Aspect-based Sentiment Analysis on Mobile Application Reviews

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Overview

- Introduction
- Methodology
- Experiments & Results
- Conclusion & Future Work

Introduction

Introduction : What is Requirement Elicitation

- Requirement Elicitation is the practice of understanding and capturing the business domain knowledge, stakeholder goals, and user needs.
- It is a critical activity in the Requirement Engineering (RE) process, and it plays a significant role in the overall quality of the RE outcome [1].
- Crowd-generated content (e.g. apps reviews) is an essential source of knowledge that can be utilized to create a customer-centric experience.
- Utilizing apps reviews instead of traditional approaches (e.g. surveys or interviews) brings huge benefits and enhancement to the requirement elicitation activity.

[1] D. Zowghi and C. Coulin, “Requirements elicitation: A survey of techniques, approaches, and tools,” in Engineering and managing software requirements. Springer, 2005, pp. 19–46

Introduction : Importance of user feedback

- User involvement is a major contributor to success of software projects [2].
- User comments can be used to improve user satisfaction of software products [5].
- Feedback typically contains multiple topics related to the application, such as user experience issues, bug reports, and feature requests [3] [4].
- Feedback content has an impact on download numbers of the application [4].
- Majority of low star rating feedback usually contains shortcomings and bug reports of the application, where as four to five star ratings mainly consist of praise and feature requests [4].

[2] M. Bano and D. Zowghi, “A systematic review on the relationship between user involvement and system success,” Information and Software Technology, vol. 58, 06 2014.
[3] D. Pagano and B. Bruegge, “User involvement in software evolution practice: A case study,” 05 2013.
[4] D. Pagano and W. Maalej, “User feedback in the appstore: An empirical study,” 07 2013.
[5] H. Li, L. Zhang, L. Zhang, and J. Shen, “A user satisfaction analysis approach for software evolution,” 2010 IEEE International Conference on Progress in Informatics and Computing, vol. 2, pp. 1093–1097, 2010.

Introduction : Why ABSA

“UI is awesome and easy to use but applications drains the battery faster.”

- Having the aspect information along with their respective sentiment leads to a fine-grained analysis [6].
- To support such analysis, we can utilize Aspect-Based Sentiment Analysis (ABSA) [7], which identifies the sentiment with respect to a specific aspect.
- Work done by N. Alturaief [8] et al is the first study that investigated the applicability of supervised ABSA to incorporate user feedback into requirement elicitation process.

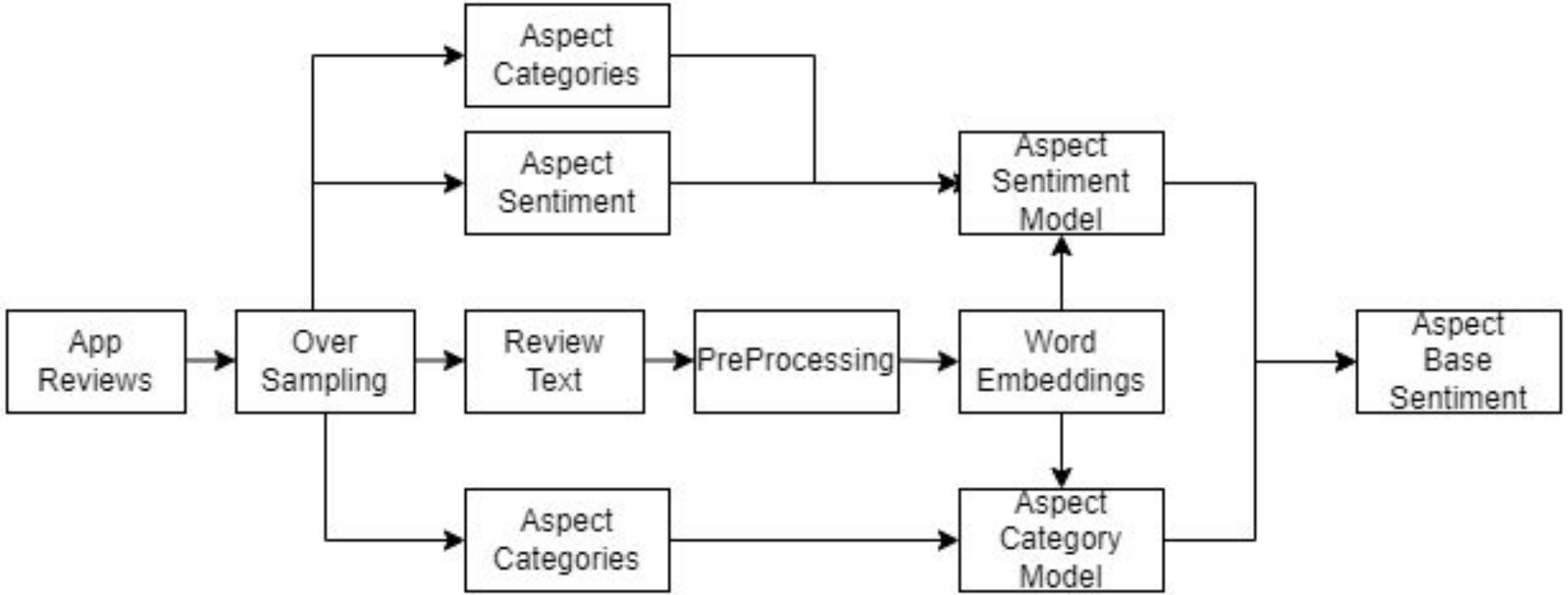
ABSA consists of three sub-tasks:

- Aspect category classification
- Aspect term extraction
- Aspect sentiment analysis.

[6] Y. Li, B. Jia, Y. Guo, and X. Chen, “Mining user reviews for mobile app comparisons,” Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 1, no. 3, pp. 1–15, 017.
[7] M. Hu and B. Liu, “Mining and summarizing customer reviews,” in Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, 2004, pp. 168–177.
[8] N. Alturaief, H. Aljamaan and M. Baslyman, ”AWARE: Aspect-Based Sentiment Analysis Dataset of Apps Reviews for Requirements Elicitation,” 2021 36th IEEE/ACM International Conference on Automated Software Engineering Workshops (ASEW), 2021, pp. 211-218, doi: 10.1109/ASEW52652.2021.00049

Methodology

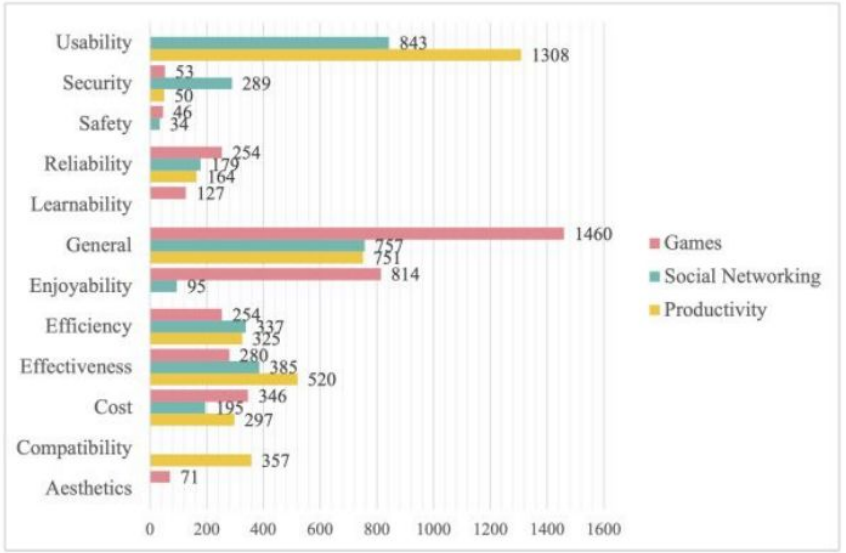
Methodology : Proposed Approach Overview



Methodology : Dataset [8]

- **AWARE** is benchmark dataset of **11,323** apps reviews that are annotated with aspect terms, categories, and sentiment.

- It contains reviews that were collected from three domains: **productivity**, **social networking**, and **games**.
- The data set contains two aspect definitions
  - **Aspect Term**: A term describing an aspect of an app that is expressed by the sentiment and that exists in the sentence.
  - **Aspect Category**: A predefined set of domain-specific categories.



[8] N. Alturaief, H. Aljamaan and M. Baslyman, "AWARE: Aspect-Based Sentiment Analysis Dataset of Apps Reviews for Requirements Elicitation," 2021 36th IEEE/ACM International Conference on Automated Software Engineering Workshops (ASEW), 2021, pp. 211-218, doi: 10.1109/ASEW52652.2021.00049

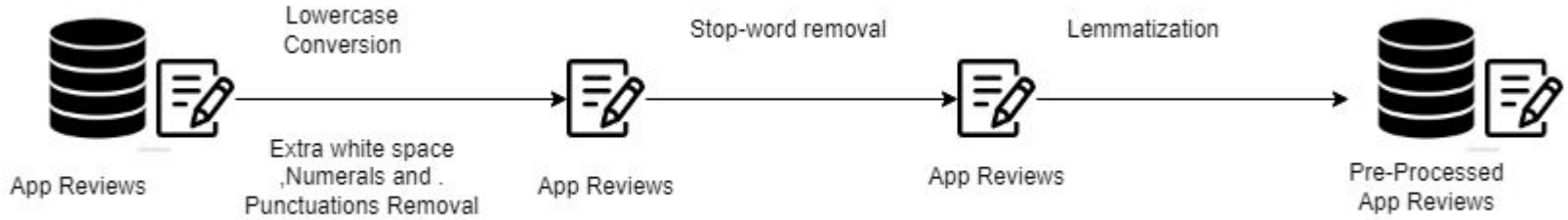
Methodology : OverSampling the Data

- Contextual augmentation by **Google Bert** [9].
  - Contextual words embeddings assigns each words a representation based on its context. We used substitute actions for augmenting data. In substitute, length of sentence is same but some words are replaced. We utilized the NLPAug [10] open source python package for data augmentation.

- Data Augmentation by Round-trip translation (**RTT**).
  - Round-trip translation (RTT) is additionally referred to as recursive, back-and forth, and bi-directional translation. it's the method of translating a word, phrase or text into another language (forward translation), then translating the results back to the first language (back translation) .RTT is used as augmentation technique to extend the training data. We used Roundtrip translation python package[11] to augment data.

[9] Kobayashi, Sosuke. (2018). Contextual Augmentation: Data Augmentation by Words with Paradigmatic Relations. 452-457. 10.18653/v1/N18-2072.
[10] https://github.com/samhavens/roundtrip.
[11] https://github.com/makcedward/nlpaug

Methodology : Preprocessing

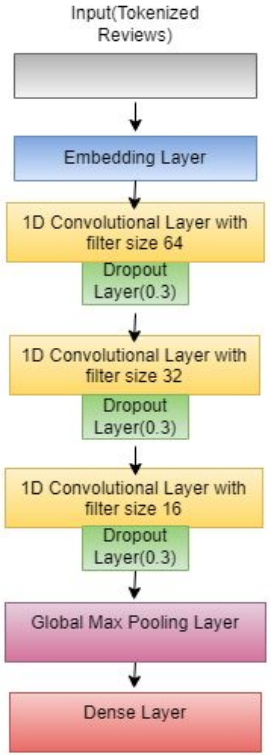


Methodology : Embeddings

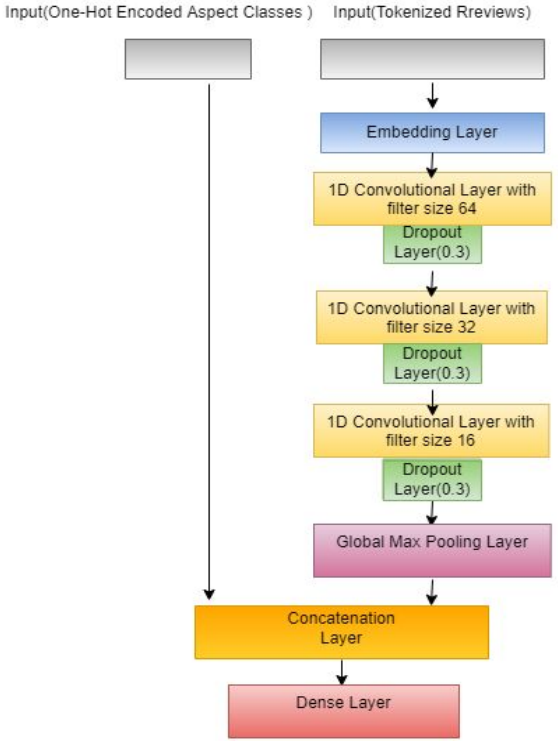
Pre-trained Models:

- FastText : Wiki-news model, with 1 million word vectors and 300 dimensions, trained on Wikipedia 2017, UMBC web based corpus and statmt.org news dataset
- Glove : Pre-trained model, trained trained on Wikipedia data with 6 billion tokens, 100 dimensions and a 400,000-word vocabulary.
- Word2Vec: Google word2vec model, trained on Google news data (about 100 billion words); it contains 3 million words and phrases and was fit using 300-dimensional word vectors.

Methodology : Feature extraction and classification



(a) Aspect Category Classification Model



(b) Aspect Sentiment Classification Model

Experiments & Results

Experiments & Results: Aspect Category Classification

Dataset	Word Embedding	Preprocessing	BERT	RTT(DE)	RTT(CN)	RTT(TR)	RTT(JP)
Productivity	Fasttext	Disabled	0.60	0.59	0.25	0.61	0.60
		Enabled	0.63	0.61	0.23	0.62	0.59
	Word2Vec	Disabled	0.61	0.62	0.24	0.61	0.61
		Enabled	0.62	0.62	0.26	0.61	0.60
	Glove	Disabled	0.54	0.53	0.24	0.52	0.55
		Enabled	0.56	0.57	0.25	0.58	0.58
Gaming	Fasttext	Disabled	0.42	0.45	0.19	0.35	0.43
		Enabled	0.40	0.39	0.22	0.28	0.45
	Word2Vec	Disabled	0.42	0.41	0.23	0.37	0.44
		Enabled	0.39	0.42	0.21	0.37	0.44
	Glove	Disabled	0.42	0.44	0.20	0.34	0.42
		Enabled	0.30	0.30	0.21	0.24	0.31
Social	Fasttext	Disabled	0.62	0.62	0.58	0.25	0.60
		Enabled	0.60	0.61	0.58	0.27	0.60
	Word2Vec	Disabled	0.60	0.62	0.61	0.29	0.61
		Enabled	0.58	0.62	0.61	0.28	0.61
	Glove	Disabled	0.54	0.56	0.54	0.27	0.55
		Enabled	0.54	0.55	0.55	0.26	0.57
Average	Fasttext	Disabled	0.55	0.56	0.34	0.41	0.55
		Enabled	0.55	0.54	0.35	0.39	0.55
	Word2Vec	Disabled	0.55	0.55	0.36	0.43	0.56
		Enabled	0.53	0.56	0.36	0.42	0.55
	Glove	Disabled	0.50	0.51	0.33	0.38	0.51
		Enabled	0.47	0.48	0.34	0.36	0.49

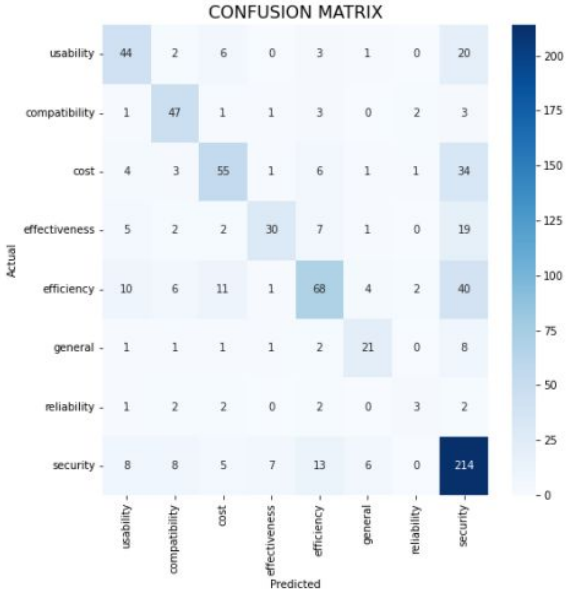
Experiments & Results: Aspect Sentiment Classification

Dataset	Word Embedding	Preprocessing	BERT	RTT(DE)	RTT(CN)	RTT(TR)	RTT(JP)
Productivity	Fasttext	Disabled	0.81	0.81	0.62	0.80	0.78
		Enabled	0.79	0.79	0.63	0.81	0.81
	Word2Vec	Disabled	0.80	0.80	0.62	0.82	0.80
		Enabled	0.79	0.79	0.64	0.82	0.81
	Glove	Disabled	0.80	0.79	0.61	0.79	0.81
		Enabled	0.79	0.80	0.62	0.80	0.77
Gaming	Fasttext	Disabled	0.70	0.71	0.68	0.65	0.70
		Enabled	0.71	0.70	0.68	0.65	0.71
	Word2Vec	Disabled	0.70	0.70	0.67	0.64	0.70
		Enabled	0.72	0.69	0.68	0.66	0.70
	Glove	Disabled	0.71	0.72	0.70	0.65	0.70
		Enabled	0.70	0.69	0.69	0.65	0.70
Social	Fasttext	Disabled	0.83	0.80	0.81	0.63	0.83
		Enabled	0.82	0.83	0.81	0.62	0.82
	Word2Vec	Disabled	0.81	0.86	0.81	0.64	0.80
		Enabled	0.82	0.86	0.82	0.64	0.83
	Glove	Disabled	0.82	0.84	0.82	0.64	0.81
		Enabled	0.79	0.85	0.82	0.63	0.81
Average	Fasttext	Disabled	0.78	0.78	0.71	0.70	0.77
		Enabled	0.78	0.78	0.71	0.70	0.78
	Word2Vec	Disabled	0.77	0.79	0.70	0.70	0.77
		Enabled	0.78	0.78	0.72	0.71	0.78
	Glove	Disabled	0.78	0.79	0.71	0.70	0.78
		Enabled	0.76	0.78	0.71	0.70	0.76

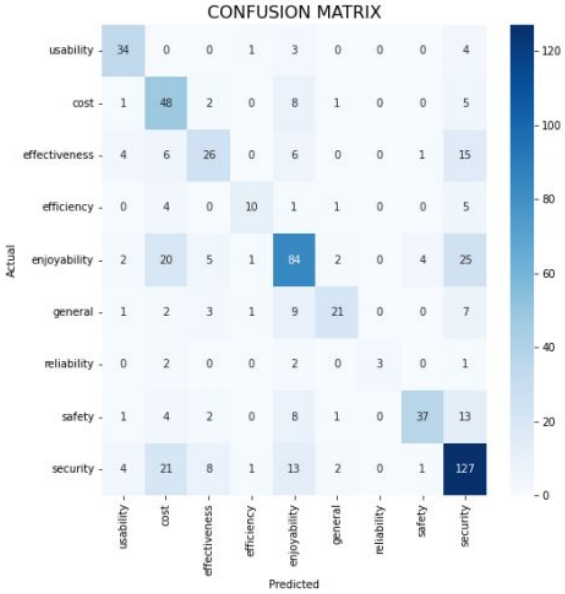
Experiments & Results: Summery

Task		Baseline	Results	Metric
Aspect Category Classification	Productivity	0.33	0.62	F1
	Social Networking	0.32	0.62	F1
	Games	0.32	0.42	F1
Aspect Sentiment Classification	Productivity	68.71%	80%	Acc.
	Social Networking	69.72%	86%	Acc.
	Games	67.49%	70%	Acc.

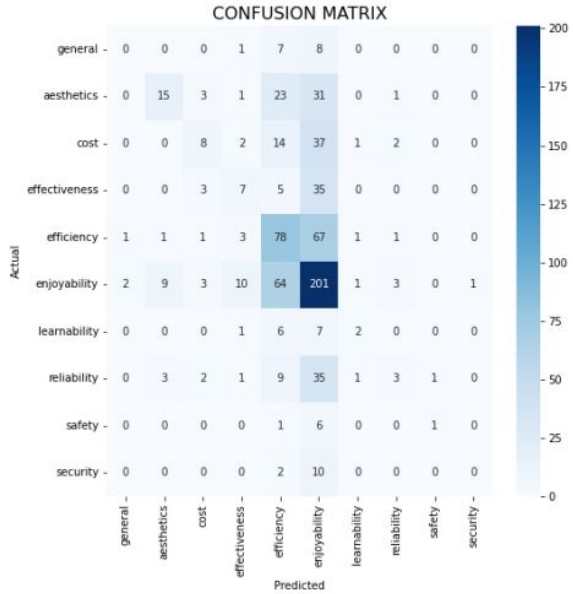
Experiments & Results: Error Analysis



(a) Productivity



(b) Social Networking



(c) Game

Conclusion & Future Work

Conclusion & Future Work

- The results showed that our approach could archive F1 scores of **0.62**, **0.42**, and **0.62** in the aspect category classification task, and accuracy of **0.80**, **0.70**, and **0.86** for the aspect sentiment classification task in **Productivity**, **Game**, and **Social Networking** domains respectively.
- As a future work we intend to investigate the possibility of using transformer based models to improve the results further.

Thank You

Q & A