Aspect-Invariant Sentiment Features Learning: Adversarial Multi-task Learning for Aspect-Based Sentiment Analysis

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Article Details

Title: Aspect-Invariant Sentiment Features Learning: Adversarial Multi-task Learning for Aspect-Based Sentiment Analysis

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Context

Aspect-Based Sentiment:

- Consists of an aspect, and a sentiment which is either positive or negative in connotation, depending on the aspect
- Example: “The movie’s action was fast-paced.”
  - Aspect is “action”
  - Sentiment is “fast-paced”
  - The key here is that “fast-paced” is not inherently negative or positive. It could be negative in another context, such as: “The book’s plot was too fast-paced.”

Aspect-Invariant Sentiment:

- Consists of an aspect and a directly positive or negative sentiment
- Example: “Mom’s cooking is good.”
- The sentiment, “good,” has a positive connotation in almost all contexts

The Main Idea

- Synthetic data samples for less common data instances (mostly aspect-invariant)
- Adversarial multi-task learning framework (AMTLF) consisting of:
  - Aspect Discrimination
  - Synthetic Sample Discrimination
  - Sentiment Discrimination
  - Aspect-Based Sentiment Prediction
- Can be integrated into pre-existing Aspect-Based Sentiment Analysis (ABSA) models and improve their performance

Synthetic Cross-Aspect Sample Generation

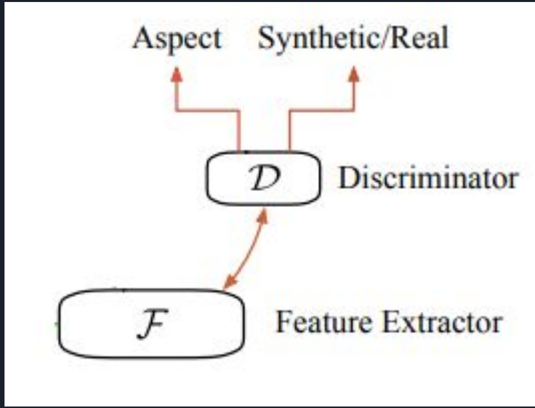
Swaps the aspects in data instances with others of the same “genre”

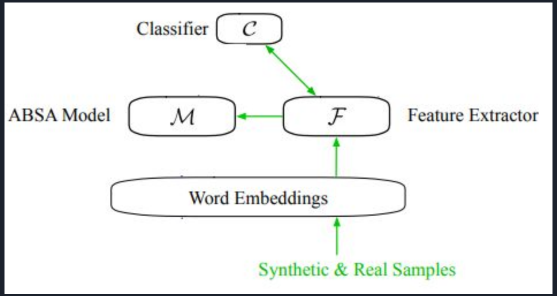
Creates data instances to populate areas of low density within the dataset

Improves performance of pre-existing ABSA models as long as the data is not noise

AMTLF: Aspect, Sentiment, & Synthetic Sample Discrimination

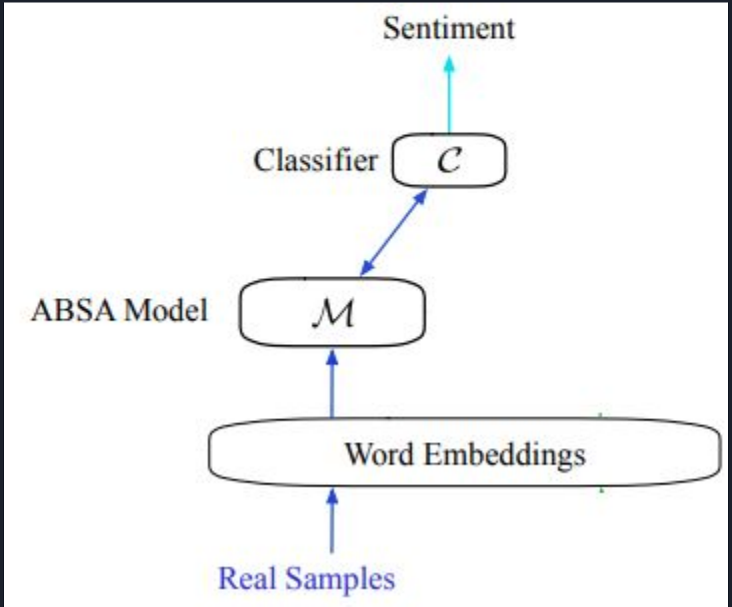
- Feature extractor takes a data instance as input
- Aspect-invariant sentiment features extracted and passed into classifier and discriminator; noise and aspect-dependent sentiments are separated
- Discriminator predicts two things:
  - The category of the aspect for that data instance
  - Whether the data instance is real or synthetic
- This is the A (Adversarial) in AMTLF:
  - The feature extractor learns to better extract aspect-invariant sentiment features while against the discriminator, which impedes that ability



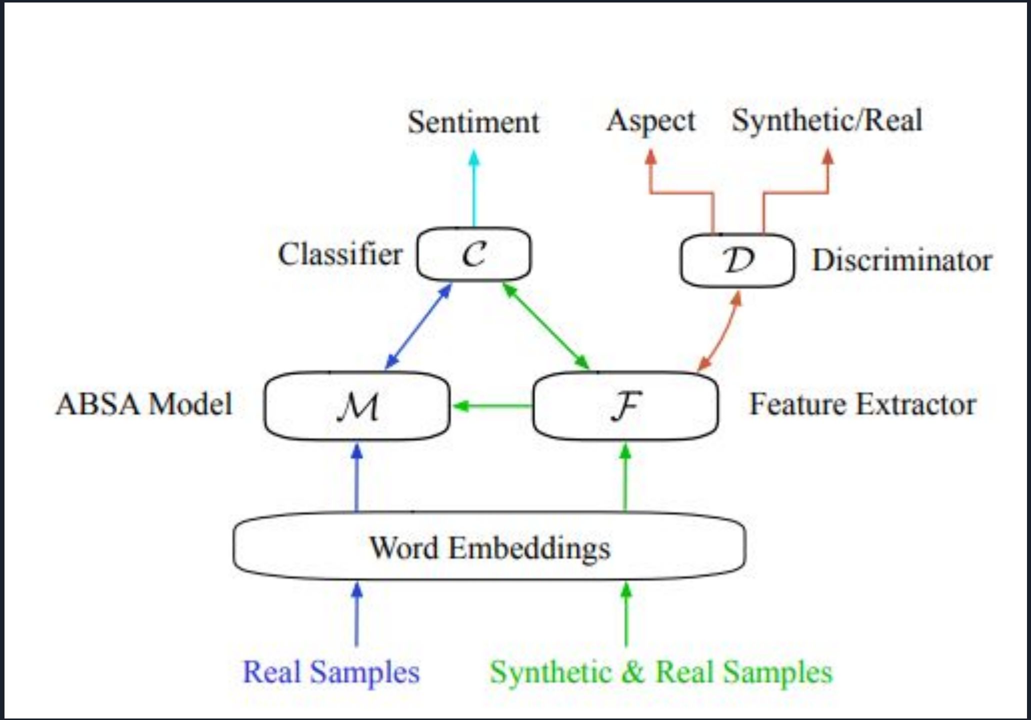


AMTLF: Aspect-Based Sentiment Prediction

- Simply a pre-trained ABSA model that the AMTLF is integrated into
- Learns to better handle aspect-invariant data, therefore increasing accuracy

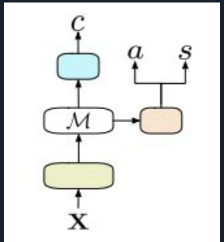


AMTLF: The Whole Picture

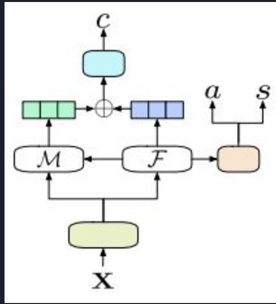


AMTLF: Three Possible Configurations

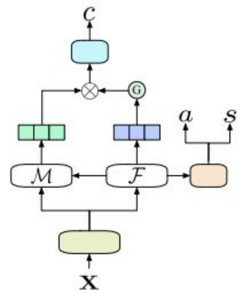
- Integration Structure (ISF)

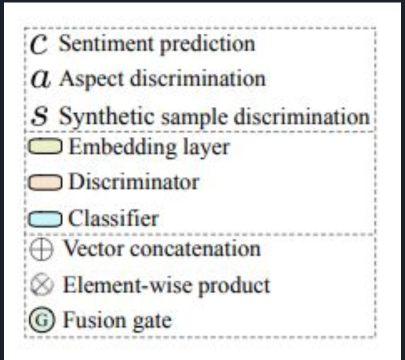


- Concatenation Structure (CSF)



- Gate Fusion Structure (GSF)





The Results

- ABSA, when used in conjunction with other state of the art models, improves performance
    - Ability to handle aspect-invariant data increases because of the synthetic cross-aspect data
- Every AMTLF configuration in conjunction with BERT performs better than baseline BERT model

BERT	82.41	64.35	88.60	73.62
ISF+BERT†	84.12	65.87	89.25	74.78
CSF+BERT†	84.62	66.53	91.29	75.57
GSF+BERT†	**85.04**	**67.98**	**91.73**	**76.12**

Comparison of BERT with datasets from Semeval 2015 (left) and Semeval 2016 (right)

Conclusion

Integrating one or more AMTLF configurations with our BERT model would significantly increase accuracy

The model will be able to handle aspect-invariant data better

It is easy to do because of the nature of the AMTLF configuration

Q&A?

Please ask any questions you might have!