ASPECT-BASED SENTIMENT ANALYSIS OF REVIEWS FOR REQUIREMENTS ELICITATION

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Content

Introduction

- **Definition of Sentiment Analysis**: Sentiment analysis is the process of detecting positive or negative sentiments in text. It's often used by businesses to detect sentiment in social data, gauge brand reputation, and understand customers.

- **Applications of Sentiment Analysis:**
  - Sentiment Analysis in Business: Understanding customer sentiments through product reviews and feedback for product development and marketing strategies [3].
  - Technological Advancements and Public Opinion Research: Advances in NLP and machine learning enhancing sentiment analysis for brand reputation and public policy informatics [4].
  - Marketing and Social Media Monitoring: Tracking public opinion and customer feedback for strategic marketing insights [5].
  - Customer Service Improvement: Analyzing feedback and interactions to improve customer satisfaction [6].
  - Applications in Software Development: Using sentiment analysis in software reviews for feature enhancements and user satisfaction [7].

- **Limitations and Scope**: Challenges in capturing nuances of emotions and cultural context affecting accuracy [8].

Research Problem

- Disparity in Model Performances: Variance in performance across datasets, particularly in classifying implicit aspect terms.
- Need for Robust Models: Essential for models to perform well in both explicit and implicit sentiment expressions in various contexts.
- Research Gaps in ABSC Models: Inconsistencies in performance metrics like F1 scores, with some models showing incomplete data across datasets.
- Transfer Learning and Fine-Tuned BERT Models: High effectiveness in specific domains but potential lack of generalizability.
- Neglect of Implicit Aspects in Current Models: Current models overlook a significant portion of data containing implicit aspects.
- Direction for Future Research: Emphasis on developing models for implicit sentiment understanding and broader dataset evaluations.

Research Objectives

1. Build a strong benchmark algorithm for sentiment analysis to extract detailed insights from diverse reviews.

2. Generate a large data set with sentiment annotations for training and evaluating different sentiment analysis techniques.

3. Introduce advanced methods/models for efficient extraction of aspect-based sentiments from various reviews, improving app development requirements elicitation processes

Literature Survey

Traditional Methods of Aspect-Based Sentiment Analysis

LEXICON-BASED METHODS

- These methods use a set list of words with assigned sentiment values to calculate the overall sentiment of a text. While straightforward, they often struggle with context-sensitive expressions and idiomatic language [9].

TRADITIONAL MACHINE LEARNING

- Involving training on annotated datasets, these methods use algorithms like SVM, Random Forests, or KNN for sentiment classification. Their effectiveness heavily depends on the training data's quality and representativeness [8].

Literature Survey

Existing Models and Their Performance in ABSA.

Model/Approach	Year	Key Features	Methodology	Aspect Extraction	Sentiment Classification	Data Requirement	Advantages	Limitations	Application Examples	Performance Metrics	Reference
SpanMlt	2020	Multi-task learning framework	Span-based approach	Extracts pairs of aspect and opinion terms	Will alternatively use BERT and BiLSTM	Requires annotated data for training	Effective in capturing relationships between aspect and opinion terms	Limited to pair-wise extraction	Aspect-opinion pair extraction	F1 scores	[4, 18]
Hierarchical Graph Convolutional Network	2020	Graph-based neural network	Uses GCNs for sentiment analysis	Categorizes aspects	Performed using GCNs	Graph-structured data	Captures complex relationships	Computationally intensive	Product reviews	Precision, Recall, Micro-F1 score	[9]
RoBERTa-based baseline	2021	Syntax awareness	Fine-tuning RoBERTa	Implicit in model	Enhanced by syntactical understanding	Pre-trained RoBERTa model, annotated data	Improves accuracy by understanding syntax	Dependency on pre-trained models	Various text analysis	Accuracy and Macro-F1	[8]
Various approaches (Survey)	2021	Overview of NLP in low-resource languages	Survey of various methods	Not the main focus	Not the main focus	Varies by method	Provides insight into handling low-resource scenarios	More general, less specific to ABSA	NLP in low-resource scenarios	NA	[10]
Fine-tuned BERT	2021	Transfer learning with BERT	Fine-tuning pre-trained BERT	Transfer learning with BERT	Enhanced by BERT's capabilities	Pre-trained BERT model, annotated data	Leverages BERT's powerful language understanding	Relies heavily on BERT's pre-training	Various text classification tasks	precision, recall, F1-score, and accuracy	[7]
Improved multi-label method	2023	Classification of emotions in short texts	Multi-label classification technique	does not explicitly focus on aspect extraction	Focuses on emotion classification	Annotated short text data	Effective for short texts	Limited to emotion classification, not general sentiment analysis	Social media analysis	Subset Accuracy (SA), Hamming Loss (HL), One-Error (OE), Ranking Loss (RL), Average Precision (AVP), Accuracy (AC), Precision (PR), Recall (RE), F-score	[21]
NLP Transformers and Emotion Ontology	2021	Emotion detection for social robots	Combination of NLP transformers and emotion ontology	Focused on emotion detection rather than aspect extraction	Focused on emotion detection	Requires ontology and transformer model data	Suited for robotic applications	Specific to emotion detection, not general sentiment analysis	Human-robot interaction	Micro F1 Score, Macro F1 Score, Precision, Recall(Micro), Accuracy, Jaccard Index	[14]
Hybrid Ontology-XLNet	2021	Classification of ADRs	Hybrid approach using Ontology and XLNet	Sentence-level	Focuses on ADR classification	Annotated data for ADRs, pre-trained XLNet	Effective in healthcare applications	Tailored for ADR classification	Healthcare, pharmacovigilance	Evaluation Metrics: Accuracy, Recall (Sensitivity), Precision, F-measure, Hamming Loss, AUC Score	[12]
BERT with Auxiliary Sentence and Domain Knowledge	2019	Incorporation of auxiliary sentences and domain knowledge	Extension of BERT model	does not focus on aspect extraction specifically	Enhanced with additional context	BERT model, domain-specific data	Improves context understanding	Requires additional domain knowledge	Various domain-specific text classification	Accuracy, Macro F1, and Precision	[20]
Span-Level Interaction Model	2021	Extraction of aspect sentiment triplets	Span-level analysis	Identifies aspects and related sentiments	Extracts sentiment related to each aspect	Annotated data for triplets	Detailed sentiment analysis	Complexity in triplet extraction	Detailed text analysis	precision, recall, F1-score	[13]

Literature Survey

Results of Existing Models

SPANMLT

Model	14lap AT	14lap OT	14lap Pair	14res AT	14res OT	14res Pair	15res AT	15res OT	15res Pair
BERT+BiLSTM+CRF	56.99	51.33	-	54.08	51.53	-	55.85	47.79	-
RCNN	74.92	67.21	-	75.18	67.95	-	74.54	64.5	-
CMLA	75.57	66.27	-	76.08	66.32	-	78.41	60.15	-
RNSCN	73.71	75.89	-	82.12	81.67	-	71.02	69.78	-
HAST-TOWE (pipeline)	79.14	67.5	53.41	82.56	75.1	62.39	79.84	68.45	58.12
JERE-MHS	74.61	64.02	52.34	79.79	77.44	66.02	75	71.38	59.64
SpanMlt (theirs)	84.51	80.61	68.66	87.42	83.98	76	81.76	78.91	64.68
RNCRF	78.42	79.44	-	84.93	84.11	-	67.47	67.62	-
CMLA	77.8	80.17	-	85.29	83.18	-	70.73	73.68	-
GMTCMLA	78.69	79.89	-	84.5	85.2	-	70.53	72.78	-
SpanMlt	77.87	80.51	-	85.24	85.79	-	71.07	75.02	-
SpanMlt-BERT-base	80.41	78.12	62.88	84.46	84.07	72.06	75.12	78.14	60.48
SpanMlt-BERT-finetune	80.78	79.51	65.45	84.06	84.11	72.72	77.14	76.47	61.06
SpanMlt-BiLSTM	81.3	77.58	64.71	83.22	83.42	73.87	70.77	78.48	59.92
SpanMlt-BiLSTM	78.69	76.83	62.88	82.55	81.22	71.9	74.18	75.12	59.21
SpanMlt-BiLSTM-ELMo	84.51	80.61	68.66	87.42	83.98	75.6	81.76	78.91	64.68
SpanMlt-BiLSTM - char embeddings	75.22	71.09	56.2	76.06	78.9	64.2	79.01	74.41	59.06

Table 1

- The SpanMlt method, as presented in the provided table, demonstrates superior performance in aspect term (AT) and opinion term (OT) extraction across several datasets.
- SpanMlt achieving the highest F1-scores, notably outperforming other models like BiLSTM+CRF, BERT+CRF, and more
- SpanMlt delivering competitive results highlights its robust performance with different base encoders, where SpanMlt-BiLSTM-ELMo outperforms others.

HIER-TRANSFORMER-BERT AND HIER-GCN-BERT

Method	Restaurant-16			Laptop-16			Restaurant-15			Laptop-15		
	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1
Cartesian-BERT	74.96	63.84	68.94	64.99	27.40	39.54	72.02	49.15	58.42	73.06	21.18	32.83
Pipeline-BERT	43.62	79.06	56.21	31.92	51.56	39.42	38.12	70.00	49.35	36.91	51.62	43.02
AddOneDim-LSTM	61.56	42.82	50.50	-	-	-	54.33	28.44	37.32	-	-	-
AddOneDim-BERT	71.75	67.95	69.79	58.83	39.49	47.23	68.84	55.86	61.67	64.17	39.57	48.94
Hier-BERT	70.97	69.65	70.30	59.51	41.93	49.19	67.46	57.98	62.36	65.47	41.26	50.61
Hier-Transformer-BERT	73.72	73.21	73.45	58.06	48.29	52.72	70.22	59.96	64.67	65.63	51.95	57.79
Hier-GCN-BERT	76.37	72.83	74.55	61.43	48.42	54.15	71.93	58.03	64.23	71.90	54.73	62.13

Table 2

- Results show that Hier-Transformer-BERT is efficient but performs lower than Hier-GCN-BERT on three datasets and slightly better only on the Restaurant 2015 dataset.

	Restaurant-16	Laptop-16	Restaurant-15	Laptop-15
1 layer	71.80	47.02	60.69	49.27
2 layers	74.55	54.15	64.23	62.13
3 layers	72.75	54.01	63.18	60.21

Table 3

- The best performance is obtained when L = 2.
- Using more than 3 layers in GCN may incorporate too much node co-occurrence information, leading to non-discriminative representations.

Literature Survey

Results of Existing Models

SPAN-ASTE

Model	Datasets and Performance											
	Rest 14			Lap 14			Rest 15			Rest 16		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
CMLA+ (Wang et al., 2017)†	39.18	47.13	42.79	30.09	36.92	33.16	34.56	39.84	37.01	41.34	42.10	41.72
RINANTE+ (Dai and Song, 2019)†	41.29	39.38	34.95	21.71	18.66	20.07	29.88	30.06	29.97	25.68	22.30	23.87
Li-unified-R (Li et al., 2019)†	41.04	67.35	51.00	40.56	44.28	42.34	44.72	51.39	47.82	37.33	54.41	43.31
Peng et al. (2019)†	43.24	63.66	51.46	37.38	30.83	48.87	40.57	57.51	52.32	46.96	64.24	54.21
Zhang et al. (2020)*	62.70	53.66	57.91	49.62	41.07	44.78	55.63	42.51	47.94	60.95	53.35	56.82
GTS (Wu et al., 2020)*	66.13	57.91	61.73	53.35	40.99	46.31	60.10	46.89	52.66	63.28	58.86	60.79
JET^{TM} (Xu et al., 2020b)†	61.50	55.13	58.14	53.03	33.89	41.35	64.37	44.33	52.50	70.94	59.70	63.21
Span-ASTE	72.52	62.43	67.08	59.85	45.67	51.80	64.29	52.12	57.56	62.75	61.75	64.37
BERT GTS	74.93	79.15	76.98	65.47	62.54	63.97	66.55	65.66	66.10	69.66	76.74	73.03
BERT Span-ASTE	79.12	79.60	79.36	68.09	65.98	67.02	70.23	70.71	70.47	71.66	79.31	74.65
Multi-Word GTS	56.85	49.26	52.78	52.26	41.27	46.12	50.28	47.34	48.77	56.63	55.29	55.95
Multi-Word Span-ASTE	61.64	55.79	58.57	54.63	44.44	49.02	50.70	57.45	53.87	62.43	63.52	62.97

Table 4

- Using BiLSTM encoder with GloVe embedding, Span-ASTE significantly surpasses the best pipeline model
- Span-ASTE shows effective encoding of the interaction between target and opinion spans, reducing error propagation.
- The use of the BERT encoder enhances the performance of all three end-to-end models, with Span-ASTE showing the most improvement.

ROBERTA

Model	Fake News Dataset			English Tweet Dataset			Extremist-Non-Extremist Dataset		
	Accuracy	Precision	F1 score	Accuracy	Precision	F1 score	Accuracy	Precision	F1 score
BERT-base	99.56	97.21	97.53	98.44	98.42	98.43	99.71	98.82	98.33
BERT-large	99.31	99.07	95.89	98.44	98.45	98.43	99.71	98.82	98.33
RoBERTa-base	99.71	99.85	98.29	96.48	96.48	96.48	99.66	99.29	98.02
RoBERTa-large	99.66	98.78	98.04	97.00	96.97	97.00	99.36	98.56	96.24
DistilBERT	99.41	96.69	96.69	98.31	98.39	98.30	99.51	96.80	97.27
ALBERT-base-v2	98.68	90.83	92.94	97.78	97.75	97.78	98.97	94.80	94.12
XLM-RoBERTa-base	99.22	96.01	95.54	98.57	98.53	98.56	99.56	99.77	97.40
Electra-small	99.17	96.85	95.14	94.52	94.66	94.52	98.73	97.42	92.02
BART-large	99.31	99.07	95.89	98.83	98.85	98.82	99.56	98.22	97.48

Table 5

- It is found that trees induced from fine-tuned RoBERTa (FT-RoBERTa) yield the best results, outperforming other trees in accuracy.
- The fine-tuning process of RoBERTa in ALSC is shown to adapt the induced tree more effectively for the task, resulting in better modeling of connections between aspects and sentiment words

LiteratureSurvey

More about Results of other Existing Models

1. **BERT Fine-Tuning for Short Texts**: Analysis of BERT on short-text datasets revealed that lower learning rates improved results, and the maximum sequence length setting was crucial for model performance.
2. **BERT Fine-Tuning for Long Texts**: Similar to short texts, lower learning rates and specific sequence treatments also enhanced performance for long-text datasets.
3. **Hidden State Vector Selections in BERT**: Utilizing different hidden state vectors from BERT's last layer showed that the [CLS] token vector was most effective.
4. **Impact of Auxiliary Sentences**: Testing different auxiliary sentences indicated a significant improvement in multi-class datasets, but mixed results for binary datasets.
5. **BERT4TC Model Comparisons**: BERT4TC models, especially with auxiliary sentences, generally outperformed other models in multi-class datasets, demonstrating the effectiveness of these methods.
6. **Post-Training BERT**: Post-training BERT with domain-specific knowledge showed mixed results, underscoring the complexity of domain adaptation.
7. **Improved MLkNN Algorithms for Emotion Classification**: Studies on MLkNN algorithms, specifically L-MLkNN, exhibited better performance in emotion classification in short texts, like tweets, compared to basic MLkNN.
8. **XLNet Transfer Learning Results**: XLNet demonstrated higher accuracy and performance metrics compared to other models like Word2vec and BERT in various sentiment analysis tasks related to adverse drug reactions.

Literature Survey

Applications

1. Opinion Summarization and Product Profiling: ABSA is key for summarizing opinions and profiling products. It helps businesses understand detailed sentiments about product features, aiding in refining products and strategies [4].
2. Enhanced Text Classification: Using models like BERT, ABSA enhances text classification by framing it as a sentence-pair problem, improving performance across various natural language processing tasks [14].
3. Emotion Classification in Short Texts: Improved algorithms like L-MLkNN are used in ABSA to classify emotions in short texts, such as tweets, which helps in understanding sentiments expressed in social media effectively [12].
4. Feature Extraction: ABSA, combined with models like XLNet, is effective for feature extraction aiding in drug safety analysis with superior semantic understanding [13].
5. Sentiment Analysis in E-commerce and Social Media: ABSA is widely used on e-commerce platforms and social media for analyzing customer reviews and opinions, employing everything from traditional machine learning to advanced deep learning techniques to gauge customer sentiments towards products or services [29, 30].

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Future Directions

1. **Refining Models and Methodologies**: Enhancing the capabilities of ABSA models to better analyze and interpret sentiments across various languages and fields, employing larger datasets and more complex classification techniques [12].
2. **Cross-Domain and Multilingual Capabilities**: Advancing ABSA models to be effective across different languages and industries, integrating task-specific knowledge with advanced neural networks, such as those based on BERT [11][14].
3. **Integration with Advanced AI Technologies**: Combining ABSA with other AI innovations, including recommendation engines and chatbots, to improve the overall effectiveness and clarity of sentiment analysis [31][32].
4. **Adapting to New Challenges**: Developing models to tackle implicit aspect extraction and intricate sentiment analysis, focusing on the nuanced relationships between aspects and sentiments within text [7][30][33].

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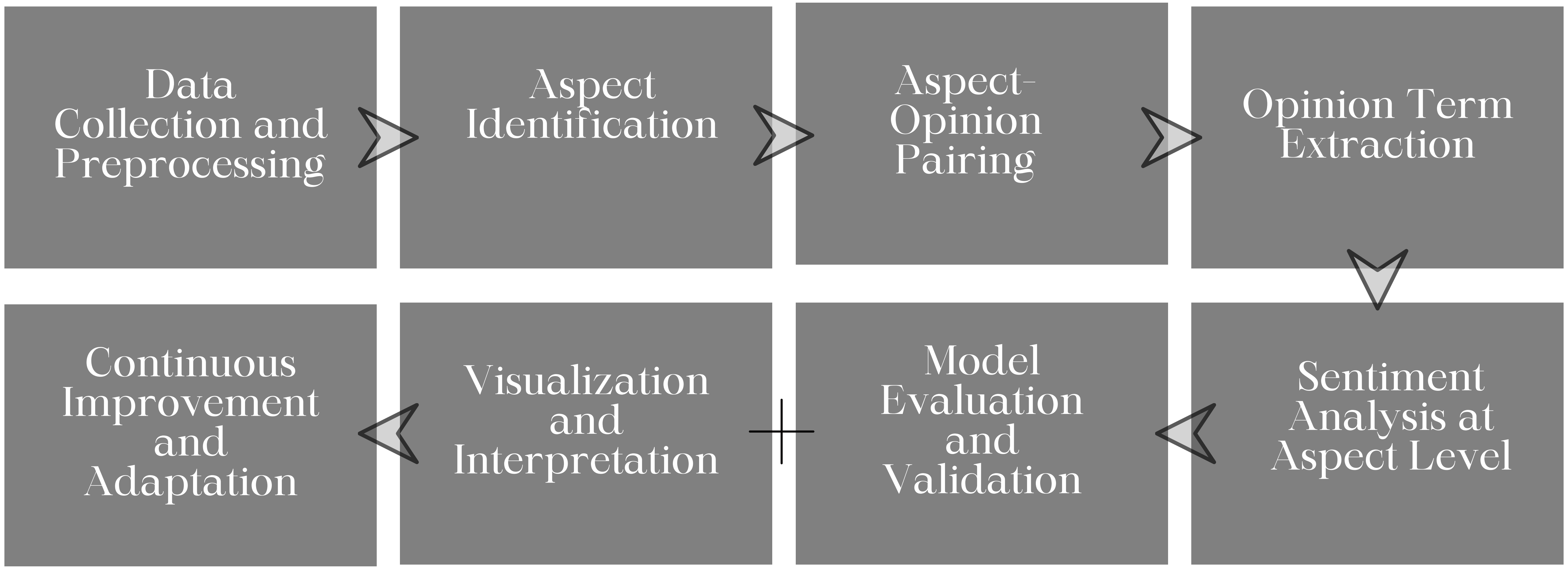
Challenges

1. **Data Representation and Algorithm Limitations**: Challenges arise due to traditional data representation methods that often miss the nuanced semantics of language, leading to algorithms that struggle with the complexities of natural language [13].
2. **Model Generalization and Data Scarcity**: Generalizing ABSA models across various languages and domains is difficult, compounded by the scarcity of labeled data, particularly for less common languages. This issue also includes the challenge of accurately capturing subtle sentiment variations [10][30][33].
3. **Aspect and Sentiment Relationship Mapping**: Identifying the semantic relationship between aspect terms and opinion words without specific domain knowledge, and improving the explainability of ABSA methods, remains a challenge [30][32].
4. **Handling Multiple Aspects and Sentiments**: ABSA faces difficulties when processing sentences that contain multiple aspects with varying sentiments. The limitation of existing datasets to simpler scenarios restricts ABSA's effectiveness in more complex contexts [33].

Datasets for ABSA

Dataset	Discription
SemEval-2016	The dataset includes 19 training and 20 testing datasets across 8 languages and 7 domains. 25 datasetsfor sentence-level and 14 for text-level Aspect-Based Sentiment Analysis(ABSA)
Twitter Streaming API	It proposes a framework for analyzing terrorism-related content on social media, particularly Twitter
Tweets with Keywords for AdaRNN	The dataset is balanced with negative, neutral, and positive sentiments, comprising 6248 training and 692 testing tweets.
ASTE-Data-V2	The datasets contain various sentences with tagged aspects, sentiments, and opinions. The datasets are refined versions of those created by Dai et al. [10], called ASTE-Data-V2, and include restaurant and laptop domain data from SemEval tasks.

Proposed Method



Datasets for the Research

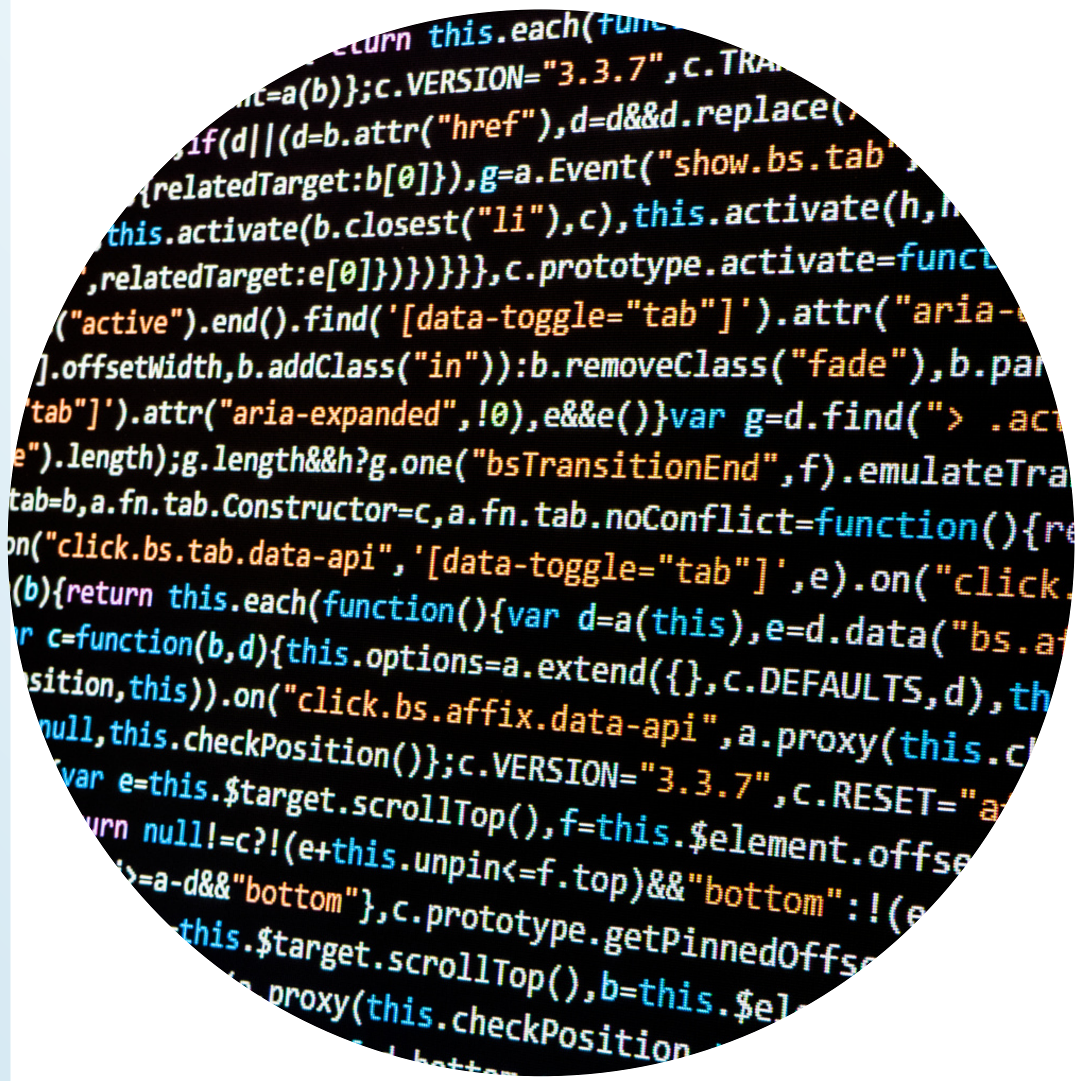
1. **Dataset Creation:**
   - Generate a new dataset using web data from popular applications (e.g., social media, e-commerce).
   - Utilize datasets with reviews, employing technologies such as GPTs and other modern tools to match with specified requirements.
2. **Data Processing:**
   - Convert collected data into a usable format.
   - Tasks may include data entry, coding, transcription, and cleaning for inconsistencies or missing values.
3. **Analysis Planning:**
   - Develop a comprehensive plan for data analysis.
   - Ensure alignment with research questions and objectives.
4. **Documentation:**
   - Maintain detailed records throughout the dataset creation process.
   - Document methodology, data collection, processing steps, and any challenges faced.
   - Enhance transparency and reproducibility of the research.

Conclusion

Aspect-Based Sentiment Analysis (ABSA) is a fascinating and rapidly evolving field within Natural Language Processing (NLP) that focuses on the fine-grained analysis of opinions and sentiments expressed in text.

Key Takeaways from Our Exploration of ABSA

- Diversity of ABSA Models: ABSA utilizes various models like BERT, RoBERTa, and DistilBERT each with unique strengths, showcasing the robustness of the field.
- The Power of Fine-Tuning: Fine-tuning pre-trained models for specific tasks and domains significantly enhances ABSA model performance, achieving higher accuracy and relevance.
- Ethical Considerations in ABSA: With increasing sophistication, it's crucial to ensure that ABSA models are unbiased, respectful, and ethically aligned.
- Multi-Label Classification and Emotion Detection: ABSA's capabilities extend to multi-label classification and emotion detection, allowing for more complex sentiment analysis and categorization.
- Performance Metrics for Assessment: Evaluating ABSA models using metrics like accuracy, precision, recall, and F1 score is essential to assess effectiveness and consider generalizability and computational efficiency.



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Thank you!