Towards Semantic Integration of Opinions: Unified Opinion Concepts Ontology and Extraction Task

Gaurav Negi, Dhairya Dalal, Omnia Zayed, and Paul Buitelaar
Insight Research Ireland Centre for Data Analytics, Data Science Institute, University of Galway

Overview

The Unified Opinion Concepts (UOC) ontology bridges the gap between the semantic representation of opinion across different formulations. It is a unified conceptualisation based on the facets of opinions studied extensively in NLP and semantic structures described through symbolic descriptions.

Key Contributions:

- UOC Ontology that improves on the existing opinion formulation in terms of expressivity and cross-compatibility.
- Formulation of Unified Opinion Concepts Extraction (UOCE) as an NLP task grounded in rich UOC semantic representations.
- Manually annotated evaluation dataset with tailored evaluation metrics.

Unified Opinion Concepts Ontology

Our formulation of Fine-Grained Opinion Representations builds on the rich literature in opinion mining. Core tasks such as Aspect Sentiment Triple Extraction (ASTE) (Wu et al., 2020), Structured Sentiment Analysis (Barnes et al., 2022), and Aspect-Category-Opinion-Sentiment (ACOS) (Cai et al., 2021) extraction have shaped progress in NLP. In addition, our approach is motivated by the MARL ontology (Westerski et al., 2011) and the opinion facets outlined by Liu (2017).

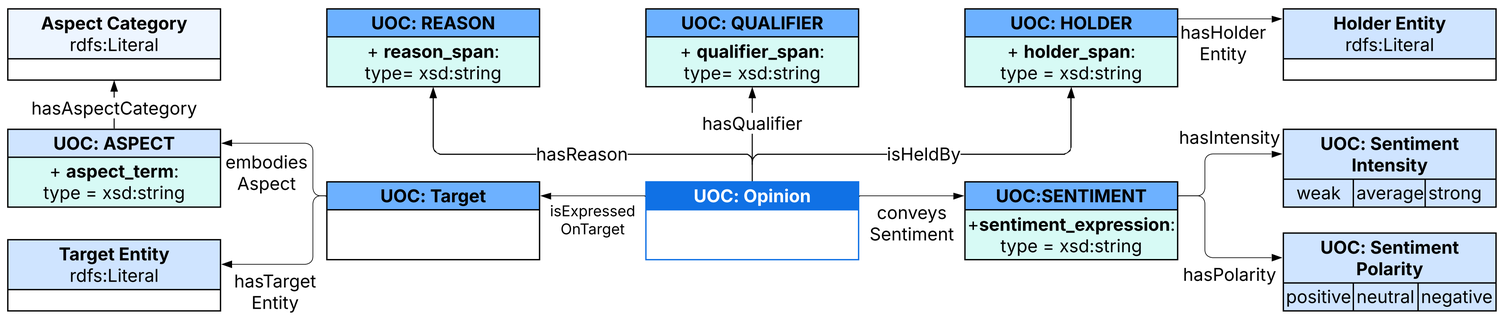

Figure 1. Unified Opinions Concepts (UOC) Ontology Diagram

Unified Opinion Concepts Extraction (UOCE) Task

Problem def. Given an input text T_i, extract an exhaustive set of opinions $O_i = \{o_{11}, o_{12} \ldots, o_{ij}\}$, where each opinion O_i where each opinion is represented by the tuple: $O_i = \{at, ac, te, se, sp, si\ hs, he, q, \text{r}\}_{i,j}$, where:

at : Aspect Term, si : Sentiment Intensity, ac : Aspect Category, hs: Holder Span , te : Target Entity, he :Holder Entity, se : Sentiment Express, q :Qualifier
sp : Sentiment Polarity, r :Reason

Baseline Methods for UOCE

Natural Language Prompt (NLPrompt): It has the definitions of opinion concepts (D), in-context examples (E) and format guidelines (F).

Model	DEF	DFE	EDF	EFD	FDE	FED	μ ± σ
Gemma2 27B	57.70	55.92	56.77	56.77	55.15	53.64	55.99 ± 1.44
Gemma2 9B	57.20	55.85	58.56	58.40	55.35	54.46	56.64 ± 1.68
GPT-4o	58.46	55.58	59.12	59.33	57.55	56.76	**57.8** ± 1.46
GPT-4o-Mini	54.67	53.88	55.59	57.00	53.29	56.26	55.12 ± 1.42
Llama 3.1 70B	46.90	46.02	48.04	44.14	44.86	46.27	46.04 ± 1.4
Llama 3.1 8B	46.36	49.88	43.84	44.73	48.79	35.54	44.86 ± 5.11
Mistral 7B	48.00	48.52	49.09	48.46	49.61	50.30	49 ± 0.85
Mixtral 8x7B	49.63	50.57	51.84	51.26	49.60	50.98	50.65 ± 0.9
μ	52.36	52.03	**52.86**	52.51	51.78	50.53	
± σ	5.17	3.80	5.53	6.19	4.24	6.97	

Table 1: F1 Score for UOCE using NLPrompts

Ontology Prompt (OntoPrompt): The definitions of concepts (D) is provided as a serialized ontology description rather instead of natural language.

Model	jsonld	man	obo	owf	owx	rdfx	ttl	μ ± σ
Gemma2 27B	57.36	56.54	57.59	55.49	57.96	55.35	58.76	57.01 ± 1.27
Gemma2 9B	54.66	54.75	54.12	43.68	54.18	44.48	54.77	51.52 ± 5.09
GPT-4o	57.71	56.41	57.47	57.65	56	57.45	58.13	**57.26** ± 0.76
GPT-4o-Mini	55.26	54.38	52.71	53.94	54.31	53.72	53.74	54.01 ± 0.78
Llama 70B	51.39	50.32	52.2	51.66	49.41	51.26	50.91	51.02 ± 0.92
Llama 8B	49.59	50.91	49.39	49.04	49.42	50.38	49.31	49.72 ± 0.67
Mistral 7B	49.07	47.97	47.91	47.45	48.52	47.25	47.27	47.92 ± 0.68
Mixtral 8x7B	51.75	50.79	50.38	50.26	50.63	49.18	51.36	50.62 ± 0.83
μ	**53.35**	52.76	52.72	51.15	52.55	51.13	53.03	
± σ	3.37	3.17	3.55	4.53	3.52	4.28	4.08	

Table 2: F1 Score for UOCE using OntoPrompts

Extracted Labels	OURS (NLPrompt)	OURS (OntoPrompt)	GEN-SCL-NAT	MVP	GOLD LABELS
Aspect Term	locations	location	N/A	N/A	N/A
Aspect Category	general	general	general	general	general
Target Entity	place	location	location	restaurant	location
Sentiment Expression	one of the best	one of the best	best	best	one of the best
Sentiment Polarity	positive	positive	positive	positive	positive
Sentiment Intensity	strong	strong	×	×	strong
Holder Span	N/A	N/A	×	×	N/A
Holder Entity	author	author	×	×	author
Qualifier	you could stay at in Boston	N/A	×	×	stay at in Boston
Reason	N/A	N/A	×	×	N/A

Example: Automatic Opinion Extraction for *"By far one of the best locations you could stay at in Boston."*

TASK	MODEL	P	R	F1
ASTE	GEN-SCL-NAT	60.25	70.14	64.82
	MVP	61.26	67.66	64.3
	Ours (NLPrompt)	75.24	74.15	74.69
	Ours (OntoPrompt)	75.87	73.67	**74.75**
ACOS	GEN-SCL-NAT	49.61	57.76	53.38
	MVP	52.83	58.35	55.46
	Ours (NLPrompt)	58.23	57.39	**57.81**
	Ours (OntoPrompt)	58.35	56.67	57.49
UOCE	GEN-SCL-NAT	39.1	45.52	42.07
	MVP	35.6	39.32	37.37
	Ours (NLPrompt)	55.22	63.62	**59.12**
	Ours (OntoPrompt)	53.9	62.1	57.71

Table 3: Comparison with GEN-SCL-NAT (Peper and Wand, 2022), and MVP (Gou et al., 2023)

Observation

The baseline methods for UOCE task outperform the state-of-the-art ASTE and ACOS tasks on evaluation dataset. It illustrate the challenges UOCE poses and the benefits to other opinion mining formulations.

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ACKNOWLEDGEMENT: This work was conducted with the financial support of Research Ireland under Grant Number SFI/12/RC/2289_P2 (Insight_2). At the time of this publication, Omnia Zayed has been supported by Taighde Éireann – Research Ireland for the Postdoctoral Fellowship award GOIPD/2023/1556 (Glór)