Weakly Supervised Content Selection for Improved Image Captioning

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Abstract

Image captioning involves identifying semantic concepts in the scene and describing them in fluent natural language. Recent approaches do not explicitly model the semantic concepts and train the model only for the end goal of caption generation. Such models lack interpretability and controllability, primarily due to sub-optimal content selection. We address this problem by breaking down the captioning task into two simpler, manageable and more controllable tasks – skeleton prediction and skeleton-based caption generation. We approach the former as a weakly supervised task, using a simple off-the-shelf language syntax parser and avoiding the need for additional human annotations; the latter uses a supervised-learning approach. We investigate three methods of conditioning the caption on skeleton in the encoder, decoder and both. Our compositional model generates significantly better quality captions on out of domain test images, as judged by human annotators. Additionally, we demonstrate the cross-language effectiveness of the English skeleton to other languages including French, Italian, German, Spanish and Hindi. This compositional nature of captioning exhibits the potential of unpaired image captioning, thereby reducing the dependence on expensive image-caption pairs. Furthermore, we investigate the use of skeletons as a knob to control certain properties of the generated image caption, such as length, content, and gender expression.

1 Introduction

Advances in neural sequence-to-sequence modeling have shown tremendous successes in conventional image captioning. Output captions shown in English (En), Hindi (Hi) and Italian (It).

Figure 1: Outline of our dual staged approach of (i) skeleton prediction and (ii) skeleton based image captioning, as compared to conventional image captioning. Output captions shown in English (En), Hindi (Hi) and Italian (It).

simple tasks: skeleton prediction \( f_\theta : l \rightarrow S \) and skeleton based captioning \( f_\phi : l, S \rightarrow C \), where \( l \) is the image, \( S \) is the skeleton and \( C \) is the caption (Kulkarni et al. 2013, Li et al. 2011, Elliott and Keller 2013, Fang et al. 2015). Here, skeleton refers to a linear sequence of explicit concept words or semantic content that should be consistent with the image. By design, this separation decouples ‘what to say’ and ‘how to say it’, reducing the misleading guidance backpropagated from the downstream consecutive caption tokens.

In this paper, we conduct extensive empirical studies to understand the benefits of this paradigm. We focus on linguistic-based skeleton (derived from captions, Kuznetsova et al. 2014, Fang et al. 2015, Dai, Fidler, and Lin 2018) rather than perception-based skeleton (derived from image, e.g., scene graphs, Wang, Beck, and Cohn 2019, Yang et al. 2019). We believe that generating a human-like meaningful and relevant description of an image requires a meta-level understanding of the image scoped well beyond object detection (Herdade et al. 2019) and image classification. As such, the skeleton prediction task should be designed to address the semantic gap (Li and Chen 2018, Yao et al. 2018).

Unlike much of the previous work in this paradigm, we illustrate the benefits of linguistic-based skeleton with an emphasis on 1) large-scale image captioning benchmarks that come with a wide variety of visual concepts and languages – Conceptual Captions in English, French, Italian, German, Spanish and Hindi (Sharma et al. 2018, Thapliyal and Soricut 2020): 2) leveraging recent advances in architectures – multi-
head self-attention in transformers (Vaswani et al. 2017) in both stages of the image captioning model, exploring various design choices while maintaining simplicity; and 3) measuring the progress via the most reliable metrics possible through human evaluation (Rohrbach et al. 2018). We believe investigating the role of content selection in these practical, up-to-date settings is valuable and provides a reliable measure to the degree of its potential real-world applicability.

Our experiments confirm our intuition that this paradigm is effective, in almost all of the languages considered. This advantage over traditional image captioning approaches is demonstrated in Figure 1, where the baseline hallucinates ‘posters’ and ‘wedding’. In our approach, the skeleton predictor first generates ‘collection’ and ‘book’, based on which a relevant caption is generated in English, Hindi and Italian. In this way, the dual staged model predicts relevant content words by denoising from a mixture of signals thereby aiding the caption generation model. Overall, we achieve +1.7% improvement in the quality of English captions and an average +1.7% improvement in the quality of 5 other languages. We also explain our results by relating it to the notion of cross-modal discourse coherence (Hobbs 1978; Phillips 1977; Alikhani et al. 2020), where an analysis of our dual staged approach shows a positive shift in the image. Finally, we provide exploratory results on other potential benefits of this paradigm: controllability of content, length (Cornia, Baraldi, and Cucchiara 2019; Deng et al. 2020), and unpaired image captioning that avoids the need for work-intensive image-caption pairs for training models.

2 Related Work

Content selection in image captioning: Our work delegates this responsibility of identifying content to the language where it is easier to find diverse concepts. The closest to our work is Dai, Fidler, and Lin (2018) that predict a list of nouns and verbs as semantic concepts of the image and uses a separate connecting module to compose caption from these words. Gu et al. (2019) advances in the direction of unpaired image captioning using a CycleGAN (Zhu et al. 2017) to align scene graphs between images and captions. Scene graph annotations with objects and relations is expensive thereby constraining the scaling of these models to captions in other languages. Kim et al. (2019), Chen et al. (2020) also use scene graphs to understand relationship between entities for the task of image captioning. While Yang et al. (2019) also rely on expensive scene graphs, they leverage an intermediate dictionary to derive more descriptive captions. We draw parallels with this work with our SkeAE model with a channel to autoencode the skeleton. We also use a much simplified content representation with syntactic-based skeleton forms. Li et al. (2019a) address the semantic gap between vision and language with a flow of multimodal information with two sub-encoders each for image and semantic encoder. Along similar lines, Li et al. (2019b) also boost the transformer model with concept guided attention in the encoder and visual guided attention in the decoder. Our model disentangles the tasks of skeleton prediction and caption generation that are clubbed in the encoders of these models.

Controlable Captioning: Thapliyal and Sorciut (2020) propose a pivot based model for cross lingual image captioning by pivoting on caption from source language in the decoder. Gu et al. (2018) perform language pivoting in captioning by reconstructing both the modalities and regularizing the language embeddings across pivoting. In addition, length can also be controlled by injecting the remaining length at each time step of the decoder Luo and Shakhnarovich (2020). More specifically, the control token in this case is the length which is predicted before decoding. Similarly, in our work, we predict the skeleton before decoding the caption. Sammani and Melas-Kyrizzi (2020) propose an iterative adaptive refinement in order to regenerate an existing caption with copy mechanism. (Ren et al. 2019) propose hybrid channels for information control with two levels of decoding: one with self study image features from a transformer, and the second with teacher guided information from ground truth captions.

3 Our Approach

Image Captioning is the task of generating a descriptive sentence from an image. This requires paired contexts of images and captions as (I, C), where c ∈ C correspond to tokens in the caption (c1, c2, c3, ..., cm). In this paradigm, standard training procedures assign full responsibility of understanding diverse contexts of C in the images, usually by recognizing image level, region level and object level features entirely on the image features. We propose to share this responsibility with surface realization of the language forms to bridge semantic gap by introducing a compositional skeleton in between that breaks down the task of fθ : I → C into two tasks fθ : I → S and fθ : I, S → C.

Baseline fθ : I → C (Img2Cap): We adopt an encoder-decoder image captioning model based on Transformers (Vaswani et al. 2017) following recent state-of-the-art approaches [Sharma et al. 2018; Yu et al. 2019; Changpinyo et al. 2019; Huang et al. 2019; Cornia et al. 2020].

As a starting point, we implement the image captioning framework of Changpinyo et al. (2019). We turn an input image I into a bag of 1 global and 16 bottom-up regional ultrafine-grained feature vectors [Anderson et al. 2018], where regional ones correspond to the top 16 box proposals from a Faster-RCNN (Ren et al. 2015) object detector trained on Visual Genome (Krishna et al. 2017), with a backbone ResNet101 (He et al. 2016) that is trained on JFT (Hinton, Vinyals, and Dean 2015) and fine-tuned on ImageNet (Kuszakovsky et al. 2015). We feature both global and regional boxes with GraphRIsUSE (Juan et al. 2019, 2020). We make modifications to the model that lead to a 0.99 improvement in the dev CIDEr score on the Conceptual Captions (1.001 vs. 0.91 of the comparable model in Changpinyo et al. 2019.) First, we encode the corners and the area of bounding boxes and apply layer normalization when fusing such geometric information with regional visual features (Lu et al. 2019a). Second, we encode each feature vector with a Linear-ReLU-LayerNormLinear instead of Linear embedding layer, where LayerNorm refers to layer normalization (Ba, Kiros, and Hinton 2016).
Figure 2: Model architecture of our skeleton-based captioning along with text as side attention mechanism between visual (v) and linguistic (w) modalities. The skeleton is present optionally in the encoder, decoder or both based on our three approaches.

Dual Staged Composition of Simplified Tasks: In this approach, we introduce an intermediate skeleton representation \( S \) between \( I \) and \( C \). This \( S \) is composed of a sequence of lemma forms of a subset of content words \( (s_1, s_2, \ldots, s_m) \) from \( c \), where \( n < m \). This reduces the output complexity of \( f_\theta : I \rightarrow C \) by simplifying \( C \) to \( S \). Hence the task of image captioning is decomposed into the first task of predicting skeleton concepts and the second task of generating the caption by utilizing this intermediate skeleton.

Stage 1: Skeleton Prediction \( f_\theta : I \rightarrow S \) (Img2Ske) The first stage in the dual staged approach is to predict the skeleton concepts from the images. For training this model, we retrieve syntax annotations (specifically parts-of-speech (POS) and word lemmas), from Google Cloud Natural Language API, for the caption texts. The following are the three variants followed by a baseline skeleton form.

1. **Nouns and Verbs**: This includes a sequence of lemmas of all the nouns and verbs in a caption sentence.

2. **Salient Nouns and Verbs**: Saliency of nouns and verbs is determined using tf-idf scores by treating each caption as document. For each caption, the top 2 highest scoring noun and verb tokens (lemma thereof) are selected. The rationale behind choosing this skeleton is to examine if saliency contributes towards effectiveness of the skeleton.

3. **Nouns**: This includes lemmas of all the nouns in a sentence. The rationale behind choosing this skeleton is to understand the role of verbs in the skeleton.

4. **Iteratively Refined Captions**: This is a baseline skeleton form that does not subselect words. Instead, the output of baseline Img2Cap model serves as the skeleton for the next stage of skeleton-based captioning. The rationale behind choosing this skeleton is to compare the utility of predicting one of the above POS-based skeletons, compared to a full caption predicted by a captioning model.

Note that none of the above skeletons constitute hierarchical syntactic structures, but are simple linear chains thereby making it possible to transfer the techniques to languages that (i) do not assume rich linguistic tools, and (ii) do not align with English syntax. Once, we have a variant of the skeleton \( S \), the next step is to train a model to predict the skeleton \( \hat{S} \). For the first three forms of representing skeleton, we ignore tokens with a frequency of less than 50 in our training data to reduce noise in the automatically curated web-scaled dataset.

1a. **Img2Ske Classification based prediction**: The problem is posed as a multilabel classification problem where the prediction of a skeleton word \( s_j \) is not conditionally dependent on the prediction of another skeleton word \( s_i \). The model is optimized with sigmoid cross entropy between the many-hot representation of the ground truth skeleton words and the predicted skeleton words.

\[
-\left[ \Sigma \cdot \log(\sigma(z_\Sigma)) + (1 - \Sigma) \cdot \log(1 - \sigma(z_{\Sigma})) \right]
\]

Model selection is performed on the basis of accuracy computed between the many-hot representation of the ground truth skeleton words and the predicted skeleton words.

However, conditional independence of skeleton words with one another also ignores the co-occurrence information of words that are capable of composing a sentence or a final caption. For instance, classification predictions are composed of words and their synonyms that are highly correlated like {person, man, singer}. These words definitely are relevant to an image but do not all necessarily co-occur in a sentence.

1b. **Img2Ske Generation based prediction**: Generation based approach addresses the problem of co-occurrences
by making the skeleton words conditionally dependent from left to right. The skeleton words $\hat{S}$ are predicted autoregressively where each word is conditioned on the previously predicted skeleton word. This gives a conditional dependence that models co-occurrences of the words more tightly with $p(s_j | I, s_{<j})$. An elegant property of this composable structure of the problem is training the same neural network structure to predict a less complex or simpler output space $\mathbb{S}$ instead of $\mathbb{C}$. So, we use the same network architecture that is used to train the baseline to also train the skeleton prediction. The words predicted by this stage are interpretable in human language which condition our second stage of the model.

**Stage 2: Skeleton Conditioned Caption Generation** $f_\phi : l, \hat{S} \rightarrow \hat{C}$: This is the second stage of the training after the first stage of skeleton prediction. The overall model architecture for Stage 2 is demonstrated in Figure 2. We propose three variants of utilizing the predicted skeleton from the previous step in separate channels conditioned via encoding, decoding and autoencoding, which are described here.

2a. **SkeEncoding**: The predicted skeleton from the previous stage is used to condition the encoder. The image encoding and skeleton embeddings are fused with a unidirectional attention mechanism, known as text as side (notated as $g$). As demonstrated in Figure 2, this model has the dotted box in the transformer encoder side, with the linguistic query, key, value, $(Q_w, K_w, V_w)$ and the visual counterpart attends to linguistic or visual key and value $(K_o + K_w, V_o + V_w)$ with a visual query $(Q_o)$. We also compared this with image-text co-attention and observed that the text as side attention mechanism resulted in qualitatively better captions.

$$\hat{c}^t \sim \prod_t Pr(\hat{c}^t | \hat{c}^{<t}, g(z_1, \hat{S}))$$

2b. **SkeDecoding**: The skeleton and the caption are concatenated and predicted by the same decoder. Note that this is not a two staged model as the model is trained jointly to predict both the skeleton and the caption. In an autoregressive manner, the model first predicts each of the skeleton words conditioned on the previously generated skeleton words and then every token in the decoded caption attends to the entire predicted skeleton in addition to the tokens of the caption decoded until that time step. The dotted box in the transformer decoder side in Figure 2 depicts this approach.

$$\hat{c}^t \sim \prod_t Pr(\hat{c}^t | \hat{c}^{<t}, z_t)$$

2c. **SkeAE**: To bring both the above models together, we simultaneously encode and decode the predicted skeleton. In this case, both the dotted boxes on encoder and decoder sides in Figure 2 are active. The encoding mechanism follows the $g$ function and the decoder preprends the caption generation task with the predicted skeleton.

$$\hat{c}^t \sim \prod_t Pr(\hat{c}^t | \hat{s}^t, \hat{c}^{<t}, g(z_1; \hat{S}))$$

### 4 Experiments and Results

We conduct experiments in English and 5 other languages. This section details an account of these datasets and results.

### 4.1 Datasets

The validity of our composable structure holds strict constraints on the coverage of $\mathbb{S}$ in the training data. To satisfy this, we rely on a large scale, automatically curated dataset that is rich and diverse in semantic concepts.

1. **Conceptual Captions (CC) $\mathbb{D}_{xy}$**: Free form natural language captions in the real world are quite different from popularly used datasets such as MSCOCO (Lin et al. 2014). Hence we use Conceptual Captions (Sharma et al. 2018) which is a large-scale dataset of 3.3M web images. Each image contains a silver reference text description derived from human authored alt-text from a diverse set of webpages. These properties make CC a strong candidate for vision and language pre-training tasks in recent work (Lu et al. 2019b), and in our case, for learning skeletons from images.

2. **Multilingual CC $\mathbb{D}_{xy}$**: To demonstrate shifts in caption realizations, we use automatic caption translations for CC (Thapliyal and Soricut 2020). The target domain $\mathbb{D}_{xy'}$ has images from the same distribution as $\mathbb{D}_{xy}$, but the caption realization varies. Note that the skeletons are still learned from, and predicted in, English and not the target language, making English skeleton act partly as interlingua for the generation process. Since multilingual captions are all pivoted on the English skeletons, this nullifies the requirements to (1) collect large-scale image captioning data in each language, and (2) obtain potentially expensive linguistic tools to analyze captions in each language. We perform experiments on 5 different languages – French, Italian, German, Spanish and Hindi – in order to test the performance with respect to varied word orders and sub-token overlap with skeleton words.

3. **Conceptual Captions T2 data**: For human evaluations of our models across all languages, we use the T2 test set that is used in CVPR 2019 Conceptual Captions Challenge. This dataset comprises of 1,000 images from Open Images Dataset (Kuznetsova et al. 2020), and are out of domain for models trained on CC.

### 4.2 Experimental Results

**Hyperparameter setup**: The captions are subword tokenized with a vocabulary size of 8,300. The models are optimized with Adam with an initial learning rate of $3.2e^{-5}$. We use a batch size of 128 and train for 1M steps. The token embedding size and filter size are both 512. The transformer model has 6 encoder and 6 decoder layers (unless specified otherwise) with 8 heads for multiheaded attention.

For each skeletal form described earlier, we train both the classifier and generation based skeleton predictors, followed by skeleton-aware captioning model. For the first stage (i.e., skeleton prediction), we report the precision, recall and for the second stage (i.e. caption generation), we report CIDEr.

Table 4 presents the comparison between classification and generation based approaches for skeleton prediction stage on English CC. The precision, recall, F-score measures indicate how well the visual content has been identified compared to the groundtruth. With the same set of labels (skeleton form of nouns and verbs), both approaches have similar F-scores. However, precision is higher for generation and recall

2http://www.conceptualcaptions.com/
Table 1: Automatic metrics for various skeleton predictors (columns). Performance for both the stages are reported – skeleton prediction (in Precision/Recall/F1), and skeleton-based captioning (using CIDEr). Note that for classification and generation, the skeleton type used is 'nouns & verbs'.

Table 2: Automatic metrics to compare the various skeleton types (such as Nouns & verbs). Img2Cap is the baseline, whose large version refers to 12 encoder and 12 decoder layers. Note that the generation-based skeleton prediction method was used for all these experiments.

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Table 3: CIDEr scores for skeleton (form: nouns & verbs, prediction approach: generation ) conditioned caption generation for multiple languages.

Table 4: CIDEr scores on validation data with ablations for unpaired captioning.

4.3 Human Evaluations

We also conduct human evaluations where captions for each image are evaluated both in relative preferences and absolute scale as well (Thapliyal and Soricut 2020). We show 1000 images each rated by 3 distinct annotators. The interface of this evaluation is displayed in Figure 4. The order in which captions are displayed on the interface is random.

Relative Rating: For each image we ask the raters to choose the caption that is most relevant to the image. When Caption A is compared to Caption B, the raters can select relative options as demonstrated in the third column in Figure 4. Wins are the percentage of images where at least 2 out of 3 annotators voted for caption generated with our approach. Similarly, losses are the percentage of images where at least 2 out of 3 annotators voted for caption generated with baseline Img2Cap approach. We compute gains in this side by side relative evaluation as Gains_{relative} = Wins - Losses.

Absolute Rating: For each of the 2 captions for an image, we also gather absolute rating. Each caption is additionally rated as acceptable if at least 2 out of 3 annotators rate it as one among acceptable, good or excellent. These absolute ratings are collected to double check the results.

Table 5 demonstrates the relative human evaluation scores for English captions across different approaches. All our proposed models with noun-and-verb skeletons improve over the baseline Img2Cap. Our SkeEncoding model attains a significant gain followed by SkeAE and then SkeDecoding. The same dual stage approach does not show improvement in iterative refinement over the baseline. This clearly shows that subselection of content skeleton improves the overall image caption.

Table 6 presents our human evaluation scores for caption generation in other target languages as well, demonstrating gains in 4 out of 5 languages.
Table 5: Human evaluation scores of different approaches and skeletons on English.

| Approach        | Skeleton | Wins | Losses | Gains |
|-----------------|----------|------|--------|-------|
| SkeAE           | Nouns and Verbs | 39.34 | 32.63 | +6.71 |
| SkeDecoding     | Nouns and Verbs | 34.83 | 34.53 | +0.3  |
| SkeEncoding     | Iterative Refinement | 19.62 | 20.52 | -1.10 |

Table 6: Human evaluation results for skeleton (form: nouns & verbs, prediction approach: generation) conditioned caption generation for multiple languages.

| Language | Wins | Losses | Gains |
|----------|------|--------|-------|
| French   | 34.43 | 29.53 | +4.90 |
| Italian  | 26.13 | 24.93 | +1.20 |
| German   | 35.23 | 33.93 | +1.30 |
| Spanish  | 34.03 | 34.33 | -0.3  |
| Hindi    | 33.13 | 28.63 | +4.50 |

Table 7: Analysis of multimodal discourse coherence relations for baseline and our model on T2 dataset. The last column shows the relative human evaluation gains over baseline caption of each type.

| Counts | Human Evaluates |
|--------|-----------------|
| Visible| Baseline 605   | Ours 640 | +5.79% | +10.93% |
| Meta   | Baseline 245   | Ours 226 | -7.76% | +13.06% |
| Story  | Baseline 129   | Ours 108 | -16.28%| +10.08% |

Figure 3: Captions generated by baseline and our dual staged approach in 6 languages and their corresponding translations.

Figure 4: Human evaluation interface: We ask the raters to compare the two captions. We also ask the raters to then give absolute ratings for each caption. For model comparisons, we use the comparative ratings only. We use the absolute ratings only as a cross-check.

4.4 Cross-modal Discourse Coherence

The work of (Alikhani et al. 2020) introduces the notion of multimodal discourse coherence relationships between image-caption pairs. For instance, a Visible relation corresponds to a caption that describes visually recognizable aspects of the image, such as ‘people’ and ‘cake’; a Meta relation corresponds to a caption that contains details regarding how/when/where the image was captured, such as in “warm summer afternoon”; a Story label implies that the caption text describes some potentially non-visible context behind the scene depicted in the image, such as “fifth anniversary”.

We hypothesize that our multi-stage approach of skeleton-based image captioning results in the generation of more captions of the Visible type, as a result of the intermediate skeleton predictor being trained to predict nouns and verbs from the image. A caption conditioned on such a skeleton is more likely to describe the visual content of an image, and, as a result, produce captions that are in a Visible relation with the image. To assess this effect, we train and deploy the relation classifier described in Sec. 4 of (Alikhani et al. 2020), and obtain discourse relation labels for the captions generated for T2-test images, by both the baseline Img2Cap model and our SkeEncoding model. Table 7 (under the Counts columns) quantifies the shift of relation label distribution towards the Visible coherence relation, confirming our hypothesis. Additionally, we study the breakdown by coherence relations using the results from our human evaluation done for the English captions. Table 7 (the Human Eval column) reports this breakdown, which indicates that, of the 11.01% gains on human evals from Table 5, the shift from non-Visible discourse to Visible discourse captions is associated with clear increases in preference from the human raters. This is attributable to the fact that the human raters are more likely to prefer captions that are in a Visible relation with respect to the image, and therefore the shift towards producing Visible-type captions can be positively quantified in terms of human preference.

5 Qualitative Discussion on Controllability

The dual-staged decomposition of a model can be a double-edged sword: it can act as an information bottleneck, limiting the ability to train the model in an end-to-end fashion; and, it can be an advantage due to increased interpretability and the ability to use the intermediate stage results to control or guide final output. Here we present qualitative aspects of caption
controllability, by altering the skeleton to explore effects on caption length, informativeness, and gender specificity.

**Effect of length of skeletons on captions:** The length of the skeleton positively correlates with the number of words in the caption, as shown in Figure 6. For two or three skeleton words, the percentage of captions is a monotonically decreasing function of the number of words in the caption, and the mode is at four-word captions. Thus, for skeletons of size two, captions of length four are much more frequent than captions of length six or eight. For longer skeletons, we see that the mode shifts to the right: with skeletons of size five, we find that caption length peaks between eight and ten words. Thus captions of length four are less frequent than captions of length eight or ten, which in turn are more frequent than those with size twelve, fourteen or sixteen. Note that, for applications that impose limits on the caption lengths due to UI restrictions, the ability to control the length is important.

The effect of varying the size of the skeleton on the length of the caption is qualitatively illustrated in Figure 7.

![Figure 5: Controllability: Effect of guiding the information through skeleton. As observed, the caption incorporates information from the skeleton that is consistent with the image. For example, in the second column of the top row, we see that peace is incorporated while harbor and heaven are not. The relevant skeleton words in other columns guide the captions accordingly.](image1)

![Figure 6: Quantitative relationship between the number of skeleton words and caption length.](image2)

![Figure 7: Controllability: Effect of varying the number of words in the skeleton on the generated caption length.](image3)

Effect of guiding the information in the skeleton: The skeleton can act as a knob enabling the model to describe different attributes of the image in the caption. The example in Figure 5 demonstrates how varying the skeletons for two different images affect their captions. The words highlighted in green are derived from skeleton words and the words highlighted in blue are image specific contents.

**Effect on gender specificity:** As a preliminary observation, we note that current captioning models are quite clumsy at correctly identifying gender, and are prone to make embarrassing mistakes. The availability of the skeleton allows one to have a direct handle for correcting such mistakes, at a pre-caption-generation stage where doing so is more robust compared to caption post-processing. This is especially relevant for highly inflected languages. To illustrate this control ability, we compare the number of times ‘man’ appears in the caption outputs generated by our baseline versus by our dual-stage model after automatically modifying the skeleton (we replace all the occurrences of ‘man’ to the gender-neutral word ‘person’ in the skeleton). Over the T2 dataset, the baseline caption generates ‘man’ 13 times, and our automatic control mechanism for the dual-stage model reduces this by 46% (to 7 occurrences) in English. In Hindi, the equivalent of ‘man’ (‘aadmi’) is generated 10 times, and it is reduced to a gender neutral word (‘vyakti’) by 70% (to 3 occurrences).

6 Conclusions and Future Directions

Humans generate language by choosing words and composing sentences based on a communication intent. Deep-learning based language generation approaches to tasks like image captioning are oblivious to this, unless explicitly conditioned to not just generate the most likely sentence, but a sentence controlled by relevant concepts. To achieve this, we split an image captioning model into two stages, where the first stage predicts a relevant skeleton, and the second stage conditions caption generation on the image and the skeleton. Our experimental results show that, while this approach does not change CIDEr much, it improves the caption quality in human evaluations, not only for English but for other languages as well (with English skeleton). Perhaps as importantly, this method creates a natural interpretable layer in the pipeline, which can be used to control the final output by modifying the content of the skeleton. We plan to explore the unpaired capability of our approach further in future.
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