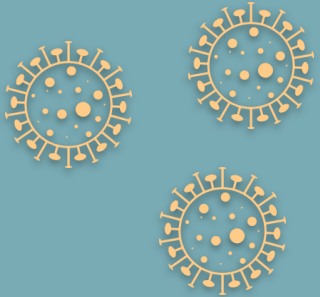

A look into Covid-19 spreading through the lodging sector



Estefania Ruiz Martinez • 30.06.2021

TOC

- Motivation and problem statement
- Research identification
- Research objectives
- Research questions
- Project setup
- Results
- Conclusions



Motivation and problem statement

Research identification

Research questions

Research objectives

Project setup

Results

Conclusions

- Better customer experience → better customer satisfaction.
- Online reviews are a type of UGC (User Generated Content) considered as the voice of the customer.
- In the light of the health crisis of Covid-19, has the customer experience been affected?

- While academics have already started to explore the behaviour of customers during the health crisis of Covid-19, none of the studies found have done it with customers of P2P accommodations.
- Up to now, no research found integrates spatial analysis with text mining techniques to reveal new aspects of the customer experience.
- This thesis aims to do so by exploring the behaviour of Airbnb customers in two geographically contrasting cities but as well located in countries highly affected by the health crisis of Covid-19

Motivation and problem statement

Research identification

Research questions

Research objectives

Project setup

Results

Conclusions

How is the experience of Airbnb users after the outbreak of COVID-19?

How was the experience of Airbnb users according to the sentiment polarity?

How was the experience of Airbnb users according to the presence/absence of covid-terms?

Where did Airbnb users experience positive, neutral, and negative sentiments?

Where did Airbnb users mention covid-terms?

Motivation and problem
statement

Research identification

Research questions

Research objectives

Project setup

Results

Conclusions

**To explore the
experience of Airbnb
users after the outbreak
of COVID-19.**

- To classify online reviews according to the sentiment polarity.

- To classify online reviews according to the presence/absence of covid-terms.

- To analyse keywords and their relationship.

- To analyse the spatial distribution of property listings according to sentiment polarity and the presence of covid-terms in property' reviews.

Motivation and problem
statement

Research identification

Research questions

Research objectives

Project setup

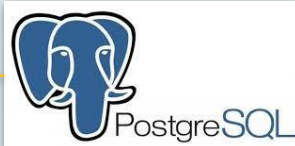
Results

Conclusions

Data source

Inside Airbnb
Adding data to the debate

Data storage



Spatial analysis



Semantic analysis



+



KDE

1

Data collection and storage

Data selection

- High corona cases
- Touristic cities



Rio de Janeiro



New York

Data content

- Property listings, including the geographic coordinates with an error between 0 and 150 m
- Reviews
- Calendar availability

2

Text preparation**First part**

Removal of:

- Automated postings (e.g., “This is an automated posting”)
- Non-English reviews → **Fasttext**
- Duplicated and empty reviews
- Reviews consisting in only two characters, numbers or NaN

Second part

- Tokenization and lowercasing
- Spelling correction, lemmatization and expansion of contractions
- Extraction of nouns, adjectives and verbs

Removal of:

- Stopwords, emojis, proper nouns, special characters, numbers, punctuations, extra whitespaces, tabs, and newlines.

Motivation and problem
statement

Research identification

Research questions

Research objectives

Project setup

Results

Conclusions

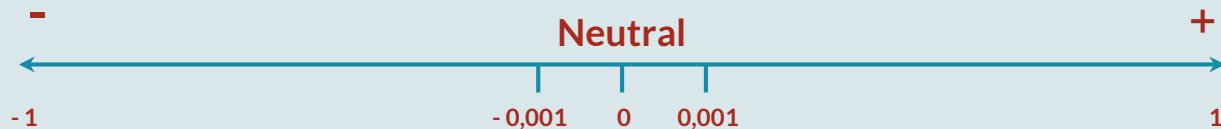
VADER

3

Text categorization

Sentiment analysis

	label	review	scores	compound
0	pos	Stuning even for the non-gamer: This sound tra...	{'neg': 0.088, 'neu': 0.669, 'pos': 0.243, 'co...	0.9454
1	pos	The best soundtrack ever to anything.: I'm rea...	{'neg': 0.018, 'neu': 0.837, 'pos': 0.145, 'co...	0.8957
2	pos	Amazing!: This soundtrack is my favorite music...	{'neg': 0.04, 'neu': 0.692, 'pos': 0.268, 'com...	0.9858
3	pos	Excellent Soundtrack: I truly like this soundt...	{'neg': 0.09, 'neu': 0.615, 'pos': 0.295, 'com...	0.9814
4	pos	Remember, Pull Your Jaw Off The Floor After He...	{'neg': 0.0, 'neu': 0.746, 'pos': 0.254, 'comp...	0.9781



3

Text categorization

Covid terms

Includes:

- ❖ Terms that appear very often in texts related the Covid situation (e.g., *mask, pandemic, lockdown*).
- ❖ Terms people use to refer to the name of the virus or the disease and their abbreviations.

Excludes:

- ❖ Open compound words
- ❖ Ambiguous words

Total: 88 terms

Sources:

- Scientific articles.
- Study by Lillo (2020) "*COVID-19, the beer flu; Or, the disease of many names*".

Motivation and problem
statement

Research identification

Research questions

Research objectives

Project setup

Results

Conclusions

Keywords and their relationship

4

Topic modelling

Frequent terms
RTF

Rare terms
TF-IDF

Network diagrams

Edges
Strength of
correlation

Nodes
Keywords

Colors
Communities, given by
*cluster Louvain
algorithm*

Motivation and problem statement

Research identification

Research questions

Research objectives

Project setup

Results

Conclusions

5

Spatial analysis

Density surface

Visualize the spatial distribution of properties

According to

Overall polarity:

Positive, neutral and negative

Time period:

Before and after the outbreak of covid

To

Identify areas with high intensity positive, neutral and negative sentiments

Identify changes after the outbreak of covid by using
Map algebra

Motivation and problem
statement

Research identification

Research questions

Research objectives

Project setup

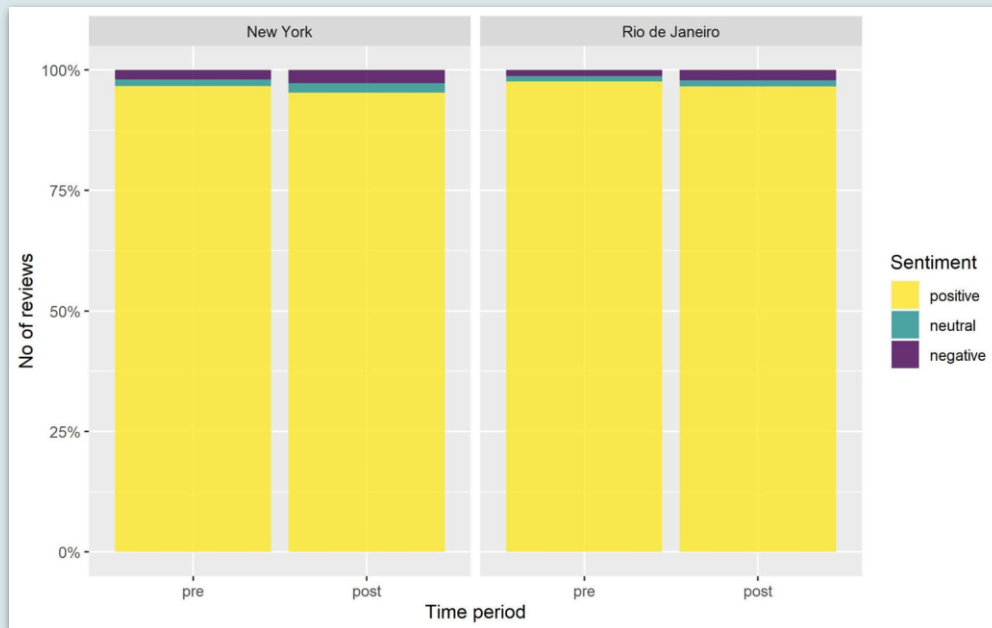
Results

Conclusions

1

Sentiment analysis

Reviews



Total reviews

NY: 486,438

RJ: 26,262

Positive reviews

NY: 2%

RJ: 1%



Neutral reviews

NY: 1%

RJ: same amount



Negative reviews

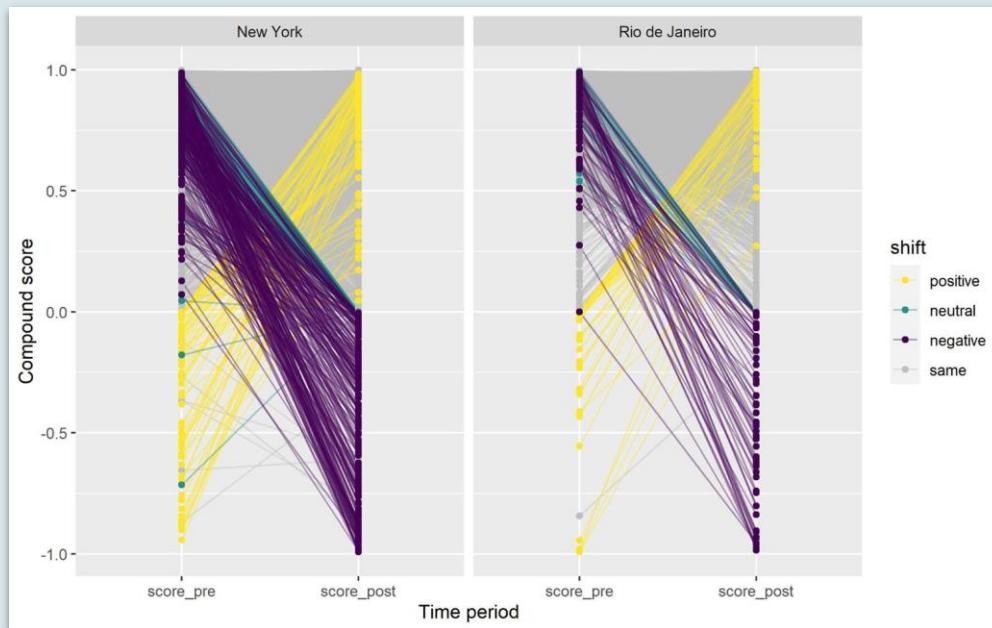
NY: 1%

RJ: 1%



1.1

Sentiment analysis

Property listings

Total properties

NY: 18,751

RJ: 3,522

Polarity shift

NY: 2,1%

RJ: 3,6%

Positive to neutral

NY: 0,44%

RJ: 0,65%

Positive to negative

NY: 1,2%

RJ: 1,7%

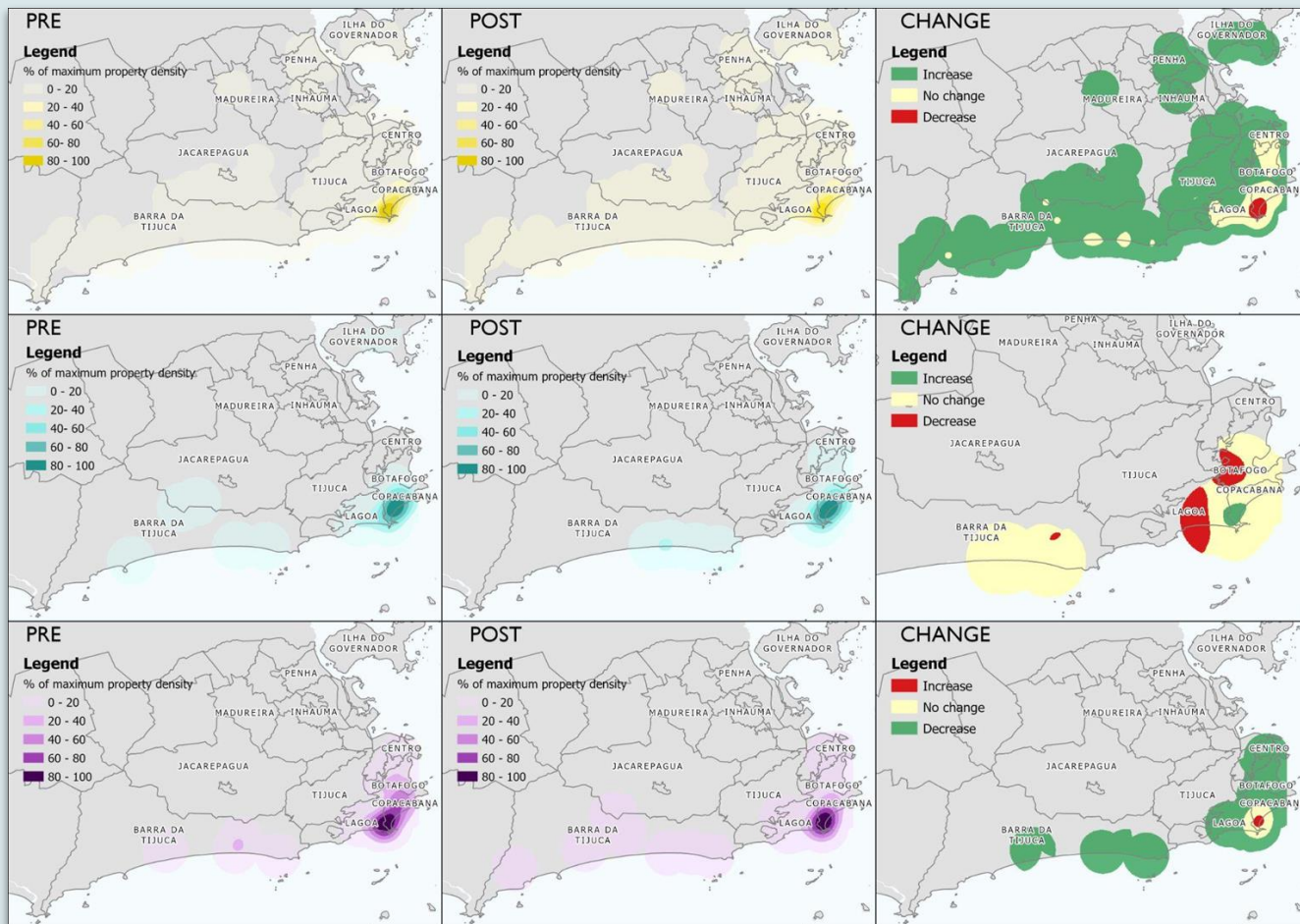
1.2

Sentiment analysis

Spatial visualization



Rio de Janeiro



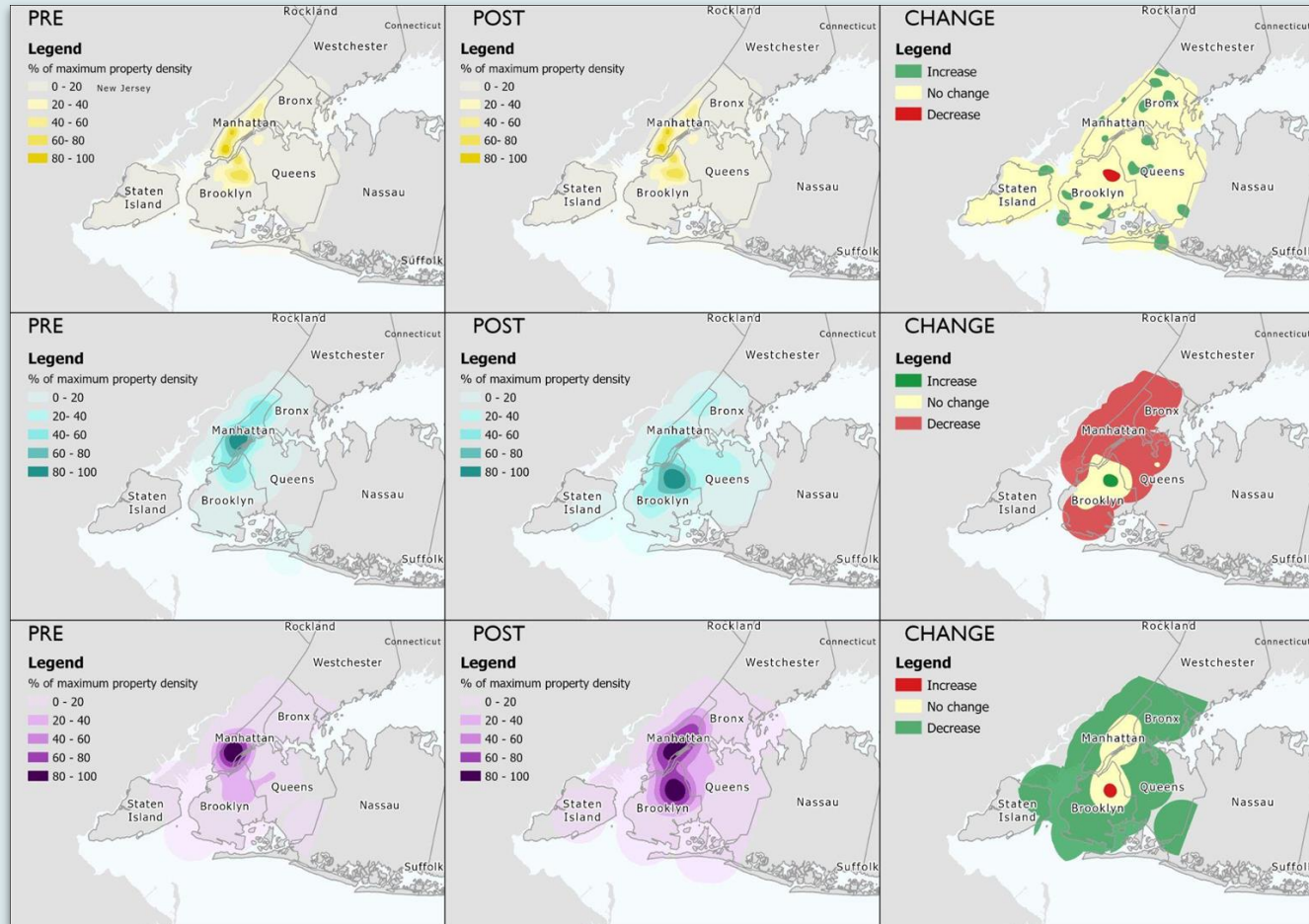
1.2

Sentiment analysis

Spatial visualization



New York



1.3

Sentiment analysis

Frequent terms



Rio de Janeiro

Pre-covid

Table 4. List with the 10 most frequent terms from reviews of properties in RJ before the outbreak of covid.

No.	Positive			Neutral			Negative		
	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.
1	place	9178	1	place	24	1	apartment	160	1
2	apartment	8113	0,88	apartment	24	1	place	120	0,75
3	location	8065	0,88	beach	24	1	host	115	0,72
4	host	5222	0,57	location	15	0,63	location	79	0,49
5	stay	4562	0,50	stay	11	0,46	day	68	0,43
6	beach	4348	0,47	host	9	0,38	stay	62	0,39
7	time	2587	0,28	room	8	0,33	room	62	0,39
8	view	2524	0,28	time	6	0,25	night	54	0,34
9	restaurant	2480	0,27	restaurant	6	0,25	issue	37	0,23
10	room	1701	0,19	price	4	0,17	work	35	0,22

Shared by all:
Place, apartment,
location and host.

Post-covid

Table 5. List with the 10 most frequent terms from reviews of properties in RJ after the outbreak of covid.

No.	Positive			Neutral			Negative		
	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.
1	place	4525	1	place	17	1	apartment	158	1
2	location	3874	0,86	beach	16	0,94	place	114	0,72
3	apartment	3839	0,85	location	12	0,71	host	76	0,48
4	host	2505	0,55	host	10	0,59	location	67	0,42
5	stay	2312	0,51	stay	9	0,53	day	61	0,39
6	beach	1967	0,43	apartment	9	0,53	time	60	0,38
7	view	1299	0,29	need	4	0,24	room	53	0,34
8	time	1263	0,28	view	3	0,18	night	49	0,31
9	restaurant	1127	0,25	street	3	0,18	water	38	0,24
10	room	829	0,18	restaurant	3	0,18	people	36	0,23

Unique to neutral
Pre: price
Post: need and street

Unique to negative
Pre: issue and work
Post: water and people

1.3

Sentiment analysis

Frequent terms



New York

Pre-covid

Table 6. List with the 10 most frequent terms from reviews of properties in NY before the outbreak of covid.

No.	Positive			Neutral			Negative		
	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.
1	place	206130	1	place	1160	1	place	3828	1
2	location	115551	0,56	location	547	0,47	room	3304	0,86
3	stay	102795	0,50	stay	536	0,46	host	2339	0,61
4	host	93211	0,45	room	345	0,30	apartment	2316	0,61
5	apartment	89161	0,43	apartment	265	0,23	night	1962	0,51
6	room	62843	0,30	subway	240	0,21	time	1553	0,41
7	space	46827	0,23	host	228	0,20	stay	1523	0,40
8	time	44286	0,21	station	216	0,19	bathroom	1514	0,40
9	home	31288	0,15	time	185	0,16	day	1448	0,38
10	area	30974	0,15	space	184	0,16	location	1431	0,37

Post-covid

Table 7. List with the 10 most frequent terms from reviews of properties in NY after the outbreak of covid.

No.	Positive			Neutral			Negative		
	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.
1	place	70122	1	place	486	1	place	1930	1
2	stay	37576	0,54	stay	302	0,62	room	1755	0,91
3	location	34874	0,50	location	220	0,45	host	1329	0,69
4	host	29807	0,43	room	175	0,36	apartment	1047	0,54
5	apartment	24587	0,35	space	112	0,23	night	911	0,47
6	room	17956	0,26	host	102	0,21	stay	870	0,45
7	space	17153	0,24	time	90	0,19	time	863	0,45
8	time	13749	0,20	apartment	86	0,18	day	861	0,45
9	home	11197	0,16	book	75	0,15	bathroom	632	0,33
10	area	8943	0,13	home	61	0,13	door	515	0,27

Shared by all:
Place, apartment, host,
room, time and stay.

Unique to neutral
Pre: subway and station
Post: book

Unique to negative
Post: door

Motivation and problem
statement

Research identification

Research questions

Research objectives

Project setup

Results

Conclusions

Keywords shared

1.3

Sentiment analysis

Frequent terms

Comparison

Shared by all:
Place, apartment,
and host.

Shared by all positive:
Place, apartment, location,
host, room, time and stay.

Shared by all neutral:
Place, apartment,
location, host and stay.

Shared by all negative:
Place, apartment, room,
host, **day** and **night**.

Pre-covid



No.	Positive		Neutral		Negative	
	Term	Score	Term	Score	Term	Score
1	year	1	year	1	sheet	1
2	word	1	xbox	1	review	1
3	wish	1	time	1	renter	1
4	wifi	1	thumb	1	pay	1
5	wife	1	stay	1	block	1
6	welcome	1	star	1	shop	0,93
7	wait	1	saucer	1	spot	0,92
8	view	1	rockstar	1	view	0,87
9	value	1	right	1	experience	0,84
10	treat	1	reply	1	clean	0,83

Post-covid

No.	Positive		Neutral		Negative	
	Term	Score	Term	Score	Term	Score
1	wow	1	view	1	reservation	1
2	worth	1	time	1	problem	1
3	work	1	supermarket	1	comment	1
4	wait	1	street	1	cold	0,93
5	visit	1	stay	1	doubt	0,82
6	view	1	star	1	mosquito	0,81
7	value	1	sim	1	guest	0,80
8	time	1	show	1	frill	0,78
9	think	1	renovation	1	change	0,77
10	thanks	1	place	1	truth	0,77

1.4

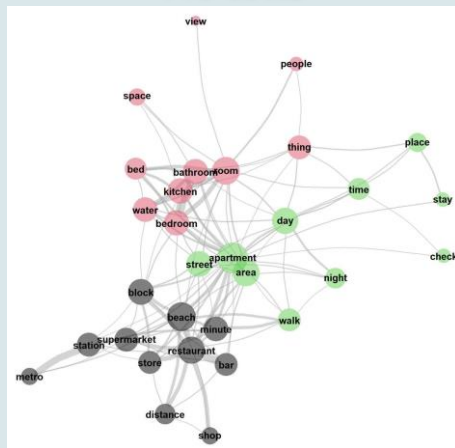
Sentiment analysis

Rare terms

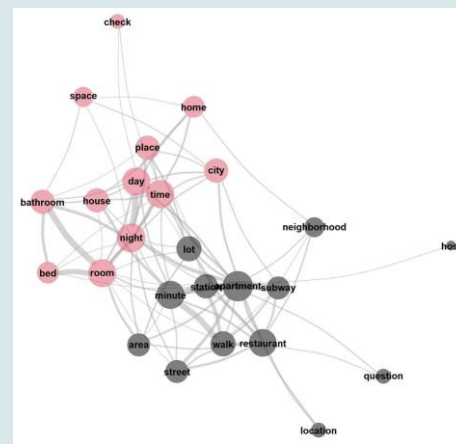
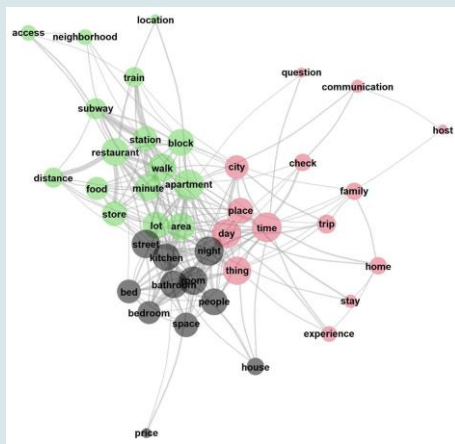
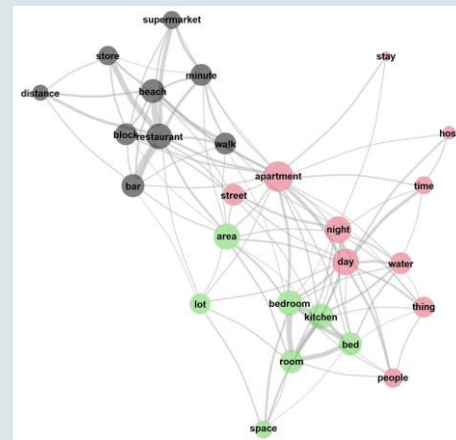
No.	Positive		Neutral		Negative	
	Term	Score	Term	Score	Term	Score
1	zone	1	way	1	train	1
2	worth	1	visit	1	thanks	1
3	worry	1	think	1	television	1
4	woman	1	term	1	stay	1
5	welcome	1	subway	1	pay	1
6	want	1	stay	1	neighborhood	0,93
7	walk	1	star	1	need	0,92
8	visit	1	spot	1	host	0,87
9	value	1	room	1	complaint	0,84
10	trip	1	review	1	comment	0,83

No.	Positive		Neutral		Negative	
	Term	Score	Term	Score	Term	Score
1	year	1	wifi	1	worth	1
2	worth	1	visit	1	thanks	1
3	window	1	time	1	stay	1
4	welcome	1	stay	1	room	0,93
5	visit	1	star	1	refund	0,82
6	view	1	spot	1	place	0,81
7	vibe	1	smoking	1	money	0,80
8	value	1	service	1	host	0,78
9	use	1	room	1	condition	0,77
10	trip	1	review	1	comment	0,77

Pre-covid



Post-covid



1.5

Sentiment analysis

Network diagrams

Positive reviews

2

Covid reviews

Sentiment analysis

Table 12. Frequency of covid terms

Covid-term	Rio de Janeiro		New York	
	Count	Percent (%)	Count	Percent (%)
corona	16	15	58	4
coronavirus	13	12	99	7
covid	14	13	319	23
lockdown	4	4	59	4
mask	9	8	132	10
pandemic	34	31	579	42
quarantine	20	18	136	10
Total	110	100	1382	100

Table 13. Number and percentage of covid reviews per sentiment polarity from properties in RJ and NY.

Sentiment	Rio de Janeiro		New York	
	Count	Percent (%)	Count	Percent (%)
Positive	74	87	1098	89,3
Neutral			5	0,4
Negative	11	13	126	10,3
Total	85	100	1229	100

2.1

Covid reviews

Spatial visualization

Legend

● Property with negative polarity

● Property with positive polarity

% of maximum frequency

○ 0,0 - 0,2

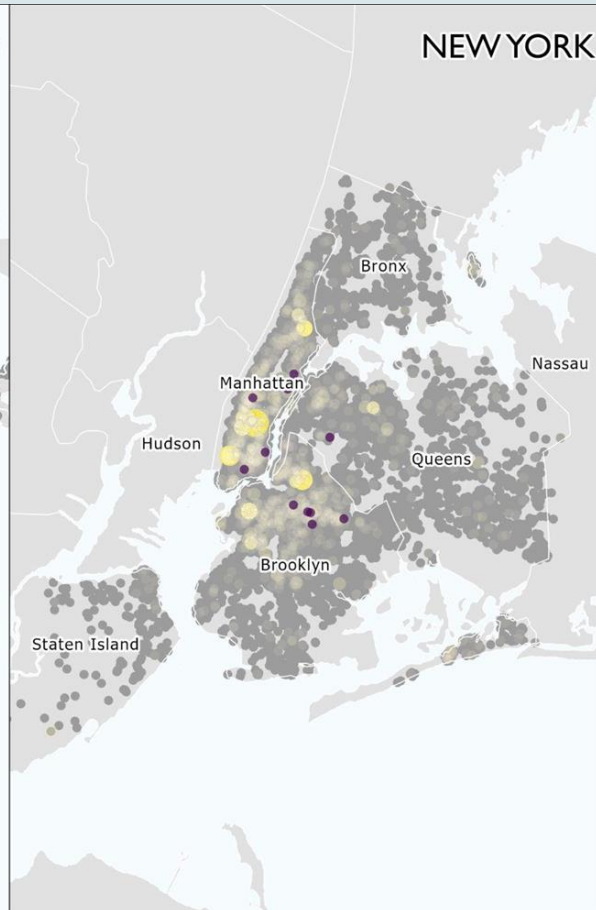
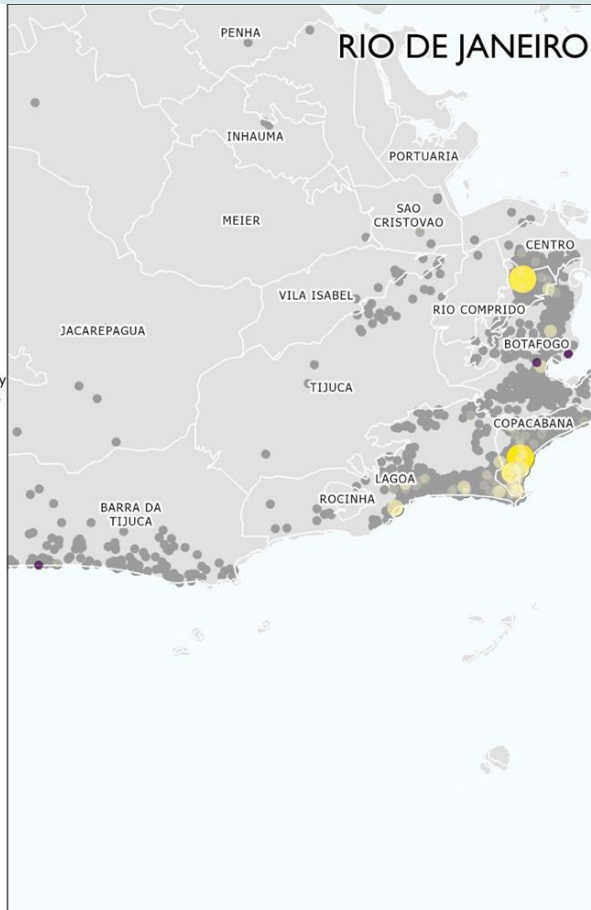
○ 0,2 - 0,4

○ 0,4 - 0,6

○ 0,6 - 0,8

○ 0,8 - 1,0

Maximum frequency: 6



2.2

Covid reviews

Frequent terms



No.	Positive			Negative		
	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.
1	place	72	1	apartment	14	1
2	apartment	55	0,76	host	13	0,93
3	stay	31	0,43	owner	11	0,79
4	location	27	0,38	place	10	0,71
5	host	26	0,36	house	9	0,64
6	beach	23	0,32	air	9	0,64
7	day	17	0,24	people	8	0,57
8	time	16	0,22	rule	7	0,50
9	month	15	0,21	refund	7	0,50
10	view	15	0,21	time	7	0,50



No.	Positive			Neutral			Negative		
	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.	Term	Freq.	R. Freq.
1	place	1038	1	bed	3	1	host	104	1
2	apartment	582	0,56	room	3	1	room	96	0,92
3	stay	515	0,50	covid	3	1	place	96	0,92
4	host	478	0,46	day	2	0,67	day	90	0,87
5	time	473	0,46	king	2	0,67	time	76	0,73
6	location	368	0,35	cabin	1	0,33	apartment	76	0,73
7	room	353	0,34	ceiling	1	0,33	stay	60	0,58
8	space	341	0,33	hostel	1	0,33	night	53	0,51
9	home	280	0,27	dorm	1	0,33	people	46	0,44
10	day	263	0,25	plug	1	0,33	issue	37	0,36

2.3

Covid reviews

Rare terms



No.	Positive		Negative	
	Term	Score	Term	Score
1	wait	0,75	covid	0,476
2	condo	0,73	quarantine	0,456
3	serve	0,72	home	0,456
4	house	0,69	friend	0,456
5	charm	0,67	apartment	0,451
6	begin	0,65	check	0,418
7	help	0,64	travel	0,407
8	deck	0,58	value	0,391
9	window	0,57	iron	0,391
10	studio	0,57	ice	0,391



No.	Positive		Neutral		Negative	
	Term	Score	Term	Score	Term	Score
1	home	1	stay	0,84	covid	1
2	eats	1	day	0,65	property	0,79
3	birthday	1	king	0,57	cancellation	0,78
4	cleaner	0,96	covid	0,54	scruple	0,76
5	value	0,94	room	0,45	crew	0,74
6	coronavirus	0,93	bed	0,45	conference	0,70
7	guideline	0,92	sleep	0,35	unit	0,69
8	covid	0,90	plug	0,35	people	0,67
9	thanks	0,89	hostel	0,35	rental	0,65
10	umbrella	0,86	eye	0,35	host	0,64

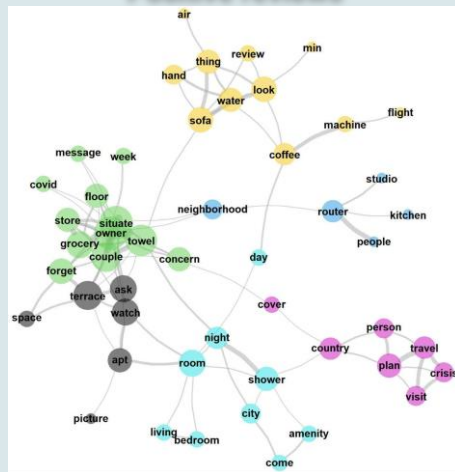
2.4

Covid reviews

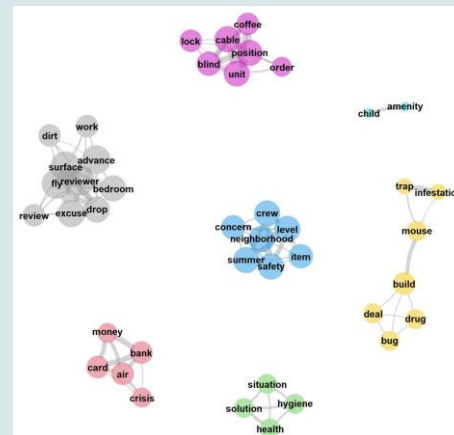
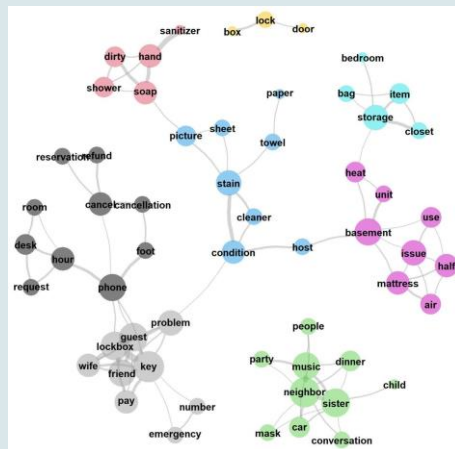
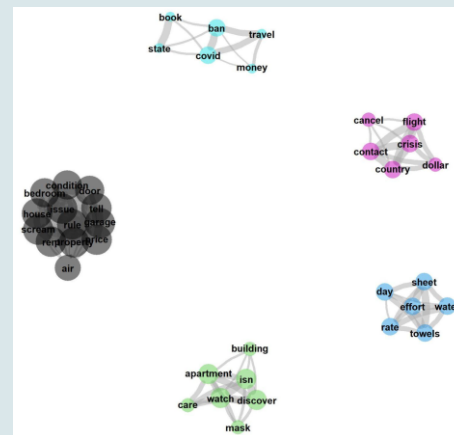
Network diagrams



Positive reviews



Negative reviews



- Not enough evidence to claim that after the outbreak of covid there was a significant change in the experience of Airbnb users in RJ and NY.
- Nevertheless, topics from covid reviews suggest that users experienced situations related with the health crisis (e.g., use of mask and hand sanitizer, etc).
- Further analyses are required to verify whether the different situations experienced after the outbreak can be linked to the Covid crisis.
- On the other hand, it was possible to visualize changes in the concentration of properties associated with overall positive, neutral and negative user experiences.
- This paper can be useful in the lodging industry to uncover other aspects of the user experience, for instance, future studies could explore the role of location of lodging places in the customer behaviour during health crises.

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*Thank you for your
attention.*

