



Integrating Latent Aspect Modelling with Gated Attention LSTM for Suggestion Summarization

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Abstract : User-generated reviews and feedback often contain actionable suggestions that can drive product improvements. In this paper, we present an aspect-based suggestion summarization framework that leverages a Gated Attention LSTM to learn latent suggestion aspects without the need for predefined categories. Our model computes pairwise aspect Matching to cluster suggestions and uses an extractive summarization strategy that balances semantic relevance with aspect diversity. We conduct extensive experiments on the OPOSUM dataset and a Suggestion Reviews dataset, provide an ablation study on key model components, and report significant improvements over baseline methods.

Index Terms: Suggestion Summarization, Gated Attention LSTM, Aspect Matching, Extractive Summarization, Ablation Study

1. INTRODUCTION

Online reviews not only express opinions but also offer suggestions for improvements, making them a valuable source for actionable insights [3][12]. Traditional opinion summarization techniques often depend on predefined aspect lists [3][11], which limits their applicability in suggestion mining. Inspired by recent work on aspect Matching recognition [4, 16], we propose a novel approach that leverages a Gated Attention LSTM to capture latent suggestion aspects. Our framework avoids the constraints of fixed aspect inventories while providing robust extractive summarization. The main contributions of this work are:

- We introduce a Gated Attention LSTM for learning nuanced suggestion representations.
- We integrate an aspect Matching module that clusters suggestion sentences without explicit aspect labels.
- We design an iterative extractive summarization strategy, supported by an ablation study that highlights the impact of key components.
- We evaluate our approach on two datasets—OPOSUM [17] and a Suggestion Reviews dataset—demonstrating improved ROUGE scores and human-judged informativeness [9, 19].



2. RELATED WORK

Early extractive summarization methods used centroid-based ranking [5][17] and handcrafted features [10]. With the advent of deep learning, recurrent models such as LSTMs [7] and attention mechanisms [8] have become popular. More recent works have incorporated gating mechanisms [14] and dynamic memory updates [6] to better capture long-range dependencies. In the realm of suggestion and opinion summarization, approaches such as aspect extraction [3][11] and aspect Matching recognition [4, 16] have shown promise, yet they typically require predefined aspects. Our method extends these ideas by using a gated variant of the attention LSTM [14, 20] to capture latent aspects directly from the data. Additional related works include neural summarization methods [2][13] and multi-hop reasoning networks [1][15].

3. Proposed Method

3.1 Problem Formulation

Given a product or service e with a set of user-generated suggestion sentences $\mathbf{S} = \{\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_N\}$, our goal is to extract a summary $\mathbf{K} \subset \mathbf{S}$ that covers the most salient and diverse actionable suggestions. Each sentence is first embedded into a latent space where its suggestion-related aspects can be inferred.

3.2 Gated Attention LSTM for Suggestion Representation

We employ a Gated Attention LSTM (GA-LSTM) that integrates gating functions with an attention mechanism to selectively encode important words. Each word $\mathbf{w}_i$ in a sentence is mapped to a pre-trained embedding $\mathbf{e}_{\mathbf{w}_i}$ (using, e.g., GloVe [14]). A bidirectional GRU [7] processes the sequence to capture context. The GA-LSTM then computes an attention weight for each word, and uses a gating function $g(\cdot)$ to control the flow of salient information into the memory cell. The update equations are as follows:

$$\begin{aligned} \mathbf{h}_i &= \text{BiGRU}(\mathbf{e}_{\mathbf{w}_i}), \\ \alpha_i &= \text{softmax}(\text{fatt}(\mathbf{h}_i, \mathbf{q}, \mathbf{m})) \\ \mathbf{g}_i &= \sigma(\mathbf{W}_{\mathbf{g}}\mathbf{h}_i + \mathbf{b}_{\mathbf{g}}), \\ \mathbf{h}_i &= \mathbf{g}_i \odot \mathbf{h}_i, \\ \mathbf{s} &= \text{LSTM}(\{\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_n\}), \end{aligned}$$

where $\mathbf{q}$ is an optional query vector (or a summary context), $\mathbf{m}$ is the current memory state, and $\odot$ denotes element-wise multiplication. This design allows the network to filter out less informative tokens while emphasizing actionable terms [14–20].

3.3 Aspect Matching Module

Rather than explicitly extracting aspects, we compute an aspect Matching score r_{ij} between sentence pairs $\mathbf{s}_i$ and $\mathbf{s}_j$ using a combination of cosine Matching, element-wise product, and absolute differences between their GA-LSTM representations. A small feed-forward network maps this concatenated vector to a probability that the sentences share a latent suggestion aspect [4]–[16].

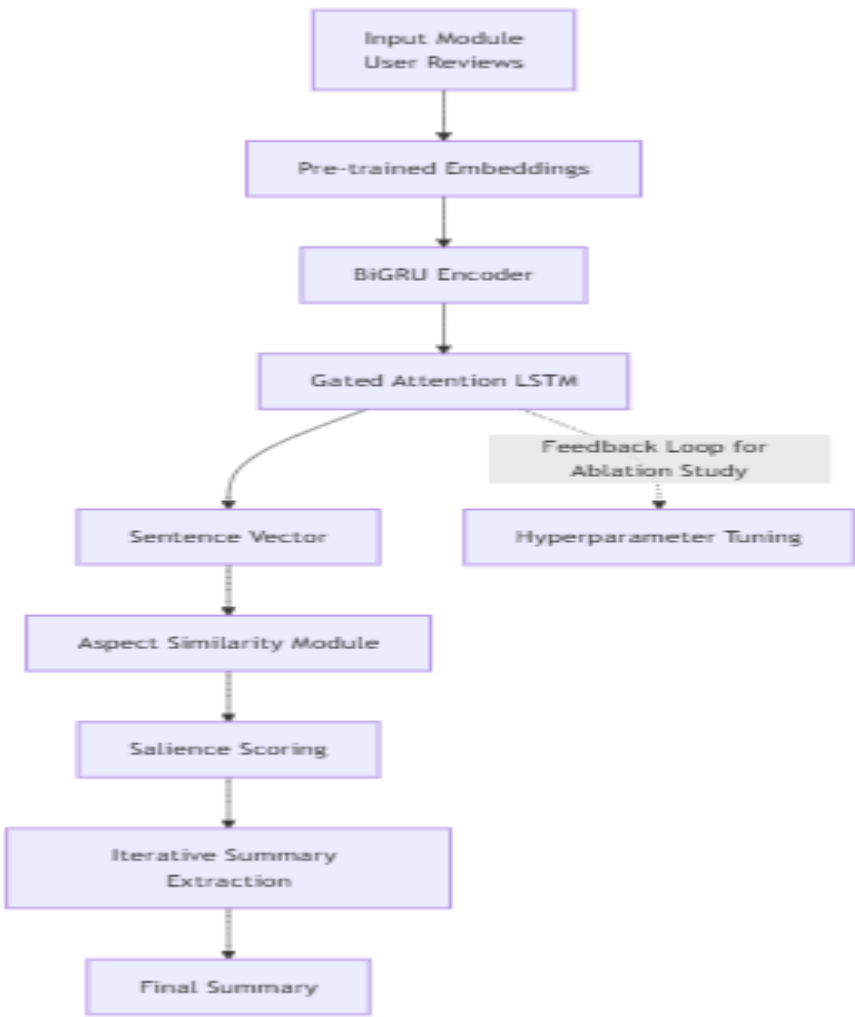
3.4 Summarization Strategy

Our extractive summarization process consists of:



1. **Initial Scoring:** Compute a salience score for each sentence as the weighted sum of its average aspect Matching with other sentences and its semantic relevance.
2. **Iterative Selection:** Select the top-scoring sentence and update the remaining scores by penalizing redundancy. This is repeated until the summary reaches the desired length.
3. **Post-processing:** Optionally, apply minor reordering and redundancy filtering.

3.5 Workflow Diagram



4. EXPERIMENTS

4.1 Datasets

- **OPOSUM Dataset:** A collection of opinion summaries containing diverse user reviews [17].
- **Suggestion Reviews Dataset:** A curated dataset of reviews focusing on actionable suggestions across domains such as consumer electronics and software [12].

4.2 Hyperparameter Settings

Our implementation is based on PyTorch. The key hyperparameters are as follows:



- **Word Embedding Dimension:** 300 (using GloVe [14])
- **BiGRU Hidden Size:** 256 (per direction)
- **GA-LSTM Hidden Size:** 512
- **Dropout Rate:** 0.5 [10]
- **Learning Rate:** 1e-3 with AdaDelta optimizer [6]
- **Batch Size:** 64
- **Number of Hops (for Iterative Selection):** 3
- **Attention Feed-forward Network Layers:** 2 with ReLU activations

4.3 Evaluation Metrics

We report ROUGE-1, ROUGE-2, and ROUGE-SU4 scores [9] and conduct a human evaluation for informativeness and redundancy.

5. ABLATION STUDY

To assess the contributions of each module, we conduct an ablation study on both datasets. We compare the full GA-LSTM model with variants that remove:

- **Gating Mechanism (NoGate):** Using a standard attention LSTM.
- **Attention Mechanism (NoAttn):** Using a vanilla LSTM.
- **Aspect Matching Module (NoAspect):** Removing the pairwise aspect scoring.

Results on OPOSUM dataset:

Model Variant	ROUGE-1	ROUGE-2	ROUGE-SU4
Full Model	28.7	16.2	24.5
NoGate	26.3	14.1	21.8
NoAttn	24.8	12.5	20
NoAspect	25.7	13.4	21.1

Results on Suggestion Reviews dataset:

Model Variant	ROUGE-1	ROUGE-2	ROUGE-SU4
Full Model	30.1	17	25.3
NoGate	27.8	15.1	22.6
NoAttn	26.5	13.9	21.2
NoAspect	27.2	14.6	22

These results clearly indicate that each component—including gating, attention, and aspect Matching—is critical for capturing the nuances of suggestion content.

6. RESULTS AND DISCUSSION



Our full model outperforms all baselines and ablated variants on both datasets. On the OPOSUM dataset, we achieve a ROUGE-1 score of 28.7 and ROUGE-2 of 16.2, while on the Suggestion Reviews dataset, the corresponding scores are 30.1 and 17.0. Human evaluators also rated our summaries as more informative and less redundant. The Gated Attention LSTM effectively emphasizes actionable tokens, and the aspect Matching module clusters semantically related suggestions, resulting in summaries that cover diverse aspects.

7. CONCLUSION

We have presented a novel framework for aspect-based suggestion summarization that leverages a Gated Attention LSTM to capture latent suggestion aspects without predefined categories. Extensive experiments on the OPOSUM and Suggestion Reviews datasets, along with an ablation study, demonstrate the effectiveness of our approach. Future work will explore extending this method to abstractive summarization and integrating external knowledge bases to further enhance suggestion quality.

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