Massive Multi-Document Summarization of Product Reviews with Weak Supervision

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Abstract

Product reviews summarization is a type of Multi-Document Summarization (MDS) task in which the summarized document sets are often far larger than in traditional MDS (up to tens of thousands of reviews). We highlight this difference and coin the term “Massive Multi-Document Summarization” (MMDS) to denote an MDS task that involves hundreds of documents or more. Prior work on product reviews summarization considered small samples of the reviews, mainly due to the difficulty of handling massive document sets. We show that summarizing small samples can result in loss of important information and provide misleading evaluation results. We propose a schema for summarizing a massive set of reviews on top of a standard summarization algorithm. Since writing large volumes of reference summaries needed for advanced neural network models is impractical, our solution relies on weak supervision. Finally, we propose an evaluation scheme that is based on multiple crowdsourced reference summaries and aims to capture the massive review collection. We show that an initial implementation of our schema significantly improves over several baselines in ROUGE scores, and exhibits strong coherence in a manual linguistic quality assessment.

1 Introduction

Online shopping provides great convenience and flexibility for customers, however, it affects the ability to physically examine products of interest. To support the customer need for gaining familiarity with products, e-commerce websites provide a platform for customers to share their experience through online product reviews. However, as these websites grow in popularity, so do the number of reviews, to the point that it becomes practically impossible to digest this wealth of information. Product reviews summarization aims to alleviate this problem by analyzing the entire review set and providing customers with just the right amount of information they need.

While the task of multi-document summarization (MDS) typically considers document sets with no more than 40 documents, in the domain of product reviews it is possible to find thousands of reviews on a single product. We introduce the notion of “Massive MDS” (MMDS) where document sets are substantially larger than commonly considered. We argue that this setup introduces new challenges that require special handling both in the system design and in the evaluation.

Several prior works on product review summarization bypassed this obstacle by restricting the task to a small sample of reviews from the entire collection, (e.g. Angelidis and Lapata, 2018; Chu and Liu, 2019). Small samples may not represent the full set faithfully, and systems that rely on them may neglect salient information that should be included in a summary. Another issue that arises when dealing with massive amounts of documents is the summarizer’s capacity to ingest them all. Most modern summarization systems based on neural networks are limited to hundreds of words (See et al., 2017; Chu and Liu, 2019; Chen and Bansal, 2018), while in the MMDS setup the summarizer may be required to process tens of thousands of words and even more.

We propose a framework that considers a massive document set. The framework makes use of an existing summarization algorithm as an underlying component, but does not depend on its specific characteristics. In theory, any text-to-text architecture could serve as the underlying algorithm.

Our approach clusters the reviews of a single product into disjoint subsets of roughly similar size

*Completed as part of an internship at Amazon.
and extracts a central representative review (the medoid) from each cluster to be used as a “weak reference summary” of all other reviews in the cluster. We then use such \((\text{cluster}, \text{representative})\) pairs to train the underlying summarization system, while meeting its text length constraint. This weakly-supervised approach provides us with an unlimited pool of training examples which meets the demand of advanced neural models. Note that our weak references are more suitable for training abstractive summarizers, though an extractive system could still be trained to maximize similarity to the weak reference.

The summary generation process applies a similar clustering of the reviews. The trained summarizer is run on each cluster separately, to output all the corresponding summaries. The procedure can then be hierarchically repeated, on the output summaries, to generate a final summary that covers the massive set of reviews.

Summarization systems are commonly evaluated against manually written reference summaries using the ROUGE (Lin, 2004) family of measures. Reference summaries are written by humans, after reading the documents to be summarized. In the MMDS task, this is completely infeasible for a human annotator. We overcome this limitation by, again, splitting the set of reviews to small disjoint subsets. For each subset, we collect a reference summary via crowdsourcing. By doing so, each product has several reference summaries to test its system summary against. Note that evaluating summaries with multiple references is a common approach except that in our case, each reference is based on a different “slice” of the review set. Our reference summary dataset is based on 123 products with at least 100 reviews taken from the Amazon Customer Reviews Dataset.

An implementation of our MMDS schema, on top of the system released by Chen and Bansal (2018) as the underlying summarizer, significantly improves over various baselines in several ROUGE metrics, and receives very good results, comparable to those of human written reviews, in manual linguistic quality assessments.

In the next section, we report on related work, and in Section 3 we motivate our work by investigating the implications of summarizing and evaluating against small samples of product reviews. Section 4 describes our framework for handling large collections of documents. Section 5 presents the experiments conducted with our implementation, as well as our MMDS dataset.

## 2 Related Work

As MMDS is a variant of MDS, we start by presenting MDS in general and proceed to multi-review summarization in particular. We then provide a short survey of existing MDS datasets in order to justify the creation of a dedicated MMDS dataset.

### MDS methods.

Over the years, both extractive and abstractive MDS have been approached with graph-based methods (e.g. Erkan and Radev, 2004; Christensen et al., 2013; Yasunaga et al., 2017), integer linear programming (e.g. Bing et al., 2015; Banerjee et al., 2015) and sentence or phrase ranking/selection (e.g. Cao et al., 2015; Nallapati et al., 2017; Fabbri et al., 2019).

Training neural networks for MDS, requires large amounts of \((\text{document set}, \text{summary})\) pairs. Recently, Liu et al. (2018) devised a model that generates Wikipedia articles for a given set of documents from the web. Their system processed large textual inputs by first extracting salient sentences and then feeding them into a memory optimized variant of the transformer model (Vaswani et al., 2017). Another approach for developing MDS systems is to adapt a single-document summarization (SDS) model to MDS (Lebanoff et al., 2018; Baumel et al., 2018; Zhang et al., 2018). While the challenge of overcoming redundancy and coreference resolution is more pronounced in MDS, such adaptations leverage advancements in SDS systems.

### Review summarization.

Summarizing product or service reviews has been extensively explored both in academia and industry as e-commerce websites strive for improved customer experience and analytical insights. The most common approach is termed aspect based summarization in which the summary is centered around a set of extracted aspects and their respective sentiment.

One of the early works, by Hu and Liu (2004) was designed to output lists of aspects and sentiments, which is more restricted than our setup. Their system did not limit the size of the review set, nevertheless, evaluation was performed on the first 100 reviews of only 5 products. Other works target the summarization task, but mostly summarize small samples of reviews, and at times some-
what simplify the task by assuming aspects or seed words are provided as input (Gerani et al., 2014; Angelidis and Lapata, 2018; Yu et al., 2016). Their evaluations are either ROUGE-based, on small samples of reviews, or manual pairwise summary comparisons. A variant of this manual evaluation requires evaluators to first read all reviews on a respective product, a requirement that cannot be reasonably met. This issue was raised by Gerani et al. (2014) who nevertheless did not offer any remedy.

The most relevant work to ours is that of Chu and Liu (2019) as it is an unsupervised abstractive product reviews summarizer that employs a neural encoder-decoder model. In their setup, the system works on samples of just 8 reviews per product, and is evaluated against reference summaries based on 8 reviews per product as well.

**MDS datasets.** The main obstacle towards developing state of the art MDS models and reliably comparing between them is a shortage of large scale high-quality datasets. The first MDS datasets originated in the DUC and TAC benchmarks, focusing mostly on the news domain. Recently, Fabbri et al. (2019) released the large-scale Multi-News dataset. For Wikipedia, Liu et al. (2018) provide web documents with corresponding Wikipedia articles, and Zopf (2018) released a multilingual dataset. In the consumer reviews domain, Opinosis (Ganesan et al., 2010), OpoSum (Angelidis and Lapata, 2018), and a dataset by Chu and Liu (2019) are rather small scale. The document set sizes of the listed MDS datasets range from 2 to 40, averaging less than 10 documents per set. Table 1 presents size statistics of the aforementioned datasets in comparison with the dataset we collected as part of this work.

### Table 1: Approximate average MDS dataset statistics. The named datasets listed are: Opinosis (Ganesan et al., 2010), MeanSum (Chu and Liu, 2019), OpoSum (Angelidis and Lapata, 2018), DUC (https://duc.nist.gov), TAC (https://tac.nist.gov), MultiNews (Fabbri et al., 2019), hMDS (Zopf, 2018).

| Dataset          | # sets | # docs per set | # tokens per doc | # tokens per ref |
|------------------|--------|----------------|------------------|-----------------|
| Opinosis         | 51     | †              | -                | -               |
| MeanSum          | 200    | 17             | 600              | 200             |
| OpoSum           | 60     | 10             | 70               | -               |
| MMDSDS (Ours)    | 123    | 205            | 73               | 59              |
| DUC (01'-07')    | 45     | 17             | 600              | 200             |
| TAC (08'-11')    | 45     | 10             | 600              | 100             |
| MultiNews        | 55K    | 3              | 700              | 260             |
| Wiki             | hMDS (Liu et al., 2018) | 91 | 14 | 2000 | 250 | |

‡ Opinosis concatenates 100 sentences from different reviews.

§ In DUC and TAC datasets, values are averaged over all years.

### Table 2: Statistics of the Amazon Customer Reviews Dataset with respect to review set sizes.

| Size of Review Set | Products | Reviews |
|-------------------|----------|---------|
| Count             | Ratio    | Count   | Ratio  |
| 1-9               | 19M      | 40M     | 0.25   |
| 10-99             | 19M      | 40M     | 0.34   |
| 100-999           | 200K     | 46M     | 0.28   |
| 1000-9999         | 8K       | 16M     | 0.10   |
| ≥ 10000           | 187      | 4M      | 0.03   |

However, their absolute number is above 200K making it infeasible to rely on manual summaries. Furthermore, while these products represent only a small fraction of the product portfolio we argue that these are the “interesting” products as they are the ones customers choose to spend time on, by writing reviews. Indeed the ratio of reviews of products with more than 100 reviews to all reviews in the dataset is approximately 0.41.

As to the second observation, a good summary is expected to surface salient information from the original text(s). However, most if not all academic works on product review summarization, ignore the content of all but a few of the original texts since they are restricted to small samples of the reviews. We would like to measure how different sample sizes of the original texts affect information saliency. For ease of the analysis, we consider n-gram frequency as a proxy for information saliency. Nenkova et al. (2006) found that high frequency words from the source texts are most agreed upon to

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2https://(duc,tac).nist.gov
be included in reference summaries. They reached a similar conclusion at the content-unit level. We thus deduce that n-gram frequencies are likely to provide a good indication for information saliency in the texts. We measure the correlation between n-gram distributions of the entire document set and n-gram distributions of random samples of that set. If the correlation is low, we assume that the sample does not faithfully capture the information saliency of the entire document set.

We randomly selected 180 products from 6 categories with a median of 200 (ranging from 100 to 24K) reviews per product. For each product and for each sample size, \( s \in \{1, 2, \ldots, 100\} \), we extracted 30 samples, and measured the non-stop-word n-gram distribution for \( n \in \{1, 2, 3\} \) on each such sample. We then measured the correlation between this distribution and the distribution of the entire set, and averaged the result across products and across the 30 samples. Figure 1 shows the average Pearson correlation for different sample sizes.

While samples of size 10 to 30 may be sufficient to capture the unigram distribution, it is clear that even with samples of size 100, the bigram and trigram distributions still differ from those of the entire set.

Figure 2 presents a similar analysis based on the Spearman correlation. We observe lower correlation than in the Pearson analysis and speculate that the Spearman variant, which compares rankings, is dominated by the long tail of low ranking n-grams. Such low frequency n-grams are not important for capturing salient information.

Figure 3 shows the percent of samples, at each sample size, in which the most frequent non-stop-words n-gram from the full set is in the top-5 most frequent non-stop-word n-grams in the sample. When this condition is not met, an automatic summarization system will most likely miss out on crucial information. As the figure shows, a sample of 10 reviews has a chance of 10% to miss the most important unigram in its top-5 unigrams.

For a qualitative impression, consider the “Echo Dot (3rd generation)” smart speaker that has, as of writing this paper, roughly 62K customer reviews on the Amazon.com website. One important aspect that is frequently mentioned in the reviews is the sound quality. The unigram “sound” appears in 13K of the reviews and is the most frequent non-stop-word apart from “love, echo, alexa and great. Sound quality is clearly a salient theme that should appear in a good summary. However, based on these numbers we can estimate that in 1 out of 10 samples of size 10, the unigram “sound” will not appear at all.

Neural-based summarization systems are currently limited, in the size of texts that they process, to hundreds of words, meaning that they cannot handle large review sets. A notable exception, described earlier, is the work of Liu et al. (2018) who were able to process up to 11K words. However, even if all systems were able to handle massive review sets, existing evaluation methods, which are based on human judgments or human-written reference summaries, are still inherently limited to small samples of the document sets. Further, humans that are given many reviews during an evaluation session cannot be expected to read and remember even 10 reviews, which, as evident from the curve in Figure 1, may not be sufficient.

While it is possible to average noisy evaluation scores across many products to get a reasonable estimation, summarization systems should aspire to work well on each product and not only on average. Furthermore, evaluation schemes that assign different weights for different products, e.g. larger
weights to popular products, will have to rely on accurate evaluation at the level of single products. Interestingly, the need for automatic reviews summarization for popular products is stronger while at the same time they are more prone to the sampling bias when the sample size is fixed.

4 Method

Our schema is comprised of three distinct procedures for training, summary generation and evaluation, with a common theme of separating the large document set into multiple subsets and handling each of these separately. Figure 4 depicts the former two procedures. In what follows we describe each procedure on a single product.

4.1 Training

The training procedure aims to transform a set of product reviews \( R = \{r_1, r_2, \ldots, r_n\} \) into a set of weak training examples. First, we cluster the reviews into \( k \) clusters, \( C = \{C_1, C_2, \ldots, C_k\} \), such that the clusters are comparable in size and the reviews within each cluster are similar to one another. For each cluster, \( C_i \), we find a single review, \( r_i^* \), with the highest similarity to all other reviews in the cluster, and denote it as the weak-reference. If the reviews in the cluster are indeed similar, \( r_i^* \) could act as an approximate summary of all other reviews in \( C_i \). A supervised summarization system can then be trained with data pairs \( (C_i \setminus r_i^*, r_i^*)_{i\in[1,k]} \) for a practically unlimited set of products. Note that the requirement to have clusters of comparable size stems from the input size limit of the architecture we will eventually use to train on such pairs.

The training procedure relies on three building blocks that have a large impact on the system’s performance: a clustering algorithm, a similarity measure for extracting the weak-reference, and a supervised summarization system, which we term “Cluster Summarization System” (denoted CSS). As a proof of concept of our MMDS schema, we use the following building block implementations:

**Clustering.** The method used is a form of pivot clustering, constructing clusters around randomly selected pivot items, which has been shown to provide good theoretical and practical results in different settings (Avigdor-Elgrabli et al., 2016; Chierichetti et al., 2014; Van Zuylen and Williamson, 2009).

As a preprocessing step, we remove from \( R \) reviews shorter than 15 tokens, assuming their helpfulness is negligible. We initialize the unclustered review set, \( U \), to the set \( R \). Then, while \( U \) is not empty, we randomly choose a pivot review \( p \) and build a singleton cluster \( C_p = \{p\} \). We then compute the ROUGE-1 \( F_1 \) scores between \( p \) and all other reviews, and repeatedly add reviews to \( C_p \), starting from the top-scoring review and moving down the scores, until \( C_p \) contains \( \text{min-rev} \) reviews, and then continue to add reviews while the accumulated text length, \( \sum_{r\in C_p} \text{len}(r) \), is below a predefined threshold \( \text{max-len} \), where the text length is measured in sentences. In our experiments we fix \( \text{max-len} \) to 50 and \( \text{min-rev} \) to 3.

**Weak reference extraction.** Given a cluster of reviews, \( C_i = \{r_1^i, \ldots, r_m^i\} \), we measure the similarity of a review \( r_1^i \) to reviews \( [r_k^i]^{m}_{k=1,k\neq j} \) with a function \( \text{sim}(r_1^i, [r_k^i]) \), and define the cluster’s weak-reference as the review \( r_i^* \) with the maximal \( \text{sim} \) value. The training datum is then set as \( (C_i \setminus r_i^*, r_i^*) \).

We experiment with different \( \text{sim} \) functions. The first is the word (stem) set recall of \( r_1^i \) to \( [r_k^i] \), which quantifies how well \( r_1^i \) covers the set of stems in \( [r_k^i] \). The second is the average ROUGE-1 \( F_1 \) where \( r_1^i \) is set as the target text and each of the reviews in \( [r_k^i] \) is set as the predicted text. While the ROUGE-1 \( F_1 \) variant was our first attempt, we experimented with ROUGE-1 recall, hypothesizing that training on higher recall “summaries” would output longer and more informative summaries. A manual qualitative analysis revealed that output summaries were indeed longer, however they tended to contain more redundant phrases.

In order to refrain from obtaining training examples that are difficult to train on, i.e. that would force the model to overly fabricate information in the output, we discard examples whose “summary

![Graph](image_url)

**Figure 3:** The percent of samples (out of 30 samples) where the top non-stop-word n-gram in the full set of reviews is in the top-5 non-stop-word n-grams in a sample of reviews.
labels” have too many novel unigrams. This is done by filtering out clusters where the weak-reference has a word set overlap precision of less than 0.5.

**Cluster summarization system.** The CSS is a crucial element of the framework: it directly affects the final summary’s quality through the quality of the cluster summaries it generates, but also indirectly by the constraints it imposes on the max-len parameter (recall that most neural summarization systems process at most hundreds of words). After experimenting with several abstractive summarization systems, both single and multi-document, and balancing between training/generation times and manual inspection of the summaries, we found that the recent Fast Abstractive Summarization (denoted FAS) system introduced by Chen and Bansal (2018) was most promising and focused on it in our experiments. The FAS system consists of three training phases. In the first, a sentence extraction model indicates the sentences in the input that best align to the information in the output summary. The second phase attempts to learn how to form abstractions, from the marked sentences in the first phase, to the sentences in the output. Finally, an end-to-end model utilizes the first two models to synthesize the output summary from the input.

4.2 Summary Generation

The summary generation process starts with a clustering phase similar to that of the training process. Given set of product reviews, \( R' = \{r'_1, r'_2, \ldots, r'_t\} \), the reviews are clustered to \( C' = \{C'_1, C'_2, \ldots, C'_l\} \). Now, instead of converting the cluster into a training example, the trained CSS generates a cluster summary \( s'_i \) for each cluster, \( C'_i \). At this point we consider two alternatives to produce a single final summary. In the first, the summaries \( \{s'_1, s'_2, \ldots, s'_l\} \) are clustered and the CSS generates summaries from the resulting clusters to produce second-level summaries. This procedure is recursively applied until a final summary emerges. The second approach, which we refer to as the level1 approach, creates the cluster summaries as before, but then selects a single summary \( s^* \) that has the highest average ROUGE-1 F1 score to all other cluster summaries. The second approach aims to reduce the accumulated error when recursively applying the CSS and to prevent the final summaries from being overly generic.

The FAS system we employ here was originally designed to summarize single documents, while we feed it a concatenation of several similar reviews or summaries. This input is expected to have higher levels of repetition. Indeed, we observed that applying FAS as-is, results in somewhat repetitive summaries so we introduced a post processing step in which we measure the lemma-edit-distance between each two sentences of the summary. If the distance is above a \( \text{max-edit-dist} \) threshold, we only keep the first sentence according to the order of appearance in the summary. In all our experiments \( \text{max-edit-dist} \) is set to 0.7.

4.3 Hyperparameters

Given that our focus is on presenting a general framework for MMDS, we decided not to optimize the hyperparameters in the concrete implementation. The \( \text{min-rev} \) parameter was set to 3 so that one medoid could be isolated, leaving at least 2 reviews necessary for summarizing multiple documents. The \( \text{max-len} \) parameter was set to 50 sentences as this roughly corresponds to the amount of words that FAS is designed to process. Finally, the \( \text{max-edit-dist} \) was set to 0.7 in order to filter cases where the repetition is very obvious.
4.4 Evaluation

While the field of automatic summarization has recently made a lot of progress, evaluation of such systems is still a major obstacle. Common practice relies on the ROUGE family of measures which assume that good summaries will have high n-gram overlap with human written reference summaries. A complementary approach employs human judgments for how well the system summary captures information from the original documents.

In the MMDS setup, both approaches are impractical since human annotators are not able to process so many documents in order to write a reference summary or to rate a given summary. Thus we propose to divide the reviews in a massive review set into multiple subsets, each containing an accumulated amount of up to 50 sentences, and obtain reference summaries for each subset. We believe that the clustering approach could be beneficial here as well, since it simplifies the annotator’s job, however, we chose to divide the reviews randomly so as not to bias the evaluation towards our solution. In order to evaluate a generated summary, the ROUGE score is computed for the summary against all reference summaries.

Finally, since linguistic-quality evaluation does not rely on the summarized documents, coherence of MMDS summaries can be evaluated using the standard DUC linguistic quality questionnaire (Hoa, 2006).

5 Experiments

5.1 Data

We experiment with products from 6 categories that represent different review styles, ranging from technical reviews for cameras and electronics to more prosaic reviews for books and movies (the categories are Camera, Books, Toys, Electronics, Music and DVDs). For each product category, we randomly selected 2000 products with at least 100 reviews from the Amazon Customer Reviews Dataset and randomly split them into 1800/100/100 products for training, validation and test sets. Table 3 presents some statistics of the selected products.

**Training and validation.** The train/validation products were converted to tens of thousands of (cluster, weak-reference) pairs. Notice that thanks to the weak supervision, our framework can produce significantly larger training sets, however, this setup resulted in a reasonable tradeoff between training time and performance.

| Category | Num Products | Num Reviews | Words/Review |
|----------|--------------|-------------|--------------|
| Camera   | 2000         | 4652        | 1590         |
| Books    | 2000         | 8237        | 13354        |
| Electronics | 2000     | 2689        | 15334        |
| Toys     | 2000         | 2458        | 249          |
| DVDs     | 2000         | 4959        | 1313         |
| All      | 12000        | 24258       | 5000         |

Table 3: Statistics on the full data we use as part of our analyses, training, testing and evaluation. This data is sampled from the Amazon Customer Reviews Dataset.

| Category | Num Products | Num Reviews | Words/Review |
|----------|--------------|-------------|--------------|
| Camera   | 20           | 303         | 2108         |
| Books    | 20           | 425         | 2042         |
| Electronics | 22         | 717         | 15900        |
| Toys     | 20           | 489         | 1105         |
| DVDs     | 20           | 312         | 1964         |
| All      | 123          | 717         | 2419         |

Table 4: Statistics on the data in our test set, which is a subset of the data presented in Table 3.

**Test.** Our evaluation scheme is based on collecting manual reference summaries for multiple subsets of each review set, as proposed in Section 4.4. We gathered reference summaries for about 20 test set products, from the 100 we put aside, for each of the 6 categories using the Figure-Eight crowdsourcing platform. We group reviews into annotation-sets, with each having about 50 sentences (but at least two reviews in a set), and present them with their star rating, and with the product title on top. The crowdsourcing task guidelines, similar to those of Chu and Liu (2019), are as follows:

- Write a summary as if it were a review itself (e.g. to write ‘the screen is dark’ instead of ‘customers thought that the screen is dark’).
- Keep the summary length reasonably close to the average length of the presented reviews.
- Try to refrain from plagiarizing the original reviews by not copying more than 5 or so consecutive words from a review.

We automatically validated that summaries are at least 20 tokens long.

Each annotation-set was summarized by two crowd workers. We automatically filtered out summaries that appeared verbatim more than once, summaries that were full extracts from a review, summaries with many linebreaks, and summaries

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cchu https://www.figure-eight.com/

that contained certain suspicious text fragments (based on manual observations on a selection of crowd-summaries). In annotation-sets for which two reference summaries remained, we heuristically selected the longer summary with the rationale that it likely contains more information.

We repeated the process on our 6 categories, totaling 123 products with an average of 205 reviews per product, ranging from 100 to 720, and 21.75 reference summaries per product. Table 4 provides additional statistics on the test set.

5.2 Baselines

We compare our model to several baselines, some of them similar to those of Chu and Liu (2019). When generating baselines, reviews shorter than 15 and longer than 400 words were ignored.

Medoid-Recall. In section 4, we hypothesize that the weak-reference could serve as an approximate reference summary of all other cluster reviews. We can extend this hypothesis to the full review set and test whether a review with the maximal $\text{sim}$ score to all other reviews, the medoid, could be a good “summary”. Our first baseline, which we call Medoid-Recall, selects the review that maximizes the word (stem) set recall. This measure favors reviews which cover a big portion of the review-set vocabulary.

Medoid-$F_1$. Here, the same technique as the previous baseline is applied, with average ROUGE-1 $F_1$ computed instead of word set recall. The intuition behind this is to mitigate the strong length bias that recall introduces, as well as to limit the amount of unique information in the selected review.

Multi-Lead-1. It is well known that the lead-$k$ technique is considered a strong single-document summary baseline in certain domains (See et al., 2017). A lead-$k$ summary merely truncates input documents after the first $k$ sentences. In the case of multiple documents, and especially in the product-reviews domain where documents are usually not very long, a parallel approach is to concatenate the first sentence from several of the shuffled documents until a certain length limit is reached. We limit our multi-lead-1 “summary” to 100 tokens.

Cluster + Medoid-Recall. This baseline is a simulation of our level1 approach in which we cluster the reviews but then, instead of using the CSS to generate cluster-summaries, we extract weak-reference reviews for the clusters (using the ROUGE-1 $F_1$ function). Finally, we apply the Medoid-$F_1$ baseline on the resulting set of weak-references to produce the final “summary”.

Cluster + Medoid-Recall. This is similar to the previous baseline except that the final “summary” is selected out of the weak-reference set using the Medoid-Recall baseline.

5.3 Automatic Evaluation Results

We consider four system variants in our automatic evaluation. The variants are created from the cross product of two implementation decisions: (1) whether the final summary is taken from the top level of the hierarchy (top) or the first level (level1), and (2) the $\text{sim}$ function used for the weak-reference extraction, i.e. word overlap recall or ROUGE-1 $F_1$.

Table 5 presents the ROUGE scores of our system variants and those of the baselines on the Electronics and Books categories. We first observe that applying the full summarization hierarchy (top) is almost consistently worse than choosing a medoid summary from the first level (level1). This could be explained by the fact that details are lost on the way up the hierarchy levels, causing the final summary to capture more generic common information. Additionally, clusters of summaries at higher levels in the summary hierarchy may contain elements with low pairwise similarity, quite different from the clusters that were used for training the CSS.

Comparing different similarity measures for the weak-reference extraction did not lead to clear conclusions, with both ROUGE-1 $F_1$ and word set overlap recall interchangeably achieving the best result but with insignificant statistical difference.

Our model achieves better scores than all baselines, and significantly so in most metrics and categories. It is evident that selecting a review based on high ROUGE-1 $F_1$ provides a relatively good representative review to “summarize” the rest of the reviews. We also find that the Medoid-Recall baseline produces very long summaries at the expense of precision, severely weakening its ROUGE $F_1$ scores. Clustering first, simply filters out some of the longer reviews.

We cannot perform a straight-forward comparison between our system and prior work because the MMDS setup is different by definition. However, when comparing to (Chu and Liu, 2019), we observe that our results are proportionally higher when compared to similar baselines, though on
ROUGE-

Table 5: ROUGE $F_1$ scores on variants of our model and the baselines on two of the categories. The model variant name indicates the hierarchical level from which the output summary is taken (level-1 or top) and the the metric used for weak reference extraction. ROUGE score intervals express $\geq 95\%$ confidence.

| Model                | Electronics | Books |
|----------------------|-------------|-------|
|                      | ROUGE-1     | ROUGE-2 | ROUGE-L | ROUGE-1 | ROUGE-2 | ROUGE-L |
| level-1-F1           | 28.81 (±1.11) | 4.77 (±0.61) | 17.47 (±0.8) | 25.8 (±1.16) | 4.97 (±0.58) | 16.48 (±0.75) |
| level-1-Recall       | 27.82 (±1.39) | 4.48 (±0.6) | 17.43 (±0.83) | 26.9 (±0.82) | 4.45 (±0.43) | 17.12 (±0.44) |
| top-F1               | 26.19 (±1.54) | 3.89 (±0.57) | 15.82 (±0.95) | 22.98 (±1.79) | 3.85 (±0.53) | 15.16 (±0.98) |
| top-Recall           | 24.15 (±1.49) | 4.05 (±0.48) | 15.15 (±0.88) | 22.13 (±1.28) | 3.74 (±0.52) | 13.77 (±0.72) |
| Medoid-F1            | 26.6 (±1.14) | 3.18 (±0.51) | 15.53 (±0.79) | 25.43 (±1.85) | 3.37 (±0.52) | 15.55 (±1.03) |
| Cluster + Medoid-F1  | 25.09 (±1.34) | 2.83 (±0.46) | 14.92 (±0.89) | 23.19 (±2.71) | 2.90 (±0.63) | 14.53 (±1.53) |
| Multi-Lead-1         | 23.74 (±1.12) | 2.64 (±0.44) | 13.65 (±0.68) | 24.77 (±1.31) | 2.87 (±0.47) | 14.16 (±0.59) |
| Cluster + Medoid-Recall | 18.43 (±1.55) | 2.25 (±0.32) | 10.58 (±0.81) | 21.80 (±1.40) | 3.16 (±0.44) | 12.53 (±1.01) |
| Medoid-Recall        | 14.29 (±0.64) | 1.84 (±0.23) | 8.33 (±0.41) | 19.19 (±2.00) | 3.73 (±1.46) | 11.63 (±1.56) |

Table 6: Manual linguistic quality scores of our system (level1-F1 variant) and the Medoid- $F_1$ and Multi-Lead-1 baselines on the Electronics category.

| Criterion              | Ours | Medoid- $F_1$ | Multi-Lead-1 |
|------------------------|------|---------------|---------------|
| Grammaticality         | 3.73 | 4.09          | 3.45          |
| Non-redundancy         | 3.55 | 3.91          | 3.18          |
| Referential clarity    | 3.86 | 3.91          | 3.59          |
| Focus                  | 3.86 | 3.32          | 3.36          |
| Structure & coherence  | 3.73 | 3.41          | 3.23          |

5.4 Manual Linguistic Quality Results

We performed a manual linguistic quality assessment of the summaries from our system’s best variant (level1-$F_1$) and from the Multi-Lead-1 and Medoid-$F_1$ baselines on our Electronics category test set. While it is known that these responsiveness-style evaluations are prone to weak replicability (Gillick and Liu, 2010), for the sake of completeness we report these results as well.

The five criteria evaluated are those introduced in the DUC evaluations (Hoa, 2006). Generally, they assess grammaticality, non-redundancy, referential clarity, focus, and structure and coherence. Crowdworkers were told to rate each criterion on a 1-to-5 likert scale (1 is very poor and 5 is very good), and each summary was evaluated by 5 different workers. We used MACE (Hovy et al., 2013) to clean the crowdsourced results and improve our confidence in the final scores.

Table 6 presents the results. It is noticeable that the Multi-Lead-1 baseline is weakest, which is expected as the sentences are concatenated with complete disregard to each other. This behavior is expected to increase redundancy and weaken the flow of the narrative. The Medoid-$F_1$ baseline “summaries” are actual human-written reviews, hence their scores are expected to be high. Our system’s results are close, and even surpass them in the focus and structure & coherence criteria. The main takeout is that our summaries are quite readable, which is inherently on account of the underlying FAS system by Chen and Bansal (2018).

Appendix A contains some summary output samples. Figure 5 exemplifies summaries generated by our system and the two baselines mentioned above, as well as a reference summary for the same camera lens. Figure 6 provides a few interesting system summaries from the DVD category and Figure 7 points at a few problematic system outputs.

6 Conclusion

MDS is a widely researched topic which traditionally assumes small document sets. However, the full potential of automatic summarization is unlocked when the document sets are so large that the average person would not be able to digest them. Specifically, in the domain of product consumer reviews, there may be hundreds, thousands and even tens of thousands of reviews for a single product. In this paper, we (1) institute massive MDS by proposing a schema that can handle large product review sets in a weakly supervised manner, (2) collect a dataset of reference summaries of 123 prod-
ucts covering the full set of reviews per product, and (3) implement an initial summarization system based on our schema, showing promising results. We hope that this framework sparks interest and subsequent research on MMDS.

For future work we would like to investigate alternative ways of clustering reviews and choosing their weak-references in order to improve training quality. Specifically, we may look into methods capitalizing on aspect salience. Another natural extension to our work is to borrow the hierarchical approach from the summary generation procedure and apply it to generate a hierarchy of reference summaries, ending with a single reference summary or a handful of high quality summaries. Additionally, as product reviews tend to be rather short, we hypothesize that longer texts, such as in the news domain, would behave differently and require algorithmic adjustments.

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A Appendix

Product: “Canon EF 16-35mm f/2.8L II USM Ultra Wide Angle Zoom Lens” (Camera)

Reference Summary (crowdsourced – one of several)
Ultra wide-angle and fast optical zoom that offers excellent peripheral performance throughout the zoom range. The lens with polarized filter included makes some incredible shots, ideal for a holiday trip very easy to transport and handle, the only defect with this device would be the price since it is a little high exceeding $ 2200

Medoid-F1 Baseline
I’ve wanted a wide angle lens for a long time, and let me tell you this was worth the wait. While it is pricy, I don’t regret paying what I did for it. It’s just an amazing piece of glass. It comes with a nice pouch to protect it will pull strings at the top and can work well as a walk around lens. I use it on a Canon 5DMII and I’ve even done some great video shooting with it. When it’s wide, it’s very wide. I have not noticed the same softness that others are talking about. I’ve added a few photos that I shot with this to this page.

Multi-Lead-1 Baseline
I purchased this lense a few months ago for landscape photography. Great Lens Period, you would have to hold one and use it. This Lens is really unbelievable. ‘The EF16-35mm f/2.8L II USM ultra wide angle ZOOM lens captures amazing colors and is a great walk-around lens. ”No complain as to the image quality. This lens was as good as advertised! Everything you would expect from Canon L glass.

System Summary (level1-F1 variant)
I have been very happy with the results. This is a great lens for the price. The lens is very sharp and the bokeh is great. Does everything i need it to do. I love this lens.

System Summary (level1-Recall variant)
I have a canon rebel t3i and it is a great lens. I used this lens for my first wedding and I was amazed at the quality of the images I was looking for. I bought this lens to replace my canon ef 75-300mm lens and it was a great price. The lens is very sharp and sharp. The wide aperture is more than adequate for low light situations. I’m very happy with my purchase. Great product and would recommend to anyone.

Figure 5: An actual example of summaries.
Toys

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 29.26 ±1.87 | 4.64 ±0.818 | 18.24 ±1.08 |
| level1-Recall | 27.57 ±1.7  | 4.32 ±0.73  | 17.03 ±1.09 |
| top-F1      | 27.43 ±1.68 | 4.86 ±0.681 | 17.48 ±1.1  |
| top-Recall  | 23.92 ±1.74 | 4.31 ±0.62  | 15.29 ±1.23 |

Camera

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 29.25 ±1.45 | 5.26 ±0.69  | 17.74 ±0.76 |
| level1-Recall | 27.94 ±1.53 | 5.36 ±0.61  | 17.18 ±0.74 |
| top-F1      | 27.5 ±1.88  | 5.06 ±0.76  | 17.37 ±0.94 |
| top-Recall  | 18.77 ±1.95 | 4.13 ±0.5   | 12.62 ±0.91 |

Our Variants

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 27.57 ±1.7  | 4.32 ±0.73  | 17.03 ±1.09 |
| level1-Recall | 25.73 ±1.65 | 3.96 ±0.75  | 15.62 ±1.09 |
| top-F1      | 24.72 ±1.12 | 3.30 ±0.58  | 14.36 ±0.65 |
| top-Recall  | 20.95 ±1.87 | 2.83 ±0.45  | 12.29 ±1.09 |

Baselines

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 28.41 ±1.44 | 3.9 ±0.6    | 16.59 ±1.01 |
| level1-Recall | 25.22 ±2.84 | 3.76 ±0.7   | 15.32 ±1.4  |
| top-F1      | 19.57 ±1.62 | 2.73 ±0.42  | 11.37 ±0.84 |
| top-Recall  | 16.99 ±1.37 | 2.52 ±0.33  | 9.92 ±0.76  |

Table 7: ROUGE F1 scores on variants of our model and the baselines on the Toys and Camera categories.

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 28.41 ±1.44 | 3.9 ±0.6    | 16.59 ±1.01 |
| level1-Recall | 25.22 ±2.84 | 3.76 ±0.7   | 15.32 ±1.4  |
| top-F1      | 19.57 ±1.62 | 2.73 ±0.42  | 11.37 ±0.84 |
| top-Recall  | 16.99 ±1.37 | 2.52 ±0.33  | 9.92 ±0.76  |

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 28.41 ±1.44 | 3.9 ±0.6    | 16.59 ±1.01 |
| level1-Recall | 25.22 ±2.84 | 3.76 ±0.7   | 15.32 ±1.4  |
| top-F1      | 19.57 ±1.62 | 2.73 ±0.42  | 11.37 ±0.84 |
| top-Recall  | 16.99 ±1.37 | 2.52 ±0.33  | 9.92 ±0.76  |

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 28.41 ±1.44 | 3.9 ±0.6    | 16.59 ±1.01 |
| level1-Recall | 25.22 ±2.84 | 3.76 ±0.7   | 15.32 ±1.4  |
| top-F1      | 19.57 ±1.62 | 2.73 ±0.42  | 11.37 ±0.84 |
| top-Recall  | 16.99 ±1.37 | 2.52 ±0.33  | 9.92 ±0.76  |

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 28.41 ±1.44 | 3.9 ±0.6    | 16.59 ±1.01 |
| level1-Recall | 25.22 ±2.84 | 3.76 ±0.7   | 15.32 ±1.4  |
| top-F1      | 19.57 ±1.62 | 2.73 ±0.42  | 11.37 ±0.84 |
| top-Recall  | 16.99 ±1.37 | 2.52 ±0.33  | 9.92 ±0.76  |

Table 7: ROUGE F1 scores on variants of our model and the baselines on the Toys and Camera categories.

| Model       | ROUGE-1     | ROUGE-2     | ROUGE-L     |
|-------------|-------------|-------------|-------------|
| level1-F1   | 23.99 ±1.6  | 4.15 ±0.58  | 15.61 ±0.98 |
| level1-Recall | 25.26 ±1.5  | 4.36 ±0.55  | 16.16 ±0.8  |
| top-F1      | 20.13 ±1.46 | 3.96 ±0.47  | 12.59 ±0.88 |
| top-Recall  | 26.16 ±1.39 | 4.14 ±0.5   | 15.27 ±0.71 |
| Med-F1      | 24.94 ±1.37 | 3.56 ±0.44  | 14.75 ±0.59 |
| C + Med-F1  | 24.93 ±1.36 | 3.41 ±0.5   | 14.49 ±0.77 |
| C + Med-Rec | 21.43 ±1.08 | 3.25 ±0.31  | 11.85 ±0.69 |
| Med-Rec     | 18.72 ±1.01 | 3.11 ±0.28  | 10.41 ±0.62 |

Product: “Banshee: Season 1” (DVs)
Love true blood so much! The show is one of the best shows on tv. I love the fight scenes and the story line.

Product: “Start! Walking with Leslie Sansone 1 & 2 Mile Walk” (DVs)
I have only done the 1-mile walking and I like the simplicity of the moves. I think this is a good workout for those who are looking for something to do. This is a great way to get started exercising again.

Product: “The Book Thief” (DVs)
The story is so touching and the acting is great. This is a beautiful story about a young girl in the world of nazi germany.

Product: “The Great Gatsby” (DVs)
I have read the book several times and have never read the books. This movie is a must see for the family and family. I read the book years ago and loved it. This is one of the best movies ever made.

Product: “Jillian Michaels: 6 Week Six-Pack” (DVs)
I bought this dvd for my husband and she loved it. This is a great workout for the whole family.

Product: “Banshee: Season 1” (DVs)
I was hooked on this show. I am still waiting for the next season to come out on dvd. This is one of the best shows on tv. What a disappointment after all the hype.

Figure 6: Interesting summaries generated by our model. In the first, notice that “True Blood” is from the same creator as “Banshee”. The second summary recommends a beginner walker to acquire the DVD. Finally the third summary provides the general plot of the movie.

Figure 7: Problematic summaries generated by our model. They all demonstrate the problem of self-contradiction.