Hone as You Read: A Practical Type of Interactive Summarization

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Abstract

We present HARE, a new task where reader feedback is used to optimize document summaries for personal interest during the normal flow of reading. This task is related to interactive summarization, where personalized summaries are produced following a long feedback stage where users may read the same sentences many times. However, this process severely interrupts the flow of reading, making it impractical for leisurely reading. We propose to gather minimally-invasive feedback during the reading process to adapt to user interests and augment the document in real-time. Building off of recent advances in unsupervised summarization evaluation, we propose a suitable metric for this task and use it to evaluate a variety of approaches. Our approaches range from simple heuristics to preference-learning and their analysis provides insight into this important task. Human evaluation additionally supports the practicality of HARE. The code to reproduce this work is available at https://github.com/tannerbohn/HoneAsYouRead.

1 Introduction

Keeping readers engaged in an article and helping them find desired information are important objectives (Calder et al., 2009; Nenkova and McKeown, 2011). These objectives help readers deal with the explosion of online content and provide an edge to content publishers in a competitive industry. To help readers find personally relevant content while maintaining the flow of natural reading, we propose a new text summarization problem where the summary is honed as you read (HARE). The challenge is to learn from unobtrusive user feedback, such as the types in Figure 1, to identify uninteresting content to hop over.

This new task is related to both query-based summarization (QS) and interactive personalized summarization (IPS). In QS, users must specify a query to guide the resultant summary (Damova and Koychev, 2010). For users performing focused research, specifying queries is useful, but for more leisurely reading, this requirement interrupts the natural flow. Approaches to IPS avoid the problem of having to explicitly provide a query. However, they suffer a similar problem by requiring users to go through several iterations of summary reading and feedback-providing before a final summary is produced (Yan et al., 2011; Avinesh et al., 2018; Gao et al., 2019; Simpson et al., 2019).

In contrast, HARE places high importance on non-intrusiveness by satisfying multiple properties detailed in Section 3.1 (such as feedback being non-invasive). We find that due to the high cost of generating a dataset for this task, evaluation poses a difficulty. To overcome this, we adapt recent research in unsupervised summary evaluation. We
also describe a variety of approaches for HARE that estimate what the user is interested in and how much they want to read. Automated evaluation finds that relatively simple approaches based on hiding sentences nearby or similar to disliked ones, or explicitly modelling user interests, outperforms the control, where no personalization is done. Human evaluation suggests that not only is deciding the relevance of sentences rather easy in practice, but that even with simple binary feedback, HARE models may truly provide useful reading assistance.

The major contributions of this work are:

1. We define the novel HARE task, and describe a suitable evaluation technique (Section 3).
2. We describe a wide range of motivated approaches for HARE that should serve as useful baselines for future research (Section 4).
3. We evaluate our approaches to gain a deeper understanding of the task (Section 5).

2 Related Work

In this section, we examine related work on QS, IPS, and unsupervised summarization evaluation.

2.1 Query-based Summarization

Both tasks of HARE and QS aim to produce personalized summaries. Unlike generic summarization where many large datasets exist (Hermann et al., 2015; Fabbri et al., 2019; Narayan et al., 2018), development in QS has been affected by a lack of suitable training data (Xu and Lapata, 2020). To cope, approaches have relied on hand-crafted features (Conroy et al., 2005), unsupervised techniques (Van Lierde and Chow, 2019), and cross-task knowledge transfer (Xu and Lapata, 2020). The approach of Mohamed and Rajasekaran (2006) highlights how query-based summarizers often work by adapting a generic summarization algorithm and incorporating the query with an additional sentence scoring or filtering component. Alternatively, one can avoid training on QS data by decomposing the task into several steps, each performed by a module constructed for a related task (Xu and Lapata, 2020).

A pervasive assumption in QS is that users have a query for which a brief summary is expected. This is reflected in QS datasets where dozens of documents are expected to be summarized in a maximum of 250 words (Dang, 2005; Hoa, 2006) or single documents summarized in a single sentence (Hasselqvist et al., 2017). However, in HARE, we are interested in a wider range of reading preferences. This includes users who are interested in reading the whole article and users whose interests are not efficiently expressed in a written query.

2.2 Interactive Personalized Summarization

The iterative refinement of summaries based on user feedback is also considered by IPS approaches. An early approach by Yan et al. (2011) considers progressively learning user interests by providing a summary (of user-specified length) and allowing them to click on sentences they want to know more about. Based on the words in clicked sentences, a new summary can be generated and the process repeated. Instead of per-sentence feedback, Avinesh and Meyer (2017) allows users to indicate which bigrams of a candidate summary are relevant to their interests. A successor to this system reduces the computation time to produce each summary down to an interactive level of 500ms (Avinesh et al., 2018). The APRIL system (Gao et al., 2019) aims to reduce the cognitive burden of IPS by instead allowing users to indicate preference between candidate summaries. Using this preference information, a summary-ranking model is trained and used to select the next pair of candidate summaries.

Shared among these previous works is that the user is involved in an interactive process which interrupts the normal reading flow with the reviewing of many intermediate summaries. In HARE, the user reads the document as it is being summarized, so that any given sentence is read at most once (if it has not already been removed). These previous works also focus on multi-document summarization, whereas we wish to improve the reading experience during the reading of individual documents.

2.3 Unsupervised Summary Evaluation

When gold-standard human-written summaries are available for a document or question-document pair, the quality of a model-produced summary is commonly computed with the ROUGE metric (Lin and Och, 2004). Driven by high costs of obtaining human-written summaries at a large scale, especially for tasks such as multi-document summarization or QS, unsupervised evaluation of summaries (i.e. without using gold-standards) has rapidly developed (Louis and Nenkova, 2013).

Louis and Nenkova (2009) found that the Jensen Shannon divergence between the word distribu-
In a summary and reference document outperforms many other candidates and achieves a high correlation with manual summary ratings, but not quite as high as ROUGE combined with reference summaries. Sun and Nenkova (2019) consider a variety of distributed text embeddings and propose to use the cosine similarity of summary and document ELMo embeddings (Peters et al., 2018). Böhm et al. (2019) consider learning a reward function from existing human ratings. Their reward function only requires a model summary and document as input and achieves higher correlation with human ratings than other metrics (including ROUGE which requires reference summaries). Stiennon et al. (2020) also consider this approach, with a larger collection of human ratings and larger models. However, Gao et al. (2020) found that comparing ELMo embeddings or using the learned reward from Böhm et al. does not generalize to other summarization tasks. Their evaluation of more advanced contextualized embeddings found that Sentence-BERT (SBERT) embeddings (Reimers and Gurevych, 2019) with word mover’s-based distance (Kusner et al., 2015) outperforms other unsupervised options. Post-publication experiments by Böhm et al. further support the generalizability of this approach\(^1\). In Section 3.3, we adapt the method of Gao et al. to HARE evaluation.

3 Task Formulation

To define the proposed task, we will first describe how a user interacts with an HARE summarizer (Section 3.1). Second, we describe a method for modelling user interests and feedback for automatic evaluation (Section 3.2). Third, we propose an evaluation metric for this new task (Section 3.3).

3.1 User-Summarizer Interaction Loop

The interaction between a user and HARE summarizer, as shown in Figure 2 and sketched in Algorithm 1, consists of the user reading the shown sentences and providing feedback on their relevance. Using this feedback, the summarizer decides which remaining sentences to show, aiming to hide uninteresting sentences. This interaction is designed to smoothly integrate into the natural reading process by exhibiting three important properties: 1) feedback is either implicit or non-intrusive, 2) sentences are presented in their original order to try maintain coherence, and 3) updates to the summary should occur beyond the current reading point so as to not distract the user. Next, we discuss how to model a user in this interaction for the purposes of automatic evaluation.

3.2 User Modelling

In order to model user interaction during HARE, we need to know what kind of feedback they would provide when shown a sentence. This requires understanding how much a user would be interested in a given sentence and how feedback is provided.

User interests For our work, user interests will be modelled as a weighted set of concept vectors from a semantic embedding space. Given a weighted set of \(k\) user interests, \(U = \{<w_1,c_1>,...,<w_k,c_k>\}\) such that \(w_i \in [0,1]\) and \(\max(w) = 1\), and a sentence embedding, \(x\), the interest level (which we also refer to as importance) is calculated with Equation 1. We use cosine distance for \(\Delta\). Intuitively, the importance of a sentence reflects the maximum weighted similarity to any of the interests. This method of computing importance is similar to that used by Avinesh et al. (2018); Wu et al. (2019); Teevan et al. (2005). However, we adapt it to accommodate modern distributed sentence embeddings (SBERT).

\[
R(U,x) = \max_{i=1,...,k} w_i (1 - \Delta(c_i,x)) \tag{1}
\]
we tie it to the users length preference to better simulate realistic behavior. When users want to read very little for example, they only accept the best sentences. If a user wants to read \( l \) out of \( |D| \), then we set \( \alpha = 1 - l/|D| \). For user modelling, we sample \( l \) uniformly from the range \([1, |D|] \).

\[
P_{\alpha,m}(\text{accept } x) = 1 - \left[ 1 + \exp \left( \frac{\alpha - r_x}{m} \right) \right]^{-1}
\]

(2)

3.3 Unsupervised Evaluation

Unsupervised evaluation is tricky to do properly. You must show that it correlates well with human judgement, but also be confident that maximizing the metric does not result in garbage (Barratt and Sharma, 2018).

As discussed in Section 2, we adapt the unsupervised summary evaluation method described by Gao et al. (2020). This metric computes a mover’s-based distance between the SBERT embeddings of the summary and a heuristically-chosen subset of document sentences (a “pseudo-reference” summary). They show that it correlates well well human ratings and that using it as a reward for training a reinforcement learning-based summarizer produces state-of-the-art models. The authors found that basing the pseudo-reference summary on the lead heuristic, which generally produces good single and multi-document summaries, worked best. For HARE, we can apply the analogous idea: when computing the summary score, we can use all document sentences in the pseudo-reference summary, but weight them by their importance:

\[
\text{score}(U, D, S) = 1 - \frac{1}{\sum_{x \in D} r_x \sum_{x \in D} \min_{s \in S} \Delta(x, s)}
\]

(3)

This metric has the behavior of rewarding cases where an important sentence is highly similar to at least one summary sentence. For this reason, coverage of the different user interests is also encouraged by this metric: since sentences drawing their importance from similarity to the same concept are going to be similar to each other, having summaries representing a variety of important concepts is better.

4 Methods

We consider three groups of approaches ranging in complexity: (1) simple heuristics, (2) adapted generic summarizers, and (3) preference learning.

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**Algorithm 1: User-Summarizer Interaction**

1. user chooses a document \( D = [x_1, ..., x_{|D|}] \) to read with help from summarizer \( M \)
2. \( S = \emptyset \) // summary sentences
3. for \( i = 1, ..., |D| \) do
4.   if \( M \) decides to show \( x_i \) to user then
5.     show sentence \( x_i \) to user
6.     \( S := S \cup \{x_i\} \)
7.   end
8.   if user is done reading then
9.     break
10. end
11. return \( S \)

**Feedback types**

Given a sentence interest score of \( r_x \in [0, 1] \), what feedback will be observed by the model? If using implicit feedback like dwell time or gaze tracking, feedback could be continuously valued. With explicit feedback, like ratings or thumbs up/down, feedback could be discrete. For an in-depth discussion on types of user feedback, see Jayarathna and Shipman (2017).

In this work, we will consider an explicit feedback inspired by the "Tinder sort" gesture popularized by the Tinder dating app\(^2\), where users swipe left to indicate disinterest, and right to indicate interest. This feedback interaction has proven to be very quick and easy. Users will routinely sort through hundreds of items in a sitting (David and Cambre, 2016). To adapt this feedback method to our interactive summarization system, we can consider users to “accept” a sentence if they swipe right, and “reject” it if they swipe left (see Figure 1a and Figure 2)\(^3\).

To model the noisy feedback a user provides, we adopt a logistic model, shown in Equation 2, following Gao et al. (2019); Viappiani and Boutilier (2010); Simpson et al. (2019). Our feedback model is parameterized by a decision threshold, \( \alpha \in [0, 1] \), and a noise level, \( m > 0 \). Low \( \alpha \) means that users are willing to accept sentences with lower importance. We consider the model to receive a feedback value of 0 if they reject a sentence, and 1 if they accept. In setting \( \alpha \) for feedback modelling, we tie it to the users length preference to better simulate realistic behavior. When users want to read very little for example, they only accept the best sentences. If a user wants to read \( l \) out of \( |D| \), then we set \( \alpha = 1 - l/|D| \). For user modelling, we sample \( l \) uniformly from the range \([1, |D|] \).

\[
P_{\alpha,m}(\text{accept } x) = 1 - \left[ 1 + \exp \left( \frac{\alpha - r_x}{m} \right) \right]^{-1}
\]

(2)

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\(^2\)https://tinder.com/?lang=en

\(^3\)If we wanted to make the feedback optional, we could simply let no swipe indicate acceptance, and left swipe indicate rejection.
4.1 Simple Heuristics
This first set of approaches are as follows:

SHOWMODULO This approach shows every $k^{th}$ sentence to the user. When $k = 1$, this is equivalent to the control, where every sentence is shown. By moving through the article faster, we suspect that greater coverage is obtained, making it more likely that important concepts are represented.

HIDENEXT This approach shows all sentences, except for the $k$ following any rejected sentence. E.g. when $k = 2$ and the user rejects a sentence, the two after it are hidden. The motivation for this model is that nearby sentences are often related, so if one is disliked, a neighbour might also be. Larger $k$ suggests a larger window of relatedness.

HIDENALLSIMILAR While HIDENEXT hides physically nearby sentences, this model hides all sentences that are actually conceptually similar to a rejected one, where similarity is measured with cosine similarity of SBERT embeddings. We also include a compromise between hiding based on physical and conceptual similarity: HIDENEXTSIMILAR. This model hides only the unbroken chain of similar sentences after a rejected one.

4.2 Adapted Generic Summarizers
This set of approaches make use of generic extractive summarizers. The motivation for considering them is that even though they are independent of user interests, they are often designed to provide good coverage of an article. In this way, they may accommodate all user interests to some degree. For a given generic summarizer, we consider the following options:

GENFIXED This approach first uses the generic summarizer to rank the sentences, and then shows a fixed percentage of the top sentences.

GENDYNAMIC This approach estimates an importance threshold, $\hat{\epsilon}$, of sentences the user is willing to read, and hides the less important sentences. Importance is computed by scoring the sentences with the generic summarizer and rescaling the values to [0, 1]. The initial estimate is $\hat{\epsilon} = 0$, which means that all sentences are important enough. Each time a sentence is rejected, the new estimate is updated to be the average importance of all rejected sentences. To help avoid prematurely extreme estimates, we also incorporate $\epsilon$-greedy exploration. With probability $1 - \epsilon$, the sentence is only shown if the importance meets the threshold, otherwise it is shown anyways. A larger $\epsilon$ will help find a closer approximation of the threshold, but at the cost of showing more unimportant sentences.

4.3 Preference Learning
The approaches in this group use more capable adaptive algorithms to learn user preferences in terms of both preferred length and concepts:

LR This approach continually updates a logistic regression classifier to predict feedback given sentence embeddings. Before a classifier can be trained, all sentences are shown. We propose two variations of this approach. The first uses an $\epsilon$-greedy strategy similar to GENDYNAMIC. The second uses an $\epsilon$-decreasing strategy: for a sentence at a given fraction, $frac$, of the way through the article, $\epsilon = (1 - frac)^{\beta}$, for $\beta > 0$.

COVERAOPT This approach explicitly models user interests and length preference. It scores potential sentences by how much they improve coverage of the user interests. However, since we do not know the user’s true interests or their length preference, both are estimated as they read.

This approach prepares for each article by using K-Means clustering of sentence embeddings to identify core concepts of the article. The initial estimate of concept importances is computed with:

$$\hat{C} = \left[1 + \exp \left(\frac{cfs}{\beta}\right)\right]^{-1} \quad (4)$$

We initialize the vector $cfs$ with the same value $c \in \mathbb{R}$ for each concept. A larger $c$ means that more evidence is required before a concept is determined to be unimportant. $\beta > 0$ controls how smoothly a concept shifts between important and unimportant (larger value means more smoothly). To update the estimate of user interests with $feedback \in \{0, 1\}$ for sentence $x$, we update $cfs$ with:

$$cfs \leftarrow cfs + 2(feedback - 0.5)concepts(x) \quad (5)$$

If $feedback = 0$ for example, this moves $cfs$ away from the article concepts represented by that sentence. The function $concepts()$ returns the relevance of each concept for the specified sentence.

After updating $\hat{C}$, we re-compute sentence importances based on their contribution to improving concept coverage, weighted by concept importance. Next, we update the estimated length preference,
\( \hat{t}_{\text{frac}} \) by averaging the importance of rejected sentences. The summary is updated to show sentences among the top \( \hat{t}_{\text{frac}} |D| \) important sentences. If the user has rejected low and medium importance sentences, then only the most coverage-improving sentences will be shown.

## 5 Experiments

In this section, we first describe the experimental setup, and then provide an analysis of the results.

### 5.1 Setup

**Dataset** We evaluate on the test articles from the non-anonymized CNN/DailyMail dataset (Hermann et al., 2015)\(^4\). We remove articles with less than 10 sentences so as to cluster sentences into more meaningful groups for user interest modelling. This leaves us with 11222 articles, with an average of 34.0 sentences per article.

**User modelling** We apply K-Means clustering to SBERT sentence embeddings for each article to identify \( k = 4 \) cluster centers/concepts. User interests are a random weighting over these concepts, as described in Section 3.2. For feedback noise, we use \( m = 0.01 \) (essentially no noise) and \( m = 0.1 \) (intended to capture the difficulty in deciding whether a single sentence is of interest or not). \( \alpha \) is chosen as described in Section 3.2.

**Metrics** Evaluation with the two noise values of \( m = 0.01 \) and \( m = 0.1 \) correspond to \( \text{score}_{\text{sharp}} \) and \( \text{score}_{\text{noisy}} \) respectively. \( \text{score}_{\text{adv}} \) corresponds to the difference between \( \text{score}_{\text{noisy}} \) and the control score (no personalization). Positive values indicate outperforming the control. Since the scores fall between 0 and 1, we multiply them by 100.

**Privileged information comparison models** We consider for comparison three oracle models and the control. ORACLEGREEDY has access to the user preferences and greedily selects sentences to maximize the score, until the length limit is reached. ORACLESORTED selects sentences based only on their interest level. ORACLEUNIFORM selects sentences at random throughout the article until the length limit is reached\(^5\).

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### Table 1: A comparison of each model proposed. For parameterized models, results with the best variation are reported (for all models, we found that the same parameters performed best for both \( \text{score}_{\text{sharp}} \) and \( \text{score}_{\text{noisy}} \)). Non-deterministic models are marked by a *.

| Model       | \( \text{score}_{\text{sharp}} \) | \( \text{score}_{\text{noisy}} \) | \( \text{score}_{\text{adv}} \) |
|-------------|----------------------------------|----------------------------------|---------------------------------|
| ORACLEGREEDY| 87.04                            | 4.89                             |                                 |
| ORACLESORTED| 82.74                            | 0.58                             |                                 |
| ORACLEUNIFORM* | 82.77                        | 0.62                             |                                 |
| Control     | 82.15                            | 0.0                              |                                 |
| SHOWMODULO  | 78.83                            | -3.32                            |                                 |
| HIDENEXT    | 82.66                            | 82.66                            | 0.51                            |
| HIDENEXTSIMILAR | 82.79                    | 82.86                            | 0.71                            |
| HIDEALLSIMILAR | 83.03                        | 83.09                            | 0.94                            |
| GENFixed    | 81.97                            | -0.19                            |                                 |
| GENDynamic* | 82.39                            | 82.24                            | 0.09                            |
| LR (\( \epsilon \)-greedy)* | 82.48                          | 82.50                            | 0.34                            |
| LR (\( \epsilon \)-decreasing)* | 82.28                         | 82.31                            | 0.15                            |
| COVERAGEOPT | 83.11                            | 82.81                            | 0.65                            |

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### 5.2 Results

Table 1 reports the results for each model with its best performing set of hyperparameters. While \( \text{score}_{\text{sharp}} \) and \( \text{score}_{\text{noisy}} \) can range from 0 to 100, the difference between the control and ORACLEGREEDY is less than 5 points (reflected in \( \text{score}_{\text{adv}} \)). This suggests that even relatively small performance differences are important. For stochastic models (marked by a * in Table 1), results are averaged across 3 trials and standard deviations were all found to be below 0.05.

Overall, we find that the simple heuristics provide robust performance, unaffected (and possibly helped) by noise. While the more complex COVERAGEOPT approach is able to perform best with low-noise feedback, it falls behind when noise increases. Next we discuss in more detail the results for each group of models, then comment on aspects of efficiency, and finally discuss the results of our human evaluation.

### 5.2.1 Privileged Information Models

ORACLEUNIFORM outperforms the control as well as ORACLESORTED. This may seem counter-intuitive, since ORACLEUNIFORM has the disadvantage of not knowing true user interests. However, the strength of ORACLEUNIFORM is that it provides uniform coverage over the whole article, weakly accommodating any interest distribution. By choosing only the most interesting sentences, ORACLESORTED runs the risk of only showing those related to the most important concept.
our user model simulated more focused interests, ORACLESORTED may perform better however.

It is also interesting to see how much higher ORACLEGREEDY is than every other model, suggesting that there is plenty of room for improvement. The reason the oracle does not reach 100 is that the summary length is restricted by user preference. If future approaches consider abstractive summarization techniques, it may be possible to move beyond this performance barrier.

5.2.2 Simple Heuristics

While we suspected that the SHOWMODULO strategy might benefit from exposing readers to more concepts faster, we found that this does not work as well as ORACLEUNIFORM. The top performance of $score_{adv} = -3.32$ is reached with $k = 2$, and it quickly drops to $-7.06$ with $k = 3$. The minimally adaptive approach of hiding a fixed number of sentences after swiped ones, as per HIDERANDOM, does help however, especially with $n = 2$.

The related models of HIDERANDOMSIMILAR and HIDENEXTSIMILAR, which simply hide sentences similar to ones the user swipes away, work surprisingly well, in both moderate and low noise. In Figure 3, we can see that their performance peaks when the similarity threshold is around 0.5 to 0.6.

![Figure 3: The performance for HIDENEXTSIMILAR and HIDENEXTSIMILAR for a range of similarity thresholds. When the threshold is high, it means that only the most similar sentences are hidden.](image)

|          | LR (constant $\epsilon$) | LR (decreasing $\epsilon$) |
|----------|--------------------------|-----------------------------|
| $\epsilon$ | $score_{adv}$ | $\beta$ | $score_{adv}$ |
| 0        | -7.27                   | 0.25          | 0.05          |
| 0.1      | -1.58                   | 0.5           | 0.09          |
| 0.2      | -0.18                   | 1             | 0.15          |
| 0.3      | 0.25                    | 2             | 0.07          |
| 0.4      | 0.34                    | 4             | -0.61         |
| 0.5      | 0.34                    |                |               |

Table 2: Results for the two LR model version. For the constant-$\epsilon$ variation, a greater $\epsilon$ indicates greater exploration. For the decreasing-$\epsilon$ variation, larger $\beta$ indicates a faster decay in exploration probability.

We find that the generic summarizer-based models always perform worse than the control when showing a fixed fraction of the article (GENFIXED). The best model of this type used the SumBasic summarizer, showing 75% of sentences. When dynamically estimating target summary length (GENDYNAMIC), the control is outperformed by only 0.09 points. This is achieved by the SumBasic summarizers with $\epsilon = 0.5$. For both variations, we find that the best hyperparameters tend to be those that make them show the most sentences.

5.2.4 Preference-learning Models

The LR models out-perform the control, as shown in Table 2, but fail to match the simpler approaches. Using a decaying $\epsilon$ actually hurt performance, suggesting that the model is simply not able to learn user preferences fast enough. However, there is a sweet spot for the rate of $\epsilon$ decay at $\beta = 1$.

We find that COVERAGEOPT consistently improves with larger initial concept weights ($c$) and a smaller concept weight-saturation rate ($\beta$), with the performance plateauing around $\beta = 4$ and $c = 5$. When both $c$ and $\beta$ are both large, there is a longer exploration phase with more evidence required to indicate that any given concept should be hidden.

5.3 Efficiency

Acceptance rate When measuring the fraction of shown sentences that are accepted, we find no consistent connection to their performance. For example, the control and the best HIDERANDOM, HIDERANDOMSIMILAR, HIDENEXTSIMILAR, and COVERAGEOPT models all have rates between 64-66% in the noisy feedback case. ORACLESORTED has the highest however, at 79%, while ORACLEGREEDY is only at 69% acceptance. As discussed in Section 5.2.1, this is because the sentence set
which maximizes the score is not necessarily the same as the set with the highest importance sum.

**Speed**  The approaches presented here are able to update the summary in real-time. Running on a consumer-grade laptop, each full user-article simulation (which consists of many interactions) takes between 100ms for the slowest model (GENFIXED with TextRank), to 2.8ms for HIDEALLSIMILAR, to 1.3ms for HIDE

**5.4 Human Evaluation**

Finally, we run a human evaluation to test a variety of approaches on multiple measures.

**Setup**  We selected 10 news articles from a variety of sources and on a variety of topics (such as politics, sports, and science), with an average sentence length of 20.6, and asked 13 volunteers to read articles with the help of randomly assigned HARE models. In total, we collected 70 trials. Participants were shown sentences one at a time and provided feedback to either accept or reject sentences. They were also able to stop reading each article at any time. After reading each article, they were asked several questions about the experience, including the coherence of what they read (how well-connected consecutive sentences were, from 1 to 5) and how easy it was to decide whether to accept or reject sentences (from 1 to 5). We also showed them any unread sentences afterwards in order to determine how many would-be accepted sentences were not shown. Coverage, roughly corresponding to our automated evaluation metric, can then be estimated with the fraction of interesting sentences that were actually shown.

**Results**  From the human evaluation, we find that making the decision to accept or reject sentences is quite easy, with an average decision-ease rating of 4.4/5. However, departing from the assumptions of our user model, people ended up reading more than an average of 50% of the articles (up to 70% for the control). This could influence the relative performance of the various models, with a skew towards models that tend to hide fewer sentences. We find the acceptance rate to vary from 47% for LR to 75% for COVERAGEOPT, with the remainder around 60%. From Figure 4 we can see that the best model (highest coverage) appears to be COVERAGEOPT. This is followed by the control and LR model, with their 90% confidence intervals overlapping. This highlights that achieving good coverage of interesting sentences is not the same as achieving a high acceptance rate. The worst performing model according to both human and automated evaluation is SHOW_MODULO. The remaining four models significantly overlap in their confidence intervals. However, it is interesting to note that HIDEALLSIMILAR performs poorer than we would expect. Given the positive correlation between the percent of the article users end up reading and the model coverage, we can guess that this is a result of the model automatically hiding too many sentences. This also leads to low reported summary coherence, as many sentences are skipped. In contrast, the control achieves the highest coherence (since nothing is skipped), with COVERAGEOPT near the middle of the pack.

**6 Conclusion**

In this paper we proposed a new interactive summarization task where the document is automatically refined during the normal flow of reading. By not requiring an explicit query or relying on time-consuming and invasive feedback, relevant information can be conveniently provided for a wide range of user preferences. We provided an approximate user model and suitable evaluation metric for this task, building upon recent advances in unsupervised summary evaluation. To guide examination of this new task, we proposed a variety of approaches, and perform both automated and human evaluation. Future research on this task includes adapting the interaction model to implicit feedback and trying more advanced approaches.
7 Ethical Considerations

Diversity of viewpoints The HARE task is intended for the design of future user-facing applications. By design, these applications have the ability to control what a user reads from a given article. It is possible that, when deployed without sufficient care, these tools could exacerbate the “echo chamber” effect already produced by automated news feeds, search results, and online communities (Pariser, 2011). However, the ability to influence what readers are exposed to can also be leveraged to mitigate the echo chamber effect. Rather than considering only what user interests appear to be at a given moment, future HARE models could incorporate a diversity factor to explicitly encourage exposure to alternative views when possible. The weighting of this factor could be tuned to provide both an engaging reading experience and exposure to a diversity of ideas.

Beneficiaries As mentioned in Section 1, those most likely to benefit from HARE applications once successfully deployed will be those using them to read (by saving time and increased engagement) as well as any content publishers who encourage their use.

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## A Experimental Setup

### Computing infrastructure
All experiments were performed on a machine with an Intel Core i7-6700HQ CPU with 16G RAM and a GeForce GTX 960M GPU.

### Hyperparameter searches
For parameterized models, grid searches over the following ranges were performed:

- **SHOWMODULO**: $k \in \{2, 3, 4, 5\}$
- **HIDE\_NEXT**: $n \in \{1, 2, 3, 4\}$
- **HIDE\_NEXT\_SIMILAR** and **HIDE\_ALL\_SIMILAR**: \( \text{threshold} \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\} \)
- **GEN\_FIXED**: \( \text{frac} \in \{0.25, 0.5, 0.75\} \)
- **GEN\_DYNAMIC**: $\epsilon \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5\}$
- **LR** (constant $\epsilon$): $\epsilon \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5\}$
Table B.1: Results for the first two simple heuristic models. For SHOWMODULO, every $k^{th}$ sentence is shown. For HIDEEXT, the $n$ sentences following a swiped one are hidden.

| $k$ | $score_{adv}$ | $n$ | $score_{adv}$ |
|-----|---------------|-----|---------------|
| 2   | -3.32         | 1   | 0.45          |
| 3   | -7.06         | 2   | 0.51          |
| 4   | -9.87         | 3   | 0.19          |
| 5   | -12.00        | 4   | -0.41         |

Table B.2: Results for the two variations of adapted generic summarizer models, for each of three extractive summarizers tested. For GENFIXED, $frac$ indicates what fraction of the document is shown, after first sorting sentences by importance. For GENDYNAMIC, $c$ is used for $\epsilon$-greedy exploration to estimate length preference.

| $frac$ (for GENFIXED) | summizer | 0.25 | 0.5 | 0.75 |
|-----------------------|----------|------|-----|------|
| LexRank               | -11.18   | -3.77| -0.79|
| SumBasic              | -10.75   | -3.22| -0.19|
| TextRank              | -12.28   | -4.99| -1.53|

| $\epsilon$ (for GENDYNAMIC) | summizer | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|-----------------------------|----------|---|-----|-----|-----|-----|-----|
| LexRank                     | -1.37    | -0.53| -0.22| -0.07| 0.01| 0.06|
| SumBasic                    | -3.19    | -1.47| -0.72| -0.28| -0.05| 0.09|
| TextRank                    | -1.95    | -1.02| -0.59| -0.31| -0.18| -0.08|

Table B.3: Results for the COVERAGEOPT model. $c$ controls the initial estimate for concept importances and $\beta$ controls how smoothly a concept shifts between important and unimportant.

To participate, volunteers were instructed to engage with the publicly accessible bot in the app and follow instructions provided therein.

Figure 5: A screenshot of the demo in action. For each sentence, users were able to accept, reject, or stop reading the article at that point.