Noisy Pairing and Partial Supervision for Stylized Opinion Summarization

Anonymous ACL submission

Abstract

Opinion summarization research has primarily focused on generating summaries reflecting important opinions from customer reviews without paying much attention to the writing style. In this paper, we propose the stylized opinion summarization task, which aims to generate a summary of customer reviews in the desired (e.g., professional) writing style. To tackle the difficulty in collecting customer and professional review pairs, we develop a non-parallel training framework, Noisy Pairing and Partial Supervision (**NAPA**), which trains a stylized opinion summarization system from non-parallel customer and professional review sets. We create a benchmark PROSUM by collecting customer and professional reviews from Yelp and Michelin. Experimental results on PROSUM and FewSum demonstrate that our non-parallel training framework consistently improves both automatic and human evaluations, successfully building a stylized opinion summarization model that can generate professionally-written summaries from customer reviews.

1 Introduction

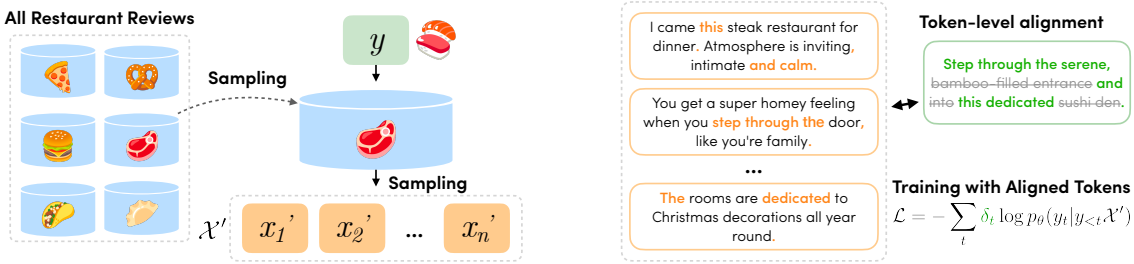
Opinion summarization, which focuses on automatically generating textual summaries from multiple customer reviews, has received increasing attention due to the rise of online review platforms. Different from single-document summarization tasks (e.g., news summarization), which can easily collect a large amount of document-summary pairs, manually creating summaries from multiple reviews is expensive; it is not easy to collect large-scale training data for opinion summarization. To address this challenge, existing studies build pseudo-reviews-summary pairs in a self-supervised fashion (Chu and Liu, 2019; Amplayo and Lapata, 2020) or use a small amount of reviews-summary pairs (Bražinskas et al., 2020a) in a few-shot manner to train opinion summarization models.

Figure 1: Comparison of conventional and stylized opinion summarization. Given multiple reviews as input, stylized opinion summarization aims to generate a summary in the desired writing style.

However, existing opinion summarization systems have focused on summarizing important opinions in reviews while not paying much attention to the writing style. They leverage customer reviews as pseudo summaries to train models, which generate summaries in the same writing style as the customer reviews as illustrated in Figure 2. On the other hand, professional reviews, such as Michelin Guide—a prestigious and popular restaurant guide, use a quite different writing style to describe the same type of information.

In this paper, we aim to fill this gap between customer and professional reviews by proposing a new branch of opinion summarization—*stylized opinion summarization*, where the goal is to generate a summary of opinions in the desired writing style. Specifically, besides customer reviews, as the input to the conventional opinion summarization task, we use a few example summaries in the desired writing style as auxiliary information to guide the model in learning the writing style. Since a few summaries in the desired writing style may not cover the same entities (e.g., restaurants) as the customer review set, the two review sets for the stylized opinion summarization task are non-parallel, which makes the task more challenging.[1]

[1]We will also evaluate the parallel setting later.



(a) **Noisy Pairing**: Given the candidate summary y, the pairs of noisy input reviews and output summary, $(\mathcal{X}', y)$, are built by retrieving the input reviews from a set of reviews from an arbitrary entity. This example retrieves the reviews from a steak restaurant given the professionally written summary of a sushi restaurant.

(b) **Partial Supervision**: After building a noisy input-output pair, we obtain the token-level alignment between the pair based on the word, stem, and synonym matching. Finally, we introduce indicator functions δ_t into the standard negative log-loss function $\mathcal{L}$ to train using only aligned tokens, highlighted in **green**.

Figure 2: Overview of our non-parallel training framework, Noisy Pairing and Partial Supervision.

To this end, we develop a non-parallel training framework, *Noisy Pairing and Partial Supervision* (**NAPA**), which builds a stylized opinion summarization model from *non-parallel* customer and professional review sets. The core idea consists of two functions: *Noisy Pairing* (§4.1) creates pseudo "noisy" reviews-summary pairs forcibly for each summary in the desired writing style by obtaining input reviews similar to the summary. Then, *Partial Supervision* (§4.2) trains a model with the collected noisy pairs by focusing on the sub-sequence of the summary that can be reproduced from the input reviews while not learning to hallucinate non-existing content. Figure 2 illustrates the two functions. In this example, for a professionally-written review of a sushi restaurant, Noisy Pairing finds reviews of a steak restaurant as noisy source reviews, which are then *partially* used by Partial Supervision to train a stylized opinion summarization model.

We also create and release a benchmark for stylized opinion summarization named PROSUM, which consists of 700 paired Yelp reviews and Michelin point-of-views. Experimental results on PROSUM confirm that **NAPA** successfully generates summaries in the desired writing style in a non-parallel training setting, significantly better than models trained by self-supervision and existing non-parallel training methods.

We further performed additional experiments using existing supervised opinion summarization benchmarks, FewSum (Bražinskas et al., 2020a), in a non-parallel setting. We observed that **NAPA** brings significant gains over self-supervised systems and competitive performance with state-of-the-art supervised systems, indicating the generalizability of the proposed method.

2 The PROSUM Corpus

Data Collection We build a stylized opinion summarization dataset, PROSUM, which pairs customer reviews and professional reviews about the same restaurant, as we need customer reviews as the input and a professional review as the summary for evaluation purposes.

We first collected 700 professionally-written restaurant reviews from `guide.michelin.com`, a famous restaurant review site. Unlike crowd-sourced opinion summaries, these reviews are written by professional writers. Thus, they include more appealing expressions and attractive information than crowd-sourced summaries. Then, we collected customer reviews from a popular customer review platform, `yelp.com`, by asking crowdsourced workers from Appen[2] to find the same restaurant for each of the restaurants we collected in the first step. We collected up to 5,000 customer reviews for each restaurant.

Filtering Since our main focus is to create a stylized opinion summarization benchmark and thousands of input reviews cannot be handled by most pre-trained language models, we filtered source customer reviews to reduce the number of input reviews to a size that can be handled by commonly used pre-trained language models.

For each reviews-summary pair, we selected source Yelp reviews so that the coverage of the target Michelin review was maximized. Specifically, we used the sum of the ROUGE-1/2 Recall scores between the selected source Yelp reviews and the target Michelin review to measure the coverage. We incrementally added source reviews until the total length exceeded 1,024 words to maximize the

[2] https://appen.com/

	Src len.	Tgt len.	% of novel n-grams in gold summary				Extractive oracle		
			Unigram	Bigram	Trigram	4-gram	R1	R2	RL
PROSUM (ours)	1162.7	139.7	38.19	84.76	97.17	99.18	42.97	10.99	22.59
Yelp (Bražinskas et al., 2020a)	453.3	58.02	31.71	83.02	95.53	98.35	47.79	15.28	25.84
Amazon (Bražinskas et al., 2020a)	446.2	56.89	31.62	82.32	95.84	98.60	46.31	14.27	25.44

Table 1: Statistics of PROSUM and FewSum Yelp/Amazon benchmarks. PROSUM has a longer source and target length compared to the FewSum benchmarks and offers more abstractive summaries with respect to the novel n-gram ratio. The source and target length is the number of BPE tokens per example using the BART tokenizer.

coverage in a greedy manner. On average, 6.7 input reviews were selected for each pair. This selection step is to ensure the target Michelin summary can be created by source Yelp reviews.

Finally, we shuffled the selected source reviews to remove the selection order bias. The final benchmark consists of 100/100/500 entities for the training/validation/test set. Note that we keep parallel data (i.e., reviews-summary pairs) in PROSUM for evaluation and for training supervised models. For **NAPA** or other non-parallel training models, we remove source reviews from the training set.

Statistics We summarize the PROSUM dataset and compare it with existing opinion summarization datasets in Table 1. We calculate novel n-grams in gold summaries to evaluate how abstractive/extractive PROSUM is and the performance of the extractive oracle summaries from the source reviews. We confirm that the PROSUM is more abstractive than the existing benchmarks. The extractive oracle performance supports the feasibility of stylized opinion summarization in PROSUM.

3 Self-supervised Opinion Summarization

This section describes the standard self-supervised framework for conventional opinion summarization and then the pseudo-reviews-summary pair construction approach (Elsahar et al., 2021), which is also used as the pre-training method in §5.

Opinion summarization is a multi-document summarization problem that aims to generate a textual summary text y that reflects the salient opinions given the set of reviews $\mathcal{X} = \{x_1, \ldots, x_N\}$. Due to the unavailability of a sufficient amount of reference summaries for training, a commonly used approach is to create a pseudo-reviews-summary training pair $(\tilde{\mathcal{X}}, \tilde{y})$ from a massive amount of reviews and trains an opinion summarization model p_θ using negative log-loss minimization,

$$\mathcal{L} = -\log p_\theta(\tilde{y}|\tilde{\mathcal{X}}) = -\sum_t \log p_\theta(\tilde{y}_t|\tilde{y}_{<t}, \tilde{\mathcal{X}}).$$

Pseudo reviews-summary pairs construction Let $\mathcal{R}_e$ denotes the set of reviews for specific entity e such as a restaurant. For each set of reviews $\mathcal{R}_e$, we treat a review in this set as a pseudo summary $\tilde{y} \in \mathcal{R}_e$ and then retrieve the relevant reviews to build a source set of reviews $\tilde{\mathcal{X}}$. Concretely, given a pseudo summary $\tilde{y}$, retrieve the source set of N reviews $\tilde{\mathcal{X}}$ by maximizing the sum of the similarity as follows:

$$\tilde{\mathcal{X}} = \underset{\mathcal{X} \subset \mathcal{R}_e \setminus \{\tilde{y}\}, |\mathcal{X}|=N}{\arg\max} \sum_{x \in \mathcal{X}} \text{sim}(x, \tilde{y}),$$

where similarity is measured by the cosine similarity of the TF-IDF vector. This operation is applied to all reviews as pseudo summaries. Then the top-K pseudo-reviews-summary pairs with the highest similarity scores $\sum_{x \in \tilde{X}} \text{sim}(x, \tilde{y})$ are retained as the final pseudo-training set $\{(\tilde{\mathcal{X}}_i, \tilde{y}_i)\}_{i=1}^K$.

4 NAPA

Although pseudo-reviews-summary pairs creation has been a standard and solid approach for conventional opinion summarization, we cannot directly use it for stylized opinion summarization, as there are two sets of *non-parallel* reviews in different writing styles.

This section describes a non-parallel training framework for stylized opinion summarization, *Noisy Pairing and Partial Supervision* (**NAPA**), which trains a summarization model from non-parallel customer and professional review sets.

4.1 Noisy Pairing

Noisy Pairing expands the existing pseudo-reviews-summary construction approach to create "noisy" reviews-summary pairs for each summary in the desired writing style by obtaining input reviews similar to the summary.

To leverage the desired style of summary y for the entity e, which is not paired with the set of reviews for the same entity $\mathcal{R}_e$, we first build the *noisy* reviews-summary pairs. Specifically, given

the summary y for entity e, we follow the pseudo data construction approach (§3) to construct the source set of reviews, but we retrieve the reviews from the *different* entity $e'(\neq e)$ with the summary:

$$\tilde{\mathcal{X}}' = \underset{\mathcal{X} \subset \mathcal{R}_{e'}, |\mathcal{X}|=N}{\arg\max} \sum_{x \in \mathcal{X}} \text{sim}(x, y).$$

For instance, given a summary of a sushi restaurant, we can use reviews of a steak restaurant to construct a noisy reviews-summary pair as illustrated in Figure 2. Then, using the similar approach used in the pseudo data construction, we obtain the final noisy training set $\{(\tilde{\mathcal{X}}', y)\}$. In particular, the top 10 noisy reviews-summary pairs of the highest similarity score are retained for each summary.

Note that this method could unintentionally select the review of the correct entity as input (i.e., $e' = e$), so in our experiments, we explicitly discarded the review of the entity used in summary to maintain the non-parallel setting.

4.2 Partial Supervision

With the noisy pairing method described above, we can build noisy reviews-summary pairs $\{(\tilde{\mathcal{X}}', y)\}$, but obviously, a model trained with these pairs will generate unfaithful summaries. However, even in such noisy reviews-summary pairs, there would be sub-sequences of the summary y that could be generated from noisy input reviews $\tilde{\mathcal{X}}'$.

To implement this intuition into the training, we first compute the *token-level alignment* between a noisy set of reviews $\tilde{\mathcal{X}}'$ and summary y, and then introduce the indicator function δ_t inside of the standard log-loss function to ignore the unaligned tokens during the training:

$$\mathcal{L}' = -\sum_t \delta_t \log p_\theta(y_t | y_{<t}, \tilde{\mathcal{X}}'),$$

where the alignment function δ_t will be 1 if the token y_t is aligned with the noisy source reviews $\mathcal{X}$ and otherwise 0 as illustrated in Figure 2b. This allows for using aligned words, such as the style and expressions used in the summary, as a training signal without increasing the likelihood of hallucinated words.

For the alignment function, we use word-level matching between the source and target reviews. Since professional writers have a rich vocabulary, which contains words that rarely appear in customer reviews, we implement word stem matching and synonym matching (e.g., serene $\sim$ calm) to increase the coverage in Partial Supervision. We discuss the design choice of the alignment function in §6.3.

5 Evaluation

We use PROSUM and an existing opinion summarization benchmark FewSum (Bražinskas et al., 2020a) to verify the effectiveness and generalizability of **NAPA**🍷. For FewSum, we discarded the source reviews from the training dataset to convert FewSum into a stylized opinion summarization benchmark (i.e., in the non-parallel setting).

5.1 Settings

Training Data For non-parallel training, we first pre-train a self-supervised opinion summarization model using pseudo-reviews-summary pairs (§3). Then, we fine-tune it using noisy reviews-summary pairs using **NAPA**🍷 (§4). Therefore, we need two sets of pseudo-reviews-summary pairs for self-supervised pre-training and noisy reviews-summary pairs for **NAPA**🍷.

As PROSUM does not contain customer reviews for training, we use the Yelp review dataset[3], which has 7M reviews for 150k entities, to collect reviews-summary pairs for PROSUM dataset. We discarded all the entities used in the Michelin reviews in PROSUM to avoid unintentionally selecting the same entity for Noisy Pairing. Then, we excluded entities that do not satisfy the following criteria: (1) in either the `restaurant` or `food` category; (2) the rating is higher than 4.0/5.0 on average. Then, we filtered reviews with 5-star ratings. Finally, we discarded entities that have less than ten reviews. After this pre-processing, we built 100k pseudo-reviews-summary pairs and 1k noisy reviews-summary pairs for self-supervised pre-training and **NAPA**🍷, respectively. The pre-processing method for the FewSum dataset is described in Appendix.

Model We instantiate our summarization models using the Transformer model (Vaswani et al., 2017) initialized with the `BART-large` checkpoint (Lewis et al., 2020) in the `transformers` library (Wolf et al., 2020). We used AdamW optimizer (Loshchilov and Hutter, 2019) with a linear scheduler and warmup, whose initial learning rate is set to 1e-5, and label smoothing (Szegedy et al., 2016) with a smoothing factor of 0.1. We tested three configurations: (1) the full version,

[3] https://www.yelp.com/dataset

(2) without Partial Supervision, and (3) without Noisy Paring and Partial Supervision—the self-supervised base model trained only using pseudo-review-summary pairs.

5.2 Baselines

For the main experiment on PROSUM, we compared the state-of-the-art opinion summarization system (BiMeanVAE) and two text-style transfer models (Pipeline and Multitask). We also evaluated the upper-bound performance of NAPA by using the *parallel* training dataset, where the customer and professionally written reviews for the same entity are correctly paired (Supervised upper-bound). For the FewSum dataset, we compared various opinion summarization models, including self-supervised models and supervised models that use parallel training data, to verify the performance of our non-parallel training framework. The details can be found in Appendix.

BiMeanVAE: BiMeanVAE (Iso et al., 2021) is a self-supervised opinion summarization model based on a variational autoencoder. We further fine-tune this model using Michelin reviews to generate summaries with the desired style.

Pipeline: We combine a self-supervised opinion summarization model and text style transfer model to build a two-stage pipeline. For the self-supervised model, we use the same self-supervised base model as **NAPA**🍷. For the text style transfer model, we use STRAP (Krishna et al., 2020), which uses inverse paraphrasing to perform text style transfer using Yelp and Michelin reviews in the non-parallel setting.

Multitask: We use a multi-task learning framework, TitleStylist (Jin et al., 2020), which combines summarization and denoising autoencoder objectives to train a summarization model that generates summaries in the desired writing style. In the experiment, we use Yelp pseudo-reviews-summary pairs (Michelin reviews) for the summarization (denoising) objective.

5.3 Automatic Evaluation

We use the F1 scores of ROUGE-1/2/L (Lin, 2004)[4] and BERTScore (Zhang et al., 2020)[5] for reference-based automatic evaluation. Additionally, we calculate the CTC score (Deng et al., 2021) to evaluate the consistency and relevance of the generated summaries. The consistency score is measured by the alignment between the source reviews and the generated summary based on the contextual embedding similarity; the relevance score is measured by the alignment between the generated summary and the reference summary multiplied by the consistency score. The contextual embeddings are obtained from the `roberta-large` model.

ProSum Table 2 shows the main experimental results on PROSUM. The self-supervised model (i.e., NAPA w/o Noisy Pairing and Partial Supervision) outperforms all the non-parallel baseline systems. The comparison shows that Pipeline, which combines the self-supervised model and STRAP, degrades the summarization quality. The result indicates that it is not easy to achieve stylized opinion summarization by simply combining a summarization model and a text style transfer model.

NAPA w/o Partial Supervision improves the summarization quality against the self-supervised model while causing degradation in consistency between generated summaries and the source reviews. This degradation is expected, as Noisy Pairing creates pseudo-reviews-summary by sampling reviews from a different entity, only considering the similarity against the pseudo-summary. We will discuss this point in detail in §6.1.

NAPA🍷 substantially outperforms the baselines for summarization quality and relevance while maintaining the same level of consistency as the best self-supervised model. This confirms that Partial Supervision successfully alleviates the consistency degradation caused by Noisy Pairing.

The experimental results demonstrate that both Noisy Pairing and Partial Supervision are essential to building a robust stylized opinion summarization model, allowing the model to take advantage of useful signals in the noisy reviews-summary pairs.

FewSum The experimental results on FewSum in the non-parallel setting shown in Table 3 also observe the substantial improvements by NAPA over the self-supervised systems. NAPA shows competitive performance against state-of-the-art supervised systems, which use parallel training data for training. The results further confirm that providing a small number of reference summaries in the desired writing style, even if they are not paired with input reviews, can help NAPA train a solid summarization model for stylized opinion summarization.

[4] https://github.com/Diego999/py-rouge
[5] https://github.com/Tiiiger/bert_score

	PROSUM					
	R1	R2	RL	BS	Consistency	Relevance
Non-parallel baselines						
Multitask (Jin et al., 2020)	23.78	1.85	15.81	80.92	95.01	89.84
Pipeline (Krishna et al., 2020)	27.19	2.69	16.76	82.88	96.69	91.99
BiMeanVAE (Iso et al., 2021)	28.15	3.49	18.68	83.10	96.83	91.98
NAPA 🍷						
Full version	**33.54**	**4.95**	**20.67**	**84.77**	96.86	**92.48**
w/o Partial Supervision	31.64	3.96	18.90	84.15	96.09	91.80
w/o Noisy Paring and Partial Supervision	28.19	3.43	17.60	83.49	**96.88**	91.92
Supervised upperbound	34.50	5.70	20.64	84.96	97.23	92.96

Table 2: Experimental results on the PROSUM dataset. R1/2/L and BS denote the F1 scores of ROUGE-1/2/L and BERTScore. **NAPA** 🍷 gives substantial improvements over the baselines. We also confirm that Partial Supervision successfully alleviates the consistency degradation caused by Noisy Pairing.

	YELP			AMAZON		
	R1	R2	RL	R1	R2	RL
Self-supervised baselines						
MeanSum (Chu and Liu, 2019)	27.50	3.54	16.09	26.63	4.89	17.11
CopyCat (Bražinskas et al., 2020b)	28.12	5.89	18.32	27.85	4.77	18.86
Supervised baselines – Parallel training						
FewSum (Bražinskas et al., 2020a)	37.29	9.92	22.76	33.56	7.16	24.49
PASS (Oved and Levy, 2021)	36.91	8.12	23.09	37.43	8.02	23.34
AdaSum (Bražinskas et al., 2022)	38.82	11.75	25.14	39.78	10.80	25.55
BART (our implementation)	39.69	11.63	25.48	39.05	10.08	24.29
NAPA 🍷 – Non-parallel training						
Full version	**38.59**	**11.23**	**25.29**	**36.21**	**9.18**	**23.60**
w/o Partial Supervision	37.41	10.51	24.18	35.30	7.45	21.92
w/o Noisy Pairing and Partial Supervision	33.39	7.64	20.67	30.18	5.24	19.70

Table 3: Experimental results on the FewSum dataset (Bražinskas et al., 2020a). NAPA shows substantial improvements over the self-supervised baselines. Note that the supervised baseline models were fine-tuned on the parallel training data (i.e., annotated reviews-summary pairs), while NAPA models were trained in the non-parallel setting.

5.4 Human Evaluation

We conducted human evaluations to compare the performance of our model (NAPA) with three baselines: Self-supervision, Pipeline, and NAPA without Partial Supervision (PS) on PROSUM with respect to the fluency, relevance, and attractiveness of the generated summary. We asked human annotators recruited from Appen to rate generated summaries on a 4-point Likert scale for each evaluation metric.

Our findings from the results shown in Figure 3 are: (1) using professionally-written summaries for training allows the model to generate more fluent and attractive summaries than other baselines (NAPA and NAPA w/o PS vs. Self-supervision and Pipeline); (2) NAPA without Partial Supervision tends to generate more irrelevant summaries (NAPA vs. NAPA w/o PS). Overall, our results demonstrate the importance of using professionally-written summaries for training to improve the fluency and attractiveness of generated summaries and the need for Partial Supervision to ensure the relevance of generated summaries.

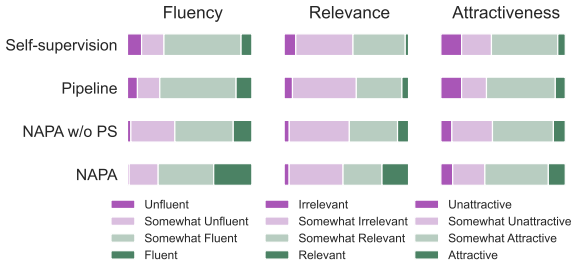


Figure 3: Human evaluations of the fluency, relevance, and attractiveness on PROSUM.

6 Analysis

6.1 Importance of Partial Supervision

The experimental results in Tables 2 and 3 show that NAPA without Partial Supervision—just using noisy reviews-summary pairs—demonstrates solid

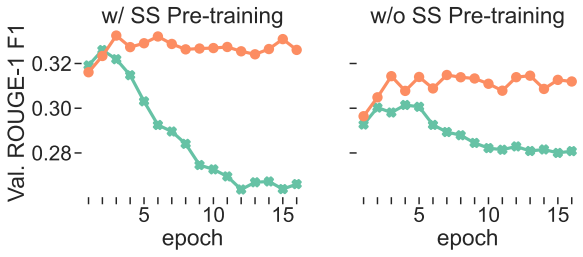


Figure 4: ROUGE-1 F1 score on validation set of PROSUM at different training stages. The **orange line** denotes the model trained *with* partial supervision (§4.2), and the **green line** denotes the model trained *without* partial supervision.

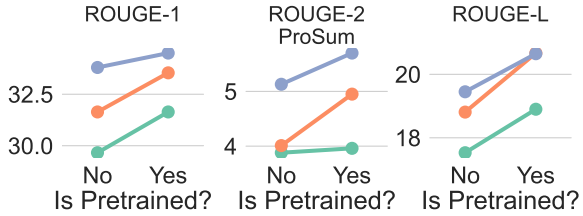


Figure 5: Comparison of summarization quality with and without pre-training. The **blue line** denotes the model trained in a supervised setting, **orange line** denotes the model trained *with* partial supervision and **green line** denotes the model trained *without* partial supervision.

performance for reference-based automatic evaluation metrics. This is a little bit counterintuitive, and this can be attributed to the positive effect of early stopping against noisy training data (Arpit et al., 2017; Li et al., 2020). To analyze this point, we conducted an additional experiment by training NAPA with and without Partial Supervision for more training epochs.

Figure 4 shows the ROUGE-1 F1 score on the validation set of PROSUM at different training epochs of the NAPA model trained *with* or *without* Partial Supervision (**orange line** and **green line**). As shown in the figure, we find that in the very early stages of training, both the models improve the ROUGE scores. In the later stage, NAPA *without* Partial Supervision (**green line**) shows continuous degradation, while NAPA *with* Partial Supervision (**orange line**) shows robust performance consistently over the entire training process.

This observation is aligned with the literature on noisy supervision, which shows that over-parametrized models learn simple patterns in the early stages of training and then memorize noise (Arpit et al., 2017). On the other hand, it is also known that early stopping is not sufficient under labeling noise (Ishida et al., 2020). We observed that NAPA *without* Partial Supervision generated summaries that were less consistent with the source reviews (Table 2) and contained more hallucinations, as described in Appendix. The results support the importance of Partial Supervision for improving the robustness of the stylized opinion summarization model in non-parallel training.

6.2 Pre-training with Self-supervision

As we observe that the self-supervised baseline (i.e., NAPA w/o Noisy Pairing and Partial Supervision) shows solid performance in Table 2 and better performance than the other self-supervised baselines in Table 3, we further investigated the effectiveness of the pre-training using pseudo-reviews-summary pairs (Self-supervision in §3) in the non-parallel training. We conducted ablation studies for the model trained *with* Partial Supervision (**orange line**), *without* Partial Supervision (**green line**), and supervised setting (**blue line**).

As shown in Figure 5, pre-training with self-supervision in all the settings helps improve summarization quality. The effect of pre-training is the most remarkable in the non-parallel settings (**orange line** and **green line**). This indicates that while non-parallel training helps learn the desired writing style for summary generation, it is difficult to determine what content to include in the summary only from the noisy-reviews-summary pairs. Therefore, we experimentally confirm the effectiveness of self-supervised pre-training for stylized opinion summarization; self-supervision pre-training teaches the model the basics of how to summarize the content, and non-parallel training introduces the model to write in the desired style. The same analysis on the FewSum dataset can be found in Appendix.

6.3 Choice of Token Alignment

As discussed in §4.2, the token alignment function should be carefully chosen to appropriately align customer and professional reviews with different vocabularies. For example, the exact word match should naively disregard semantically similar words (e.g., serene and calm). Thus, we further performed a comparative analysis of the token alignment function. We compared NAPA with different variants of Partial Supervision that use: (1) exact word matching, (2) stem matching, and (3) synonym matching.

As shown in Table 4, No Partial Supervision (first row) generates too many novel n-grams, indi-

	Reference based metrics				Novel n-gram ratios			
	R1	R2	RL	BS	Unigram	Bigram	Trigram	Four-gram
NAPA 🍷								
No Partial Supervision ($\delta_t = 1$ for all t)	31.64	3.96	18.90	84.15	31.52	80.38	96.54	99.23
+ word match	32.88	4.77	19.98	84.50	12.78	64.10	91.63	97.69
+ word or stem match	32.49	4.82	20.03	84.45	13.23	66.60	92.27	97.94
+ word or stem or synonym match	33.54	4.95	20.67	84.77	15.54	67.19	92.24	97.75
Supervised upperbound	34.50	5.70	20.65	84.96	14.59	58.84	83.20	91.38

Table 4: Comparison of summaries generated with different alignment criteria; + word match is the strictest alignment criterion; adding + stem and + synonym match allows for more relaxed alignment criteria allowing more words to be used for training. As the alignment criteria are relaxed, more novel n-grams can be generated.

cating significant hallucinations; it shows the worst summarization performance. We confirm that the model tends to generate more novel n-grams when the alignment criterion is relaxed and also improves summarization performance, suggesting that the stem and synonym matching functions can successfully consider semantically similar tokens to incorporate into training without degradaging the summarization performance.

7 Related Work

Opinion Summarization Due to the challenges in collecting training data, many studies have developed unsupervised solutions for opinion summarization systems (Chu and Liu, 2019; Amplayo and Lapata, 2020). Recent studies have explored few-shot learning approaches that utilize a small number of review-summary pairs for training (Bražinskas et al., 2020a; Oved and Levy, 2021).

Our technique falls in the middle of these two approaches, as we do not use annotated reviews-summary pairs for training while using a large number of customer reviews and a small number of professional reviews as auxiliary supervision signals.

Text Style Transfer Text style transfer is a technique to rewrite the input text into the desired style (McDonald and Pustejovsky, 1985). The primary approach for text style transfer is *sentence-level*, which is used as our baselines (Pipeline (Krishna et al., 2020) and Multitask Jin et al. (2020)).

Based on the observation that both Pipeline and Multitask do not perform well for the stylized opinion summarization task (in Table 2), we confirm that applying sentence-level style transfer cannot offer high-quality stylized opinion summarization and it requires *paragraph-level* text style transfer, which needs further exploration (Jin et al., 2022).

Noisy Supervision Learning statistical models under labeling noise is a classic challenge in machine learning (Angluin and Laird, 1988; Natarajan et al., 2013) and is an active research field because of the increasing availability of noisy data (Han et al., 2020; Song et al., 2022). Among the major approaches for noisy supervision, the loss adjustment approach is widely used in the NLP community, as it can be coupled with any type of commonly used Transformer-based language models (Devlin et al., 2019; Brown et al., 2020)

In text generation, previous studies have attempted to improve the model faithfulness by treating hallucinated summaries as noisy supervision (Kang and Hashimoto, 2020; Goyal et al., 2022). Our study is different from the line of work in the sense that we combine noisy-reviews-summary pairs and noisy supervision to develop a non-parallel training framework for stylized opinion summarization.

8 Conclusions

This paper proposes stylized opinion summarization, which aims to summarize opinions of input reviews in the desired writing style. As parallel reviews-summary pairs are difficult to obtain, we develop a non-parallel training framework named Noisy Pairing and Partial Supervision (**NAPA** 🍷); it creates noisy reviews-summary pairs and then trains a summarization model by focusing on the sub-sequence of the summary that can be reproduced from the input reviews. Experimental results on a newly created benchmark PROSUM and an existing opinion summarization benchmark FewSum demonstrate that our non-parallel training framework substantially outperforms self-supervised and text-style transfer baselines while competitively performing well against supervised models that use parallel training data.

9 Ethical Considerations

We do not see any ethical issues, but we would like to mention some limitations. This study investigates the use of a limited number of unpaired desired summaries during training. We employ partial supervision to reduce the risk of hallucination, but there is still a potential to generate unfaithful summaries. Thus, the model may generate inconsistent opinions with the source reviews. There is also a trade-off between the quality and diversity of our token-level alignment method. We decided to use exact, stem, and synonym-based matching, but these methods may introduce alignment errors, leading to noisier training. For the annotation tasks, we paid $0.96 for each summary for the crowd workers on Appen.

References

Reinald Kim Amplayo and Mirella Lapata. 2020. Unsupervised opinion summarization with noising and denoising. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1934–1945, Online. Association for Computational Linguistics.

Dana Angluin and Philip Laird. 1988. Learning from noisy examples. *Machine Learning*, 2(4):343–370.

Devansh Arpit, Stanisław Jastrzębski, Nicolas Ballas, David Krueger, Emmanuel Bengio, Maxinder S. Kanwal, Tegan Maharaj, Asja Fischer, Aaron Courville, Yoshua Bengio, and Simon Lacoste-Julien. 2017. A closer look at memorization in deep networks. In *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pages 233–242. PMLR.

Arthur Bražinskas, Mirella Lapata, and Ivan Titov. 2020a. Few-shot learning for opinion summarization. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4119–4135, Online. Association for Computational Linguistics.

Arthur Bražinskas, Mirella Lapata, and Ivan Titov. 2020b. Unsupervised opinion summarization as copycat-review generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5151–5169, Online. Association for Computational Linguistics.

Arthur Bražinskas, Ramesh Nallapati, Mohit Bansal, and Markus Dreyer. 2022. Efficient few-shot fine-tuning for opinion summarization. In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 1509–1523, Seattle, United States. Association for Computational Linguistics.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.

Eric Chu and Peter Liu. 2019. MeanSum: A neural model for unsupervised multi-document abstractive summarization. In *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 1223–1232. PMLR.

Mingkai Deng, Bowen Tan, Zhengzhong Liu, Eric Xing, and Zhiting Hu. 2021. Compression, transduction, and creation: A unified framework for evaluating natural language generation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7580–7605, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Jesse Dodge, Suchin Gururangan, Dallas Card, Roy Schwartz, and Noah A. Smith. 2019. Show your work: Improved reporting of experimental results. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2185–2194, Hong Kong, China. Association for Computational Linguistics.

Hady Elsahar, Maximin Coavoux, Jos Rozen, and Matthias Gallé. 2021. Self-supervised and controlled multi-document opinion summarization. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 1646–1662, Online. Association for Computational Linguistics.

Tanya Goyal, Jiacheng Xu, Junyi Jessy Li, and Greg Durrett. 2022. Training dynamics for text summarization models. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 2061–2073, Dublin, Ireland. Association for Computational Linguistics.

Bo Han, Quanming Yao, Tongliang Liu, Gang Niu, Ivor W Tsang, James T Kwok, and Masashi Sugiyama. 2020. A survey of label-noise representation learning: Past, present and future. *arXiv preprint arXiv:2011.04406*.

Ruining He and Julian McAuley. 2016. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In *proceedings of the 25th international conference on world wide web*, pages 507–517.

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for NLP. In *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 2790–2799. PMLR.

Takashi Ishida, Ikko Yamane, Tomoya Sakai, Gang Niu, and Masashi Sugiyama. 2020. Do we need zero training loss after achieving zero training error? In *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pages 4604–4614. PMLR.

Hayate Iso, Xiaolan Wang, Yoshihiko Suhara, Stefanos Angelidis, and Wang-Chiew Tan. 2021. Convex Aggregation for Opinion Summarization. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 3885–3903, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Di Jin, Zhijing Jin, Zhiting Hu, Olga Vechtomova, and Rada Mihalcea. 2022. Deep learning for text style transfer: A survey. *Computational Linguistics*, 48(1):155–205.

Di Jin, Zhijing Jin, Joey Tianyi Zhou, Lisa Orii, and Peter Szolovits. 2020. Hooks in the headline: Learning to generate headlines with controlled styles. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5082–5093, Online. Association for Computational Linguistics.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2017. Bag of tricks for efficient text classification. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 427–431, Valencia, Spain. Association for Computational Linguistics.

Daniel Kang and Tatsunori B. Hashimoto. 2020. Improved natural language generation via loss truncation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 718–731, Online. Association for Computational Linguistics.

Kalpesh Krishna, John Wieting, and Mohit Iyyer. 2020. Reformulating unsupervised style transfer as paraphrase generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 737–762, Online. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.

Mingchen Li, Mahdi Soltanolkotabi, and Samet Oymak. 2020. Gradient descent with early stopping is provably robust to label noise for overparameterized neural networks. In *Proceedings of the Twenty Third International Conference on Artificial Intelligence and Statistics*, volume 108 of *Proceedings of Machine Learning Research*, pages 4313–4324. PMLR.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. In *International Conference on Learning Representations*.

David D. McDonald and James D. Pustejovsky. 1985. A computational theory of prose style for natural language generation. In *Second Conference of the European Chapter of the Association for Computational Linguistics*, Geneva, Switzerland. Association for Computational Linguistics.

Nagarajan Natarajan, Inderjit S Dhillon, Pradeep K Ravikumar, and Ambuj Tewari. 2013. Learning with noisy labels. In *Advances in Neural Information Processing Systems*, volume 26. Curran Associates, Inc.

Nadav Oved and Ran Levy. 2021. PASS: Perturb-and-select summarizer for product reviews. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 351–365, Online. Association for Computational Linguistics.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Hwanjun Song, Minseok Kim, Dongmin Park, Yooju Shin, and Jae-Gil Lee. 2022. Learning from noisy labels with deep neural networks: A survey. *IEEE*

	Train	Dev	Test
PROSUM	100	100	500
Yelp	30	30	40
Amazon	28	12	20

Table 5: Details of dataset splits. Note that we eliminate the source reviews for training to ensure the non-parallel setting.

Transactions on Neural Networks and Learning Systems.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. 2016. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2818–2826.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with bert. In *International Conference on Learning Representations*.

A Additional Experimental Details

A.1 Dataset splits

We show the details of dataset splits in Table 5. Note that we eliminate the source reviews for training to ensure the non-parallel setting. We only utilized the paired dataset to build the supervised upperbound model.

A.2 Pre-processing decision on FewSum

For the Yelp dataset, we used reviews provided in the Yelp Open Dataset. [6] For the Amazon dataset, we used reviews in the Amazon product review dataset (He and McAuley, 2016). We specifically select 4 categories: *Electronics; Clothing, Shoes and Jewelry, Home and Kitchen; Health and Personal Care*. Both datasets are available for academic purposes.

We first filter out the reviews shorter than 40 words and longer than 70 words and then remove the non-English reviews using the language identifier model implemented in `fasttext` (Joulin et al., 2017). Finally, we build the same approach to build pseudo and noisy pairs explained in §3 and §4.

A.3 Baselines on FewSum

- **MeanSum** (Chu and Liu, 2019): the unsupervised single entity opinion summarization models based on autoencoders. It generates summaries from the averaged latent representations of reviews.
- **CopyCat** (Bražinskas et al., 2020b): a single entity opinion summarization solution based on variational autoencoder models trained with leave-one-out objectives.
- **FewSum** (Bražinskas et al., 2020a): an extension of CopyCat model fine-tuned on FewSum dataset.
- **PASS** (Oved and Levy, 2021): Fine-tuned transformer models initialized with T5 checkpoint (Raffel et al., 2020) on FewSum dataset and LkO perturbations to select the subset of the representative input reviews to generate summaries.
- **AdaSum** (Bražinskas et al., 2022): Fine-tuned BART models on FewSum dataset with Adapter-tuning (Houlsby et al., 2019) for parameter-efficient adaptation.

A.4 Training details

Major hyper-parameters for training models are reported in Table 6 following the "Show-You-Work" style suggested by Dodge et al. (2019).

B More Analysis

B.1 Pre-Training with Self-supervision

We show the same analysis with §6.2 on Yelp and Amazon datasets in Table 6. We observed the same trends with the PROSUM dataset, showing the importance of pre-training with self-supervision across all three datasets used in the paper.

[6] https://www.yelp.com/dataset

Computing infrastructure	NVIDIA A100
Pre-training duration	24h
Fine-tuning duration	2h
Search strategy	Manual tuning
Model implementation	[MASK]
Model checkpoint	[MASK]

Hyperparameter	**Search space**	**Best assignment**
# of self-supervision steps	100,000	100,000
# of fine-tuning steps	2,000	2,000
batch size	8	8
initial checkpoint	`facebook/bart-large`	`facebook/bart-large`
label-smoothing (Szegedy et al., 2016)	*choice*[0.0, 0.1]	0.1
learning rate scheduler	linear schedule with warmup	linear schedule with warmup
warmup steps	1,000	1,000
learning rate optimizer	AdamW (Loshchilov and Hutter, 2019)	AdamW (Loshchilov and Hutter, 2019)
AdamW β_1	0.9	0.9
AdamW β_2	0.999	0.999
learning rate	1e-5	1e-5
weight decay	*choice*[0.0, 1e-3, 1e-2]	1e-3
gradient clipping	1.0	1.0

Table 6: NAPA search space and the best assignments.

C Qualitative Examples

We present summaries of the PROSUM data generated by Self-supervision (SS), Pipeline, SS + Noisy Pairing, and SS + Noisy Pairing + Partial Supervision in Table 7.

For the self-supervised system (SS), the generated summary is a factually consistent summary with the source reviews, but it is a more review-like summary that includes first-person pronouns (e.g., I, my) and subjective opinions (e.g., *The salmon skin hand roll and spicy tuna hand roll are two of my favorite things*).

Using the style transfer model (Pipeline), the generated summary contains attractive adjectives such as terrific, but the content of the summary cannot be changed by the style transfer model, so the summary still contains subjective opinions and first-person pronouns generated by the self-supervised system and introduce non-factual contents as well, e.g., crispy pork was terrific .

The model trained with the noisy paired dataset generates a more Michelin-like summary because it is fine-tuned with the same style of summaries. However, because the noisy training pairs are used without partial supervision, the model generates a lot of non-factual content, such as the location of the restaurant (i.e., San Francisco) or the name of the chef (i.e., Yoshihiko Kousaka).

Finally, partial supervision (SS + Noisy Pairing + Partial Supervision) enabled the model to generate Michelin-like summaries while maintaining factual correctness, such as chef's name, Kiminobu Saito .

C.1 Human evaluation

We show the annotation screen in Figure 7. The annotators are asked to select three aspects of summaries based on the system's generation.

NAPA 🍷: Chef Kiminobu Saito has been at this spot for years , and it 's no surprise that he 's become one of the city 's most beloved chefs . His attention to detail is evident in every single detail of this restaurant , from the cleanliness of the dining room to the attentive service . The omakase is the only way to go here , and the quality of the fish is just as important as the service . Start your meal with a cup of miso soup , then move on to a selection of handrolls , like the salmon skin hand roll and the toro , which are both tender and flavorful . The chef 's personal touch is also evident in the presentation of each piece of fish , and you 'll be hard pressed to find a better one than the one on offer here .
w/o Partial Supervision: If you 're looking for a laid-back , family-friendly sushi bar in the heart of downtown San Francisco , this is the place to be . The dining room may be small , but the mood is upbeat and the service is warm and friendly . Chef Yoshihiko Kousaka is the man behind the counter , and his skillfully curated omakase is evident in every morsel of food he prepares . The quality of each morsel is impeccable , and you can tell that he takes great pride in every detail of his work-whether it 's hand-rolls , hand-formed karaage , or hand-tossed morsels of fish in a wood-fired oven . Highlights include a trio of handrolls made with house-made sashimi , each with its own unique flavor profile and texture , and a hand-ground toro that pairs perfectly with a glass of sake or sake-battered sake .
w/o Noisy Pairing and Partial Supervision: Sushi Note is one of the best sushi restaurants I 've ever been to in my life . The service is impeccable , the food is amazing , and Chef Kiminobu Saito is an absolute pleasure to talk to . The omakase is the way to go if you want to experience the full experience of sushi and wine pairings . The salmon skin hand roll and spicy tuna hand roll are two of my favorite things on the menu . I 'm not a huge fan of spicy tuna , but the spicy tuna was so good that I had to order it again the next time I went . The scallop with truffle truffle and toro is also a must try . If you 're in the mood for sushi , this is the place to go . It 's a little pricey , but it 's worth it for the quality of the food and the service .
Pipeline: In fact , I 've never been to a better sushi bar in my life . The service is terrific , the food is terrific , and Chef Kiminobu Saito is a terrific talker . Once inside , order a cocktail and admire the full sushi and wine experience . The salmon roll and spicy tuna hand roll are my favorite . Do n't like spicy tuna , but the crispy pork was terrific . Starters like truffle and truffle are also a must try with these truffle and truffle . It 's the right place to go to the sushi counter . It 's worth every second for this quality of the food and the service .

Table 7: Qualitative examples on PROSUM dataset. Faithful/unfaithful contents are highlighted in green / orange .

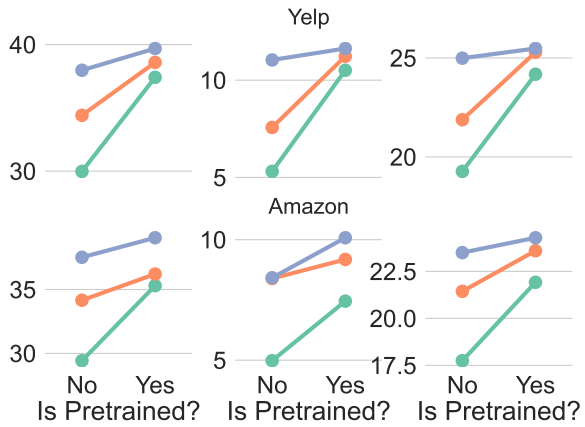


Figure 6: Comparison of summarization quality with and without pre-training on Yelp and Amazon datasets. The **blue line** denotes the model trained in a supervised setting, **orange line** denotes the model trained *with* partial supervision and **green line** denotes the model trained *without* partial supervision. While pre-training with pseudo-training data improved the performance in all settings, we found a significant improvement, especially in the non-parallel settings (**orange line** and **green line**).

Reviews:

Review 1

My friend and I came here specifically for the frog and we were n't disappointed ! We shared the following : 1 . Stinky tofu - this was a very interesting dish . I've had this back in my hometown which is the province adjacent to Hunan and we make it a bit differently . This was a lot crispier (actually borderline hard) and less . stinky. ? Regardless , we enjoyed it . 2 . Hunan charcuterie - a nice platter of beef stomach , beef tripe , pig ear , and smoked bean curd that's thankfully not drenched in chili oil . But we thought it was just okay . 3 . Flaming frog - oh the flavor of this dish ! I have very high tolerance for spicy food so personally I did n't find this dish too spicy but appreciated that it had a nice kick to it . Lots of garlic though and it's easy to get confused with the frog bits ! Also for those of you who's never eaten frogs before , beware that there are lots of little bones to tease out . The sleek and modern decor and the open kitchen definitely elevated our dining experience to the next level .

Review 2

Yet another noodle shop in the East Village , and this ones another excellent ride noodle one with a chef that was formerly an artist . You can tell even from the outside looking in through the big floor to ceiling window that it's the restaurant of a former artist , as the place is beautiful . The rice noodles are of course the thing , and you should get the great Fish Fillet one ($ 28) , which cooks at the table in a piping hot pork and fish broth . The other dishes are excellent too , especially the Smoked Pork with Bean Curd ($ 12) . The Frog Legs ($ 20) were delicious too , but beware if you're lazy like me that there's a lot of bone to deal with .

Review 3

Food : One of the most amazing Chinese food I have had for a long time ! The food portions were quite generous which is great because it can be shared with a small group of friends . I can not recall one dish exceeding the other , each with its own unique flavor , each just as delicious as the next . Definitely try to get one of their noodle dishes and the whole fish (if you dare !) . We definitely left with full happy bellies without breaking the bank . Absolutely must go-to place in the east village . Drink : Its's BOYB ! Can not get better than that ! Plus no corkage fee ! Vibe : Elegant and traditional . Though a small location , the long tables made good use with the space . Loved the small flower arrangements and the ceiling lights . Great aesthetics ! Would recommend this place for a date or small group of friends . Service : Loved the super fast service as everything came out quickly , which was perfect since we all were starving . We made reservations beforehand by calling and we were seated immediately . The waiters were so attentive all the time an

Review 4

I've almost never left a review on yelp . Mostly because I've had a good experience and I am lazy . But oh man , is n't this place disappointing . I'm a big fan of ramen and rice noodles so when I heard about this place's opening I was excited to try . The prices on the menu were at least 20 % higher than other rice noodle shops in town : $ 32 for a bowl of fish fillet mifen , which took about 40 minutes to serve . And , the waiting was n't worth it : the fish was overcooked , broth way too spicy , noodles of mediocre quality . Meh . Another dish I feel is way , way overpriced is a cold dish , Hunan Charcuterie . $ 18 for such a small portion ! It's NOTHING like the photo that the owner themselves posted here : yelp.com/biz_photos/huna . We also ordered String Bean Mifen , and it was just okay . To be fair it's only soft opening so there might be a reason to expect a beta (pun intended !) experience later . But I do n't think I'm going back soon with so many other alternatives available .

Review 5

The decor and service here are top notch . How they plate each dish is very much Michelin-starred level in my opinion . Most importantly , everything we ordered tastes as good as they look ! Strongly recommend Hometown Lufen and skewed beef , if you are into spicy . I'm a real noodle lover and the Mifen here can make you scream `` YUM" ! Also the green bean desert soup was delicious and refreshing , very fitting for summertime . Food portion was big , and food was super fast . My husband and I did not have enough mifen , then we ordered string bean mifen for takeout and it was equally delicious . Will definitely come back soon !

Review 6

Clean , fast , and delicious . A modernized take on Hunan classics without compromising the rich flavors and spices . We ordered the whole fish , house salad (stuffed eggplants) , and the irresistable hometown lu fen .

Review 7

I am impressed although I am not a noodle person . The food has good quality , looks fresh , had a lot of flavor . The portion is good . the price is a little bit high considering the location and type of the food . The restaurant is really clean , modern , tasteful . The service is amazing , the waiters are polite , professional and well trained . Would like to go back to try more dishes .

Review 8

Super good and really easy to get a reservation ! The hometown lu fen is really good , as is the spicy octopus and spicy chicken . All the portions are very big/filling and there is SO much flavor in every bite . The ambiance is also very nice and relaxing - it has a beautiful light fixture . Would recommend !

System 1:

If you're a big fan of spicy food , this is the place for you . It's the kind of place that makes you feel like you've been transported to the heart of Hunan , where the cooking is just as authentic as it is delicious . The space is clean and bright , and the service is friendly and attentive . The menu is simple , but the food is so good that it's hard to pick just one dish . Start with a bowl of the spicy bean curd soup , then move on to a plate of the beef and chicken mifen , which is served with a generous portion of tender beef and bean noodles . The chicken is tender and juicy , while the noodles are just the right amount of chewy and chewy . For dessert , you can choose from a selection of freshly made ice cream , or a delicious selection of chocolates .

Fluency (required)

Fluent	Somewhat Fluent	Somewhat Unfluent	Unfluent
○	○	○	○

Relevancy (required)

Relevant	Somewhat Relevant	Somewhat Irrelevant	Irrelevant
○	○	○	○

Attractiveness (required)

Attractive	Somewhat Attractive	Somewhat Unattractive	Unattractive
○	○	○	○

Figure 7: Human evaluation task