
Give it a go!



Maybe once in a while...

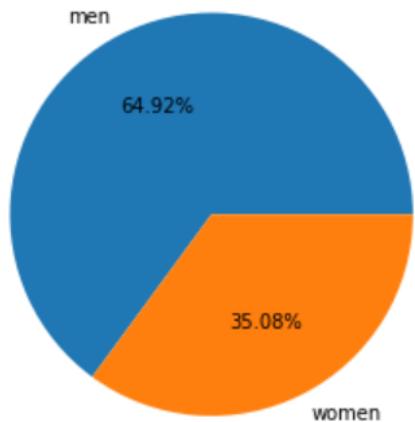
Business_Name	polarity_score	Count_of_reviews
BOUGATSA BANTIS	0.420580	75.0
MENU ME...NOU	0.422440	33.0
THE BACKROOM	0.435356	33.0
VOGATSIKOU 3	0.461843	53.0
DA VINCI	0.467343	26.0
EVORA EATERY	0.467901	47.0
ON THE ROAD	0.471508	23.0
FALAFEL HOUSE	0.475996	22.0
BEER O' CLOCK	0.494002	21.0
LA PASTERIA	0.510186	21.0

Business_Name	polarity_score	Count_of_reviews
NARGIS INDIAN RESTAURANT	0.114171	52.0
OLIVE OIL & OREGANO	0.207828	26.0
SOLOMONIDIS FILETO	0.209954	24.0
NOODLE BAR	0.217656	56.0
H KOUZINA TIS AGLAIAS	0.224221	25.0
ESTRELLA	0.230627	122.0
OUZERI TSINARI	0.236954	50.0
TO MIKRAKI	0.238385	30.0
NEA FOLIA	0.239944	98.0
OUZO STON PINAKA	0.244421	63.0

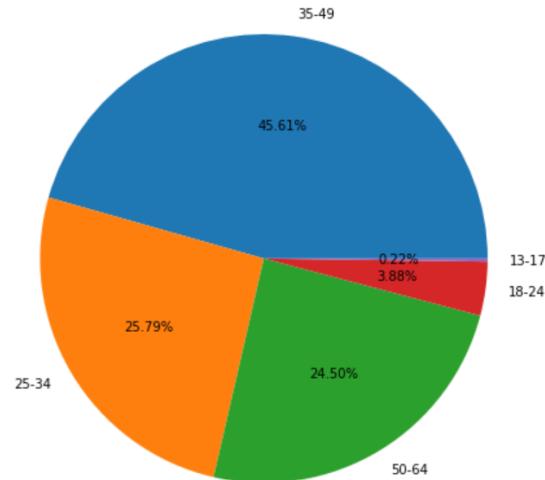


User Profiling

- Most reviewers are men



- Most reviewers are middle-aged
- Few minors





User Profiling

Features:

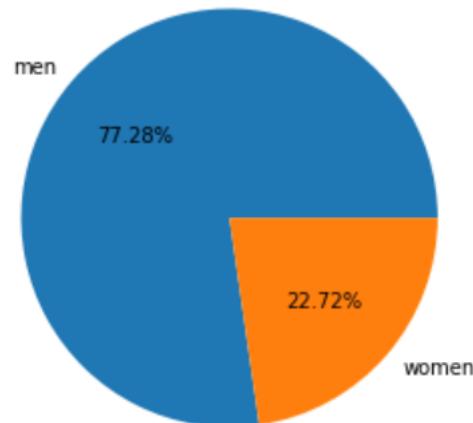
- Review Text
 - TF-IDF
 - Polarity
- Review Distribution
- Score

Dataset

- About $\frac{1}{3}$ of data was labeled

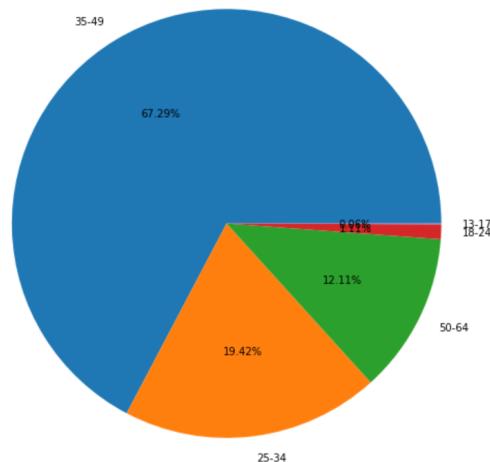
Random Forest

Accuracy = 0.70



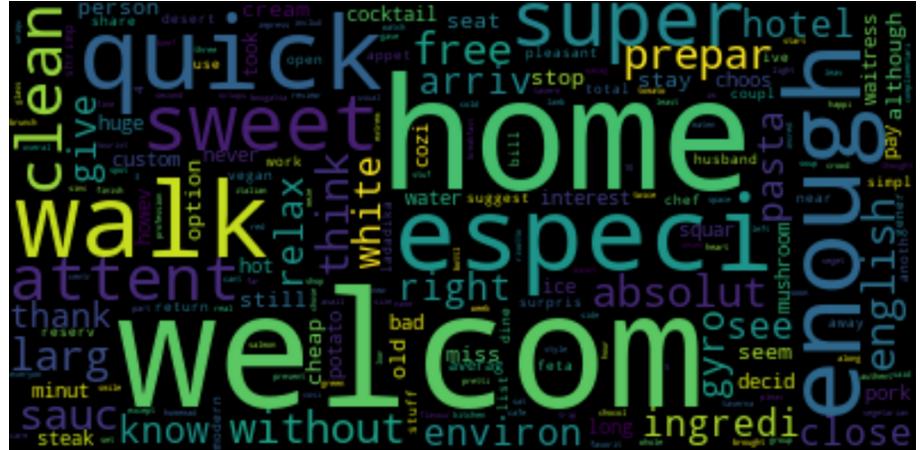
Logistic Regression

Accuracy = 0.47



User Profiling - Gender

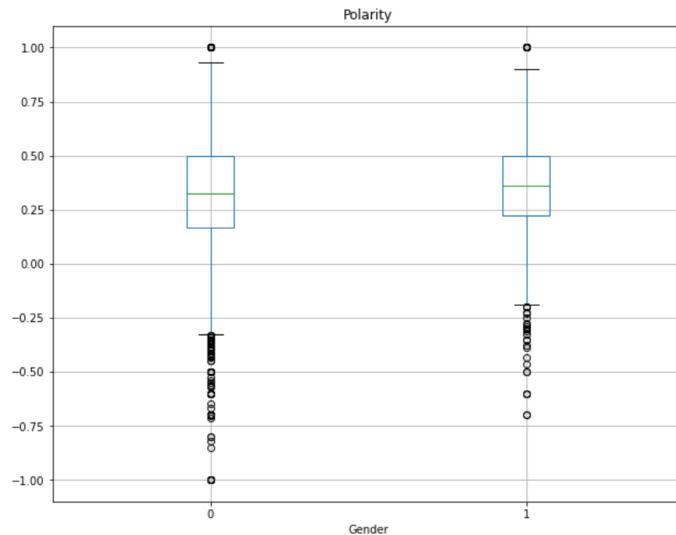
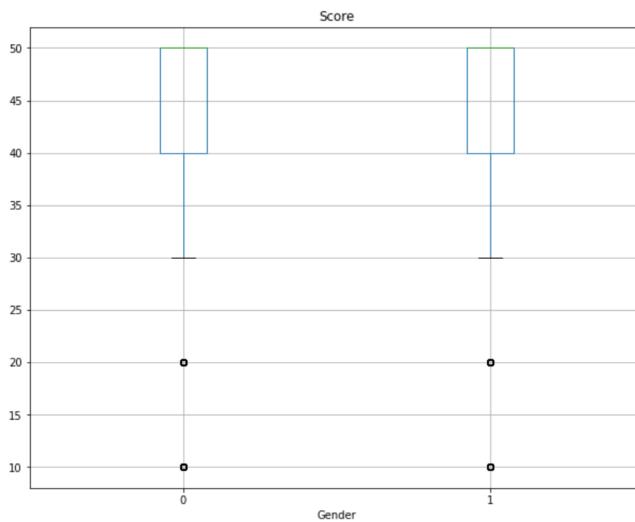
- Wordcloud for Men
 - Wordcloud for Women





User Profiling - Gender

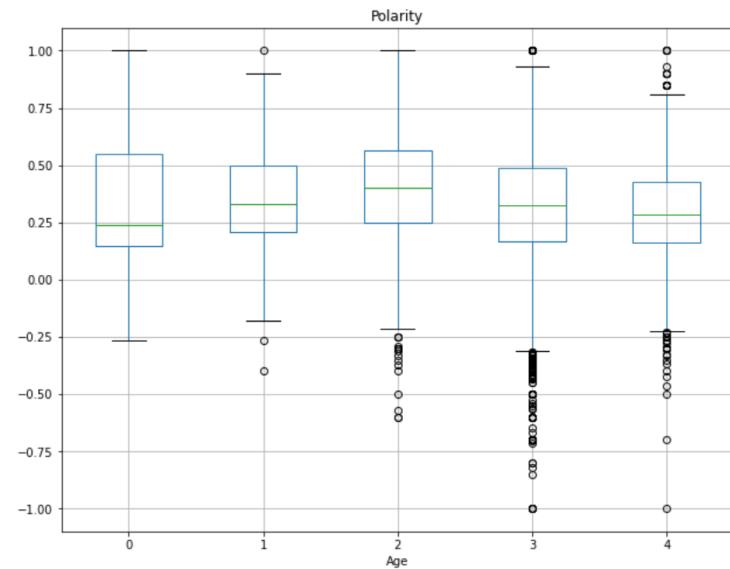
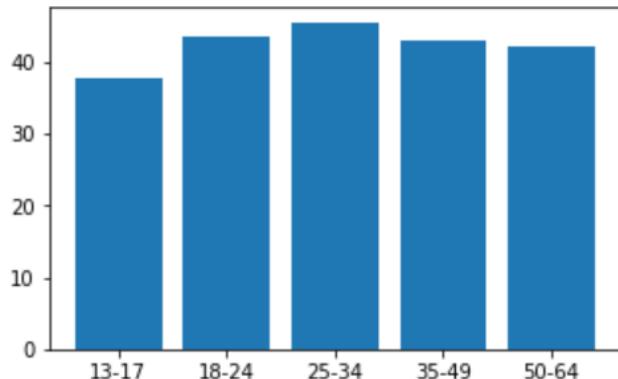
Comparison in Score and Polarity between men and women





User Profiling - Age

Comparison in mean Score and Polarity between each age group





**Thank you!
Any Questions?**