StreamHover: Livestream Transcript Summarization and Annotation

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Abstract

With the explosive growth of livestream broadcasting, there is an urgent need for new summarization technology that enables us to create a preview of streamed content and tap into this wealth of knowledge. However, the problem is nontrivial due to the informal nature of spoken language. Further, there has been a shortage of annotated datasets that are necessary for transcript summarization. In this paper, we present StreamHover, a framework for annotating and summarizing livestream transcripts. With a total of over 500 hours of videos annotated with both extractive and abstractive summaries, our benchmark dataset is significantly larger than currently existing annotated corpora. We explore a neural extractive summarization model that leverages vector-quantized variational autoencoder to learn latent vector representations of spoken utterances and identify salient utterances from the transcripts to form summaries. We show that our model generalizes better and improves performance over strong baselines. The results of this study provide an avenue for future research to improve summarization solutions for efficient browsing of livestreams.

1 Introduction

One of the most powerful communication mediums is livestreaming. New platforms such as YouTube Live, Twitch, Instagram Live and TikTok encompass a variety of topics, ranging from video games to social media to professional sports. We are particularly interested in livestreams that are distinguished by three characteristics: Excessive length, the recordings could last from several minutes to several hours; Verbal communication, the use of natural language is the primary means of communication, in contrast to gestures or facial expressions; Informal nature, the streamers’ language is mostly informal and unplanned, unlike news broadcasts. Without an effective mechanism to summarize such streamed content, livestreaming platforms may not fully meet the needs of their customers.

Figure 1: An example of streamed content on Behance, a streaming platform for artists and designers to showcase creative work related to Adobe Photoshop, Illustrator, Fresco, UI/UX, photography and more. Top: The videos are each 27 minutes long. Bottom: One video is being broadcast live, the other is >2 hours long.

Our goal in this work is to create a text preview of the streamed content. When a user hovers over the thumbnail or scrolls past a video, they are shown a preview of the content. We present a dataset of over 500 hours of video footage, which were streamed live on a social media platform (behance.net) created to showcase and discover creative work. Figure 1 shows an example of the streams, where the artists showcase the use of Adobe Photoshop and Illustrator in designing holiday cards and posters. It is necessary to point out that video analysis is not suitable here, as the video only mirrors the artists’ screen content. As a first step towards automatic creation of a text preview, we focus on identifying salient utterances to produce an extract from the livestream transcript.

We make use of vector-quantized variational autoencoders (VQ-VAE; van den Oord et al., 2017) to identify salient utterances. The model has been applied successfully to opinion summarization that learns in-domain sentence representations (Angelidis et al., 2021), which is essential for adaptation of general-domain models. We refrain from using sequential methods for utterance selection. First,
it is difficult to scale up sequential prediction to process transcripts that exceed the maximum allowed length, even with models that handle long text (Beltagy et al., 2020; Zhao et al., 2020). Second, sequential methods (Narayan et al., 2018b; Xiao and Carenini, 2019) may not give enough flexibility to select salient utterances on-the-fly when content is being streamed live, thus they are unsuitable for our case.

There has been a shortage of annotated datasets that are necessary for livestream transcript summarization. We build a browser-based user interface for summary annotation that provides to the annotators a clip of the livestream recording alongside a synchronized display of the transcript. The interface allows annotators to conveniently label summary utterances and write an abstractive summary using their own words (Figure 3). With a total of 500 hours of annotated video footage, our dataset is notably larger than existing annotated corpora for transcript summarization (Janin et al., 2003; Carletta et al., 2006). We compare our summarization approach with strong baselines on the dataset and shed light on the task of livestream transcript summarization. Our contributions are as follows.

- We create a detailed annotation interface and new benchmark dataset for automatic summarization of livestream transcripts. An informative preview of streamed content is of crucial importance to users when considering whether to hit play.

- We present StreamHover, a unsupervised model based on VQ-VAE to identify salient utterances from livestream transcripts to form preview summaries. We evaluate the method across multiple dimensions and discuss its strengths and weaknesses. Empirical results show that our method outperforms strong summarization baselines.¹

2 Related Work

Closed captions are often provided onscreen, turning streaming videos into text on an unprecedented scale (Besik, 2020). However, there are very few summarization studies that attempt to generate text previews of streaming videos to help users browse or re-find information that has been watched before. Neural text summarizers have focused primarily on written text, including news articles, reviews, scientific papers and book chapters (See et al., 2017; Tan et al., 2017; Chen and Bansal, 2018; Narayan et al., 2018a; Gehrmann et al., 2018; Cohan et al., 2018; Liu and Lapata, 2019; Fabbri et al., 2019; Bražinskškas et al., 2020; Ladhak et al., 2020; Song et al., 2021). Despite their success, it remains unclear as to if and how the summarizers can be extended to spoken text, whose utterances may have very low information density.

It is crucial to identify salient content from transcripts where a substantial number of utterances are devoted to informal chit-chats in an attempt to connect with the audience (Figure 2). We investigate extractive rather than abstractive approaches as the latter are prone to generate hallucinated content that does not exist in the source text (Cao et al., 2017; Kryscinski et al., 2019; Lebanoff et al., 2019; Maynez et al., 2020). The problem could be exacerbated by ungrammatical spoken utterances and transcription errors. Instead, we consider VQ-VAE, an unsupervised representation learning technique (van den Oord et al., 2017; Jin et al., 2020; Angelidis et al., 2021) for content extraction. Unsupervised training of the VQ-VAE model and its inference could potentially be performed at the same time, allowing important utterances to be extracted from a transcript segment on-the-fly during streaming, without interrupting the learning process. It is also easier to tailor the model to specific domains compared to contemporary extractive methods (Yasunaga et al., 2017; Dong et al., 2018; Xu and Durrett, 2019; Wang et al., 2020).

¹Our annotations and source code are available at https://github.com/ucfnlp/streamhover
Our work contributes to a refined understanding of transcript summarization, which is understudied relative to its importance and potential. The transcripts may be obtained from channels such as movies and TV's (Papalampidi et al., 2020; Chen et al., 2021), interviews (Zhu et al., 2021), multi-party meetings (Murray and Carenni, 2008; Wang and Cardie, 2013; Li et al., 2019b; Koay et al., 2020, 2021; Zhong et al., 2021), telephone speech (Kafle and Huenerfauth, 2018) and more. The main thrust distinguishing our work with others is the combination of a benchmark summarization dataset, novel summarization methods and a challenging new domain where salient content is scattered throughout the transcript and mixed with substantial chit-chats. We do not make use of video event detection or multi-modal fusion (Zhu et al., 2018; Palaskar et al., 2019; Li et al., 2020) as little information could be gleaned from videos that mirror the artists’ desktop. Instead, we focus on generating short descriptions from transcripts and leave for future work cross-modality research. We describe our data annotation process in the following section.

### 3 Our Dataset

We aim to create a large and representative corpus containing transcripts and summaries of streamed videos. We explore a leading social media platform (Behance.net) supported by Adobe Creative Cloud that features livestreams of creative work by artists and designers. The website boasts over 10 million users, who watch artists and designers livestream when they create. Our data are extracted from this website, containing a large quantity of streamed videos (>5,000), the length of which ranges from minutes to several hours. The streamers’ language is unplanned, instead of rehearsed as that of TED talks (Hernandez et al., 2018).

We obtain a total of 5,398 streamed videos. The metadata of a video includes its ID, duration, title, a short description and the transcript. Automatic transcription was provided by Microsoft Automatic Speech Recognition which helps make videos accessible to a wide audience. Each transcript contains a set of segments, each corresponds to about 30 seconds of audio. Each segment contains a set of utterances.

![Figure 2](image_url)

**Figure 2** An example of the segments and utterances. The offset of the segment indicates the number of minutes since the beginning of the recording.

When a user hovers over the thumbnail or scrolls past a video, we expect a textual summary to give a glimpse of the verbal content. This view of summarization leads us to annotate salient content across the video in an equally detailed manner. It naturally avoids lead bias that is ubiquitous in news (Grenander et al., 2019). We segment a video into 5-minute clips and annotate each clip for summary-worthy content. A clip contains an average of 51 utterances and 460 words. Due to time and budget constraints, we select 370 streamed video for summary annotation.

![Figure 3](image_url)

**Figure 3** An example of our browser-based annotation interface. It includes a clip of the streamed video alongside a display of the transcript (omitted for space). The streamer talks about *Digital Painting with Maddy Bellwoar* to create fairytale themed images. The annotators are asked to write a concise summary of this clip using their own words (Task A) and identify summary utterances (Task B).

## Table 1: Comparison of Our Annotated Corpus with Previous Datasets

| Dataset          | Duration Range | Number of Segments | Number of Utterances | Number of Words |
|------------------|----------------|--------------------|----------------------|-----------------|
| Switchboard      | Minutes        | 20-60              | 30                   | 150             |
| ICSI             | Minutes        | 20-60              | 30                   | 150             |
| AMI              | Minutes        | 30-60              | 60                   | 300             |

*Details of video selection are provided in Supplementary.*
Table 1: A comparison of the transcript summarization datasets with manually annotated extractive/abstractive summaries. “Yes/No” indicate a summary type is available or not. † suggests only small pilot summary annotations are available for the Switchboard dataset (Penn and Zhu, 2008). With a total duration of over 500 hours, our dataset is notably larger than similar datasets.

Table 2: Statistics of our dataset.

4 Summarization

Let \( \mathcal{X} \) denote a sequence of spoken utterances from a segment of the transcript. Our summarizer aims to extract a subset of utterances \( \mathcal{Y} \subset \mathcal{X} \) that convey the essential content of the input. We experiment with an unsupervised summarizer that leverages vector-quantized variational autoencoders (VQ-VAE; van den Oord et al., 2017) to learn utterance representations and identifies summary utterances. The method was explored for opinion summarization (Angelidis et al., 2021) and machine translation (Prato et al., 2020). We are interested in using the method to account for domain characteristics of livestreams, which showcase new and creative work of artists and designers on their use of Photoshop, Illustrator, and other tools.

VQ-VAE is a powerful framework for learning latent variable models using deep neural networks. It learns discrete vector representations for an utterance, which is then used to categorize the utterance along various dimensions. E.g., “Good morning Hi Everybody” suggests a greeting and opens up a dialogue; “I had probably 3 or 4 different customers on YouTube and ... on Facebook asked me how the heck do you burn an audio CD in Adobe Audition” engages the audience and introduces the

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4 We use 10-second intervals rather than utterances as measuring units as the duration of utterances vary. If annotators all selected some content, or no content at all, from a 10-second interval, they are in agreement.

5 A show may have more than one host, their utterances are treated indistinguishably due to speaker diarization that identifies different speakers in the audio is not provided.
We define a codebook $\mathbf{E}$ which we seek to reconstruct the input utterance, which involves the input decoder ($\theta$), the convolutional encoder and decoder that use tied parameters ($\varphi$), and embeddings of the codebook $\mathbf{E}$.

$$\mathbf{E} = \{e_1, \cdots, e_K\}$$

We next describe the loss function used to learn these parameters. The loss function of our model comprises of three parts, including a cross-entropy term between the original and reconstructed utterance $\mathbf{XEnt}(x, \tilde{x})$ that optimizes the BERT embedder $\theta$, Transformer generator $\phi$, and convolutional encoder and decoder $\varphi$, as shown in Figure 4. The gradients will, however, bypass the latent code embeddings due to the straight-through estimator (Bengio et al., 2013).

$$\mathbf{h} = \text{Embed}_\theta(x) \in \mathbb{R}^H$$

$$[\mathbf{q}_1, \cdots, \mathbf{q}_H] = \text{ConvEncoder}_{\varphi}(\mathbf{h}), \mathbf{q}_i \in \mathbb{R}^D$$

$$z_i = \arg \max_k -\|\mathbf{q}_i - \mathbf{e}_k\|_2, \ i \in [H]$$

$$\mathbf{h} = \text{Embed}_\theta(x) \in \mathbb{R}^H$$

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$$z_i = \arg \max_k -\|\mathbf{q}_i - \mathbf{e}_k\|_2, \ i \in [H]$$

At test time, we define summary utterances as those associated with prominent latent codes/topics. Given a set of $N$ utterances, we obtain latent codes from the $n$-th utterance using Eq. (3), denoted by $\{z_i^{(n)}\}_{i=1}^H$. This gives a total of $N \times H$ codes from which we find prominent ones. They are denoted by...
which contains a set of most frequently occurring codes. A score $S(x_n)$ is assigned to utterance $x_n$ that computes how often it is associated with those prominent codes $\mathcal{P}$. In Eq. (7), $\sum_{i=1}^{H} I[z_i^{(n)} = k]$ indicates the number of times the $n$-th utterance is assigned to code $k$, where $k$ belongs to $\mathcal{P}$. Finally, we extract $K$ highest-scoring utterances to form an extractive summary of the input.

\[
S(x_n) = \sum_{k \in \mathcal{P}} \sum_{i=1}^{H} I[z_i^{(n)} = k] \tag{7}
\]

Our method draws on the convolutional encoder and decoder to transform BERT’s semantic space to map each dimension to a latent code. The summary selection process is deterministic and our encoder takes full advantage of a large, pre-trained model to produce initial utterance representations. This design sets our method apart from that of Angelidis et al. (2021). Moreover, the method has the potential for modelling topic transitions between utterances to improve summarization of livestreams, which we leave for future work.

5 Experiments

Dataset. Finding salient content from livestream transcripts is a “needle-in-the-haystack” problem. Our summarization dataset contains a total of 370 videos split into short clips of 5 minutes each. The annotators manually annotated 5,421 clips (∼451 hours) with extractive and abstractive summaries. 582 clips (∼49 hours) are removed because they are identified to contain only chit-chats. The dataset is divided into training, validation and test splits:

- 3,884 clips (320 videos / 323 hours) in training,
- 728 clips (25 videos / 61 hours) in validation,
- 809 clips (25 videos / 67 hours) in test split.

We call our summarizer “StreamHover.” When a user hovers their mouse over a video’s timeline, a summary preview is shown and keeps updating. As a first attempt, StreamHover focuses on extracting salient utterances from individual clips instead of whole streams to encourage selected utterances to be mostly evenly distributed across the stream. When the content is provided live, the stream can be divided into short clips and our algorithm consumes one clip at a time to produce summaries on-the-fly. It is important to note that extracting summary utterances remains challenging even for modern neural summarizers. E.g., Kedzie et al. (2018) reveal that summarizers may not effectively identify summary content without a dependency on intentional lead bias in news writing. Our setting is challenging as not only are there few utterances deemed to be summary-worthy but such utterances can occur anywhere in a video clip.

Baselines. We compare StreamHover with state-of-the-art extractive and abstractive summarizers. The abstractive summarizers generate an abstract from the transcript of a clip without tuning. These include BART-large, BART-large-cnn (Lewis et al., 2020) and T5 (Raffel et al., 2020), which are some of the strongest performing neural abstractive summarizers that are pre-trained on language modeling and summarization tasks.

The unsupervised extractive summarizers extract salient utterances from a clip. LexRank (Erkan and Radev, 2004) and TextRank (Mihalcea and Tarau, 2004) are graph-based models that extract relevant sentences based on eigenvector centrality. SumBasic (Vanderwende et al., 2007) assigns higher scores to sentences containing frequently occurring content words. We further compare to a novel unsupervised graph-based summarization method for speech transcripts: FluCovRank (Shang et al., 2018) groups utterances into clusters, generates an abstractive sentence from each cluster, then selects the best elements from abstractive sentences under a budget constraint. Finally, we compare our approach with the Quantized Transformer (Angelidis et al., 2021), which uses a clustering interpretation of the quantized space and two-step sampling algorithm to extract summary sentences from reviews.

Settings. We use pretrained BERT-BASE as our embedder $\text{Embed}_\theta(\cdot)$. The model has 12 layers, 12 heads per layer and a hidden size ($H$) of 768. A 6-layer Transformer decoder is used as the generator $\text{Generate}_\phi(\cdot)$ to reconstruct the original utterance. The model has 8 heads per layer, a hidden size of 768, and randomly initialized parameters. The convolutional encoder and decoder use a kernel size of 3. Because our embedder is pretrained and the remaining parameters are not, we divide them into two groups $\mathcal{E}=\{\theta\}$ and $\mathcal{R}=\{\phi, \varphi\}$, then apply separate training schedules. Following Liu and Lapata (2019) we use two Adam optimizers:

\[
\begin{align*}
    lr_\mathcal{E} &= \tilde{lr}_\mathcal{E} \cdot \text{min}(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}_\mathcal{E}^{-1.5}), \\
    lr_\mathcal{R} &= \tilde{lr}_\mathcal{R} \cdot \text{min}(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}_\mathcal{R}^{-1.5})
\end{align*}
\]

where the learning rate for the embedder $\tilde{lr}_\mathcal{E}=7e^{-4}$

\footnote{In a similar vein, our summarizer uses the transcripts to learn model parameters. It does not require utterance labels.}
### Table 3: Classification performance of extractive summarizers on identifying ground-truth summary utterances.

| System          | 3-Sentence Output | 4-Sentence Output | 5-Sentence Output |
|-----------------|-------------------|-------------------|-------------------|
|                 | P (%)  R (%)  F (%) #Wrds | P (%)  R (%)  F (%) #Wrds | P (%)  R (%)  F (%) #Wrds |
| LEAD-N          | 18.83  9.57  12.5  38.53 | 18.63  12.61  14.77  51.35 | 18.71  15.76  16.82  64.04 |
| SumBasic        | 8.32   4.15  5.45  29.44 | 8.47   5.61  6.63  39.97 | 8.83   7.44  7.92  51.54 |
| QuantizedTran   | 10.44  13.35 11.07  80.09 | 10.44  17.67 12.60  104.66 | 10.58  21.86 13.72  128.35 |
| LexRank         | 23.94  12.14 15.86  59.51 | 23.34  15.96 18.57  77.33 | 23.47  20.03 21.19  94.43 |
| TextRank        | 30.45  15.37 20.10  73.35 | 28.18  18.92 22.24  92.46 | 27.00  22.59 24.17 110.42 |
| StreamHover     | 36.18  18.21 23.87  88.04 | **34.86** 23.29 27.52 113.40 | **33.92** 28.42 30.47 137.02 |

Table 3: Classification performance of extractive summarizers on identifying ground-truth summary utterances.

### Table 4: Results of extractive and abstractive summarizers evaluated by ROUGE. Extractive summarizers generate a 5-utterance summary for each clip. Oracle contains ground-truth summary utterances. StreamHover achieves the highest scores on R-2 and R-L.

| System          | Abstract | Extract | Overall |
|-----------------|----------|---------|---------|
|                 | R-1      | R-2     | R-L     | #Wrds   |
| BART-large      | 22.98    | 8.35    | 15.04   | 123.05  |
| BART-large-cnn  | 23.03    | 8.03    | 16.62   | 43.13   |
| T5-large        | 24.20    | 8.55    | 17.56   | 50.98   |
| FluCovRank      | 25.29    | 10.93   | 18.72   | 50.00   |
| LEAD-5          | 24.65    | 9.54    | 17.59   | 64.04   |
| SumBasic        | 23.15    | 5.57    | 14.76   | 51.54   |
| QuantizedTran   | 23.90    | 7.90    | 15.37   | 128.35  |
| LexRank         | **26.14**| 10.18   | 18.24   | 94.43   |
| TextRank        | 25.94    | 12.70   | 19.33   | 110.42  |
| StreamHover     | 25.62    | **12.70**| **19.33**| **137.02**|
| Oracle (Extract)| 43.42    | 30.58   | 37.99   | 110.51  |

Table 4: Results of extractive and abstractive summarizers evaluated by ROUGE. Extractive summarizers generate a 5-utterance summary for each clip. Oracle contains ground-truth summary utterances. StreamHover achieves the highest scores on R-2 and R-L.

### Table 5: Results of human evaluation regarding fluency, informativeness and the overall quality of system summaries using Best-Worst Scaling.

| System        | Fluency | Informat. | Overall |
|---------------|---------|-----------|---------|
| FluCovRank    | -0.95   | -0.93     | -0.97   |
| LexRank       | 0.25    | 0.11      | 0.17    |
| BART-large    | 0.28    | 0.31      | 0.28    |
| StreamHover   | **0.52**| **0.52**  | **0.52**|

Table 5: Results of human evaluation regarding fluency, informativeness and the overall quality of system summaries using Best-Worst Scaling.

is smaller than that of the rest params $\sim r = 4e^{-2}$. Its warmup period is longer: warmup$_{P} = 3,000$ for the embedder and warmup$_{R} = 1,500$ for the rest. It allows the pretrained embedder to be updated in a slower pace until other model parameters start to generate accurate gradients.

All of our models are trained for 30 epochs on dual NVIDIA V100 GPUs with gradient accumulation every ten steps. We experiment with different numbers of filters, $D = \{64, 100, 128\}$, for the convolutional encoder and decoder. The number of latent codes are varied in $K = \{512, 1024, 2048\}$. The coefficient $\beta$ used for commitment loss is set to 0.25 (Eq. (6)). These hyperparameters are tuned on the validation set. We keep only utterances that contain >5 words in consideration. The final training set contains 168,111 utterances.
when I look at the sheet but I would say top left and bottom right give me the most like happy feels. So yeah, if you guys want to grab the reference images, you can find them in the stream description below the individual images.

**LexRank**

- I hope you guys are having a good day so far.
- So I’m going to be painting from these images and these beautiful photos are from various photographers.
- Those yeah well top right also is like very Contra high contrast that tends to like grab my attention when I look at the sheet but I would say top left and bottom right give me the most like happy feels.
- So yeah, if you guys want to grab the reference images, you can find them in the stream description below the individual images.

**BART-Large**

- Hello good morning everybody welcome to the stream. I hope you guys are having a good day so far. Is there a lot of buffering or are we doing alright? I got a little message that there was some connectivity issue. For a moment there, so I hope I hope it’s OK. Yeah, I’ll just keep going. So yeah, if you guys want to grab the reference images, you can find them in the stream description below the individual images.

**Quantized Transformer**

- Good to see you were going to be doing cloud studies today.
- The stream in the description.
- One of them is from Morguefile, One is from unsplash, well, two are from Unsplash and one is from pixels there a little bit from all over the place, but you can find the photographers below if you’d like.
- Hey Jennifer, saw the images.
- Let’s see top left, bottom right.

**StreamHover (Ours)**

- So if anybody is interested in joining in, if you want to work on some skies for your landscapes for future landscapes, this is what we’re going to be doing.
- One of them is from Morguefile, One is from unsplash, well, two are from Unsplash and one is from pixels there a little bit from all over the place, but you can find the photographers below if you’d like.
- Those yeah well top right also is like very Contra high contrast that tends to like grab my attention when I look at the sheet but I would say top left and bottom right give me the most like happy feels.
- So yeah, if you guys want to grab the reference images, you can find them in the stream description below the individual images.

Table 7: A snippet from Digital Painting Studies with Maddy Bellowar–Clouds. We show the most prominent latent codes and their representative utterances (‘X’). Human annotated summary utterances are colored gray and ultra-short utterances are crossed out. Interpret without context. In contrast, StreamHover can identify on-topic and informative utterances related to digital painting. We provide more examples in the supplementary materials.

In Table 7, we study the most prominent latent codes (C1-3) and their associated utterances. We define representative utterances as those frequently assigned to these codes (Eq. (3)). We observe that C1 usually contains a skewed number of utterances that are commonly seen in the data and not representative of the input; C2 contains lengthy but not necessarily summary-worthy utterances. In our experiments, we exclude C1/C2 before performing grid search on all codes to find the set of prominent codes; we use $P=50$ tuned on the valid set which is effective in helping identify summary utterances.\(^9\)

We conduct a human evaluation to assess how StreamHover compares to strong extractive and abstractive baselines. They are (a) LexRank (Erkan and Radev, 2004), (b) FluCoVRank (Shang et al., 2018) and (c) BART-Large (Lewis et al., 2020); the latter two are abstractive systems. Each evaluator is shown a video clip with a synchronized display of the transcript followed by four system summaries, shown in random order to remove any positional

\(^9\)For increased training stability of variational autoencoder (VAE) models, we refer the reader to (Li et al., 2019a).
bias. The evaluator is asked to select the best and worst of the summaries according to each of these criteria: **Fluency/Coherence**: is the summary well-presented, grammatically correct and easy to read? **Informativeness**: does the summary provide useful information about the video clip? **Overall Quality**: is the summary of good quality considering both content and linguistic aspects?

We randomly sample 100 clips from the test set. Each clip and its summaries are judged by five evaluators that we recruit from Amazon mechanical turk. Table 5 shows the performance of all systems measured by Best-Worst Scaling (Kiritchenko and Mohammad, 2016), where the score of a system is computed as the percentage of times it was selected as the best minus the worst. The range of scores is [-1,1]. Figure 5 shows how frequently a system is chosen to produce the “best summary.” We observe that StreamHover achieves an overall score of 0.52 and it is selected as the best summary in over half of the times.

### 6 Conclusion

We present StreamHover, a new framework for annotating and summarizing livestream transcripts. Our dataset contains over 500 hours of videos annotated with extractive and abstractive summaries. We explored an extractive method leveraging VQVAE to identify salient summary utterances and obtained strong results. Future work includes boosting summarization solutions to provide users a concentrated overview of streamed content.

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A Bēhance Dataset

We collect a total of 5,398 streamed videos from Bēhance.net. Some streamers opt-out of the transcription service provided by Microsoft Automatic Speech Recognition, so transcripts are not available for these videos. We create a list of domain keywords by finding 50 most frequently appearing words from video titles (stopwords are excluded). Examples include ‘fresco’, ‘adobe’, ‘photoshop’, ‘illustration’, ‘art’, ‘painting’, ‘drawing’, ‘illustrator’, ‘character’, ‘design.’ The keywords are used to select videos for human annotation. 2,360 videos have transcripts available and contain at least one of our domain keywords in their titles. These videos are split into clips of 5-minute each. Some clips contain little or no verbal content. We thus remove clips that contain very few words (≤ 333 words) or utterances (≤ 38 utterances). These thresholds are determined using the average values of all clips. Videos with less than 5 valid clips are also removed from consideration. This preprocessing step gives 6,003 clips from 381 videos. During annotation, our annotators find 582 clips to contain only chit-chats, suggesting that these clips are uninformative. 11 videos contain only chit-chat clips, they are subsequently removed from the dataset, yielding a total of 5,421 clips from 370 videos that are split into train, validation and test sets.

B Baseline Summarizers

Our neural abstractive baselines include pre-trained BART-large (Lewis et al., 2020), BART-large-cnn, and T5-large (Raffel et al., 2020). We follow the HuggingFace implementation (Wolf et al., 2020). Utterances that are longer than 5 words are concatenated into a flat sequence, which is used as the input to each summarizer. The model parameters include: the maximum and minimum summary lengths are 150 and 15 tokens, respectively. We use a beam size of 5 with early stopping. The length penalty is 1.0. “no_repeat_ngram_size” is set to 3, such that a trigram cannot occur more than once in the summary.

Our extractive baselines include LexRank (Erkan and Radev, 2004), TextRank (Mihalcea and Tarau, 2004), and SumBasic (Vanderwende et al., 2007). They are implemented using the Sumy library where we adopt the default text parser and stemmer. Our unsupervised summarizer for speech transcript summarization (Shang et al., 2018) uses the following settings: we report the FluCovRank scores. The number of components used in LSA is 25. The number of utterance communities is 35. The number of clusters is 6, with a scaling factor of 1.3 and lambda of 0.4. The size of the summary is set to 50 words.

C Example Summaries

We show example summaries generated by different summarizers: FluConvRank (Shang et al., 2018), LexRank (Erkan and Radev, 2004), BART-large (Lewis et al., 2020) and StreamHover. We also show the top-3 most prominent latent codes and their associated utterances. We choose 5 representative utterances for each code that are most frequently assigned to this code. We observe that C1 utterances are frequently seen in the data (chit-chats) and not representative of the input. C2 is associated with lengthy but not necessarily summary-worthy utterances. C3 utterances are both comprehensive and contain diverse information. In our experiments, we exclude C1/C2 before performing grid search on all codes to find the set of prominent codes. It allows us to effectively identify summary utterances without biasing towards the lengthy ones.
Table 8: Example system summaries from Digital Painting with Maddy Bellwoar. BART summary is fluent but its content lacks specificity, as is the case for LexRank. Summary segments selected by FluCovRank are ungrammatical. StreamHover identifies on-topic and informative utterances related to digital painting.

Table 9: A transcript snippet from Digital Painting with Maddy Bellwoar. We show the most prominent latent codes and their representative utterances (‘X’). Human annotated summary utterances are colored gray and ultra-short utterances are crossed out.
Table 10: Example system summaries from Virtual Plein Air Landscape Painting. The BART summary is fluent but its content lacks specificity, as is the case for LexRank. The summary segments selected by FluCovRank are ungrammatical. StreamHover identifies on-topic and informative summary utterances.

| Utterances                                                                 | C1 | C2 | C3 |
|----------------------------------------------------------------------------|----|----|----|
| 0 Trying to figure out those relationships near the end or like force them if they’re not working. | ☐  | ☐  | ☐  |
| 1 So I’m going to start to work on the foreground now and this is going to be tricky, so this is one of the things that made me choose to paint this reference. | ☐  | ☐  | X |
| 2 cause I wanted to figure out how to paint this kind of situation. | ☐  | ☐  | ☐  |
| 3 The rushing water in the foreground kind of coming towards us and the ripples that it creates an the little bubbles and all that kind of stuff. | ☐  | ☐  | ☐  |
| 4 So I hope I can achieve that feeling of the water is really moving there. | ☐  | ☐  | ☐  |
| 5 Might give some inspiration alright let’s see got an artstation link. | ☐  | ☐  | ☐  |
| 6 Oh, cool. | ☐  | ☐  | ☐  |
| 7 Good, value good value. | ☐  | ☐  | ☐  |
| 8 Other desert desert scene. | ☐  | ☐  | ☐  |
| 9 Yeah, it’s always really satisfying the color combination in these kind of desert scenes, the nice blue Sky and like the Warm Reds and oranges. | ☐  | ☐  | ☐  |
| 10 I like the one I’m working on 2 cause. | ☐  | ☐  | ☐  |
| 11 It’s like you get the extra bonus of like some purple thrown in there and that’s just perfect. | ☐  | ☐  | ☐  |
| 12 Team. | ☐  | ☐  | ☐  |
| 13 Yeah, that’s cool thank you. | ☐  | ☐  | ☐  |
| 14 Team says, I was looking for a nice location on map French and I found this alright. | ☐  | ☐  | ☐  |
| 15 I’m ready for some dog like with half his body has been overlapped by a boat. | ☐  | ☐  | ☐  |
| 16 Sometimes the image stitching just has some weird stuff that happens, Oh team. | ☐  | ☐  | ☐  |
| 17 Oh, if you want to share a link for map crunch. | ☐  | ☐  | ☐  |
| 18 You have to click the share button and then copy the link that is there if you copy the link from the URL above it’s not going to send the right image. | ☐  | ☐  | ☐  |
| 19 So what you can do is click right here where it says share and then copy this. | ☐  | ☐  | ☐  |
| 20 Alright, that should work this time. | ☐  | ☐  | ☐  |
| 21 You know where some of the really, really fantastic ones come from. | ☐  | ☐  | ☐  |
| 22 But people will be on the boat on foot. | ☐  | ☐  | ☐  |
| 23 Alright that will be the right one, ’cause I think it sent the wrong one from you. | ☐  | ☐  | ☐  |
| 24 OK, so these so right now, I’m just going to start with a darker shadows. | ☐  | ☐  | ☐  |
| 25 Of where I see the ripples. | ☐  | ☐  | ☐  |
| 26 I’m not worried about putting like every ripple in the right spot. | ☐  | ☐  | ☐  |
| 27 But we couldn’t get the overall feel this. | ☐  | ☐  | ☐  |
| 28 Some more shown here. | ☐  | ☐  | ☐  |
| 29 Alright that should work this time. | ☐  | ☐  | ☐  |
| 30 What’s wrong with that picture? | ☐  | ☐  | ☐  |
| 31 Does actually seem nice. | ☐  | ☐  | ☐  |
| 32 I don’t see anything wrong with that landscape Timo? | ☐  | ☐  | X |
| 33 When you when you’re using map crunch you’re going to get a lot of like side of the road road views because you know if you think about where the car is going. | ☐  | ☐  | ☐  |
| 34 Order fact that it’s your in the Google Maps. | ☐  | ☐  | ☐  |
| 35 People are in a car traveling there, you get a lot of side of the road like kind of bland images, but then you also get like the most amazing pictures and people also upload images and stuff, I think that might be. | ☐  | ☐  | ☐  |
| 36 You know where some of the really, really fantastic ones come from. | ☐  | ☐  | ☐  |
| 37 But people will be on the boat on foot. | ☐  | ☐  | ☐  |
| 38 You know, I’ve seen people like riding camels and stuff, he’s taking pictures for Google. | ☐  | ☐  | ☐  |
| 39 Maps years was a fitness studio, yeah, there’s all kinds of stuff. | ☐  | ☐  | ☐  |
| 40 Yeah, but sometimes you get something weird because the 3D or the 360 Panorama. | ☐  | ☐  | ☐  |
| 41 View is created by them stitching images together. | ☐  | ☐  | ☐  |
| 42 So, sometimes you have weird situations where stuff overlaps. | ☐  | ☐  | ☐  |
Table 12: Example system summaries from Creating ABC Childrens Book Art on Adobe Fresco and Adobe Illustrator Part 18. BART summary is fluent but its content lacks specificity, as is the case for LexRank. Summary segments selected by FluCoVRank are ungrammatical. StreamHover identifies on-topic and informative summary utterances.

Table 13: A transcript snippet from Creating ABC Childrens Book Art on Adobe Fresco and Adobe Illustrator Part 18. We show the most prominent latent codes and their representative utterances (‘X’). Human annotated summary utterances are colored gray and ultra-short utterances are crossed out.
And then once I get my general OK this is what the hairstyle my stuff. You know? draw. learn pro and You I used to do that a lot when I was younger where I would call me formative summary utterances. grammatical. StreamHover identifies on-topic and in- its content lacks specificity, as is the case for LexRank. just giving up. then figure out you can’t draw it or you have a hard time drawing it and then just giving up. 35.36...

Table 15: A transcript snippet from Call me Derek: Value Study. We show the most prominent latent codes and their representative utterances (‘X’). Human annotated summary utterances are colored gray and ultra-short utterances are crossed out.
Definitely, I think it’s important to seek out advice from professional artists and take the advice with a grain of salt like. See I do think people do though Omar, like maybe maybe you’re not relating to it ‘cause it’s just not what your preferences are but. Definitely, I think it’s important to seek out advice from professional artists and from people who know what.

Or what I meant is that some people start off always drawing characters, for example like they just from. An anyway, some artists just like for example, love drawing characters and always draw them and never get into environments, and they go on and become a good working concepts are it could work in visual development as a character artist who knows what. Just because someone specializes, it doesn’t necessarily mean that they like tried all the other things first.

Some people sort of specialized the whole time just because that was their preference, you know.

| Utterances | C1 | C2 | C3 |
|------------|----|----|----|
| 0 Pence Maybe I’ll wait on that. | | | X |
| 1 David says, I also think if you were a person who really likes doing all sorts of different things, you wouldn’t be happy. | | | |
| 2 Specialized | | | |
| 3 Yeah, people are different or personalities. | | | |
| 4 Some people like to have things mixed up all the time where they get bored and other people find that one thing they like and never tire of it. | | | |
| 5 And it really depends. | | | |
| 6 Personally, depends. | | |
| 7 I think that’s why you have to take advice with a grain of salt like. | | |
| 8 Definitely, I think it’s important to seek out advice from professional artists and from people that have that sort of gone down the path that you’re trying to go down. | | |
| 9 That’s going to make things easier for you, but you know, take the advice with a grain of salt because. | | |
| 10 What might work for them isn’t necessarily right for you for any number of reasons, like what David said just from person to person, those preferences can be really different. I for example, prefer environment designed the character design, and even though I like looking at character art by prefer to make environments and that’s not. I think that’s why you have to take advice with a grain of salt like. See I do think people do though Omar, like maybe maybe you’re not relating to it ‘cause it’s just not what your preferences are but. Definitely, I think it’s important to seek out advice from professional artists and from people who know what. | | |
| 11 Exactly Pablo is at the end of the day. | | |
| 12 It’s about what you like doing. | | X |
| 13 Alright, I’m gonna grab a little more textured brush again. | | |
| 14 I’m kind of going back and forth with harder brushes and textured brushes. | | |
| 15 I really works good to see you. | | |
| 16 It’s not about that. | | |
| 17 A specialist most of the time is someone with more experience. | | |
| 18 That’s why he’s a specialist. | | X |
| 19 Oh, I understand your thoughts on that. | | |
| 20 I would agree for the most part, but I guess the part I would disagree on is that. | | |
| 21 Or what I meant is that some people start off always drawing characters, for example like they just from. | | |
| 22 I mean I like for example, I started drawing in like when I was a kid and when I was in middle school and high school was drawn. | | |
| 23 All my favorite characters from Sailor Moon and all that kind of stuff. | | |
| 24 An anyway, some artists just like for example, love drawing characters and always draw them and never get into environments, and they go on and become a good working concepts are it could work in visual development as a character artist who knows what. | | |
| 25 Just because someone specializes, it doesn’t necessarily mean that they like tried all the other things first. | | |
| 26 Maybe they did. | | |
| 27 It’s possible they did, but I don’t think that it has to be that you have to do everything before you specialize. | | |
| 28 Some people sort of specialized the whole time just because that was their preference, you know. | | |
| 29 From the beginning. | | |
| 30 If anybody is just coming in. | | |
| 31 Mohammed roller, I can show you what we did so far. | | X |
| 32 This was the first study. | | |
| 33 We’re doing cloud studies for part of the art club were doing clouds in different scenarios, this time different. | | X |
| 34 Like lightings, different times of day. | | |
| 35 This was the second one. | | X |
| 36 And. | | |
| 37 This is what we’re working on right now. | | |
| 38 See I do think people do though Omar, like maybe maybe you’re not relating to it ‘cause it’s just not what your preferences are but. | | X X |
| 39 I for example, prefer environment designed the character design, and even though I like looking at character art by prefer to make environments, and that’s not. | | |
| 40 You know, that’s just my preference. | | |
| 41 All thanks claires you thank you. | | |

Table 16: Example system summaries for Digital Painting Studies with Maddy Bellwoar–Clouds. The BART summary is fluent but its content lacks specificity, as is the case for LexRank. The summary segments selected by FluCoVRank are ungrammatical. StreamHover identifies on-topic and informative summary utterances.