
Summarization of instructional video transcripts using BERT

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Abstract

1 In this paper, we study summarization of narrated instructional videos and various
2 written texts. Unlike traditional video summarization which focuses on condensing
3 select video frames, our work transfers unique step-by-step learning from written
4 articles and videos to generate short summaries given video transcripts. We show-
5 case how a top performing document-level encoder based on BERT can boost the
6 fluency and generalizability of summaries across a wide variety of instructional
7 text and videos. In addition to our fine tuning and ordered training methods, we
8 present a novel dataset with over 5,000 transcripts extracted and constructed from
9 open-domain videos and an online dataset written by different researchers. We
10 demonstrate that our model is highly generalizable and produces summaries com-
11 parable to human written texts. To capture the semantic adequacy of our results,
12 we use Content F1, Meteor, and human evaluations with a new framework that we
13 designed for this project to score summaries.

1 Introduction

15 Google Insights states that how-to-videos are one of the most top watched videos on YouTube
16 every year. Video content is rapidly growing and continues to be a prominent source for sharing
17 information. With the increase in content, there has been a large demand for generating attractive
18 content, keywords, and descriptions for marketing videos on such online platforms. Currently, many
19 descriptions for video content are human written and configured to maximize results through search
20 engine optimization. Our research attempts to address these issues by improving the semantic quality
21 of short, textual summaries associated with such videos. We help contextualize videos by offering
22 meaningful descriptions to enhance user engagement and experience. Natural language processing
23 tasks such as sentiment analysis, question and answering, and natural language generation have
24 greatly advanced with the development of transformers and pre-trained models. Summarization,
25 which is the task of condensing textual information into a short and concise form, has been improved
26 on structured datasets. News articles and single documents are often used to enhance summary model
27 performance. (citation). In abstractive video summarization, models which incorporate variations of
28 LSTM and deep layered neural networks have become state of the art performers. More recently,
29 multi-modal summarization, which combines speech, visual, and textual modalities seek to enhance
30 summaries has emerged. However, the lack of human annotated data has limited the amount of
31 benchmarked datasets available for such research. Additionally, most work in the field of video
32 summarization has traditionally focused on the isolation and concatenation of important video frames
33 using natural language processing techniques. Summarizing videos given conversational text is
34 difficult to model. There are often inconsistencies and stylistic changes that are difficult to translate
35 from spoken words. In this work, we challenge video summarizations by transferring top performing
36 pretrained language models in single-document domains to that of open-domain videos.

37 2 Prior work

38 2.1 Text Summarization

39 Text summarization is the task of generating shorter versions of documents while maintaining
40 important information [need link]. This area of research in the natural language processing community
41 has grown rapidly over the past several years due to its practical applications among various industries
42 such as news, reviews, education. Summarization systems take two general approaches: extractive and
43 abstractive. Extractive summarization provides users with textual summaries that have been copied
44 and concatenated from important parts of a document. It is a reliable task capable of maintaining
45 sentence structure and factual correctness. Abstract summarization generates a summary with content
46 that is not always found in the underlying text. It is a complex task that mimics human summarization
47 by generalizing and paraphrasing key points made in the document.

48 Prior to 2014, summarization was centered on extracting lines from single documents using statistical
49 models and neural networks had limited success[6, 7]. Sutskever et al. and Cho et al work on
50 sequence to sequence models opened up new possibilities for neural networks in natural language
51 processing. From 2014 to 2015, LSTMs (variety of RNN) became the dominant approach that
52 achieved state of the art results. They became successful in tasks such as speech recognition, machine
53 translation, parsing, image captioning, etc. It paved the way for abstractive summarization, which
54 began to score competitively against extractive summarization. In 2017, Attention is all you need
55 [8] provided a solution to the ‘fixed length vector’ problem, enabling neural networks to focus on
56 important parts of the input for prediction tasks. Transformers with attention became more dominant
57 for certain tasks [9].

58 3 Problem Statement

59 In our work we set a challenge to train a BERT-based model that generates summaries from ASR
60 (speech-to-text) scripts of competitive quality to human-curated descriptions on YouTube amateur
61 narrated instructional . This challenge breaks down to the following low-level goals:

- 62 • Curate and publish a single source of truth data set of text and summaries aggregated and
63 formatted from WikiHow articles, How2 videos, and CNN/DM stories;
- 64 • Finetune existing BERT-based text summarization models to make them applicable to
65 auto-generated scripts from instructional videos;
- 66 • Augment automated metrics [Chin-Yew Lin] for evaluation of summaries with a framework
67 for formalized expert assessment based on our research and criteria proposed by previous
68 works.

69 4 Methodology

70 From the initial exploration and data analysis we saw that in the process of applying existing
71 summarization models to Youtube video scripts we will deal with challenges imposed by parsing
72 speech-to-text output add more complexity to text summarization. For example, in one of the sample
73 videos in our test data set closed captioning confuses the speaker’s words “*how you get a text from*
74 *a YouTube video*” for “*how you get attacks from a YouTube video*”. So, our work includes several
75 iterations of the process described below:

- 76 • Collection and aggregation of data from multiple sources (HowTo video scripts, WikiHow,
77 CNN stories, YouTube)
- 78 • Preprocessing of video scripts to make them fit the text summarization models (e.g. errors in
79 word recognition, lack of punctuation in closed captioning, getting rid of special characters
80 etc., aligning inputs aggregated from multiple sources to common format)
- 81 • Text summarization models: selection, deployment, training, and fine-tuning
- 82 • Experiments: applying models to the data and evaluation of the outputs using ROUGE
83 metrics and human expert judgements

84 4.1 Data Collection

85 We hypothesized that the more labelled summarization data we bring, the more our model will benefit
86 in the training process in terms of generalizability.

- 87 • **CNN/Daily Mail dataset** provided by Hermann et. al 2015, the How2 Dataset, and Wikihow.
88 The datasets illustrate different summary styles that range from single sentence phrases
89 to short paragraphs. CNN and Daily Mail includes a combination of news articles and
90 story highlights written with an average length of 119 words per article and 83 words per
91 summary.
- 92 • **Wikihow dataset**, a large scale text summarization containing over 200,000 single document
93 summaries. Wikihow is a consolidated set of recent 'How To' instructional texts compiled
94 from wikihow.com, ranging from topics such as 'How to deal with coronavirus anxiety' to
95 'How to play Uno.' The articles inside the dataset vary in size and topic but are structured to
96 drive instructions across to the user. The first sentences of each paragraph are concatenated
97 for form a summary for each article.
- 98 • **How2 Dataset** of 8,000 videos (approximately 2,000 hours). This YouTube compilation has
99 videos averaging 90 seconds long and 291 word transcript length. It includes human written
100 summaries where video owners were instructed to write with the interest of the viewer in
101 mind. Summaries were two to three sentences in length with an average length of 33 words.
102 Our research explored different combinations of the listed data during model training.

103 As part of this research, we are exploring different combinations of data during training of summa-
104 rization models and evaluate how they perform on instructional video scripts in any domain.

105 4.2 Preprocessing

106 Due to diversity and complexity of our input data, a lot of our effort went into building a preprocessing
107 pipeline out of blocks. The format of CNN/Daily Mail stories, wikiHow articles, and howTo scripts
108 is different. We invested substantial efforts into converting them to a format that can be used. For the
109 convenience of other researchers who may want to use similar methodology, we shared the results of
110 aligning them to the same format that can be training.

111 Another stream of work we have done at this stage is based on the heuristics observed during
112 evaluation of results. Many scripts from YouTube (for the videos that we dupmed and HowTo100M
113 dataset) have no punctuation, or it is not comprehensive. As a result, the model is misinterpreting text
114 segment boundaries and produces low quality summaries or no summaries at all. With the help of
115 Spacy library, we were able to fix this and restore sentence structures.

116 We expected the differences in conversational style of the video scripts and writtent text of news stories
117 (on which the models were pretrained) will impact quality of the output. In our first experiments with
118 applying extractive summarization model that was pretrained on CNN/DM dataset, it manifested
119 in a very distinct way. The model considered the first one-two sentences to be very important for
120 summaries (this phenomena is referred to by [15] as N-lead, where N is the number of important
121 first sentences), and we ended up with getting many summaries looking like "hi!" and "hello, this
122 is <first and last name>". It inspired us for implementing an improvement by using entity detection
123 spacy and nltk to remove introduction from the text that we feed to summarization model.

124 The CNN/Daily Mail dataset has been preprocessed to remove news anchor introductions. For
125 our Wikihow and How2 transcripts, we did tokenization using the Stanford Core NLP toolkit and
126 preprocessed the data in the same method used by (See et. al.).

127 4.3 Summarization models

128 We used the BertSum model created by Yang trained on CNN and Daily Mail [Yang] for our
129 paper. This paper has 2 separate models for Extractive and abstractive summarization. Extractive
130 summarization is generally a binary classification task with labels indicating whether sentences
131 should be included in the summary. Abstractive summarization, on the other hand, requires language
132 generation capabilities to create summaries containing novel words and phrases not found in the
133 source text.

134 The architecture in the Figure 1 shows the BERTSUM model. It uses a novel documentation level
 135 encoder based on BERT which can encode a document and obtain representation for the sentences.
 136 CLS token is added to every sentence instead of just 1 CLS token in the original BERT model.
 137 Abstractive model uses an encoder-decoder architecture, combining the same pretrained BERT
 138 encoder with a randomly initialized Transformer decoder. The model uses a special technique where
 139 the encoder portion is almost kept same with a very low learning rate and a separate learning rate is
 140 used for the decoder to make it learn better.

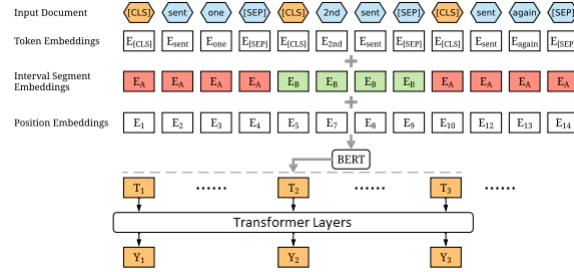


Figure 1: BERTSUM Architecture

141 We used a 4-GPU Linux machine and first trained on a small model with 10,000 steps using Extractive
 142 summarization in the beginning. Extractive summarization uses BERT base uncased and took around
 143 12 hours to train. We fine tuned the whole model including the BERT layer. We established the
 144 baseline by training on 5,000 samples from the How2 dataset. We tuned few hyper parameters with
 145 different steps, batch sizes and epochs sizes. Then, we added CNN/Dailymail,full how2 dataset and
 146 3,097 samples from Wikihow with a 50,000 step size to the training set and got better summaries.

147 Finally, we used the Abstractive summarization model and all the datasets(CNN/DM, Wikihow and
 148 how2 datasets) and trained for 210,000 steps in a specific order to get novel words and to get fluent
 149 summaries. This was done at the end as the abstractive model was very big and it took 4 days to train
 150 this model. These models are very demanding in terms of both memory and computational resources.
 151 The model has more than 180 million parameters and has 2 Adam optimizers with $\beta_1=0.9$ and β_2
 152 $=0.999$ for encoder and decoder respectively. Encoder uses a learning rate of 0.002 and the decoder
 153 has a learning rate of 0.2. This is to make sure that the encoder is trained with more accurate gradients
 154 when the decoder is becoming stable.

155 4.4 Scoring of results

156 We have observed examples of bad summaries with high ROUGE score, such as in Figure 2, and
 157 good summaries with low ROUGE score. We believe that ROUGE is fine as a starting point for
 158 comparison, but the real evaluation of the output quality still requires human experts.

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*****
Reference: now that you have spent the time cleaning your oven learn how to keep it clean with expert tips in this free h
ow to video on how to better clean your oven

Hypothesis: make sure your oven is clean .<q>clean your oven .<q>make sure you want to clean the oven with a towel .<q>ge
t your food .<q>put your food in your baking soda and water .<q>do n't go to the kitchen .

rouge-1:      P: 29.55      R: 40.62      F1: 34.21
rouge-2:      P:  6.98      R:  9.68      F1:  8.11
rouge-3:      P:  2.38      R:  3.33      F1:  2.78
rouge-4:      P:  0.00      R:  0.00      F1:  0.00
rouge-l:      P: 24.16      R: 31.50      F1: 27.34
rouge-w:      P: 14.23      R:  9.78      F1: 11.59
*****
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Figure 2: An example where ROUGE metric is confusing.

159 This is why we added another score to the rating - Content F1, which was proposed in Carnegie
 160 Mellon university | to focus on the relevance of content. In calculation it is very similar to ROUGE,
 161 but discounts stop words and buzz words that frequently occur in the domain (in our case it was
 162 "learn from experts how to in this free online video").

163 In addition to automatically calculated scores, it is important to have human judges review the results.
 164 We have been doing this at all stages, but in addition to that we wanted to come up with a more
 165 formalized, objective and reusable process for engaging independent experts. In this effort we came
 166 up with a framework of criteria for evaluation that we implemented using Python, Google Forms, and
 167 Excel spreadsheets. Summaries for the surveys are randomly sampled to avoid biases. In order to
 168 avoid leaking a hint about whether a summary was created by a human or our AI, we lower-cased
 169 all summaries, since the output of our model is uncased. We had two types of questions: one, a
 170 version of famous Turing test, was a challenge to distinguish AI from human-curated descriptions.
 171 Second was to give quality ratings to the summaries, so that we can see where to focus for further
 172 improvements. Below are definitions of criteria for clarity:

- 173 • Fluency: Does the text have a natural flow and rhythm?
- 174 • Usefulness: Does it have enough information to make a user decide whether they want to
 175 spend time watching the video?
- 176 • Succinctness: Does the text look concise or does it have redundancy?
- 177 • Consistency: Are there any ambiguous, confusing or contradicting statements in the text?
- 178 • Realisticity: Is there anything that seems far-fetched and bizarre in words combinations, or
 179 do the statements look "normal"?

180 Options for grading of results are as follows: 1: Bad 2: Below Average 3: Average 4: Good 5: Great.

181 5 Experiments and Results

182 5.1 Training

183 Our baseline results were obtained from applying the state-of-the-art extractive BertSum model
 184 pretrained on CNN/DailyMail. With the super power of BERT, we hoped to also see decent scores
 185 on howto videos, but that didn't happen. Even more was our disappointment when we looked at
 186 the summaries the model generated: useless, confusing, and extremely funny, examples of which
 187 you can see in this slide. However, that experiment produced a ton of learnings: first, we saw that
 188 the model was doing relatively good on the health domain that is substantially covered in the news,
 189 and extremely poorly with topics like sports, arts, or culinary. Next, we realized that extractive
 190 summarization is not the right choice for our goal: that's because most youtube videos are in very
 191 casual conversational style, while summaries have to be formal; so our only way is abstractive
 192 summarization, even though it's harder.

193 In order to create a generalizable abstractive model, we trained on large corpus of news. This allows
 194 our model to understand structured texts. We then introduced a comprehensive instructional text
 195 called Wikiphow, which introduces the model to the how-to domain. Finally, we train and validate on
 196 the how-to dataset, narrowing the focus of the model to a selectively structured format.

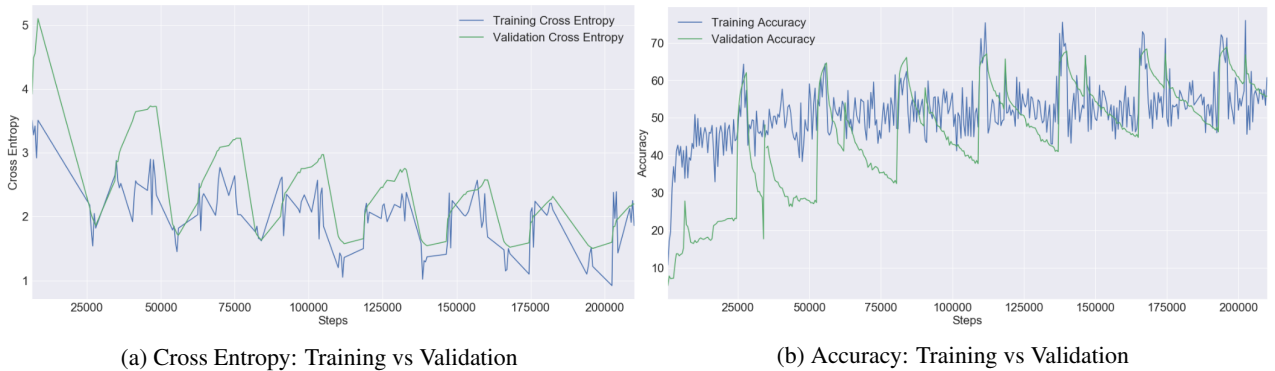


Figure 3: BertSum Abstractive Summarization: Model Performance

197 The cross entropy chart in the Figure 3a shows that the model is neither overfitting nor underfitting
 198 the training data. We want to see the lines meet and as seen here the model seems to be a good

fit. Figure 3b shows the model’s accuracy metric on the training and validation sets. The model is validated using the how2 dataset against the training dataset that includes all 4 sources. The model improves as expected with more steps(or epochs).

5.2 Evaluation

The BertSum model created by Yang trained on CNN and Daily Mail [Yang] resulted in SOTA scores when applied to samples from those datasets. However, when tested on our How2 Test dataset, it gave very poor performance and a lack of generalization in the model (see Table 1). Looking at the data, we found that the model tends to pick the first one or two sentences for the summary. This can be explained by the fact that the first paragraph of a news article often captures the gits of it, which the model learned. However, in the case of our instructional videos, the first sentences would be a non-informative introduction, such as "Hi there! My name is ...". Based on that, we hypothesized that removing introudctions from the text will help improve ROUGE scores. Indeed, we got a few points better after applying preprocessing described in the Section 4.2 above. Yet another improvement in the score was accomplished by taking advantage of one more observation: most curated summaries follow a template that starts with "Learn how ...". So, we added these two words in the beginning of the summary at post-processing stage. With all that, we still couldn’t get higher than 22.5 ROUGE-1 F1 and 20 ROUGE-L F1. Reviewing scores and texts of individual summaries showed that the model is doing better on some topics, such as medicine, and worse on others, such as sports. Again, this makes sense for a model that is trained on news: it isn’t reasonable for it to be good with yoga-specific terminology, while news about health care are very common.

So, in our next series of experiments, we used our own dataset for training. We were able to push the scores higher: by 4 for ROUGE-1 and 2.5 ROUGE-L F1 on the results with and without preprocessing, compared to the CNN-trained model. Current best results was accomplished with setting shuffling parameter to false when we train on CNN, HowTo Wiki, and HowTo Video scripts. Our results for videos have reached the level of the best scores for news [1]. However, there is still some room for improvement, as more specialized model by [Shruti et.al.] claims to go above 50 ROUGE score.

Table 1: Comparison of results

Experiment			
Model	Pretraining Data	Rouge-1	Rouge-L
1. BertSum	CNN and Daily Mail	18.08	18.01
2. BertSum with preprocessing	CNN and Daily Mail	20.51	18.86
3. BertSum with pre- and postprocessing	CNN and Daily Mail	22.47	20.07
4. BertSum	How-To, WikiHow, CNN and Daily Mail	24.4	21.45
5. BertSum with postprocessing	How-To, WikiHow, CNN and Daily Mail	26.32	22.47
6. BertSum with no shuffling and more training data	How-To, WikiHow, CNN and Daily Mail	48.26	44.02

Even though the difference in ROUGE scores for the results on [1-3] are not drastically different from [4-5], the quality of summaries from the perspective of human judges is qualitatively different. From anecdotal paragraphs that made no sense, we went to very fluent and understandable video descriptions which give a clear idea about the content. However, our scores are not beating the scores from other researchers, even though we are using BERT and they had a mix of rule-based extractive and abstractive model running on much older engine. Closer look at comparison of the texts, though, showed that our summaries are in fluency and usefulness of summaries. Some examples are given below:

- Summary 1: growing rudbeckia requires full hot sun and good drainage. grow rudbeckia with tips from a gardening specialist in this free video on plant and flower care. care for rudbeckia with gardening tips from an experienced gardener
- Benchmark 1: growing black - eyed - susan is easy with these tips, get expert gardening tips in this free gardening video .
- Reference 1: growing rudbeckia requires full hot sun and good drainage. grow rudbeckia with tips from a gardening specialist in this free video on plant and flower care. care for rudbeckia with gardening tips from an experienced gardener.
- Summary 2: camouflage thick arms by wearing sleeves that are not close to the arms and that have a line that goes all the way to the waist. avoid wearing jackets and jackets with tips from an image consultant in this free video on fashion. learn how to dress for fashion modeling
- Benchmark 2: hide thick arms and arms by wearing clothes that hold the arms in the top of the arm. avoid damaging the arm and avoid damaging the arms with tips from an image consultant in this free video on fashion .
- Reference 2: hide thick arms by wearing clothes sleeves that almost reach the waist to camouflage the area .conceal the thickness at the top of the arms with tips from an image consultant in this free video on fashion.

Based on that observation, we decided that the model is mature enough for us move on to the final stage and leverage the power of independent experts and evaluate the quality of our summaries in comparison to descriptions that users provide for their videos on Youtube. We recruited a diverse group of 30 volunteers (27 have responded at the time of writing this paper) to blindly evaluate a set of 25 randomly selected video summaries that were generated by our model and descriptions of videos on Youtube from the dataset that we curated and HowTo100M (13 AI + 12 human-curated). We had two types of questions: one, a version of famous Turing test, was a challenge to distinguish AI from human-curated descriptions and used the framework described in section 4.4. You can see aggregated results for both evaluations in Figures ?? - ?? . We can see that nobody has been able to get 100% accuracy in their Turing test answers, with many false positives and false negatives. This means that quality of the model output is comparable to average youtube summaries. Second, as we expected, the fluency of our summaries is almost as good as human-curated text. Realisticity is the main growth opportunity, because the abstractive model makes up weird things, like “use chicken for an easy vegetarian recipe”.

6 Conclusion

We are continuing to work on improving summarization for instructional videos, as measured by both ROUGE and human experts. By the end of the project, we hope to accomplish scores that are comparable to current SOTA, but more generalizable. We also plan to provide a more detailed analysis on correlations between features of a video (e.g. topic, length, number of likes) and the quality of summaries produced on our experiments, as well as a more detailed description of our expert evaluation process.

Broader Impact

The contribution of our research is three-fold:

- We created and published a data set of how-to videos with time-tagged scripts, machine-generated summaries ¹
- We explored different combinations of data during training of summarization models and evaluated how they perform on instructional video scripts in different domains
- We generalized existing text summarization models to the scripts extracted from instructional videos

¹<https://github.com/alebryvas/berk266/> - it's not public repository yet, but we can provide access upon request

280 • We augmented ROUGE metrics [Chin-Yew Lin] for evaluation of the results with a frame-
 281 work for formalized expert assessment based on our research and criteria proposed by
 282 previous works [that's in work]

283 At a high level, we hope that our analysis of transferability of summarization techniques from text to
 284 videos will have both practical and theoretical impacts by helping identify promising directions for
 285 future research.

286 References

287 **We will align the formatting of references for the final submission. Current list is accurate,**
 288 **but not standardized.**

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