Would You Like Sashimi Even If It’s Sliced Too Thin?
Selective Neural Attention for Aspect Targeted Sentiment Analysis (SNAT)

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Abstract
Sentiments in opinionated text are often determined by both aspects and target words (or targets). We observe that targets and aspects interrelate in subtle ways, often yielding conflicting sentiments. Thus, a naive aggregation of sentiments from aspects and targets treated separately, as in existing sentiment analysis models, impairs performance.

We propose SNAT, an approach that jointly considers aspects and targets when inferring sentiments. To capture and quantify relationships between targets and context words, SNAT uses a selective self-attention mechanism that handles implicit or missing targets. Specifically, SNAT involves two layers of attention mechanisms, respectively, for selective attention between targets and context words and attention over words based on aspects. On benchmark datasets, SNAT outperforms leading models by a large margin, yielding (absolute) gains in accuracy of 1.8% to 5.2%.

1 Introduction
People share their opinions about almost anything: tourist attractions, restaurants, car dealerships, and products. Such opinionated texts do not merely help people make decisions in their daily life, but also help businesses measure consumer satisfaction to improve their offerings.

Sentiment analysis involves many aspects of Natural Language Processing, including negation handling, coreference resolution, and entity recognition (Cambria et al., 2013). Importantly, opinionated texts often convey conflicting sentiments. Distinct sentiments may refer to distinct aspects of the domain in question—e.g., food quality of a restaurant or battery life of a smartphone. These predefined domain aspects may or may not appear in the texts. Aspect-Based Sentiment Analysis (ABSA) approaches (Wang et al., 2016b; Xue and Li, 2018; Liang et al., 2019) predict sentiments from text about a given aspect. And, Target-Based Sentiment Analysis (TBSA) approaches (Chen et al., 2017; Fan et al., 2018; Li et al., 2018; Du et al., 2019a; Zhang et al., 2019) predict sentiments from text about given target words or targets that may appear in an opinionated text. Targets are usually entities in a review: e.g., a dish for a restaurant and a salesperson for a car dealership.

We posit that aspects and targets provide subtle, sometimes contradictory, information about sentiment and should therefore be modeled, not in isolation, but jointly. Considering them separately, as ABSA and TBSA approaches do, impairs performance. Take this review sentence from SemEval-15 as an example:

Conflicting Sentiments on Aspect

We both had the filet, very good, didn’t much like the frites that came with.

If we ask about aspect Food#Quality, by disregarding targets during training, ABSA models fail to address the contradiction in sentiment about filet and frites, as do TBSA models, which focus on targets and disregard aspects. In the following review sentence from SemEval-16, the target fish is associated with opposite sentiments: positive for Food#Quality and negative for Food#Style options.

Conflicting Sentiments on Target

The fish was fresh, though it was cut very thin.

Opinionated text is often not structured. Users may not always mention targets explicitly. In some cases, the entities in a sentence are not the targets associated with the sentiment. In other cases, users mention multiple targets with sentiments in a sentence, but we need the overall sentiment. Consider the following two sentences from SemEval-16:
Table 1: Output examples of SNAT. Targets are marked in bold. (a): Same target paired with different aspects; (b): Different aspects paired with same or different targets; (c) Same aspects paired with different targets; (d) Aspect with no target; (e) Different aspects with or without target. ABSA handles (a), (b), (d), and (e). TBSA handles (c).

| Sentence | Aspect | Sent. |
|----------|--------|-------|
| (a) The fish was fresh, though it was cut very thin | Food#Quality | POS |
| Food wise, its ok but a bit pricey for what you get considering the restaurant isn’t a fancy place | Food#Quality | NEU |
| Food wise, its ok but a bit pricey for what you get considering the restaurant isn’t a fancy place | Restaurant#Prices | NEG |
| Food wise, its ok but a bit pricey for what you get considering the restaurant isn’t a fancy place | Ambience#General | NEU |
| The music playing was very hip, 20-30 something pop music, but the subwoofer to the sound system was located under my seat, which became annoying midway through dinner | Ambience#General | POS |
| The music playing was very hip, 20-30 something pop music, but the subwoofer to the sound system was located under my seat, which became annoying midway through dinner | Ambience#General | NEG |
| As part of a small party of four, our food was dropped off without comment | Service#General | NEG |
| Endless fun, awesome music, great staff!!! | Ambience#General | POS |
| Endless fun, awesome music, great staff | Service#General | POS |
| Endless fun, awesome music, great staff | Restaurant#General | POS |

2 Related Work

2.1 Document-Level Sentiment Analysis

Document-level sentiment analysis aims at classifying sentiment polarities or ratings for a set of sentences. Tang et al. (2015) use Convolutional Neural Networks (CNN) with filters of different sizes to generate sentence embeddings. They use Gated Recurrent Neural Networks (GRU) to encode sentence semantics and relations into document embeddings. Yang et al. (2016) use two Bidirectional GRUs with attention layers to encode sentences and documents, respectively. Du et al. (2019b) build document embeddings in a bottom-up manner using Bidirectional Long Short-Term Memory (BiLSTM) as word and sentence encoder with convolution-based attention. Unlike these models, SNAT works at the sentence level and considers aspects and targets when inferring sentiments.

2.2 Sentence-Level Sentiment Analysis

Socher et al. (2011; 2012; 2013) use recursive autoencoders to capture compositional semantics within sentences for sentiment classification. Wang et al. (2016a) use convolutional and max pooling layers to encode local word features and dependencies and an LSTM layer to capture long-distance dependencies. Qian et al. (2017) incorporate linguistic resources including sentiment lexicon and negation word and intensity word lists into a BiLSTM as regularizers. All these models ignore aspect and target information, however.

2.3 Aspect-Based Sentiment Analysis (ABSA)

For ABSA task, Wang et al. (2016b) concatenate aspect embeddings with LSTM hidden states and apply attention mechanism to focus on different parts of a sentence given different aspects. Xue and Li (2018) extracts features from text using a convolutional layer and propagates the features to a...
max pooling layer based on either aspects or targets. Liang et al. (2019) uses an aspect-guided encoder with an aspect-reconstruction step to generate either aspect- or target-specific sentence representation. The above models do not jointly consider aspects and targets and suffer when a target has conflicting sentiments toward different aspects.

2.4 Target-Based Sentiment Analysis (TBSA)

For TBSA task, Tang et al. (2016a) concatenate target and context word embeddings and use two LSTM models to capture a target’s preceding and following contexts. Chen et al. (2017) builds position-weighted memory using two stacked BiLSTMs and the relative distance of each word to the left or right boundary of each target. Li et al. (2018) dynamically associates targets with sentence words to generate target specific word representation and uses adaptive scaling to preserve context information. Majumder et al. (2018) uses a GRU with attention to generate an aspect-aware sentence representation and a multihop memory network to capture aspect dependencies. Fan et al. (2018) uses BiLSTM with attention mechanism to computes coarse-grained attention using averaged target embeddings and context words. It leverages word similarity to build fine-grained attention. Xu et al. (2019) prepend target tokens to a given text sequence, and predict sentiment based on BERT sequence embeddings. Du et al. (2019a) leverages capsule network and uses interactive attention capsule routing mechanism to learn the relationship between targets and context words.

3 Problem Definition

The input of our sentiment analysis task is a sequence of words, with an aspect, or a target, or both. Our goal is to identify the sentiment polarity associated with the aspect and the target. Formally, SNAT has three inputs,

- Sequence of words: $W = \{w_1, \ldots, w_N\}$,
- Target $T_i = \{t_1, \ldots, t_M\}$ where $t_i \in W$, and
- Aspect $a_i \in A = \{a_1, \ldots, a_{|A|}\}$ where $A$ is a set of aspects.

The remaining words that are not part of the target are context words $C = \{c_1, \ldots, c_{N-M}\}$.

4 SNAT Model Overview

Figure 1 shows the SNAT architecture. To infer the sentiment for an aspect and a target composed of words from the sequence, first, SNAT uses BERT to generate word embeddings. Second, SNAT uses a selective attention mechanism to compute context word and target attention weights and applies them to word embeddings to generate targeted contextual embeddings. Third, SNAT constructs aspect embeddings and uses the embeddings to compute aspect attention over target and context words.

SNAT uses a multihead architecture to learn attention in diverse embedding subspaces. It fuses and normalizes embeddings from each head and uses a linear classification layer with a softmax activation for sentiment classification. To introduce nonlinearity, SNAT uses feed-forward networks (shown in grey), each comprising two fully connected layers followed by a nonlinear activation.

4.1 BERT Embeddings

SNAT uses Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) to generate word embeddings. BERT is a contextualized language representation model, pretrained on large corpora and fine-tuned on downstream tasks, including token-level classification (named
entity recognition and reading comprehension) and sequence-level classification (semantic similarity and sentiment analysis). Despite its success on various benchmarks, BERT ignores the relationships among target words, context words, and aspects, which are crucial for sentiment analysis.

### 4.2 Selective Self-Attention Mechanism

Words connect with one another to form semantic relations and create meanings in different contexts. Self-attention (Vaswani et al., 2017) seeks to quantify this process. To capture relationships between words, it learns to represent each word using itself, which are crucial for sentiment analysis.

Self-attention can be represented as:

$$A_t = \text{softmax}(F_q \cdot [F_k \oplus F_v])^T.$$  \hspace{1cm} (6)

where $F_k, F_q, F_v \in \mathbb{R}^{M \times d_F}$ are keys and queries of targets, $F_{q_k}, F_{q_v} \in \mathbb{R}^{N \times d_F}$ are keys and queries of context words, $F_k \in \mathbb{R}^{(M+N) \times d_F}$ are values for both kinds of words, $\odot$ means matrix vertical concatenation, $W_c$ is parameters to learn, and we omit the bias for simplicity.

**Target WordAttention.** SNAT constructs an affinity matrix $A_t = \{\alpha_{t1}, \ldots, \alpha_{tM}\} \in \mathbb{R}^{M \times (M+N)}$ by computing dot products of each target with each word in the sentence.

$$A_t = \text{softmax}(F_q \cdot [F_k \oplus F_v]^T).$$  \hspace{1cm} (6)

$A_t$ is normalized row-wise to generate a list of attention weights for each target. These attention weights quantify relations between words and describe the amount of focus the encoder should place on other words when encoding a target. For sentences with no target, SNAT uses BERT’s [CLS] token as a surrogate target to leverage the aggregated sentence information.

**Context WordAttention.** SNAT creates a mask matrix $K_c = \{k_{c1}, \ldots, k_{cN}\} \in \mathbb{R}^{N \times (M+N)}$. Here, $k_{ci}$ equals 1.0 if the corresponding position is context word $c_i$ or a target and zero otherwise. SNAT constructs the affinity matrix $A_c = \{\alpha_{c1}, \ldots, \alpha_{cN}\} \in \mathbb{R}^{N \times (M+N)}$ by computing the dot products of each context word with itself and each target in the sentence masked by $K_c$, where $\odot$ denotes Hadamard product.

$$A_c = \text{softmax}(F_{q_k} \cdot [F_k \oplus F_{q_k}]^T \odot K_c).$$  \hspace{1cm} (7)

$A_c$ is normalized row-wise to generate a list of attention weights for each context word. These attention weights quantify dependencies between each context word and each target. Our mask removes noisy dependencies between the context words.
Targeted Contextual Embeddings. Given target attention $A_t$ and context word attention $A_c$, SNAT computes targeted contextual embeddings $P \in \mathbb{R}^{(M+N) \times d_F}$ as follows.

$$P = [A_t \oplus A_c] \cdot F_v.$$  \hfill (8)

4.3 Aspect Attention

How the aspects and words in a sentence relate is vital in inferring sentiments. As the second review sentence in Section 1 shows, one target can associate with different sentiments for different aspects. To incorporate aspect information, given $L$ aspects, $A = \{a_1, \ldots, a_L\}$, SNAT learns a list of aspect embeddings, $E = \{e_{a_1}, \ldots, e_{a_L}\}$, where $e_{a_i} \in \mathbb{R}^{d_E}$ and $d_E$ is the dimension of the aspect embeddings. To introduce nonlinearity, SNAT encodes aspect embeddings using a feed-forward network comprising two fully connected linear layers connected by a GELU activation.

$$F_A = W_{A_1} \cdot \text{GELU}(W_{A_2} \cdot E),$$  \hfill (9)

where $F_A = \{f_{a_1}, \ldots, f_{a_L}\} \in \mathbb{R}^{L \times d_E}$, $W_{A_1}$ and $W_{A_2}$ are weights to learn, and bias is omitted for simplicity. To capture the relationships, SNAT builds the affinity matrix $A_a \in \mathbb{R}^{M+N}$ between aspect embeddings $e_{a_i}$ and targeted contextual embeddings $P$ of the sentence. An illustrative example of aspect attention is shown in Figure 3.

$$A_{a_i} = \text{softmax}(f_{a_i} \cdot P^T).$$  \hfill (10)

The aspect and targeted contextual embeddings $Q_{a_i}$ for aspect $a_i, Q_{a_i} \in \mathbb{R}^{d_E+d_F}$, are computed as

$$Q_{a_i} = [A_{a_i} \cdot P] \odot f_{a_i},$$  \hfill (11)

where $\odot$ denotes horizontal matrix concatenation.

4.4 Multihead Fusion

To attend in parallel to relation information from different dimensional subspaces, SNAT uses a multihead architecture with $V$ heads. The final aspect and targeted contextual embeddings $H_{a_i} \in \mathbb{R}^{V \times (d_E+d_F)}$ for aspect $a_i$ is the fusion of all heads.

$$H_{a_i} = [Q_{a_i}^{h_1} \odot \ldots \odot Q_{a_i}^{h_V}].$$  \hfill (12)

4.5 Sentiment Classification

For sentiment classification, SNAT first applies layer normalization (Ba et al., 2016) on the multihead fusion. Then, it uses a fully connected linear layer followed by a softmax activation to project $H_{a_i}$ to $y \in \mathbb{R}^S$, the posterior probability over $S$ sentiment polarities, is $y$ (omitting the bias):

$$y = \text{softmax}(W_y \cdot H_{a_i}),$$  \hfill (13)

where $W_y$ is parameter to learn.

5 Empirical Evaluation

5.1 Data

We train and evaluate SNAT on six benchmark datasets, described in Table 2, from three domains.
5.2 Parameter Settings

We set the dimension of aspect embeddings $d^E$ to 1,024. For all feed-forward networks, we use 1,024 as the dimension of both inner and outer states $d^F$. We train SNAT with 16 attention heads and freeze aspect embeddings during training. We follow the literature in that we do not further split SemEval training sets into training and validation sets due to their size. Instead, we use SentiHood-dev for parameter tuning. For regularization, we add dropouts with a rate of 0.1 between the two fully connected layers in each nonlinear feed-forward network. For optimization, we use Adam (Kingma and Ba, 2015) and set $\beta_1 = 0.9$, $\beta_2 = 0.99$, weight decay = 0.01, and the learning rate = 1e-5, with a warmup over 0.1% of training.

For all experiments, we train SNAT for 10 epochs on mini-batches of 32 randomly sampled sequences of 128 tokens. We repeat the training and testing cycle five times using different random seeds. Our evaluation metrics include accuracy and macro $F_1$ score. We perform the two-sample t-test on the improvement of SNAT over BERT. As reported in (Devlin et al., 2019), we observe unstable performance for both SNAT and BERT. We perform several restarts and select best performed models. We will release the code upon publication.

5.3 Baselines

We compare the performance of SNAT against the following published models.

NRC-Canada, DCU, Sentiue, and XRCE are feature-based models, requiring feature engineering based on linguistic tools and external resources. Of these, NRC-Canada and DCU achieve the best performance on SemEval 2014 sentiment classification for aspect category and aspect term, respectively. Sentiue and XRCE are the best performing for SemEval 2015 and 2016, respectively.

MemNet (Tang et al., 2016b) is a memory network consists of multiple computational layers. Within each layer, the model uses target embeddings to select important evidence from sentences through an attention mechanism.

RAM (Chen et al., 2017) builds position-weighted memory using two stacked BiLSTMs and the relative distance of each word to the left or
right boundary of each target. It uses a GRU with multiple attention computed using the memory.

**TNet-AS** (Li et al., 2018) dynamically associates targets with sentence words to generate target specific word representation and uses adaptive scaling to preserve context information.

**GCAE** (Xue and Li, 2018) is a CNN with two convolutional layers that use different nonlinear gating units to extract aspect-specific information.

**AGDT** (Liang et al., 2019) contains an aspect-guided encoder which consists of an aspect-guided GRU and a deep transition GRU to extract aspect-specific sentence representation.

**Sentic LSTM** (Ma et al., 2018) uses an LSTM with a hierarchical attention mechanism to model target and aspect attention. It incorporates commonsense knowledge into sentence embeddings.

**MGAN** (Fan et al., 2018) is an attention network based on BiLSTM that computes coarse-grained attention using averaged target embeddings and context words and leverages word similarity to build fine-grained attention.

**IACapsNet** (Du et al., 2019a) leverages capsule network to construct vector-based feature representation. It uses interactive attention EM-based capsule routing mechanism to learn the semantic relationship between targets and context words.

**ASGCN-DG** (Zhang et al., 2019) builds Graph Convolutional Networks over dependency trees and uses masking and attention mechanisms to generate aspect-oriented sentence representations.

**BERT** has three pretrained models for uncased English: BERT\textsubscript{BASE}, BERT\textsubscript{LARGE}, and BERT\textsubscript{LARGE}-WWM (Whole Word Masking). We compare SNAT with all three models. We include results for BERT\textsubscript{LARGE}-WWM, which performs best, and place the rest in Appendix A.

### 5.4 Results

Table 3 compares SNAT with baselines on SemEval datasets. For SemEval-14-A, AGDT outperforms GCAE, demonstrating the effectiveness of generating aspect-guided sentence representation. SNAT outperforms AGDT and NRC-Canada with accuracy gains of 5.2% and 3.8%, respectively. Since SemEval-14-A does not contain target information, SNAT uses BERT [CLS] token as the target. The result shows the benefit of selective attention to capture implicit target information. Let us explain why SNAT doesn’t perform better than BERT. We find that SemEval-14-A contains sentences with conflicting sentiments toward the same aspect. For example, the testing split contains 52 sentences having conflicting sentiments among 146 sentences that are labeled NEU. For example, “the falafal was rather over cooked and dried but the chicken was fine” is labeled NEU for aspect food but contains positive sentiment toward target chicken and negative sentiment toward target falafal. It appears that such data defects lower SNAT’s performance to that of BERT.

SemEval-14-T does not contain aspect labels. SNAT treats it as one aspect. SNAT outperforms all baselines with an accuracy gain of 3.8% and a $F_1$ gain of 5.7% compared with the best performing baseline, IACapsNet. SNAT achieves 4.9% higher accuracy than feature-based baseline DCU.

SemEval-15 and SemEval-16 contain sentiment associated with both aspect and targets. SNAT outperforms all baselines. We observed that SNAT obtains a 3.0% and 1.8% accuracy improvement over BERT on SemEval-15 and SemEval-16, respectively. The $F_1$ improvements over BERT are 2.3% and 2.5%. Also, SNAT outperforms the top feature-based models, Sentiue and XRCE. The results demonstrate the benefit of jointly considering aspects and targets.

Table 4 shows the results on SentiHood. We observe that SNAT outperforms the state-of-the-art Sentic LSTM with accuracy gains of 3.7% and 2.3% on dev and test, respectively. Sentic LSTM jointly considers both aspects and targets through a hierarchical attention mechanism. We attribute this performance gain to SNAT’s nonrecurrent architecture and selective attention mechanism. The nonrecurrent architecture alleviates the dependency range restriction in LSTM. The selective attention mechanism reduces noisy dependency information from irrelevant relations.

To further evaluate SNAT’s capability of handling sentences with conflicting sentiments, we apply trained BERT and SNAT only on the conflicting samples from SemEval-15, SemEval-16, and SentiHood-test. There are 152, 96, 343 conflicting samples in SemEval-15, SemEval-16, and SentiHood-test, respectively. Table 5 shows the results. We see that for all datasets, SNAT outperforms BERT with a large margin. The accuracy gains are 29.1%, 29.4%, and 37.1%, respectively.
5.5 Ablation Study

To understand the contribution of aspects, targets, and selective attention, we evaluate three variants of SNAT on SemEval-15. As Table 6 shows, using target selective attention (SNAT-Sel) yields 1.3% better accuracy but similar $F_1$ as using aspect attention (SNAT-Asp). Note that combining aspect attention with target self-attention (SNAT-Asp-Full) hurts performance and stability, as seen in the lower accuracy and $F_1$, indicating that simply applying self-attention on targets and context words introduces noisy information. Replacing self-attention with selective attention (SNAT) yields gains in accuracy and $F_1$ of 5.2% and 10% respectively, indicating that selective attention is effective in combating noise.

Table 6: Comparing model variants on SemEval-15.

| Model      | Aspect | Target | Acc. | $F_1$ |
|------------|--------|--------|------|-------|
| SNAT-Asp   | Yes    | –      | 84.09\textsuperscript{\dagger} | 65.20$^*$ |
| SNAT-Sel   | –      | Selective | 85.16 | 65.21 |
| SNAT-Asp-Full | Yes  | Self   | 82.01$^*$ | 61.08 |
| SNAT       | Yes    | Selective | 86.27 | 67.17 |

6 Discussion and Conclusion

The main innovation of SNAT is to jointly consider aspects and targets. It uses selective attention to model the relationships between target and context words, and aspects to attend to targeted contexts to predict sentiments. Users can “query” SNAT about sentiment of a particular aspect or target, or both. Our evaluation shows that SNAT outperforms state-of-the-art models on SemEval, SentiHood, and conflicting sentiment datasets. Our ablation study shows that jointly modeling aspects and targets with selective attention is superior to selective attention only, aspect attention only, and aspect with self-attention.
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A Appendices

We present additional results here.
Table 7: Comparing performance of SNAT, BERT<sub>BASE</sub>, and BERT<sub>LARGE</sub> on all tasks. Each experiment is repeated five times with different random seeds. Here, "sd" indicates one standard deviation.

| Model         | SemEval-14-A         | SemEval-14-T         | p-value | SemEval-14-A         | SemEval-14-T         | p-value | SemEval-14-A         | SemEval-14-T         | p-value |
|---------------|----------------------|----------------------|---------|----------------------|----------------------|---------|----------------------|----------------------|---------|
|               | Accuracy             | F<sub>1</sub>        | Accuracy| F<sub>1</sub>        | Accuracy             | F<sub>1</sub>        | Accuracy| F<sub>1</sub>        | Accuracy             | F<sub>1</sub> |
| BERT<sub>BASE</sub> | 84.16, sd 0.53       | 76.37, sd 0.84       | 79.19, sd 0.62 | 67.88, sd 1.39       | BERT<sub>LARGE</sub> | 85.17, sd 0.55       | 77.41, sd 0.80       | 79.82, sd 0.34       | 68.31, sd 0.84       | SNAT-BERT<sub>BASE</sub> | 84.53, sd 0.13       | 77.15, sd 0.48       | 82.93, sd 0.57       | 74.96, sd 1.02       | p-value | 0.16 | 0.11 | 9.04e-6 | 1.63e-05 |
| p-value       | 1.00                 | 0.91                 | 8.21e-8 | 1.44e-7             |                     |                     |                     |                     |                     |
| BERT<sub>LARGE</sub> | 85.17, sd 0.52       | 77.46, sd 0.77       | 83.30, sd 0.25 | 74.96, sd 0.25       | SNAT-BERT<sub>LARGE</sub> | 84.85, sd 0.46       | 64.96, sd 1.19       | 90.45, sd 0.63       | 74.61, sd 2.37       | p-value       | 1.00 | 0.91 | 8.21e-8 | 1.44e-7 |

Table 8: Comparing accuracy of SNAT and BERT on all tasks. Each experiment is repeated five times with different random seeds. "sd" indicates one standard deviation. The p-value row indicates if the accuracy of BERT is significantly different from SNAT, measured by two sample t-test. We compare each of the 25 combination of experiments between BERT and SNAT. The "BERT ≥ SNAT" row counts the number of combinations where BERT is no worse than SNAT, and how many of them are significant, measured by McNemar test. Similarly, "BERT < SNAT" counts the number of combinations where BERT is worse than SNAT. For example, on SemEval-14-A, BERT is no worse than SNAT in 12 combinations, none of which are significant. BERT performs worse than SNAT in the other 13 combinations, none of which are significant either.

| Model         | SemEval-14-A         | SemEval-14-T         | SemEval-15 | SemEval-16 | SentiHood-dev | SentiHood-test |
|---------------|----------------------|----------------------|------------|------------|--------------|---------------|
|               | Accuracy             | F<sub>1</sub>        | Accuracy   | F<sub>1</sub> | Accuracy     | F<sub>1</sub>   |
| BERT<sub>BASE</sub> | 86.15, sd 0.52       | 80.39, sd 0.63       | 83.72, sd 0.96 | 88.52, sd 0.49 | 87.60, sd 0.17 | 87.09, sd 0.20 |
| SNAT<sub>BASE</sub> | 86.03, sd 0.16       | 84.90, sd 0.45       | 86.27, sd 0.57 | 90.10, sd 0.22 | 92.17, sd 0.37 | 91.34, sd 0.31 |
| p-value       | 0.64                 | 1.16e-6              | 9.22e-4    | 1.64e-4    | 8.32e-9      | 5.08e-9       |
| BERT ≥ SNAT   | 12 (0)               | 0 (0)                | 0 (0)      | 0 (0)      | 0 (0)        | 0 (0)         |
| BERT < SNAT   | 13 (0)               | 25 (25)              | 25 (17)    | 25 (8)     | 25 (25)      | 25 (25)       |

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Table 9: Comparing accuracy of SNAT model variants on SemEval-15. Each experiment is repeated five times with different random seeds. ‘‘, sd ’’ indicates one standard deviation. The p-value column indicates if the accuracy of the variant is significantly different from SNAT, measured by two sample t-test. We compare each of the 25 combination of experiments between the variants and SNAT. The “variant ≥ SNAT” column counts the number of combinations where the variant is better than SNAT, and how many of them are significant, measured by McNemar test. Similarly, “variant < SNAT” counts the number of combinations where the variant is worse than SNAT. For example, SNAT-Sel is better than SNAT in eight combinations but none of them are significant. SNAT is better than SNAT-Sel in 17 combinations where nine of them are significant. SNAT is better than SNAT-Sel in 17 combinations where nine of them are significant.

| Model      | Aspect | Target | Accuracy     | p-value     | variant ≥ SNAT | variant < SNAT |
|------------|--------|--------|--------------|-------------|----------------|----------------|
| SNAT-Asp   | Yes    | –      | 84.09, sd 0.68 | 2.23e-8     | 0 (0)          | 25 (14)        |
| SNAT-Sel   | –      | Selective | 85.16, sd 1.24 | 4.65e-6     | 8 (0)          | 17 (9)         |
| SNAT-Asp-Full | Yes  | Self  | 82.01, sd 1.95  | 5.72e-6     | 0 (0)          | 25 (14)        |
| SNAT       | Yes    | Selective | 86.27, sd 0.57  | –           | –              | –              |