Evaluating Methods for Extraction of Aspect Terms in Opinion Texts in Portuguese – the Challenges of Implicit Aspects

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Presentation

Sentiment analysis

Definition:

Area of study at the intersection between Computer Science and Linguistics that aims to automatically determine sentiments in a text [Taboada, 2016] in order to analyze people's opinions, feelings, assessments, attitudes and emotions concerning products, services, organizations, individuals, issues, topics, and their attributes [Liu, 2012].

Aspect Based Sentiment Analysis

Example with explicit aspect:

"The hotel room was very small"

- Entity: hotel
- Aspect: room
- Sentiment: negative
- Author: ???
- Time: ???

SemEval tasks [Pontiki et al., 2014]:

- Aspect term extraction
- Aspect term polarity
- Aspect category detection
- Aspect category polarity

Implicit Aspect Clues (IACs)

"The hotel was too **expensive**."

- Aspect: price
- IAC: expensive

"The smartphone is too **small**."

- Aspect: size
- IAC: small

"The smartphone barely **fits in my pocket**."

- Aspect: size
- IAC: fits in my pocket

Identifying Implicit Aspects in Portuguese

Challenges:

- Few works deal directly with the implicit aspects [Ravi and Ravi, 2015, Rana and Cheah, 2016, Pereira, 2020];
- Between 15% and 30% of aspects are implicitly mentioned [Panchendrarajan et al., 2016, Zhang and Zhu, 2013];
- Most of the researches in the area addresses only explicit aspects due to:
  - difficult implementation;
  - high frequency of the explicit ones;
- Most works analyze texts written in English or Chinese [Tubishat et al., 2018, Ganganwar and Rajalakshmi, 2019];

Data and Methods

In order to improve this scenario of scarcity of resources related to implicit aspects for the Portuguese language:

- We implemented and tested several methods for extracting aspect terms, focusing on their effect on implicit aspects;

Datasets

- Vargas and Pardo [Vargas and Pardo, 2017]: 180 reviews of cameras, books, and smartphones;
- Freitas and Vieira [d. Freitas and Vieira, 2015]: 194 reviews about hotels collected from the TripAdvisor website, with the annotation of the implicit aspect terms [Machado et al., 2022];

Domains	Reviews	Words	Aspects	Expl.	Impl.
Cameras	60	3,997	352	299	53
Books	60	5,515	330	304	26
Smartphones	60	6,210	455	387	68
Hotels	194	13,940	1,417	999	415

Typology of Implicit Aspect Clues

Category	Subcategory	Aspect	Corresponding IAC
Event (Action/Process/State)	Verb	Price	to pay
	Non-verbal form	Price	payment
Feature	Attribute	Design	material
	Equivalence	Cleanliness	hygiene
	Is-a	Food	breakfast
	Part-of	Facilities	bathroom
Qualification	Adjective	Design	beautiful
	Equivalence	Facilities	plain hotel
	Nominal form	Design	beauty
Contextual	Location	Location	in the center of the region
	Related	Cleanliness	musty smell

Methods for Aspect Extraction

- Freq-Baseline (Freq)
  - W2V pruning step (FreqW2V)
- Hu & Liu (HuLiu)
  - W2V pruning step (HuLiuW2V)
  - infrequent W2V pruning step (HuLiuInfW2V)
- Traditional machine learning:
  - Multinomial Naive Bayes (MNB)
  - Stochastic Gradient Descent (SGD)
  - Perceptron
  - Passive Aggressive (PA)
  - Conditional Random Fields (CRF)
- BERT
  - Multilingual and Portuguese models
  - In domain and cross domain

Results per domain

	Book		Camera		Smartphone		Hotel	
Method	**F1**	**Imp**	**F1**	**Imp**	**F1**	**Imp**	**F1**	**Imp**
Freq	0.60	0.00	0.55	0.00	0.48	0.04	0.61	0.12
FreqW2V	0.63	0.00	0.61	0.00	0.51	0.00	0.60	0.15
HuLiu	0.53	0.00	0.35	0.00	0.46	0.08	0.58	0.08
HuLiuW2V	0.53	0.00	0.35	0.00	0.41	0.08	0.59	0.09
HuLiuInfW2V	0.55	0.00	0.40	0.00	0.41	0.04	0.58	0.08
MNB	0.49	**0.20**	0.50	**0.31**	0.31	0.12	0.52	0.14
PA	0.72	0.00	0.56	0.08	0.56	0.25	0.77	0.18
Perceptron	0.28	0.00	0.58	0.08	0.58	**0.29**	0.76	0.18
SGD	0.71	0.00	0.56	0.08	0.54	0.25	0.73	0.13
CRF	0.72	0.00	**0.69**	0.23	**0.59**	0.25	**0.81**	0.23
BERT	0.75	0.00	0.55	0.23	0.54	0.17	0.79	**0.26**
BERT-cross	0.72	0.00	0.53	0.08	0.55	0.17	0.77	0.24
BERT-pt	**0.76**	0.00	0.58	0.15	0.53	**0.29**	0.78	0.25
BERT-pt-cross	0.73	**0.20**	0.57	0.08	**0.59**	0.12	0.80	0.25

Aspects detected from the subcategories of the Event category

Method	Non-verbal	Verb	Total
Aspects	12	45	57
Freq	2	0	2 (3%)
FreqW2V	2	0	2 (3%)
HuLiu	2	0	2 (3%)
HuLiuW2V	**3**	0	3 (5%)
HuLiuInfW2V	2	0	2 (3%)
MNB	2	2	4 (7%)
PA	2	2	4 (7%)
Perceptron	2	2	4 (7%)
SGD	2	2	4 (7%)
CRF	**3**	3	6 (10%)
BERT	2	**5**	**7 (12%)**
BERT-cross	2	3	5 (8%)
BERT-pt	2	**5**	**7 (12%)**
BERT-pt-cross	2	3	5 (8%)

Aspects detected from the subcategories of the Feature category

Method	Attribute	Equivalence	Is-a	Part-of	Total
Aspects	10	84	55	124	273
Freq	0	12	4	37	53 (19%)
FreqW2V	0	13	4	45	62 (23%)
HuLiu	0	9	5	30	44 (16%)
HuLiuW2V	0	9	6	32	47 (17%)
HuLiuInfW2V	0	9	6	31	46 (17%)
MNB	**2**	27	6	41	76 (28%)
PA	0	26	7	36	69 (25%)
Perceptron	0	16	7	49	72 (26%)
SGD	0	9	6	31	46 (17%)
CRF	0	**29**	**9**	**54**	**92 (33%)**
BERT	0	**29**	**9**	53	91 (33%)
BERT-cross	0	**29**	9	41	79 (29%)
BERT-pt	1	**29**	8	40	78 (29%)
BERT-pt-cross	0	28	7	51	86 (31%)

Aspects detected from the subcategories of the Qualification category

Method	Adjective	Equivalence	Nominal	Total
Aspects	107	10	10	127
Freq	0	1	**1**	2 (1%)
FreqW2V	0	1	**1**	2 (1%)
HuLiu	10	1	0	11 (8%)
HuLiuW2V	9	1	0	10 (8%)
HuLiuInfW2V	7	1	0	8 (6%)
MNB	38	1	**1**	40 (31%)
PA	44	1	**1**	46 (36%)
Perceptron	45	1	**1**	47 (37%)
SGD	41	1	**1**	43 (34%)
CRF	44	1	**1**	46 (36%)
BERT	42	**2**	**1**	45 (35%)
BERT-cross	**48**	**2**	**1**	**51 (40%)**
BERT-pt	46	**2**	**1**	49 (38%)
BERT-pt-cross	47	**2**	**1**	50 (39%)

Aspects detected from the subcategories of the Contextual category

Method	Location	Related	Total
Aspects	36	68	104
Freq	0	0	0 (0%)
FreqW2V	0	0	0 (0%)
HuLiu	0	1	1 (1%)
HuLiuW2V	0	1	1 (1%)
HuLiuInfW2V	0	1	1 (1%)
MNB	0	3	3 (3%)
PA	0	4	4 (4%)
Perceptron	0	3	3 (3%)
SGD	0	2	2 (2%)
CRF	5	**13**	18 (17%)
BERT	6	12	18 (17%)
BERT-cross	6	8	14 (13%)
BERT-pt	**8**	11	**19 (18%)**
BERT-pt-cross	6	9	15 (14%)

Final Remarks:

Results:

- Machine learning methods performed better than Freq-Baseline and Hu & Liu;
- Freq-Baseline performed better than Hu & Liu;
- Machine learning methods with a bag-of-words model achieved satisfactory results;
- CRF algorithm and BERT achieved good results;

Final Remarks:

Typology:

Easily provided a view of the strengths and weaknesses of each method:

- Elaboration of rules related to verbs or adjectives in Hu & Liu;
- The identification and use of relations (equivalence, is-a, and part-of) as features for the classifiers;
- Contextual category requires diverse and world knowledge to identify its aspects;

Final Remarks:

More information at:

- POeTiSA project: `https://sites.google.com/icmc.usp.br/poetisa`
- `https://github.com/mtarcinalli/LREC-Extraction-of-Aspect-Terms`
- mateusmachado@usp.br

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