Concadia: Tackling Image Accessibility with Descriptive Texts and Context

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Abstract

Images have become an integral part of online media. This has enhanced the dissemination of knowledge, but it poses serious accessibility challenges. The HTML “alt” field is hidden by default and designated for supplying a description that could replace the image, but it is rarely used. By contrast, image captions appear alongside the image and are more abundant, but they are written to supply additional information and generally lack the details required for accessibility. These terms are often treated as synonyms, but we argue that a distinction is essential. To address this, we introduce the publicly available Wikipedia-based corpus Concadia, which consists of 96,918 images with corresponding English-language descriptions, captions, and surrounding context. We use Concadia to characterize the commonalities and differences between descriptions and captions. This leads us to the hypothesis that captions, while not substitutes for descriptions, can provide a useful signal for creating effective descriptions. We substantiate this hypothesis by showing that image description systems trained on Concadia benefit from having caption embeddings as part of their inputs. Finally, we provide evidence from a human-subjects experiment that human-created captions and descriptions have distinct communicative purposes, and that our generated texts follow this same pattern. These experiments begin to show how Concadia can be a powerful tool in addressing the underlying accessibility issues posed by image data.

1 Introduction

Images are pervasive across many contexts on the Web and have become an important part of how we communicate (Hackett et al., 2003; Bigham et al., 2006; Buzzi et al., 2011; Voykinska et al., 2016; Gleason et al., 2019). This has been a boon for creative expression and the dissemination of knowledge, but it poses serious accessibility challenges. In case images are not accessible, readers must rely on human-generated text that communicates the central image information. The HTML “alt” tag is designated for supplying such descriptions, but it is rarely used (Bigham et al., 2006; Morris et al., 2016; Guinness et al., 2018; Gleason et al., 2019; von Ahn et al., 2006), which is problematic, especially for the low vision community.

The lack of availability of texts that can replace images creates the need for systems that can generate them. Recent advances in deep learning have led to a surge of models that create text from images (e.g., Karpathy and Fei-Fei, 2015; Xu et al., 2016; Lu et al., 2017; Anderson et al., 2018; Biten et al., 2019) and a variety of datasets to train them on (Lin et al., 2014; Sharma et al., 2018; Gurari et al., 2020). However, the texts these systems generate tend to be generic and often unreliable (Dognin et al., 2020; Sharma et al., 2018; Biten et al., 2019). This has been a boon...
et al., 2019; Guinness et al., 2018).

We argue that the communicative purpose a text is intended to fulfill needs to play a central role in designing datasets and models that help with accessibility. In this work, we seek to address this challenge with Concadia, a Wikipedia-based corpus of 96,918 images with associated English-language captions, “alt” text descriptions, and accompanying context from the respective Wikipedia article.1 This resource supports a clear distinction between descriptions and captions. Descriptions are created for the purpose of replacing the image, providing information about the image’s visual features. Captions relate images to the broader context, e.g., specifying the event the image presents. Figure 1 illustrates a typical example from Concadia. In general, only descriptions can address the accessibility challenge, which makes a clear distinction between the two text forms crucial for further progress.

To substantiate our claim about the distinction between descriptions and captions, we report on a systematic linguistic analysis of their commonalities and differences in Wikipedia (Section 4). In addition, we develop and assess neural image “captioners” (Section 5) and find that the task of description generation is easier than caption generation, as predicted by the tighter relationship between descriptions and images. We further provide evidence from a human-subjects experiment (Section 6) that descriptions and captions serve distinct communicative purposes, and that our model-generated texts follow the same pattern. The experiment also serves to further validate that systems trained to generate captions are inadequate for the task of generating descriptions. Overall, the results highlight the importance of specifying the purpose a text is intended to fulfill – both for dataset creation and model evaluation.

Finally, our findings also indicate that captions, which are much more abundant than descriptions, might have a positive role to play in generating descriptions. To pursue this hypothesis, we train text-to-image models on Concadia. We find that such models consistently benefit from having paragraph-level BERT representations (Devlin et al., 2019) of the caption as part of their inputs. Since captions are abundant, this points the way to making use of available data to solve the accessibility issue using NLP systems. More generally, these experiments begin to show how Concadia can be a powerful tool in addressing the accessibility issues posed by image data.

2 Background and Related Work

2.1 Image Accessibility

Articles, tweets and other forms of writing make rich use of visual media such as images (Hackett et al., 2003; Bigham et al., 2006; Buzzi et al., 2011; Voykinska et al., 2016; Morris et al., 2016; Gleason et al., 2019). However, only a small fraction of images are made accessible through human-generated alt descriptions. The highest coverage of alt descriptions for images has been found for the most frequently visited websites, estimated at 72% (Guinness et al., 2018). However, overall coverage only amounts to 25% (von Ahn et al., 2006) and the rate of alt descriptions in specific domains such as social media can even drop down to 0.1% (Gleason et al., 2019). To mitigate the data sparsity, Guinness et al. (2018) propose Caption Crawler, a program which finds duplicates of the same image online and if available, transfers a given alt description to all image instances. This method could add alt descriptions to 12% of images that previously lacked them. However, this still leaves out all images that are infrequent or very recent additions to the Web. Those still remain inaccessible for the visually impaired community, which creates obstacles to staying socially connected (Morris et al., 2016; MacLeod et al., 2017; Buzzi et al., 2011; Voykinska et al., 2016), and informed about research advancements (Gleason et al., 2019) and news events (Morris et al., 2016).

Our work contributes to the growing research that tries to improve accessibility on the Web. Understanding the distinction between captions and descriptions is crucial for meaningfully enhancing accessibility, and our finding concerning the value of additional textual context points to one way that we can make progress while relying on available data.

2.2 Image/Text Relations

The relationship between texts and accompanying images has been explored in the communication sciences (e.g., Martinec and Salway, 2005) but has been generally absent from considerations of dataset creation and model assessments in com-

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1 Repository link will be shared in non-anonymous version.
puter science. Otto et al. (2020) aim to bridge this disconnect, and propose image/text classes based on their relative importance to each other. They distinguish text supporting the image (Anchor-age), an image supporting the text (Illustration), and a bilateral relation where both are equally relevant (Complementary). They add to a growing body of work which notes that image and text content is closely connected in current image “captioning” datasets such as MS-COCO (Lin et al., 2014) but only loosely connected in news and advertisements (Oostdijk et al., 2020).

2.3 Caption/Description Relations
There is also debate about the relationship between, what we call, captions and descriptions. Biten et al. (2019) suggest that captions are simply a less generic form of descriptions with more prior knowledge, making them more challenging to generate but more useful in practice. Dognin et al. (2020) allude to a distinction of purpose by differentiating between goal-oriented captions, which are necessary for low vision people to know what’s written on a sign, and generic captions, which do not have these aims. Hodosh et al. (2013) discuss the lack of descriptive content in captions on Flickr and reason that it would be redundant with the image and therefore violate Grice’s Maxims of Relevance and Quantity (Grice, 1975). Most recent work acknowledges a general noisy semantic alignment between images and text, which is addressed by cleaning the naturally obtained captions to more tightly bind the text to the image (Kuznetsova et al., 2014; Sharma et al., 2018; Ordonez et al., 2011; Dodge et al., 2012).

Our work provides further evidence for a clear distinction between description and caption generation by showing that these texts fulfill separate purposes and pose distinct challenges that need to be addressed on their own.

2.4 Caption/Description Datasets
There are a variety of datasets for what is generally referred to as “image captioning”. Building on the insights of Otto et al. (2020), we distinguish between datasets which rather aim for a descriptive purpose (e.g., image replacement) or a captioning purpose (e.g., contextualizing the image).

Datasets such as MS-COCO (Lin et al., 2014) and Flickr8k30k (Young et al., 2014; Hodosh et al., 2013) are artificially generated corpora where crowd workers were instructed to describe the content of an image. The decontextualization of the presented image and the instruction to describe suggests that the text is intended to support the image (Anchorage relation), which makes them datasets of descriptions. For purposes of enhanced accessibility, their primary shortcoming is that their descriptions tend to be short, partial, and generic.

The sparsity of human generated alt descriptions led to the development of Conceptual Captions, a dataset constructed from alt descriptions across the Web (Sharma et al., 2018). While its content originates from intended description texts, the authors discarded descriptions that show a high noun ratio and replaced proper nouns by hypernyms, which could work against their original communicative purpose (see Section 4.3). Again, the texts in this dataset are rather anchored in the image instead of providing complementary information, which is why we consider it a description dataset as well.

Recent news datasets pair images and captions from printed articles (Biten et al., 2019; Ramisa et al., 2017). These texts are intended to contextualize the image, which is why we consider them captioning datasets.

3 Concadia: A Contextualized Corpus of Image Captions and Descriptions from Wikipedia
Possibly due to the often overlooked distinction between the concepts of caption and description, existing corpora pick out only one text form in correspondence with their images. A corpus which would allow for a principled comparison between the two text forms is therefore needed. Furthermore, existing corpora mostly detach their images and texts from the broader context. However, recent work on caption generation has shown benefits of making use of the available context, for instance, to inform the integration of proper names and locations (Biten et al., 2019; Jing et al., 2020). We hypothesize that similar techniques will be useful for description generation as well.

We introduce Concadia, Contextualized captions and alt descriptions from Wikipedia, a corpus extracted from Wikipedia consisting of images with their naturally occurring alt descriptions, captions, and surrounding context. To our knowledge, this is the first corpus that contains descriptions in context, and the first that contains
both descriptions and captions, allowing direct comparison between the two text forms.

As of December 2020, English Wikipedia consisted of over 20 million articles with around 50 million images. For Concordia, we extracted all images from Wikipedia that have captions as well as alt descriptions. Images were excluded where the picture wasn’t publicly available at Wikimedia Commons, descriptions contained reference to the caption (e.g., refer to caption), consisted of fillers (e.g., alt text, text), or where any associated text was shorter than 3 characters.

Table 1 provides basic corpus statistics. The final corpus consists of 96,918 images with descriptions, captions, and surrounding text from 41,143 articles. Additionally, we include the copyright information for each image, as provided by Wikipedia, and a train/dev/test split for the data. Images that occur multiple times and that have an identical caption and description are sorted into the training set to ensure the highest quality in the validation and test sets. All other datapoints are randomly assigned. The scripts for constructing the corpus are freely available at https://github.com/elisakreiss/concordia.

### 4 Captions vs. Descriptions

We now seek to further substantiate our core distinction between descriptions and captions via case studies conducted on the full English Wikipedia and on Concordia.

#### 4.1 Difference of Distribution and Purpose

Where present, captions are accessible for all readers, often printed below their respective image. Image descriptions are harder to access, since they’re usually defined in the image’s HTML alt tag. These different distributions of occurrence indicate distinct purposes. We suggest that captions contextualize an image while descriptions are meant to replace it. Consequently, a caption without an image is out of place and a description with an image is redundant.

This contrast relates to a contrast in status. In the terms of Otto et al. (2020) and Martinec and Salway (2005), captions are Complementary (i.e., image and text contribute equally to the overall meaning), whereas descriptions are more similar to Anchorage (i.e., text supporting the image). Our example in Figure 1 illustrates. The Context consists of an excerpt about a specific historic event, which is supplemented with an image and a caption. The caption relates the event displayed in the image to the broader context, which means that image and caption stand in a complementary relationship to each other. The description contains contextually relevant aspects of the image, e.g., focusing on the agents in the image and their appearance (see Section 4.3), which means that the text is primarily anchored in the image.

#### 4.2 Occurrence Frequency on Wikipedia

The scarcity of alt descriptions online is widely established, but existing studies have focused on social media in particular (Morris et al., 2016) and most frequently visited websites overall (Bigham et al., 2006; Guinness et al., 2018). We expect to see a similar pattern on Wikipedia: captions do not replace image information but instead connect the content of the image with the article, whereas descriptions are not visible for most Wikipedia users, and a possible lack of awareness of their usefulness might decrease the frequency with which they

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Table 1: Overview of our Wikipedia-based caption and description dataset Concordia. Captions are on average shorter than descriptions but contain longer words. Captions make use of a larger vocabulary.

| split | datapoints | unique articles | avg length (words) | avg word length | vocab size |
|-------|------------|-----------------|--------------------|-----------------|------------|
|       |            |                 | caption:            | description:     |            |
| train | 77,534     | 31,240          | 12.79              | 14.53           | 82,745     |
|       |            |                 | caption: 6.07       | description: 5.69 | 54,893     |
| dev   | 9,693      | 4,952           | 12.91              | 14.57           | 24,063     |
|       |            |                 | caption: 6.10       | description: 5.70 | 16,800     |
| test  | 9,691      | 4,951           | 12.67              | 14.29           | 23,650     |
|       |            |                 | caption: 6.10       | description: 5.71 | 16,610     |
| all   | 96,918     | 41,143          | 12.79              | 14.51           | 96,908     |
|       |            |                 | caption: 6.07       | description: 5.69 | 63,884     |
occur naturally (Gleason et al., 2019).

To estimate the sparsity of alt descriptions and captions for images on Wikipedia, we randomly sampled 10,000 articles, extracted the number of images, and counted how many of those contained captions and how many contained descriptions. We then took the average proportion of captions and descriptions per image for each article, which yields the data distribution displayed in grey in Figure 2.

Our approximation suggests that while around 91% of all images are associated with a caption, only 6% contain alt description tags. Moreover, this small subset still includes alt descriptions that simply say alt text or Image. The number of informative alt descriptions is likely to be much lower.

4.3 Similarity of Captions and Descriptions

Using Concadia, we investigate the semantic similarity between captions and descriptions. If captions and descriptions show perfect similarity, captions could simply replace descriptions when they are absent. If they are completely dissimilar, captions are most likely unhelpful for inferring or generating descriptions. Crucially, if the content of captions and descriptions is partially related, the content of the frequently occurring captions might inform automatic description generation.

To investigate the semantic similarity between captions and descriptions, we computed the cosine similarity for their embeddings. Embeddings were obtained using pretrained SBert3 (Reimers and Gurevych, 2019) and similarity was calculated for all matching description/caption pairs, yielding an average of 0.46 (see Figure 3 in red). Descriptions and captions are significantly more similar than would be assumed under a baseline where descriptions and captions are randomly paired (in blue; two-sample Kolmogorov-Smirnov test: \( p < 0.0001 \)), suggesting that they share item-specific content. (We obtained essentially the same results using Jaccard distance of the raw strings.)

Having established that there is a semantic similarity between captions and descriptions, we turn to how they come apart. A quantitative analysis of the Parts-of-Speech (POS) shows distinct patterns for descriptions and captions. POS tags for each token were assigned using the NLTK tokenizer and POS tagger (Bird et al., 2009).

The results are shown in Figure 4 and reveal clear differences. While proper nouns constitute 26.3% of all tokens in captions, descriptions contain only 12.6%, which is significantly less (\( p < 0.0001 \)). In contrast, adjectives (captions: 5.4%, descriptions: 9.4%, \( p < 0.0001 \)) and nouns (captions: 16.8%, descriptions: 26.2%, \( p < 0.0001 \)) occur more frequently in descriptions. This aligns with previous work on news captions (Biten et al., 2019), which found that proper nouns contribute 20% of captions from NYT articles while they’re completely absent in datasets such as MS-COCO (a description corpus). The same holds for the distribution of adjectives and nouns (Biten et al., 2019; Ramisa et al., 2017).

There are informative sub-patterns as well. For example, while there is a clear over-representation of adjectives in descriptions, this pattern quali-
Figure 4: Aggregated proportions of Part-of-Speech frequencies for descriptions and captions with 95% confidence intervals. The following POS tags constitute the categories on the x axis: proper nouns (NNP, NNPS), nouns (NN, NNS), adjectives (JJ, JJR, JJS), verbs (VB, VBD, VBG, VBN, VBP, VBZ), pronouns (PRP, PRPS).

Figure 5: Most frequent bigrams, excluding stopwords (i.e., highly frequent words such as pronouns, prepositions, and forms of to be).

We speculate that superlatives are potentially more evaluative and therefore less appropriate in descriptions. There is also a clear over-representation of determiners in descriptions, which we attribute to the higher frequency of common nouns over proper names, since in English the man is grammatical but *the Jesse is not.

The distinct patterns between POS occurrence in captions and descriptions is also qualitatively observable from inspecting the most frequent bigrams. The results are shown in Figure 5. Descriptions are dominated by descriptive attributes such as people’s looks (e.g., white shirt, baseball cap, dark hair), and meta information about the image (e.g., colour photograph). The most frequent bigrams in captions are dominated by proper noun compounds such as San Francisco or Tour de France, as well as common places and times (e.g., national park, 19th century).

5 Model Experiments

Our investigation of the similarity between captions and descriptions in Section 4.3 suggests these texts differ in principled ways but that they are not unrelated. This suggests that, while captions on their own might not be able to replace descriptions, they can potentially inform their content when we automatically generate descriptions. We now pursue this hypothesis in the context of large-scale caption and description generation.

5.1 Architecture

The crucial requirement for our model architecture is the ability to receive image as well as textual input to generate a label (description/caption). We took inspiration from the importance of attention mechanisms on the input image as used in state-of-the-art “captioning” models (Xu et al., 2016; Lu et al., 2017; Anderson et al., 2018) and extend them to the context input. An overview of the model architecture is displayed in Figure 6. As the basis, we use an LSTM decoder (Hochreiter and Schmidhuber, 1997) that generates a label token-by-token. Each decoding step is dependent on the previously generated token, the previous LSTM hidden state and attention on the original input representations (Xu et al., 2016). Dependent on the condition, the model is trained on predicting description or caption labels and receives as context captions, descriptions, or nothing.

Encoders Two pretrained encoders create image and context representations which are input to an LSTM with attention. As an image encoder, we used ResNet-101 (He et al., 2016), pretrained on ImageNet. For the context representation, we used pretrained BERT (Devlin et al., 2019). When predicting labels in absence of context, we induced an uninformative context representation by setting all values to 1. This way, we ensured that potential model performance improvements are not due to an increase of model complexity when adding context. This is also one of the reasons why neither image nor context encoders were finetuned. To establish the importance of input components, e.g., context, we needed to fix the number of trainable parameters to avoid conflations from changes in model complexity.

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5We used the pretrained weights available with Pytorch’s torchvision module version 0.8.2.
6We used the pretrained weights available with the Python module pytorch-pretrained-bert version 0.6.2.
Decoder with Attention  The initial input to the LSTM hidden states of the decoder is a vector concatenating an image and a context representation. The LSTM decoder generates each token in a predicted label based on a previous token, the previous hidden state and an attention vector. The attention vector is obtained by using soft attention (Xu et al., 2016; Bahdanau et al., 2015) separately parameterized on the image and the context and then concatenating the resulting representations.

5.2 Implementation  

The models were implemented in PyTorch (Paszke et al., 2019) using a codebase that has successfully replicated results from Xu et al. (2016). Additional details on model training and optimization will be available in our code release.

5.3 Evaluation Metrics  

Since the dataset is extracted from naturally occurring data, each image is only associated with a single ground-truth caption and description. Current evaluations of text generated from images rely on multiple references to reliably estimate performance. As suggested in previous work (Biten et al., 2019), we consider CIDEr (Vedantam et al., 2015) to be most appropriate for cases of few ground-truth references and a high proportion of proper names. Firstly, CIDEr has been shown to outperform BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004) specifically when reference sentences are sparse (Vedantam et al., 2015; Anderson et al., 2016). While METEOR (Denkowski and Lavie, 2014) and SPICE (Anderson et al., 2016) achieve slightly higher accuracy with human judgments on some datasets with few references, their incorporation of soft-similarity and lemmatization is not well-defined for proper names (Biten et al., 2019) which make up more than 26% of the caption data and more than 15% of the description data (see Section 4.3).

We used beam search of size 5 to generate captions and descriptions, both for performance evaluation and to generate descriptions and captions for the human judgment task in Section 6.

5.4 Experiment 1  

This experiment probes how the distinction between the tasks of description and caption generation affects model performance.

Predictions  If descriptions are meant to replace an image while captions are meant to complement it, we expect models to perform better at generating descriptions from image input alone, as compared to captions. In Experiment 1, we test this prediction by evaluating the model’s description and caption generation performance from images alone. We compare them to baselines obtained by randomly assigning images to captions/descriptions in the training set. We expect performance to improve in both conditions, and that the performance gain is larger for descriptions than captions due to the higher mutual information with the image. Furthermore, a high performance gap between the two conditions would highlight the necessity of differentiating those tasks to address their distinct challenges.

Results  Figure 7 shows the performance on the validation set for description (in green) and caption generation (in orange), as well as their shuffled baselines (dashed). For both caption and description generation, performance is higher than their corresponding baselines where the model was trained on randomly chosen images. Overall, the model achieves higher performance on the description data than the caption data. We attribute this to the smaller vocabulary in descriptions, a higher proportion of proper nouns in captions, and a higher n-gram overlap across descriptions. As predicted, the qualitative performance improvement over baselines is higher for image description than caption generation. This suggests that the information from the image alone is more helpful to description generation, suggesting a closer connection between the two.
5.5 Experiment 2

This experiment tests whether performance specifically on description generation benefits from receiving contextual information. To do so, we provide the caption as additional input to the description generation model.

Predictions Under the assumption that captions and descriptions are distinct but exhibit certain semantic similarities, we test whether providing a model with one of them improves the generation quality of the other. Since captions often add context to the image (such as the event, location, and proper names; see Section 4.3), we expect captions to improve the quality of generated descriptions. We also test the reverse case where we supply the caption model with the descriptions.

Results The dark lines in Figure 7 show the model performance when it additionally receives descriptions or captions as input. Performance improves for both description and caption generation compared to the image-only input baselines, suggesting that the model benefits from the additional context. Furthermore, this improvement goes beyond the performance improvements achieved by training on random captions from the training set which suggests the model makes use of item-specific information. The improvement is slightly higher for description than caption generation which aligns with the observation that the information in descriptions is primarily redundant with the image information. Overall, this provides initial evidence suggesting that description and caption models might generally benefit from receiving contextual information.

5.6 Discussion

The results from the model experiments suggest that there is a clear distinction in difficulty between generating descriptions and captions. This can be connected to the challenges posed by the separate tasks: a description primarily requires the image information alone while a caption needs to incorporate external information. Furthermore, we find that providing context in form of captions or descriptions improves performance of the generated descriptions and captions, respectively. Specifically, for addressing the issue of sparse descriptions, our results suggest that models trained to generate descriptions might benefit from receiving the more frequently available caption information as additional input.

6 Human Evaluation

In Section 4.3 and Section 5, we provided qualitative evidence that descriptions and captions fulfill separate communicative purposes. We now present a human-subject experiment in which we test quantitatively whether captions are more suitable than descriptions for providing information that can’t be obtained from the image alone, and whether descriptions are more useful than captions for replacing an image. Furthermore, we investigate whether our models capture these differences.

Our quantitative and qualitative hypotheses, along with our exclusion criteria and the analyses, were preregistered. 8

8OSF preregistration link will be shared in non-anonymous version of the paper
6.1 Participants

We recruited 421 participants over Amazon’s Mechanical Turk, restricted to participation within the US and a previous average approval rate above 98%. Participants were paid $2.60 for participation with an average completion time of 12 minutes ($13/hr). Participants were only allowed to complete the experiment once.

6.2 Materials & Procedure

300 images were randomly sampled from the validation set in Concadia with their original descriptions and captions. We also added model-generated descriptions and captions, resulting in four text conditions for each image. The model epochs used to generate the data were selected according to best performance on the validation set using the CIDEr metric. Consequently, we chose the models that made use of additional context.

Each participant completed 32 trials (30 critical, 2 attention checks). In a trial, a participant saw an image on the left and a short text right next to it. Below, there were two questions (see Figure 8), each associated with a continuous scale, underlyingly coded ranging from zero to one and initialized at zero. Participants assessed how useful the text would be to help someone imagine the picture (rated from not useful to very useful), and how much they learned from the text that they couldn’t have learned from the image (rated from nothing to a lot). Participants could further opt out of responding to the questions by selecting a checkbox to indicate that image and text seemed to be unrelated.

Throughout the experiment, participants never saw the same picture twice. The text was sampled from one of the four conditions: the original description from Wikipedia, the original caption from Wikipedia, the model-generated description, and the model-generated caption. Each participant saw at least seven samples of each text condition, resulting in 28 trials. The last two trial conditions were randomly sampled. Image selection and trial order was completely randomized and question order was randomized between participants.

6.3 Data Exclusions

Participants were excluded based on their self-reported native language, their self-assessment of task performance, two attention check questions, and their overall response. Firstly, we only included participants who indicated that English is among their native languages (12 exclusions), and who reported that they thought they did the experiment correctly (74 exclusions). We constructed attention check questions where the text clearly described something different than what was displayed in the image and excluded participants who didn’t select the checkbox “Can’t say because image and text seem to be unrelated” (85 exclusions). Furthermore, we excluded participants who selected the checkbox in more than 80% of all trials (6 exclusions). Overall, we excluded 177 participants (42%). Furthermore, we excluded trials from the quantitative analysis where participants indicated that text and image didn’t relate. If more than 80% of participants agreed that image and text didn’t relate, we excluded that data sample from our quantitative analysis as well (13,942 out of 15,616 datapoints (89.3%) remain).

6.4 Predictions

Overall, we predicted that descriptions and captions fulfill different communicative purposes which can be queried in human subject evaluations. Concretely, we made the following quantitative predictions for the original human-generated descriptions and captions in Concadia:

(H1) The original descriptions are more useful for imagining the picture than the original captions, and
(H2) A reader receives more extra-image information from the original captions than from the original descriptions.

We further predicted that models should be capable of reflecting these differences when trained on descriptions and captions separately. Prediction (H1) and (H2) should therefore also hold for model-generated descriptions and captions.

Finally, we qualitatively predicted that generated descriptions should be more similar to original descriptions than the original captions would be, and vice versa for generated captions. This would highlight that captions are unsuitable replacements for descriptions and automatically generated alternatives show a promise to add use.

6.5 Results

To test our quantitative predictions, we performed a Bayesian mixed effects regression analysis, using R’s brms package (Bürkner, 2017), where we predicted continuous slider ratings from the centered categorical text condition variable. We used
the zero_one_inflated_beta distribution to approximate the continuous slider scale. We included the maximum random effects structure of random intercepts and slopes for each participant and image.

We find strong evidence for all of our four quantitative predictions and we also see the predicted qualitative patterns, as shown in Figure 8. The results lead us to two main conclusions. Firstly, there are multiple dimensions in which an image-text pair can be successful. We identify two, which actually reverse whether a description or a caption is more appropriate for an image: ability of reconstructing the image from the text in its absence, and amount of information learned from the text in its presence. Secondly, our model captures core aspects of these differences between descriptions and captions. Even with its limitations, the generated descriptions and captions provide more useful alternatives for their original counterparts than original captions and descriptions, respectively. This is further evidence that captions alone are unsuitable for communicating the information required when alt descriptions are absent, and demonstrate the usefulness of automatically generated descriptions.

Unsurprisingly, we find that the generated text was more often rejected as being unrelated to the image than the original descriptions and captions were, which were only rejected in less than 5% of all trials. These results underline the data quality of Concadia and also show the remaining necessity of developing models that can generate descriptions which better reflect the image.

Overall, our results highlight the importance of specifying the purpose a text is intended to fulfill in the image-text generation domain – both for dataset creation and model evaluation. The questions posed for evaluation have to be assessed against the purpose that they’re intended to fulfill. This speaks against current efforts that try to determine a universal evaluation metric that attempts to determine performance from an image-text pair alone (Hessel et al., 2021). Dependent on the intended communicative purpose, captions and descriptions can be considered more or less useful and evaluation therefore needs to reflect that.

7 Conclusion
As images come to play an ever larger role in online written media, there is an increasing need to make those images more accessible. In this work, we argue for a clear distinction between descriptions, i.e., text intended to replace an image, and captions, i.e., text intended to contextualize an image, and we provide evidence for their similarities and differences through linguistic analyses and human subject evaluations. We argue that the high frequency of captions, specifically in information platforms such as Wikipedia, provides a promising opportunity to improve the generation of descriptions, which are only sparsely available. Our analysis of the semantic relatedness between descriptions and captions bolsters this hypothesis, and our modeling and human evaluation results begin to show that it can have practical value for automatic description generation. In addition, we provide a corpus, Concadia, consisting of images and their corresponding alt descriptions, captions and context, which we hope can play a role in making alt descriptions more available, reliable and contextually relevant.

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