# Open Domain Suggestion Mining using Fine-Grain Analysis

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# Objectives

- The primary objective of the work is Suggestion Mining. Suggestion Mining can be defined as the classification of reviews as Suggestion or Non-Suggestion which helps firms enhance their services according to the customers' needs.
- This objective is further decomposed into a multi-task problem which classifies the domain of the reviews classified as suggestions. This is also known as Open-Domain Suggestion Mining.

# Dataset

The ***ODSM*** Dataset by Negi et al. has been used, which has reviews across the following domains:

- Hotel
- Electronics
- Travel
- Software

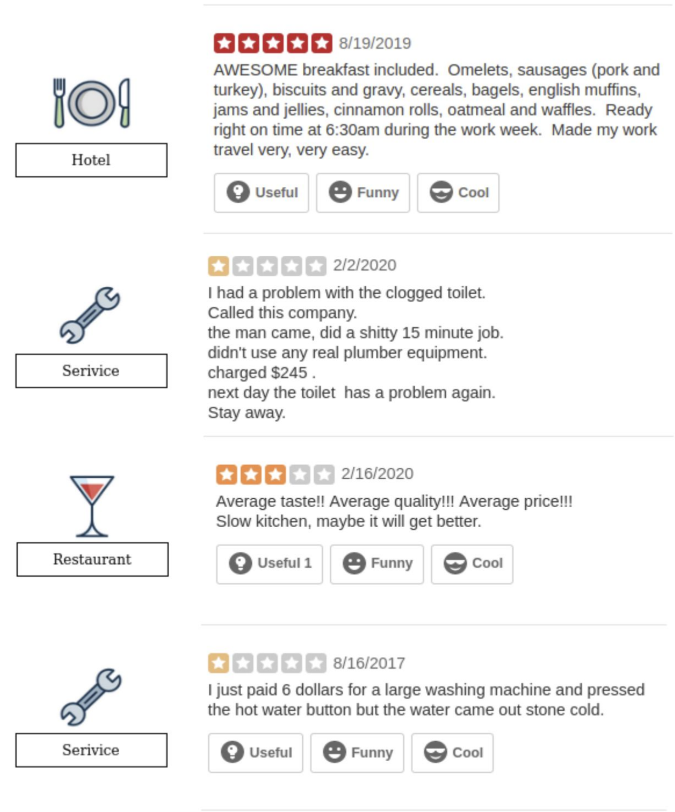


**Fig. 1**: Manually provided multi-domain reviews on Yelp.

# Related Work

Related work across the following three domains have been investigated:

- Suggestion Mining
- Open-Domain Suggestion Mining
- Imbalanced Classification

| Baseline | ID | OD | DB | AM |
|---|---|---|---|---|
| Ramanand et al. [3] | ✓ | ✗ | ✗ | ✗ |
| Brun et al. [4] | ✓ | ✗ | ✗ | ✗ |
| Wicaksono et al. [5] | ✓ | ✗ | ✗ | ✗ |
| Negi et al. (a) [6] | ✓ | ✗ | ✗ | ✗ |
| Negi et al. (b) [2] | ✓ | ✓ | ✗ | ✗ |
| Negi et al. (c) [7] | ✓ | ✓ | ✗ | ✗ |
| Jain et al. [8] | ✓ | ✓ | ✓ | ✗ |
| Ours | ✓ | ✓ | ✓ | ✓ |

**Table 1**: Relative comparison of various baselines. **ID**: In-Domain Suggestion Mining **OD**: Open-Domain Suggestion Mining **DB**: Data Balancing **AM**: Attention Modelling

# Challenges

- **Highly imbalanced data**: The suggestion:non-suggestion distribution is very low leading to biased results.
- **Very long reviews**: In most of the cases, the length of a review is very big as compared to the actual suggestion presented in the review.

| Dataset Identifier | Suggestion : Non-Suggestion |
|---|---|
| Travel Train | 1314/3869 (0.34) |
| Travel Test | 229/871 (0.26) |
| Hotel Train | 448/7086 (0.06) |
| Hotel Test | 404/3000 (0.13) |
| Electronics Train | 324/3458 (0.09) |
| Electronics Test | 101/1090 (0.09) |
| Software Train | 1428/4296 (0.33) |
| Software Test | 296/742 (0.39) |

**Table 2**: Details of the Open Domain Suggestion Mining (ODSM) dataset.

# Oversampling Algorithm

The Discourse-Marker based oversampling algorithm involves the following 3 steps:

- Training baseline classifier
- Discourse marker enhancement
- Inference based pruning

**Input:** Reviews ( R )<br>
Pretrain a baseline suggestion classifier C<br>
Let M be the set of traditional Discourse Markers<br>
**for** $d$ *in* $\mathcal{D}$ **do**<br>
    **for** $r_i$ *in* $\mathcal{R}$ **do**<br>
        **for** $m$ *in* $M$ **do**<br>
            **if** $\mathcal{C}(r_i) = 1 \wedge d \in r_i$ **then**<br>
                $\mathrm{r}_i = \{s_{h_i}, m, s_{t_i}\}$<br>
                `// SWAP Operation`<br>
                Add $\{\ s_{t_i}, d, s_{h_i}\ \}$ to the dataset.<br>
                **if** $\mathcal{C}(s_{h_i}) = 1$ **then**<br>
                    `// CROP Operation`<br>
                    Add $s_{h_i}$ to the dataset.<br>
                **if** $\mathcal{C}(s_{t_i}) = 1$ **then**<br>
                    `// CROP Operation`<br>
                    Add $s_{t_i}$ to the dataset.<br>
        **end**<br>
    **end**<br>
**end**

**Algorithm 1**: Discourse Marker based Over-Sampling

# Preliminaries

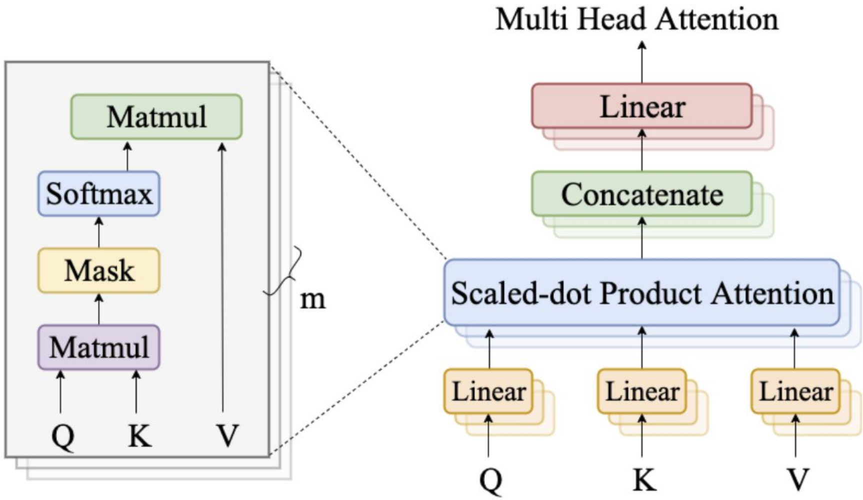


**Fig. 2**: Internal structure of the Multi-Headed Self-Attention Mechanism in a Transformer block explaining the various operations involved in obtaining the multi-head attention heat-maps .

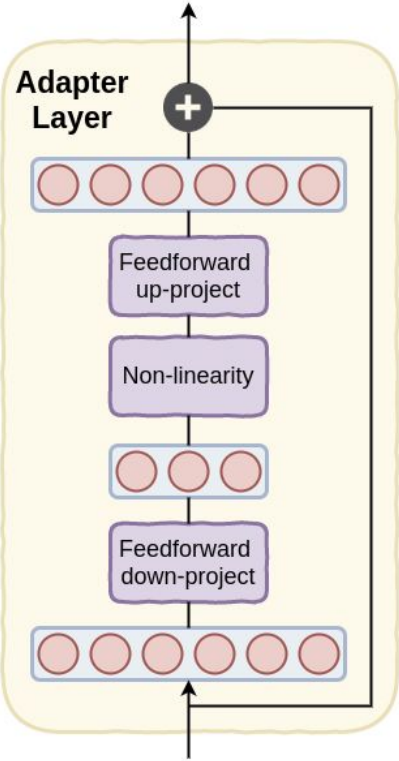


**Fig. 3:** Internal structure of the Adapter layer used for Transfer Learning.

# Proposed Architecture

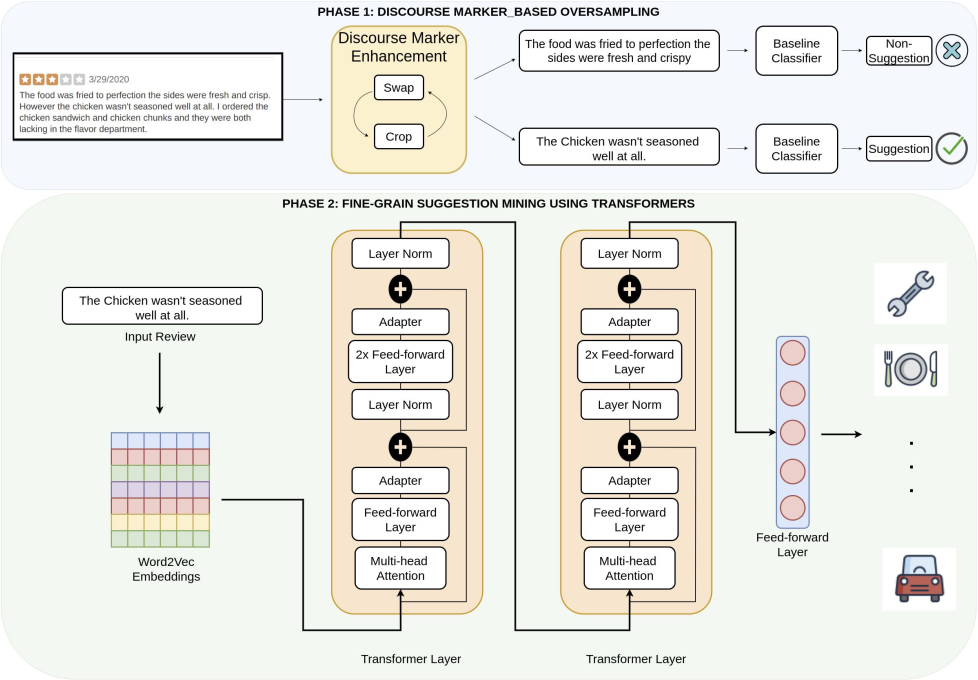


**Fig. 4**: Overall architecture demonstrating the various phases of the proposed pipeline.

# Results

| Method | Hotel | Electronics | Travel | Software | Pooled (Fine-Grain) |
|---|---|---|---|---|---|
| **Baseline (SVM) [6]** | 0.79 | 0.78 | 0.66 | 0.72 | 0.33 |
| **Baseline (LSTM) [2]** | 0.79 | 0.77 | 0.64 | 0.75 | 0.68 |
| **FastText** | 0.85 | 0.85 | 0.57 | 0.78 | 0.81 |
| **FLAIR** | 0.86 | 0.86 | 0.68 | 0.82 | 0.82 |
| **Casual Transformer** | 0.88 | 0.86 | **0.80** | **0.91** | 0.84 |
| **SMOTE + FastText** | 0.85 | 0.83 | 0.73 | 0.87 | 0.85 |
| **Jain et al. [8]** | 0.86 | 0.83 | 0.71 | 0.88 | 0.85 |
| **SMOTE + FLAIR** | 0.87 | 0.84 | 0.76 | 0.89 | 0.87 |
| **SMOTE + Casual Transformer** | 0.89 | **0.88** | 0.78 | 0.88 | 0.90 |
| **Discourse Marker + FastText** | 0.89 | 0.87 | 0.78 | 0.89 | 0.87 |
| **Discourse Marker + FLAIR** | **0.91** | 0.87 | 0.77 | **0.91** | 0.89 |
| **Discourse Marker + Casual Transformer** | **0.91** | **0.88** | **0.80** | 0.90 | **0.91** |

**Table 3**: Performance evaluation using F1 score.In all the cases, the discourse marker-based oversampling leads to a significant improvement over the baseline classifiers. Furthermore, qualitative analysis reveals the confusing nature of the reviews of Travel domain as the reason for the unusually low F1 values.

# Qualitative Analysis

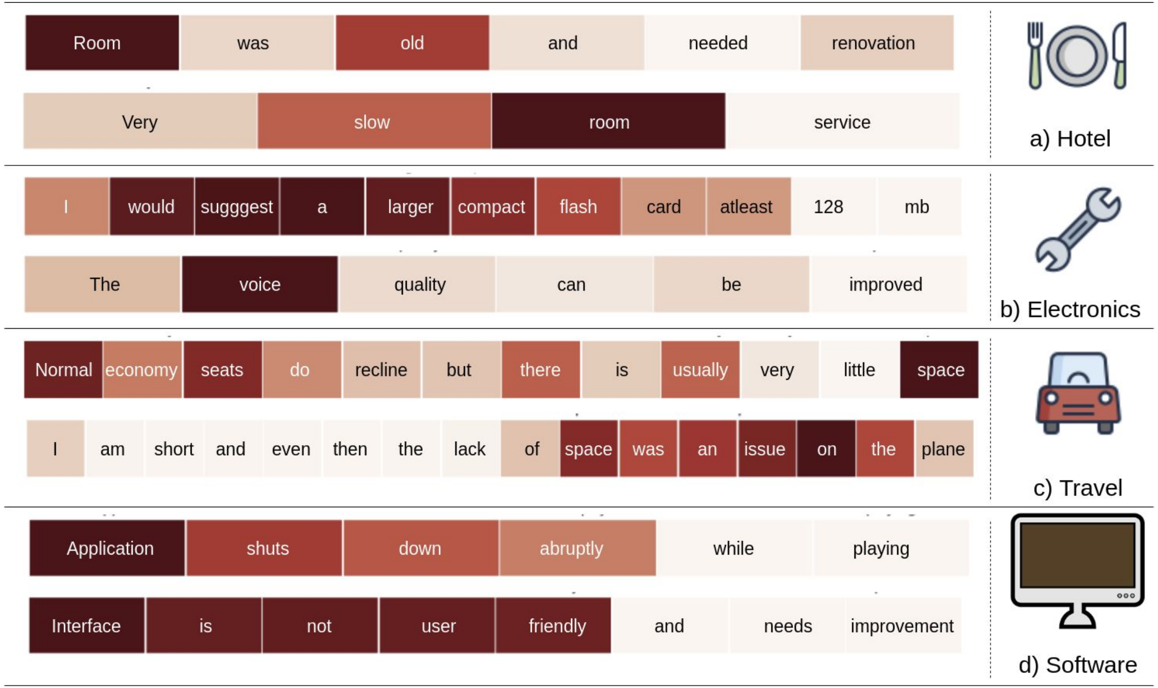


**Fig. 5**: Qualitative Analysis of the word-wise heatmaps representing the relative attention scores for the suggestions in various domains under study.

# Limitations

7/11/2019

The hotel room I was in was nicely renovated however there was no bathtub just a standing shower. I had to unplug the mini fridge with how noisy it was, and the complimentary breakfast was just wheat toast, apples and oranges.

**Fig. 5**: Review demonstrating the limitation of our approach in capturing suggestions modelled as assertions.