Sentiment Analysis For Touristic Attractions: A Case Study On The Alhambra

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CONTENTS

- 1. INTRODUCTION
- 2. DATA
- 3. CLASSIFICATION ANALYSIS
- 4. SUBGROUP DISCOVERY
- 5. CONCLUSION

BACKGROUND AND MOTIVATION

Tourism



Source: http://fr.123rf.com/photo_7306498_avion-detourisme-icones-sentier-volant-dans-le-monde-entier.html

Web 2.0



Source: https://www.emaze.com/@AZILZITO/WEB-2.01

Data



Source: https://www.youtube.com/watch?v=wWcgYZWCAXg

What tourists think about touristic attractions?

OBJECTIVES

First approach to sentiment analysis into touristic attractions domain

More precisely...

1. Download and analyse reviews

More precisely...

- 1. Download and analyse reviews
- 2. Study correlation between human and machine sentiment

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- 3. Classify opinions

More precisely...

- 1. Download and analyse reviews
- 2. Study correlation between human and machine sentiment
- 3. Classify opinions
- 4. Dicover interesting patterns in negative opinions

2. DATA

Where do we get the data?



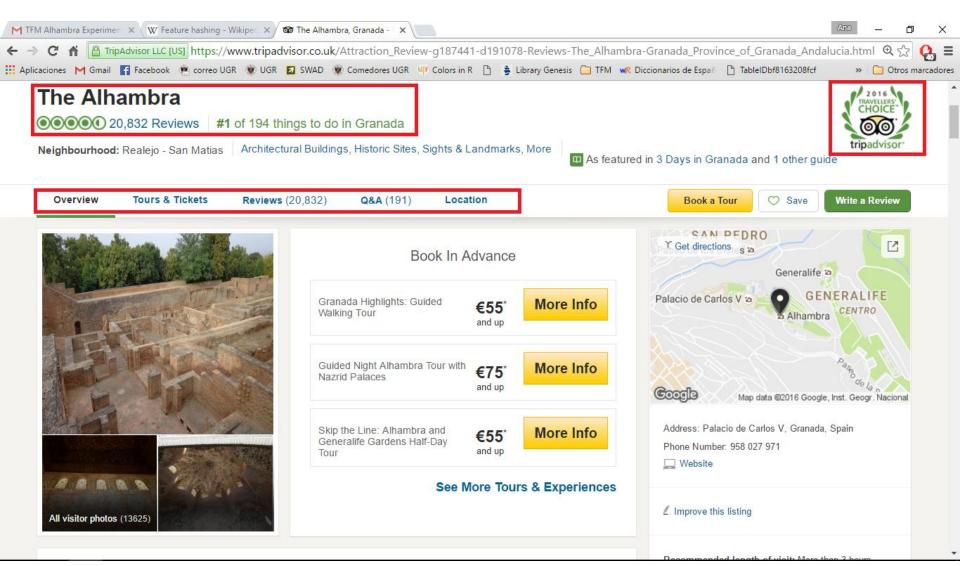
TripAdvisor logo



The Alhambra

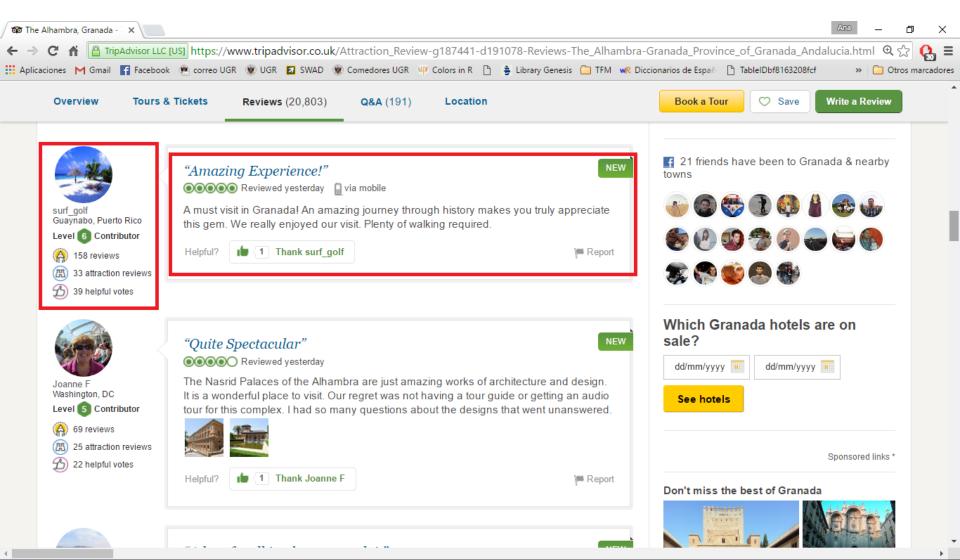
2. DATA

SCRAPPING



2. DATA

SCRAPPING



8140 instances



TripAdvisorAlhambra data set

8140 instances



TripAdvisorAlhambra data set

10 features

id
username
location
userop
quote
review
quote+review
rating
date
page





data set

10 features

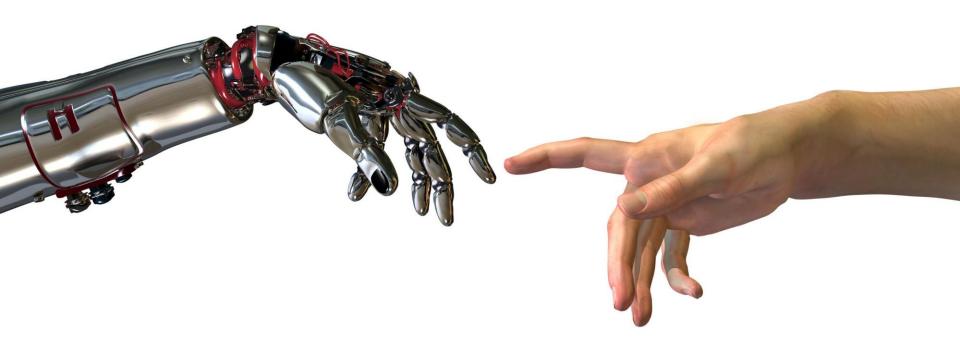
id
username
location
userop
quote
review
quote+review
rating
date
page

2 class labels

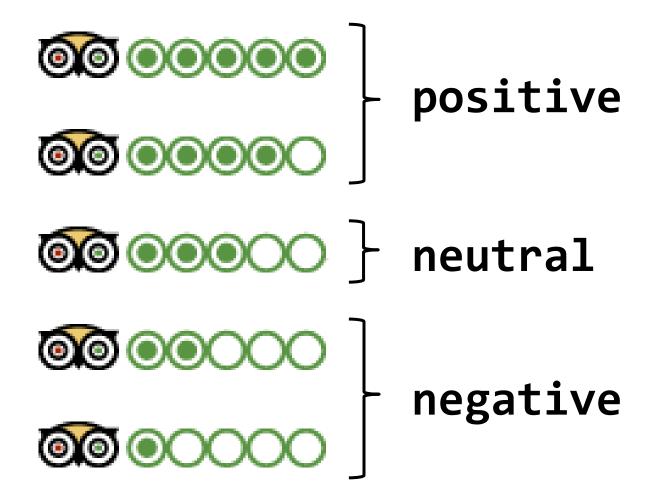
Class labels

SentimentCoreNLP

SentimentValue



SentimentValue





SentimentCoreNLP



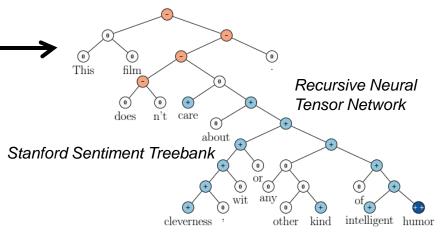
SentimentCoreNLP

CoreNLP toolkit



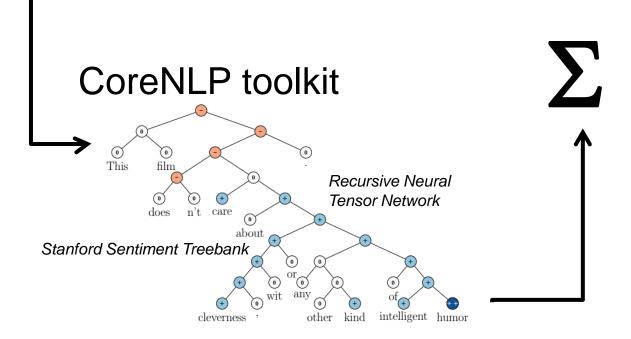
SentimentCoreNLP

CoreNLP toolkit



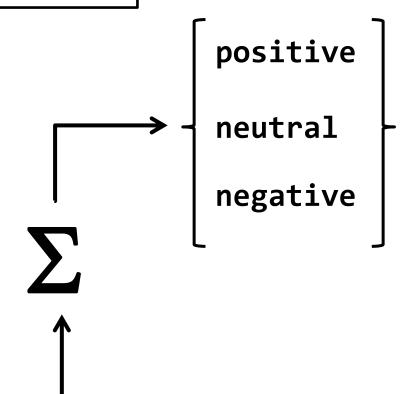


SentimentCoreNLP

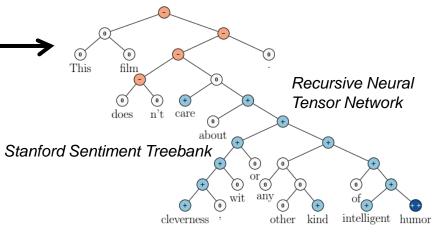




SentimentCoreNLP



CoreNLP toolkit



ANALYSIS OF CORRELATION BETWEEN CLASS LABELS

CORRELATION CLASS LABELS

	Sent			
SentimentValue	positive	neutral	negative	Total
positive	4,049	1,071	2,508	7,628
neutral	51	32	260	343
negative	5	6	158	169
Total	4,105	1,109	2,926	8,140

Table 4.2: Correlation between SentimentValue and SentimentCoreNLP

53.08 % of coincidence

CORRELATION CLASS LABELS

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Table 4.2: Correlation between SentimentValue and SentimentCoreNLP

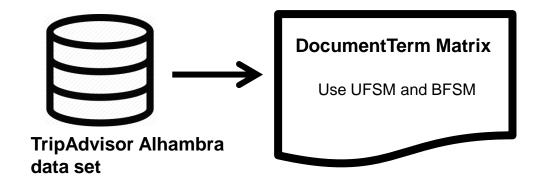
93.49 % of coincidence

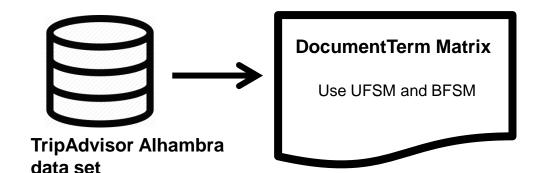
CLASSIFICATION ANALYSIS

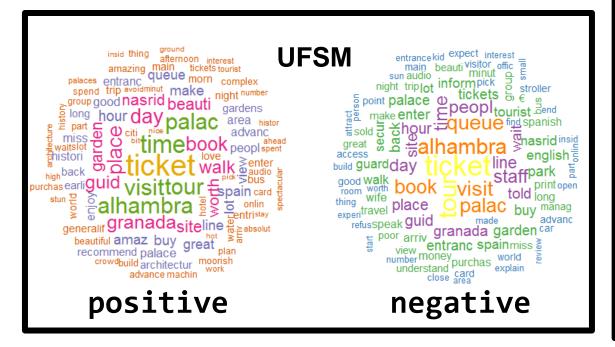
CLASSIFICATION ANALYSIS



CLASSIFICATION ANALYSIS

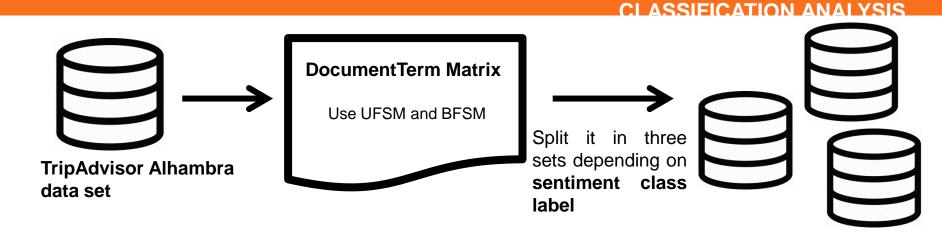


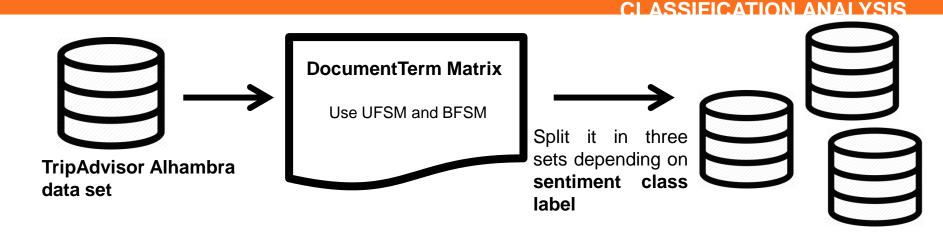




positive a great a good granada and our ticket to walkthe histori you dont we visitto buy palace and a ticket to book the visit a nasrid palac a bit a buy your in spain worth a in spain worth a day in advance the ground the tour in advance to be able to grant advance the ground the tour in advance to be able to grant advance to grant adv g worth th to visit -a lot gardens and is veria tour your ticket be guided four number of tickets for the nasrid an amaz the view in granada go gardens ar time slot be missedpalace i was veri the citi well worth alhambra and beautiful and the generalif the audio to the sit a veri views of buy ticket to the beautine queue book in the beautine queue book alhambra wa **BFSM** in english wanted to to alhambra tour wa tickets and tickets to in spanish to granada granada and the rest of peopl my wif in advance access to waste of palace i were toldyour ticket due to my ticket line for a ticket alhambra and palace and was told a great the palace the garden in adv the guid saudio guid to find the nasrid to visit so we arrival of the ticket of the visit to find the nasrid to visit so we arrival of the ticket of the visit so we arrival of the ticket of the visit so we arrival of the ticket of the visit so we arrival of the ticket of the visit so we arrival of the ticket of the visit so we arrival of the ticket of the visit so we are the visit so we m in spain the palac the day lot of decided to to book tickets for to makour ticket alhambra i > the queutoid that the bus a tour in granada the entrback to wife and buy ficket the tour the staff of ticket § 9 security guard Nasrid palacthe sit an hour nenter that to pay was veri told us inside that pm number of hours to the peopl tickets wer managed to world heritag arrived at to queu negative

ASSIFICATION ANALYSIS





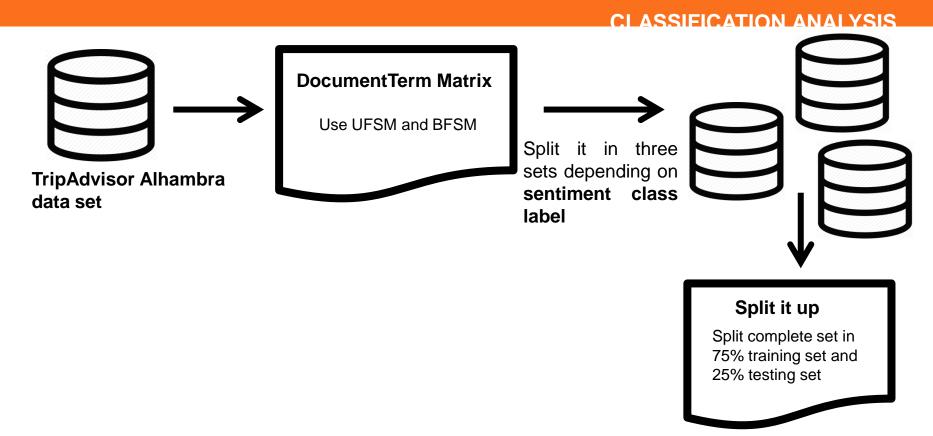
SentimentValue

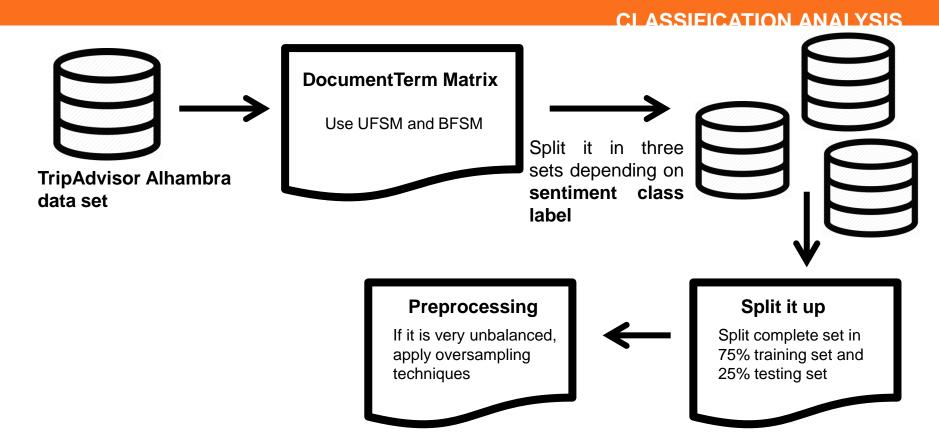
SentimentValue

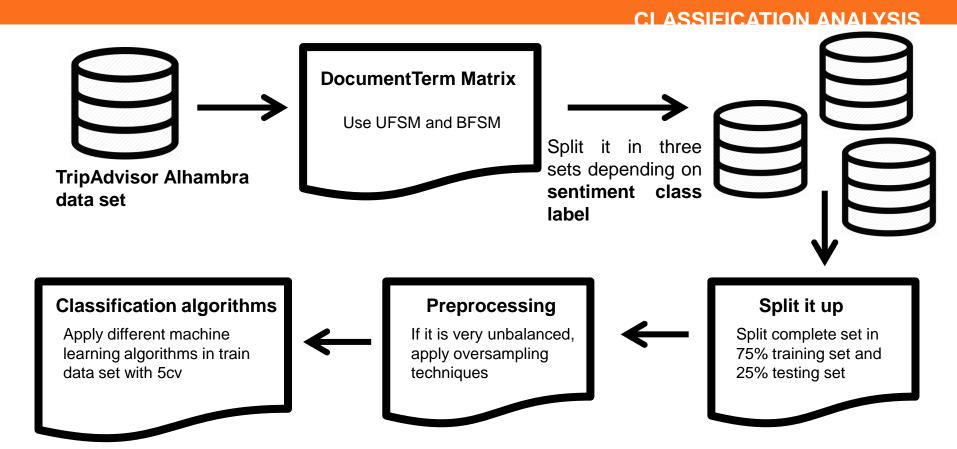
SentimentCoreNLP

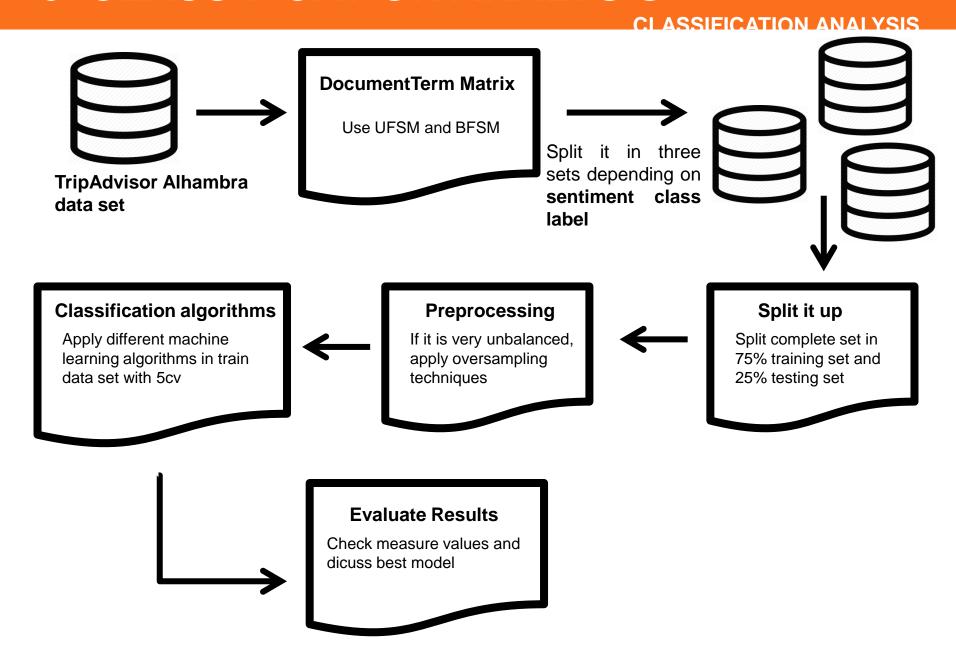
SentimentCoreNLP

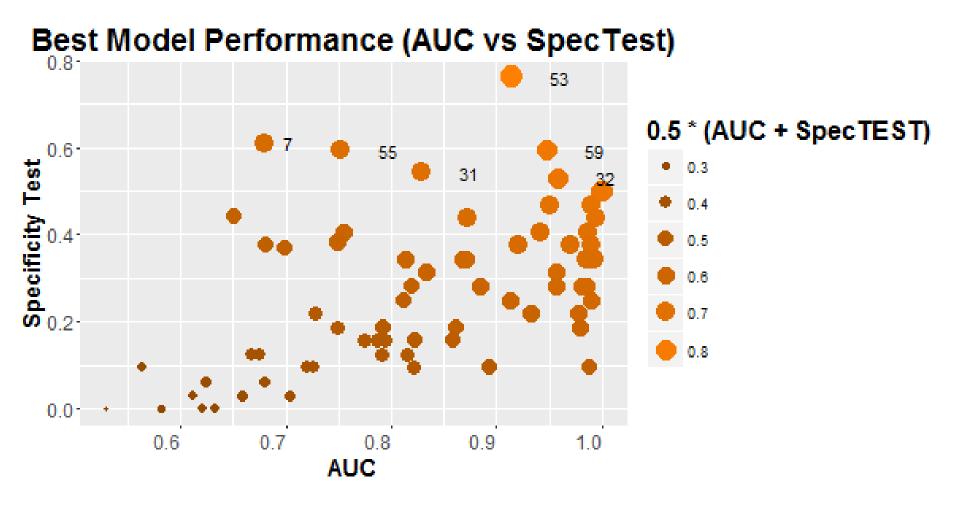
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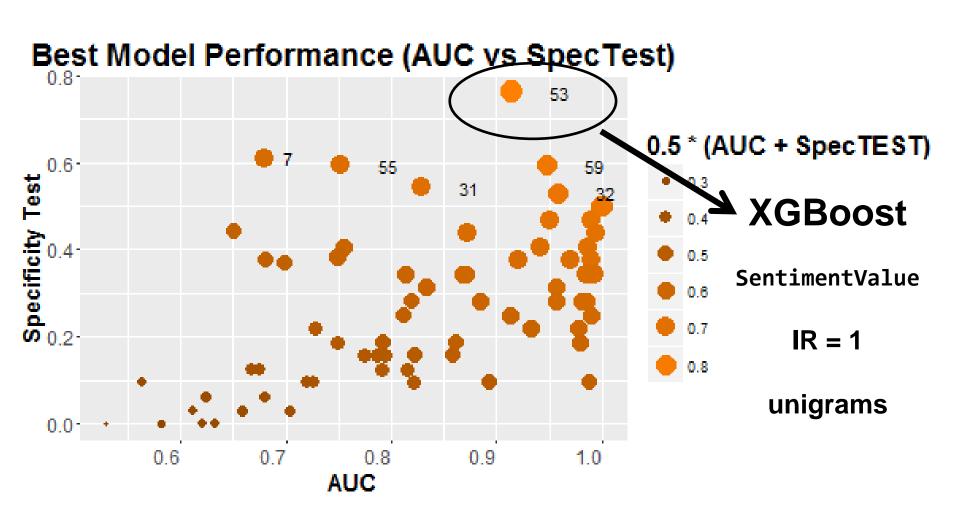












DISCOVERING INTERESTING PATTERNS IN NEGATIVE OPINIONS

 $R: Cond \longrightarrow Target_{value}$

negative

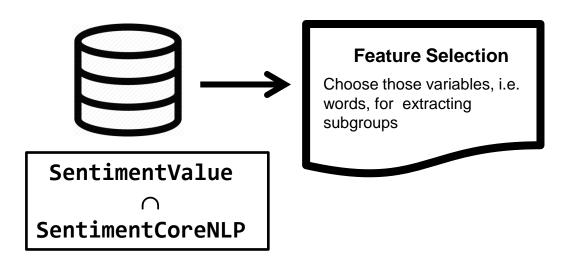
INTERESTING PATTERNS

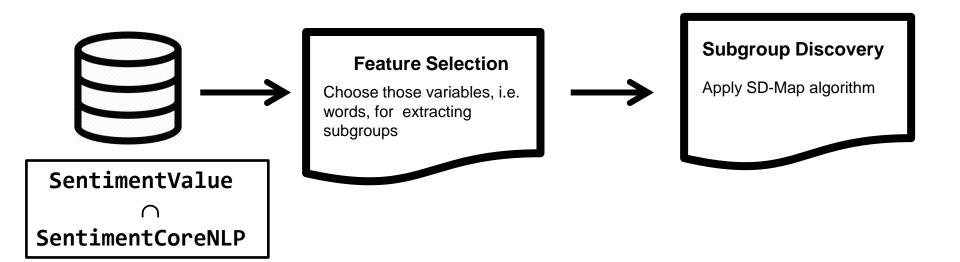


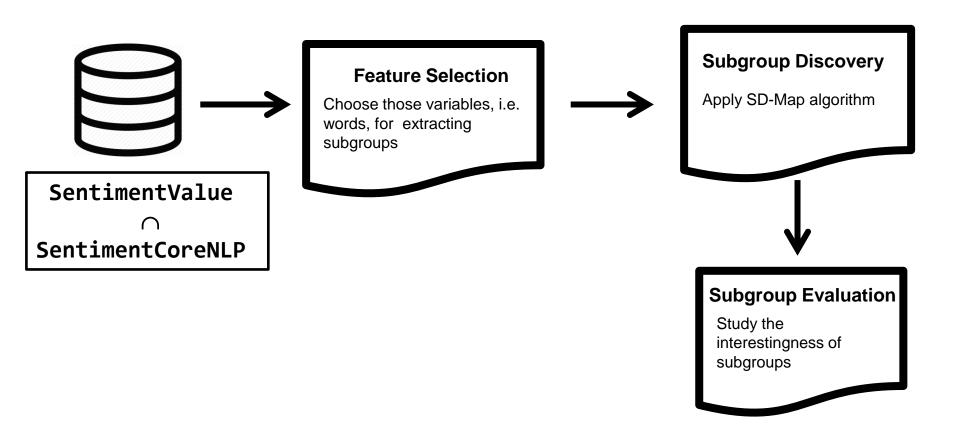
SentimentValue

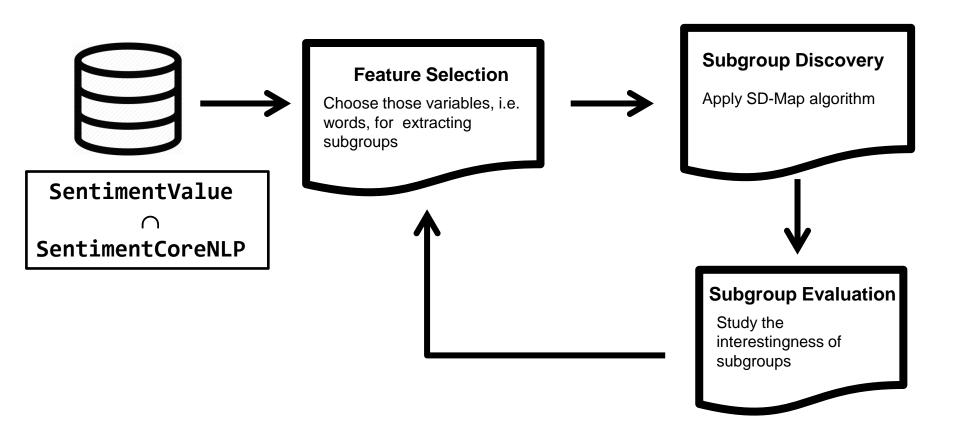


SentimentCoreNLP









q_{BT}	p	n	Description	
17.17	0.82	22	guard=1	
16.21	0.81	21	terribl=1	
12.29	0.68	19	rude=1	
3.85	1	4	rude=1, guard=1	
2.89	1	3	terribl=1, guard=1	
2.77	0.5	6	babi=1	
1.85	0.5	4	babi=1, strollX=1	
1.6	0.06	64	strollX=1	
30.33	0.46	71	staff=1	
6.7	0.88	8	attitud=1	
3.85	1	4	horribl=1	
3.85	1	4	attitud=1, staff=1	
3.85	1	4	horribl=1, staff=1	
1.92	1	2	horribl=1, attitud=1, staff=1	
30.33	0.14	284	queueX=1	
27.06	0.06	1303	time=1	
21.55	0.19	145	queueX=1, time=1	
5.21	0.29	21	wheelchair=1	
4.66	0.56	9	disabl=1	
2.85	0.75	4	disabl=1, wheelchair=1	
8.19	0.08	208	night=1	
7.2	0.08	181	night=1, light=0	
1.41	0.06	69	light=1	
0.99	0.07	27	light=1, night=1	
0.42	0.05	42	light=1, night=0	
0.03	0.29	79	speakX=1	
14.13	0.17	103	english=1	
6.62	0.7	10	staff=1, english=1, speakX=1	
7.62	0.8	10	email=1	
5.47	0.43	14	confirm=1	
3.85	1	4	email=1, confirm=1	

Table 5.2: Subgroups generated from feature correlation.

CONCLUSIONS

In general...

1. Tourists are **satisfied** with the Alhambra

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2. The Alhambra should rethink the **ticket** system

More precisely...

1. Suitable TripAdvisor Alhambra **data set** for applying sentiment analysis

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More precisely...

- 1. Suitable TripAdvisor Alhambra **data set** for applying sentiment analysis
- 2. **Low correlation** between human and machine sentiment
- 3. **Good** model performance in the **classification** analysis
- 4. Poor analysis of subgroup discovery

FURTHER WORK

Next months...

1. Talk to **Patronato** about this project

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- 2. Work on the sentiment labels

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- 4. Improve **subgroup discovery** method
- 5. Consider **neutral** sentiment

- 1. Talk to **Patronato** about this project
- 2. Work on the **sentiment labels**
- 3. Apply **aspect-sentiment** algorithms
- 4. Improve subgroup discovery method
- 5. Consider **neutral** sentiment
- 6. Develop **tool** for touristic attraction managers

THANKS!

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