Concadia: Tackling image accessibility with context

Elisa Kreiss¹  Noah D. Goodman²  Christopher Potts¹

¹Department of Linguistics  ²Department of Psychology
Stanford University
Stanford, CA 94305 USA
{ekreiss, ndg, cgpotts}@stanford.edu

Abstract

Images have become an integral part of online media. This has enhanced self-expression and the dissemination of knowledge, but it poses serious accessibility challenges. Adequate textual descriptions are rare. Captions are more abundant, but they do not consistently provide the needed descriptive details, and systems trained on such texts inherit these shortcomings. 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 further characterize the commonalities and differences between descriptions and captions, and 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 captioning systems trained on Concadia benefit from having caption embeddings as part of their inputs. These experiments also 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 (Morris et al., 2016; MacLeod et al., 2017; Buzzi et al., 2011; Voykinska et al., 2016). If images are not accessible, readers have to rely on human generated text that communicates the central image information, as usually assigned in the image’s HTML alt tag. However, these human generated texts are rare (Bigham et al., 2006; Morris et al., 2016; Guinness et al., 2018; Gleason et al., 2019; von Ahn et al., 2006), which especially has consequences for the visually impaired 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; Guinness et al., 2018), which greatly reduces their value when it comes to making inaccessible images accessible (MacLeod et al., 2017; Morris et al., 2016; Dognin et al., 2020; Salisbury et al., 2017).
In this work, we seek to address this accessibility challenge with **Concadia**, a Wikipedia-based corpus of 96,918 images with associated English-language captions, alt 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.

To further substantiate our claim about the distinction between descriptions and captions, we report on a systematic analysis of their commonalities and differences in Wikipedia (Section 4). This analysis underlines the importance of making a clear distinction between the two kinds of text. This begins to quantify the accessibility challenge and seems to pose an obstacle to training NLP systems to create descriptions as well.

However, our findings also indicate that captions 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 description prediction is easier than caption prediction, which bodes well for addressing the underlying societal issue. In addition, we show that such models consistently benefit from having SentenceBERT representations (Reimers and Gurevych, 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 computer 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 (Anchorage), 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).

¹https://github.com/elisakreiss/concadia
2.3 Caption/Description Relations

There is also debate about the relationship between 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 visually impaired 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 Captioning 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 Flickr8k/30k (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 descriptive data, they discard descriptions that show a high noun ratio and replace proper nouns by hypernyms which potentially works 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.

Recently, news datasets have come out that comprise images with their captions, as printed in the article (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, 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 with contextual information, 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 Concadia, we extracted all images from Wikipedia that have captions as well as alt descriptions, and surrounding context. To our knowledge, this is the first corpus that contains descriptions with contextual information, 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 Concadia, 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

2commons.wikimedia.org/
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/concadia.

### 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 Concadia.

#### 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 Anchorage. 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 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). The results still support the observation of distinctness between captions and descriptions since the Jaccard distance in the ordered set is still high (0.78).

Having established that there is a semantic similarity between captions and descriptions, we turn to how they semantically 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 5 and reveal clear differences. While proper nouns constitute 26.3% of all tokens in captions, descriptions contain only

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³https://www.sbert.net/
Figure 5: 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, PRP$). A full list of POS tokens and their explanations is shown in the Appendix, Table 2.

Figure 6: Most frequent bigrams, excluding stopwords (i.e., highly frequent words such as pronouns, prepositions, and forms of to be).

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, which we would categorize as 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 qualitatively flips for superlatives. 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 6. 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

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 completely 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

As the basis for our investigation, we used the image captioning model proposed by Xu et al. (2016). This is well-suited to our task since it is a simple architecture, optimized for interpretability, but still achieves comparable results with state-of-the-art models (see Li et al. 2019; Bai and An 2018; Jing et al. 2020; Hossain et al. 2019; Liu et al. 2019 for large-scale comparative analyses). For Experiment 1, a pretrained encoder creates an image embedding which is input to a bidirectional LSTM with attention to the image. As an encoder, we used ResNet-101 (He et al., 2016), pretrained on ImageNet, without finetuning since we did not expect it to be a relevant variable for our investigation. Dependent on the condition, the model is trained on description or caption labels.

In Experiment 2, the input to the decoder is the concatenation of an image and further context. If the model learns to generate descriptions, it receives the caption as additional context input, and vice versa for caption generation. By using pre-trained SBert (Reimers and Gurevych, 2019), we obtain an embedding vector of size 768 for each
context. To avoid potential finetuning artifacts, we instead apply a linear transformation from 768 to 500 dimensions which enables the model to potentially normalize the values in the context embedding before concatenating them with the image embedding. The attention remains on the image alone.

5.2 Implementation

The models were implemented in Pytorch (Paszke et al., 2019) using a codebase that has successfully replicated the original results from (Xu et al., 2016). Appendix B.1 provides additional details on how the models were set up and optimized.

6 Experiments

6.1 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).

To get an impression of the loss the model optimizes for, we also present perplexity, which is the by-item exponentiated cross entropy loss. This metric is less useful for comparison between models since it is sensitive to the number of parameters and size of the lexicon.

6.2 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. 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 (here CIDEr score) 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.

6.3 Experiment 2

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

Predictions According to our conceptualization of captions as connecting the image to the surrounding context, we expect performance improvements over the model that only receives the image as input. We also test the reverse case where we supply the caption model with the descriptions. If the mutual information of descriptions and images is high, supplying descriptions as additional information
to caption generation should only result in small performance gains. 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.

**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. As predicted, the improvement is higher for description than caption generation which aligns with the observation that the information in descriptions is primarily redundant with the image information. This provides initial evidence suggesting that description models might benefit from receiving contextual information.

The CIDEr metric clearly shows that the model doesn’t overfit to the training data but instead improves its predictions with subsequent training. Provided its close connection to the loss term, we would then expect that perplexity reduces over training epochs. Instead, it quickly starts to rise after only three to four epochs. We therefore note a clear mismatch between CIDEr as a final performance metric and the loss the model internally optimizes for.

### 6.4 Discussion

While the model results in Figure 7 are promising, we suspect that additional gains will be straightforward to achieve using Concadia. Here we highlight what seem like productive next steps towards realizing this potential.

First, we expected the model to show higher performance improvements than are present in Figure 7. This might trace to the detachment of the paragraph encoder and the model decoder in the model architecture (Section 5). Perhaps more tightly integrated architectures will make the additional textual content more accessible to the decoder.

Second, while these results indicate that providing captions benefits description generation, we are currently aiming to determine more precisely what gives rise to the performance improvement and what information the more complex models make use of. How relevant is the image information when the model has access to the caption? Which specific information does the model benefit from in the captions? We think Concadia is a valuable tool for addressing such questions.

In summary, the presented model results are further evidence for the necessity of a meaningful distinction between descriptions and captions, and, specifically, the results suggest that captions provide a promising resource for informing description generation.

### 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. 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 results begin to show that it can have practical value for automatic caption generation. In addition, we provide a corpus, Concordia, 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.

Acknowledgments

This work is supported in part by a Google Faculty Research Award. We are grateful to all members of Stanford’s CoCoLab and Jessica Mankewitz for their insightful comments on this work, and to Mike Wu for sharing useful materials.

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Appendix

A Similarity of Captions and Descriptions

In Section 4.3, we present differences in occurrence frequencies of the syntactic categories *proper nouns, nouns, adjectives, verbs*, and *pronouns* for descriptions and captions. However, the Part-of-Speech (POS) tag analysis using the Python library NLTK (Bird et al., 2009) allows for much more fine-grained distinctions. Figure 9 contains all analyzed POS tags and shows the proportion at which they occur in captions and descriptions of the Concordia corpus. Proportions are computed by dividing the number of occurrences of a POS tag by the number of all tokens in that specific text form. This allows for a direct comparison between descriptions and captions, even though captions contain more tokens overall. Table 2 contains an overview of all POS tags and their respective definition, as provided by NLTK (Bird et al., 2009). Section 4.3 also addresses qualitative semantic differences between captions and descriptions. Due to space constraints, we only use the most frequent bigrams (without stopwords) to demonstrate these differences in the main paper. Figure 8 illustrates the most frequent trigram frequencies when including stopwords. Similarly to the bigrams in Figure 6, the most frequent trigrams in captions have instances of event descriptions and proper names (e.g., *the battle of, Tour de France*). For descriptions, there are again primarily descriptive attributes for people (e.g., *man wearing a, is wearing a*), and meta information about the image (e.g., *(black) and white photograph, in the foreground)*.

A similar pattern arises when directly comparing which words occur more frequently in captions and descriptions, as shown in Figure 10. Words that lie on the dashed line occur equally often in both text forms. Words below that line occur more

| POS tag   | Explanation                        |
|-----------|------------------------------------|
| CC        | Coordinating Conjunction           |
| CD        | Cardinal Digit                     |
| DT        | Determiner                         |
| EX        | Existential There                   |
| FW        | Foreign Word                       |
| IN        | Preposition/Subordinating Conjunction |
| JJ        | Adjective                          |
| JJR       | Adjective, Comparative             |
| JJS       | Adjective, Superlative             |
| LS        | List Marker 1                      |
| MD        | Modal                              |
| NN        | Noun, Singular                     |
| NNS       | Noun Plural                        |
| NNP       | Proper Noun, Singular              |
| NNPS      | Proper Noun, Plural                |
| PDT       | Predeterminer                      |
| POS       | Possessive Ending                  |
| PRP       | Personal Pronoun                   |
| PRP$      | Possessive Pronoun                 |
| RB        | Adverb                             |
| RBR       | Adverb, Comparative                |
| RBS       | Adverb, Superlative                |
| RP        | Particle                            |
| TO        | to                                 |
| UH        | Interjection                       |
| VB        | Verb, Base Form                    |
| VBD       | Verb, Past Tense                   |
| VBG       | Verb, Gerund/Participle            |
| VBN       | Verb, Past Participle              |
| VBP       | Verb, Sing. Present, non-3d Person |
| VBZ       | Verb, Sing. Present, 3rd Person    |
| WDT       | wh-determiner                      |
| WP        | wh-pronoun                         |
| WPS       | possessive wh-pronoun              |
| WRB       | wh-abverb                          |

Table 2: Part-of-speech tokens from Figure 9 with explanations.
frequently in descriptions and words above it occur more often in captions. Words that occur more frequently in descriptions focus on descriptive adjectives and nouns such as hat, bearded, or blouse. Words that occur more frequently in captions rather refer to an event, e.g., award or winner, and use more evaluative language, e.g., achieved.

These additional perspectives are in further support of the quantitative and qualitative analyses of the principled ways in which the content of captions and descriptions differs (see Section 4.3).

B Model

B.1 Hyperparameters

As explained in Section 5.2, we built our presented models on a codebase that has successfully replicated the original results in Xu et al. (2016). We used the hyperparameters suggested in this codebase. The only exception is that we used a reduced batch size (35 instead of 80) since our models that include context have more parameters.

Overview of hyperparameters:

- dimension of image encoder output: 2048 (predetermined by the pretrained ResNet-101 (He et al., 2016) output size)
- dimension of word embeddings: 512
- dimension of attention linear layers: 512
- dimension of decoder RNN: 512
- dropout: 0.5
- loss function: cross-entropy loss
- optimizer: Adam (Kingma and Ba, 2015)
- batch size: 35
- learning rate for decoder: 4e-4
- clip gradients at an absolute value of 5.
- regularization parameter for “doubly stochastic attention”: 1.

The models that include context as supplementary input contain additional hyperparameters:

- dimension of context embedding: 768 (predetermined by the pretrained SBert (Reimers and Gurevych, 2019) output size)
- dimension of linear transformation: 500 (higher dimensionality results in slightly higher performance gains)

B.2 Supplemental performance evaluations

We trained the models for at least 30 epochs. Since performance afterwards didn’t show any substantial improvements, we present evaluations until that mark. Model performance on the training set, as shown in Figure 12, suggests that the model successfully learned to generate the data.

In Figure 11, we present validation set performance according to a variety of state-of-the-art
Figure 11: Model performance on validation split across training epochs. The metrics reported in the paper are CIDEr and perplexity.

Figure 12: Model performance on train split across training epochs. As expected, loss decreases, as suggested by perplexity and average cross-entropy loss, and performance increases, as measured by top-5 accuracy.

metrics. In the main paper, we discuss CIDEr and perplexity. Other metrics such as BLEU, METEOR and ROUGE have been shown to perform less well on few ground-truth reference labels or are unstable with a high number of proper names (see Section 6.1). Across metrics, there is a consistent pattern where (1) description models achieve higher performance than caption models, (2) baselines achieve the lowest performance in caption and description generation, and (3) the models with additional caption or description context achieve the highest performance.

This consistent performance pattern shows that the results presented in Section 5 are not simply due to artifacts of the CIDEr metric but that there are performance gains that persist across measures.