Abstract
We consider the problem of better modeling query-cluster interactions to facilitate query focused multi-document summarization (QFS). Due to the lack of training data, existing work relies heavily on retrieval-style methods for estimating the relevance between queries and text segments. In this work, we leverage distant supervision from question answering where various resources are available to more explicitly capture the relationship between queries and documents. We propose a coarse-to-fine modeling framework which introduces separate modules for estimating whether segments are relevant to the query, likely to contain an answer, and central. Under this framework, a trained evidence estimator further discerns which retrieved segments might answer the query for final selection in the summary. We demonstrate that our framework outperforms strong comparison systems on standard QFS benchmarks.

1 Introduction
Query Focused Multi-Document Summarization (QFS; Dang 2006) aims to create a short summary from a set of documents that answers a specific query. It has various applications in personalized information retrieval and recommendation engines where search results can be tailored to an information need (e.g., a user might be looking for an overview summary or a more detailed one which would allow them to answer a specific question).

Neural approaches have become increasingly popular in single-document text summarization (Nallapati et al., 2016; Paulus et al., 2018; Li et al., 2017b; See et al., 2017; Narayan et al., 2018; Gehrmann et al., 2018), thanks to the representational power afforded by deeper architectures and the availability of large-scale datasets containing hundreds of thousands of document-summary pairs (Sandhaus, 2008; Hermann et al., 2015; Grusky et al., 2018). Unfortunately, such datasets do not exist in QFS, and one might argue it is unrealistic they will ever be created for millions of queries, across different domains (e.g., news vs user reviews), and languages. In addition to the difficulties in obtaining training data, another obstacle to the application of end-to-end neural models is the size and number of source documents which can be very large. It is practically unfeasible (given memory limitations of current hardware) to train a model which encodes all of them into vectors and subsequently generates a summary from them.

In this paper we propose a coarse-to-fine modeling framework for extractive QFS which incorporates a relevance estimator for retrieving textual segments (e.g., sentences or longer passages) associated with a query, an evidence estimator which further isolates segments likely to contain answers to the query, and a centrality estimator which finally selects which segments to include in the summary. The vast majority of previous work (Wan et al., 2007; Wan, 2008; Wan and Xiao, 2009; Wan and Zhang, 2014) creates summaries by ranking textual segments (usually sentences) according to their relationship (e.g., similarity) to other segments and their relevance to the query. In other words, relevance and evidence estimation are subservient to estimating the centrality of a segment (e.g., with a graph-based model). We argue that disentangling these subtasks allows us to better model the query and specialize the summaries to specific questions or topics (Katrakadda and Varma, 2009). A coarse-to-fine approach is also expedient from a computational perspective; at each step the model processes a de-
creasing number of segments (rather than entire documents), and as a result is insensitive to the original input size and more scalable.

Our key insight is to treat evidence estimation as a question answering task where a cluster of potentially relevant documents provides support for answering a query (Baumel et al., 2016). Advantageously, we are able to train the evidence estimator on existing large-scale question answering datasets (Rajpurkar et al., 2016; Joshi et al., 2017; Yang et al., 2018), alleviating the data paucity problem in QFS. Existing QFS systems (Wan et al., 2007; Wan, 2008; Wan and Xiao, 2009; Wan and Zhang, 2014) employ classic retrieval techniques (such as TF-IDF) to estimate the affinity between query-sentence pairs. Such techniques can handle short keyword queries, but are less appropriate in QFS settings where query narratives can be long and complex. We argue that a trained evidence estimator might be better at performing semantic matching (Guo et al., 2016) between queries and document segments. To this effect, we experiment with two popular QA settings, namely answer sentence selection (Heilman and Smith, 2010; Yang et al., 2015) and machine reading comprehension (Rajpurkar et al., 2016) which operates over passages than isolated sentences. In both cases, our evidence estimators take advantage of powerful pre-trained encoders such as BERT (Devlin et al., 2019), to better capture semantic interactions between queries and text units.

Our contributions in this work are threefold: we propose a coarse-to-fine model for QFS which we argue allows to introduce trainable components taking advantage of existing datasets and pre-trained models; we capitalize on the connections of QFS with question answering and propose different ways to effectively estimate the query-segment relationship; we provide experimental results on two benchmark datasets (DUC 2006, 2007) which show that our model consistently outperforms strong comparison systems in both automatic and human evaluation.

2 Related Work

Existing research on query-focused multi-document summarization largely lies on extractive approaches, where systems usually take as input a set of documents and select the sentences most relevant to the query for inclusion in the summary.

Centrality-based approaches have generally shown strong performance in QFS. In Figure 1(a), we provide a sketch of classic centrality-based approaches where all sentences within a document cluster, together with their query relevance, are jointly considered in estimating centrality. Under this framework, Wan (2008) propose a topic-sensitive version of the Markov Random Walk model which integrates sentence relevance, while Wan and Zhang (2014) incorporate predictions about information certainty. Another line of graph-based work uses manifold-ranking algorithms (Wan et al., 2007; Wan and Xiao, 2009; Wan, 2009) to estimate sentence importance scores based on the assumption that nearby points are likely to have similar rankings. To alleviate the mismatch between queries and document sentences, Nastase (2008) employs Wikipedia as a knowledge resource for query expansion.

More recently, Li et al. (2015) estimate the salience of text units within a sparse-coding framework by additionally taking into account reader comments (associated with news reports). Li et al. (2017a) use a cascaded neural attention model to find salient sentences, whereas in follow-on work Li et al. (2017b) employ a generative model together with a data reconstruction model. The generative model maps sentences to a latent semantic space based on variational autoencoders (Kingma and Welling, 2013; Rezende et al., 2014) while the reconstruction model estimates sentence salience. There are also feature-based approaches achieving good results by optimizing sentence selection under a summary length constraint (Feigenblat et al., 2017).

In contrast to previous work, our proposed framework does not simultaneously perform segment selection and query matching. We introduce a coarse-to-fine approach that incorporates progressively more accurate components for selecting segments to include in the summary, making model performance relatively insensitive to the number and size of input documents. Drawing inspiration from recent work on QA, we take advantage of existing datasets in order to reliably estimate the relationship between the query and candidate segments. We focus on two QA sub-tasks which have attracted considerable attention in the literature, namely answer sentence selection which aims to extract answers from a set of pre-selected sentences (Heilman and Smith, 2010; Yao et al., 2013; Yang et al., 2015) and machine reading comprehension (Rajpurkar et al., 2016; Welbl et al., 2018; Yang et al., 2018), which aims
at answering a question after processing a short text passage (Chen, 2018). An outstanding difference between QA and QFS is that extractive QA models aim at finding the best answer in a span or sentence, while QFS models learn to extract a set of sentences considering user preferences and the content of the input documents (Wan, 2008; Wan and Zhang, 2014).

3 Problem Formulation

Let $Q$ denote an information request and $D = \{d_1, d_2, \ldots, d_M\}$ a set of topic-related documents. It is often assumed (e.g., in DUC competitions) that $Q$ consists of a short title (e.g., Amnesty International) highlighting the topic of interest, and a query narrative which is considerably longer and detailed (e.g., What is the scope of operations of Amnesty International and what are the international reactions to its activities?).

We illustrate our proposed framework in Figure 1(b). We first decompose documents into segments, i.e., passages or sentences, and retrieve those which are most relevant to query $Q$ (Relevance Estimator). Then, a trained estimator quantifies the semantic match between selected segments and the query (Evidence Estimator) to further isolate segments for consideration in the output summary (Centrality Estimator). We propose two variants of our evidence estimator; a context agnostic variant infers evidence scores over individual sentences, while a context aware one infers evidence scores for tokens within a passage which are further aggregated into sentence-level evidence. Passages might allow for semantic relations to be estimated more reliably since neighboring context is also taken into account.

3.1 Relevance Estimator

Document Segmentation Our QFS system operates over documents within a cluster which we segment into sentences. The latter serve as input to the context agnostic evidence estimator. For the context aware variant, we obtain passages with a sliding window over continuous sentences in the same document. Considering the maximum input length BERT allows (512 tokens) and the query length (to be later concatenated with passages), we set the maximum passage size to 8 sentences (with maximum sentence length of 50 tokens). To ensure all sentences are properly contextualized, we use a stride size of 4 sentences to create overlapping passages.

Adaptive Retrieval During inference, we first retrieve the top $k_i^{IR}$ answer candidates (i.e., sentences or passages) which are subsequently processed by our evidence estimator. We do this following an adaptive method that allows for a variable number of segments to be selected for each query. Specifically, for the $i$th query-cluster pair, we first rank all segments in the cluster based on term frequency with respect to the query, and determine $k_i^{IR}$ such that it reaches a fixed threshold $\theta \in [0, 1]$. Formally, $k_i^{IR}$, the number of re-
retrieved segments, is given by:

$$k^\text{IR}_i = \max_k \sum_{j=1}^k r_{i,j} < \theta$$  \(1\)

where \(r_{i,j}\) is the relevance score for segment \(j\) (normalized over segments in the \(i\)th cluster). Although we adopt term frequency as our relevance estimator, there is nothing in our framework which precludes the use of more sophisticated retrieval methods (Dai and Callan, 2019; Akkalyoncu Yılmaz et al., 2019). We investigated approaches based on term frequency-inverse sentence frequency (Allan et al., 2003) and BM25 (Robertson et al., 2009), however, we empirically found that they are inferior, having a bias towards shorter segments which are potentially less informative for summarization.

### 3.2 Evidence Estimator

We argue that relevance matching is not sufficient to capture the semantics expressed in the query narrative and its relationship to the documents in the cluster. We therefore leverage distant supervision signals from existing QA datasets to train our evidence estimator and use the trained estimators to rerank answer candidates selected from the retrieval module. For the \(i\)th cluster, we select the top \(\min\{k^\text{QA}, k^\text{IR}_i\}\) candidates as answer evidence (where \(k^\text{QA}\) is tuned on the development set).

#### Sentence Selection

Let \(Q\) denote a query (in practice a sequence of tokens) and \(\{S_1, S_2, \ldots, S_N\}\) the set of candidate answers (also token sequences) obtained from the retrieval module. Our learning objective is to find the correct answer(s) within this set. We concatenate query \(Q\) and candidate sentence \(S\) into a sequence \([CLS], Q, [SEP], S, [SEP]\) to serve as input to a BERT encoder. Let \(T = [t_i]_{i=1}^N\) denote the contextualized vector representation of the entire sequence obtained from BERT. We feed \(T\) into two separate dense layers to predict probabilities \(p_S\) and \(p_E\):

$$p^i_S = \frac{\exp(t^i_1W_S)}{\sum_j \exp(t^i_jW_S)}$$  \(4\)

$$p^i_E = \frac{\exp(t^i_1W_E)}{\sum_j \exp(t^i_jW_E)}$$  \(5\)

where \(w_S\) and \(w_E\) are two learnable vectors denoting the beginning and end of the (answer) span, respectively. During training we optimize the log-likelihood of the correct start and end positions. For passages without any correct answers, we set these to 0 and default to the \([CLS]\) position.

At inference time, to allow comparison of results across passages, we remove the final softmax layer over different answer spans. Specifically, we first calculate the (unnormalized) start and end scores for all tokens in a sequence:

$$u = \exp(Tw_S), v = \exp(Tw_E).$$  \(6\)

And collect sentence scores from token scores as follows. For each sentence starting at token \(i\) and ending at token \(j\), we obtain score matrix \(Q\) via:

$$\tilde{Q} = \left(u_{[i,j]}v_{[i,j]}^\top A\right)^{1/2}$$  \(7\)

$$Q = \tanh(\tilde{Q}).$$  \(8\)

where \(A\) is an upper triangular matrix masking all illegitimate spans whose end comes before the start. The \(\tanh\) function scales the magnitude of extreme scores (e.g., scores over 100 or under 0.01), as a means of reducing the variance of \(\tilde{Q}\). We collect all possible span scores within a sentence in matrix \(S\) where \(S_{i,j}\) denotes the span score from token \(i\) to token \(j\) \((i \leq i' < j' \leq j).\)
And finally, we use max pooling to obtain a scalar evidence score $q$:

$$q = \max\text{-pool}(Q) \in (0, 1). \quad (9)$$

It is possible to produce multiple evidence scores for the same sentence since we use overlapping passages; we select the score with the highest value in this case.

### 3.3 Centrality Estimator

#### Graph Construction

Inspired by Wan (2008), we introduce as our centrality estimator an extension of the well-known LexRank algorithm (Erkan and Radev, 2004), which we modify to incorporate the evidence estimator introduced in the previous section.

For each document cluster, LexRank builds a graph $G = (V, E)$ with nodes $V$ corresponding to sentences and (undirected) edges $E$ whose weights are computed based on similarity. Specifically, matrix $E$ represents edge weights where each element $E_{i,j}$ corresponds to the transition probability from vertex $i$ to vertex $j$. The original LexRank algorithm uses TF-IDF (Term Frequency Inverse Document Frequency) to measure similarity; since our framework operates over sentences rather than "documents", we use TF-ISF (Term Frequency Inverse Sentence Frequency), with ISF defined as:

$$\text{ISF}(w) = 1 + \log\left(\frac{|C|}{\text{SF}(w)}\right) \quad (10)$$

where $C$ is the total number of sentences in the cluster, and $\text{SF}(w)$ the number of sentences in which $w$ occurs.

We integrate our evidence estimator into the original transition matrix as:

$$\tilde{E} = \phi \ast \tilde{q} + (1 - \phi) \ast E \quad (11)$$

where $\phi \in (0, 1)$ controls the extent to which query-specific information influences sentence selection for the summarization task; and $\tilde{q}$ is a distributional evidence vector which we obtain after normalizing the evidence scores $q \in \mathbb{R}^{1 \times |V|}$ obtained from the previous module ($\tilde{q} = q / \sum_{v} q_v$).

#### Summary Generation

In order to decide which sentences to include in the summary, a node’s centrality is measured using a graph-based ranking algorithm (Erkan and Radev, 2004). Specifically, we run a Markov chain with $\tilde{E}$ on $G$ until it converges to stationary distribution $e^*$ where each element denotes the salience of a sentence. In the proposed algorithm, $e^*$ jointly expresses the importance of a sentence in the document and its semantic relation to the query as modulated the evidence estimator and controlled by $\phi$. We rank sentences according to $e^*$ and select the top $k$ Sum ones, subject to a budget (e.g., 250 words). To reduce redundancy, we apply the diversity algorithm proposed in Wan (2008) which penalizes the salience of sentences according to their overlap with those already selected to appear in the summary.

### 4 Experimental Setup

#### Datasets

We performed QFS experiments on the DUC 2005-2007 benchmark datasets. We show summary statistics in Table 1. We used DUC 2005 as a development set to optimize hyperparameters and evaluated model performance on DUC 2006 and 2007 (test sets).

We used three datasets for training our evidence estimator, including WikiQA (Yang et al., 2015), TrecQA (Yao et al., 2013), and SQuAD 2.0 (Rajpurkar et al., 2018). WikiQA and TrecQA are benchmarks for answer sentence selection while SQuAD 2.0 is a popular machine reading comprehension dataset (which we used for span selection). Compared to SQuAD, WikiQA and TrecQA are benchmarks for answer sentence selection while SQuAD 2.0 is a popular machine reading comprehension dataset (which we used for span selection). Compared to SQuAD, WikiQA and TrecQA are smaller and we therefore follow Yang et al. (2019) and integrate them for model training. We show statistics for these datasets in Table 2 and examples in the Appendix.

| Dataset       | Sentence | Span |
|---------------|----------|-----|
| WikiQA       | TrecQA   | Total | SQuAD  |
| #Train       | 8,672    | 53,417 | 62,089 | 130,318 |
| #Dev         | 1,130    | 1,148   | 2,278   | 11,872   |

Table 1: Question answering dataset statistics. We use the union of WikiQA and TrecQA for answer sentence selection and SQuAD for span selection.

| DUC-Year | 2005 | 2006 | 2007 |
|----------|------|------|------|
| #Clusters| 50   | 50   | 45   |
| #Documents/Cluster | 32 | 25 | 25 |
| #Summaries | 4-9 | 4 | 4 |
| #Words/Summary | 250 | 250 | 250 |

Table 2: DUC statistics.
where the coefficient was set to 0.9.

Table 3: System performance on DUC 2006 and 2007. R-1, R-2 and R-SU4 stand for the F1 score of ROUGE 1, 2, and SU4, respectively. Results with * were obtained based on our own implementation.

**Implementation Details** We used the publicly released BERT model\(^1\) and fine-tuned it on our QA tasks. For the answer sentence selection model, BERT was fine-tuned with a learning rate of $3 \times 10^{-6}$ and a batch size of 16 for 3 epochs. For span selection, we adopted a learning rate of $3 \times 10^{-5}$ and a batch size of 64 for 5 epochs. During inference, the confidence threshold for the relevance estimator was set to $\theta = 0.75$ (Kratzwald and Feuerriegel, 2018) for both sentence and passage retrieval. For the evidence estimator, $k_{QA}$ was tuned on the development set. We obtained 90 and 110 evidence sentences from the sentence selection and span selection models, respectively. For the centrality estimator, the influence of the query was set to $\phi = 0.15$ (Wan, 2008; Wan and Zhang, 2014).

We also built an ensemble version of our model, by linearly interpolating evidence scores from the two estimators based on sentence selection and span extraction. Let $(E^S, q^S)$ and $(E^P, q^P)$ denote the selected sentence sets and their evidence scores produced by the sentence selection estimator and span extraction estimator, respectively. We obtain the ensemble score for sentence $e$ via:

$$q_e = \begin{cases} \mu \cdot q^S_e + (1 - \mu) \cdot q^P_e & e \in E^S \cap E^P \\ \mu \cdot q^S_e & e \in E^S \land e \notin E^P \\ -\infty & e \notin E^S \end{cases}$$

where the coefficient was set to $\mu = 0.9$.

Table 4: Results of ablation studies when removing individual modules from our framework (absolute performance decrease/increase denoted by $\downarrow$/$\uparrow$).

**5 Automatic Evaluation**

Following standard practice in DUC evaluations, we used ROUGE as our automatic evaluation metric\(^2\) (Lin and Hovy, 2003) We report F1 for ROUGE-1 (unigram-based), ROUGE-2 (bigram-based), and ROUGE-SU4 (based on skip bigram with a maximum skip distance of 4).

**Model Comparisons** Our results are summarized in Table 3. The first block in the table reports the upper bound performance (GOLD) which we estimated by treating a (randomly selected) reference summary as a hypothetical system output and comparing it against the remaining (three) ground truth summaries. ORACLE uses reference summaries as queries to retrieve summary sentences, and LEAD returns all leading sentences (up to 250 words) of the most recent document.

The second block in Table 3 compares our model to various graph-based approaches which include: LEXRANK (Erkan and Radev, 2004), a widely used unsupervised approach based on Markov random walks. LEXRANK is query-free; it measures relations between all sentence pairs in a cluster and sentences recommend other similar sentences for inclusion in the summary. GRSUM (Wan, 2008), a Markov random walk model that integrates query-relevance into a Graph Ranking algorithm; and CTSUM (Wan and Zhang, 2014) which is based on GRSUM but additionally considers sentence Certainty information in ranking.

The third group in the table shows the performance of autoencoder-based neural approaches. C-ATTENTION (Li et al., 2017a) is based on Cascaded attention with sparsity constraints for compressive multi-document summarization.

\(^1\)https://github.com/huggingface/pytorch-transformers

\(^2\)We used pyrouge with the following parameter settings: ROUGE-1.5.5.pl -a -c 95 -m -n 2 -2 4 -u -p 0.5 -l 250.
comparison systems on both DUC test sets: we can see, our models outperform strong
query results in Table 4 for query coarse-to-fine framework. We present re-
experiments to verify the effectiveness of the pro-
Ablation Studies We also conducted ablation
the human upper bound. Perhaps unsurprisingly, both models fall behind
results with distant supervision based on iso-
UERY which we call Q
ent variants of our query-focused summarizer
selects VPs and NPs to create the final summary.
2007). They further integrate their salience esti-
mantes which combines both. As can be seen, our models outperform strong
comparison systems on both DUC test sets: QUERYSUM achieves the best R-1 while
QUERYSUMP achieves the best R-2 and R-SU4. Perhaps unsurprisingly, both models fall behind
the human upper bound.

Ablation Studies We also conducted ablation experiments to verify the effectiveness of the proposed
course-to-fine framework. We present results in Table 4 for QUERYSUMS and QUER-
SUMP when individual modules are removed. In the −Relevance setting, all text segments
(i.e., sentences or passages) in a cluster are given as input to the evidence estimator module. The
−Evidence setting treats all retrieved segments as
evidence for summarization. Note that since our
summarizer operates on sentences, we can only
assess this configuration with the QUERYSUMS model; we take the top kQA sentences from the
retrieval module as evidence. The −Centrality setting treats the (ranked) output of the evidence
estimator as the final summary.

As can be seen, removing the retrieval mod-
ule leads to a large drop in the performance of
QUERYSUMS. This indicates that the (deep) sem-
antic matching model trained for sentence selec-
tion can get distracted by noise which a (shallow)
relevance matching model can help pre-filter. In-
terestingly, when the matching model is trained
on passages, the retrieval module seems more or
less redundant, there is in fact a slight improve-
ment in ROUGE scores, except for R-1 (see row
QUERYSUMP, − Relevance in Table 4). This sug-
ests that the evidence estimator trained on pas-
ages is more robust and captures the semantics of
the query more faithfully. Moreover, since it takes
textual signals into account, it is able to rec-
ognize irrelevant information and unanswerabil-
ity is explicitly modeled. We show in Figure 2
how ROUGE-2 varies over kIR best evidence sentences selected by estimators trained on sentences and passages (development set).

Figure 2: Performance (ROUGE-2 Recall) over kIR best retrieved segments (development set). S and P refer
to sentence and passage retrieval, respectively. Full is the concatenation of the query title and narrative.

Figure 3: Performance (ROUGE-2 Recall) over kQA best evidence sentences selected by estimators trained on sentences (development set).

VAESUM (Li et al., 2017b) employs a generative
model based on VARIational autoEncoders
(Kingma and Welling, 2013; Rezende et al., 2014)
and a data reconstruction model for sentence
salience estimation. VAESUM represents the state-of-the-art of neural systems on DUC (2006, 2007).3 They further integrate their salience estimation module in an integer linear program which selects VPs and NPs to create the final summary.

The fourth block in Table 3 presents different
variants of our query-focused summarizer which we call QUERYSUM. We show automatic
results with distant supervision based on iso-
lated Sentences (QUERYSUMS), Passages (QUERYSUMP), and an ensemble model (QUERYSUMS+P) which combines both. As
can be seen, our models outperform strong comparison systems on both DUC test sets: QUERYSUMS achieves the best R-1 while
QUERYSUMP achieves the best R-2 and R-SU4. Perhaps unsurprisingly, both models fall behind
the human upper bound.

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3Similar to our experimental setting, its hyperparameters are optimized on a development set. For fair comparison, we
leave aside a few symbolic approaches that take advantage of query expansion techniques, and task-specific predictors such as
position bias.
evidence component is estimated on passages and sentences for the full model. As can be seen, the model trained on passages surpasses the model trained on sentences roughly when \( k^{QA} = 80 \). For comparison, we also show the performance of the retrieval module by treating the top sentences as evidence. The retrieval curve is consistently under the passage curve, and under the sentence curve when \( k^{QA} < 140 \). Since the quality of top sentences directly affects the quality of the summarization module, this further demonstrates the effectiveness of evidence estimation in terms of reranking retrieved segments.

Finally, Table 4 shows that the removal of the centrality estimator decreases performance even when the query and appropriate evidence are taken into account. These experiments suggest that the centrality estimator further learns to select important sentences from the available evidence that are summary worthy. We further assessed the effectiveness of the query component \( \tilde{q} \) in estimating centrality (see Equation (11)) by setting \( \tilde{q} \) to a uniform distribution. Again, we observe that in most cases performance decreases which indicates that this component provides a slight benefit over and above filtering segments according to their relevance to the query.

### 6 Human Evaluation

We further evaluated the summaries created by our model in a judgment elicitation study via Amazon Mechanical Turk. Specifically, native English speakers (self-reported) were provided with query-summary pairs and asked to rate the summaries on two dimensions: **Succinctness** (does the summary avoid unnecessary detail and redundant information?) and **Coherence** (does the summary make logical sense?). The ratings were obtained using a five point Likert scale. In addition, participants were asked to assess the **Relevance** of the summary to the query. Specifically, crowdwork-

| Method   | Rel  | Suc  | Coh  | All  |
|----------|------|------|------|------|
| LEAD     | 3.75 | 3.60 | 4.27 | 3.96 |
| VAESUM   | 4.28 | 3.62 | 4.05 | 4.03 |
| QUERYSUM | 4.32 | 3.93 | 4.27 | 4.22 |
| GOLD     | 4.36 | 3.93 | 4.35 | 4.26 |

Table 5: Human evaluation results: average **Relevance**, **Succinctness**, **Coherence** ratings; **All** is the average across ratings; \( \dagger \): sig different from VAESUM; \( \ddagger \): sig different from QUERYSUM; \( \circ \): sig different from Gold (at \( p < 0.1 \), using a pairwise t-test).

Participants assessed summaries created by VAESUM\(^4\), the previous state-of-the-art system, QUERYSUM, and the LEAD baseline. We also included a randomly selected GOLD standard summary as an upper bound. We sampled 20 clusters from DUC 2006 and 2007 test sets (10 from each set) and collected three responses per query-summary pair. Table 5 shows the ratings for each system. As can be seen, participants find QUERYSUM summaries more relevant to the queries and with less redundant information compared to LEAD and VAESUM. Our multi-step estimation process also produces more coherent summaries (as coherent as LEAD) even though coherence is not explicitly modeled. Overall, participants perceive QUERYSUM summaries as significantly better (\( p < 0.1 \)) compared to LEAD and VAESUM (see the Appendix for examples of system output).

### 7 Conclusions

In this work, we proposed a coarse-to-fine estimation framework for query focused multi-document summarization. We explored the potential of leveraging distant supervision signals from Question Answering to better capture the semantic relations between queries and document segments. Experimental results across datasets show that the proposed model yields results superior to competitive baselines contributing to summaries which are more relevant and less redundant. We have also shown that disentangling the tasks of relevance, evidence, and centrality estimation beneficial allowing us to progressively specialize the summaries to the semantics of the query. In the future, we would like to generate abstractive summaries following an unsupervised approach (Baziotis et al., 2019; Chu and Liu, 2019) and investigate how recent advances in open domain QA (Wang et al., 2019; Qi et al., 2019) can be adapted for query focused summarization.

\(^4\)We are grateful to Piji Li for providing us with the output of their system.
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