ETMS@IITKGP at SemEval-2022 Task 10: Structured Sentiment Analysis Using A Generative Approach

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NAACL 2022

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
NoReC_fine	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.

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.

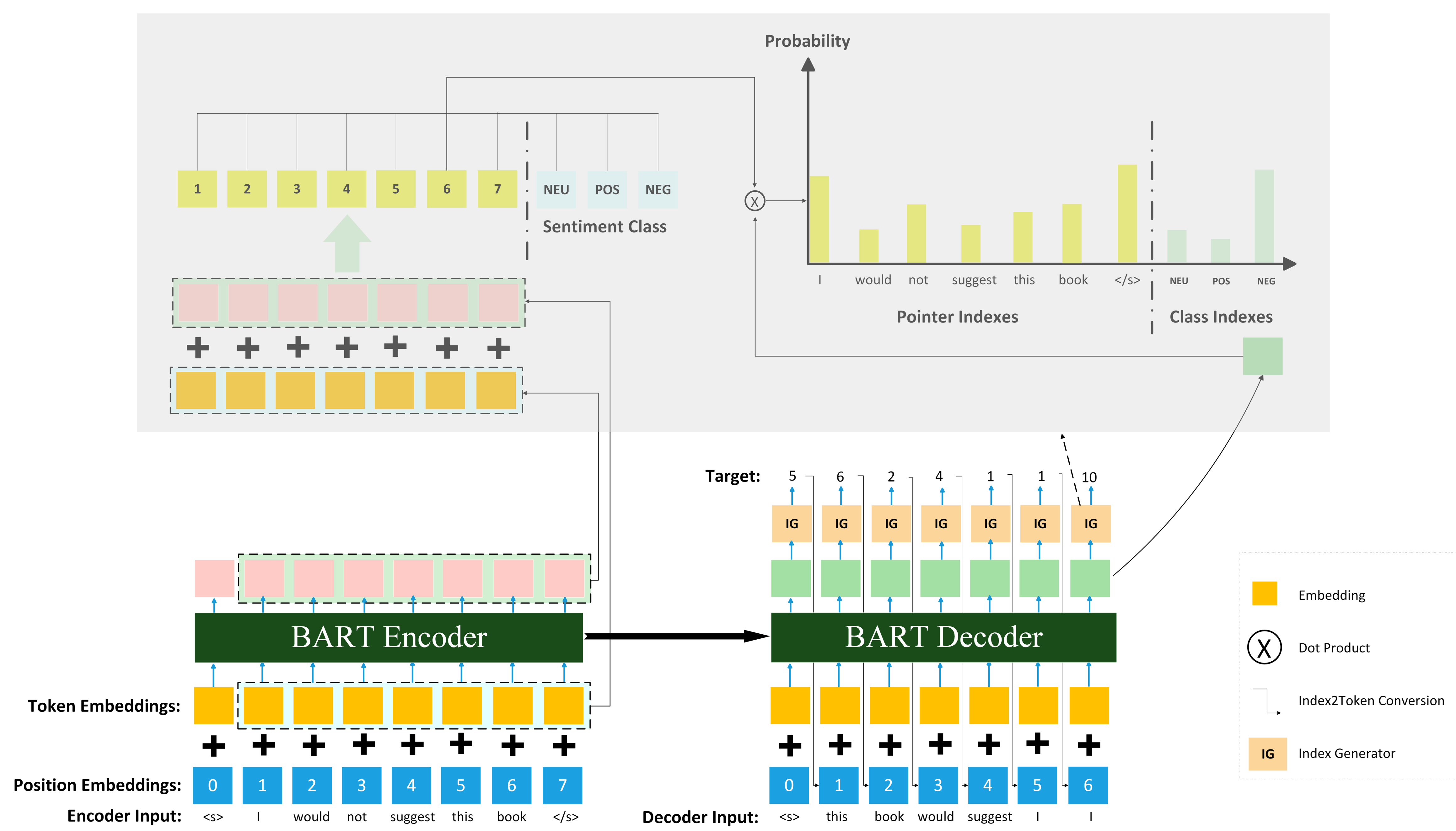

Figure: Model Components and Architecture

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 cross-lingual experiments.

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 (MultiBooked_eu)	0.431
EN-CA (MultiBooked_ca)	0.506
EN-ES (OpeNER_es)	0.542

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

Detailed results are available in the paper.

Key Contributions

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

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