Rationale-based Learning using Self-Supervised Narrative Events for Text Summarisation of Interactive Digital Narratives

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Abstract

This paper explores using rationale-based learning with supervised attention to focus the training of text summarisation models on words and sentences surrounding choice points for Interactive Digital Narratives (IDNs). IDNs allow players to interact with the story via choice points, making choices central to these narratives. Exploiting such knowledge about narrative structure during model training can help ensure key narrative information appears in generated summaries of narrative-based text and thus improve the quality of these summaries. We experiment with using word-level and sentence-level rationales indicating the proximity of words and sentences to self-supervised choice points. Our results indicate that rationale-based learning can improve the ability of attention-based text summarisation models to create higher quality summaries that encode key narrative information better for different playthroughs of the same interactive narrative. These results suggest a promising new direction for narrative-based text summarisation models.

Keywords: Interactive Digital Narratives, Text Summarization, NLP, Rationale based learning

1. Introduction

Interactive Digital Narratives (IDNs), such as choose-your-own-adventure games and story-rich video games, are narratives that support player interaction. IDNs are becoming increasingly more prevalent with the growing popularity of narratives in mediums such as video games and interactive mixed-reality experiences. However, while there are some studies on how external information about narrative structures can be introduced into narrative summarisation(Papalampidi et al., 2020), there is not much research investigating what prior information about *interactive* narrative structure can be introduced for interactive narrative summarisation and how this can be done. This is what we address in this paper.

In IDNs, while interaction can occur in many ways, making choices that affect the course of the story is a popular interaction pattern, with the plot and gameplay being closely entwined with the choices made by the player. In such IDNs, the context in which choices are presented, the player choices and their consequences heavily influence which parts of the narrative are salient enough to be included in the summary. Therefore, understanding the significance of narrative events is often enhanced by considering them in the context of player choices. For example, the player may have chosen to kill a Non-Player Character (NPC) who appeared to be the evil, but later in the story, they may find out that they were innocent. Finding out about the NPC's innocence becomes more significant in the context of the choice the player had to make earlier in the game. In this paper, we investigate leveraging this knowledge regarding the importance of choices to enhance IDN summarisation.

To incorporate this knowledge into the training process, we explore for the first time, choice-focussed rationale-based learning for extractive summarisation of IDN. Our approach is motivated by the text classification model of (Kanchinadam et al., 2020), which used word-level rationale-based learning with supervised attention to help focus model training on areas of the text that human annotators considered important. Inspired by this approach, we explore sentence-level and word-level rationale-based learning for extractive summarization of IDN narratives, using proximity to choice points as a self-supervised proxy for human rationales. This paper is focussed on IDNs and choice points but the proposed approach can also be extended to traditional narrative-based text to incorporate knowledge about narrative structure like the importance of emotion using emotion detection techniques to automatically generate rationales.

The novelty of our approach is in the formulation of the data and training objectives for this unique domain (IDN). While the outlined approach can be extended to various types of attention-based architectures, applying supervised attention to model architectures with multi-head attention can involve additional layers of complexity. Therefore, in this paper, we first investigate the efficacy of this approach on variants of the classic SummaRuNNer model equipped with simple attention layers. Our results show that choice-focussed rationale-based learning delivers a significant improvement in ROUGE scores when compared against gold-

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standard human-authored abstractive reference summaries, encouraging further research in this direction. To summarise, the contributions of this paper are as follows:

1. A novel method using word and sentence level rationales applied to an existing RNN-based model (SummaRunner) for Interactive Digital Narratives (IDN) summarisation, addressing a domain that remains relatively underexplored.
2. Empirical results showing that using choice points for self-training rationales outperforms similar models trained traditionally.
3. Manual Qualitative and Fault analyses providing deeper insights into model limitations to guide future researchers in this area.
4. To the best of our knowledge, this is the first self-trained rationale-based method for narrative summarization.

We review related work in section 2 before outlining, in detail, our rationale-based training approach and the models we train in section 3. Section 4 reports results from our automatic and manual evaluation and analysis of variability of generated summaries across different playthroughs of the same interactive narrative, which we discuss and conclude in section 5 and section 6.

2. Related Work

Previous studies on extractive summarisation have focussed on various techniques including RNN-based models (Nallapati et al., 2017), language model-based methods (Liu, 2019) and graph-based methods (Antognini and Faltings, 2019). However, these methods are most commonly trained and tested on datasets like news (Hermann et al., 2015) and academic articles (Gupta et al., 2021). While some approaches for summarisation of traditional narratives have been explored, like using GCNs for screenplay summarisation (Lapata, 2021) and taking turning point information into account (Papalampidi et al., 2020), summarisation of interactive narratives has not been explored in much depth. IDN-Sum (Revi et al., 2022) is a dataset introduced for studying interactive narrative extractive summarisation and is used for the experiments in this paper. Interactive narratives are unique from other domains where summarisation has been explored in that they often have complex structures arising from the ability of players to interact with the story.

Rationale-based learning, or explanation-based learning, is an approach that uses rationales to guide the training of machine learning models (Gao et al., 2022a). This has been applied in a variety of NLP tasks including Text Classification (Arous et al., 2021; Choi et al., 2020), Natural Language Inference (Camburu et al., 2018; Stacey et al., 2022) and Sentiment Analysis (Zhong et al., 2019). Both local explanations (Gao et al., 2022b) and global explanations have been applied to guide training (Liu and Avci, 2019) in this way. Rationales are incorporated into training through various means including supervised attention (Kanchinadam et al., 2020), which is the approach we have used in this paper. However, in this paper, we investigate the effectiveness of choices as rationales in the novel context of summarising IDNs. We also experiment with different kinds of explanations applied at both word and sentence levels.

3. Method

3.1. Choice Focussed Rationales

We will introduce information regarding the importance of choices in IDN summarisation into the training process through rationales that indicate the proximity of words and sentences to choice points. In IDN-Sum dataset(Revi et al., 2022) used in this paper, choice points are marked using a choice tag, "CHOICE :". Using this tag, sentence and word rationales were embedded as tensors in the following way:

$$rs_i = \begin{cases} 1 & \text{if } CT \in [s_{i-ws}, s_{i+ws}] \\ 0 & \text{otherwise} \end{cases}$$

$$rw_i = \begin{cases} \text{tfidf}(w_i) & \text{if } w_i \in CW \\ 0 & \text{otherwise} \end{cases}$$

where CW is the set of all words that fall inside a window of size ws around the choice tag given by,

$$CW = \{w_i \, \epsilon \, W \mid CT \; in \; (w_{i-ws} : w_{i+ws})\}$$

CT stands for the choice tag, rs_i and rw_i stand for the rationale for sentence/ word at index i, ws stands for window size, s_i and w_i stands for sentence/ word at index i and notations $s_i : s_j$ and $w_i : w_j$ represents concatenation of sentences/ words at indexes from i to j.

Then, following the method used in previous work in supervised attention (Kanchinadam et al., 2020), to use rationales in training, training loss was calculated in the following way:
For sentence attention model:

$$L = \alpha * L_l + (1 - \alpha) * L_s$$

For word attention model :

$$L = \alpha * L_l + (1 - \alpha) * L_w$$

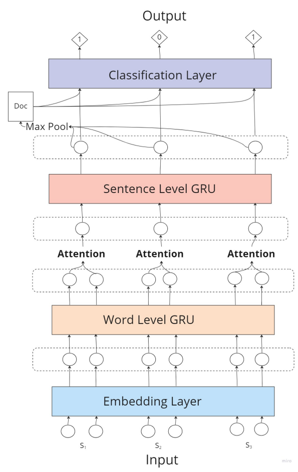

Figure 1: Summarunner modified to use attention instead of max pooling at word level (wordonlyAttnRNN).

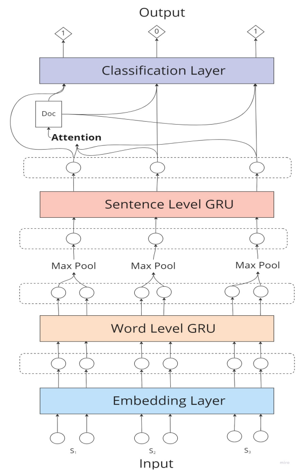

Figure 2: Summarunner modified to use attention instead of max pooling at sentence level (sentonlyAttnRNN).

For attention model with sentence and word level attention :

$$L = \alpha * L_l + \alpha_1 * L_s + \alpha_2 * L_w$$

where: α + α_1 + α_2 = 1,
L = Total Loss,
L_l = Cross-entropy loss calculated for the output of the model against the target labels,
L_s = Cross-entropy loss calculated for sentence attention scores against sentence rationales and
L_w = Cross-entropy loss calculated for word attention scores against word rationales.

This essentially tells the model to pay more attention to sentences and words surrounding the choice points when generating internal representations and deciding whether to include the given sentence in the extractive summary or not.

3.2. Base Models

While our training approach could theoretically be applied to any model with an attention layer, introducing supervised attention to recent Pretrained Language Models (PLMs) and other transformer based models with multi-head attention introduces additional layers of complexity when applying supervised attention (eg. how many and which attention heads do we align with the rationales). Another significant limitation of many PLMs (at the time this experiment was performed) is their fixed context length, making them unsuitable for direct application to datasets like IDNSum with an average document length of 22,900 tokens. Therefore, in this paper, we first test our approach on a simple attention layer, saving other attention types for future research.

In our experiments, we utilize models based on SummaRunner, an RNN-based model for extractive summarisation with simple attention layers added to it. We chose SummaRunner as the base model because of its superior performance on the IDNSum dataset, outperforming even PLM based models like Longformer(Beltagy et al., 2020) on this dataset(Revi et al., 2022) and its renowned and consistent performance as a standard for extractive summarisation, allowing us to contextualize the efficacy of our proposed approach within a widely recognized model. The model referred to as RNN, in this paper, represents the original architecture used in Summarunner, modified to truncate documents at 3000 sentences instead of 100.

In Summarunner, word representations are combined into sentence representations and sentence representations are combined into document representations using max pool. Attention layers are added to this model so that rationales can be incorporated through supervised attention. In order to test the effectiveness of rationale-based learning at both the word and sentence level, max pool is replaced with attention layers at different levels in the following three ways, inspired by Hierarchical Attention Networks (HAN) (Yang et al., 2016) to produce three types of attention models: The first attention model is the Word level AttnRNN model(**wordonlyAttnRNN**), which only uses attention at the word level to combine the outputs of the word level GRU into sentence representations. This model architecture is illustrated in Figure 1. The second modified architecture is the Sentence level AttnRNN model (**sentonlyAttnRNN**), where attention is used only to pool the outputs of the sentence level GRU into document representations. This is illustrated in Figure 2. The third modified ar-

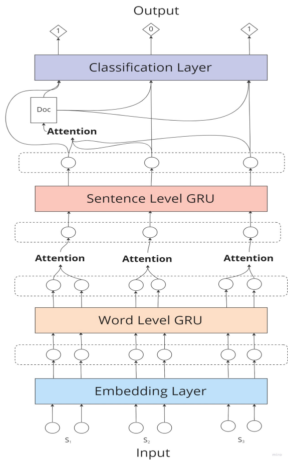

Figure 3: Summarunner modified to use attention instead of max pooling at both word and sentence level(AttnRNN).

chitecture is **AttnRNN**, modelled after Hierarchical Attention Networks (Yang et al., 2016), which uses attention at both the word and sentence level and is illustrated in Figure 3. In this paper, versions of these models trained with rationales is indicated by the suffix "+ rationale".**sentonlyAttnRNN + rationale** represents sentonlyAttnRNN trained with sentence rationale labels. **wordonlyAttnRNN + rationale** represents wordonlyAttnRNN trained with word rationale labels. **AttnRNN + rationale** represents AttnRNN trained with both rationales. All these models have approx 1.7M parameters.

3.3. Experiment Set Up

3.3.1. Dataset

The IDN-Sum dataset (Revi et al., 2022) was used to train each model. The dataset contains 10000 documents consisting of 1250 simulated playthroughs per episode of two interactive narrative games: *Before the Storm* developed by Deck Nine and released in 2017 and *Wolf Among Us* developed by TellTale Games and released in 2013. The dataset also contains the fan-written abstractive summaries for each episode and automatically generated extractive summaries for each playthrough. The extractive summary is represented through sentence-wise binary annotation indicating whether the sentence is included in the summary or not. The models were trained using the default split of this dataset (playthroughs of 3 episodes from Wolf Among Us in the training set, the remaining 2 episodes of Wolf Among Us in the validation set and the 3 episodes from Before the Storm in the test set.)

3.3.2. Models

We use the implementations provided on Github [1] as the starting point for the modifications described in section 3.2. These modified versions are made available on Gihutb[2]. Default settings were used except for the following parameters - since IDN documents are larger, the models were trained using batches of 1 document at a time to fit GPU memory. The parameter "report every" was reduced to 30 to monitor the training process more closely since IDN-Sum has many repeated sentences between data points making models more prone to overfitting when training on this dataset. The parameters window size (ws) and the coefficients (alpha) were tuned manually using the validation set within the bounds 0.99 - 0.25 for alpha and values [2,4,8,16] for was for sentence rationales and values [20,40,80,160] for word rationales. The best model, according to validation f1 scores, for which results are reported, was trained with parameters - ws = 2, alpha =0.95 for sentonly AttnRNN + rationale, ws=20, alpha = 0.5 for wordonly AttnRNN + rationale and ws=8,80 and alpha = 0.5, alpha1 = 0.25, alpha2 = 0.25 for AttnRNN + rationale.

In addition to the original SummaRuNNer model, we also show the performance using the more recent Longformer(Beltagy et al., 2020) (PLM for long documents with approx 149M parameters) and a zero shot LLM-based approach using Google's flan-t5-base model(Chung et al., 2022a) (instruction tuned LLM with 250m parameters) for comparison. For Longformer, we use the implementation from TransformerSum[3]. This implementation had a 4096 context window for pretrained extractive summarisation models at the time this experiment was run and documents were truncated at this length. We finetune the model using the same training, validation, test split and default parameters. For flan-t5, we get the pretrained model from Huggingface[4]. Summaries are generated in a zero-shot setting, 25 sentences at a time, to fit the context window and strung together at the end to get the final summary. The prompt and hyperparamters were manually tuned. The prompt used was: *"Create an extractive summary for the document. The summary should contain up to 3 sentences from the original text that best capture the essence of the document. \n Document: {25 sentence document} \n Extractive Summary:"* Refer Appendix 10.1 for the full list of hyperparameters and Appendix 10.2 for hardware details.

[1] The RNN model and Hierarchical Attention Network model from https://github.com/hpzhao/SummaRuNNer are used in this paper as RNN and AttnRNN, respectively.

[2] https://github.com/AshwathyTR/IDN_SR

[3] https://github.com/HHousen/TransformerSum

[4] https://huggingface.co/google/flan-t5-base

3.3.3. Evaluation

We evaluated the performance of our models using ROUGE-1(R1), ROUGE-2(R2), and ROUGE-L(RL). The performance of these models with and without attention and trained with and without rationales for the attention models were also compared. ROUGE scores were calculated against the human-authored abstractive summaries. ROUGE scores against the branch-wise extractive summaries and ROUGE scores calculated with and without the stop word filter is shown in the Appendix in section 10.3.

Some studies rely solely on ROUGE for comparing summarisation approaches(Zhong et al., 2020; Yuan et al., 2023; Cui et al., 2020). The ROUGE metric and automatic evaluation for summarisation face many challenges and several studies supplement the ROUGE based evaluation with manual human evaluation. However, the novelty of the domain and length of source documents and summaries for the IDN-Sum dataset makes large-scale human evaluation challenging and resource intensive. Therefore, following the approach used in recent work(Tang et al., 2022), we provide examples of the model-generated summaries and reference summaries for human evaluation in the Appendix 10.5 and perform a qualitative analysis to compare and illustrate intuitive aspects of quality that the ROUGE-based evaluation is unable to capture.

IDN-Sum dataset is characterised by a high overlap of text between data points caused as a result of generating different playthroughs through the same game. IDN summaries are hence most useful when these differences are captured. We analyse the variation between summaries generated by the model for different playthroughs through the same episode by calculating the average overlap of sentences between each pair of model summaries of the same episode in the test set to understand how varied the generated summaries are.

In addition to the comparison of approaches, we also perform a manual fault analysis to understand the limitations of our approach and encourage further research. The fault analysis was performed on 10 summaries generated by the best model (SentAttn + rationale) from each of the three episodes in the test set. These summaries were sampled randomly from the set of summaries that had a ROUGE score below the mean for that episode. This was done to get a deeper insight into the type of errors made by the model. In the first pass, the main error classes in the model-generated summaries were identified. Then, in the second pass, each sentence in model generated summary was coded against the error classes.

4. Results

4.1. Automatic Evaluation

Table 1 shows the ROUGE scores calculated against the human-authored abstractive summary. The corresponding validation scores is shown in the Appendix in Table 6. A breakdown of these scores by episode is also provided in Appendix in Table5. The evaluation scripts are also shared on Github [5].ROUGE score was calculated with Porter stemmer on and the stop filter turned off. Additional analysis showing ROUGE scores with the stop word filter turned on and ROUGE scores calculated against the automatically aligned extractive summary is also provided in the Appendix in Tables 7 and 4. The versions of the attention models trained with different types of rationales are compared with those trained without rationales and the RNN model which does not incorporate attention or rationales.

The rationale-based models outperform the RNN model and the corresponding attention models trained without rationales. This indicates that choice focussed rationale-based learning can improve the performance of summarization models for IDN. The model that incorporated rationales at the sentence level (sentonly AttnRNN + rationale) shows the most improvement when measured against human-annotated abstractive summaries. R1 and R2 scores show an increase of approximately 14% and 12% respectively compared to the sentonly AttnRNN model and by 7% and 5% respectively compared to the RNN model.

We also show the performance of more recent approaches (using Longformer and flan-t5 models) for comparison. The relatively lower performance of Longformer is mainly because the documents had to be truncated to fit the context window. Despite the instruction to generate extractive summaries, the flan-t5 model tended to paraphrase the sentences from the original text and produced many hallucinations leading to lower scores. These results are reported to contextualise the performance of our method rather than claim state of the art. Fine tuning flan-t5 and optimising the prompt could result in better performance. Similarly, alternate strategies for handling long documents in case of both models could improve their performance. Additionally, by employing our rationale based learning on them, we could potentially get even better performance. This will be explored in future work.

4.2. Human Evaluation

The best and worst scoring summaries from Episode 1 of Before the Storm from the base RNN

[5]https://github.com/AshwathyTR/IDN_SR

Model	R1(abs)	95% CI	R2(abs)	95% CI	RL(abs)	95% CI
SummaRuNNer (RNN)	0.47757	0.47689 - 0.47825	0.12379	0.12323 - 0.124358	0.46460	0.46403 - 0.4651
sentonly AttnRNN	0.44569	0.44464 - 0.44671	0.11624	0.11550 - 0.11697	0.43477	0.43382 - 0.43572
sentonly AttnRNN + rationale	**0.50852**	0.50767 - 0.50936	**0.13036**	0.12977 - 0.13095	**0.49223**	0.49150 - 0.49299
wordonly AttnRNN	0.46508	0.46446 - 0.46568	0.12082	0.12012 - 0.12155	0.45205	0.45152 - 0.45258
wordonly AttnRNN + rationale	0.48124	0.48032 - 0.48209	0.12386	0.12331 - 0.12439	0.46764	0.46681 - 0.46839
AttnRNN	0.44044	0.43983 - 0.44107	0.11081	0.11018 - 0.11142	0.42832	0.42782 - 0.42884
AttnRNN + rationale	0.48637	0.48542 - 0.48725	0.13337	0.13265 - 0.13407	0.47231	0.47147 - 0.47309
Longformer	0.30881	0.30754 - 0.31007	0.06692	0.06641 - 0.06748	0.30237	0.30117 - 0.30354
Google flan-t5-base	0.46577	0.46519 - 0.46637	0.11833	0.11800 - 0.11866	0.41051	0.40997 - 0.41112

Table 1: Mean ROUGE-1 (R1), ROUGE-2 (R2) and ROUGE-L (RL) scores and confidence interval (CI) of generated summaries of IDNSum playthroughs calculated against gold standard human written abstractive summaries(abs).

model (RNN) and Sentence Attention model trained with and without rationales (sentonlyAttnRNN and sentonlyAttnRNN+rationale) were reviewed manually to get an understanding of subjective aspects of quality that automatic metrics are unable to capture. All the output summaries is made available on GitHub[6] and one example is shown in Appendix in section 10.5 for reference.

Summaries produced by the RNN model appear to contain more sentences from the beginning scenes of the games, with a lot of redundant information in the earlier scenes and missing information in the middle and later scenes. The attention based models cover all the scenes in a more balanced way. When comparing the attention-based models trained with and without rationales, it is not immediately obvious if the improvement in the scores comes from including more information that is related to choices and their consequences. While summaries from the rationale-based model appear to be clearer and more relevant overall, both summaries contain sentences that are related to choice points. Further research is required to understand what aspects of summarisation improve when making use of rationales and why.

The summaries from the best model with the best ROUGE score from each episode were also analysed qualitatively. To someone reading the summary without any other context,it only provides a vague, fragmented view of the plot. However, to someone already familiar with the story, the summary can serve as a recap of the plot to some extent. This is because most of the plot elements are not directly conveyed but can be inferred. However, there is some variability in how easy it is to do so from the extracts. It was also noted that even with increased attention to choice points, many important choices and related events were missed.

4.3. Variability Analysis

Table 2 shows the average amount of overlap in the summaries produced by the SummaRuNNer variants with and without rationales. This is calculated by taking the average number of overlapping sentences between each pair of summaries produced by the model of playthroughs from the same episode. Models incorporating sentence-level rationales show lower overlap indicating that they are able to produce summaries that better capture the differences between playthroughs. For example, sentonly Attn + rationale model shows 6% less overlap compared to RNN and 16% less overlap compared to sentonlyAttn model.

4.4. Fault Analysis

Through manual inspection of the model summaries from the best model, sentonly Attention model trained with rationales, four error classes were observed. The error classes are described below and the frequency of occurrence of the error classes is shown in table 3.

1. **Irrelevant Information** *(Common)*: Sentence cannot be matched to any part of the refer-

[6] https://github.com/AshwathyTR/IDN_SR

Model	Avg overlap
RNN	47.85
sentonly Attn	53.48
sentonly Attn + rationale	44.76
wordonly Attn	50.84
wordonly Attn + rationale	49.66
AttnRNN	49.21
AttnRNN + rationale	45.88

Table 2: Average number of overlapping sentences for every pair of summaries from each episode for each model (out of a total of 81 sentences).

ence summary. This includes sentences like *"two firefighters show up as well, and one of them speaks to the officer"* which is from a section of the text not covered by the reference summary. The information contained in such extracts is not contained in the reference summmary and is hence considered irrelevant. This also includes sentences like *"frank and his friend are hanging out next to his rv at the old mill."* which is roughly from the portion of the script covered by a sentence in reference summary: *"the episode ends showing each character's reaction to the wildfire seen in the sky."*, but since the extract itself does not talk about their reaction to the fire, it is considered irrelevant.

2. **Incomplete Information** *(Common)*: Given the model summary, reference summary and the script, the sentence can be matched, but the model summary alone is insufficient to convey the relevant information. It needs additional extracts to be useful. This is different from the previous error case in that some relevant information is contained within this sentence, however, the summary lacks enough context for it to convey the necessary information. This mainly happens due to unclear references to pronouns, need for additional information or inference. An example is, *"chloe: (thinking) let 's get these to david so he can drive away."* which can be matched to a sentence in the reference summary : *"chloe'll have to pick the keys from her stepfather, david madsen, and take them to him since he'll be taking her to school today."*. However, the information is not clearly conveyed by that extract alone. This also includes cases where the reference summary contains a brief mention of a high level event and the model summary captures some detail of the event without conveying the big picture. For example, the reference summary contains the information, *"Cloe can talk to hayden jones , dana ward , and travis keaton"*, and the model summary contains the extract *"budding dramaturge , may your propitious appearance counteract the tragedy of stephanie gingrich 's sudden recusal ."* which is from the conversation between Chloe and Travis Keaton and can be matched as such, but, the fact that a conversation between Chloe and Mr Keaton is happening is not explicitly captured by the extract.

3. **Redundant Information** *(Common)*: Information covered by this sentence is better captured by other sentences already present in the summary. For example, the information conveyed by the extract, *"then she falls on her back and continues crying on the ground."* is better conveyed by *"chloe approaches the car and starts hitting its hood with her fists and crying ."* where the associated sentence in the reference summary is *"she then has a meltdown upon seeing her late father 's car."*.

4. **Unclear /Short Sentences** *(Rare)* : Sentence is too short and generic to be useful. This includes sentences like *"figures."* and *"yeah."* that appear in the summary without any surrounding context. Note that such sentences were coded as such only when the relevant context was not provided by in the surrounding sentences in the summary.

Analysis was done at the sentence level. Ten summaries from each episode were sampled randomly from the summaries that had a ROUGE score below the mean for that episode. Each of the sentences in the sampled summaries was coded against the above error classes. In cases where when there is more than one extract that indirectly or incompletely conveys the same information, the least indirect or incomplete sentence is coded as "Incomplete" and the others are coded as "Redundant". For example, the reference summary for episode 1 says that Chloe has the option of playing a role playing game. The introductory sentence of the game *"you are both famous heroes in the kingdom of avernon , a once peaceful land , now laid to waste by the bloodthirsty raiders of the black well"* conveys this better than an extract from the middle, *"to your left , the raiders ' training ground ."*. Therefore, even though both are indirect, the former is coded as "incomplete" and the latter is coded as "redundant" since it conveys no new information that was not better captured by other sentences in the summary. The results showing prevelance of these errors in the summaries generated by the best model (sentonly attention + rationale) in terms of average number of sentences coded with the error for each of the episodes is shown in table 3. Redundant sentences, sentences having incomplete information and irrelevant sentences are more

Error Type	Ep 1	Ep 2	Ep 3	Avg
Redundant	16.5	13.9	22.3	17.57
Incomplete	18.9	17.4	13.9	16.73
Irrelevant	15.2	17.4	21.5	18.03
Unclear	0.1	0.5	0.1	0.23

Table 3: Fault Analysis: Error types in model summaries and the average number of sentences exhibiting these errors out of a total 81 sentences per summary.

prevalent than unclear sentences, but these three errors are similarly prevalent.

5. Discussion

The results of the experiments show that incorporating rationales in the form of annotations indicating proximity of sentences to choice points improves the performance of attention-based models for extractive summarization of IDN by up to 14% while producing more varied summaries across playthroughs. This suggests that automatically generated choice point annotations can act as effective rationales for IDN since choices are central to the narrative structure of IDN.

Rationale-based learning provides a way to incorporate knowledge and assumptions about narrative structure into training. The work presented in this paper has demonstrated this successfully in the case of choice-based rationales in interactive narratives. This encourages future work that experiments with using rationale-based learning for the summarisation of other types of narratives with rationales indicating aspects that are central to those types of narratives. For example, for traditional narratives including novels and movie scripts, elements like emotion and plot are considered to be central. Approaches used in previous work for tasks like emotion detection in narratives (Kim et al., 2017), turning point identification (Papalampidi et al., 2019) and other heuristics inspired by narrative structure may be used to generate such rationales automatically.

Choices and plot are often heavily entwined in IDNs. This work demonstrates a way to control the relative emphasis placed on choices while generating summaries by setting different values for alpha and window sizes. By focusing on parts of the text that vary most across playthroughs, this could potentially lead to a better understanding of how to generate summaries with more variability. Further analysis exploring the relationship between setting different values for these parameters and the resulting document representations for each playthrough is another future direction that could be explored.

Some limitations of this work are that the fault analysis was only done by one annotator. This creates some subjectivity in the relative prevalence of the error classes. Currently, there are very few resources available for interactive narrative summarisation, so another limitation is that we had only one type of IDN to use in the study. The effectiveness of this approach on other types of IDN is yet to be determined. In this paper, we have used a simple attention mechanism as provided by SummaRuNNer's GitHub repository[7]. While this approach can be applied to other model architectures and other types of attention, testing them empirically is outside the scope of this paper. We also do not empirically prove our results can be transferred to non-interactive narrative text sumamrisation, even though we hypothesise this based on our experience in this domain. The results reported are for single runs with specified hyperparameters. While we have used default values for most hyperparameters, it is worth noting that IDN-Sum has many differences from datasets like CNN-DM on which model hyperparameters were tuned by their original creators. Note that the smaller size and repeated sentences across documents in IDN-Sum, can potentially make the model more prone to overfitting and hence more sensitive to hyperparameters and non-determinism. However, due to time and resource constraints, hyperparameter tuning was performed only on the newly introduced hyperparameters - window_size and alpha.

6. Conclusion

IDNs are becoming increasingly more prevalent, especially as the commercial gaming industry continues to integrate richer narratives into their offerings. Choices are a central mechanic in many interactive narratives and in this paper, we have explored choice focussed self-supervised rationale-based learning at the word and sentence level to improve IDN extractive text summarisation. Our results not only advance the field of IDN, but the positive results obtained in this domain also encourage the application of rationale-based learning to other types of narratives, suggesting a wider impact.

Evaluation using ROUGE metrics shows that models trained using these rationales perform up to 14% better than those trained without. An analysis of variability of the produced summaries also indicates that summaries produced by models placing special emphasis on the choices are up to 16% more varied across playthroughs. Manual fault analysis and qualitative analysis were performed which highlighted that the main types of errors present are redundant information, incomplete information and irrelevant information. These

[7]https://github.com/hpzhao/SummaRuNNer

analyses also indicate that summaries may be useful in giving a recap of events to readers already familiar with the narrative. However, coverage of choices and differences across playthroughs still appears low.

These results suggest a promising new direction for narrative-based text summarization models. Future work will include evaluation of this approach on more datasets and model architectures with different attention mechanisms, and performing task-based evaluations with IDN authors to assess the utility of these summaries as authoring feedback.

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9. Language Resource References

n/a

10. Appendix

10.1. Training details for SummaRuNNer variants

Full list of parameters:
embed_dim = 100
embed_num = 100
pos_dim = 50
pos_num = 3000
seg_num = 10
hidden_size = 200
lr = 1e-3
batch_size = 1
epochs = 5 with early stopping if no improvement was observed within 5 validation rounds.

seed = 66
report_every = 30
seq_trunc = 50
topk = 81

Optimal hyperparameters were found through manual tuning within range : 2-8 sentences and 20-80 words for ws and 0.25 - 0.99 for alpha.

10.2. Infrastructure

The models were trained on compute cluster containing Nvidia Tesla V100 and Nvidia GTX 1080Ti graphics cards. Only 1 GPU was used for training each model.

10.3. Further Analysis

Table 4 shows ROUGE scores of the model summaries calculated against the automatically generated extractive summaries from IDNSum rather than the abstractive summaries shown in Table 1 It is worth noting that when considering these ROUGE scores, no improvement is observed when rationales were introduced and attention models trained without rationale seem to perform best. To investigate this further, ROUGE scores with stop word filter turned on were also calculated against the human authored abstractive summaries and automatically aligned extractive summaries. This is shown in table 7. Here, we again see that rationale-based models perform better in all cases. This suggests that the better ROUGE scores shown by the attention models without rationales are due to keyword overlap on insignificant words while the rationale based models perform better when considering significant words.

10.4. Validation Scores

Table 6 shows the corresponding validation scores for the test score shown in table 1.

10.5. Model Outputs

This Appendix shows an example of model output from each of models. The human authored abstractive summary for the IDN is also included for reference.

10.5.1. Human authored abstractive summary

the episode starts with a hooded chloe price smoking a cigarette and standing at the railroad tracks , waiting for the train to come . after its passage , she takes off her hood and goes towards the old mill , ignoring the " no trespassing " sign after jumping over a fence . in order to get inside the mill , she starts an argument with the bouncer , in which she can win and be allowed inside or have to use the backdoor to get in if she fails . after entering , she can interact with people , objects , graffiti and even steal a shirt and some money (or not) . if she steals the money , she 'll have the option of buying weed from frank bowers or save the money for later . after this , she 'll try to go through the crowd in order to see the band that 's playing and ends up bumping into two skeevy guys , the taller one being somewhat aggressive towards her . however , she 'll manage to see the band by going upstairs , even with the floor there being rotten . she enjoys the music for a while until the two guys from before appear and confront her . she 's saved by rachel amber , in her very first appearance , and will have the first major choice of the game : attack one of the guy s or run without doing nothing . after running downstairs , the two girls stop and look at frank , who notices what 's going to happen and quickly stops the guys , causing both of them to get angry and leave the mill . rachel pulls chloe along with her , and they enjoy the firewalk show for the rest of the night . the next morning , chloe is shown waking up in her room , at the price household . she sits up and takes her red ' oregon ' ashtray and starts smoking a cigarette (or weed , if she bought it from frank earlier with the stolen money) . chloe can look at a photo of her and max caulfield as kids along with her dad , william price and can also look at her diary . after being called by her mother , joyce price , for breakfast downstairs , she 'll get up from her bed and will be able to interact with many objects around her room . she 'll change clothes before leaving her room (the player gets to choose her outfit) . due to having drunk too much , chloe notices her phone is missing . she then goes to her mother 's room to call her phone with her mother 's phone . there , she can interact with another object before using her mother 's phone . by doing this , chloe finds her phone in the bathroom , and just after she takes it , her mother asks her from downstairs to bring her purse along with her phone , causing her to go back to the room . when she finally goes downstairs , she can interact with the objects around the living room and even get some information that can be used later on . she 'll then talk with her mother about several topics , and at the end of the conversation , she 'll have to choose between being comprehensive towards joyce or saying how she actually feels . depending on her choice , joyce will be either kind or tough towards her . chloe'll have to pick the keys from her stepfather , david madsen , and take them to him since he 'll be taking her to school today . after leaving the house and going to david , he 'll ask her to get the tools he needs to fix his car in the garage . after this , she gets in the car and david will try to start a conversation with her . she can either start a fight with him or listen to what he has to say . after the talk , chloe will fall asleep and have a weird

Model	R1(ext)	R2(ext)	RL(ext)
RNN	0.60399	0.27518	0.59484
sentonly AttnRNN	0.61649	0.27374	0.60744
sentonly AttnRNN +rationale	0.60082	0.29412	0.59181
wordonly AttnRNN	0.61835	0.28871	0.61041
wordonly AttnRNN +rationale	0.61178	**0.30197**	0.60336
AttnRNN	**0.61975**	0.25674	**0.61095**
AttnRNN +rationale	0.61073	0.29291	0.60227
Google flan-t5-base (zero-shot)	0.50939	0.15510	0.45585

Table 4: ROUGE scores against automatically generated extractive summary. Rationales do not seem to show an improvement here in case of SummaRuNNer models. Refer Table 7 for further analysis of why.

dream about being in a car with her dad , going to pick up her mom from the grocery store . the dream abruptly ends with a truck crashing through william 's car . when she wakes up , she 's already at blackwell academy . there , she can talk to eliot hampden (and choose whether or not she wants to watch the tempest play with him) , victoria chase (with the option of sabotaging her homework if doing so) , skip matthews (with the option of listening to the demo of his band , pisshead , and giving him your opinion on it if doing so) , principal wells (only if she sits on a crate on the stage and with the option of starting a backtalk challenge with him if doing so) , michelle grant , mikey north and steph gingrich (in order to get her dvd and with the additional option of playing a tabletop game with them) , and other students . afterwards , she 'll go towards the school entrance , but she 'll be interrupted by drew north and nathan prescott , who are starting a fight . a student called samantha myers urges chloe to do something to help nathan , and chloe can either backtalk drew and defend nathan or just ignore them , which will cause samantha to either thank chloe or be upset with her for not helping . when the fight is over , she can finally enter the school , and just as she opens the door , rachel appears on the other side and pulls her along with her to the drama lab where travis keaton is rehearsing with dana ward and hayden jones . rachel will ask for her opinion on miranda 's love for fernando , both portrayed by dana and hayden respectively in " the tempest " play , and chloe can choose whether to say it 's true love or not . after the class is over , everyone will leave the room , except for chloe and rachel . rachel will change to normal clothes and ask chloe to get her belt from her bag and bring it to her . after doing this , they 'll have a short conversation before rachel invites chloe to skip school , and they end up in a train carriage where , after finding some crates to sit on , they play the game two truths and a lie . chloe can either cheat or follow the game rules . after their game , chloe will have the option of sharing or not her earbuds with rachel during their trip . upon arriving at overlook park , they 'll play another game using the viewfinders to spy on people around the park . however , the viewfinder that they intend to use it broken . chloe asks rachel for something sharp like a knife and she gives her a nail file , which chloe uses to unscrew a deducation plate from a park bench and then uses it to break open the viewfinder , allowing them to use it for free . when they get a closer view of the last couple available , a man and a woman under a tree , rachel gets distressed when they start kissing and puts an end to their game , telling chloe she needs to get drunk . they 'll then go to the other side of the park , where a couple is having a picnic and have a bottle of wine on their table . rachel approaches the couple and starts acting sick , throwing herself to the ground and pretending to be in need of resuscitation . chloe can encourage the man to help her , either succeeding or failing on doing so resulting in the man " saving " rachel 's life or t he woman seeing through their ploy . whatever the outcome is , the two girls will get the wine . after this , they 're shown walking on the train tracks . chloe invites rachel to explore a junkyard nearby and rachel lets her explore on her own . after a long conversation between the two , no matter what choices the player has made so far , rachel will leave , but not before chloe tries to convince her to stay . chloe has the option to say that they have a real friendship or something more . once rachel leaves , chloe gets angry and breaks everything around her . she then has a meltdown upon seeing her late father 's car . she 'll fall asleep and have another dream about her father , this time , with him advising / warning her on her relationship with rachel , in which chloe will see rachel outside of the car , who will then catch fire . when she wakes up , it 's already night and she goes back to the overlook where she finds rachel . upon a brief dialogue , in which rachel reveals the man they had seen at the park was her dad , and that he was cheating on her mother with that woman . rachel takes out a photo of her as a kid with her father , asks chloe for her lighter which she uses it burn the photo , throwing it into a nearby trash bin , and starting a

Episode	Model	R1(abs)	95% CI	R2(abs)	95% CI	RL(abs)	95% CI
1	RNN	0.49521	0.49458 - 0.49581	0.14029	0.13992 - 0.14066	0.47715	0.47655 - 0.47771
	sentonly AttnRNN	0.46148	0.46081 - 0.46218	0.13227	0.13188 - 0.13267	0.44461	0.44396 - 0.44527
	sentonly AttnRNN + rationale	0.52077	0.52029 - 0.52125	0.14416	0.14385 - 0.14448	0.50083	0.50037 - 0.50128
	wordonly AttnRNN	0.47804	0.47747 - 0.47857	0.14499	0.14468 - 0.14528	0.46269	0.46215 - 0.46318
	wordonly AttnRNN + rationale	0.50659	0.50618 - 0.50699	0.15451	0.15422 - 0.15481	0.48582	0.48543 - 0.48621
	AttnRNN	0.45932	0.45868 - 0.45999	0.13294	0.13255 - 0.13331	0.44133	0.44072 - 0.44196
	AttnRNN + rationale	0.50419	0.50376 - 0.50466	0.15559	0.15525 - 0.15595	0.48506	0.48462 - 0.48553
2	RNN	0.47952	0.47877 - 0.48031	0.12999	0.12961 - 0.13037	0.46674	0.46602 - 0.46752
	sentonly AttnRNN	0.47179	0.47118 - 0.47246)	0.13235	0.13204 - 0.13270	0.46128	0.46070 - 0.46190
	sentonly AttnRNN + rationale	0.52678	0.52622 - 0.52737	0.14139	0.14108 - 0.14170	0.50906	0.50856 - 0.50960
	wordonly AttnRNN	0.47025	0.46958 - 0.47100	0.12487	0.12448 - 0.12529	0.45602	0.45544 - 0.45669
	wordonly AttnRNN + rationale	0.51053	0.51001 - 0.51111	0.14033	0.13998 - 0.14067	0.49634	0.49584 - 0.49686
	AttnRNN	0.43672	0.43611 - 0.43730	0.10995	0.10963 - 0.11028	0.42527	0.42469 - 0.42585
	AttnRNN + rationale	0.50444	0.50385 - 0.50507	0.14004	0.13968 - 0.14041	0.49010	0.48955 - 0.49066
3	RNN	0.45837	0.45787 - 0.45885	0.10118	. 0.10089 - 0.10147	0.45031	0.44979 - 0.45079
	sentonly AttnRNN	0.40413	0.40347 - 0.40481	0.08416	0.08388 - 0.08443	0.39872	0.39807 - 0.39936
	sentonly AttnRNN + rationale	0.47840	0.47748 - 0.47938	0.10560	0.10525 - 0.10596	0.46718	0.46626 - 0.46815
	wordonly AttnRNN	0.44729	0.44684 - 0.44776	0.09265	0.09240 - 0.09291	0.43778	0.43732 - 0.43822
	wordonly AttnRNN + rationale	0.44883	0.44826 - 0.44943	0.09939	0.09909 - 0.09967	0.44074	0.44020 - 0.44131
	AttnRNN	0.42565	0.42504 - 0.42624	0.08958	0.08930 - 0.08985	0.41872	0.41814 - 0.41929
	AttnRNN + rationale	0.45080	0.45012 - 0.45151	0.10455	0.10426 - 0.10485	0.44208	0.44143 - 0.44280

Table 5: ROUGE Scores against human annotated abstraction summary calculated per episode.

wildfire by kicking the bin into a tree nearby . rachel then screams , increasing the fire 's intensity . the episode ends showing each character 's reaction to the wildfire seen in the sky .

10.5.2. Summary from SummaRuNNer (RNN)

: sc : s0 : chloe price , standing on train tracks and wearing a black hoodie , flicks her lighter a few times and lights up her cigarette . she takes a deep breath , then takes the cigarette out of her

Model	R1(abs)	R2(abs)	RL(abs)
RNN	0.42111	0.09644	0.40740
sentonlyAttn	0.40682	0.12015	0.39555
sentonlyAttn + rationale	0.43766	0.11078	0.42361
wordonlyAttn	0.41792	0.11259	0.40328
wordonlyAttn + rationale	0.42995	0.12193	0.41441
AttnRNN	0.40909	0.10419	0.39591
AttnRNN + rationale	0.42980	0.11872	0.41367

Table 6: Validation ROUGE scores against human written abstractive summary.

mouth and breathes out the smoke . a train begins to approach her . chloe takes another couple hits from her cigarette before letting it fall in between the tracks . she jumps out of the way of the train at the last second , watching it go by , then takes off her hood and looks at the sawmill across from her . this place is awesome . [scoffs] meaning you . yeah , your problem . those guys need to get a room . man 1 then slaps man 2 . i really get it now , i — i do . it 's not a bad fake , kid . the bouncer throws her id on the ground . chloe picks it up and walks away from him . or can something around here help me convince him ? [ex] s0 : chloe can try to walk past the bouncer to the door . he holds out his arm to block her and she turns around exasperation . i heard firewalk is playing here tonight . just follow the lights and the sound . [ex] chloe : (thinking) still a dick . that guy 's a dick . chloe releases the parking brake and the car slides down . the vendor goes talk to the truck driver . [ex] s0 : chloe spots a box with money near the shirts . [ex] : sc : s0 : chloe sees the crowd and tries to push through it . look at that getup . what are you even doing here ? hard to get to the stage . i could definitely use something to take the edge off . after a few moments , the guy she ran into earlier and his friend come to confront her . guy 2 goes to help guy 1 who 's on the floor and chloe runs to rachel . they look at each other and notice guy 2 helping guy 1 to get up . they run downstairs and rachel frees her hand from chloe 's . rachel takes chloe 's hand again and they run towards the entrance to the show . frank sees them and chloe stops , looking at the guys behind him . he then jumps in front of the guys . rachel blows them a kiss and pulls chloe by the hand , who also blows them a kiss and flips them off . in front of the stage , rachel and chloe dance together . the night ends with chloe making one last pose before going back to dancing . [ex] : sc : : sc : s0 : chloe 's alarm clock starts playing music and she wakes up . she rolls on her side and picks up her ashtray , then she puts the ashtray below her chest and starts smoking . after a few moments she stops smoking , puts the ashtray away and sits up on her bed . daily rituals are important , even when they involve writing unread letters to friends who 've forgotten you ... i smell like cigarettes and beer . okay , mom 's phone is probably in her room . i can use it to call mine , then figure out where the hell i left it . she then gets her mom 's phone from the nightstand and unlocks it . how can mom look at this every day and not see what a tool she 's dating ? chloe follows the sound and finds her phone on the bathroom floor , under a towel , beside the toilet . you can put my purse on the dining table . might still have time for breakfast if you hurry . i know what time you came home last night . just let me know so i can stop fighting with blackwell to keep you on scholarship . but sometimes we need to make more room in our hearts for new people . okay , david 's waiting . chloe looks back to see if joyce is not looking and quickly puts the money in her mom 's purse . the car , too . chloe throws the keys to david and he catches them in time , putting them in his back pocket . better just get the socket wrench and get this over with . she goes to his toolbox , leans down and opens it . she then takes the socket wrench . he frowns at her and holds out his hand , and she gives him the socket wrench . he takes it and goes back to fixing his car . he takes the toolbox from the ground and walks towards a table in the corner . burnin ' the midnight oil again . blackwell theater at its most pretentious . skip gets his phone and plays the demo to chloe . after it ends he puts his phone in his back pocket . well ... the prescotts have made an extremely generous donation to the school , which is good , but instead of going to support more science and mathematics , it 's all being dedicated to the arts . principal wells approaches chloe and she gets up from the crate , jumping off the stage and landing in front of him . rachel climbs into a carriage on the train , then helps chloe as she joins her . they come across the american rust salvage yard . chloe picks the bat up from the ground and looks around angrily . rachel puts her hand on the glass , chloe puts hers on the other side . a truck appears outside the window and crashes into the left side of william 's car . she gets out of it and leans on the hood one last time . then she goes towards the train tracks and starts walking back to the overlook , as a raven flies overhead . as the garbage inside the can starts burning , she takes a step back . frank stares in shock at the fire and smoke in the distance . james amber and principal wells are talking to a police officer at the blackwell parking lot . the woman seen kissing james is sitting on a bench at the overlook park , looking at the fire .

Model	R1(abs)	R2(abs)	R1(ext)	R2(ext)
RNN	0.32315	0.03680	0.45616	0.20193
sentonly AttnRNN	0.32272	0.03865	0.45859	0.19988
sentonly AttnRNN + rationale	0.33955	0.03969	0.46052	0.21759
wordonly AttnRNN	0.33317	0.03699	0.47849	0.21426
wordonly AttnRNN + rationale	**0.34771**	**0.04240**	0.49499	**0.23106**
AttnRNN	0.31796	0.03191	0.45885	0.17821
AttnRNN + rationale	0.34716	0.04234	**0.50062**	0.22407

Table 7: Rouge Scores calculated against the human-authored abstractive summary (abs) and automatically aligned extractive summary (ext) with the stop word filter turned on for Summarunner variants. Results show rationale-based models performing better in all cases indicating that the higher rouge scores for non-rationale-based models in table 4 are due to overlap on insignificant words.

10.5.3. Summary from Sentonly SummaRuNNer trained without rationales (sentonly AttnRNN)

: sc : s0 : chloe price , standing on train tracks and wearing a black hoodie , flicks her lighter a few times and lights up her cigarette . a train begins to approach her . she then walks down toward the mill . the bouncer throws her id on the ground . chloe picks it up and walks away from him . the pitbull does n't bark at chloe . the vendor goes talk to the truck driver . [ex] : sc : s0 : chloe sees the crowd and tries to push through it . you 're trying too hard . after a few moments , the guy she ran into earlier and his friend come to confront her . they look at each other and notice guy 2 helping guy 1 to get up . the men leave and frank looks back to see that rachel and chloe are gone . she rolls on her side and picks up her ashtray , then she puts the ashtray below her chest and starts smoking . after a few moments she stops smoking , puts the ashtray away and sits up on her bed . how can mom look at this every day and not see what a tool she 's dating ? chloe follows the sound and finds her phone on the bathroom floor , under a towel , beside the toilet . oh , can you grab my cellphone too ? she then goes downstairs . you used to love to learn . i used to think drugs were lame , too . money 's tight enough as it is . he 's a good man . and you will say thank you . try not to kill each other . the car , too . she goes to his side and he starts talking . he takes it and goes back to fixing his car . then , both he and chloe get into the car . william does n't answer . i know what a spark plug does , jerkwad . a truck crashes into the left side of the car , hitting william , and then everything goes black . eliot sees her , puts down the book he 's reading , and approaches her . stopped any gang wars lately ? so i went to the mill last night , caught firewalk live . potion would n't have worked . you 're asking me ? you are an elf barbarian . we 're supposed to kill the dur - dude . upon arriving at the training ground you are spotted by a heavyset orc , who immediately shouts and points . there are a dozen raiders on the training field , all of whom raise their weapons and charge ! the heavyset orc sergeant still remains . the orc clutches his groin , never to father children again . what about the loot ? my dad lost his job at the shipyard when your dad closed it down . mr. keaton , sorry to interrupt , but does this look better ? first she pulls out a photo of a young rachel with her father . a rhetorical question ? rachel climbs into a carriage on the train , then helps chloe as she joins her . wish max were here , so i could ask . rachel moves to sit on the floor of the train carriage . second , i was born in new york , the land of fashion and broadway , to which i will one day return when my heinous exile here in arcadia bay comes to an end . rachel takes chloe 's marker and writes " rachel amber " on the floor of the train carriage with her right hand and then repeats the same successfully with her left hand . but i 've passed by your locker a few times , and i 've seen that old photo of a cat you keep in there . luckily , we 've got some high - tech surveillance equipment right here . i 'd love to get it working for her . but you 've been on me for three hours ! stealing a dedication plate takes ... persistence . at chloe 's mark , the man and the woman start kissing . oh , honey , i think we used the vibrating bed for too long . last i checked , you 're supposed to be chloe price . or we could go try to find a liquor store instead ? the man and woman get up and go over to rachel . talk about committing to a performance . [ex] s0 : chloe tries to snatch the wine , but the couple notices her . there 's a ranger station on the other side of the park . you 'd better run away before it gets you too . guess we 're leaving now . but i want to find out . " burning the midnight oil " song is still playing on the radio . william turns it off and looks at chloe . the raven suddenly appears on the hood of the car , and almost immediately disappears . a truck appears outside the window and crashes into the left side of william 's car . then she goes towards the train tracks and starts walking back to the overlook , as a raven flies overhead . i do n't know how to talk about this . so when i saw he got a text from an unknown number ... asking him to meet ... frank and his friend are hanging out next to his rv at the old mill . they both look at the fire and david puts his arm around her . the three of them look at the fire . james amber and principal wells are talking to a police officer at the blackwell parking lot . the woman seen kissing james is sitting on a bench at the overlook park , looking at the fire . while smoking a cigarette , she starts smiling mysteriously .

10.5.4. Summary from Sentonly SummaRuNNer trained with rationales (sentonly AttnRNN + rationale)

: sc : s0 : chloe price , standing on train tracks and wearing a black hoodie , flicks her lighter a few times and lights up her cigarette . a train begins to approach her . chloe releases the parking brake and the car slides down . after a few moments , the guy she ran into earlier and his friend come to confront her . guy 2 goes to help guy 1 who 's on the floor and chloe runs to rachel . they look at each other and notice guy 2 helping guy 1 to get up . frank sees them and chloe stops , looking at the guys behind him . frank looks at the guys and back to chloe and rachel . he then jumps in front of the guys . the men leave and frank looks back to see that rachel and chloe are gone . if she attacked the skeevy guys , she will now have a bruise under her eye . she rolls on her side and picks up her ashtray , then she puts the ashtray below her chest and starts smoking . after a few moments she stops smoking , puts the ashtray away and sits up on her bed . i can use it to call mine , then figure out where the hell i left it . how can mom look at this every day and not see what a tool she 's dating ? chloe follows the sound and finds her phone on the bathroom floor , under a towel , beside the toilet . she then goes downstairs . you can put my purse on the dining table . [ex] s0 : choice : slip money in joyce 's purse (stole vendor 's money and did n't buy weed from frank) he takes the toolbox from the ground and walks towards a table in the corner . you are both famous heroes in the kingdom of avernon , a once peaceful land , now laid to waste by the bloodthirsty raiders of the black well . alone , you have fought your way through the raider camps , seeking their warlord leader , duurgaron the unscarred . to your left , the raiders ' training ground . upon arriving at the training ground you are spotted by a heavyset orc , who immediately shouts and points . there are a dozen raiders on the training field , all of whom raise their weapons and charge ! the orc clutches his groin , never to father children again . rachel takes chloe 's hand and pulls her into the building . first she pulls out a photo of a young rachel with her father . rachel has her back turned to chloe and is wearing jeans and a bra . to tell the truth , i went to bed last night wishing it never had to end . a rhetorical question ? rachel puts more makeup on chloe 's bruise . when she 's done , the bruise is no longer visible . rachel climbs into a carriage on the train , then helps chloe as she joins her . rachel moves to sit on the floor of the train carriage . second , i was born in new york , the land of fashion and broadway , to which i will one day return when my heinous exile here in arcadia bay comes to an end . rachel takes chloe 's marker and writes " rachel amber " on the floor of the train carriage with her right hand and then repeats the same successfully with her left hand . so new york 's on the bucket list ? but i 've passed by your locker a few times , and i 've seen that old photo of a cat you keep in there . hate to break it to you , but chloe price is n't exactly renowned throughout arcadia bay as a bastion of trust and empathy . rachel smiles , takes an earbud from chloe and puts it in . after they finish listening to the music , both girls take out their earbuds and chloe puts them away . this game involves spying on people from afar . luckily , we 've got some high - tech surveillance equipment right here . i admit , it was really dumb to lock the keys in the car . stealing a dedication plate takes ... persistence . chloe uses the plate to pry open the viewfinder . she throws the plate to the ground and takes the quarter from inside the viewfinder . she approaches rachel and holds out the quarter triumphantly . the girls see a man and a woman , meeting under the oak tree . at chloe 's mark , the man and the woman start kissing . oh , honey , i think we used the vibrating bed for too long . last i checked , you 're supposed to be chloe price . they have a bottle of wine . or we could go try to find a liquor store instead ? there 's a ranger station on the other side of the park . rachel and chloe walk down a train track . rachel is drinking the wine that the two of them stole from the picnickers and chloe is balancing on the rails . they come across the american rust salvage yard . [ex] s0 : chloe scans the area , and looks almost relieved when she finds a baseball bat leaning against one of the old rusted cars . " burning the midnight oil " song is still playing on the radio . william turns it off and looks at chloe . the raven suddenly appears on the hood of the car , and almost immediately disappears . [ex] s0 : chloe sees rachel , walking towards the oak tree , as william 's car passes it by . a truck appears outside the window and crashes into the left side of william 's car . she gets out of it and leans on the hood one last time . then she goes towards the train tracks and starts walking back to the overlook , as a raven flies overhead . so when i saw he got a text from an unknown number ... asking him to meet ... rachel sets the photo on fire and lets it fall into the trash can . as the garbage inside the can starts burning , she takes a step back . its burning contents fall out towards the oak tree , setting it on fire . rachel starts screaming loudly , and at the same time a gust of wind comes from behind her , spreading the fire to the entire tree . frank and his friend are hanging out next to his rv at the old mill . his friend is on the phone and frank is drinking a bottle of beer . frank stares in shock at the fire and smoke in the distance . they both look at the fire and david puts his arm around her . [ex] s0 : nathan is sitting at the fountain , looking through his picture book . then he notices steph , mikey and drew , hanging at the picnic table far from him . the three of them look at the fire . james amber and principal wells are talking to a police officer at the blackwell parking lot . the woman seen kissing james is sitting on a bench at the overlook park , looking at the fire .

10.5.5. Summary from wordonly SummaRuNNer trained without rationales (wordonly AttnRNN)

: sc : s0 : chloe price , standing on train tracks and wearing a black hoodie , flicks her lighter a few times and lights up her cigarette . she takes a deep breath , then takes the cigarette out of her mouth and breathes out the smoke . a train begins to approach her . chloe takes another couple hits from her cigarette before letting it fall in between the tracks . she jumps out of the way of the train at the last second , watching it go by , then takes off her hood and looks at the sawmill across from her . she then walks down toward the mill . the bouncer throws her id on the ground . chloe picks it up and walks away from him . he holds out his arm to block her and she turns around exasperation . the pitbull does n't bark at chloe . just follow the lights and the sound . [ex] s0 : chloe bends down and pets the pitbull . you looking to get beat ? chloe releases the parking brake and the car slides down . the vendor goes talk to the truck driver . [ex] s0 : chloe spots a box with money near the shirts . [ex] : sc : s0 : chloe sees the crowd and tries to push through it . studs ? you 're trying too hard . after a few moments , the guy she ran into earlier and his friend come to confront her . they look at each other and notice guy 2 helping guy 1 to get up . frank sees them and chloe stops , looking at the guys behind him . the men leave and frank looks back to see that rachel and chloe are gone . the night ends with chloe making one last pose before going back to dancing . if she attacked the skeevy guys , she will now have a bruise under her eye . she rolls on her side and picks up her ashtray , then she puts the ashtray below her chest and starts smoking . after a few moments she stops smoking , puts the ashtray away and sits up on her bed . okay , mom 's phone is probably in her room . i can use it to call mine , then figure out where the hell i left it . i think i saw mom 's purse in her room . [ex] s0 : chloe goes back to joyce and david 's room and takes her purse . oh , can you grab my cellphone too ? [ex] s0 : chloe slips joyce 's phone into her purse and leaves the room . she then goes downstairs . you can put my purse on the dining table . you used to love to learn . you 'll need to bring him his keys from the ashtray . [ex] s0 : choice : slip money in joyce 's purse (stole vendor 's money and did n't buy weed from frank) the car , too . she goes to his side and he starts talking . [ex] david : chloe , is that a black eye ? she goes to his toolbox , leans down and opens it . he takes it and goes back to fixing his car . then , both he and chloe get into the car . [ex] s0 : chloe looks at the purse beside her . [ex] s0 : chloe hears a horn three times and approaches william in panic . a truck crashes into the left side of the car , hitting william , and then everything goes black . out of the car , chloe . [ex] s0 : chloe opens the door , gets out of the car and stands holding the door looking at david . i 'd rather have my eyes gouged out with rusted forks . after it ends he puts his phone in his back pocket . if i had known the celestial avenger was bloodied , i would have totally given him my potion . you stand at a three - way crossing . to your left , the raiders ' training ground . rachel has her back turned to chloe and is wearing jeans and a bra . a rhetorical question ? rachel starts running after the passing train . both girls take off running . rachel climbs into a carriage on the train , then helps chloe as she joins her . rachel moves to sit on the floor of the train carriage . rachel takes chloe 's marker and writes " rachel amber " on the floor of the train carriage with her right hand and then repeats the same successfully with her left hand . i admit , it was really dumb to lock the keys in the car . stealing a dedication plate takes ... persistence . chloe uses the plate to pry open the viewfinder . the girls see a man and a woman , meeting under the oak tree . oh , honey , i think we used the vibrating bed for too long . or we could go try to find a liquor store instead ? i think it 's contagious . you 'd better run away before it gets you too . the raven suddenly appears on the hood of the car , and almost immediately disappears . a truck appears outside the window and crashes into the left side of william 's car . she gets out of it and leans on the hood one last time . then she goes towards the train tracks and starts walking back to the overlook , as a raven flies overhead . so when i saw he got a text from an unknown number ... asking him to meet ... plus you came along with me , no questions asked . my mom might skip grounding and just go straight to the death penalty . they both look at the fire and david puts his arm around her . [ex] s0 : nathan is sitting at the fountain , looking through his picture book . the three of them look at the fire . the woman seen kissing james is sitting on a bench at the overlook park , looking at the fire . while smoking a cigarette , she starts smiling mysteriously .

10.5.6. Summary from wordonly SummaRuNNer trained with rationales (wordonly AttnRNN + rationale)

: sc : s0 : chloe price , standing on train tracks and wearing a black hoodie , flicks her lighter a few times and lights up her cigarette . chloe picks it up and walks away from him . the pitbull does n't bark at chloe . she reaches the shirt and the vendor slaps her hand away . chloe releases the parking brake and the car slides down . the vendor goes talk to the truck driver . [ex] : sc : s0 : chloe sees the crowd and tries to push through it . a man in crowd elbows chloe backward and she bumps into a man , spilling his beer . [ex] s0 : chloe looks at the stairwell near the entrance . after a few moments , the guy she ran into earlier and his friend come to confront her . they look at each other and notice guy 2 helping guy 1 to get up . frank sees them and chloe stops , looking at the guys behind him . he then jumps in front of the guys . rachel blows them a kiss and pulls chloe by the hand , who also blows them a kiss and flips them off . the men leave and frank looks back to see that rachel and chloe are gone . she rolls on her side and picks up her ashtray , then she puts the ashtray below her chest and starts smoking . after a few moments she stops smoking , puts the ashtray away and sits up on her bed . okay , mom 's phone is probably in her room . i can use it to call mine , then figure out where the hell i left it . chloe follows the sound and finds her phone on the bathroom floor , under a towel , beside the toilet . [ex] s0 : chloe slips joyce 's phone into her purse and leaves the room . she then goes downstairs . you 'll need to bring him his keys from the ashtray . the car , too . she goes to his side and he starts talking . he takes it and goes back to fixing his car . [ex] s0 : david goes to the garage and puts back the socket wrench inside his toolbox . he takes the toolbox from the ground and walks towards a table in the corner . then , both he and chloe get into the car . chloe looks at the socket wrench in front of her . a truck crashes into the left side of the car , hitting william , and then everything goes black . out of the car , chloe . [ex] s0 : chloe opens the door , gets out of the car and stands holding the door looking at david . i 'd rather have my eyes gouged out with rusted forks . so i went to the mill last night , caught firewalk live . if i had known the celestial avenger was bloodied , i would have totally given him my potion . rachel takes chloe 's hand and pulls her into the building . chloe and rachel are left alone . rachel has her back turned to chloe and is wearing jeans and a bra . rachel starts running after the passing train . rachel climbs into a carriage on the train , then helps chloe as she joins her . rachel moves to sit on the floor of the train carriage . rachel takes chloe 's marker and writes " rachel amber " on the floor of the train carriage with her right hand and then repeats the same successfully with her left hand . his name was bongo . he was a gift from my dad . hate to break it to you , but chloe price is n't exactly renowned throughout arcadia bay as a bastion of trust and empathy . after they finish listening to the music , both girls take out their earbuds and chloe puts them away . i admit , it was really dumb to lock the keys in the car . stealing a dedication plate takes ... persistence . chloe uses the plate to pry open the viewfinder . she throws the plate to the ground and takes the quarter from inside the viewfinder . at chloe 's mark , the man and the woman start kissing . oh , honey , i think we used the vibrating bed for too long . last i checked , you 're supposed to be chloe price . or we could go try to find a liquor store instead ? the girls run to the parking lot . rachel and chloe walk down a train track . rachel is drinking the wine that the two of them stole from the picnickers and chloe is balancing on the rails . they come across the american rust salvage yard . rachel 's been acting kind of standoffish ever since we left the park . chloe smashes the mannequin 's head off . after some random smashing , chloe hits the truck 's tailgate . there she sees her fathers wrecked car and drops the bat . william turns it off and looks at chloe . the raven suddenly appears on the hood of the car , and almost immediately disappears . [ex] s0 : chloe sees rachel , walking towards the oak tree , as william 's car passes it by . [ex] s0 : chloe looks at one of the objects around her . a truck appears outside the window and crashes into the left side of william 's car . she gets out of it and leans on the hood one last time . then she goes towards the train tracks and starts walking back to the overlook , as a raven flies overhead . my mom might skip grounding and just go straight to the death penalty . as the garbage inside the can starts burning , she takes a step back . its burning contents fall out towards the oak tree , setting it on fire . frank and his friend are hanging out next to his rv at the old mill . frank stares in shock at the fire and smoke in the distance . they both look at the fire and david puts his arm around her . [ex] s0 : nathan is sitting at the fountain , looking through his picture book . then he notices steph , mikey and drew , hanging at the picnic table far from him . james amber and principal wells are talking to a police officer at the blackwell parking lot . the woman seen kissing james is sitting on a bench at the overlook park , looking at the fire . while smoking a cigarette , she starts smiling mysteriously .

10.5.7. Summary from SummaRuNNer with both sentence and word level attention trained without rationales (AttnRNN)

: sc : s0 : chloe price , standing on train tracks and wearing a black hoodie , flicks her lighter a few times and lights up her cigarette . she takes a deep breath , then takes the cigarette out of her mouth and breathes out the smoke . a train begins to approach her . she then walks down toward the mill . the bouncer throws her id on the ground . chloe picks it up and walks away from him . the pitbull does n't bark at chloe . you looking to get beat ? the vendor goes talk to the truck driver . [ex] : sc : s0 : chloe sees the crowd and tries to push through it . [ex] s0 : chloe tries to leave , but the guy steps in her way . you 're trying too hard . after a few moments , the guy she ran into earlier and his friend come to confront her . they look at each other and notice guy 2 helping guy 1 to get up . the men leave and frank looks back to see that rachel and chloe are gone . if she attacked the skeevy guys , she will now have a bruise under her eye . she rolls on her side and picks up her ashtray , then she puts the ashtray below her chest and starts smoking . after a few moments she stops smoking , puts the ashtray away and sits up on her bed . [ex] s0 : chloe goes to her drawer and gets changed . i can use it to call mine , then figure out where the hell i left it . oh , can you grab my cellphone too ? [ex] s0 : chloe slips joyce 's phone into her purse and leaves the room . she then goes downstairs . you used to love to learn . david 's had some hard times , too , you know . unless he tries to give me advice . [ex] s0 : choice : slip money in joyce 's purse (stole vendor 's money and did n't buy weed from frank) she goes to his side and he starts talking . [ex] david : chloe , is that a black eye ? [ex] s0 : david goes to the garage and puts back the socket wrench inside his toolbox . then , both he and chloe get into the car . william does n't answer . chloe sees the said family photo with david replacing william . [ex] s0 : chloe hears a horn three times and approaches william in panic . [ex] s0 : chloe opens the door , gets out of the car and stands holding the door looking at david . i 'd rather have my eyes gouged out with rusted forks . stopped any gang wars lately ? so i went to the mill last night , caught firewalk live . if i had known the celestial avenger was bloodied , i would have totally given him my potion . here 's a character sheet . you stand at a three - way crossing . to your left , the raiders ' training ground . " the raiders could have some good loot at the training ground . [ex] s0 : chloe walks behind the dressing screen . a rhetorical question ? now about that eye ... that 's a hell of a battle scar . both girls take off running . rachel climbs into a carriage on the train , then helps chloe as she joins her . i think we should play two truths and a lie . but i 've passed by your locker a few times , and i 've seen that old photo of a cat you keep in there . after they finish listening to the music , both girls take out their earbuds and chloe puts them away . i 'd love to get it working for her . [ex] s0 : chloe tries opening the viewfinder with the nail file . stealing a dedication plate takes ... persistence . chloe uses the plate to pry open the viewfinder . oh , honey , i think we used the vibrating bed for too long . or we could go try to find a liquor store instead ? talk about committing to a performance . [ex] s0 : chloe tries to snatch the wine , but the couple notices her . i think it 's contagious . you 'd better run away before it gets you too . the girls run to the parking lot . i could use a drink after trying to keep up with you . [ex] chloe : i 've heard that actors are moody , but , wow , rachel . i know i 'm not the easiest person to be around . i asked you to leave me alone . i guess it 's easier to be alone if you decide it 's a choice . then she falls on her back and continues crying on the ground . the raven suddenly appears on the hood of the car , and almost immediately disappears . [ex] s0 : chloe looks at one of the objects around her . a truck appears outside the window and crashes into the left side of william 's car . she gets out of it and leans on the hood one last time . then she goes towards the train tracks and starts walking back to the overlook , as a raven flies overhead . [ex] chloe : the ones who were making out ? [ex] i 've felt like my dad 's been lying about something for a while . so when i saw he got a text from an unknown number ... asking him to meet ... plus you came along with me , no questions asked . my mom might skip grounding and just go straight to the death penalty . they both look at the fire and david puts his arm around her . the three of them look at the fire . the woman seen kissing james is sitting on a bench at the overlook park , looking at the fire .

10.5.8. Summary from SummaRuNNer with both sentence and word level attention trained without rationales (AttnRNN + rationale)

chloe releases the parking brake and the car slides down . hard to get to the stage . after a few moments , the guy she ran into earlier and his friend come to confront her . frank sees them and chloe stops , looking at the guys behind him . he then jumps in front of the guys . she rolls on her side and picks up her ashtray , then she puts the ashtray below her chest and starts smoking . she then goes downstairs . he takes the toolbox from the ground and walks towards a table in the corner . then , both he and chloe get into the car . so i went to the mill last night , caught firewalk live . wait , you went to the mill last night ? rachel takes chloe 's hand and pulls her into the building . rachel has her back turned to chloe and is wearing jeans and a bra . when she 's done , the bruise is no longer visible . rachel climbs into a carriage on the train , then helps chloe as she joins her . rachel moves to sit on the floor of the train carriage . so , which is the lie ? rachel takes chloe 's marker and writes " rachel amber " on the floor of the train carriage with her right hand and then repeats the same successfully with her left hand . he was a gift from my dad . after they finish listening to the music , both girls take out their earbuds and chloe puts them away . i admit , it was really dumb to lock the keys in the car . chloe uses the plate to pry open the viewfinder . she throws the plate to the ground and takes the quarter from inside the viewfinder . she approaches rachel and holds out the quarter triumphantly . the girls see a man and a woman , meeting under the oak tree . at chloe 's mark , the man and the woman start kissing . oh , honey , i think we used the vibrating bed for too long . last i checked , you 're supposed to be chloe price . rachel brings chloe to the picnickers . or we could go try to find a liquor store instead ? rachel starts breathing heavily and collapses to the ground . there 's a ranger station on the other side of the park . the girls run to the parking lot . rachel takes the bottle from chloe and starts drinking , then offers it to chloe . rachel and chloe walk down a train track . rachel is drinking the wine that the two of them stole from the picnickers and chloe is balancing on the rails . they come across the american rust salvage yard . i know i 'm not the easiest person to be around . acknowledging her request , she stands up and takes the bat from chloe and examines it . i asked you to leave me alone . rachel turns away and heads back towards the tracks . but i want to find out . chloe picks the bat up from the ground and looks around angrily . chloe smashes the mannequin 's head off . after some random smashing , chloe hits the truck 's tailgate . there she sees her fathers wrecked car and drops the bat . chloe approaches the car and starts hitting its hood with her fists and crying . then she falls on her back and continues crying on the ground . " burning the midnight oil " song is still playing on the radio . william turns it off and looks at chloe . the raven suddenly appears on the hood of the car , and almost immediately disappears . in the next shot david is sitting in the driver 's seat , but in a moment he is replaced by william . this time she turns her head in chloe 's direction . the car stops next to rachel , who is looking at chloe with wide eyes . rachel puts her hand on the glass , chloe puts hers on the other side . suddenly rachel catches on fire . a truck appears outside the window and crashes into the left side of william 's car . she gets out of it and leans on the hood one last time . then she goes towards the train tracks and starts walking back to the overlook , as a raven flies overhead . rachel stands under the oak tree , crying , while chloe silently approaches her from behind . so when i saw he got a text from an unknown number ... asking him to meet ... rachel takes a picture of her and her father out of her pocket . my mom might skip grounding and just go straight to the death penalty . rachel sets the photo on fire and lets it fall into the trash can . as the garbage inside the can starts burning , she takes a step back . after a moment of hesitation , rachel kicks the trash can over . its burning contents fall out towards the oak tree , setting it on fire . rachel starts screaming loudly , and at the same time a gust of wind comes from behind her , spreading the fire to the entire tree . rachel is breathing heavily and crying . then she lets out another scream , and another gust of wind comes blowing at the fire . both girls look on in shock as the fire starts spreading to other trees . frank and his friend are hanging out next to his rv at the old mill . his friend is on the phone and frank is drinking a bottle of beer . frank stares in shock at the fire and smoke in the distance . they both look at the fire and david puts his arm around her . then he notices steph , mikey and drew , hanging at the picnic table far from him . the three of them look at the fire . james amber and principal wells are talking to a police officer at the blackwell parking lot . james looks at the fire . the woman seen kissing james is sitting on a bench at the overlook park , looking at the fire . while smoking a cigarette , she starts smiling mysteriously .

10.5.9. Summary from flan-t5-base (zero shot)

chloe price is standing on train tracks and wearing a black hoodie. The bouncer throws her id on the ground and chloe picks it up and walks away from him. The bouncer and chloe are going to the firewalk concert. The vendor is selling a shirt for twenty bucks. chloe is in the crowd and tries to push through it. chloe is trying to see a band but it's too packed to get to the stage chloe is a good friend of guy 1. rachel and chloe dance together in front of the guys. The narrator's mother is in the room. chloe goes back to joyce and david's room and takes her purse. Joyce and chloe are having a conversation before school. chloe is worried about her grades and her mother's disregard for her rules. David is a good man and he's a good man. chloe and joyce are talking about their mother and dad. chloe takes the keys from the ashtray and puts them in his back pocket. chloe and david are talking about the spark plug. David finishes fixing the car and closes the hood. He takes the toolbox from the ground and walks towards a table in the corner. chloe is hurting for her ex. chloe is in panic and is unable to get out of the car. chloe and eliot are going to see the tempest in blackwell theater tomorrow. Skip and chloe are in a band Skip and chloe are at a house party. grant's chemistry class starts today. grant's sincerity is overwhelming. grant's chloe's generosity is overwhelming. grant's new donors disagree with her. People are taking victoria seriously since she won the beacon's young artist award for her photography. chloe price chloe and blackwell are discussing their drug use and tolerance issues. evan and steph are discussing the first encounter of the celestial avenger. chloe and steph are playing a game of chess The elf barbarian is a famous hero in the kingdom of avernon. elamon is a wizard and he is battling the undead. The orc sergeant is a heavyset orc sergeant and he is armed with a warhammer. chloe is about to climb the stairs but gets knocked down by nathan prescott chloe and nathan are talking about their dad's loss at the shipyard. chloe and rachel enter the hayden and dana rehearse under mr. keaton's supervision rachel and chloe are having trouble with their affections. chloe and rachel are left alone after the first period improv with freshmen. chloe looks into rachel's backpack and finds her belt. chloe and rachel are going to see the show live. rachel and chloe are going to seattle. chloe and rachel are having a conversation about the weather and the weather. rachel and chloe are having a party. chloe and rachel are on the train in arcadia bay. rachel and chloe are talking about their feelings about the truth and how they should cheat. chloe is allergic to cats and has seen an old photo of a cat she kept in her locker. rachel is impressed with chloe price's ability to lie. chloe is unsure of her own identity and is not sure who to call if she needs to get out of a ticket. chloe and rachel are sharing a music playlist. rachel and chloe are playing a game of improvisation. chloe and rachel are discussing how to use a viewfinder. chloe is angry at the man for not coming to her party. rachel and chloe are playing a game of spying on people. chloe and rachel are ditching school for hours. The man and woman are going to try to save a lifeguard from drowning in the park. The girl is in trouble and she is waiting for help. The man is going to check her pulse and he will keep watch. The woman is going to the ranger station and she will keep watch. chloe and rachel are drinking and s0 is trying to keep up with them. rachel and chloe are exploring the junkyard. chloe is alone and wants to be alone. rachel is leaving and chloe is waiting for her. rachel and chloe are talking about their relationship. chloe is crying and hitting the car hood with her fists and crying on the ground. chloe is crying and rachel is crying. chloe and rachel are upset about their dad's death. rachel owes chloe an apology. rachel and chloe are going to leave this place forever. nathan and steph look at the fire.