ETMS@IITKGP AT SEMEVAL-2022 TASK 10: STRUCTURED SENTIMENT ANALYSIS USING A GENERATIVE APPROACH



Problem Statement

Structured Sentiment Analysis (SSA) aims to predict all the structured sentiment graphs present in a given text. A graph is formally represented by opinion tuples O = $O_1, O_2, ..., O_n$, where each opinion tuple O_i consists of a quadruple of the holder h, the target t, the sentiment expression e, and the sentiment polarity p.

> Even though **the price** is **decent** for Paris, I would not recommend this hotel.

- Quadruplet 1: (<none>, the price, decent, POSITIVE)
- Quadruplet 2: (I, this hotel, would not recommend, NEGATIVE) Figure: Example text with its corresponding opinion quadruples

Datasets

We are provided with a total of 7 datasets, spanning across 5 different languages. Each dataset is a collection of sentences, along with their corresponding annotated opinion tuples, each consisting of (Source, Target, Polar *Expression*, and *Polarity*).

Dataset Name	Language
NoReCfine	Norwegian
MultiBooked_eu	Basque
MultiBooked_ca	Catalan
OpeNER_es	Spanish
OpeNER_en	English
MPQA	English
Darmstadt_unis	English

Table: Task Datasets

Task Paradigms

- Monolingual: Train and test on the same language, for both English and Non-English datasets.
- **Crosslingual**: Train on the combination of English datasets and test on the individual non-English datasets.

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The Objectives

• Build a system to mine opinion tuples (holder, opinion expression, target, polarity) from the given text • Extrapolate and test the system's capability in monolingual and crosslingual paradigms

Model Architecture

We present a novel unified generative method to solve Structured Sentiment Analysis (SSA), by leveraging a BART-based encoder-decoder architecture and suitably modifying it to generate, given a sentence, a sequence of opinion tuples.



Experimental Setup

For the monolingual setting, we used the train, validation, and test splits of the same datasets. While experimenting on the English datasets, we use **BART-base** as the backbone. For the Non-English datasets, we use **BART-large-MNLI** as the backbone. In the cross-lingual setting, we trained our models using the combined training data from all English datasets and evaluated them on the test sets of respective Non-English datasets (NoReC not included as part of this setting). We used **BART-large-MNLI** as the backbone for all our crosslingual experiments.

We present a novel generative approach to tackle the task of Structured Sentiment Analysis. We formulate the task as a structured prediction problem, using our BART-based encoder-decoder architecture. **For Further Information**

Codes:



Results

Monolingual Paradigm:

Our model performs the best on OpeNER_en and OpeNER_es, and has a relatively poor performance on MPQA, Darmstadt_unis and NoReC_fine.

Dataset	SG-F1
NoReC_fine	0.351
MultiBooked_eu	0.438
MultiBooked_ca	0.508
OpeNER_es	0.544
OpeNER_en	0.626
MPQA	0.327
Darmstadt_unis	0.330

Table: Monolingual SubTask: Test Set SG-F1 Scores.

Crosslingual Paradigm:

In this paradigm, we used all the English datasets for training our model, and tested our best trained models on the test sets of the respective Non-English datasets.

Dataset	SG-F1
EN-EU	0 /21
(MultiBooked_eu)	0.401
EN-CA	0 506
(MultiBooked_ca)	0.500
EN-ES	0 5/19
(OpeNER_es)	0.942

Table: Corsslingual SubTask: Test Set SG-F1 Scores.

Detailed results are available in the paper.

Key Contributions

Preprint: https://arxiv.org/abs/2205.00440 https://github.com/Sherlock-Jerry/ SSA-SemEval