Summary-Source Proposition-level Alignment: Task, Datasets and Supervised Baseline

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Abstract

Aligning sentences in a reference summary with their counterparts in source documents was shown as a useful auxiliary summarization task, notably for generating training data for salience detection. Despite its assessed utility, the alignment step was mostly approached with heuristic unsupervised methods, typically ROUGE-based, and was never independently optimized or evaluated. In this paper, we propose establishing summary-source alignment as an explicit task, while introducing two major novelties: (1) applying it at the more accurate proposition span level, and (2) approaching it as a supervised classification task. To that end, we created a novel training dataset for proposition-level alignment, derived automatically from available summarization evaluation data. In addition, we crowdsourced dev and test datasets, enabling model development and proper evaluation. Utilizing these data, we present a supervised proposition alignment baseline model, showing improved alignmentquality over the unsupervised approach.

1 Introduction

Text summarization aims to extract the salient information out of a single document or a set of topically-related documents, and to generate a coherent summary. Inherently, summarization needs to address, either explicitly or implicitly, several embedded subtasks, such as salience detection, redundancy removal, and text generation.

Attempting to cope with this encompassing challenge, summarization research often involves developing models for specific summarization subtasks, utilized either as system components or for auxiliary purposes such as training data creation. In this paper, we draw attention to the particular auxiliary task of *summary-source alignment*, which was utilized as a supporting data generation step in the summarization literature, for both single and multi document summarization. Given a gold summarization dataset, the task aligns information pieces in a reference summary with corresponding information in the source documents. Such alignments were generated automatically over large summarization datasets, most typically at the full sentence level. Then, (noisy) training data for certain summarization subtasks was automatically derived from these alignments (§2), notably for salience detection (Gehrmann et al., 2018; Chen and Bansal, 2018; Lebanoff et al., 2019), but also for redundancy recognition (Cho et al., 2019) and text rephrasing and fusion (Zhang et al., 2018; Lebanoff et al., 2019). Even though the quality of the subsequent trained models relies on alignment quality, the intermediate alignment methods were neither optimized nor evaluated explicitly, making them difficult to compare and improve.

In this paper, we establish summary-source alignment as a stand-alone auxiliary task, with corresponding novel datasets, model, and intrinsic evaluation. As a major contribution, aiming to yield more precise alignments, we propose aligning source-summary information at the more finegrained level of propositions, rather than at the common sentence level. Specifically, we align information at the level of individual proposition spans, termed *information units* (IUs), as exemplified in Fig. 1. This level provides much tighter alignments compared to the sentence level used in prior work, since aligned full sentences would typically include both matching propositions as well as non-matching ones. An illustration for the tighter alignment at the proposition-level, over random examples, is shown in Table 1, where full sentences usually include additional non-matching content. Table 1 also demonstrates that the ROUGE-L score between matching propositions tends to be much higher than between sentences, unless the semantic matching is abstractive (rather than lexical), where ROUGE is not informative.

To support research on the advocated

Prime Minister Hun Sen insisted that talks take place in Cambodia				
while opposition leaders Ranariddh and Sam Rainsy, fearing arrest at home, wanted them abroad.				
Cambodian leader Hun Sen on Friday rejected opposition parties' demands for talks outside the country, accusing them of trying to "internationalize" the political crisis.	"I would like to make it clear that all meetings related to Cambodian affairs must be conducted in the Kingdom of Cambodia," Hun Sen told reporters after a Cabinet meeting on Friday.	Negotiations to form the next government have become deadlocked, and opposition party leaders Prince Norodom Ranariddh and Sam Rainsy are out of the country following threats of arrest from strongman Hun Sen.		

Figure 1: Aligning IUs between a summary sentence (top) and sentences from documents (bottom). For fuller example see Appendix B.

proposition-level alignment, we first developed an elaborate crowdsourcing methodology and created high-quality development and test datasets (§3). Next, we automatically derive a larger-scale training dataset consisting of 23K alignment instances from available Multi-Document Summarization (MDS) evaluation data, available as reliable Pyrmaid annotations (Nenkova and Passonneau, 2004) (§4). This data is utilized to train a supervised alignment baseline model (§5), which outperforms traditional unsupervised alignment approaches.¹ Moreover, thanks to this novel training dataset, we show $(\S5.4)$ that our baseline aligner is capable of producing "abstractive" alignments, where there is almost no lexical overlap, while traditional aligners fail to do so. We further show intrinsically that our proposition-level aligner extracts better salient sentences than common sentence-level aligners. Notably, while our datasets are derived from MDS sources, the data and model are applicable also for alignments over Single Document Summarization data. In concluding discussion, we suggest using our dataset suite to further develop improved proposition-level aligners, which in turn may trigger appealing research on proposition-based summarization methods.

2 Background and Related Work

As mentioned above, several methods leveraged automatically generated reference-source sentence alignments, to derive (noisy) training sets for summarization subtasks (Zhang et al., 2018; Cho et al., 2019). For example, training datasets for sentence salience detection were derived from referencesource alignments, by marking as salient those source sentences that were aligned with a summary sentence (e.g. Chen and Bansal (2018)). As another example, Lebanoff et al. (2019) leveraged alignments to create a sentence fusion dataset: the input for each fusion instance consists of a pair of source sentences that are aligned to the same summary sentence, while the aligned summary sentence is regarded as the output fused sentence.

The underlying sentence alignments, from which the above training datasets were derived, were extracted automatically from large summarization datasets. Alignments were detected using unsupervised sentence similarity measures, typically based on ROUGE score (Lin, 2004) (see §6 for more details). Typically, models trained over the alignmentbased datasets were evaluated only on the final summary. Yet, alignment quality, which determines the quality of the utilized training datasets, was never optimized or assessed explicitly, as we do in this paper.

Notably, alignment of matching pieces of information provided the basis for the prominent Pyramid method for summarization evaluation (Nenkova and Passonneau, 2004), capturing information overlap between system summaries and reference summaries. Alignments were performed at the level of individual propositions, termed Summary Content Units (SCUs) (similar to the information units marked in Fig. 1). Matching information at the proposition level was favored over the more coarse sentence level, since a system summary sentence may include some propositions that match the reference and some that don't. Later works attempted to automate the Pyramid procedure, using Open IE (Yang et al., 2016; Peyrard and Eckle-Kohler, 2017) or Elementary Discourse Units (EDU) (Hirao et al., 2018), to extract proposition-level units. As propositional units (like SCUs) may share their arguments (such as in conjunctions and other constructions, e.g. "The boy went home and ate dinner"), and may be discontiguous ("The boy...ate dinner"), Open IE output, which satisfies these requirements, is best suitable for extracting such units (while EDU format

¹All corresponding datasets and code are publicly available at https://github.com/oriern/SuperPAL.

Summary Sentence	Document Sentence	R-L
The BBC reports 56-year-old Allan Matthews pleaded guilty	It is the crown's case that <i>Matthews is not qualified</i>	
Wednesday to removing another man's left hand at an	or authorised to perform such a procedure, and is	17.85 / 28.57
Australian motel despite not being qualified to practice medicine.	not a qualified or registered medical practitioner.	
The lawsuit, which also alleges a hostile work environment	Campbell alleges that events like those construe a	
and retaliation, claims the sexist culture at Magic Leap created a	hostile working environment, and is asking for	
"dysfunctional" workplace and is part of the reason the company	punitive damages from Magic Leap.	25.00 / 50.00
has yet to actually release a product		
A U.S. House resolution criticized Hun Sen's regime	Cambodia's ruling party responded Tuesday to criticisms	
while the opposition tried to cut off his access to loans.	of its leader in the U.S. Congress with a lengthy	20.40/ 21.05
	defense of strongman Hun Sen's human rights record.	
<i>Ecevit</i> , a former prime minister, <i>was asked to form a</i>	<i>Ecevit must now try to build a government</i> that includes	25.80/ 50.00
new government.	their center-right parties but not them as individuals.	23.80/ 50.00

Table 1: ROUGE-L score between *aligned* IUs and their corresponding sentences.

does not satisfy these properties). Inspired by these works, we align proposition spans (§3), extracted automatically using Open IE (§5).

3 Dev and Test Alignment Datasets

This section presents the manually-annotated development and test datasets for reference-source alignments, including their structure (§3.1), source data (§3.2) and annotation process (§3.3). These datasets allow direct tuning and evaluation of alignment algorithms, lacking in prior work (§1).

3.1 Dataset Structure

In the typical MDS setting, a summarization instance consists of a set of topically-related documents, often termed a topic, and corresponding gold reference summary(ies) (NIST, 2014; Fabbri et al., 2019). For such an instance, we collect all alignments between each proposition span in the reference summary and the corresponding propositions, conveying the same information, in the source documents. We choose the proposition-span level, termed information unit (IU), as the basis for alignment following the rationale of similar SCU-level alignments in the well-established Pyramid evaluation method (\S 2). To facilitate crowdsourcing, we adapt a somewhat looser definition for our IUs (Task 1 below). Figure 1 illustrates some IU spans and their alignments.

3.2 Source Data

We leverage three MDS datasets to create our alignment dataset: DUC 2004, DUC 2007 (NIST, 2014), and the recent Multi-News (Fabbri et al., 2019). We sampled 21 topics: 9 topics (4 dev, 5 test) from MultiNews, each with 3-4 documents and 1 reference summary, and 6 topics (3 dev, 3 test) from each of the DUC datasets, sampling 7 documents and 1 reference summary per topic.

3.3 Annotation

Our annotation process relied mostly on crowdsourcing, while involving limited expert effort to obtain high quality dev and test sets. The crowdsourcing process was divided into three tasks, conducted on Amazon Mechanical Turk with total cost of \$3,163. We required workers from native English speaking countries, with > 98% approval rate and > 500 approved tasks.

To estimate the recall of the crowdsourced annotations in each task, we tested them, as reported below, against meticulous expert annotation of 6 topics, conducted by one of the authors (using the DUCView annotation tool (Sigelman, 2006)). Further, to assure alignment precision, all obtained crowdsourced alignments were filtered or corrected by one of the authors, thus ensuring expert-level precision for our dataset.

To evaluate one alignment against another (such as crowdsourced against expert), we first need to determine whether a span identified in one alignment should be considered as matching a span in the other. Since determining exact proposition boundaries may be somewhat subjective, we follow an "intersection over union" soft matching approach, often used in similar cases (e.g. (Roit et al., 2020)). In our case, we apply Jaccard similarity, measuring intersection-over-union between the two spans' character-level position indices with respect to the beginning of their sentence. For two span annotations $span_A$, $span_B$ in sentence sent, the corresponding character position indices sets are: $A = \{i \mid sent[i] \in span_A\},\$ $B = \{i \mid sent[i] \in span_B\},$ respectively. The Jaccard score is then defined as:

$$Jaccard = \frac{A \cap B}{A \cup B} \tag{1}$$

As explained below, we tuned a threshold t for



Figure 2: Propositional alignment annotation process: A summary sentence is divided into IUs ((a), **Task 1**). Then, each IU is paired with all document sentences, yielding sets of candidate pairs. These sets are filtered automatically, and then manually, to reduce annotation complexity ((b1) & (b2), **Task 2**). Finally, workers mark the aligned propositional IUs in the remaining candidate pairs ((c), **Task 3**).

the Jaccard similarity, above which two spans are considered as matching.

Next we describe the three tasks of our annotation pipeline. The full process is illustrated in Figure 2, and full annotation guidelines can be found in Appendix A.

Task 1: Summary IU extraction. In this task, workers are asked to mark all IU spans within the reference summary sentences. The task instructions, accompanied with illustrating examples, define an IU as a standalone fact, covering the (possibly non-consecutive) span of a predicate and all its arguments, as exemplified in Fig. 1.² To calculate the recall of the crowdsourced annotation, we consider an expert IU as being matched if its Jaccard score with at least one crowdsourced IU is beyond a threshold t. Through manual examination, we found that t = 0.25 closely approximates appropriate matches, yielding almost perfect coverage of the expert IUs. We adopt this tuned threshold for evaluating the output of the next tasks as well. Overall, we collected 203 dev and 238 test IUs.

Task 2: Filtering unlikely candidate alignments. In Tasks 2 and 3, we find, for each summary \mathbb{IU} , all its aligned \mathbb{IU} s in the source documents of the topic. In Task 2, for each reference summary \mathbb{IU} , we filter source document sentences that are unlikely to include an aligned \mathbb{IU} , keeping all remaining sentences as candidates for alignment. Then, in Task 3, we ask annotators to verify whether alignment indeed holds, and if so, annotate it at the \mathbb{IU} -span level. Task 2 thus reduces the burden on the actual \mathbb{IU} alignment annotation

²The annotation instructions for all tasks are embedded in the annotation interface, included in our Github release.

in Task 3, filtering the vast amount of irrelevant source sentences for each summary \mathbb{IU} .

The Task 2 filtering process consists of two steps, automatic and crowdsourced. First, we automatically filter candidate pairs of a summary IU and a document sentence that do not satisfy a certain similarity criterion, which is is composed of several similarity scores: the BERT-based similarity measure BERTscore (Zhang et al., 2019), an entailment score based on RoBERTa fine-tuned on MNLI (Liu et al., 2019), and ROUGE-1 precision (Lin, 2004).³ Next, we filter the remaining pairs via crowdsourcing. Given a summary IU, bolded within its sentence, and a candidate document sentence, the workers determine whether the source sentence contains an IU that should be aligned with the given summary IU. Overall, 94% of the candidate summary IU and sentence pairs were filtered in Task 2, while yielding a recall of 83% relative to the expert alignments.

<u>Task 3:</u> IU-level alignment. In this task, annotators are given a summary IU, highlighted in bold within its sentence, and a candidate source sentence, which was judged in Task 2 as being aligned with the summary IU. The worker should then mark the aligned IU span in the source sentence, or state that no alignment resides. As mentioned earlier, these alignment annotations underwent a final expert review, eventually yielding 345 development and 312 test reference-source IU alignments (with expert-level precision).

We then measured the recall of the alignments

³For BERT and ROUGE scores, the summary \mathbb{IU} is considered as the candidate and the document sentence as the reference; for entailment score, the summary \mathbb{IU} is the hypothesis and the document sentence is the premise.

obtained in Tasks 2 and 3 against the expert annotation (of 6 topics, mentioned above). An expert alignment was considered as covered if it matched at least one crowdsourced alignment, where the Jaccard match score was above t = 0.25 for both the summary and source sides, yielding 76% recall. The average Jaccard similarity of the matched alignments in our data is about 0.85, indicating that most alignments were off by only one or two words relative to expert annotation. Overall, our (dev and test) crowdsourced dataset is the first to provide effective means for tuning and comparing alternative alignment models , as shown in Section 5.

4 Pyramid-Based Training Dataset

To obtain larger amounts of alignments for training supervised models, we derive them automatically from existing MDS evaluation data. While these alignments are less exhaustive, compared to the manual processes in §3, they are of fairly high quality and proved useful for model training.

We follow Copeck et al.'s line of work (Copeck and Szpakowicz, 2005; Copeck et al., 2006, 2007, 2008), which established a sentence alignment dataset based on the Pyramid evaluation method (Nenkova and Passonneau, 2004), applied for the DUC 2005-2007 and TAC 2008 summarization benchmarks. As many of the systems participating in these benchmarks were extractive, system summary sentences directly link to document sentences. These links, along with the Pyramid's expert mapping between reference summary spans and system summary spans, enabled Copeck et al. to transitively align reference summary sentences to document sentences, yielding a *sentence-level* alignment dataset.

We take this process one step further, aligning in a similar manner \mathbb{IU} spans in the reference summaries (rather than full sentences) to corresponding \mathbb{IU} spans in documents. This is possible thanks to the Pyramid's annotated mappings, which link spans between reference and system summaries. Such derived alignments are not exhaustive, since the Pyramid-based alignments cover only sentences included in the evaluated system summaries. Nevertheless, this provides a novel large-scale alignment dataset at the proposition-level, consisting of 18,505 alignments, sufficient for training neural alignment models.

The alignments obtained thus far involve spans that were detected manually by the Pyramid annotators. Yet, our alignment model (Section 5) needs to align IUs that were extracted automatically, a step that we implemented using OpenIE (OIE) (Stanovsky et al., 2018). In order to train our alignment model appropriately, we create an additional version of the training set, in which the aligned IUs were detected automatically by our OIE-based extraction (Section 5). To that end, we first apply the IU extractor over the summaries and source documents. Then, we consider a candidate pair of (OIE-based) summary IU and source IU as matching if each of these IUs matches the corresponding IUs in a Pyramid-based alignment, with a Jaccard similarity score above the t = 0.25 threshold (based on Section 3). This process yielded 23,492 OIE-based alignments, as some of the original spans matched several OIE spans, while others did not match any.

Next, we add negative instances to our dataset. First, we include challenging negative instances by selecting all non-aligning source-summary OIE combinations that have BERTscore (Zhang et al., 2019) above 0.89. In addition we include naturallydistributed negative instances, by taking a summary IU that has an alignment in a certain document and combining it with all non-aligned candidate IUs in that document. Since our training dataset is based on alignment to extractive system summaries, we consider in this process only document sentences that are included in these system summaries. Overall, we sampled 219,772 negative examples, where 22% of them were selected for high BERTscore.

We estimated our data quality by manually counting errors in random samples, including 80 positive examples and 80 negative examples of each of the two negative example types. The respective error rates were 11% in the positive sample and 5% in each of the negative samples, suggesting the highquality of our automatically-derived data. Its actual effectiveness for model training is assessed next. A few samples from the data are presented in Table 2.

5 IU Alignment Methods and Evaluation

This section describes two baseline methods (\$5.1, \$5.2) and our proposed supervised method (\$5.3) for summary-source IU-level alignment. We compare their performance (\$5.4) against our manually-created test set, showing the substantial advantage of the supervised aligner, trained over our automatically-derived training dataset (\$4).

The presented alignment methods require a pre-

	Orig Summary Span	OIE Summary Span	Orig Document Span	OIE Document Span
(a)	European Union (EU) na- tions agreed that a single currency (the Euro) will go into effect on January 1, 1999	that a single currency Euro) will go into effect on January 1, 1999.	the 1999 introduction of the single European cur- rency, the euro	The mass printing of the banknotes of the single Eu- ropean currency euro would be started at the be- ginning of 1999
(b)	president's line-item vetoof 38 military construction projects	In October 1997 Congress overrode the president's line-item veto against 36 of 38 military construction projects.	U.S. President Bill Clinton used his line-item vetoto strike outprojectsfrom a military construction bill	his line-item veto power to strike out 38 projects worth 287 million U.S. dollars
(c)	N/A	500 anti-government activists surrendered in March 1999.	N/A	a total of 15 anti- government ethnic armed groups have made peace with the government
(d)	N/A	the suit filed by the record- ing industry.	N/A	Metallicaalleging that Napster's software encour- aged users to freely trade the band's songs without permission.
(e)	N/A	US tobacco companies ap- pear capable of sustaining strong momentum.	N/A	yesterday reported a more modest 10.9 per cent ad- vance in net earnings

Table 2: Examples from alignment training data. (a) and (b) are positive examples, where original aligned spans have been extracted manually by Pyramid annotators. For our data, we used only OpenIE spans with high overlap with the original ones. (c) and (d) are challenging negative examples with high BERTscore, while (e) is taken from the naturally distributed negative sample. Negative samples were extracted in OpenIE format directly, and do not have original annotated spans (N/A).

liminary step that extracts candidate \mathbb{IU} spans to be aligned. As mentioned earlier, we found Open IE (OIE) (Stanovsky et al., 2018) suitable for this purpose, simply collecting as a (possibly non-consecutive) \mathbb{IU} span the union of a predicate and its arguments in an OIE extraction. Using OIE loses around 10% of the correct (gold) alignments due to missed \mathbb{IU} extractions, limiting the automatic alignment recall to an upper-bound of 90%.

5.1 ROUGE-based Lexical Model

As described in §2, the most common alignment approach, previously applied at the sentence level, is based on ROUGE lexical similarity. Typically, a reference summary sentence is aligned with one or two source sentences which are most similar to it. We adjust this approach to the IU level, denoted ROUGE_{IU}. Accordingly, each summary IU is matched with the k document IUs of highest ROUGE similarity, choosing k = 2, which worked best on the dev set.⁴

	Ref.	$R_{0.25}$	$P_{0.25}$	F_1	$Cov_{0.25}$	$F_{1,cov}$
	Dev Set	33.91	37.76	35.73	50.26	43.12
ROUGE _{IU}	Test Set	28.85	29.97	29.40	47.34	36.71
Sim-Ensemble	Dev Set	43.48	41.01	42.21	59.79	48.65
	Test Set	37.18	34.77	35.93	52.66	41.89
SuperPAL	Dev Set	47.83	66.29	55.56	55.56	60.45
	Test Set	43.59	65.85	52.46	54.44	59.60

Table 3: Automatic aligners scores

5.2 Semantic Similarity Ensemble Model

As a distantly supervised approach for matching semantically-equivalent IUs, we developed and tuned an ensemble of various existing semantic matching models, denoted "Sim-Ensemble". Specifically, we ended up with a two-stage approach, where we first align a summary IU with the three source sentences most similar to it. The similarity score at this stage was a tuned combination of ROUGE, RoBERTa-MNLI (Liu et al., 2019) and BERTscore (Zhang et al., 2019). Then, to find aligned spans, we applied a word aligner (Sultan et al., 2014) to align words between a document sentence and the summary IU, and aligned the consecutive text spans between the first and last aligned words on each side (filtering pairs with too few word alignments).

⁴Our ROUGE similarity is an average of recall R-1, R-2, and R-L, where the summary-IU is considered the reference. We also experimented with setting a threshold over the similarity score, but the common top-k approach worked best.

5.3 Supervised Model

This model is a binary classifier, deciding whether two given IUs align. We follow the standard usage of RoBERTa for paraphrasing tasks (Liu et al., 2019). Specifically, we take a RoBERTa encoder fine-tuned on MNLI and augment it with a new binary classification layer. This model is then further fine-tuned with our Pyramid-based dataset (§4). We denote this model as "SuperPAL", for Supervised Propositional ALignment.

5.4 IU-level Results

The alignment methods are evaluated using the same character-level Jaccard similarity, which was used for evaluating the crowdsourcing annotations (Eq. 1). Here, we define recall $(R_{0.25})$, precision $(P_{0.25})$ and F-1 (F_1) , where a predicted and a gold alignment are considered matching if they yield a Jaccard score surpassing the threshold t = 0.25 for the \mathbb{IU} pairs in both summary and document sides. In addition, since alignment may be utilized eventually to compose a summary, the requirement of finding all aligned document IUs for each summary IU, as measured by $R_{0.25}$, might be superfluous. To that end, a *Coverage* $(Cov_{0.25})$ measure was added, measuring the proportion of summary $\mathbb{I}\mathbb{U}s$ covered by at least one aligned pair. Respectively, an $F_{1,cov}$ balances between $Prec_{0.25}$ and $Cov_{0.25}$. The methods are evaluated against our gold dev and test datasets, as in Table 3.

As shown, the SuperPAL model substantially outperforms the other two baselines. The lexical ROUGE-based baseline, typical of prior work (which was not evaluated intrinsically), performs worst. The Sim-Ensemble model, which was trained on generic NLI and text similarity data, surpasses the unsupervised ROUGE-based model by 6 F_1 points. Yet, it scores 16 F_1 points lower than the supervised model, which was trained for the IU alignment task using our new training data. Finally, the average Jaccard score for matching predicted and gold IUs for SuperPAL is 0.67, indicating a high match with gold annotation.

It is further illuminating to examine the results of $ROUGE_{IU}$ and SuperPAL by a breakdown over the DUC and MultiNews parts of our datasets, shown in Table 4. Clearly, while DUC is generally more challenging, the performance of Super-PAL degrades more gracefully relative to Multi-News, while the $ROUGE_{IU}$ performance on DUC collapses drastically. This might be caused by the

	Method	$R_{0.25}$	$P_{0.25}$	F_1	$Cov_{0.25}$	$F_{1,cov}$
DUC	ROUGE _{IU}	29.25	23.71	26.19	44.05	30.82
DUC	SuperPAL	36.73	67.59	47.59	40.48	50.63
MN	ROUGE _{IU}	36.97	48.43	41.93	55.68	51.80
IVIIN	SuperPAL	49.09	64.2	55.63	60.23	62.15

Table 4: Span alignment scores of $ROUGE_{IU}$ and SuperPAL aligners, on the DUC and MultiNews datasets. Examined on the dev & test sets together.

opposition leaders Ranariddh and	
Sam Rainsywanted them abroad.'	
<i>Opposition leaders</i> Prince Norodom <i>Ranariddh</i>	
and Sam Rainsy citing Hun Sen's threats'	

Table 5: An incorrect alignment example of ROUGE_{IU} , where despite the large *word overlap*, the two IUs do not mean the same.

more abstractive nature of DUC relative to Multi-News (Fabbri et al., 2019), suggesting that due to its lexical nature ROUGEIU is inadequate to identify abstractive alignments with low lexical overlap. In addition, a manual inspection suggested that ROUGE_{*IU*} tends to be misled by non-aligned \mathbb{IU} s that exhibit high lexical overlap, as exemplified in Table 5. On the other hand, SuperPAL is more capable in identifying lexically-dissimilar paraphrases, as exemplified in Table 6. This behavior may be attributed to the large abstractive dataset on which our model was trained, along with the use of a pretrained contextualized embedding model, which is known to capture semantic similarities. Overall, the much larger gap between the two models for the more abstractive DUC suggests the appeal of SuperPAL for abstractive semantic matching.

To enable development of new proposition-based summarization methods using our alignments (as explained in §7), we release our proposition-based alignments, produced by our supervised aligner, for the MultiNews MDS dataset (Fabbri et al., 2019) and for the CNN/DailyMail Single Document Summarization dataset (Hermann et al., 2015).

6 IU-enhanced Sentence Alignment

As mentioned in §2, most previous alignment approaches operate on the sentence-level. In this section, to fairly compare to sentence-level methods, we apply our SuperPAL aligner to extract salient sentences, based on the predicted IU alignments (denoted as "SuperPAL_{sent}"). We first show, intrinsically, that our method yields a more accurate set of salient sentences than those derived by common sentence-level ROUGE-based alignments

' <i>The</i> SPLC's most outstanding successeshave
been in its civil lawsuits against hate groups.'
'The Southern Poverty Law Center won
major legal fights against the Ku Klux Klan
and other white supremacist groups.'

Table 6: A correct alignment example of Super-PAL with small *overlap* between the IUs.

(§6.1). Additionally, we show that the performance of a prominent alignment-based summarization model is not harmed, and even slightly improves, when trained with salient sentences extracted by our method (§6.2). Overall, this section demonstrates that our proposition-level alignments are not inferior to prior sentence-alignments, even when ported to a sentence-based setting.

6.1 Salient-sentence Extraction

Our method for extracting salient sentences for training a salience model first scores each document sentence based on the aligned IUs it contains. This is done by combining the alignment classification scores for these IUs, weighted by the respective IUs lengths. Then, we select the sentences with the highest scores, until all aligned summary IUs are covered by alignments of IUs within the selected sentences.

We consider two characteristic baselines:

Full summary ROUGE. This widely used baseline, proposed by Nallapati et al. (2017) and denoted here ROUGE_{full} , does not exploit explicit alignments. Rather, it greedily selects source sentences that yield the highest ROUGE with respect to the *entire* reference summary, until none of the remaining candidate sentences marginally improves the ROUGE score.

Sent2Sent ROUGE aligner. This baseline, denoted ROUGE_{sent}, was proposed by Chen and Bansal (2018); Lebanoff et al. (2019), yielding competitive summarization results. Similar to our ROUGE-based lexical model in §5, it aligns each summary sentence to one or two document sentences with which it has the highest ROUGE score. The generated salience training data consists of all the aligned document sentences.

To intrinsically assess the quality of the salientsentences training data generated by these methods, we compare them against a gold set of salient sentences which we derived from our manuallyannotated (IU-level) test data. To that end, a document sentence is considered salient if it contains an aligned IU, as this indicates that the correspond-

	#sents	R-1	R-2	R-L
ent	2	40.06 (±.22)	17.77 (±.23)	35.93 (±.22)
$UGE_{s_{i}}$	3	39.81 (±.22)	18.05 (±.21)	36.16 (±.21)
DD	4	37.43 (±.21)	17.47 (±.19)	34.36 (±.20)
Roi	5	34.65 (±.20)	$16.6 (\pm .19)$	32.07 (±.19)
ent	2	39.76 (±.23)	17.20 (±.22)	35.62 (±.23)
AL_s	3	40.40 (±.22)	18.26 (±.22)	36.79 (±.21)
SuperPAL	4	38.29 (±.21)	17.78 (±.20)	35.23 (±.20)
Sup	5	35.85 (±.19)	17.05 (±.18)	33.24 (±.19)

Table 7: ROUGE-1, -2 and -L results, with $\geq 95\%$ confidence intervals , on CNN/DM for the ROUGE_{sent} and SuperPAL_{sent} for several predicted summary lengths.

ing content is included in the summary, and hence salient. We use two metrics to evaluate the quality of an extracted set of salient sentences, as follows. (1) *Recall*: the percent of summary IUs that are covered, through IU alignments, by the extracted salient sentences, which reflects the amount of covered summary information; (2) *Precision*: The percent of tokens in the extracted sentences that are part of aligned IUs; this reflects the proportion of salient information within the extracted sentences. The results, in Table 8, indicate that our alignment-based salient sentences match the gold set substantially better, showing higher correlation with the reference summary in terms of both recall and precision.

Method	Recall	Precision	F_1
ROUGE _{full}	63.43	40.59	49.50
ROUGE _{sent}	73.88	36.97	49.27
SuperPAL _{sent} (Ours)	75.37	52.03	61.75

Table 8: Salient sentence detection evaluation

6.2 Extrinsic Summarization Evaluation

Having generated improved sentence salience data, we wish to assess its impact on overall summarization results. To that end, we replaced the original ROUGE_{sent} salience training set, used within an extractive salience component in a popular competitive and highly-efficient summarization model (Chen and Bansal, 2018), with our SuperPAL_{sent} training set. Both training sets were extracted from the CNN/Daily Mail single-document summarization dataset (Hermann et al., 2015).

In evaluation, we generated and compared summaries at various lengths, since the number of sentences to select is commonly considered a parameter. The results, in Table 7, indicate that choosing only two document sentences for the summary gives a small advantage to the ROUGE-based

Reference Summary	Aligned Sentence-based Summary	Aligned Propositions-based Summary
	Air Force veteran who allegedly tried to join	
Tairod Nathan Webster Pugh enters	ISIS in Syria but was turned back by Turkish	The war-torn country entered a not
not guilty plea to terror-related	authorities before he could get to the war	guilty plea to terror-related charges
charges .	-torn country entered a not guilty plea to terror	Wednesday in a federal court.
	-related charges Wednesday in a federal court.	
	The defendant, a former avionics instrument	
Pugh flew to Turkey on January 10,	system specialist in the Air Force, <i>flew from</i>	The defendant flew from Egypt to
authorities say .	Egypt to Turkey on January 10, weeks after	Turkey on January 10
	being fired from a job as an airplane mechanic.	
	Among the evidence, prosecutors allege:	
Authorities allege a letter on his	Investigators discovered on his laptop	Among the evidence prosecutors allege:
laptop told his wife he was	<i>computer a letter</i> saying he wanted to "use	Investigators discovered on his laptop
a mujahedeen .	the talents and skills given to me by Allah"	computer a letter.
	and a chart of points where ISIS controls.	

Table 9: Illustration of alignment-based summaries, over aligned full sentences vs. propositions

training data. However, for longer summaries our SuperPAL_{sent} outperforms the ROUGE-based approach in all measures, statistically significantly according to 95% confidence intervals. In fact, the longer the summary, the larger the difference between the two aligners becomes. As the average summary length of CNN/Daily Mail is 3.8 sentences, the advantage of the SuperPAL_{sent} in those lengths stresses its benefit over ROUGE. Moreover, the SuperPAL_{sent} data achieved the highest global result across all summary lengths.

7 Conclusion and Discussion

We advocate the potential of summary-source proposition-level alignment to extract cleaner and more accurate alignments than through the common sentence-level approach. To that end, we establish a new proposition-level alignment task by releasing high-quality dev and test datasets, and an automatically-derived training set. Our proposed supervised baseline alignment model, trained on the released data, outperforms existing lexical and semantic similarity methods. Notably, it exhibits an excessive ability to yield abstract alignments.

These resources provide fertile ground for developing improved proposition-based alignment methods that, similar to sentence-level aligners, can supply training datasets for several summarization subtasks. A proposition-level salience dataset, for example, can be derived by marking each aligned \mathbb{IU} in a source document as salient. Accordingly, such datasets can be used to train proposition-based models for various summarization components.

In future work, proposition-based extractive summarization has the potential to yield bulletstyle summaries with optimized content (similar to CNN/DailyMail (Fabbri et al., 2019)), albeit somewhat less coherent. An example of such potential summary, illustrated by an oracle-system summary derived from our supervised aligner predictions on CNN/DailyMail, is shown in Table 9. Alternatively, our data can contribute to the recent highlighting task (Arumae et al., 2019; Cho et al., 2020), where salient information fragments are marked inside a document, thus circumventing the need to generate coherent text. Further, propositions may be fused together to generate a coherent abstractive summary. Recently, such a cascaded approach (Lebanoff et al., 2020), consisting of text fragment selection followed by a generation step, exhibited comparable or improved results over end-to-end systems.

Overall, we suggest that our released resources would encourage appealing future research on proposition-based summarization approaches, as well as on developing improved alignment models, addressing a challenging semantic matching task.

Acknowledgments

We thank the anonymous reviewers for their constructive comments. This work was supported in part by the German Research Foundation through the German-Israeli Project Cooperation (DIP, grant DA 1600/1-1); by the Israel Science Foundation (grant 1951/17); by a grant from the Israel Ministry of Science and Technology; and by grants from Intel Labs. MB and RP were supported by NSF-CAREER Award 1846185 and a Microsoft PhD Fellowship.

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A Annotation Guidelines

The crowdsourcing instructions are as follows:

Task 1: Information Unit Extraction Your task is to divide a sentence to its standalone facts. Each fact is called "information unit". The units must cover the whole sentence.

Each unit contains one verb and all its arguments. In some cases, where one verb can't stand alone without another verb- the unit will contain more than one verb (e.g. "...insisted that the ceremony take place in..."). In such cases one of the verbs uses the other as an argument.

A unit doesn't have to be grammatically valid or continuous.

For example, the sentence:

Twenty-one people were injured and received treatment from MDA when an explosives-rigged car blew up Friday at Jerusalem's Mahane Yehuda market.

should be divided into:

- 1. Twenty-one people were injured
- 2. Twenty-one people...received treatment from MDA
- 3. an explosives-rigged car blew up Friday at Jerusalem's Mahane Yehuda market.

You may follow these guidelines to help you extract the information units:

- 1. Find all verbs.
- 2. Split the sentence according to the verbs. One verb (and all its arguments) should be included in each information unit.
- 3. Try to include the subject in the unit, even if the unit becomes discontinuous. It is OK that a word is used in several units, but do not repeat a whole fact twice.

Task 2: Non-Alignment Filtering In this task, you get one primary sentence with a bold span, and several secondary sentences. Your task is to decide whether each one of the secondary sentences contains the bold span's significant information. In that case, the two sentences are called "aligned". In addition, you should mark the aligned span from the secondary sentence. The full primary sentence is presented only for context. You only need to match the information in the bold span.

You may follow these questions to help you to decide for alignment:

- Does the information in the secondary sentence repeat the information in the bold span?
- Can the bold span replace a part of the secondary sentence without changing the meaning and without deteriorating the information (except for side details)?
- Does the secondary sentence implicate the bold span?

Notice! in order to be aligned, the sentence should talk specifically on the same information of the bold span.

For example, the sentence:

Prime Minister Hun Sen insisted that talks take place in Cambodia while opposition leaders Ranariddh and Sam Rainsy, fearing arrest at home, wanted them abroad.

is aligned to:

Cambodian leader Hun Sen on Friday rejected opposition parties' demands for talks outside the country, accusing them of trying to "internationalize" the political crisis.

because if Hun Sen on Friday rejected opposition parties' demands for talks outside the country it implicates Prime Minister Hun Sen insisted that talks take place in Cambodia

However, the sentence:

Prospects were dim for resolution of the political crisis in Cambodia in October 1998.

is not aligned to:

Cambodian leader Hun Sen on Friday rejected opposition parties' demands for talks outside the country, accusing them of trying to "internationalize" the political crisis.

although the struggle that was presented in the sentence, may point on a political crisis, if the bold span replace the aligned span we will lose significant information. The spans should be 100% aligned (except for side details).

<u>Task 3:</u> Information Unit Alignment In this task, you get one primary sentence with a bold span, and one secondary sentence. Your task is to highlight the maximal joint information in both sentences.

First, highlight a span from the secondary sentence that contains the bold span's significant information. The bold span and your highlighted span are called "aligned". Try to maximize the highlighted span as much as possible, without adding non-shared information. The shared information must be a standalone fact (usually includes: verb, subject, object). Names/objects only without any fact, are not considered aligned. [('John went home';'John ate pizza') 'John' is not aligned.] However, you should add words (such as: verb, subject, object) that make the span a standalone fact, even if they are not exactly aligned to the primary sentence.

Next, highlight a maximal sub-span from the bold span (in the primary sentence) that contains only the shared information with the highlighted span from the secondary sentence. Non-shared information should be omitted from both highlighted spans.

The full primary sentence is presented only for context. You only need to match the information in the bold span. In case there is no joint information between the two sentences, you may choose "Not aligned".

You may follow these questions to help you to decide for alignment:

- Does the information in the secondary sentence repeat the information in the bold span?
- Can the bold span replace a part of the secondary sentence without changing the mean-

ing and without deteriorating the information (except for side details)?

• Does the secondary sentence implicate the bold span

Notice! in order to be aligned, the sentence should talk specifically about the same information as the bold span.

For example, the sentence:

On Wednesday, Prime Minister Hun Sen insisted that talks take place in Cambodia while opposition leaders Ranariddh and Sam Rainsy, fearing arrest at home, wanted them abroad.

is aligned to:

<u>Cambodian leader Hun Sen</u> on Friday <u>rejected</u> <u>opposition parties' demands for talks outside the</u> <u>country</u>, accusing them of trying to "internationalize" the political crisis.

because if Hun Sen...rejected opposition parties' demands for talks outside the country it implicates Prime Minister Hun Sen insisted that talks take place in Cambodia

Please notice we omitted "On Wednesday," from the primary sentence, because it is not included in the secondary sentence.

B A Full Alignment Example

An illustration of the alignment data is presented in Figure 3. Alignment pairs are marked in the same color. Although our data is pairwise only, pairs could be consolidated through a shared summary IU, which creates an alignment cluster (see red spans in the document).

Summary:

In 1783, after the British soldiers left New York City, George Washington is believed to have stopped for a celebratory drink at the Bull's Head tavern. Now a preservationist thinks he's found the historic site and if he's right, it could be the oldest building in Manhattan. Adam Woodward had heard that the building at 50 Bowery, currently scheduled to be demolished so a hotel can go up, might have "the Bull's Head's structure, cellar, bones," he tells CBS New York. ... Since that time, the building has housed a drugstore, a Chinese restaurant, and a beer garden, among other things.

Document:

A preservationist says he has found evidence that a Manhattan building is the former site of an 18thcentury tavern where George Washington is believed to have enjoyed a celebratory drink during the American Revolution. If it is indeed the home of the legendary watering hole, the discovery could mean that the building that is perhaps Manhattan's oldest is slated to demolished. "After the English had marched up the Bowery and out of the city (in 1783), George Washington and Governor (George) Clinton stopped at the Bull's Head (tavern)," preservationist Adam Woodward told WCBS 880's Alex Silverman. ... The building at 50 Bowery, which has had many faces since, is being prepared for demolition so a hotel can be built at the site. Legend had it that "the Bull's Head's structure, cellar, bones" were still inside, Woodward said.

Figure 3: Example of alignments between a summary and a source document. In this example, there are no intersecting IUs for ease of presentation, though IUs can indeed intersect.