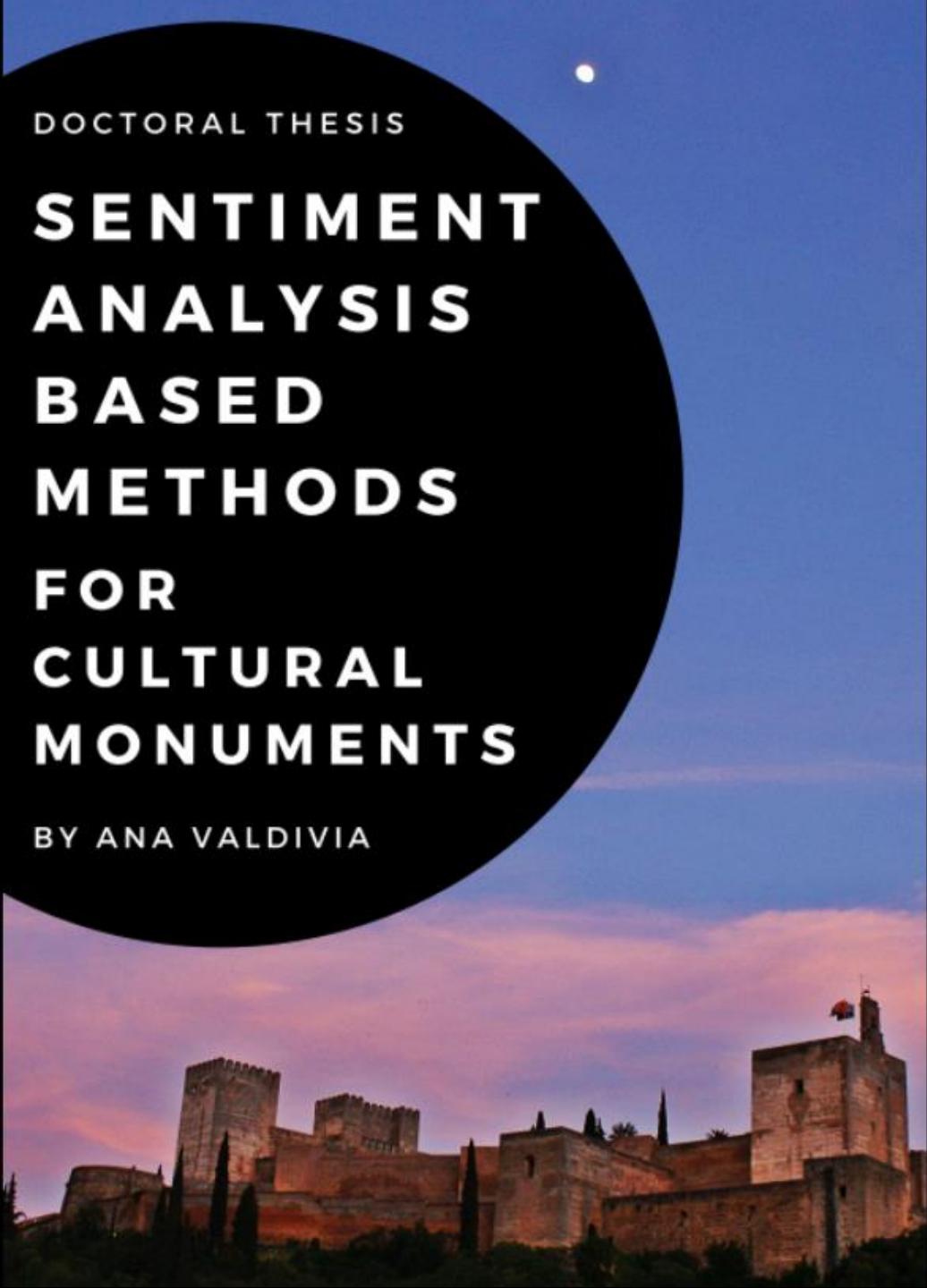


DOCTORAL THESIS

**SENTIMENT
ANALYSIS
BASED
METHODS
FOR
CULTURAL
MONUMENTS**

BY ANA VALDIVIA



**PhD Dissertation
of
Ana Valdivia**

Supervisors:

Francisco Herrera & M. Victoria Luzón

1st February, 2019



**UNIVERSIDAD
DE GRANADA**

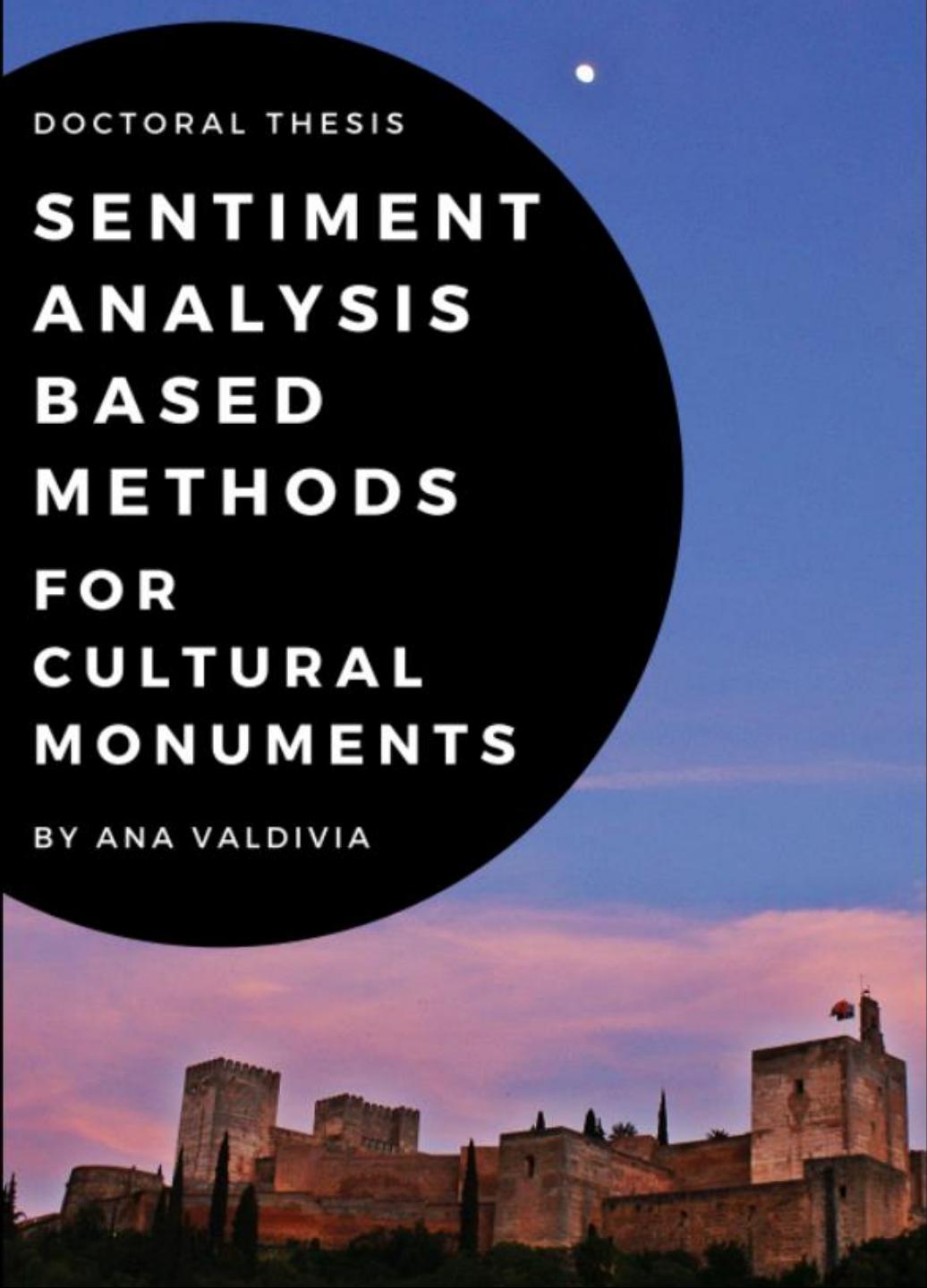


- 1 INTRODUCTION
- 2 PRELIMINARIES
- 3 OBJECTIVES
- 4 RESULTS
- 5 CONCLUSIONS

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**SENTIMENT
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INTRODUCTION



**UNIVERSIDAD
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Basic concepts

Opinion

- It is an **expression** that is given in a **conscious way** due to an emotion.
- We can express an opinion through facial expressions or words.

Web 2.0

- A **second generation** in the development of the World Wide Web, conceived as a combination of concepts, trends, and technologies that **focus on user collaboration, sharing of user-generated content, and social networking**.



Source: op4g.com

Basic concepts

TripAdvisor

- It is a travel website company that shows hotel and restaurant reviews, accommodation bookings and other travel-related content. It also includes interactive travel forums.



(1)

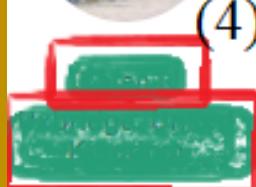


Reviewed [REDACTED] ago

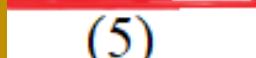
(2)

Must-see fortress

We had an excellent local guide telling us about the history as we walked round. Tickets are inspected frequently and even in October, it was very busy in the main palace buildings. The gardens were still green and the fountains were working but they must be so much more spectacular when all the flowers are in bloom. It was quite chilly and we had a little rain but our photos have the snow-topped mountains in the background which we weren't expecting.



(4)



(5)

(3)

This review is the subjective opinion of a TripAdvisor member and not of TripAdvisor LLC



tripadvisor

Basic concepts

Europe's heritage at risk from economic crisis

As budget cuts across Europe put heritage under pressure, some say it should be a spur towards better management

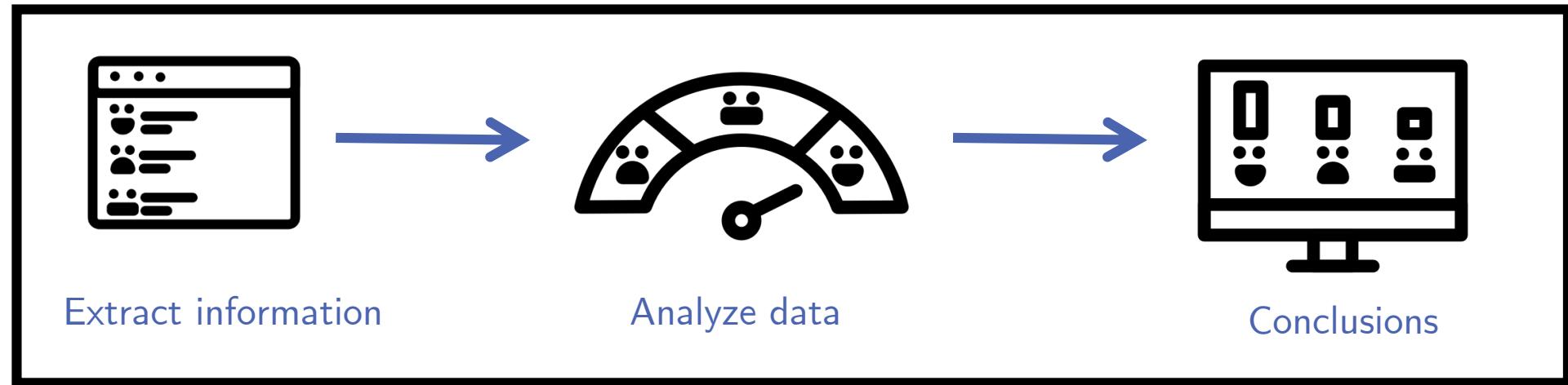
How cultural monuments analyze people's opinion?



Survey's drawbacks

- {
- What happens if we don't ask key questions?
 - What happens if people don't want to answer questions?
 - ...

How cultural monuments **may** analyze people's opinion?



Web 2.0 and social networks

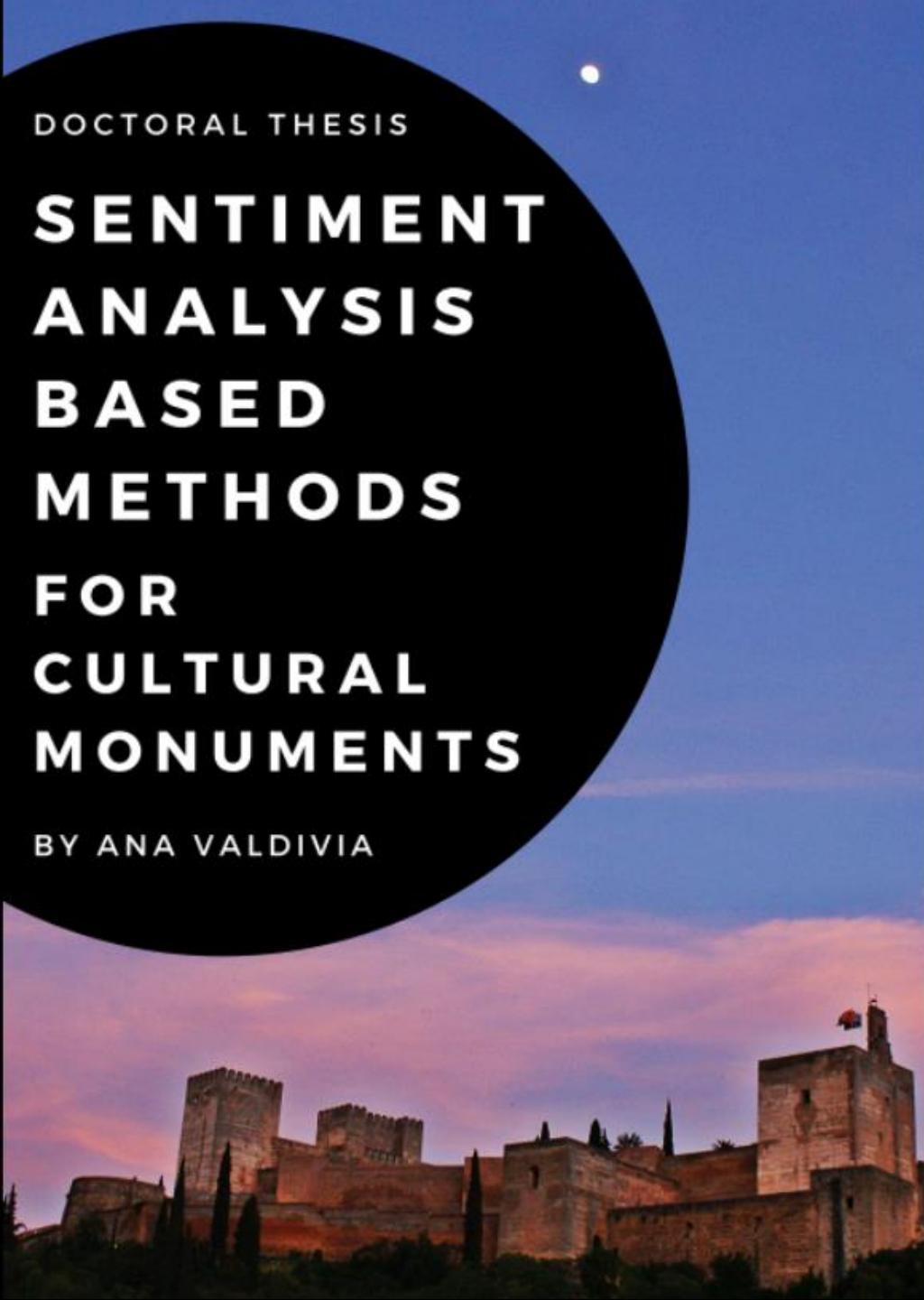


Machine and Deep Learning
Sentiment Analysis

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PRELIMINARIES



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Sentiment Analysis

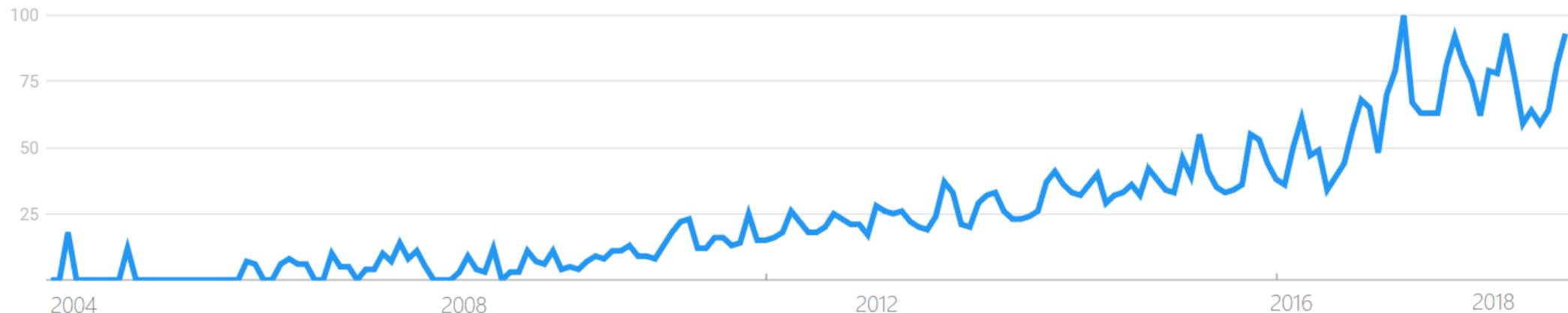
Liu's definition

- ❑ It is the field of study that **analyzes people's opinions**, sentiments, appraisals, attitudes, and emotions towards **entities** and their **attributes** expressed in written text.

Cambria's definition

- ❑ The **set of computational techniques** for **extracting, classifying, and assessing** the **opinions** expressed in various on-line news sources, social media comments, and other user-generated contents.

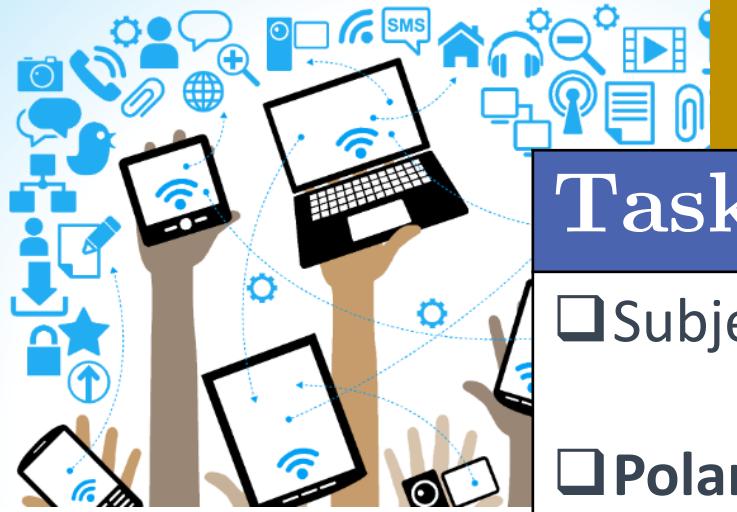
Sentiment Analysis



Sentiment Analysis search trend in Google.

Tasks

- Subjectivity classification.
- Polarity extraction and classification.**
- Opinion summarization.
- Opinion visualization.
- Sarcasm detection.
- Entity/Aspect extraction.
- ...



Polarity

- Label of the sentiment.
- Different categories:
 - {positive, neutral, negative}
 - {very positive, positive, neutral, negative, very negative}
 - {1, 2, 3, 4, 5}
 - [0, 1]



Levels of analysis

- Document
- Sentence
- Entity/Aspect

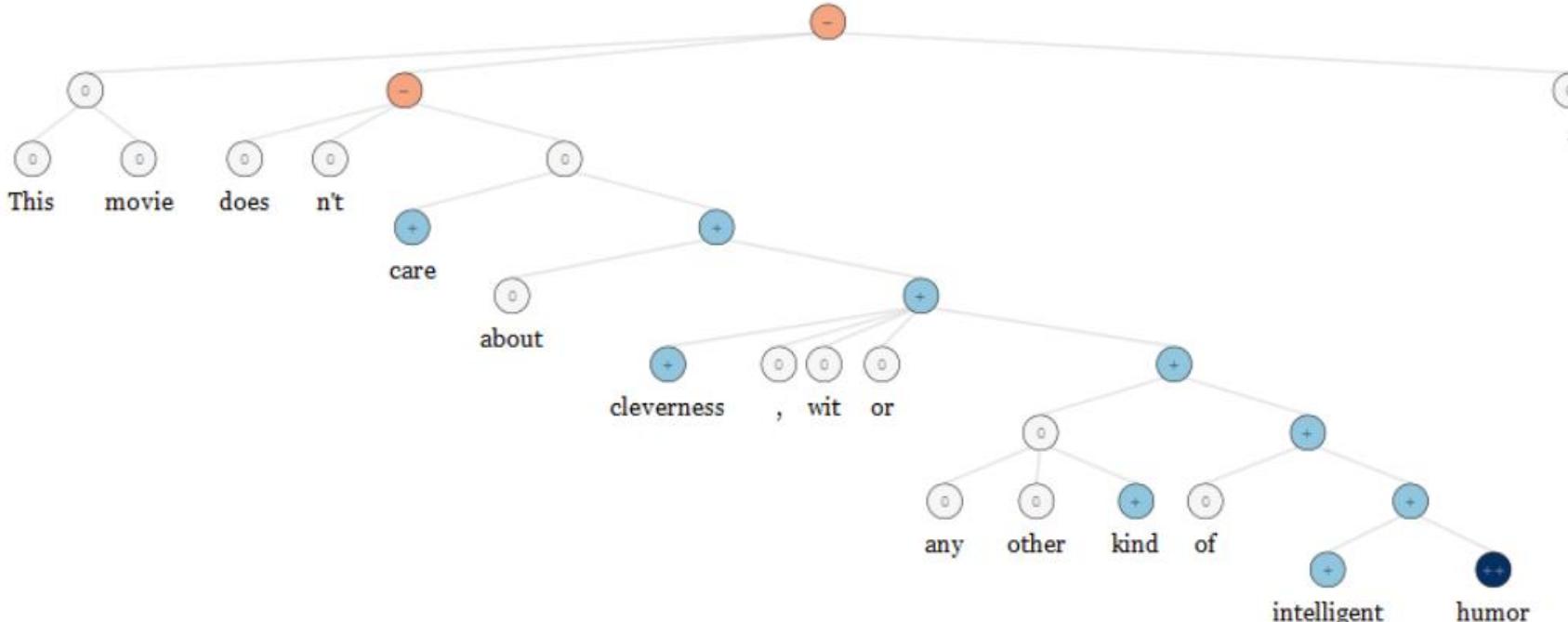
Basic concepts

Sentiment Analysis Methods (SAMs)

- ❑ Algorithms that extract **automatically** polarities from text.
- ❑ Drawbacks:
 - Domain adaptation
 - Corpus creation
 - Labelling cost

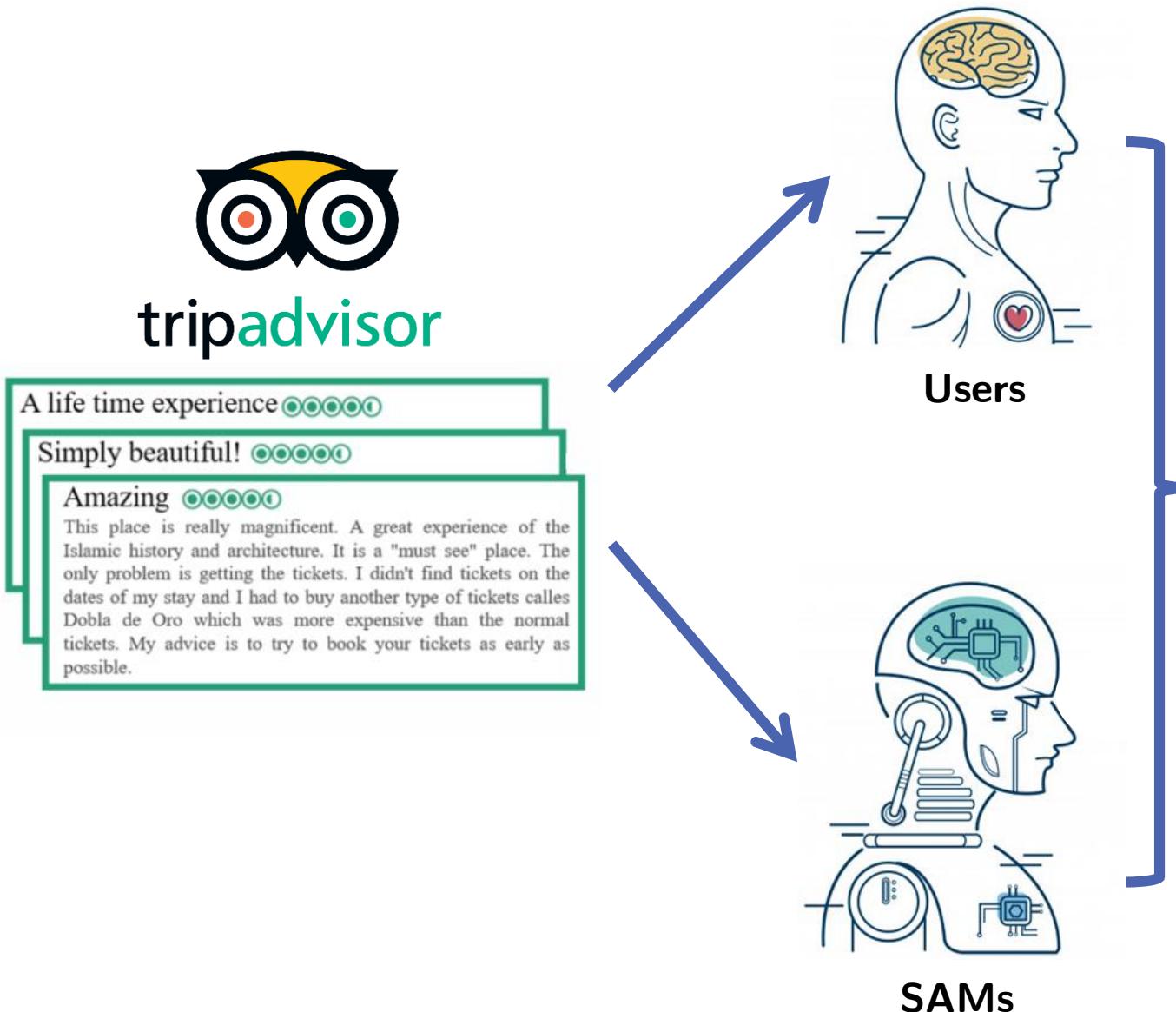
Example of SAM

CoreNLP

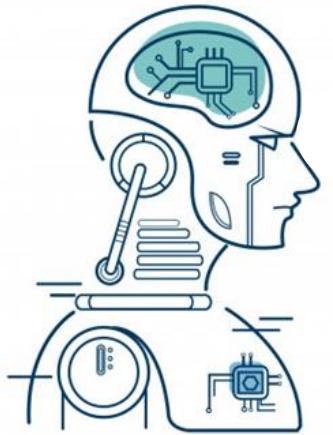


Manning, Christopher, et al. (2014). **The Stanford CoreNLP natural language processing toolkit.** *Proceedings of 52nd annual meeting of the association for computational linguistics: system demonstrations.*

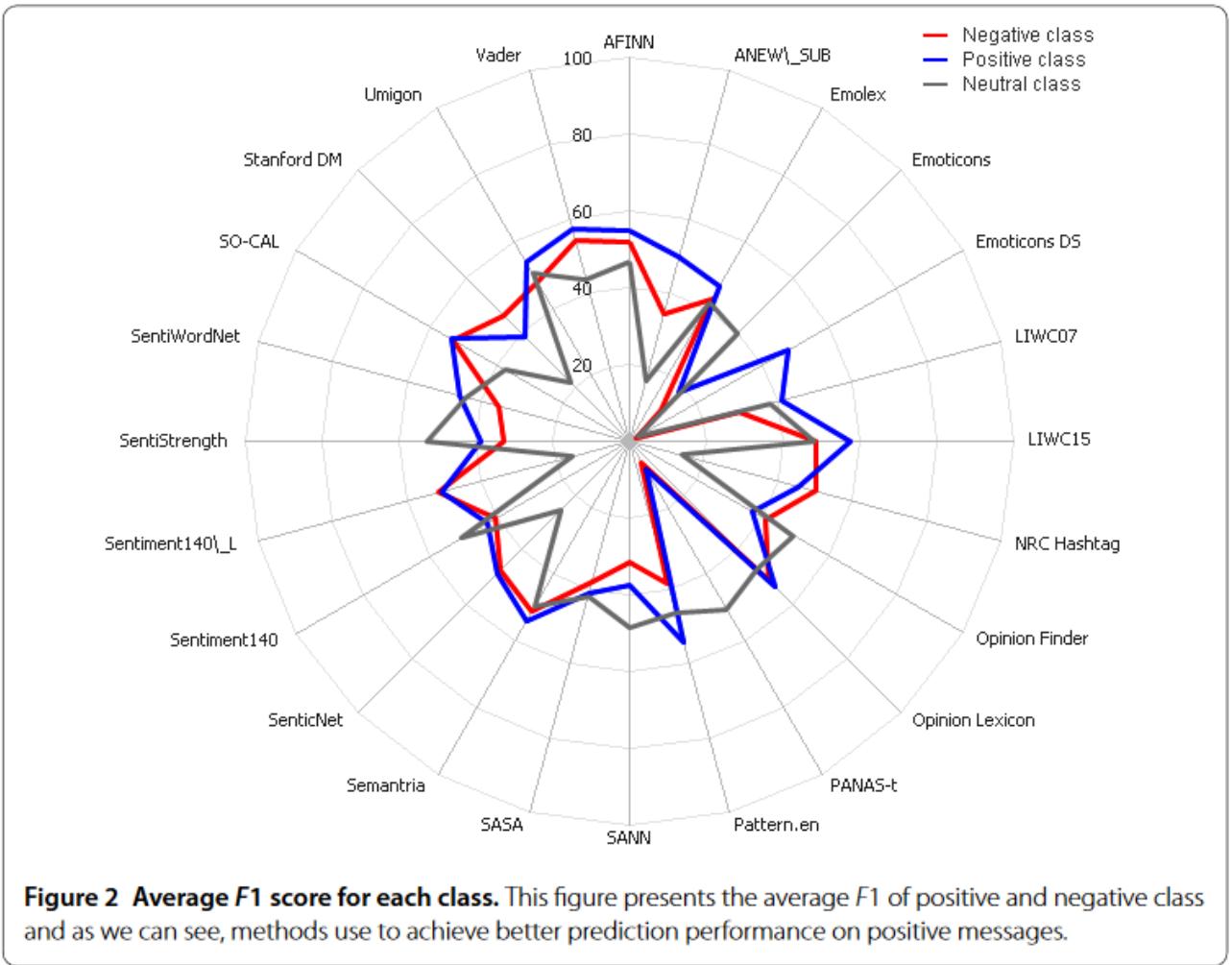
1. Relation between Users and SAMs?



2. Neutrality

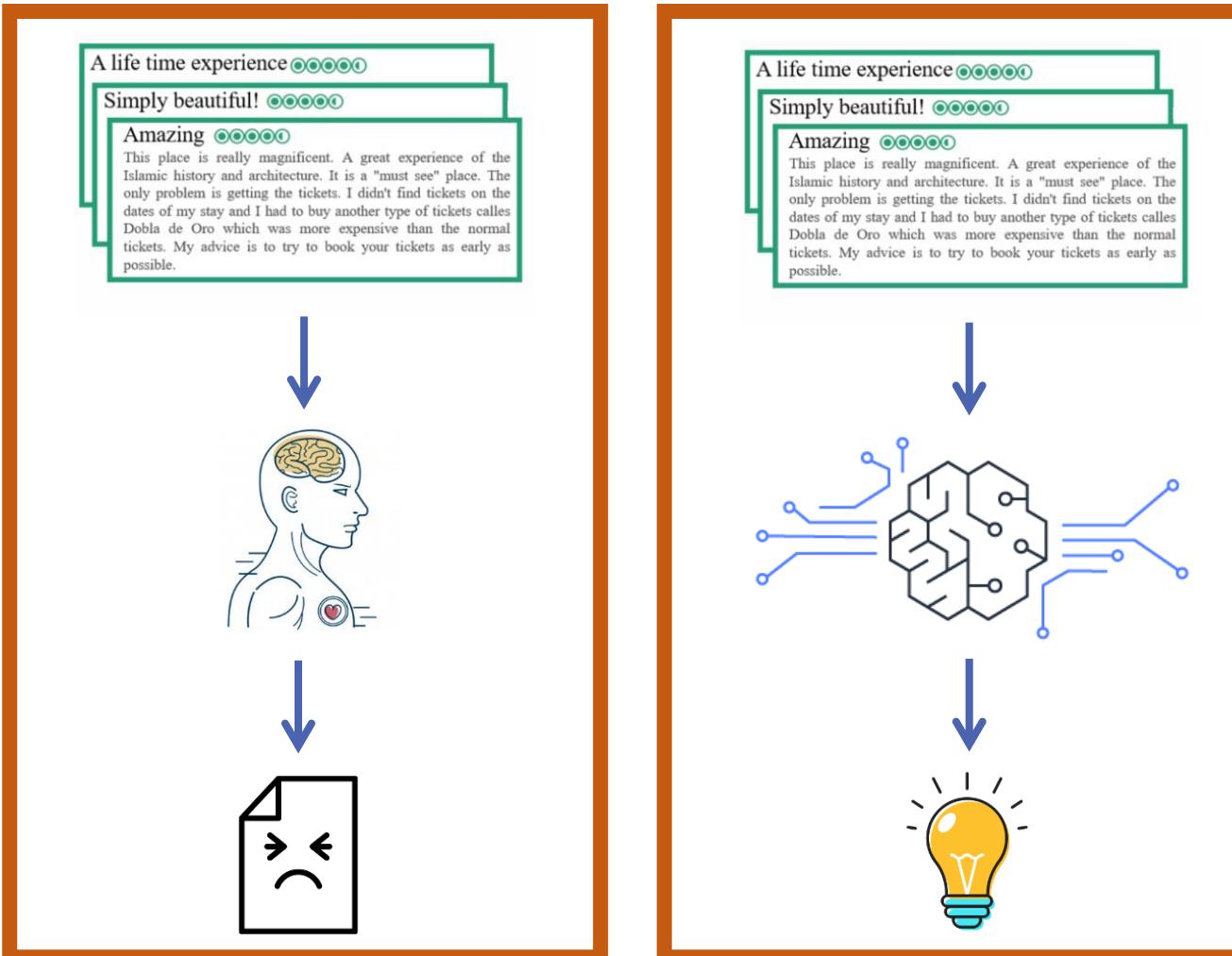


Are neutral polarities a key for a better classification performance?



Ribeiro, F. N., Araújo, M., Gonçalves, P., Gonçalves, M. A., & Benevenuto, F. (2016). **Sentibench-a benchmark comparison of state-of-the-practice sentiment analysis methods.** *EPJ Data Science*, 5(1), 1-29.

3. How to represent thousand reviews?

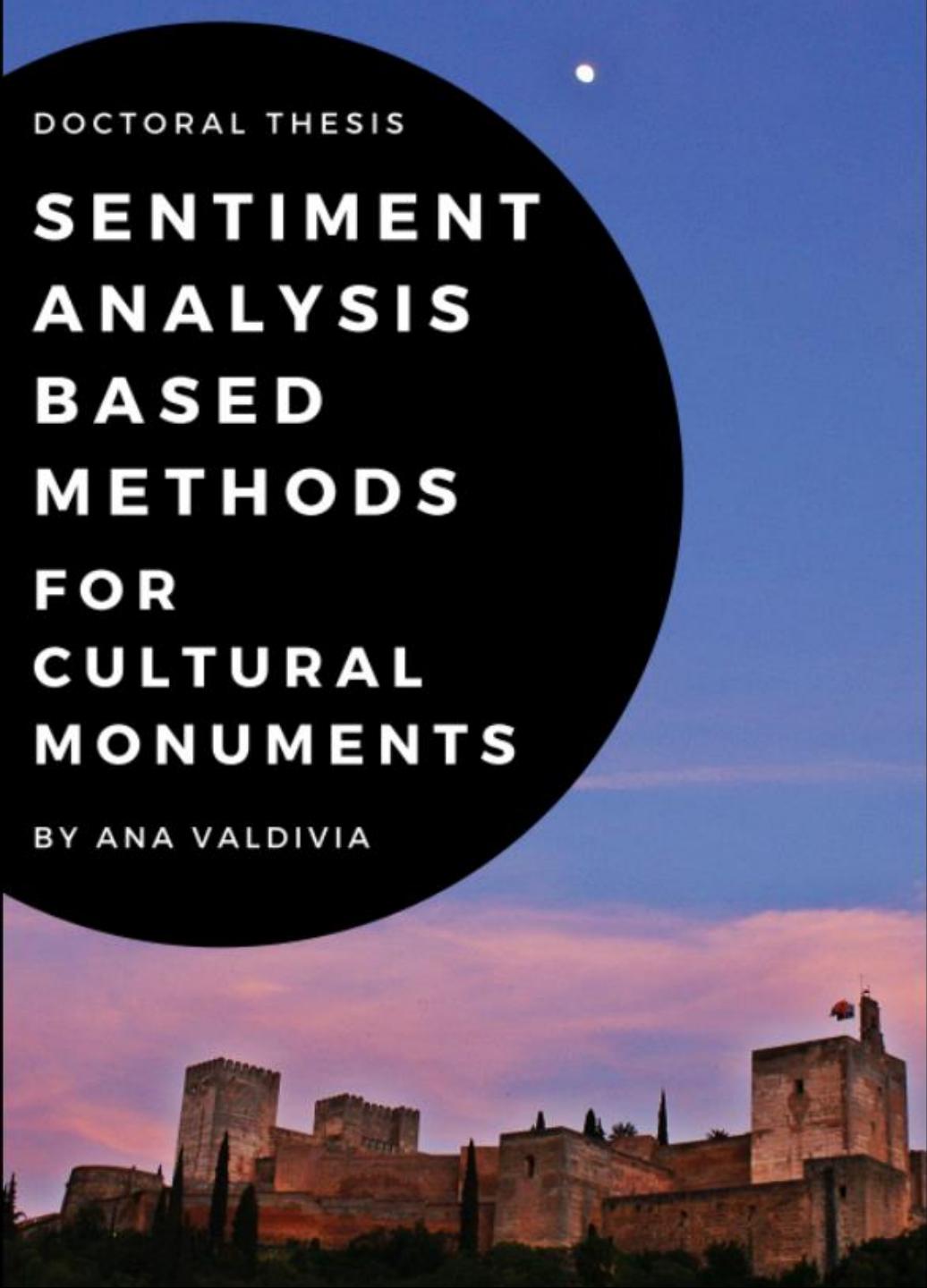


Can Machine Learning techniques help humans to understand thousand reviews?

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OBJECTIVES

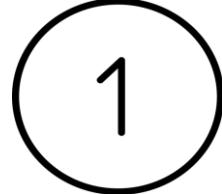


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- 1 To consider the advisability of TripAdvisor as a source for cultural monument reviews
- 2 To develop techniques to address the domain adaptation problem of SAMs
- 3 To address sentiment's inconsistencies detected on cultural monument reviews
- 4 To improve polarity classification by filtering neutral polarities
- 5 To develop a methodology that summarizes a large quantity of cultural reviews



INCONSISTENCIES



To consider the advisability of TripAdvisor as a source for cultural monument reviews



To develop techniques to address the domain adaptation problem of SAMs



To address sentiment's inconsistencies detected on cultural monument reviews

NEUTRALITY



To improve polarity classification by filtering neutral polarities

OPINION SUMMARIZATION

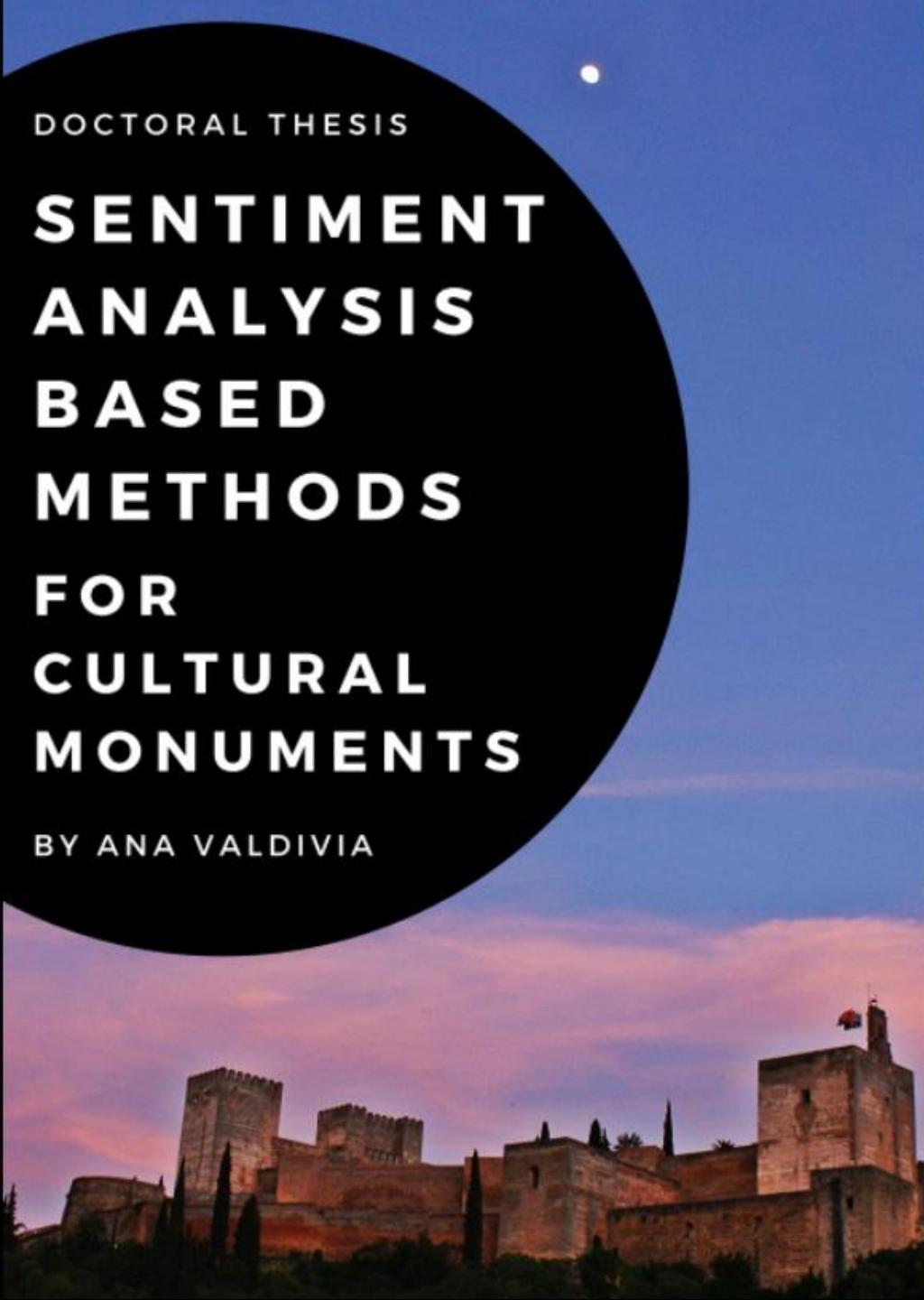


To develop a methodology that summarizes a large quantity of cultural reviews

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RESULTS

- The problem of inconsistencies
- Neutrality Detection
- Opinion Summarization



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Motivation

- TripAdvisor as a source for cultural heritage.
- Apply several off-the-shelf SAMs between Users polarities on TripAdvisor reviews.

Objectives

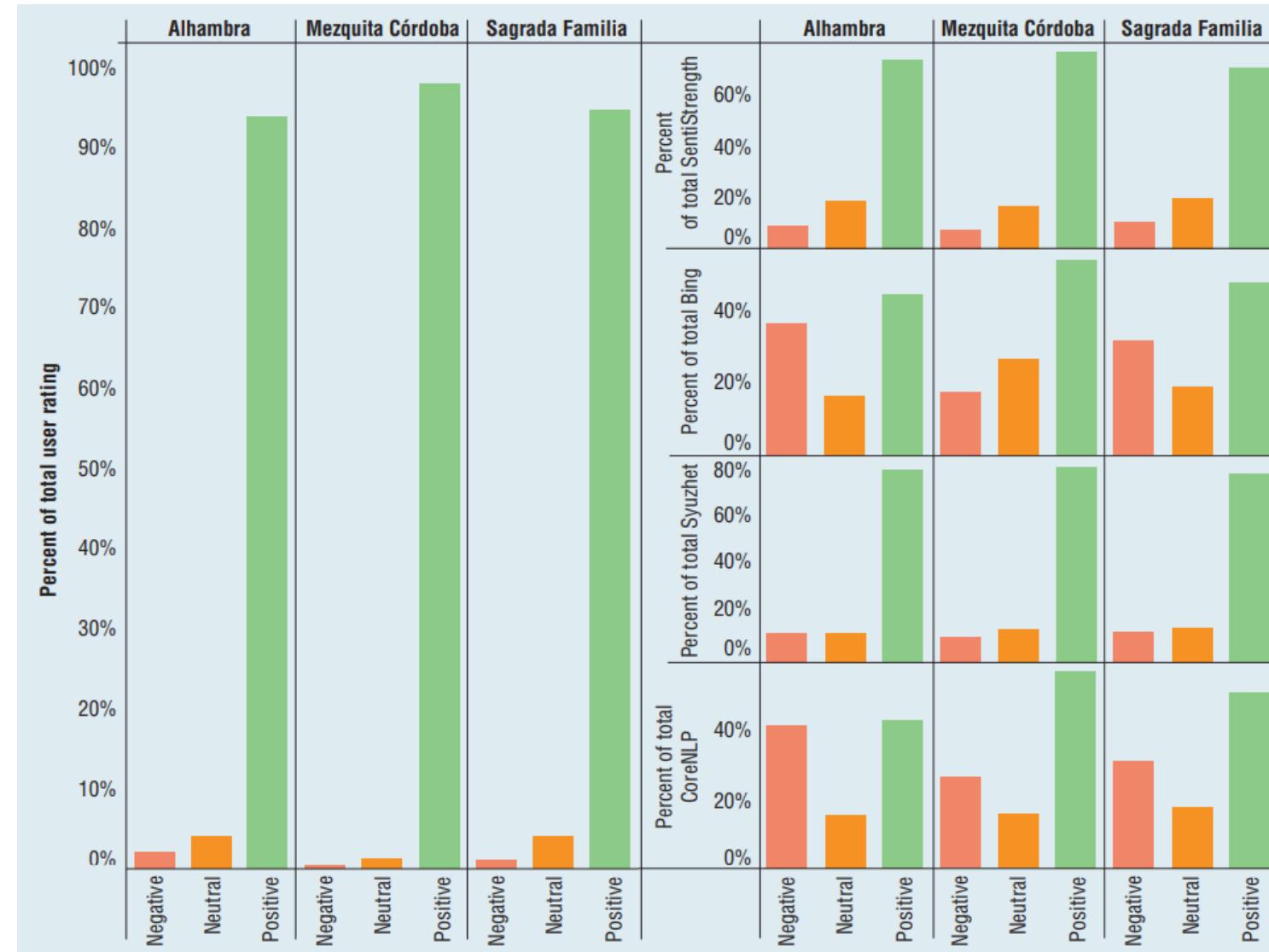
- Analyze the correlation between SAMs and Users polarities.
- Address SAM inconsistencies problem.



TripAdvisor for cultural monuments.

The problem of inconsistencies

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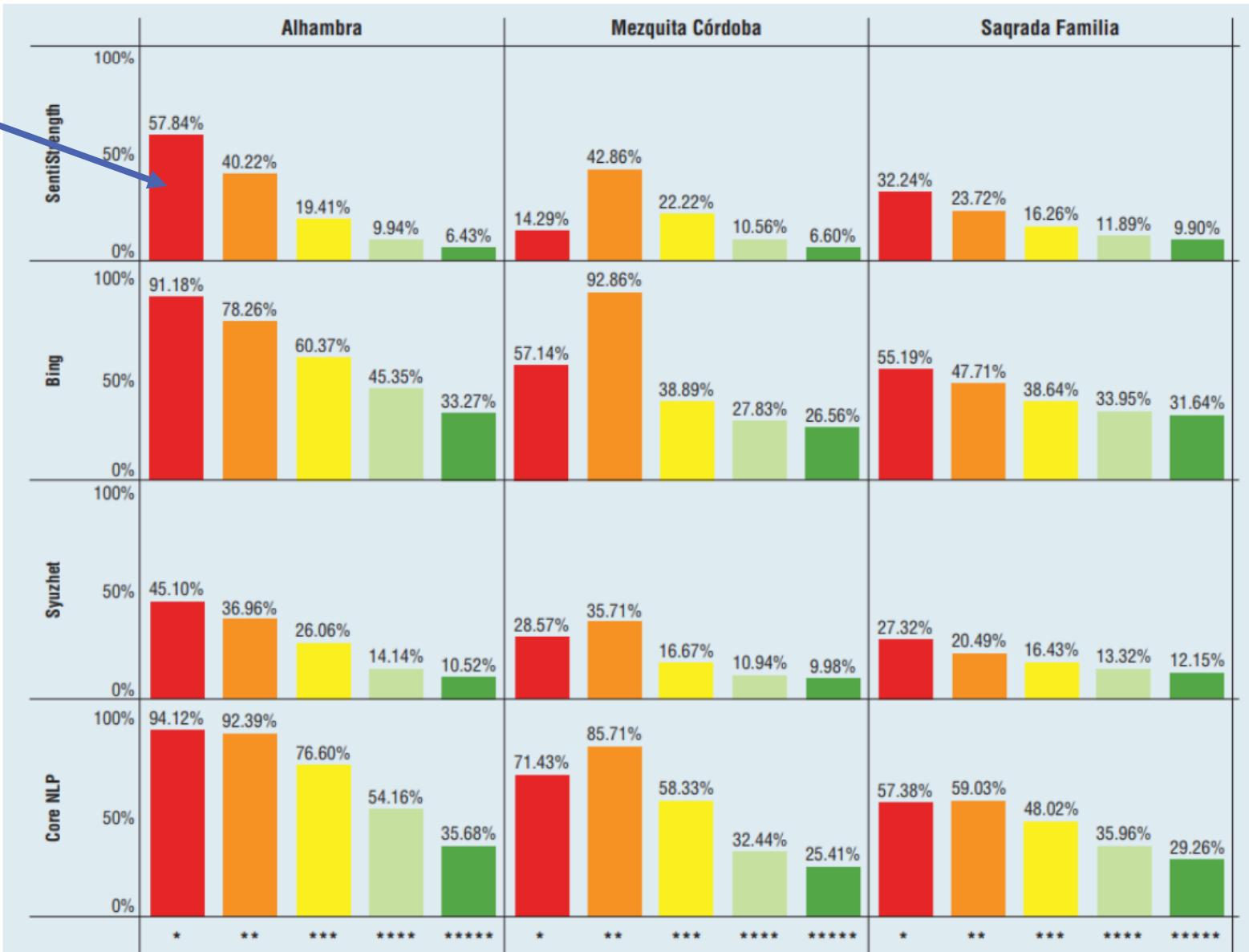


Detected inconsistencies.

The problem of inconsistencies

R E S U L T S

SentiStrength
detects as
negative a
57.84 % of all
reviews with
one Bubble (*).



The problem of inconsistencies

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tripadvisor

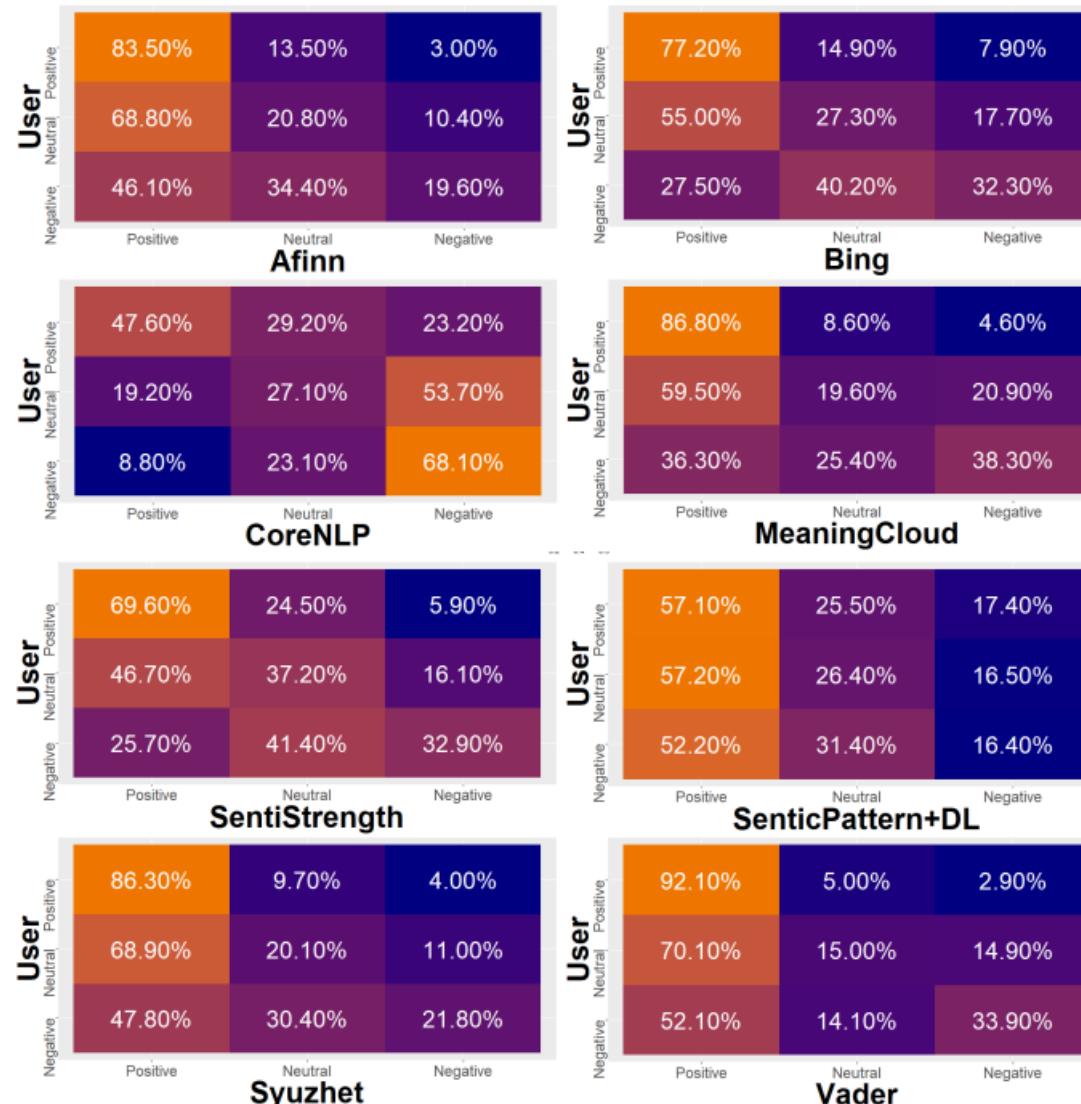


	Reviews	Words	Sentences	Avg. # words	Avg. # sentences	Avg. User Polarity
Alhambra	7,217	676,398	35,867	93.72	4.97	4.69
Grand Canal	10,730	539,465	47,943	50.28	4.47	4.67
Mezquita de Córdoba	3,526	217,640	13,083	61.72	3.70	4.84
Pantheon	17,279	774,765	76,720	44.84	4.44	4.68
Sagrada Familia	34,558	2,220,719	136,181	64.26	3.94	4.72
Trevi Fountain	15,572	764,998	70,407	49.13	4.52	3.93

Summary of text properties of 6 datasets.

The problem of inconsistencies

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Correlation matrices between SAMs and User Sentiments.

Polarity Aggregation Model

- We create a new **polarity index** that takes into account both user and SAMs for **overcoming the inconsistency problem**.
- We propose an **aggregation model** guided by the **geometrical mean**, a variant including a parameter to control one variable influence.

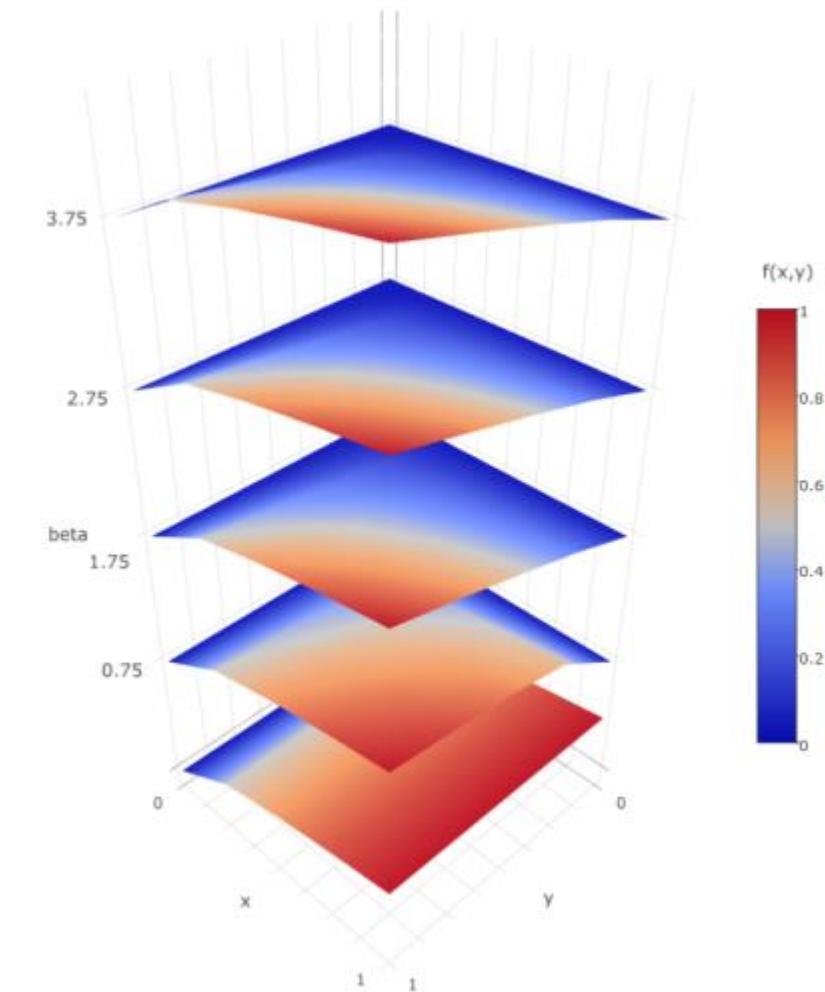
$$f(x, y) = \sqrt{xy^\beta}$$

where:

- x is the **Normalized User Polarity** of the i th-opinion.
- y is the **k th-Normalized SAM Polarity** of the i th-opinion.
- β is the parameter to control the SAMs polarity influence.

Polarity Aggregation Model

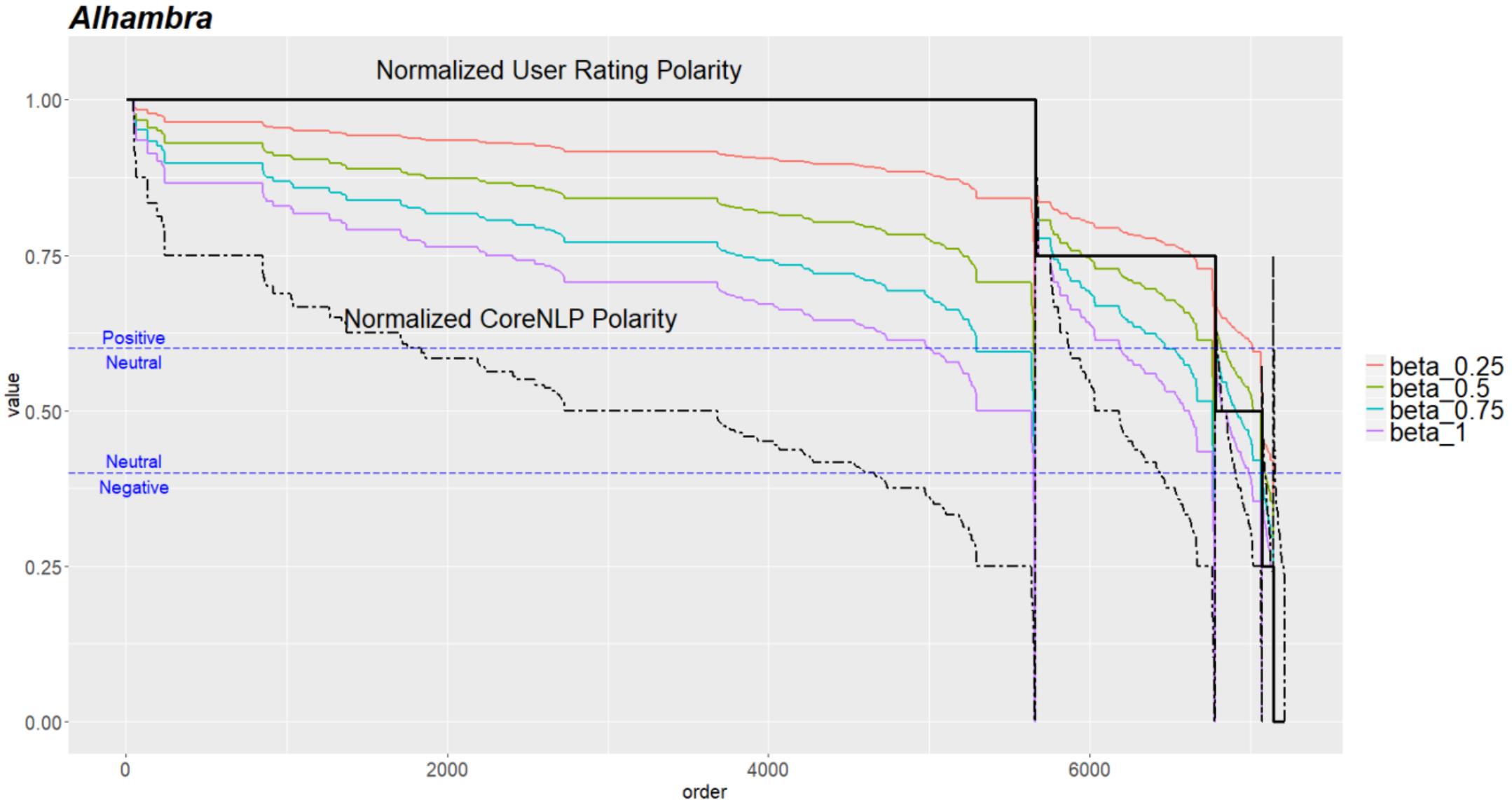
- We create a new **polarity index** that takes into account both user and SAMs for **overcoming the inconsistency problem**.
- We propose an **aggregation model** guided by the **geometrical mean**, a variant including a parameter to control one variable influence.



Distribution of the Polarity Aggregation Model for different β values (0, 0.75, 1.75, 2.75 and 3.75). Bluer colors represent more negative aggregated polarities, more orange colors more positive aggregated polarities.

The problem of inconsistencies

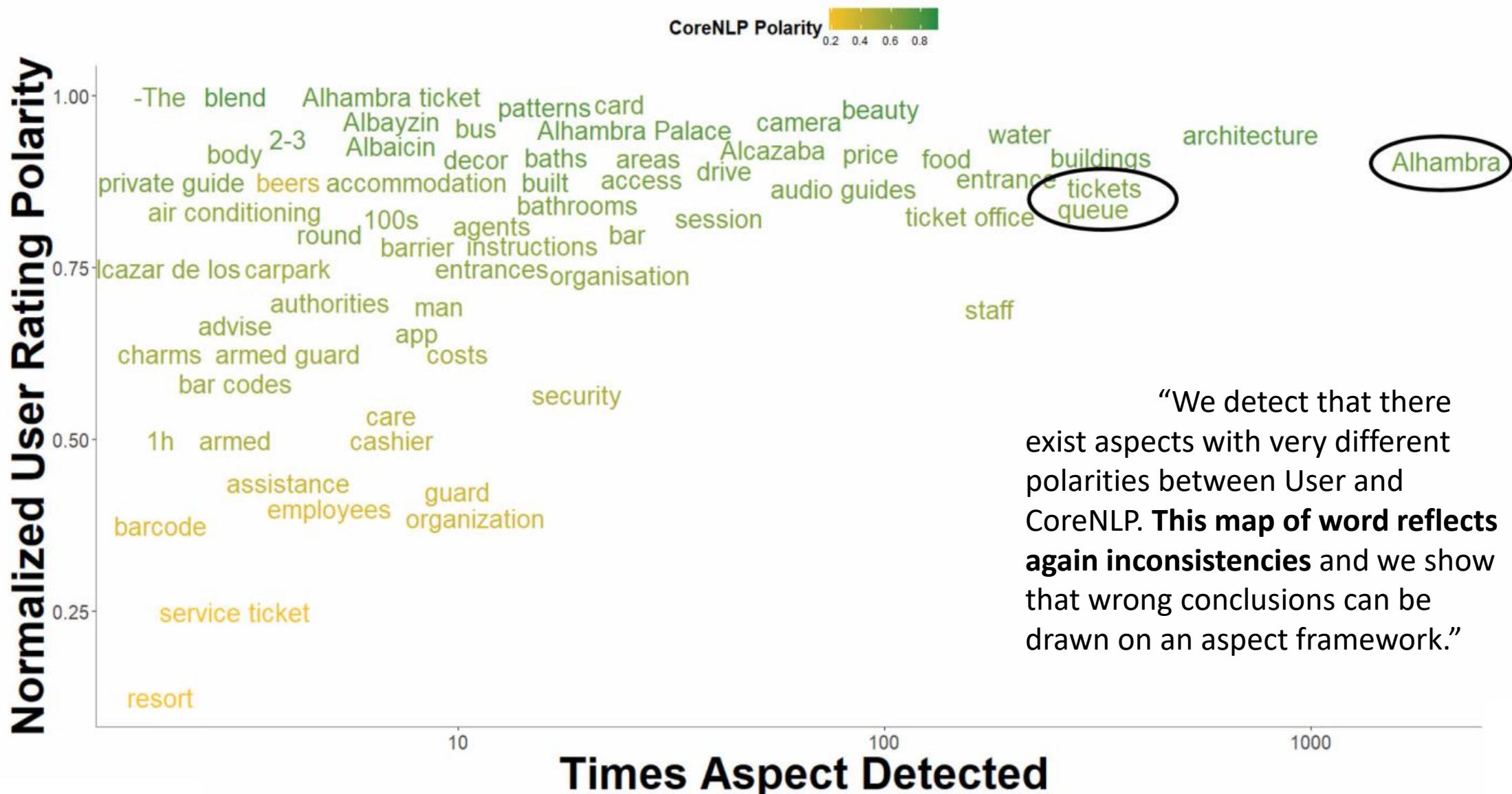
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Reviews are sorted on the x label in ascending order, from most positive (left) to most negative (right).

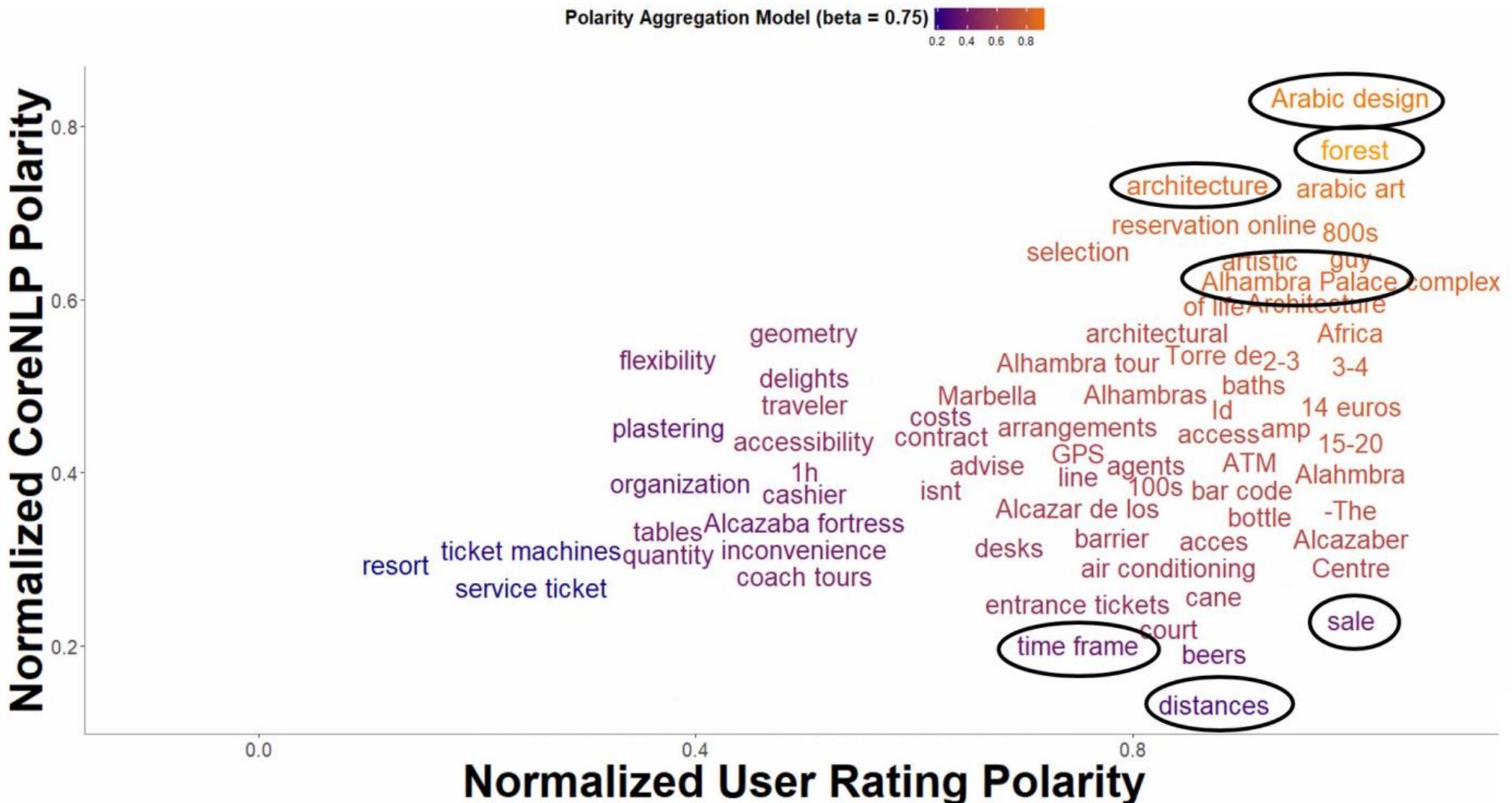
The problem of inconsistencies

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The problem of inconsistencies

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Conclusions

- ❑ Inconsistencies are detected between SAMs and Users.
- ❑ This is because:
 - Humans do not use the same sentiment in every sentence.
 - Domain adaptation of SAMs.
- ❑ Polarity Aggregation Model solves the correlation problem.



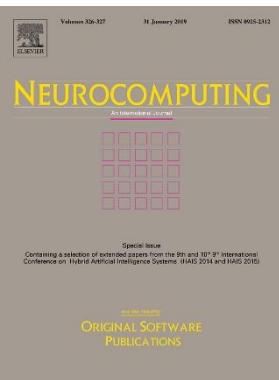
The problem of inconsistencies

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A. Valdivia, MV. Luzón, F. Herrera. **Sentiment analysis in tripadvisor.** IEEE Intelligent Systems 32 (4), 72-77 (2017)

- Status: **Published.**
- Impact Factor (JCR 2017): **2.596**



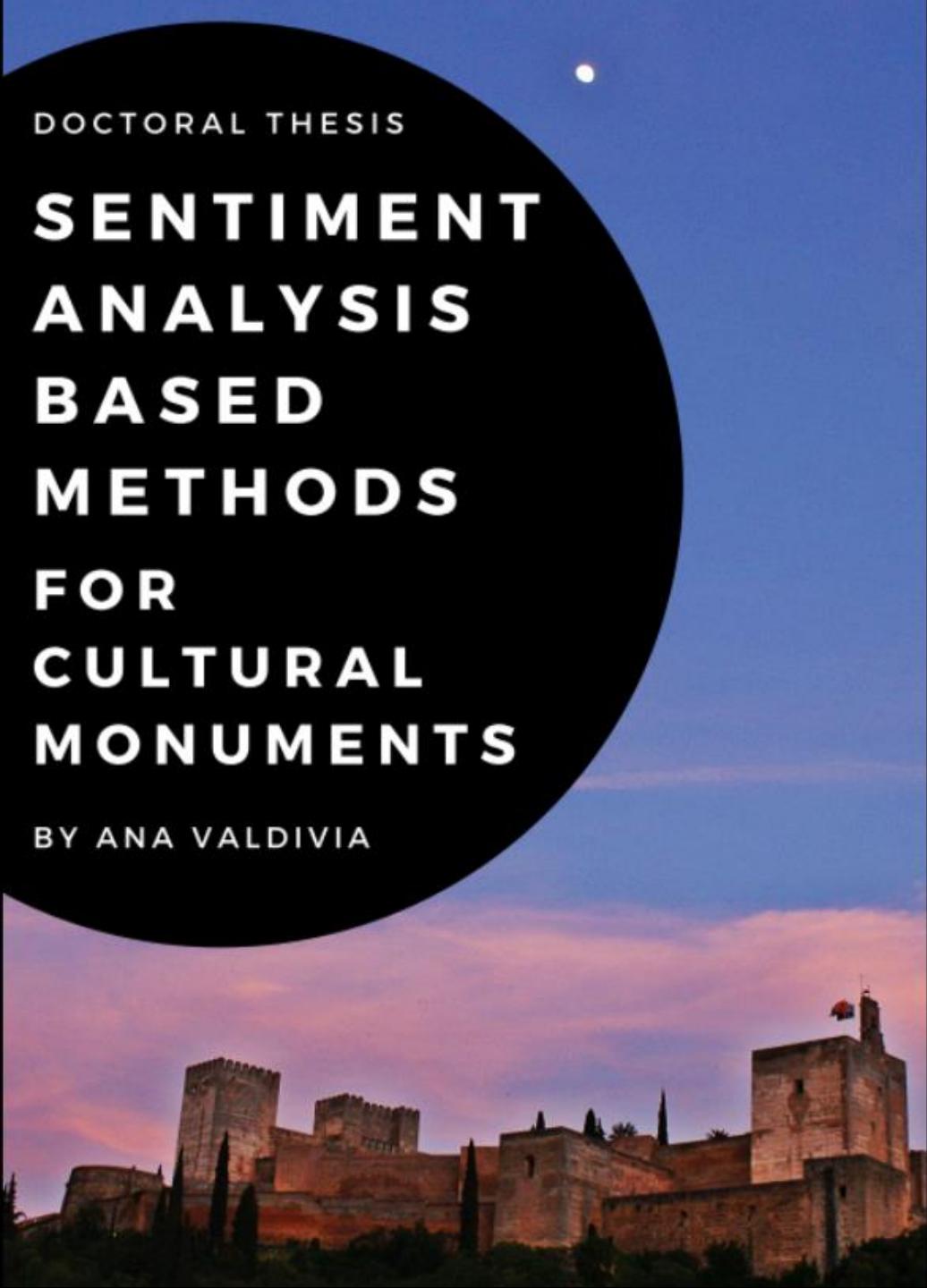
A. Valdivia, E. Hrabova, I. Chaturvedi, MV. Luzón, L. Troiano, E. Cambria, F. Herrera. **The inconsistencies on TripAdvisor reviews: a unified index between users and sentiment analysis methods.** Neurocomputing.

- Status: **Accepted.**
- Impact Factor (JCR 2017): **3.241**

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BY ANA VALDIVIA



RESULTS

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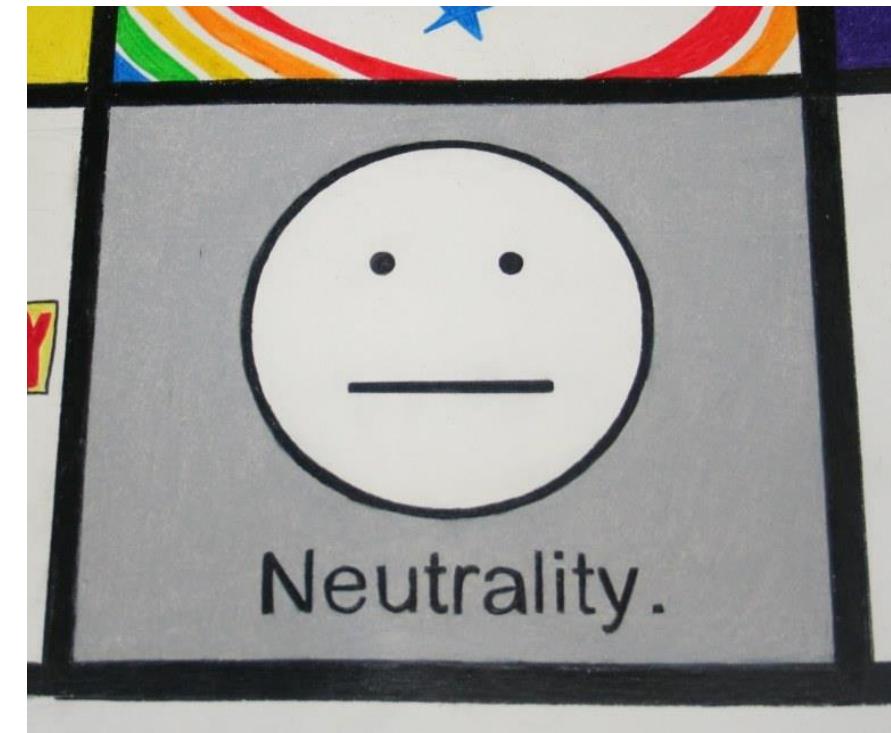
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Motivation

- Neutrality is widely considered as an ambiguous class in SA literature.
- Neutrality is also ignored in many SA applications.
- Low consensus on detecting neutral reviews.

Objective

- Enhance SA classification by detecting and filtering neutral reviews through consensus models.



Neutrality detection

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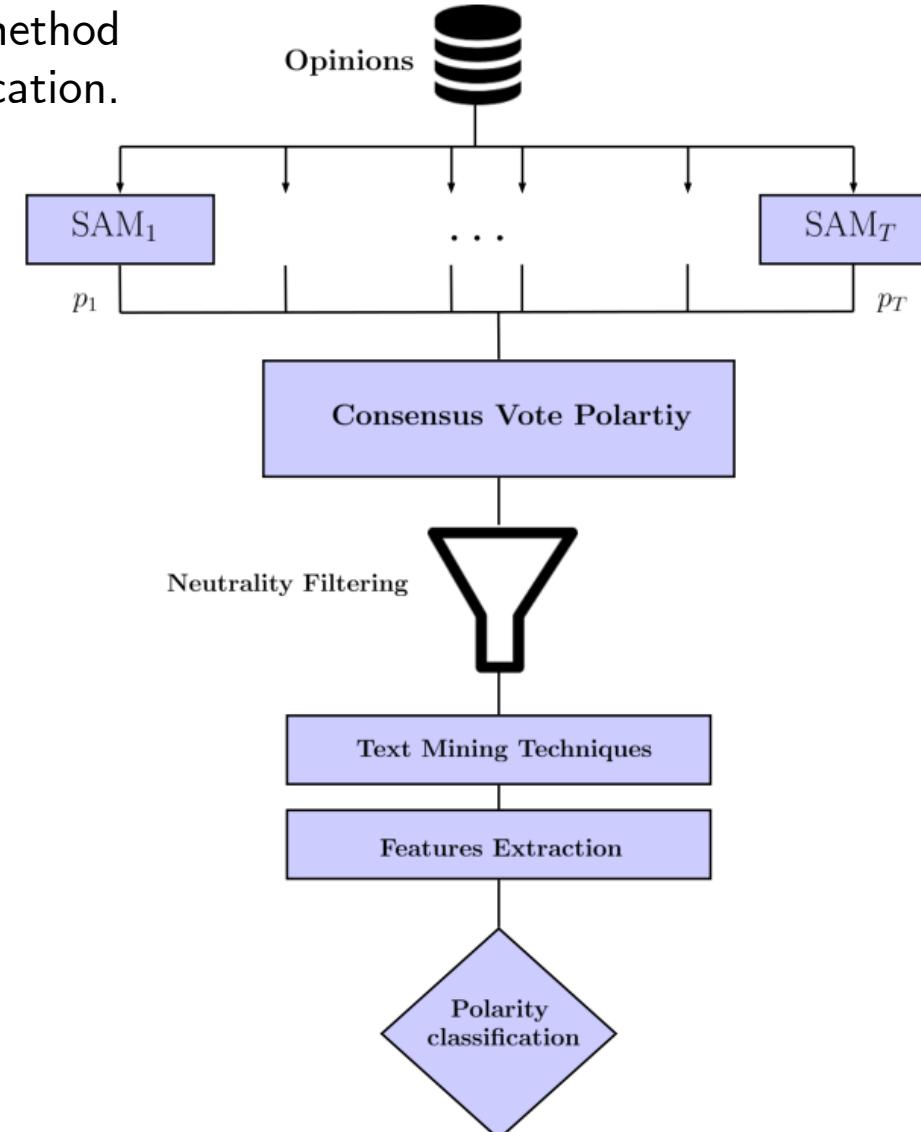
Number of Neutrality Consensus per Corpus

Corpus (500 reviews per Corpus)	AllAgree	AtLeastOneAgree
Amazon	3	404
ClintonTrump	9	433
Food	0	422
Cinema	3	377
Movies	0	357
RW	0	441
Ted	0	388
TA-Sagrada Familia	0	348
TA-Alhambra	0	369

Neutrality detection

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Workflow of the proposed method
for enhancing polarity classification.

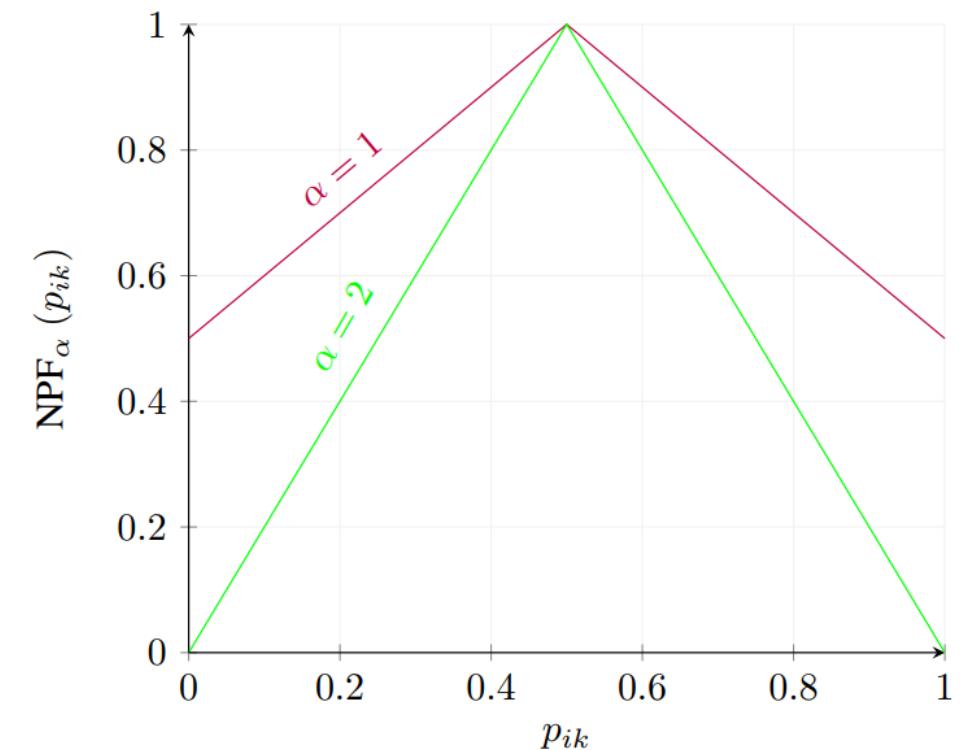


Neutrality Proximity Function (NPF)

The NPF is a function that measures the proximity of polarity p_{ik} to the neutrality, rising its absolute maximum when $p_{ik} = 0.5$.

We propose to use the following parametric function of NPF with $\alpha \in (0, 2]$:

$$NPF_\alpha: [0, 1] \rightarrow [0, 1]$$
$$p_{ik} \mapsto 1 - \alpha|p_{ik} - 0.5|, \alpha \in (0, 2].$$



Representation of NPF for $\alpha = 1$ and $\alpha = 2$.

8 aggregation functions

2 NPF-based aggregations

ProN

ProNE

1 Average aggregation

AvgN

5 Linguistic quantifiers-based aggregations

Many As Possible

At Least Half

Most of

MinN

MaxN

Neutrality detection

Number of neutral reviews by consensus

Number of Neutral Instances of **Individual SAMs**, I=(0.4, 0.6)

Corpus	Bing	CoreNLP	MC	Microsoft	SentiStr	VADER
Amazon	115	105	186	144	251	193
ClintonTrump	277	221	115	93	228	130
Food	239	209	61	40	102	22
Cinema	283	34	92	52	152	110
Movies	124	42	124	86	174	150
RW	236	211	114	50	156	87
Ted	147	55	107	98	194	155
TA-Sagrada Familia	80	222	66	36	99	34
TA-Alhambra	99	239	54	22	84	16
Average	177.778	148.667	102.111	69.000	160.000	99.667

Number of Neutral Instances of **Aggregation Models**, I=(0.4, 0.6)

Corpus	MinN	MaxN	AvgN	ProN	ProNE	MAP-ProN	ALH-ProN	MO-ProN
Amazon	3	404	221	245	287	183	182	174
ClintonTrump	9	433	207	228	298	163	225	149
Food	0	422	115	151	329	60	258	77
Cinema	3	377	143	167	239	103	156	106
Movies	0	357	199	220	289	175	168	157
RW	0	441	175	214	333	123	270	128
Ted	0	388	144	172	247	119	134	98
TA-Sagrada Familia	0	348	119	158	331	61	260	76
TA-Alhambra	0	369	96	132	307	41	281	61
Average	1.667	393.222	157.667	187.444	295.556	114.222	214.889	114.000

Results on Individual SAMs

Test AUC for SVM models, **Individual SAMs**

Corpus	Bing	CoreNLP	MC	MSAzure	SentiStr	VADER	Average
Amazon	0.407	0.800	0.576	0.663	0.851	0.734	0.672
ClintonTrump	0.878	0.721	0.816	0.694	0.723	0.755	0.764
Food	0.763	0.647	0.500	0.613	0.469	0.413	0.567
Cinema	0.387	0.628	0.507	0.343	0.368	0.381	0.436
Movies	0.360	0.431	0.398	0.546	0.362	0.509	0.434
RW	0.697	0.751	0.505	0.559	0.682	0.596	0.632
Ted	0.804	0.260	0.263	0.341	0.215	0.346	0.371
TA-Sagrada Familia	0.850	0.656	0.714	0.651	0.690	0.724	0.714
TA-Alhambra	0.647	0.895	0.763	0.751	0.592	0.565	0.702
Average	0.644	0.643	0.560	0.573	0.550	0.558	0.588

Test AUC for XGBOOST models, **Individual SAMs**

Corpus	Bing	CoreNLP	MC	MSAzure	SentiStr	VADER	Average
Amazon	0.400	0.265	0.434	0.613	0.853	0.690	0.542
ClintonTrump	0.795	0.735	0.767	0.719	0.711	0.731	0.743
Food	0.507	0.648	0.692	0.564	0.566	0.629	0.601
Cinema	0.485	0.387	0.518	0.367	0.438	0.595	0.465
Movies	0.529	0.471	0.437	0.574	0.415	0.409	0.472
RW	0.291	0.710	0.579	0.498	0.498	0.418	0.499
Ted	0.366	0.318	0.302	0.296	0.252	0.358	0.315
TA-Sagrada Familia	0.529	0.643	0.439	0.622	0.653	0.746	0.605
TA-Alhambra	0.678	0.870	0.916	0.592	0.501	0.541	0.683
Average	0.509	0.561	0.565	0.538	0.543	0.569	0.547

Results on Aggregation Models

Test AUC for SVM models, **Aggregation Models**

Corpus	MinN	AvgN	ProN	ProNE	MAP-ProN	ALH-ProN	MO-ProN
Amazon	0.302	0.795	0.853	0.752	0.633	0.730	0.757
ClintonTrump	0.461	0.733	0.870	0.620	0.683	0.790	0.824
Food	0.456	0.407	0.302	0.500	0.613	0.609	0.609
Cinema	0.440	0.473	0.218	0.740	0.612	0.719	0.558
Movies	0.638	0.396	0.429	0.645	0.645	0.532	0.524
RW	0.349	0.375	0.631	0.652	0.713	0.737	0.530
Ted	0.305	0.215	0.230	0.286	0.713	0.708	0.757
TA-Sagrada Familia	0.535	0.891	0.693	0.693	0.875	0.776	0.629
TA-Alhambra	0.819	0.824	0.941	0.941	0.507	0.845	0.767
Average	0.478	0.568	0.574	0.648	0.666	0.716	0.662

Test AUC for XGBOOST models, **Aggregation Models**

Corpus	MinN	AvgN	ProN	ProNE	MAP-ProN	ALH-ProN	MO-ProN
Amazon	0.336	0.776	0.819	0.730	0.600	0.767	0.737
ClintonTrump	0.372	0.671	0.827	0.415	0.648	0.724	0.656
Food	0.671	0.234	0.344	0.324	0.687	0.637	0.538
Cinema	0.444	0.425	0.371	0.500	0.657	0.448	0.514
Movies	0.435	0.598	0.471	0.427	0.568	0.434	0.440
RW	0.315	0.375	0.640	0.708	0.691	0.704	0.717
Ted	0.346	0.215	0.264	0.323	0.701	0.810	0.686
TA-Sagrada Familia	0.499	0.859	0.667	0.667	0.721	0.756	0.551
TA-Alhambra	0.768	0.792	0.932	0.932	0.606	0.743	0.652
Average	0.465	0.549	0.593	0.559	0.653	0.669	0.610

Results SVM

	Best SAM	Best Aggregation
Amazon	0.851	0.853
ClintonTrump	0.878	0.870
Food	0.763	0.613
Cinema	0.628	0.740
Movies	0.546	0.645
RW	0.751	0.737
Ted	0.804	0.757
TA-SagradaFamilia	0.850	0.891
TA-Alhambra	0.895	0.941

Results XGBOOST

	Best SAM	Best Aggregation
Amazon	0.853	0.819
ClintonTrump	0.795	0.827
Food	0.795	0.687
Cinema	0.595	0.657
Movies	0.574	0.598
RW	0.710	0.717
Ted	0.366	0.810
TA-SagradaFamilia	0.746	0.859
TA-Alhambra	0.916	0.932

Conclusions

- This study have shown that **detecting neutrality** based on a consensus **improves classification precision**.
- The **ALH-ProN** model gets **the best** results on average.
- The **aggregation for detecting neutrality is also positive for neutrality detection** via polarity aggregation.

Neutrality detection

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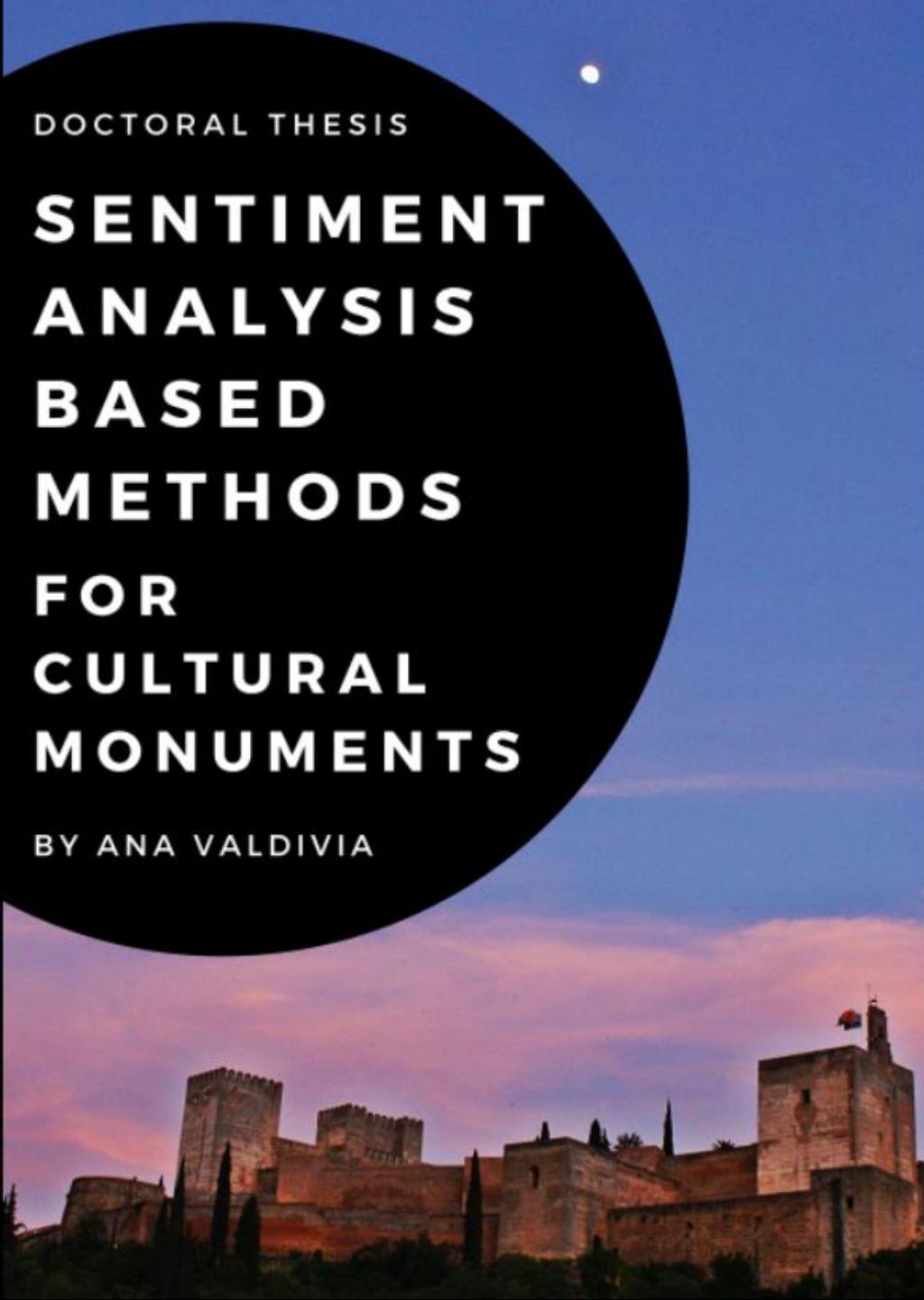
A. Valdivia, MV. Luzón, E. Cambria, F. Herrera. **Consensus vote models for detecting and filtering neutrality in sentiment analysis.** *Information Fusion* 44 126-135 (2018).

- Status: **Published.**
- Impact Factor (JCR 2017): **6.639**

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RESULTS

- The problem of inconsistencies
- Neutrality Detection
- Opinion Summarization



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Motivation

- Need of summarization a large quantity of reviews.
- Improve the decision-making of cultural heritage operators.

Objective

- To depict negative opinions from cultural monuments in order to detect those features that need to be enhanced.
- We propose a novel methodology that extract aspects and summarize reviews in a rule-based visualization.



Opinion Summarization

R
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Corpus of reviews

A life time experience

Simply beautiful!

Amazing

This place is really magnificent. A great experience of the Islamic history and architecture. It is a "must see" place. The only problem is getting the tickets. I didn't find tickets on the dates of my stay and I had to buy another type of tickets called Dobra de Oro which was more expensive than the normal tickets. My advice is to try to book your tickets as early as possible.

Aspect Extraction

Reducing dimensionality of aspects

Aspects Clustering

Descriptive
Rules

Review-Aspect
Matrix

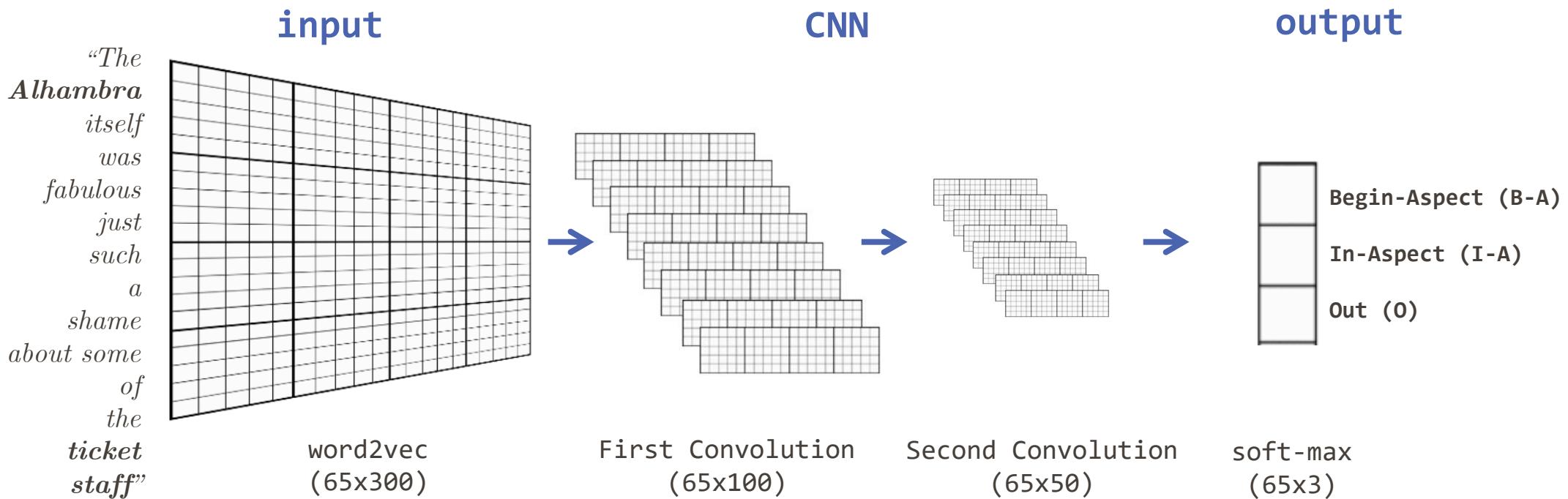
$\{a = 0\} \rightarrow \{\text{sentiment} = \text{negative}\}$
 $\{b = 1, c = 1\} \rightarrow \{\text{sentiment} = \text{negative}\}$

Proposed workflow for summarizing reviews based on aspect level.

a	b	c	sent
1	0	0	+
0	1	1	-
1	0	1	+
0	0	0	+
0	1	0	-

I. Aspect extraction

Aspect Based Sentiment Analysis (ABSA) focuses on **extracting aspects** and **entities** that have been evaluated in the reviews and **gives a more detailed information** about the purpose of the **opinion**.



II. Aspect Clustering

The great **diversity of language** implies:

1. **High dimensionality** of aspects.
2. Aspects with **similar meanings** have **different representations**.

ticket → {*onsite ticket office, senior ticket, ticket area, garden ticket, ticket check points, ticket office, entry ticket, ticket seller, service ticket, machine ticket, ticket tip, ticket staff, ticket box, ticket master, ticket price, ticket process, ticket desks, ...*}.

word
embeddings
+
k-means

Given a set of elements $\{w_1, \dots, w_n\}$, k-means aims to cluster n observations in k clusters ($\{C_1, \dots, C_k\}$), minimizing the function:

$$\arg \min_C \sum_{i=1}^k \sum_{w \in C_i} \|w - \mu_i\|^2, \quad (1)$$

where μ_i is the mean of points in C_i .

III. Descriptive Rules

Subgroup Discovery. It aims at discovering interesting rules fixing a class label.

Aspect –
Review matrix



	Staff	Wheel Chair	Ticket	sentiment
	1	0	0	negative
	0	1	0	negative
	0	1	0	negative
	1	0	0	positive
	1	0	1	positive
	0	1	0	negative
	1	0	0	positive

III. Descriptive Rules

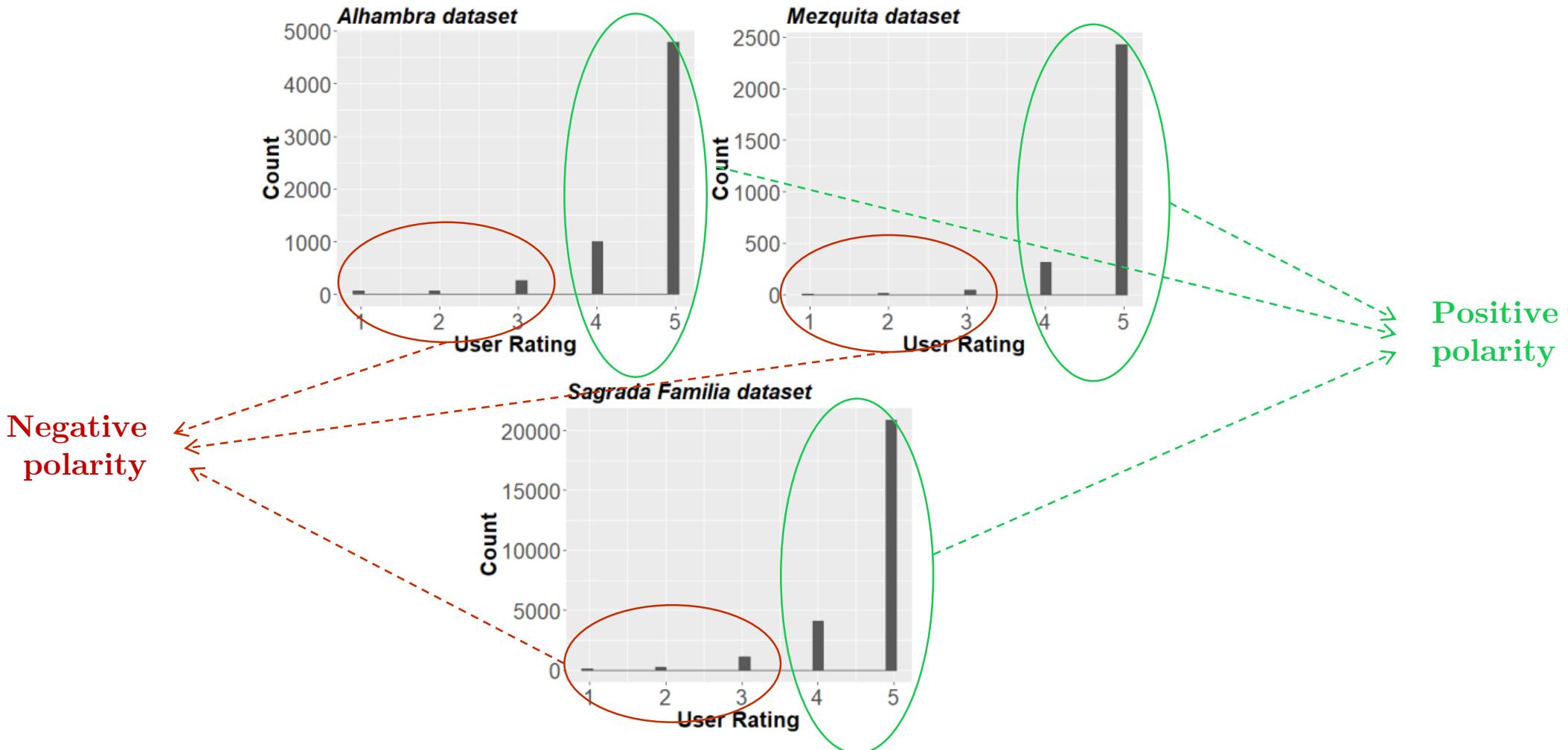
Subgroup Discovery. It aims at discovering interesting rules fixing a class label.

$R_1: \{\text{Staff} = 1\} \rightarrow \{\text{Sentiment} = \text{negative}\},$

$R_2: \{\text{Wheel Chair Accessible} = 1, \text{Staff} = 0\} \rightarrow \{\text{Sentiment} = \text{positive}\},$

$R_3: \{\text{Ticket} = 1, \text{Staff} = 1\} \rightarrow \{\text{Sentiment} = \text{negative}\}.$

User Rating Distribution

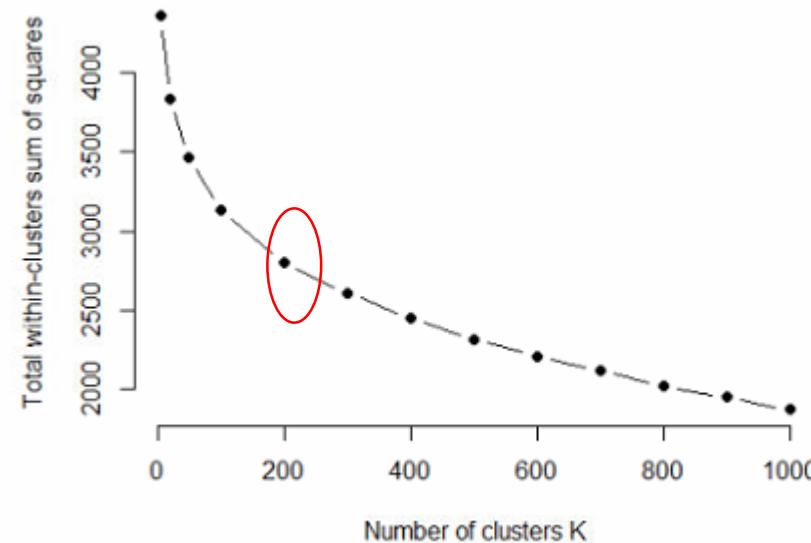
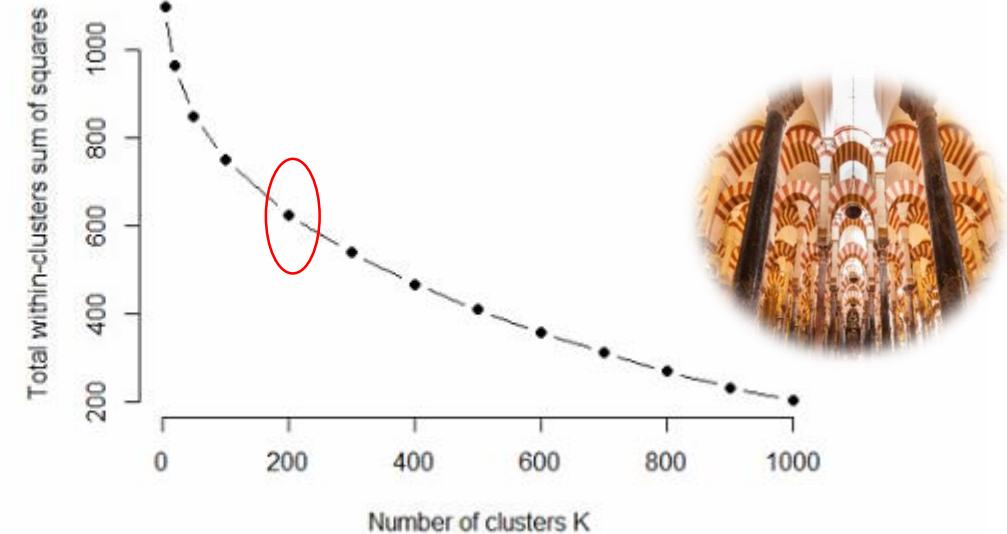
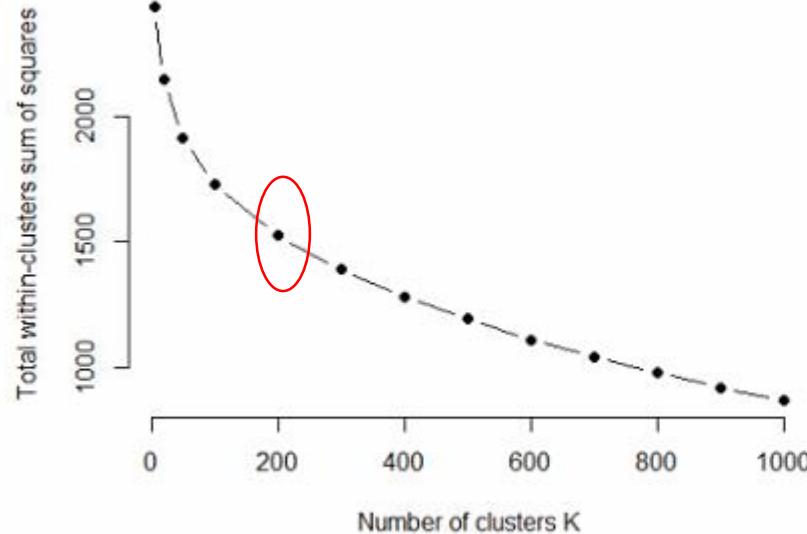


Distribution of User Rating in TripAdvisor reviews.

Opinion Summarization

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Results



R E S U L T S

Results

Monument	Cluster Label	Cluster Content
Alhambra	BDA	staff, staff member, local staff, hotel staff, map staff, ground staff, male staff
Alhambra	GG	tickets, individual tickets, garden tickets, access tickets, internet tickets
Alhambra	BFD	gardens, garden, generalife gardens, gardens water features, garden ticket, beauty of the gardens, general life gardens, main garden, generalife garden
Mezquita	BJB	ceiling, floors, marble ceiling, walls, vaulted ceiling, marble floor, roof
Mezquita	EG	guard, security guard, security guard berating
Mezquita	GG	audio guide, audio guide available, audio guides, map audio guide, auto lingual guide, audio guide facility
Sagrada Familia	GI	lift, lift up amp, lift amp lift ride 65m, lift elevator, tower lift, lift down, towers lift up, lift down wait, lift service
Sagrada Familia	BAI	ticket online, tickets on-line online tickets, tickets online, entrance tickets online, online ticket, entrance ticket online, prepurchased online tickets, book your ticket online
Sagrada Familia	BFJ	shop, souvenir shop, gauds shop, bookshop, citys souvenir shops

Examples of aspects grouped into clusters, with $k = 200$.

Results



Aspect	Rule	Cov	Sup	Conf	WRAcc
staff	{ BDA = 1 } \rightarrow { negative }	0.03	< 0.01	0.28	< 0.01
guard	{ BDG = 1 } \rightarrow { negative }	< 0.01	< 0.01	0.38	< 0.01
cashier	{ HH = 1 } \rightarrow { negative }	< 0.01	< 0.01	0.27	< 0.01
queue	{ BDI = 1 } \rightarrow { negative }	< 0.01	< 0.01	0.15	< 0.01
staff, price	{ BDA = 1, BGI = 1 } \rightarrow { negative }	< 0.01	< 0.01	0.48	< 0.01

Most relevant rules of the Alhambra monument.



Aspect	Rule	Cov	Sup	Conf	WRAcc
mosque	{ BHF = 1 } \rightarrow { negative }	0.18	< 0.01	0.02	0
garden	{ BHB = 1 } \rightarrow { negative }	0.06	< 0.01	0.03	< 0.01
architecture	{ BEJ = 1 } \rightarrow { negative }	0.17	< 0.01	0.02	0
place	{ DJ = 1 } \rightarrow { negative }	0.06	< 0.01	0.03	0
arches	{ BIC = 1 } \rightarrow { negative }	0.07	< 0.01	0.02	0

Most relevant rules of the Mezquita monument.

Results



Aspect	Rule	Cov	Sup	Conf	WRAcc
ceiling	{ CJ = 1 } → { negative }	< 0.01	< 0.01	0.1	< 0.01
natural	{ HG = 1 } → { negative }	0.04	< 0.01	0.07	< 0.01
entry	{ CI = 1 } → { negative }	0.01	< 0.01	0.07	< 0.01
queue	{ BCD = 1 } → { negative }	< 0.01	< 0.01	0.05	0
sagrada familia	{ BEJ = 1 } → { negative }	0.01	< 0.01	0.07	< 0.01

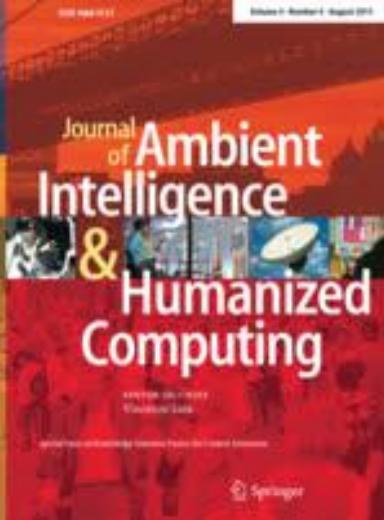
Most relevant rules of the Sagrada Familia monument.

Conclusions

- ❑ The results shown that **the proposed methodology is effective** for **describing reviews**.
- ❑ Data sparsity and the unbalanced dataset **affect** to **measures of generality**.
- ❑ Using the **polarity of the review** for all the aspects may led to a **misinterpretation** of the text.

Opinion Summarization

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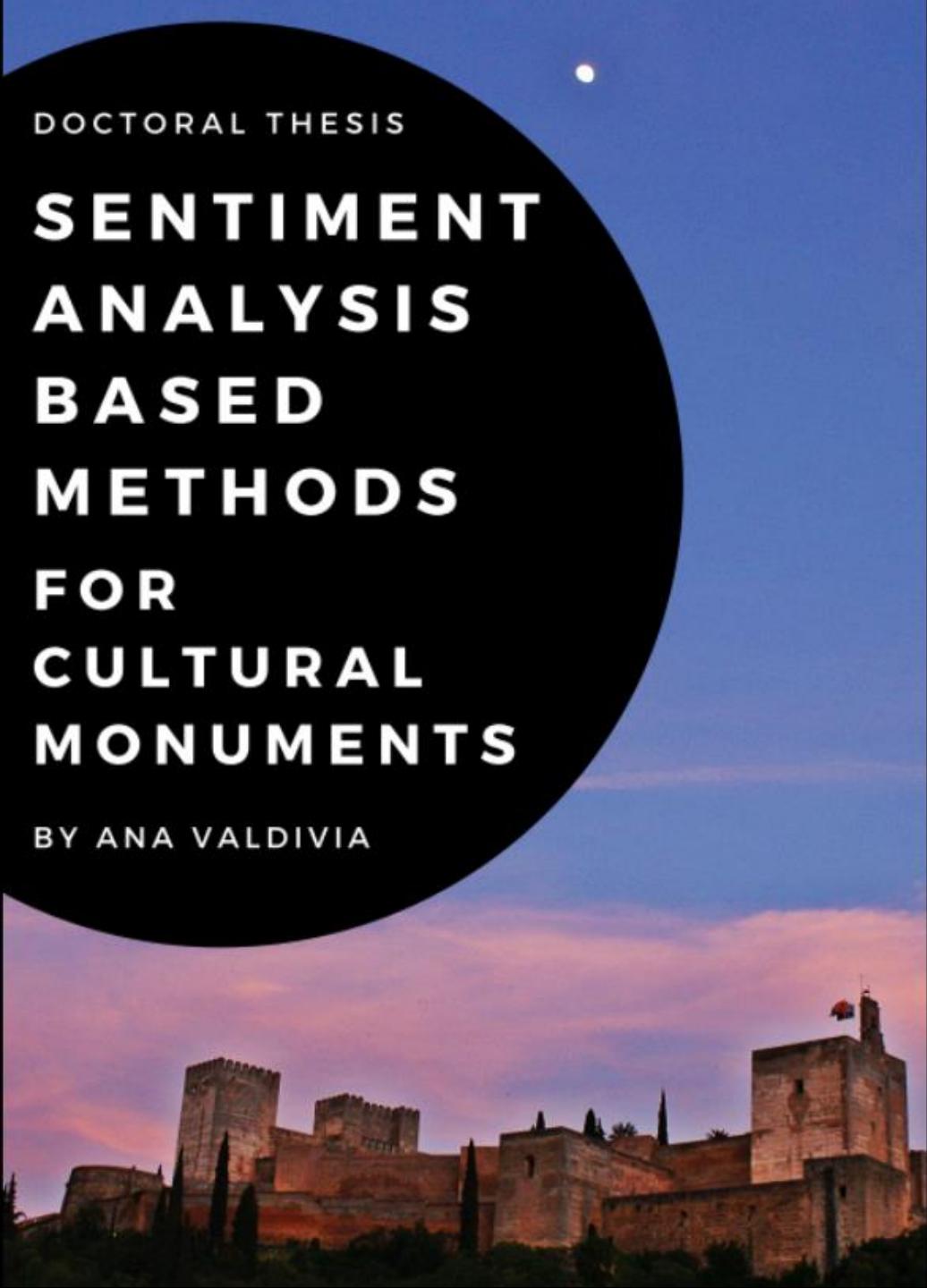
Valdivia, A., Martínez-Cámara, E., Chaturvedi, I., Luzón, M. V., Cambria, E., Ong, Y. S., & Herrera, F. (2018). *What do people think about this monument? Understanding negative reviews via deep learning, clustering and descriptive rules*. *Journal of Ambient Intelligence and Humanized Computing*, 1-14.

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DOCTORAL THESIS

**SENTIMENT
ANALYSIS
BASED
METHODS
FOR
CULTURAL
MONUMENTS**

BY ANA VALDIVIA



CONCLUSION

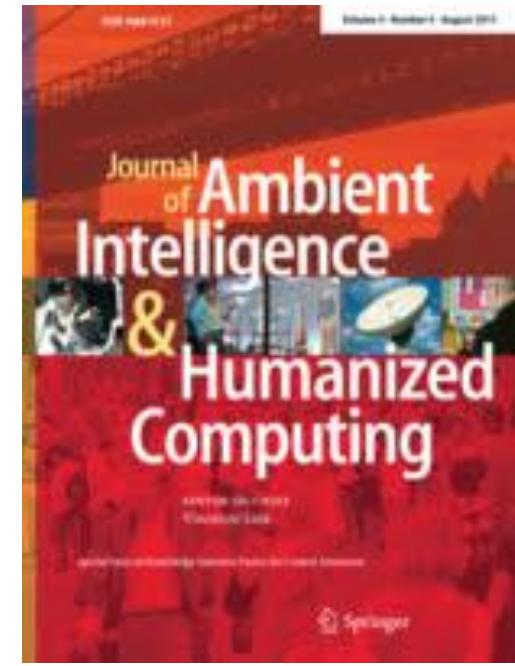
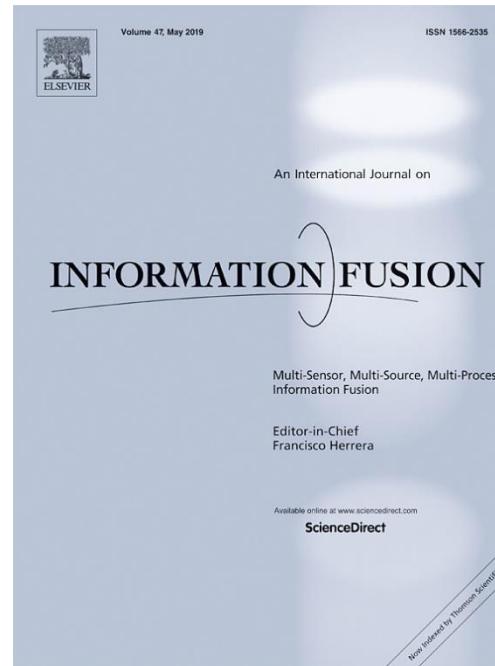
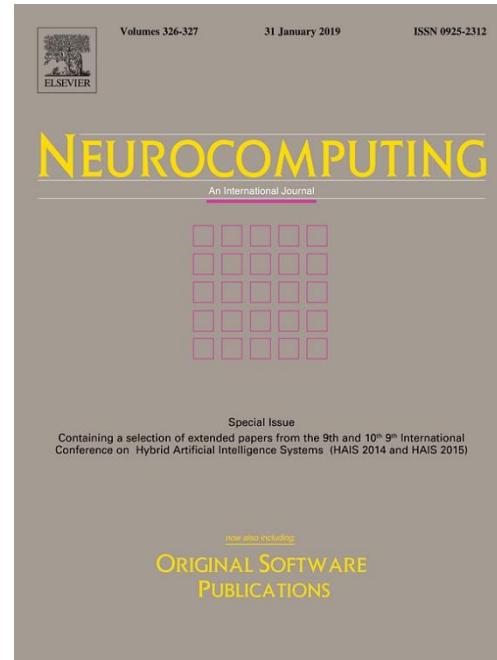


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Conclusions

- This thesis has presented a broad study about SAMs applied to cultural monument reviews using social media data.
- INCONSISTENCIES. The Polarity Aggregation Method improves the inconsistencies between SAMs and User polarities.
- NEUTRALITY. Neutral reviews are a key for enhancing polarity classification.
- OPINION SUMMARIZATION. Rule-based approaches are efficient for summarizing reviews.

Results of this thesis



Sentiment Analysis in TripAdvisor (Q2)

Inconsistencies in TripAdvisor (Q1)

Neutrality Detection (Q1)

Opinion Summarization (Q3)

3 International Conferences



**HAIS
2016**

Hybrid Artificial Intelligence Systems



**FUZZ-IEEE 2017
NAPLES, ITALY**



**CAEPIA 2018
Granada**

XVIII Conference of the Spanish Association for Artificial Intelligence

Future work

- Evaluation studies between Sentiment Analysis and Surveys for cultural monuments.**
- Creation of corpus for cultural heritage reviews.**
- Extension of SA-based methods for other languages.**
- Adaptation domain problem.**

PhD Dissertation
of
Ana Valdivia

Supervisors:

Francisco Herrera & M. Victoria Luzón

1st February, 2019



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DOCTORAL THESIS

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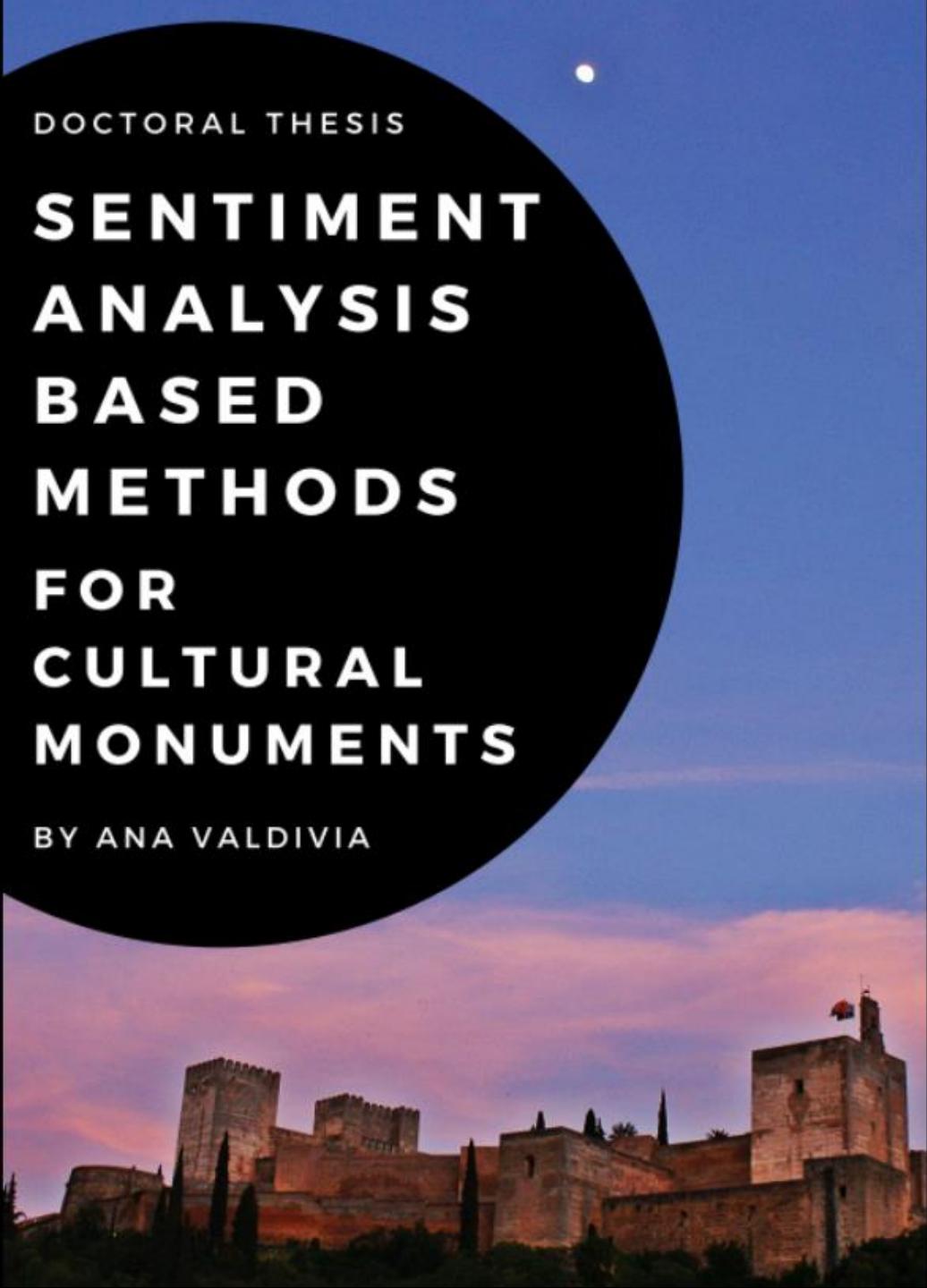
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APPENDIX



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Examples

Table 1

Main characteristics of the SAMs used in our evaluation.

Name	Description	Approach	Output	Domain	Genre
Azure	Supervised ML method that works at document level. It was trained with a large corpus of reviews.	ML	$[0, 1] \in \mathbb{R}$	General	Reviews
Bing [17]	SO method that works at document level. It uses an opinion lexicon, and the polarity value of the document is the average polarity value of its sentences.	SO	$\{-1, 0, 1\}$	General	NA
CoreNLP [26]	Supervised ML method that works at document/sentence level. It is based on a Recursive Neural Tensor Network (RNTN), and classifies 5 intensity levels of opinion.	ML	$\{0, 1, 2, 3, 4\}$	Review	Movie reviews
MeaningCloud	SO method that works at document level. It is grounded in the pos-tags of the words and the use of an opinion lexicon, and it classifies 5 intensity levels of opinion.	SO	$\{0, 1, 2, 3, 4\}$	NA	NA
SentiStrength [43]	Supervised ML method grounded in features built upon opinion lexicons that work at document/sentence level. The output is the positive (Pos) and the negative (Neg) value of the input text.	SO & ML	Neg: $[-5, -1] \in \mathbb{Z}$; Pos: $[1, 5] \in \mathbb{Z}$	General	Social media
Syuzhet	SO method that works at document/sentence level. It uses an opinion lexicon. The document polarity value is the average of the polarity value of its sentences.	SO	$\{-1, 0, 1\}$	General	Novels
Vader [18]	SO method that works at document level and uses an opinion lexicon.	SO	$[-1, 1] \in \mathbb{R}$	General	Micro-blogging

López, M., Valdivia, A., Martínez-Cámara, E., Luzón, M. V., & Herrera, F. (2018). **E2SAM: Evolutionary Ensemble of Sentiment Analysis Methods for Domain Adaptation.** *Information Sciences*.

Opinion

Example

Opinion

- An opinion is a 5-tuple contain the target of the opinion (entity), the attribute of the target at which the opinion is directed, the polarity, the opinion holder and the date when the opinion was emitted:

$$(e_i, a_{ij}, s_{iijk}, h_k, t_l)$$

where:

- e_i is the i -th entity,
- a_{ij} is the j -th attribute of the entity,
- s_{iijk} is the polarity of the opinion,
- h_k is the k -th opinion holder,
- t_l is the l -th time when the opinion was emitted.

Lucy, 15/12/2018

I went there with some friends to work on a project and we loved it! We all ordered hot chocolate drinks and thought they were absolutely delicious! Very cool atmosphere with jazz music, but it is very dark if you wish to work with your laptop in there. The waitress was also very kind!

Opinion

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5-Tuple	Entity	Aspect	Sentiment	Opinion holder	Time
$(e_1, a_{11}, s_{1111}, h_1, t_1)$	$e_1 = \text{coffee shop}$	$a_{11} = \text{drinks}$	$s_{1211} = \text{positive}$	$h_1 = \text{Lucy}$	$t_1 = 15/12/2018$
$(e_1, a_{12}, s_{1211}, h_1, t_1)$	$e_1 = \text{coffee shop}$	$a_{12} = \text{drinks}$	$s_{1211} = \text{positive}$	$h_1 = \text{Lucy}$	$t_1 = 15/12/2018$
$(e_1, a_{13}, s_{1211}, h_1, t_1)$	$e_1 = \text{coffee shop}$	$a_{13} = \text{place}$	$s_{1311} = \text{brightness}$	$h_1 = \text{Lucy}$	$t_1 = 15/12/2018$
$(e_1, a_{14}, s_{1411}, h_1, t_1)$	$e_1 = \text{coffee shop}$	$a_{14} = \text{service}$	$s_{1411} = \text{positive}$	$h_1 = \text{Lucy}$	$t_1 = 15/12/2018$

Examples

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Text Properties

Table 3: Summary of Quantitive Text Analysis of Datasets (Words and Sentences)

Corpus	NumWords	AVGNumWords	NumSentences	AVGNumSentences
Amazon	7,787	15.57	500	1.00
ClintonTrump	8,674	17.35	881	1.76
Food	40,775	81.55	2,512	5.02
Cinema	10,433	20.87	564	1.13
Movies	9,623	19.25	523	1.05
RW	34,871	69.74	2,337	4.67
Ted	8,971	17.94	502	1.00
TA-Sagrada Familia	30,520	61.04	2,033	4.07
TA-Alhambra	45,665	91.33	2,800	5.60

2 NPF

Definition 2 *Pro-Neutrality Weight Based Model (ProN).* The *ProN*, Φ_{ProN} , is an aggregation model for sentiment polarities which defines the weighting vector W guided by the $NPF_{\alpha=1}$, i.e., $w_{ik} = NPF_{\alpha=1}(p_{ik}) = 1 - |p_{ik} - 0.5|$ and it is expressed such that:

$$\begin{aligned}\Phi_{ProN} &: [0, 1]^T \rightarrow [0, 1] \\ (p_{1k}, \dots, p_{Tk}) &\mapsto \sum_{i=1}^T \frac{w_{ik}}{\sum_{i=1}^T w_{ik}} p_{ik}.\end{aligned}$$

Definition 3 *Pro-Neutrality Extreme Weight Based Model (ProNE).* The *ProNE*, Φ_{ProNE} , is an aggregation model for sentiment polarities which defines the weighting vector W guided by the $NPF_{\alpha=2}$, i.e., $w_{ik} = NPF_{\alpha=2}(p_{ik}) = 1 - 2|p_{ik} - 0.5|$ and it is expressed such that:

$$\begin{aligned}\Phi_{ProNE} &: [0, 1]^k \rightarrow [0, 1] \\ (p_{1k}, \dots, p_{Tk}) &\mapsto \sum_{h=1}^T \frac{w_{ik}}{\sum_{h=1}^T w_{ik}} p_{ik}.\end{aligned}$$

1 AVG

Definition 4 *Average Based Model (AVG)*. The AVG is an aggregation model for sentiment polarities which defines the weighting vector by $W = \frac{1}{T}$ and it is expressed such that:

$$\begin{aligned}\Phi_{AVG} &: [0, 1]^T \rightarrow [0, 1] \\ (p_{1k}, \dots, p_{Tk}) &\mapsto \frac{1}{T} \sum_{h=1}^T p_{ik}.\end{aligned}$$

Note that this model is equivalent to the *arithmetic mean* over the k polarities.

5 LINGUISTIC QUANTIFIERS

Definition 5 *OWA* Yager (1988); Chiclana et al. (2007). An *OWA operator* of dimension n is a mapping $\phi : \mathbb{R}^n \rightarrow \mathbb{R}$ that has an associated weighting vector W such that $w_i \in [0, 1]$, $\sum_{i=1}^n w_i = 1$, and is defined to aggregate a list of values $\{p_1, \dots, p_n\}$ following this expression:

$$\phi(p_1, \dots, p_n) = \sum_{i=1}^n w_i p_{\sigma(i)},$$

being $\sigma : \{1, \dots, n\} \rightarrow \{1, \dots, n\}$ a permutation such that $p_{\sigma(i)} \geq p_{\sigma(i+1)}$, $\forall i = 1, \dots, n - 1$.

Definition 6 *IOWA* Yager and Filev (1999); Chiclana et al. (2007). An *IOWA operator* of dimension n is a mapping $\Psi : (\mathbb{R} \times \mathbb{R})^n \rightarrow \mathbb{R}$ that has an associated weighting vector W such that $w_i \in [0, 1]$, $\sum_{i=1}^n w_i = 1$, and it is defined to aggregate the set of second arguments of a list of n 2-tuples:

$$\Psi(\langle u_1, p_1 \rangle, \dots, \langle u_n, p_n \rangle) = \sum_{i=1}^n w_i p_{\sigma(i)},$$

being $\sigma : \{1, \dots, n\} \rightarrow \{1, \dots, n\}$ a permutation such that $u_{\sigma(i)} \geq u_{\sigma(i+1)}$, $\forall i = 1, \dots, n - 1$.

The vector of values $U = (u_1, \dots, u_n)$ is defined as the *order-inducing* vector and (p_1, \dots, p_n) as the *values of the argument variable*. In this way, the *order-inducing* reorders the *values of the argument variable* based on its magnitude.

5 LINGUISTIC QUANTIFIERS

Linguistic quantifiers are widely used for modeling the concept of quantification to represent the fuzzy majority Pasi and Yager (2006). *At least half*, *Most of* and *Many as possible* are some examples of these quantifiers

$$Q_{(a,b)}(x) = \begin{cases} 0 & \text{if } 0 \leq x < a, \\ \frac{x-a}{b-a} & \text{if } a \leq x \leq b, \\ 1 & \text{if } b \leq x \leq 1 \end{cases}$$

The values that are used for the pair (a, b) are Kacprzyk (1986):

$$Q_{\text{At least half}}(x) = Q_{(0,0.5)}(x)$$

$$Q_{\text{Most of}}(x) = Q_{(0.3,0.8)}(x)$$

$$Q_{\text{Many as possible}}(x) = Q_{(0.5,1)}(x)$$

5 LINGUISTIC QUANTIFIERS

Linguistic quantifiers are widely used for modeling the concept of quantification to represent the fuzzy majority Pasi and Yager (2006). *At least half*, *Most of* and *Many as possible* are some examples of these quantifiers

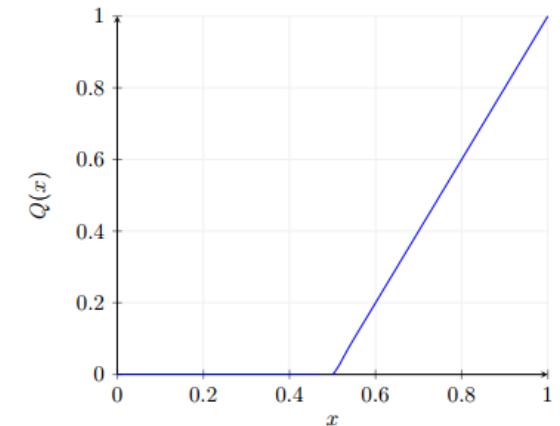
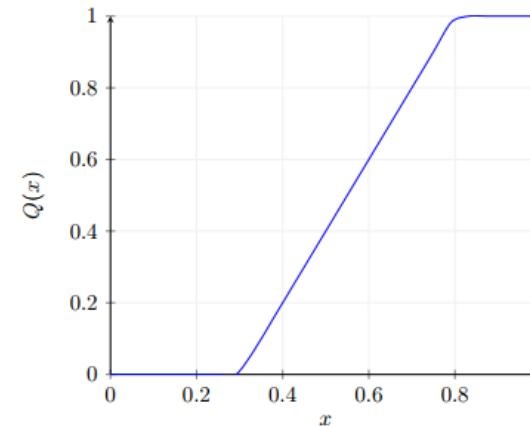
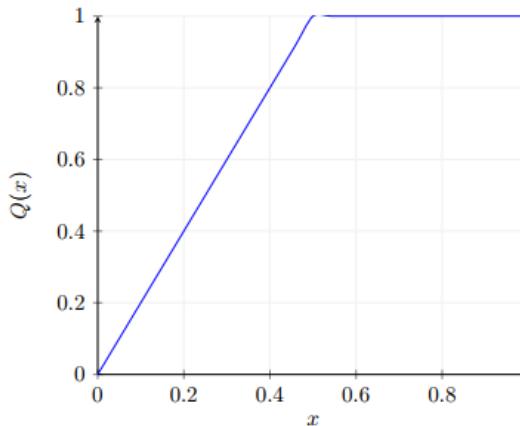


Fig. 17: Linguistic Quantifiers Represented as Fuzzy Sets: *At least half*, *Most of* and *Many as possible*, respectively.

5 LINGUISTIC QUANTIFIERS

Definition 7 *IOWA At Least Half Pro-Neutrality System Based (ALH-ProN).* The *IOWA ALH-ProN operator* of dimension T is a mapping $\Psi_{ALH-ProN} : ([0, 1] \times [0, 1])^T \rightarrow [0, 1]$ that has an associated weighting vector W such that $w_i^{(0,0.5)}$ and it is defined to aggregate the set of second arguments of a list of T 2-tuples:

$$\Psi_{ALH-ProN}(\langle u_1, p_{1k} \rangle, \dots, \langle u_T, p_{Tk} \rangle) = \sum_{i=1}^T w_i^{(0,0.5)} p_{\sigma(i)k},$$

being $\sigma : \{1, \dots, T\} \rightarrow \{1, \dots, T\}$ a permutation such that $u_{\sigma(i)} \geq u_{\sigma(i+1)}$, $\forall i = 1, \dots, T - 1$, and $u_i = NPF_{\alpha=1}(p_{ik}) = 1 - |p_{ik} - 0.5|$.

Definition 8 *IOWA Most Of Pro-Neutrality System Based (MO-ProN).* The *IOWA MO-ProN operator* of dimension T is a mapping $\Psi_{MO-ProN} : ([0, 1] \times [0, 1])^T \rightarrow [0, 1]$ that has an associated weighting vector W such that $w_i^{(0.3,0.8)}$ and it is defined to aggregate the set of second arguments of a list of T 2-tuples:

$$\Psi_{MO-ProN}(\langle u_1, p_{1k} \rangle, \dots, \langle u_T, p_{Tk} \rangle) = \sum_{i=1}^T w_i^{(0.3,0.8)} p_{\sigma(i)k},$$

being $\sigma : \{1, \dots, T\} \rightarrow \{1, \dots, T\}$ a permutation such that $u_{\sigma(i)} \geq u_{\sigma(i+1)}$, $\forall i = 1, \dots, T - 1$, and $u_i = NPF_{\alpha=1}(p_{ik}) = 1 - |p_{ik} - 0.5|$.

5 LINGUISTIC QUANTIFIERS

Definition 9 *IOWA Many As Possible Pro-Neutrality System Based (MAP-ProN).* The *IOWA MAP-ProN operator* of dimension T is a mapping $\Psi_{MAP-ProN} : ([0, 1] \times [0, 1])^T \rightarrow [0, 1]$ that has an associated weighting vector \mathbf{W} such that $w_i^{(0.5,1)}$ and it is defined to aggregate the set of second arguments of a list of T 2-tuples:

$$\Psi_{MAP-ProN}(\langle u_1, p_{1k} \rangle, \dots, \langle u_T, p_{Tk} \rangle) = \sum_{i=1}^T w_i^{(0.5,1)} p_{\sigma(i)k},$$

being $\sigma : \{1, \dots, T\} \rightarrow \{1, \dots, T\}$ a permutation such that $u_{\sigma(i)} \geq u_{\sigma(i+1)}$, $\forall i = 1, \dots, T - 1$, and $u_i = NPF_{\alpha=1}(p_{ik}) = 1 - |p_{ik} - 0.5|$.

5 LINGUISTIC QUANTIFIERS

Definition 10 *IOWA Minimum Neutrality (MinN).* The *IOWA MinN* of dimension T is a mapping $\Psi_{MinN} : ([0, 1] \times [0, 1])^T \rightarrow [0, 1]$ that has an associated weighting vector \mathbf{W} and it is defined to aggregate the set of second arguments of a list of T 2-tuples:

$$\Psi_{MinN}(\langle u_1, p_{1k} \rangle, \dots, \langle u_T, p_{Tk} \rangle) = \sum_{i=1}^T w_i p_{\sigma(i)k},$$

being $\sigma : \{1, \dots, T\} \rightarrow \{1, \dots, T\}$ a permutation such that $u_{\sigma(i)} \geq u_{\sigma(i+1)}$, $\forall h = 1, \dots, T - 1$, and $u_i = NPF_{\alpha=1}(p_{ik}) = 1 - |p_{ik} - 0.5|$ with $w_T = 1$ and $w_i = 0$ for $\forall i = 1, \dots, T - 1$.

Definition 11 *IOWA Maximum Neutrality (MaxN).* The *IOWA MaxN* of dimension T is a mapping $\Psi_{MaxN} : ([0, 1] \times [0, 1])^T \rightarrow [0, 1]$ that has an associated weighting vector \mathbf{W} and it is defined to aggregate the set of second arguments of a list of T 2-tuples:

$$\Psi_{MaxN}(\langle u_1, p_{1k} \rangle, \dots, \langle u_T, p_{Tk} \rangle) = \sum_{h=1}^T w_i p_{\sigma(i)k},$$

being $\sigma : \{1, \dots, T\} \rightarrow \{1, \dots, T\}$ a permutation such that $u_{\sigma(i)} \geq u_{\sigma(i+1)}$, $\forall h = 1, \dots, T - 1$, and $u_i = NPF_{\alpha=1}(p_{ik}) = 1 - |p_{ik} - 0.5|$ with $w_1 = 1$ and $w_i = 0$ for $\forall h = 2, \dots, T$.

The problem of inconsistencies

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Aspect	Text	User	CoreNLP	$\beta = 0.75$
time frame	<p>This place is amazing and should not be missed, no need to add to the thousands other good reviews written hear. I would like to write about my purchasing experience to possibly help someone out in getting this done the easiest way. Trying to get a ticket to see the Alhambra is a project you kind of have to study to know how to do so. I understand why many find it confusing and end up not getting it right. I can only recommend doing it the way I did, as it was simple as 1-2-3: 1. Go to Ticketmaster.es (the Spanish site) and search for tickets for the Alhambra. We got the cheapest best value ones- 15 euro for the general entrance, 2. Purchase tickets to either morning session (ends at 14) or afternoon session (starts at 14 ends at 18/20 depending on season). Know that you are allowed to be at the grounds within that time frame but that would be forced to exit, or not allowed in before/after your session. 3. Know that the specific time selected for your ticket indicates a 30 minute window for you to enter the Nasarid palace (but you can tour the rest of the grounds before or/and after visiting the palace) [...].</p>	1	0.40	0.71
time frame	<p>I tried to book a ticket for this place month in advance and my credit card was declined all the time. Even called the local ticket office and they couldn't help, so in desperation asked the hotel I stayed to try to get tickets-well. I think what they try to do is to discourage you to buy the 'cheap' 14 euro ticket and pay 35 or 50 euros for a guided tour-since you have to book a time frame. We thought that it will give you space to move around-certainly. It's not-hundreds of people lining up at every corner and rooms, so it's grossly overcrowded.</p>	0.5	0	0

Results



Some examples:

“**Staff** of information of the Alhambra are there only for decoration. “

“Found the ““**guards**”” inflexible and occasionally rude.”



Some examples:

“I would skip the audioguide because although it gives a lot of information, it is difficult to identify where you are as none of the **places** it describes are marked inside the Mosque-Cathedral.”

“The **arches** and pillars of later construction are in much worse conditions than those of earlier times.”

R E S U L T S

Results

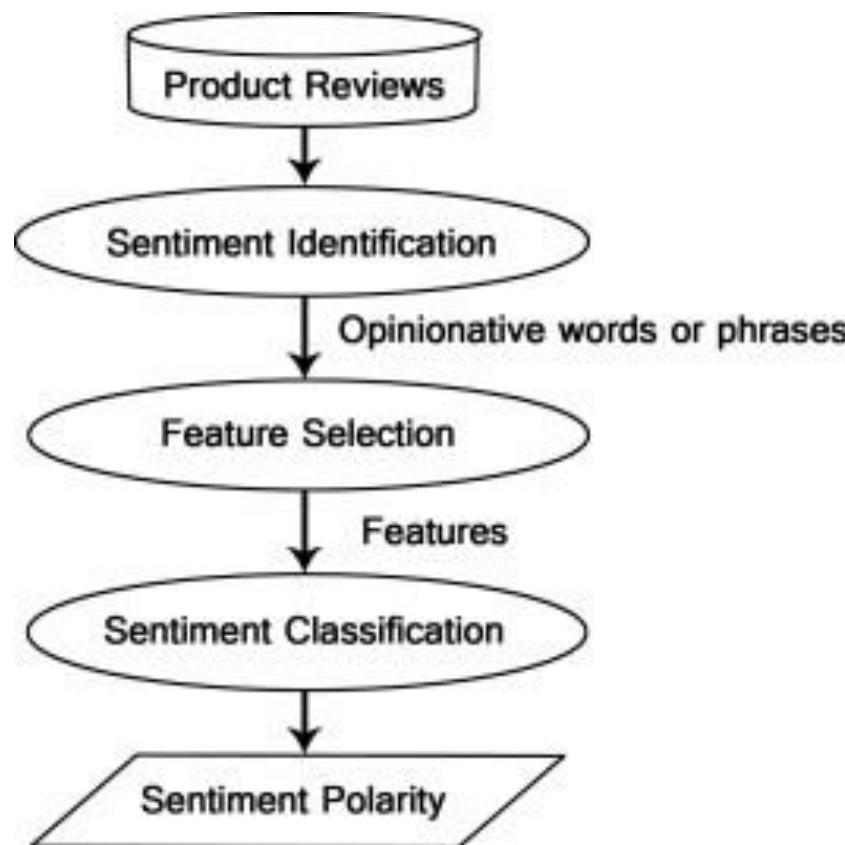


Some examples:

“Buy tickets before you go for the earliest **entry** (9 am, usually) so crowds will be much thinner and no wait time”

“We didn't go inside as the prices (and the **queues**) are crazy.”

Workflow of SAMs

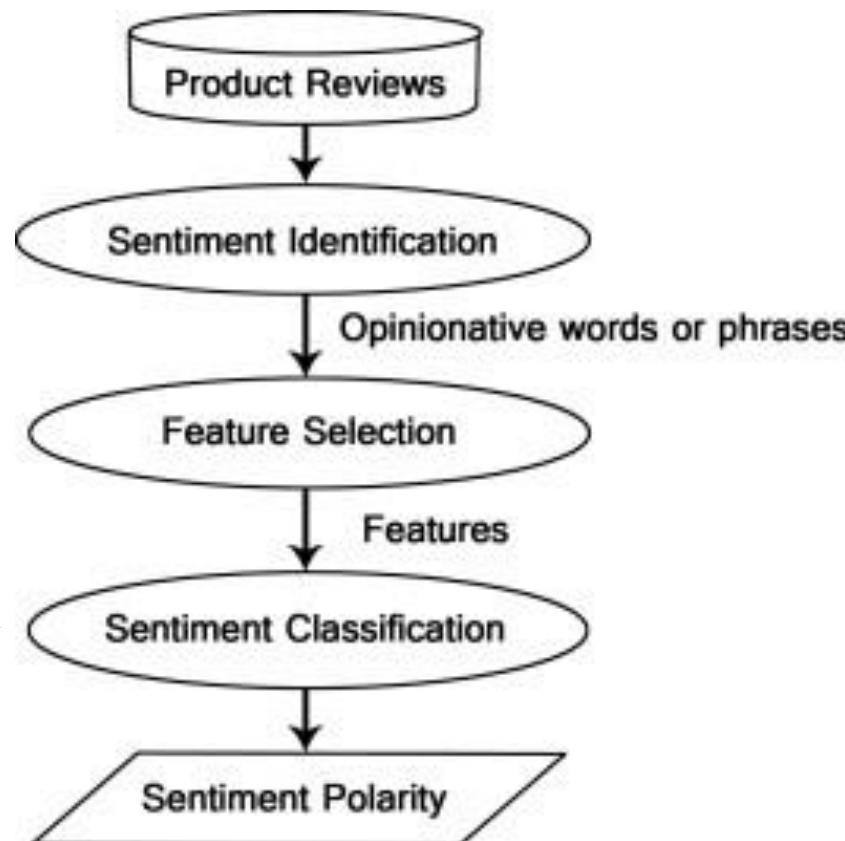


Medhat, W., Hassan, A., & Korashy, H. (2014). **Sentiment analysis algorithms and applications: A survey**. *Ain Shams Engineering Journal*, 5(4), 1093-1113

Workflow of SAMs

Term-Document Matrix

$$\begin{pmatrix} & T_1 & T_2 & \dots & T_t \\ D_1 & w_{11} & w_{21} & \dots & w_{t1} \\ D_2 & w_{12} & w_{22} & \dots & w_{t2} \\ : & : & : & & : \\ : & : & : & & : \\ D_n & w_{1n} & w_{2n} & \dots & w_{tn} \end{pmatrix}$$

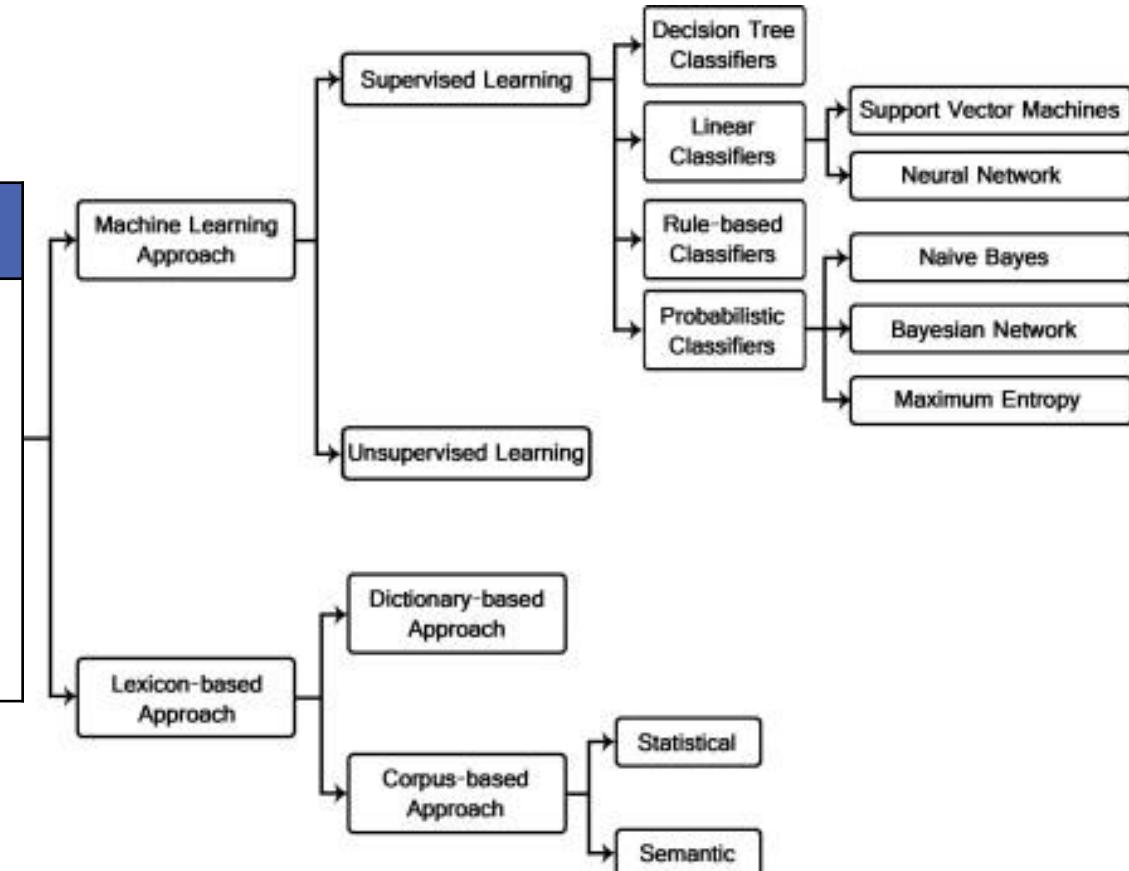


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Basic concepts

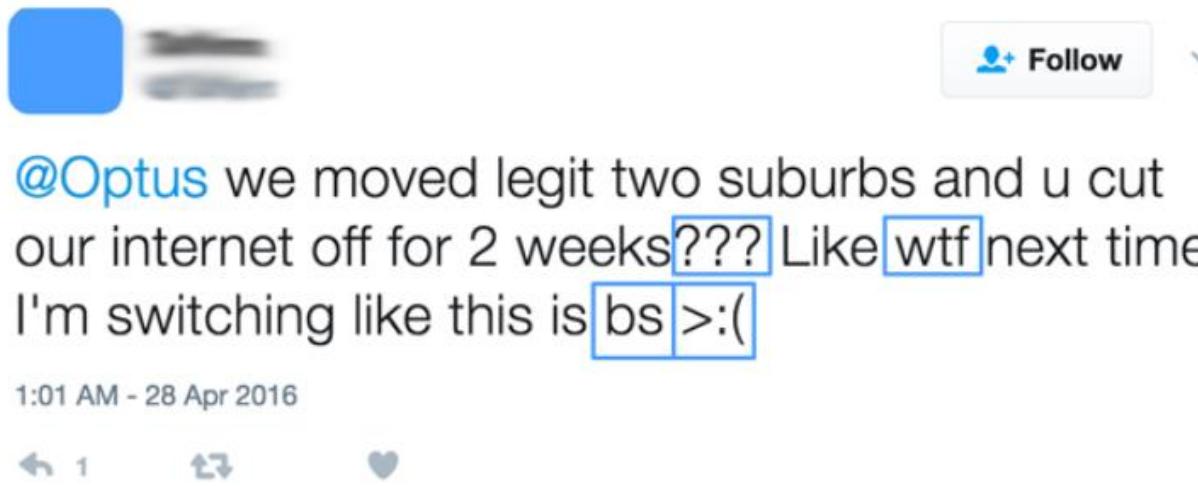
Sentiment Analysis Methods

- Algorithms that extract polarities from written text.
- Drawbacks:
 - Domain adaptation
 - Corpus creation
 - Labelling cost



Medhat, W., Hassan, A., & Korashy, H. (2014). **Sentiment analysis algorithms and applications: A survey**. *Ain Shams Engineering Journal*, 5(4), 1093-1113

Vader



Gilbert, CJ Hutto Eric. (2014). **Vader: A parsimonious rule-based model for sentiment analysis of social media text.** *Eighth International Conference on Weblogs and Social Media (ICWSM-14)*. Available at (20/04/16) <http://comp.social.gatech.edu/papers/icwsm14.vader.hutto.pdf>.