REPORT OUT: ASPECT BASED SENTIMENT ANALYSIS USING BART

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Target Audience: Sentiment Analysis of client comments

CONTENTS

SECTION 1: QUESTIONS TO ANSWER

- Discover perceptions based on online reviews (Sentiment Analysis) is nowadays essential for appropriate managerial marketing strategies
- Fine-grained task of Aspect Based Sentiment Analysis aims to find targets and related sentiments simultaneously, thereby adding values to the market.
- Avoid high-computing power detrimental over training phase
- Compensate for insufficient training examples in deep learning models

SECTION 2 : INITIAL HYPOTHESIS

- We expect that Sentiment analysis reaches higher metrics scores via deep learning-based models than lexicon-based and machine learning-based models.
- We expect that Transfer Learning knowledge from pretrained model on large corpora avoids common deep learning issues such as high-computing power detrimental over the training phase and compensate for insufficient training examples.
- We expect that thanks to the above properties, namely low computational power and small data resources, our model can be installed without the need for a central server to upload the new taken data and carry out further elaboration, thereby enabling an easily scalable detection.

SECTION 3: APPROACH

- **Training model.** For Aspect Based Sentiment Analysis, we have chosen zero-shot classification with a BART model pretrained on the Multi-genre Natural Language Inference (NLI) dataset. It is based on the BART-large-MNLI repository by Hugging Face. For the sake of this online version, we show the model potentials through two public datasets: the Yahoo answers and emotion datasets. We have also restricted multi-class classification to four classes per dataset: Society & Culture, Science & Mathematics, Health, Education & Reference for topics and Joy, Love, Sadness, Anger for emotions.
- **Implementation.** Zero-shot classification is performed via inference with the BART-large-M-NLI model. The input to the model is obtained via transformation of the topic and emotion detection dataset from a classification task to a M-NLI task.

SECTION 3: PRE-TOKENIZATION

- Name features in **dataset**
- Filter out input examples equal to None
- Check that the dataset is balanced (even number of points per classes)
- Concatenate questions and answers (as some are long one word) for better inference
- Convert dataset to list and remove special characters with the use of regex
- Track true labels for later plotting
- Define **labels** for **classification**: Topics and/or Emotions

SECTION 3: ZERO-SHOT CLASSIFICATION

- Pipeline of the BART-large M-NLI model calls on examples and labels, namely topics and/or emotions.
- Pipeline transforms each example-label pair in a premise-hypothesis pair
- Pipeline tokenizes the premise-hypothesis pair
- Pipeline infers entailment of the premise-hypothesis pair: **fine tuning via zero-shot classification**
- Logits corresponding to the output of the entailment inference are directly used for classification of topics and emotions

TECHNICAL CHALLENGES

- For reducing computation time, zero-shot inference on the Yahoo answer dataset is carried out only on 400 sequences corresponding to 4 different topics evenly distributed (balanced dataset): Society & Culture, Science & Mathematics, Health and Education & Reference.
- Similarly for the emotion dataset we have carried out inference only on 400 sequences corresponding to 4 different emotions evenly distributed (balanced dataset): Joy, Love, Sadness and Anger.

LABELLED DATA in Topics Dataset: class-answer pair to be used as premise-hypothesis pair

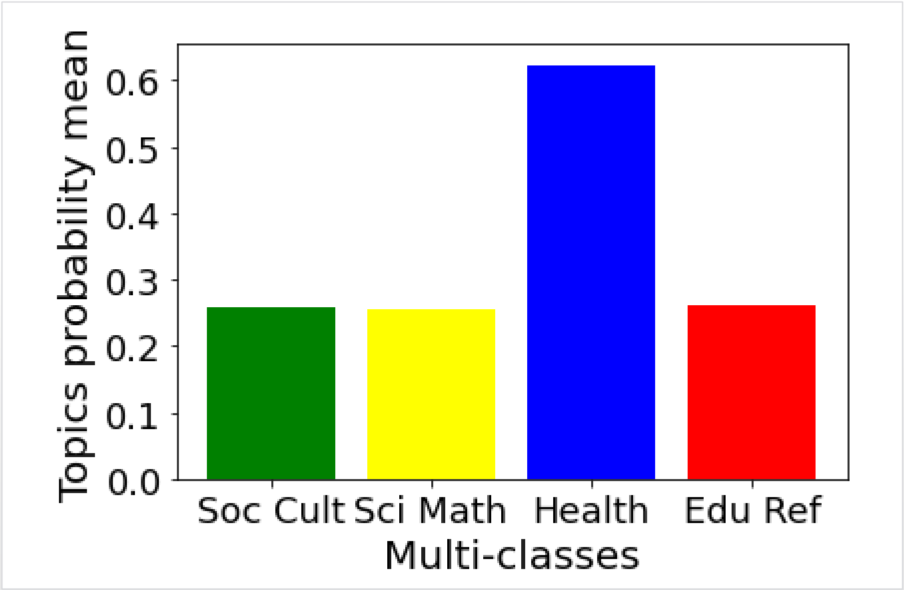
class index	**question title**	**best answer**
2	Why does Zebras have stripes?	this provides camouflage - predator vision is ...
4	What did the itsy bitsy sipder climb up?	waterspout
4	What is the difference between a Bachelors and...	One difference between a Bachelors and a Maste...

class index	**class label**
1	Society & Culture
2	Science & Mathematics
3	Health
4	Education & Reference

- Note that, here, class label refers to the true label. However, during zero-shot classification, entailment will be inferred between hypothesis and each true label of the topics as well as topics emotions.

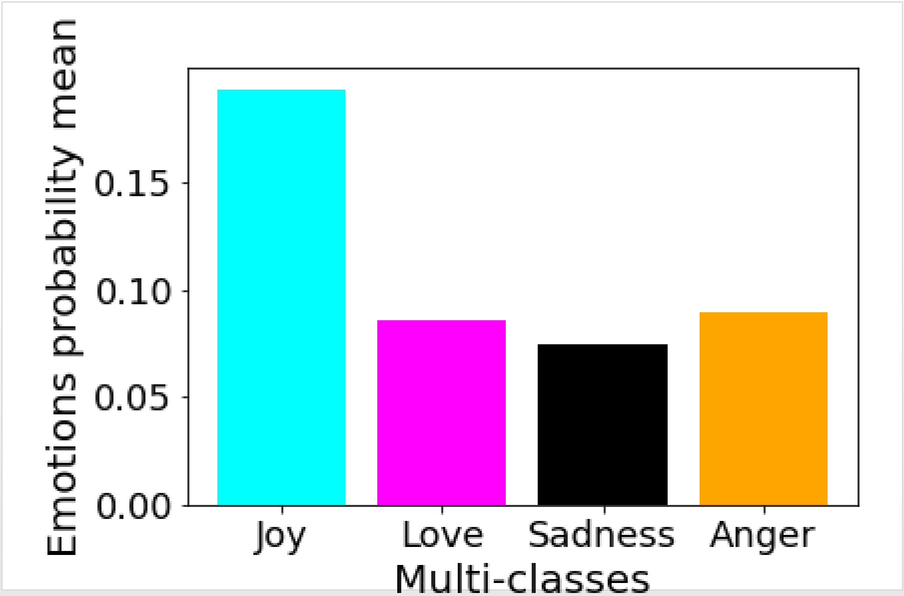
INITIAL FINDINGS on Topics Dataset

- The Zero-shot classifier on the topics multi-class candidates predicts a F1 score of 40.
- The probability mean for the true positives cases is reported in the histogram on the right. Each bar represents the true positive examples per candidate. This gives information about precision and recall and so it is directly comparable to the F1 score.
- We can see how the model well predicts the topics Health, above all others.

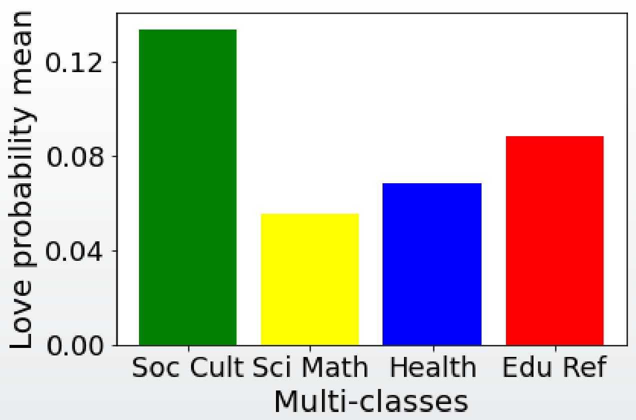


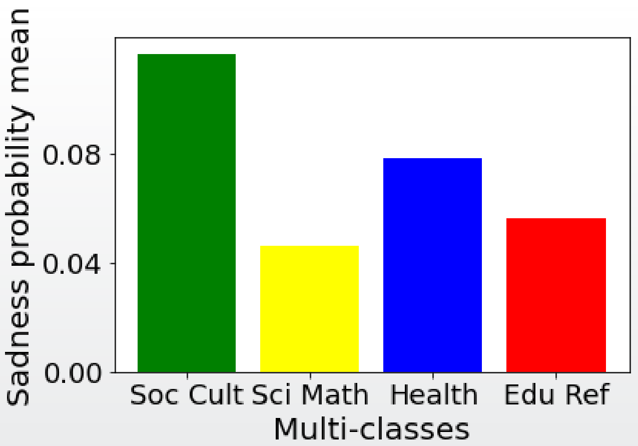
DEEPER ANALYSIS on Topics Dataset

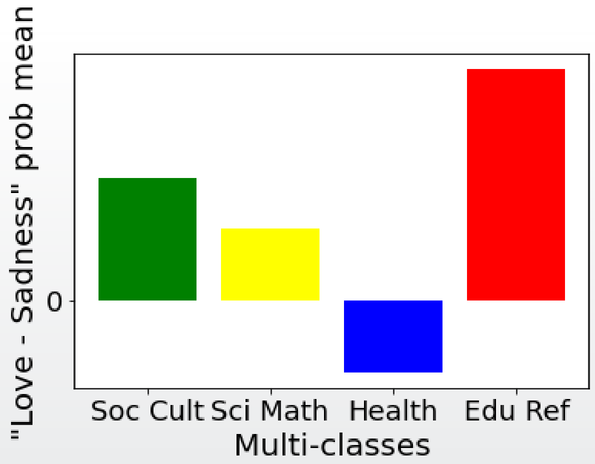
- Here we report the predictions of the Zero-shot classifier on emotions candidates (no true labels).
- The probability mean for the positive and negative cases is reported in the histogram on the right. Each bar represents all examples per emotion candidate class.
- Interestingly, by combining this emotion classifier with the topics classifier from the previous slide we could perform Aspect Based Sentiment Analysis.



DEEPER ANALYSIS on Topics Dataset



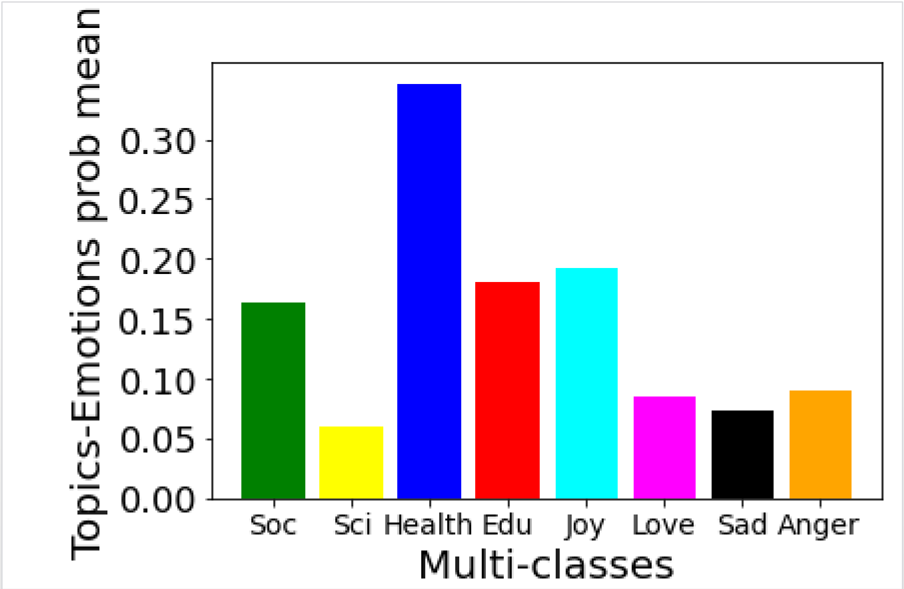




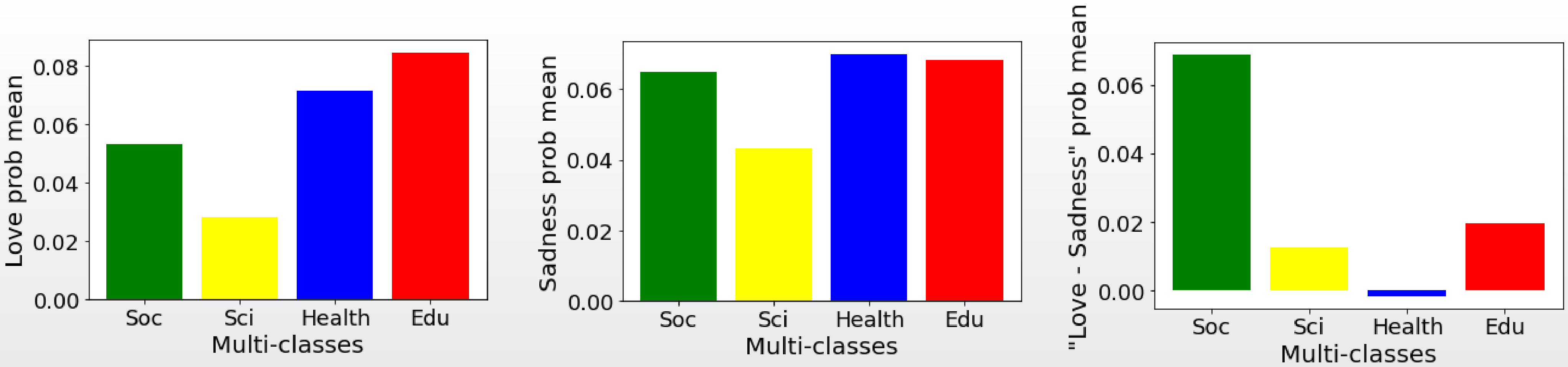
- The histograms above show predictions of the Zero-shot classifier on two different emotions candidates, namely love and sadness.
- By reporting the emotion probabilities for those examples true positive in the Zero-shot classifier performed on topics candidates, we can actually relate sentiments to aspects.
- In particular, the third histogram reports the subtraction between love and sadness probabilities, showing that more positive comments can be found in Education and Society topics rather than in Science and Health.

DEEPER ANALYSIS on Topics Dataset

- The Aspect based Sentiment Analysis presented in the previous slides is based on two-step classification: one that finds the true positive topics, with F1=40, and the other that guesses emotions.
- However, we can also perform one zero-shot classification at once on topics and emotions in parallel.
- From the histogram we can see that emotions probabilities are the same as in the case of the two-step classifier, while topics probabilities are slightly different due to the fact that here we report both positive and negative cases.
- Again we can note that the model well predicts the topics Health, above all others, and that positive emotions are more frequent than negative ones.



DEEPER ANALYSIS on Topics Dataset



- The histograms above show a zoom of the one-step Zero-shot classifier on two different emotions candidates, namely love and sadness, where examples have been chosen to be positive on the 4 topics candidates.

- In analogy with the two-step classifier, the third histogram reporting the subtraction between love and sadness probabilities, tells that Education and Society topics are more positive than Science and Health.

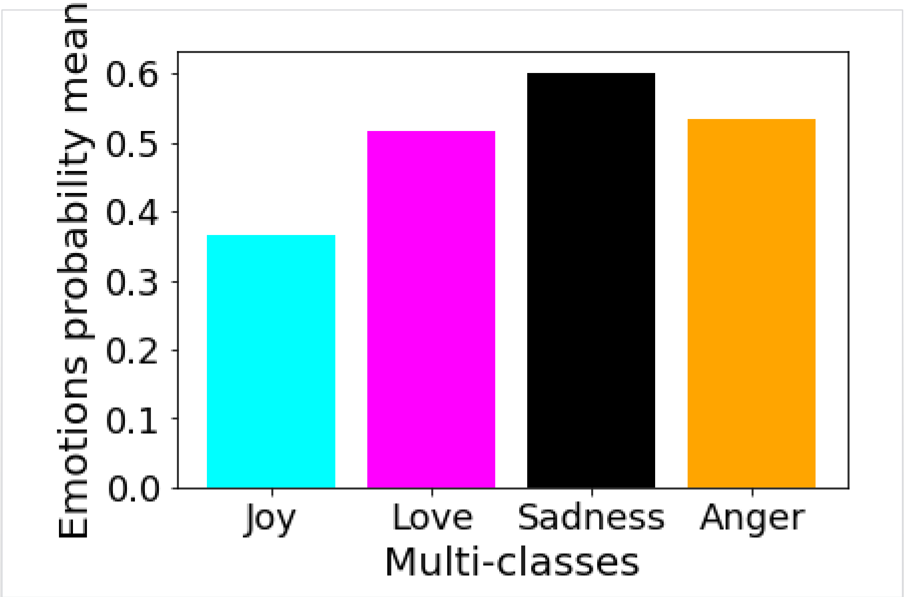
LABELLED DATA in Emotion Dataset: class-comment pair to be used as premise-hypothesis pair

class label	Comment
joy	RT @daveweigel: Hypocrisy and politics go hand...
joy	RT @DavidCornDC: This may be outrageous. It is...
joy	RT @DavidCornDC: If only we could catch Trump ...

- Note that, here, class label refers to the true label. However, during zero-shot classification, entailment will be inferred between hypothesis and each true label of the emotions as well as topics labels.

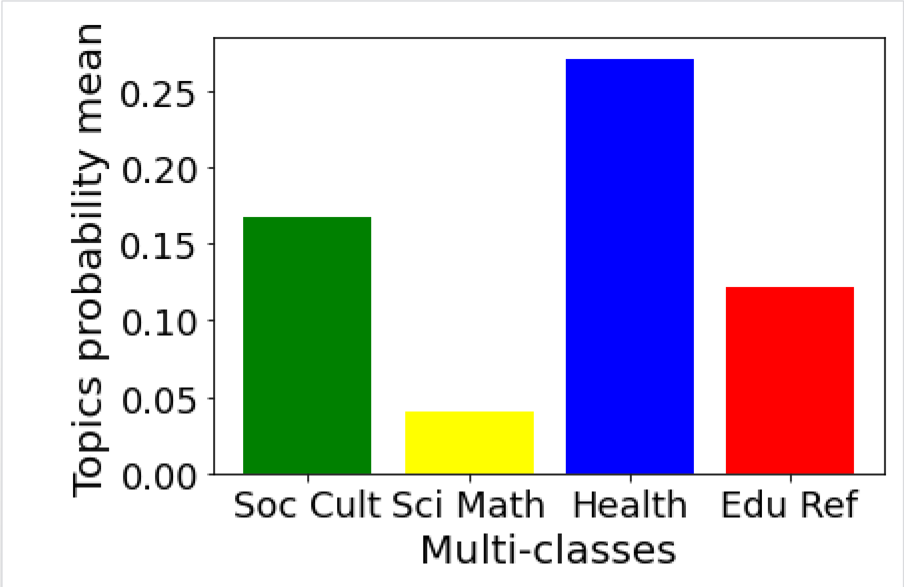
INITIAL FINDINGS on Emotion Dataset

- Let's now move to the analysis of the emotion dataset
- The Zero-shot classifier on the emotion candidates predicts a F1 score of 45.
- The probability mean for the true positives cases is reported in the histogram on the right. Each bar represents the true positives examples per candidate. This gives information about precision and recall and so it is directly comparable to the F1 score.
- We can see how the model predicts best negative sentiments than positive ones.



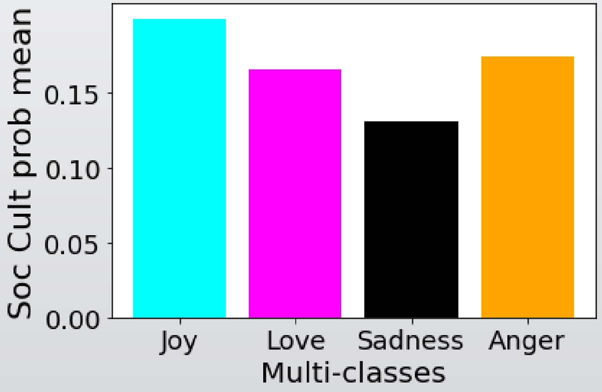
DEEPER ANALYSIS on Emotion Dataset

- Here we report the predictions of the Zero-shot classifier on topics candidates (no true labels).
- The probability mean for the positive and negative cases is reported in the histogram on the right. Each bar represents all examples per topics candidate class.
- Interestingly, by combining this emotion classifier with the emotion classifier from the previous slide we could perform Aspect Based Sentiment Analysis.



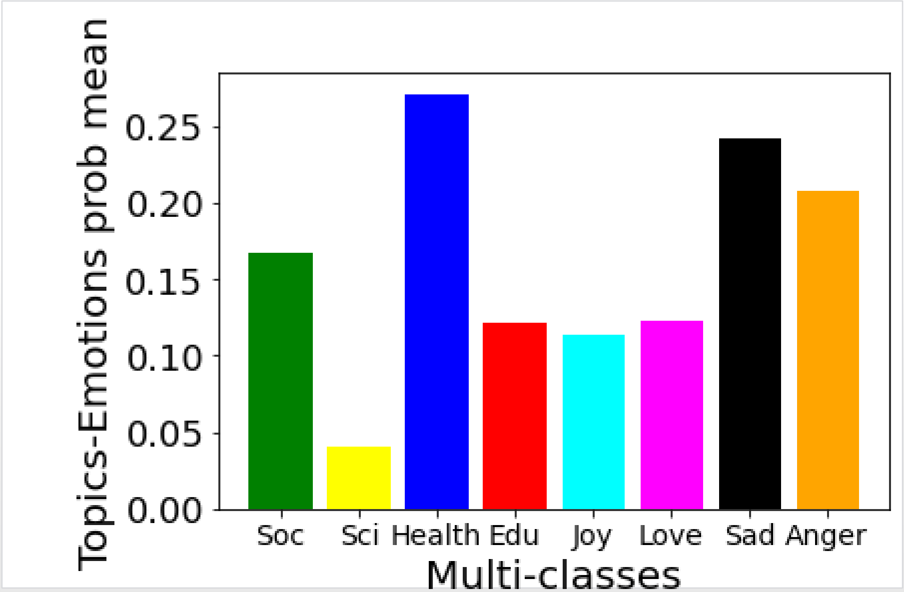
DEEPER ANALYSIS on Emotion Dataset

- The histograms show predictions of the Zero-shot classifier on two different topics candidates, namely health and society.
- By reporting the topics probabilities for those examples true positive in the Zero-shot classifier performed on emotions candidates (colored bars), we can actually relate aspects to sentiments.
- In particular, we note that negative sentiment examples tend to be more related to health and that positive examples are more related to society topics.

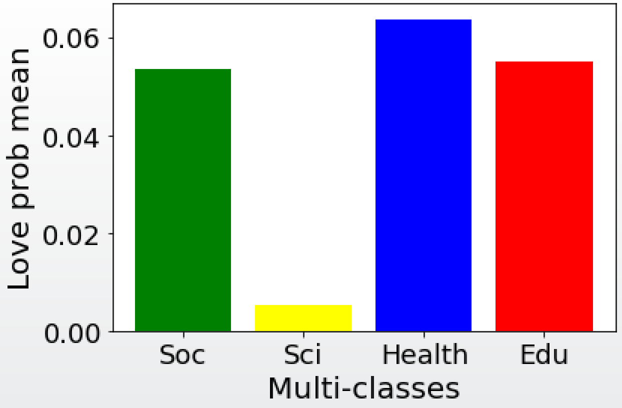


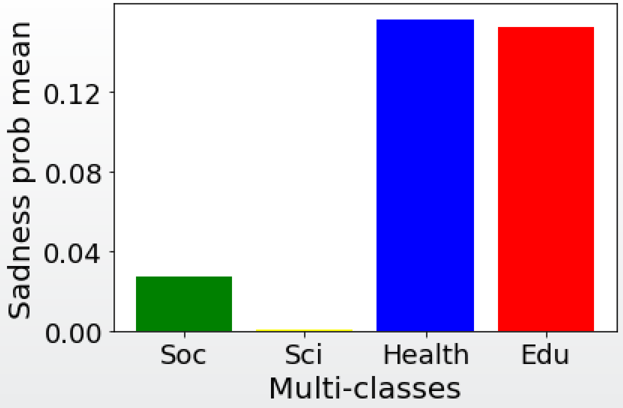
DEEPER ANALYSIS on Emotion Dataset

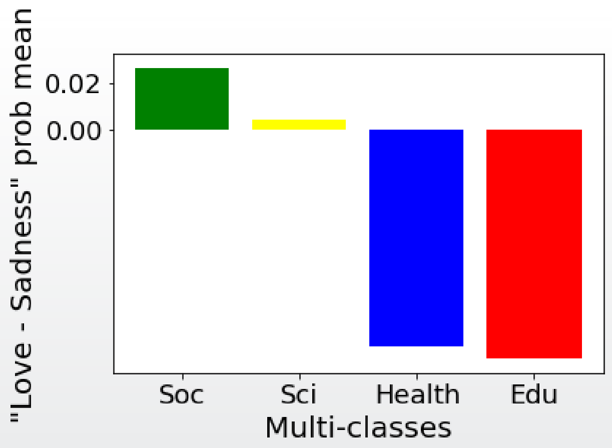
- The Aspect based Sentiment Analysis presented in the previous slide is based on two-step classification: one that finds the true positive emotions with F1=45, and the other that guesses topics.
- However, we can also perform one zero-shot classification at once on topics and emotions in parallel.
- From the histogram we can see that topics probabilities are the same as in the case of the two-step classifier, while emotions probabilities are slightly different due to the fact that here we report both positive and negative cases.
- Again we can note that the model well predicts the topics Health, above all others, and that negative emotions are more frequent than positive ones.



DEEPER ANALYSIS on Emotion Dataset





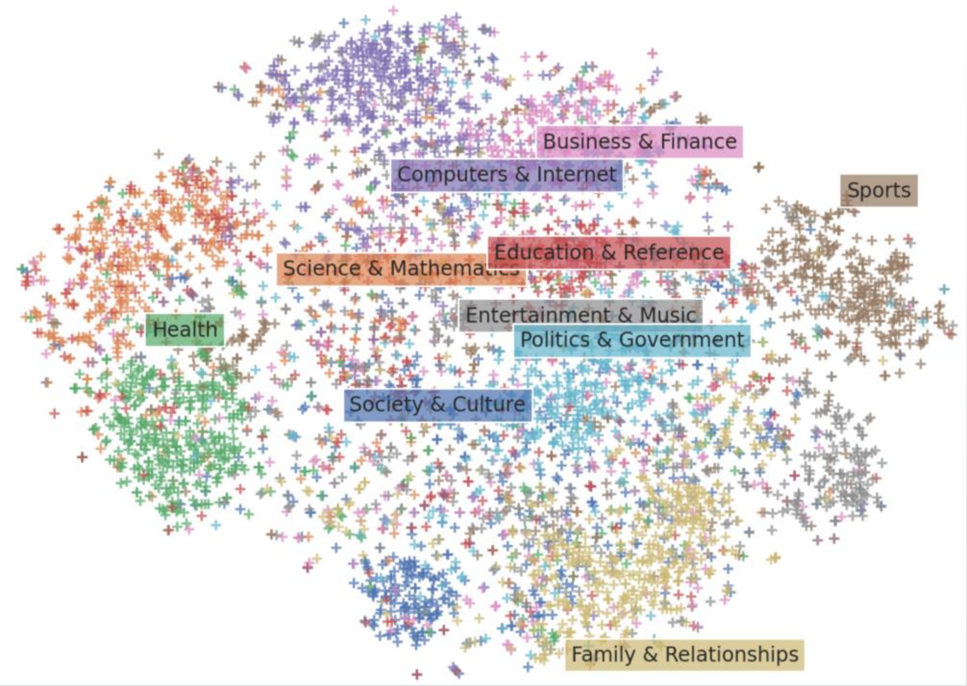


- The histograms above show a zoom of the one-step Zero-shot classifier on two different emotions candidates, namely love and sadness, where examples have been chosen to be positive on the 4 topics candidates.

- In particular, the third histogram reports the subtraction between love and sadness probabilities, showing that Society topics are more positive than Health and Education, as already seen in the two-step classification.

FEATURE WORKS :VISUALIZE EMBEDDINGS

- For further assessing the model performance, we can visualize examples embeddings trained by the BART-large M-NLI model and reduced into 2D vectors via the t-SNE algorithm.
- As shown in the blog of [Joe Davison]() (see graph on the right on Yahoo answers dataset), visualizing embeddings is informative of the distance between true labels and example embeddings.



SBERT to Wordvec projection embeddings of Yahoo dataset

IMPLEMENTATION – Decentralized Inference

- The model here presented has been implemented to serve with the local dataset of our client. The latter can be directly inferred via the zero-shot classification pipeline offered by Hugging Face.
- The local dataset needs to be treated for pre-tokenization, similarly to the public datasets shown in this presentation.
- As the model only needs the inference phase, installation has been decentralized and carried out by using the low-computational power resources of our client.
- The model is then available at the client site to infer into future marketing trends.

HYPOTHESIS RESULTS :

- Thanks to the use of deep learning-based models, Aspect based Sentiment Analysis has been performed with higher metrics scores, F1= 40 and 45 on the topics and emotion datasets, than lexicon-based and machine learning-based models*.
- Zero-shot classification with a BART pretrained model enables low computing power thanks to the direct classification inference and compensates for insufficient training examples thanks to the use of a model pretrained on large dataset such us BART-large and M-NLI, respectively.
- With the detection inference delegated to low-computational power resources, we avoid the bottle-neck of uploading data to the server.
- For faster time inference (about three times) but similar F1 score, we recommend a different architecture based on sentence-based BERT and Graph embeddings**.

*Seo et al. IEEE Express 2020, Yin et al. arXiv:1909.00161. 2019

**Chen, Q., et al. *IEEE Int of Things Journal (2021).*