Multi-Dimensional Explanation of Ratings from Reviews

Diego Antognini

Claudiu Musat

Artificial Intelligence Laboratory Swisscom École Polytechnique Fédérale de Lausanne claudiu.musat@swisscom.com Lausanne, Switzerland

diego.antognini@epfl.ch

Boi Faltings

Artificial Intelligence Laboratory École Polytechnique Fédérale de Lausanne Lausanne, Switzerland boi.faltings@epfl.ch

Abstract

Automated predictions require explanations to be interpretable by humans. However, neural methods generally offer little transparency, and interpretability often comes at the cost of performance. In this paper, we consider explaining multi-aspect sentiments with text snippets from reviews, which suffice to make the prediction. Earlier work used attention mechanisms as a way of finding words that predict the sentiment towards a specific aspect and improving recommendation or summarization models. In our work, we propose a neural model that generates, in an unsupervised manner, *probabilistic multi-dimensional masks* that are interpretable and predict multi-aspect sentiment ratings. We show how using multi-task learning improves both interpretability and F1 scores. Our evaluation shows that on two datasets in different domains, our model outperforms strong baselines and generates masks that are strong feature predictors and have a meaningful interpretation.

1 Introduction

Neural networks have become the standard for many natural language processing tasks. Despite the significant performance gains achieved by these complex models, they offer little *transparency* concerning their inner workings. Thus, they come at the cost of *interpretability* (Jain and Wallace, 2019).

In many domains, automated predictions have a real *impact* on the final decision, such as treatment options in the field of medicine. Therefore, it is important to provide the underlying reasons for such a decision. We claim that integrating interpretability in a (neural) model should supply the reason for the prediction and should yield better performance. However, *explaining* a prediction might be ambiguous and challenging. Prior work includes various methods that find the explanation in an input text—also called rationale or mask of a target variable. The *mask*¹ is defined as one or multiple pieces of text fragments from the input text. Each should contain words that altogether are short, coherent, and alone sufficient for the prediction as a substitute of the input (Lei et al., 2016).

Many works have been applied to single-aspect sentiment analysis for reviews, where the *ambiguity* of what is meant by an explanation is minimal. In this case, we define an aspect as an attribute of a product or service, such as *Location* or *Cleanliness* for the hotel domain. Three different methods exist to generate masks: using reinforcement learning and a trained model (Li et al., 2016), generating masks in an unsupervised manner and jointly with the loss function (Lei et al., 2016), or including annotations during training (Bao et al., 2018).

A hard assignment of words to aspects might lead to ambiguities that are difficult to capture with a binary mask: in the text "The room was large, clean and close to the beach.", "room" refers to the aspects

¹In the rest of the paper, we will use the terms mask, explanation and rationale interchangeably.

Attention model Trained on ℓ_{sent} and no constraint

$\frac{\text{Multi-Aspect Masker (Ours)}}{\text{Trained on } \ell_{sent} \text{ with } \lambda_p, \, \ell_{sel}, \, \text{and } \ell_{cont}}$



i stayed at daulsol in september 2013 and could n't have asked for anymore for the price!! it is a great location only 2 minutes walk to jet, space and sankeys with a short drive to ushuaia. the \star hotel is basic but cleaned daily and i did \star in have any problems at all with the bathroom or kitchen facilities. the \star lady at reception was really helpful and explained everything we needed to know even when we managed to miss our flight she let us \star stay around and use the facilities until we got on a later flight. there are loads of restaurants in the vicinity and supermarkets and shops right outside. i loved these apartments so much that i booked to \star come back for september 2014!! can not wait:)

Aspect Changes ★: 30

Aspect Changes ★: 5

Figure 1: Explanation obtained for a hotel review, with an attention model and our Multi-Aspect Masker model, where the colors represent the aspects: Service, Cleanliness, Value, Location, and Room. Masks lead to mostly long sequences describing clearly each aspect (one switch \star per aspect), while attention to many short and interleaving sequences (30 changes \star between aspects), where most relate to noise or multiple aspects. Highlighted words correspond to the highest aspect-attention scores above 1/L (i.e., higher than a uniform distribution), and the aspect a_i maximizing $P(m_{a_i}^l|x^\ell)$.

Room, *Cleanliness* and *Location*. Finally, collecting human-provided rationales at scale is expensive and thus impractical.

In this work, we study interpretable multi-aspect sentiment classification. We describe an architecture for generating a *probabilistic* (*soft*) *multi-dimensional mask* (one dimension per aspect), in an unsupervised and multi-task learning manner, and predicting the sentiment of *multiple* aspects jointly. We show that the induced mask (e.g., Figure 1 right) is beneficial for identifying simultaneously what parts of the review relate to what aspect, and capturing ambiguities of words belonging to multiple aspects. Thus, the induced mask provides fine-grained interpretability and improves the final performance.

Traditionally interpretability came at a cost of reduced performance. In contrast, our evaluation shows that on two datasets, in the beer and hotel domain, our model outperforms strong baselines and generates masks that are **strong feature predictors** and have a **meaningful interpretation**. We show that it can be a benefit to 1) guide the model to focus on different parts of the input text, and 2) further improve the sentiment prediction for all aspects. Therefore, interpretability does not come at a cost anymore. The contributions of this work can be summarized as follow:

- We propose a Multi-Aspect Masker (MAM), an end-to-end neural model for multi-aspect sentiment classification that provides fine-grained interpretability in the same training. Given a text review as input, the model generates probabilistic multi-dimensional masks, with one dimension per aspect. It predicts the sentiments of multiple aspects, and highlights long sequences of words explaining the current rating prediction for each aspect;
- We show that interpretability does not come at a cost: our final model significantly outperforms strong baselines and attention models, both in terms of performance and mask coherence. Furthermore, the level of interpretability is controllable using two regularizers;
- Finally, we release a new dataset for multi-aspect sentiment classification: 140k reviews from Tri-pAdvisor, each with five aspects and their corresponding rating.²

²We will make the code and data available.

2 Related Work

2.1 Interpretability

Developing interpretable models is of considerable interest to the broader research community, even more pronounced with neural models (Doshi-Velez and Kim, 2017). Many works analyzed and visualized state activation (Montavon et al., 2018), learned sparse and interpretable word vectors (Herbelot and Vecchi, 2015) or analyzed attention (Jain and Wallace, 2019). Our work differs from these in terms of what is meant by an explanation. Our system identifies one or multiple short and coherent text fragments that — as a substitute of the input text — **are sufficient for the prediction**.

2.2 Attention-based models

Attention models (Vaswani et al., 2017) have been shown to improve prediction accuracy, visualization, and interpretability. The most popular and widely used attention mechanism is soft attention (Bahdanau et al., 2015) over hard (Luong et al., 2015) and sparse ones (Martins and Astudillo, 2016). According to Jain and Wallace (2019); Serrano and Smith (2019), standard attention modules noisily predict input importance; the weights cannot provide safe and meaningful explanations. Our approach differs in two ways from attention mechanisms: the loss includes two regularizers to favor long word sequences for interpretability; the normalization is not done over the sequence length, but over the aspect set for each word: each has a probability distribution over the aspects.

2.3 Multi-Aspect Sentiment Classification

Multi-aspect sentiment classification is sometimes seen as a sub-problem (McAuley et al., 2012; Pappas and Popescu-Belis, 2014), by utilizing heuristic-based methods or topic models. Neural models achieved significant improvements with less feature engineering. Yin et al. (2017) built a hierarchical attention model with aspect representations by using a set of manually defined topics. Li et al. (2018) extended this work with user attention and additional features such as overall rating, aspect, and user embeddings. The disadvantage of these methods is their limited interpretability, as they rely on many features in addition to the review text.

2.4 Rationale-Based Models

The idea of including human rationales during training is explored in Bao et al. (2018). Although they have been shown to be beneficial, they are expensive to collect and might vary across annotators. In our work, no annotation is used.

The work most closely related to ours is Li et al. (2016) and Lei et al. (2016). Both generate *hard* rationales and address *single-aspect* sentiment classification. Their model must be trained *separately* for each aspect, which leads to ambiguities. Li et al. (2016) developed a post-training method that removes words from a review text until another trained model changes its prediction. Lei et al. (2016) provided a model that learns an aspect sentiment and its rationale jointly, but hinders the performance and relies on assumptions on the data, such as a small correlation between aspect ratings.

In contrast, our model: 1) supports *multi-aspect* sentiment classification, 2) generates *soft multi-dimensional* masks in a *single* training; 3) the masks provide interpretability and improve the performance significantly.

3 Method: Multi-Aspect Masker (MAM)

Let X be a review composed of L words $x^1, x^2, ..., x^L$ and Y the target A-dimensional sentiment vector, corresponding to the different rated aspects. Our proposed model, called Multi-Aspect Masker, is composed of three components: 1) a Masker module that computes a probability distribution over aspects for each word, resulting in A+1 different masks (including one for not-aspect); 2) an Encoder that learns a representation of a review conditioned on the induced masks; 3) a Classifier that predicts the target variables. The overall model architecture is shown in Figure 2. Our framework generalizes for other tasks, and each neural module is interchangeable with other models.

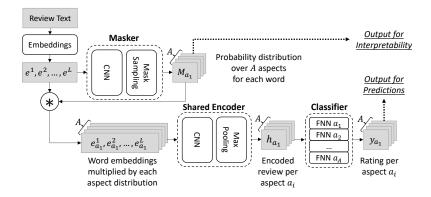


Figure 2: The proposed Multi-Aspect Masker (MAM) model architecture for A aspects.

The *Masker* first computes a hidden representation h^ℓ for each word x^ℓ in the input sequence, using their word embeddings $e^1, e^2, ..., e^L$. Many sequence models could realize this task, such as recurrent, attention, or convolution networks. In our case, we chose a convolutional network because it led to a smaller model, faster training, and empirically, performed similarly to recurrent models. Let a_i denote the i^{th} aspect for i=1,...,A, and a_0 the *not-aspect* case, because many words can be irrelevant to every aspect. We define $M^\ell \in \mathbb{R}^{(A+1)}$, the aspect distribution of the input word x^ℓ as:

$$P(\mathbf{M}|X) = \prod_{\ell=1}^{L} P(M^{\ell}|x^{\ell}) = \prod_{\ell=1}^{L} \prod_{i=0}^{A} P(m_{a_i}^{\ell}|x^{\ell})$$
 (1)

Because we have categorical distributions, we cannot directly sample $P(M^{\ell}|x^{\ell})$ and backpropagate the gradient through this discrete generation process. Instead, we model the variable $m_{a_i}^{\ell}$ using the Straight Through Gumbel Softmax (Jang et al., 2017; Maddison et al., 2017), to approximate sampling from a categorical distribution. We model the parameters of each Gumbel Softmax distribution M^{ℓ} with a single-layer feedforward neural network followed by applying a log softmax, which induces the log-probabilities of the ℓ^{th} distribution: $\omega_{\ell} = \log(\operatorname{softmax}(Wh^{\ell} + b))$. W and b are shared across all tokens, to have a constant number of parameters with respect to the sequence length. We control the sharpness of the distributions with the temperature parameter τ . Compared to attention mechanisms, the word importance is a probability distribution over the targets: $\sum_{t=0}^T P(m_{a_t}^{\ell}|x^{\ell}) = 1$, instead of a normalization over the sequence length, $\sum_{\ell=1}^L P(a^{\ell}|x^{\ell}) = 1$.

Given a soft multi-dimensional mask $\mathbf{M} \in \mathbb{R}^{(A+1)\times L}$, we define each sub-mask $M_{a_i} \in \mathbb{R}^L$ as:

$$M_{a_i} = P(m_{a_i}^1 | x^1), P(m_{a_i}^2 | x^2), ..., P(m_{a_i}^L | x^L)$$
(2)

We weight the word embeddings by their importance towards an aspect a_i with the induced sub-masks, such that $E_{a_i} = M_{a_i} \odot E = P(m_{a_i}^1 | x^1) \cdot e_1, ..., P(m_{a_i}^L | x^L) \cdot e_L$. Thereafter, each modified embedding E_{a_i} is fed into the *Encoder* block. Note that E_{a_0} is ignored because M_{a_0} only serves to absorb probabilities of words that are insignificant to every aspect.³

The *Encoder* includes a convolutional network, for the same reasons as earlier, followed by a maxover-time pooling to obtain a fixed-length feature vector. It produces the hidden representation h_{a_i} for each aspect a_i . To exploit commonalities and differences among aspects, we share the weights of the encoders for all E_{a_i} . Finally, the *Classifier* block contains for each aspect a_i a two-layer feedforward neural networks followed by a softmax layer to predict the sentiment \hat{y}_{a_i} .

if $P(m_{a_0}^\ell|x^\ell) \approx 1.0$, it implies that $\sum_{i=1}^A P(m_{a_i}^\ell|x^\ell) \approx 0$ and consequently, $e_{a_i}^\ell \approx \vec{0}$.

3.1 Interpretable Masks

The first objective to optimize is the sentiment loss, represented with the cross-entropy between the true aspect sentiment label y_{a_i} and the prediction \hat{y}_{a_i} :

$$\ell_{sent} = \sum_{i=1}^{A} \ell_{cross_entropy}(y_{a_i}, \hat{y}_{a_i})$$
(3)

Training Multi-Aspect Masker to optimize ℓ_{sent} will lead to meaningless sub-masks M_{a_i} , as the model tends to focus on certain key-words. Consequently, we guide the model to produce long and meaningful sequences of words, as shown in Figure 1. We propose two regularizers: the first controls the number of selected words, and the second favors consecutive words belonging to the same aspect. For the first term ℓ_{sel} , we calculate the probability p_{sel} of tagging a word as aspect and then compute the cross-entropy with a parameter λ_p . The hyper-parameter λ_p can be interpreted as the prior on the number of selected words among all aspects, which corresponds to the expectation of Binomial (p_{sel}) , as the optimizer will try to minimize the difference between p_{sel} and λ_p .

$$p_{sel} = \frac{1}{L} \sum_{\ell=1}^{L} \left(1 - P(m_{a_0}^{\ell} | x^{\ell}) \right)$$

$$\ell_{sel} = \ell_{binary_cross_entropy}(p_{sel}, \lambda_p)$$
(4)

The second regularizer discourages aspect transition between two consecutive words, by minimizing the mean variation of two consecutive aspect distributions. We generalize the formulation in Lei et al. (2016), from a hard binary single-aspect selection, to a soft probabilistic multi-aspect selection.

$$p_{dis} = \frac{1}{L} \sum_{\ell=1}^{L} \left[\frac{1}{A+1} \sum_{a=0}^{A} |P(m_{a_i}^{\ell} | x^{\ell}) - P(m_{a_i}^{\ell-1} | x^{\ell-1})| \right]$$

$$\ell_{cont} = \ell_{binary_cross_entropy}(p_{dis}, 0)$$
(5)

We train our Multi-Aspect Masker in an end-to-end manner, and optimize the loss $\ell_{MAM} = \ell_{sent} + \lambda_{sel} \cdot \ell_{sel} + \lambda_{cont} \cdot \ell_{cont}$, where λ_{sel} and λ_{cont} control the impact of each constraint.

4 Experiments

In this section, we assess our model on two dimensions: the quality of the explanations, obtained from the induced masks, and the predictive performance. We first measure the quality of the induced sub-masks using aspect sentence-level annotations, and an automatic topic model evaluation method. In the second experiments, we evaluate our Multi-Aspect Masker (*MAM*) on the multi-aspect sentiment classification task in two different domains.

4.1 Experimental Details

For each model, the review encoder was either a bi-directional single-layer forward recurrent neural network using Long Short-Term Memory (Hochreiter and Schmidhuber, 1997) with 64 hidden units or the multi-channel text convolutional neural network, similar to (Kim et al., 2015), with 3, 5, 7 width filters and 50 feature maps per filter. Each aspect classifier is a two-layer feedforward neural network with ReLU activation function (Nair and Hinton, 2010). We used the 200-dimensional pre-trained word embeddings of Lei et al. (2016) for beer reviews. For the hotel domain, we trained word2vec (Mikolov et al., 2013) on a large collection of hotel reviews with an embedding size of 300.

We used dropout (Srivastava et al., 2014) of 0.1, clipped the gradient norm at 1.0 if higher, added L2-norm regularizer with a regularization factor of 10^{-6} and trained using early stopping with a patience of three iterations. We used Adam (Kingma and Ba, 2015) for training with a learning rate of 0.001, $\beta_1=0.9$, and $\beta_2=0.999$. The temperature τ for Gumbel-Softmax distributions was fixed at 0.8. The two regularizer terms and the prior of our model are $\lambda_{sel}=0.03$, $\lambda_{cont}=0.03$, and $\lambda_p=0.15$ for the

Beer dataset; and $\lambda_{sel}=0.02$, $\lambda_{cont}=0.02$ and $\lambda_p=0.10$ for the Hotel dataset. We ran all experiments for a maximum of 50 epochs with a batch-size of 256 and a Titan X GPU. For the model of Lei et al. (2016), we reused the code from the authors.

4.2 Datasets

McAuley et al. (2012) provided 1.5 million beer reviews from BeerAdvocat. Each contains multiple sentences describing various beer aspects: *Appearance*, *Smell*, *Palate*, and *Taste*; users also provided a five-star rating for each aspect.

To evaluate the robustness of models across domains, we crawled 140k hotel reviews from TripAdvisor. Each review contains a five-star rating for each aspect: *Service*, *Cleanliness*, *Value*, *Location*, and *Room*. Compared to beer reviews, hotel reviews are longer, noisier, and less structured. Additionally, both datasets do not contain annotations or masks.

As in Bao et al. (2018), we binarize the problem: ratings at three and above are labeled as positive and the rest as negative. We further divide the datasets into 80/10/10 for train, development, and test subsets.

4.3 Baselines

We compared our Multi-Aspect Masker (*MAM*) with various baselines. We group them in three levels of interpretability:

- *None*: we cannot identify what parts of the review are important for the prediction;
- *Coarse-grained*: we observe what parts of the reviews discriminate **all** aspect sentiments, without knowing what part corresponds to what aspect;
- Fine-grained: we identify what parts are used to predict each sentiment aspect and thus, explain it.

We first used a simple baseline, *SENT*, that reports the majority sentiment across aspects. Because this information is not available at testing, we trained a model to predict the majority sentiment of a review using Wang and Manning (2012). The second baseline we used is a shared encoder followed by *A* classifiers, that we denote *BASE*. This model does not offer any interpretability. We extended it with a shared attention mechanism (Bahdanau et al., 2015) after the encoder, noted *SAA*, that provides a *coarse-grained interpretability*: for all aspects, *SAA* focuses on the same words in the input.

Our final goal is to achieve the best performance and provide *fine-grained interpretability*: to visualize what sequences of words a model focuses on and to predict the aspect sentiments. To this end, we included other baselines: two trained *separately* for each aspect and two trained with a *multi-aspect* sentiment loss. We employed for the first ones: the well-known *NB-SVM* of Wang and Manning (2012) for sentiment analysis tasks, and the Single Aspect-Mask (*SAM*) model from Lei et al. (2016), each trained *separately* for each aspect. The two last methods are composed of a separate encoder, attention mechanism, and classifier for each aspect. We utilized two types of attention mechanism: additive (Bahdanau et al., 2015), and sparse (Martins and Astudillo, 2016). We call each variant Multi Aspect-Attentions (MAA) and Multi Aspect-Sparse-Attentions (MASA). More details can be found in Table 2, Table 3, and Appendix A.3.

Finally, to demonstrate that the induced sub-masks $M_{a_1},...,M_{a_A}$ computed from MAM 1) bring fine-grained interpretability, and 2) are meaningful for other models to improve final predictions, we extracted and concatenated the masks to the word embeddings, resulting in contextualized embeddings (Peters et al., 2018). We trained BASE with the contextualized embeddings and denote this variant MAM^C .

4.4 Mask Interpretability

In these experiments, we verify that MAM generates masks $M_{a_1}, ..., M_{a_A}$ that are meaningful and can be interpreted, compared to models offering fine-grained interpretability.

4.4.1 Mask Precision

Evaluating explanations that have short and coherent pieces of text is challenging because there is no gold standard provided with reviews. McAuley et al. (2012) provided 994 beer reviews with aspect sentence-level annotations, although our model computes masks at a finer level. Each sentence of the dataset is annotated with one aspect label, indicating what aspect that sentence covers. We evaluate the precision of words highlighted by each model. We used trained models on the *Beer* dataset, and extracted a similar number of selected words for a fair comparison.

We show that the generated sub-masks M_{a_1} , M_{a_2} , M_{a_3} obtained with our Multi-Aspect Masker (MAM) correlate best with human judgment. Table 1a presents the precision of the masks and attentions computed on sentence-level aspect annotations. We reported the results of the models in Lei et al. (2016): NB-SVM, the Single Aspect-Attention (SAA) and Single Aspect-Mask (SAM) — trained separately for each aspect because they find hard masks for a single aspect. In comparison to SAM, MAM model obtains significant higher precisions with an average of +1.13. Interestingly, NB-SVM and attention models (SAA, MASA, MAA) perform poorly compared with mask models: especially MASA, which focuses only on a couple of words due to the sparseness of the attention.

4.4.2 Mask Coherence

	Precision / % Highlighted words						
Model	Smell	Palate	Appearance				
NB-SVM*	21.6 / 7%	24.9 / $7%$	38.3 / $13%$				
SAA^*	88.4 / 7%	65.3 / $7%$	80.6 / $13%$				
SAM*	95.1 / 7%	80.2 / $7%$	96.3 / $14%$				
MASA	87.0 / $4%$	42.8 / $5%$	74.5 / 4%				
MAA	51.3 / $7%$	32.9 / $7%$	44.9 / $14%$				
MAM (Ours)	96.6 / $7%$	81.7 / 7%	96.7 / $14%$				

^{*} The model has been trained separately for each aspect.

⁽a) Precision of selected words for each aspect for the *Beer* dataset. Percentage of words indicates the number of highlighted words of the full review.

				NPMI			
Model	N=5	10	15	20	25	30	Mean
			Bee	r			
SAM^*	0.046	0.120	0.129	0.243	0.308	0.396	0.207
	0.020						
MAA	0.064	0.189	0.255	0.273	0.332	0.401	0.252
MAM	0.083	0.187	0.264	0.348	0.410	0.477	0.295
			Hote	el			
SAM^*	0.041	0.103	0.152	0.180	0.233	0.281	0.165
MASA	0.043	0.127	0.166	0.295	0.323	0.458	0.235
MAA	0.128	0.218	0.352	0.415	0.494	0.553	0.360

MAM 0.134 0.251 0.349 **0.496 0.641 0.724 0.432** * The model has been trained separately for each aspect.

Table 1: Performance on Human Evaluation (Table 1a) and Automatic Evaluation (Table 1b).

In addition to evaluating masks with human annotations, we computed their semantic interpretability. According to Aletras and Stevenson (2013); Lau et al. (2014), NPMI is a good metric for qualitative evaluation of topics, because it matches human judgment most closely. However, the top-N topic words used for evaluation are often selected arbitrarily. To alleviate this problem, we followed Lau and Baldwin (2016): we computed the topic coherence over several cardinalities N, and report the results and the average; the authors claim that the mean leads to a more stable and robust evaluation.

We show that generated masks by MAM obtain the highest mean NPMI and, on average, superior results in both datasets, while only needing a single training. Results are shown in Table 1b. Our model MAM significantly outperforms SAM and attention models (MASA and MAA) for $N \geq 20$ and N = 5. For N = 10 and N = 15, MAM obtains higher scores in two out of four cases (+0.033 and +0.009), and for the two others, the difference is only below 0.003. Regarding SAM, it obtains poor results in all cases, and must be trained as many times as the number of aspects.

We also analyzed the top words for each aspect by conducting a human evaluation to identify intruder words, i.e., words not matching the corresponding aspect. Generally, our model finds better topics words: approximately 1.8 times fewer intruders than other methods for each aspect and each dataset. More details are available in Appendix A.2.

Metric that correlates best with human judgment (Lau and Baldwin, 2016).

⁽b) Average Topic Coherence (NPMI) across different top-N words for each dataset. Each aspect a_i is considered as a topic and the masks/attentions are used to compute $P(w|a_i)$.

						'I Score	,	
Interp.		Model	Params	Macro	A_1	A_2	A_3	A_4
None	SENT BASE	Sentiment Majority $Emb_{200} + Enc_{CNN} + Clf$	$560k \\ 188k$	$73.01 \\ 76.45$	$71.83 \\ 71.44$	$75.65 \\ 78.64$	$71.26 \\ 74.88$	73.31 80.83
Coarse- grained	SAA	$\begin{aligned} & \text{Emb}_{200} + \text{Enc}_{\text{CNN}} + \text{A}_{\text{Shared}} + \text{Clf} \\ & \text{Emb}_{200} + \text{Enc}_{\text{LSTM}} + \text{A}_{\text{Shared}} + \text{Clf} \end{aligned}$	$\begin{array}{c} 226k \\ 219k \end{array}$	77.06 78.03	$73.44 \\ 74.25$	$78.68 \\ 79.53$	75.79 75.76	80.32 82.57
Fine- grained	NB-SVM SAM MASA MAA —————————————————————————	(Wang and Manning, 2012) (Lei et al., 2016) Emb ₂₀₀ + Enc _{LSTM} + A ^{Sparse} _{Aspect-wise} + Clf Emb ₂₀₀ + Enc _{LSTM} + A _{Aspect-wise} + Clf Emb ₂₀₀ + Masker + Enc _{CNN} + Clf (Ours)	$4 \cdot 560k$ $4 \cdot 644k$ $611k$ $611k$ $$ $289k$	72.11 76.62 77.62 78.50 78.55	72.03 72.93 72.75 74.58 74.87	74.95 77.94 79.62 79.84 79.93	68.11 75.70 75.81 77.06 77.39	73.35 79.91 82.28 82.53 82.02
	MAM ^C	$\mathbf{Emb}_{200+4} + \mathbf{Enc}_{\mathbf{CNN}} + \mathbf{Clf}(\mathbf{Ours})$	191k	78.94		80.17		

F1 Score

Table 2: Performance of the best models of each architecture for the *Beer* dataset.

						FIS	core		
Interp.		Model	Params	Macro	A_1	A_2	A_3	A_4	A_5
None	SENT BASE	Sentiment Majority Emb ₃₀₀ + Enc _{CNN} + Clf	$\begin{array}{c} 309k \\ 263k \end{array}$	85.91 90.30	89.98 92.91	$90.70 \\ 93.55$	92.12 94.12	$65.09 \\ 76.65$	91.67 94.29
Coarse- grained	SAA	$\begin{aligned} & Emb_{300} + Enc_{CNN} + A_{Shared} + Clf \\ & Emb_{300} + Enc_{LSTM} + A_{Shared} + Clf \end{aligned}$	$\begin{array}{c} 301k \\ 270k \end{array}$	90.12 88.22	92.73 91.13	93.55 92.19	93.76 93.33	76.40 71.40	94.17 93.06
Fine- grained	NB-SVM SAM MASA MAA MAM MAM ^C	(Wang and Manning, 2012) (Lei et al., 2016) Emb ₂₀₀ + Enc _{LSTM} + A ^{Sparse} _{Aspect-wise} + Clf Emb ₃₀₀ + Enc _{LSTM} + A _{Aspect-wise} + Clf Emb ₃₀₀ + Masker + Enc _{CNN} + Clf (Ours) Emb ₃₀₀₊₅ + Enc _{CNN} + Clf (Ours)	$5 \cdot 309k$ $5 \cdot 824k$ $1010k$ $1010k$ $$ $404k$ $267k$	87.17 87.52 90.23 90.21 89.94 90.79	90.04 91.48 93.11 92.84 92.84	90.77 91.45 93.32 93.34 92.95	92.30 92.04 93.58 93.78 93.91	71.27 70.80 77.21 76.87 76.27 77.47	91.46 91.85 93.92 94.21 93.71

Table 3: Performance of the best models of each architecture for the *Hotel* dataset.

4.5 Multi-Aspect Sentiment Classification

In this section, we enquire whether fine-grained interpretability can become a benefit rather than a cost in performance.

4.5.1 Beer Reviews

Overall F1 scores (macro and for each aspect A_i) for the *Beer* dataset is shown in Table 2. We find that our Multi-Aspect Masker (*MAM*) model, with 2.1 times fewer parameters than aspect-wise attention models (*MAA* and *MASA*), performs better on average than all other baselines, and provides fine-grained interpretability.

The contextualized variant MAM^C , which has approximately 1.5 times smaller than MAM, achieved a macro F1 score absolute improvement of 0.44 compared to MAM, and 2.49 compared to BASE. These results highlight that the inferred sub-masks are meaningful to improve performance while bringing finegrained interpretability to BASE, which is smaller, simpler, and has a significantly faster inference time.

NB-SVM, which offers fine-grained interpretability and is trained *separately* for each aspect, significantly underperform compared to *BASE* and surprisingly to *SENT*. To understand better why the majority sentiment baseline performs better, we calculated the sentiment correlation between any pair of aspects of the *Beer* dataset and found an average correlation of 71.8%. In other words, by predicting the sentiment of one aspect correctly, there is a high probability than other aspects might share the same polarity. We suspect that the linear model *NB-SVM* cannot capture the correlated relationships between aspects, unlike other non-linear models, such as neural models, having a higher capacity.

Shared attention models (SAA) perform better than BASE, but provide only coarse-grained interpretability. SAM is outperformed by all other model besides SENT, BASE, and NB-SVM. It might be counterintuitive that SAM performs better than BASE, but we claim that its behavior comes from the

high correlation between aspects (Lei et al., 2016): SAM selects words that should belong to aspect a_i to predict the sentiment of aspect a_j (where $a_i \neq a_j$). Moreover, in Section 4.4.2, we show that a single-aspect mask from SAM cannot be employed for interpretability.

Finally, we provide in Figure 3 a visualization of a beer review, with the computed sub-masks $M_{a_1}, ..., M_{a_A}$ and attentions by different models. Not only do sub-masks enable the reach of higher performance; they better capture parts of reviews related to each aspect compared to other methods. Other visualizations are available in Appendix A.1.2.



75cl bottle shared with larrylsb , pre - grad . bright hazy gold with a big white head the flavor has bursting fruit and funky yeast with tropical and peach standing out . the flavor has the same intense fruitiness , with a funky , lightly tart edge , and a nice hop balance . dry and refreshing on the tongue . medium bodied with perfect carbonation that livens up the palate . this was just beautiful stuff that i 'm already craving more of .

75cl bottle shared with larrylsb , pre - grad . bright , hazy gold with a big white head . the flavor has bursting fruit and funky yeast with tropical and peach standing out . the flavor has the same intense fruitiness , with a funky , lightly tart edge , and a nice hop balance . dry and refreshing on the tongue . medium bodied with perfect carbonation that livens up the palate . this was just beautiful stuff that i 'm already craving more of .

AppearanceSmell PalateTasteAppearanceSmell PalateTasteMulti Aspect-AttentionsMulti Aspect-Sparse-Attentions

75cl bottle shared with larrylsb , pre - grad . bright , hazy gold with a big white head . the flavor has bursting fruit and funky yeast with tropical and peach standing out . the flavor has the same intense fruitiness , with a funky , lightly tart edge , and a nice hop balance . dry and refreshing on the tongue . medium bodied with perfect carbonation that livens up the palate . this was just beautiful stuff that i 'm already craving more of .

75cl bottle shared with larrylsb , pre - grad . bright , hazy gold with a big white head . the flavor has bursting fruit and funky yeast with tropical and peach standing out . the flavor has the same intense fruitiness , with a funky , lightly tart edge , and a nice hop balance . dry and refreshing on the tongue . medium bodied with perfect carbonation that livens up the palate . this was just beautiful stuff that i 'm already craving more of .

Figure 3: A sample review from the *Beer* dataset, with computed masks from different methods. *MAM* achieves near-perfect annotations, while *SAM* highlights only two words where one is ambiguous with respect to four aspects. *MAA* mixes between the aspect *Appearance* and *Smell*. *MASA* identifies some words but lacks coverage.

4.5.2 Model Robustness - Hotel Reviews

Table 3 presents the results on the *Hotel* dataset. The learned mask M from Multi-Aspect Masker MAM is again meaningful, by increasing the performance and adding interpretability. The contextualized variant MAM^C outperforms all other models significantly, with an absolute macro F1 score improvement of 0.49. Moreover, it achieves the best individual F1 score for each aspect A_i . Regarding MAM, we observe that it performs slightly worse than aspect-wise attention models (MASA and MAA), but has 2.5 times fewer parameters. A visualization of a hotel review with masks and attentions is available in Figure 1. The interpretability comes from the long sequences that MAM identifies, unlike attention models. The sub-masks better capture parts of reviews related to each aspect and enable the reach of higher performance. Other visualizations are available in Appendix A.1.1.

SAM is the neural model obtaining the lowest relative macro F1 score in the two datasets compared with MAM^C : a difference of -3.27 and -2.32 for the Hotel and Beer dataset respectively. This proves that the model is not meant to provide rationales and increase the performance simultaneously.

Finally, we show that inducing soft multi-dimensional masks along training objectives achieves strong predictive results. Using these to create contextualized word embeddings and train a simple baseline model with, provides the best performance across the two datasets and brings interpretability.

5 Conclusion

We propose Multi-Aspect Masker, an end-to-end neural network architecture that predicts multi-aspect sentiment ratings for reviews with explainable masks, improving both interpretability and performance. Our model predicts aspect sentiments while generating *probabilistic* (*soft*) *multi-dimensional masks* (one dimension per aspect) simultaneously, in an unsupervised and multi-task learning manner. We showed that the induced masks 1) could be used as an explanation of a prediction, 2) are beneficial to guide the model to focus on different parts of the review and further improve the final performance, and 3) could be integrated in smaller models with a faster inference time. Our evaluation shows that our model generates masks in the absence of any explicit annotations, provides **interpretability**, embeds **high-quality representations**, and outperforms strong baselines on datasets in two domains. Finally, our framework can be generalized for other tasks.

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A Appendix

A.1 Visualization of the Multi-Dimensional Facets of Reviews

We randomly sampled reviews from each dataset and computed the masks and attentions of four models: our Multi-Aspect Masker model (*MAM*), the Single Aspect-Mask method (*SAM*) of Lei et al. (2016) and two attention models with additive and sparse attention, called Multi Aspect-Attentions (*MAA*) and Multi Aspect-Sparse-Attentions (*MASA*) respectively (more details in Section 4.3). Each color represents an aspect and the shade its confidence. All models generate soft attentions or masks besides SAM, which does hard masking. Samples for the *Beer* and *Hotel* dataset are shown below.

A.1.1 Hotel Dataset

Service Cleanliness Value Location Room

Multi Aspect-Masks (Ours)

i stayed at daulsol in september 2013 and could n't have asked for anymore for the price!! it is a great location only 2 minutes walk to jet, space and sankeys with a short drive to ushuaia . the hotel is basic but cleaned daily and i did nt have any problems at all with the bathroom or kitchen facilities. the lady at reception was really helpful and explained everything we needed to know even when we managed to miss our flight she let us stay around and use the facilities until we got on a later flight . there are loads of restaurants in the vicinity and supermarkets and shops right outside . i loved these apartments so much that i booked to come back for september 2014!! can not wait:)

Service Cleanliness Value Location Room Multi Aspect-Attentions

n't have asked for anymore for the price!! it is a great location only 2 minutes walk to jet, space and sankeys with a short drive to ushuaia. the hotel is basic but cleaned daily and i did nt have any problems at all with the bathroom or kitchen facilities . the lady at reception was really helpful and explained everything we needed to know even when we managed to miss our flight she let us stay around and use the facilities until we got on a later flight, there are loads of restaurants in the vicinity and supermarkets and shops right outside . i loved these apartments so much that i booked . i loved these apartments so much that i booked

Service Cleanliness Value Location Room

Single Aspect-Mask (Lei et al., 2016)

i stayed at daulsol in september 2013 and could n't have asked for anymore for the price!! it is a great location only 2 minutes walk to jet, space and sankeys with a short drive to ushuaia. the hotel is basic but cleaned daily and i did nt have any problems at all with the bathroom or kitchen facilities the lady at reception was really helpful and explained everything we needed to know even when we managed to miss our flight she let us stay around and use the facilities until we got on a later flight. there are loads of restaurants in the vicinity and supermarkets and shops right outside . i loved these apartments so much that i booked to come back for september 2014!! can not wait:)

Service Cleanliness Value Location Room

Multi Aspect-Sparse-Attentions

i stayed at daulsol in september 2013 and could i stayed at daulsol in september 2013 and could n't have asked for anymore for the price!! it is a great location only 2 minutes walk to jet, space and sankeys with a short drive to ushuaia. the hotel is basic but cleaned daily and i did nt have any problems at all with the bathroom or kitchen facilities . the lady at reception was really helpful and explained everything we needed to know even when we managed to miss our flight she let us stay around and use the facilities until we got on a later flight . there are loads of restaurants in the vicinity and supermarkets and shops right outside to come back for september 2014!! can not wait:) to come back for september 2014!! can not wait:)

Figure 4: MAM emphasizes consecutive words, identifies important spans while having a small amount of noise. SAM focuses on certain specific words and spans, but labels are ambiguous. The MAA model highlights many words, ignores a few important key-phrases, and labels are noisy when the confidence is not high. MASA provides noisier tags than MAA.

Multi-Aspect Masker (Ours)

stayed at the parasio 10 apartments early april 2011 . reception staff absolutely fantastic, great customer service .. ca nt fault at all! we were on the 4th floor, facing the front of the hotel.. basic, but nice and clean. good location, not too far away from the strip and beach (10 min walk). however .. do not go out alone at night at all! i went to the end of the street one night and got mugged ... all my money, camera .. everything! got sratches on my chest which has now scarred me, and i had bruises at the time . just make sure you have got someone with you at all times, the local people renound for this went to police station the next day (in old town) and there was many english in there reporting their muggings from the day before . shocking!! apart from this incident (on the first night we arrived: () we had a good time in the end, plenty of laughs and everything is very cheap! beer - 1euro! fryups - 2euro. would go back again, but maybe stay somewhere else closer to the beach (sol pelicanos etc) .. this hotel is next to an alley called 'muggers alley

Service Cleanliness Value Location Room Multi Aspect-Attentions

stayed at the parasio 10 apartments early april 2011 . reception staff absolutely fantastic , great customer service .. ca nt fault at all ! we were on the 4th floor, facing the front of the hotel.. basic, but nice and clean, good location, not too far away from the strip and beach (10 min walk). however .. do not go out alone at night at all! i went to the end of the street one night and got mugged .. all my money, camera .. everything! got sratches on my chest which has now scarred me, and i had bruises at the time . just make sure you have got someone with you at all times, the local people are very renound for this . went to police station the next day (in old town) and there was many english in there reporting their muggings from the day before . shocking!! apart from this incident (on the first night we arrived :() we had a good time in the end, plenty of laughs and everything is very cheap! beer - 1euro! fryups - 2euro. would go back again, but maybe stay somewhere else closer

to the beach (sol pelicanos etc).. this hotel is next

to an alley called 'muggers alley'

stayed at the parasio 10 apartments early april 2011 . reception staff absolutely fantastic , great customer service .. ca nt fault at all! we were on the 4th floor, facing the front of the hotel.. basic, but <u>nice</u> and clean. good location, not too far away from the strip and beach (10 min walk). however .. do not go out alone at night at all! i went to the end of the street one night and got mugged ... all my money, camera .. everything! got sratches on my chest which has now scarred me, and i had bruises at the time . just make sure you have got someone with you at all times, the local people are very renound for this . went to police station the next day (in old town) and there was many english in there reporting their muggings from the day before . shocking!! apart from this incident (on the first night we arrived :() we had a good time in the end, plenty of laughs and everything is very cheap! beer - 1euro! fryups - 2euro. would go back again, but maybe stay somewhere else closer to the beach (sol pelicanos etc).. this hotel is next to an alley called 'muggers alley'

Service Cleanliness Value Location Room Multi Aspect-Sparse-Attentions

stayed at the parasio 10 apartments early april 2011 . reception staff absolutely fantastic, great customer service .. ca nt fault at all! we were on the 4th floor, facing the front of the hotel.. basic, but nice and clean good location, not too far away from the strip and beach (10 min walk). however .. do not go out alone at night at all! i went to the end of the street one night and got mugged .. all my money, camera .. everything! got sratches on my chest which has now scarred me, and i had bruises at the time . just make sure you have got someone with you at all times, the local people are very renound for this . went to police station the next day (in old town) and there was many english in there reporting their muggings from the day before . shocking!! apart from this incident (on the first night we arrived :() we had a good time in the end, plenty of laughs and everything is very cheap! beer - 1euro! fryups - 2euro. would go back again, but maybe stay somewhere else closer to the beach (sol pelicanos etc).. this hotel is next to an alley called 'muggers alley'

Figure 5: Our *MAM* model finds most of the important span of words with a small amount of noise. *SAM* lacks coverage but identifies words where half are correctly tags and the others ambiguous. *MAA* partially correctly highlights words for the aspects *Service*, *Location*, and *Value* while missing out the aspect *Cleanliness*. *MASA* confidently finds a few important words.

A.1.2 Beer Dataset

Appearance Smell Palate Taste

Multi Aspect-Masks (Ours)

sa 's harvest pumpkin ale 2011 . had this last year , loved it , and bought 6 harvest packs and saved the pumpkins and the dunkel 's ... not too sure why sa dropped the dunkel, i think it would make a great standard to them . pours a dark brown with a 1" bone white head, that settles down to a thin lace across the top of the brew . smells of the typical pumpkin pie spice, along with a good squash note . tastes just like last years , very subtle , nothing over the top . a damn good pumpkin ale that is worth seeking out when i mean everything is subtle i mean everything . nothing is overdone in this pumpkin ale, and is a great representation of the original style. mouthfeel is somewhat thick , with a pleasant coating feel . overall , i loved it last year, and i love it this year. do n't get me wrong, its no pumpking, but this is a damn fine pumpkin ale that could hold its own any day among all the others . i would rate this as my 4th favorite pumpkin ale to date . i 'm not sure why the bros rated it so low, but do n't take their opinion, make your own!

Appearance Smell Palate Taste Multi Aspect-Attentions

sa 's harvest pumpkin ale 2011 . had this last year , loved it, and bought 6 harvest packs and saved the pumpkins and the dunkel's ... not too sure why sa dropped the dunkel, i think it would make a great standard to them . pours a dark brown with a 1" bone white head, that settles down to a thin lace across the top of the brew . smells of the typical pumpkin pie spice, along with a good <mark>squash note</mark> . tastes just like last <mark>years</mark> , very <mark>subtle</mark> , nothing over the top . a damn good pumpkin ale that is worth seeking out when i mean everything is subtle i mean everything I nothing is overdone in this pumpkin ale, and is a great representation of the original style. mouthfeel is somewhat thick , with a pleasant coating feel . overall , i loved it last year, and i love it this year. do n't get me wrong, its no pumpking, but this is a damn fine pumpkin ale that could hold its own any day among all the others. i would rate this as my 4th favorite pumpkin ale to date it is 'm not sure why the bros rated it so low, but do n't take their opinion, make your own!

Appearance Smell Palate Taste

Single Aspect-Mask (Lei et al., 2016)

sa 's harvest pumpkin ale 2011. had this last year loved it, and bought 6 harvest packs and saved the pumpkins and the dunkel 's ... not too sure why sa dropped the dunkel, i think it would make a great standard to them . pours a dark brown with a 1 " bone white head, that settles down to a thin lace across the top of the brew . smells of the typical pumpkin pie spice, along with a good squash note . tastes just like last years , very subtle , nothing over the top . a damn good pumpkin ale that is worth seeking out . when i mean everything is subtle i mean everything . nothing is overdone in this pumpkin ale, and is a great representation of the original style . mouthfeel is somewhat thick , with a pleasant coating feel . overall , i loved it last year, and i love it this year. do n't get me wrong, its no pumpking, but this is a damn fine pumpkin ale that could hold its own any day among all the others . i would rate this as my 4th favorite pumpkin ale to date . i 'm not sure why the bros rated it so low, but do n't take their opinion, make your own!

Appearance Smell Palate Taste Multi Aspect-Sparse-Attentions

sa 's harvest pumpkin ale 2011 . had this last year loved it, and bought 6 harvest packs and saved the pumpkins and the dunkel 's ... not too sure why sa dropped the dunkel, i think it would make a great standard to them . pours a dark brown with a 1" bone white head, that settles down to a thin lace across the top of the brew . smells of the typical pumpkin pie spice, along with a good squash note . tastes just like last years, very subtle , nothing over the top . a damn good pumpkin ale that is worth seeking out. when i mean everything is subtle i mean everything . nothing is overdone in this pumpkin ale, and is a great representation of the original style . mouthfeel is somewhat thick with a pleasant coating feel . overall , i loved it last year, and i love it this year. do n't get me wrong, its no pumpking, but this is a damn fine pumpkin ale that could hold its own any day among all the others . i would rate this as my 4th favorite pumpkin ale to date . i 'm not sure why the bros rated it so low, but do n't take their opinion, make your own!

Figure 6: *MAM* can identify accurately what parts of the review describe each aspect. Due to the high imbalance and correlation between aspects, *MAA* provides very noisy labels, while *MASA* highlights only a few important words. We can see that *SAM* is confused and performs a poor selection.

A.2 Topic Words per Aspect

For each model, we computed the probability distribution of words per aspect by using the induced sub-masks $M_{a_1}, ..., M_{a_A}$ or attention values. Given an aspect a_i and a set of top-N words $\boldsymbol{w_{a_i}^N}$, the Normalized Pointwise Mutual Information (Bouma, 2009) coherence score is:

$$NPMI(\boldsymbol{w_{a_i}^N}) = \sum_{j=2}^{N} \sum_{k=1}^{j-1} \frac{\log \frac{P(w_{a_i}^k, w_{a_i}^j)}{P(w_{a_i}^k) P(w_{a_i}^j)}}{-\log P(w_{a_i}^k, w_{a_i}^j)}$$
(6)

Top words of coherent topics (i.e., aspects) should share a similar semantic interpretation and thus, interpretability of a topic can be estimated by measuring how many words are not related. For each aspect a_i and word w having been highlighted at least once as belonging to aspect a_i , we computed the probability $P(w|a_i)$ on each dataset and sorted them in decreasing order of $P(w|a_i)$. Unsurprisingly, we found that the most common words are stop words such as "a" and "it", because masks are mostly word sequences instead of individual words. To gain a better interpretation of the aspect words, we followed the procedure in McAuley et al. (2012): we first computed averages across all aspect words for each word w: $b_w = \frac{1}{|A|} \sum_{i=1}^{|A|} P(w|a_i)$, which generates a general distribution that includes words common to all aspects. The final word distribution per aspect is computed by removing the general distribution: $\hat{P}(w|a_i) = P(w|a_i) - b_w$.

After generating the final word distribution per aspect, we picked the top ten words and asked two human annotators to identify intruder words, i.e., words not matching the corresponding aspect. We show in subsequent tables the top ten words for each aspect, where **red** denotes all words identified as unrelated to the aspect by the two annotators. Generally, our model finds better sets of words across the three datasets compared with other methods. Additionally, we observe that the aspects can be easily recovered given its top words.

	Model	Top-10 Words
Apperance	SAM MASA MAA MAM (Ours)	nothing beautiful lager nice average macro lagers corn rich gorgeous lacing head lace smell amber retention beer nice carbonation glass head lacing smell aroma color pours amber glass white retention head lacing smell white lace retention glass aroma tan thin
Smell	SAM MASA MAA MAM (Ours)	faint nice mild light slight complex good wonderful grainy great aroma hops nose chocolate caramel malt citrus fruit smell fruits taste hints hint lots t- starts blend mix upfront malts taste malt aroma hops sweet citrus caramel nose malts chocolate
Palate	SAM MASA MAA MAM (Ours)	thin bad light watery creamy silky medium body smooth perfect smooth light medium thin creamy bad watery full crisp clean good beer carbonation smooth drinkable medium bodied nice body overall carbonation medium mouthfeel body smooth bodied drinkability creamy light overall
Taste	SAM MASA MAA MAM (Ours)	decent great complex delicious tasty favorite pretty sweet well best good drinkable nice tasty great enjoyable decent solid balanced average malt hops flavor hop flavors caramel malts bitterness bit chocolate malt sweet hops flavor bitterness finish chocolate bitter caramel sweetness

Table 4: Top ten words for each aspect from the *Beer* dataset, learned by various models. **Red** denotes intruders according to two annotators. Found words are generally noisier due to the high correlation between *Taste* and other aspects. However, *MAM* provides better results than other methods.

	Model	Top-10 Words
Service	SAM MASA MAA MAM (Ours)	staff service friendly nice told helpful good great lovely manager friendly helpful told rude nice good pleasant asked enjoyed worst staff service helpful friendly nice good rude excellent great desk staff friendly service desk helpful manager reception told rude asked
Cleanliness	SAM MASA MAA MAM (Ours)	clean cleaned dirty toilet smell cleaning sheets comfortable nice hair clean dirty cleaning spotless stains cleaned cleanliness mold filthy bugs clean dirty cleaned filthy stained well spotless carpet sheets stains clean dirty bathroom room bed cleaned sheets smell carpet toilet
Value	SAM MASA MAA MAM (Ours)	good stay great well dirty recommend worth definitely friendly charged great good poor excellent terrible awful dirty horrible disgusting comfortable night stayed stay nights 2 day price water 4 3 good price expensive paid cheap worth better pay overall disappointed
Location	SAM MASA MAA MAM (Ours)	location close far place walking definitely located stay short view location beach walk hotel town located restaurants walking close taxi location hotel place located close far area beach view situated location great area walk beach hotel town close city street
Room	SAM MASA MAA MAM (Ours)	dirty clean small best comfortable large worst modern smell spacious comfortable small spacious nice large dated well tiny modern basic room rooms bathroom bed spacious small beds large shower modern comfortable room small spacious nice modern rooms large tiny walls

Table 5: Top ten words for each aspect from the *Hotel* dataset, learned by various models. **Red** denotes intruders according to human annotators. Besides *SAM*, all methods find similar words for most aspects except the aspect *Value*, where *MAM* does not have an intruder.

A.3 Baseline Architectures

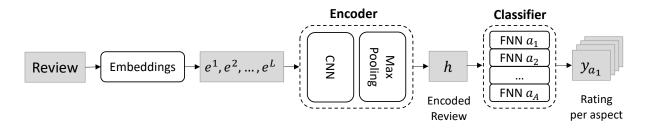


Figure 7: Baseline model Emb + Enc_{CNN} + Clf (*BASE*).

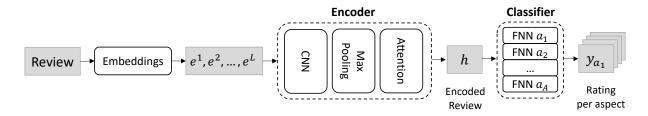


Figure 8: Baseline model Emb + Enc_{CNN} + A_{Shared} + Clf (SAA, CNN variant).

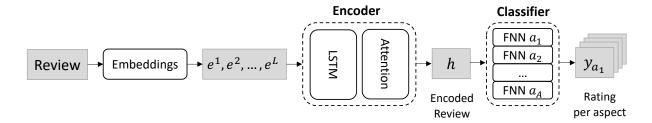
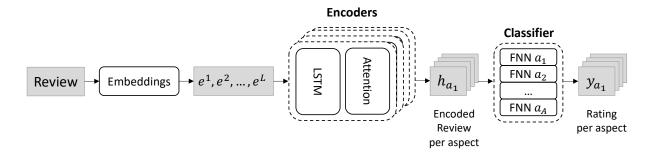


Figure 9: Baseline model Emb + Enc_{LSTM} + A_{Shared} + Clf (SAA, LSTM variant).



 $Figure \ 10: \ Baseline \ model \ Emb + Enc_{LSTM} + A_{Aspect-wise}^{[Sparse]} + Clf. \ Attention \ is \ either \ additive \ (\textit{MAA}) \ or \ sparse \ (\textit{MASA}).$