Denoising Large-Scale Image Captioning from Alt-text Data using Content Selection Models

Anonymous ACL submission

Abstract

Training large-scale image captioning (IC) models demands access to a rich and diverse set of training examples that are expensive to curate both in terms of time and man-power. Instead, alt-text based captions gathered from the web is a far cheaper alternative to scale with the downside of being noisy. Recent modeling approaches to IC often fall short in terms of performance in leveraging these noisy datasets in favor of clean annotations. We address this problem by breaking down the task into two simpler, more controllable tasks – skeleton prediction and skeleton-based caption generation. Specifically, we show that *sub-selecting content words as skeletons* helps in generating improved and denoised captions when leveraging rich yet noisy alt-text–based *uncurated* datasets. We also show that the predicted English skeletons can further cross-lingually be leveraged to generate non-English captions, and present experimental results covering caption generation in French, Italian, German, Spanish and Hindi. We also show that skeleton-based prediction allows for better control of certain caption properties, such as length, content, and gender expression, providing a handle to perform human-in-the-loop interpretable semi-automatic corrections.

1 Introduction

In the last demi-decade, most of the NLP fields ventured into reaping the benefits of utilizing large scale raw data *(uncurated)* from web-crawls. This trend resonated with new uncurated image-captioning datasets like Conceptual Captions (Sharma et al., 2018). While this uncurated alt-texts are superior in terms of size and diversity in the dataset, they are inferior to the well curated datasets (Lin et al., 2014; Wang et al., 2019b) in terms of noisiness in the captions. The content in the alt-text for the image is often distorted in favor of the intent or the context in which the image is presented. For example, the ground truth alt-text caption for a house is *'house for sale'* instead of *'front view of a house'*. This noise hinders exploiting these very large datasets to the fullest.

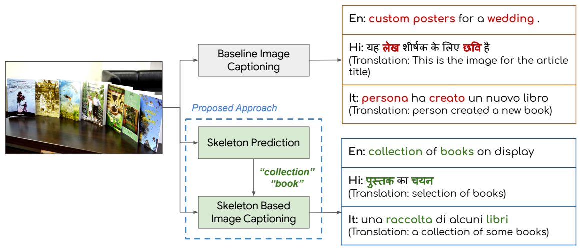


Figure 1: Overview of our approach: (1) skeleton prediction & (2) skeleton based IC; compared to conventional IC. Output captions shown in English (En), Hindi (Hi) and Italian (It).

We present a simple two-staged approach by separating the content selection from caption generation as illustrated in Figure 1. In contrast to most IC approaches (Hossain et al., 2018; Sharma et al., 2020), which hallucinate incorrect content from noisy training data (i.e 'custom posters' and 'wedding'), our approach first focuses on *denoising* the content words (i.e 'collection' and 'book') that are further used to generate a relevant caption. We refer to this sequence of concept words that are key pieces of information consistent with the image as a *skeleton*. Sub-selecting skeleton words that curb noisiness are automatically extracted from the alt-text captions. We focus on language-based skeletons that are derived from captions (Kuznetsova et al., 2014; Fang et al., 2015; Dai et al., 2018), rather than expensive visual-based skeletons derived from image, e.g., scene graphs, (Wang et al., 2019a; Yang et al., 2019), which are hard to scale. More concretely, we introduce an intermediate task of distantly supervised skeleton prediction in the end to end IC pipeline: The end-to-end task of IC is ($f_\theta : \mathbb{I} \rightarrow \mathbb{C}$) is broken down into a dual-staged pipeline: skeleton prediction ($f_\theta : \mathbb{I} \rightarrow \mathbb{S}$) and skeleton based captioning ($f_\phi : \mathbb{I}, \mathbb{S} \rightarrow \mathbb{C}$), where $\mathbb{I}$ is the image, $\mathbb{S}$ is the skeleton, and $\mathbb{C}$ is the caption (Kulkarni et al., 2013; Li et al., 2011;

Elliott and Keller, 2013; Fang et al., 2015). We present a comparison between encoding, decoding and autoencoding these skeletons. As such, our skeleton prediction solution addresses the *semantic gap* problem (Li and Chen, 2018; Yao et al., 2018).

We illustrate the effectiveness of this approach on uncurated noisy datasets in the following ways. (1) We demonstrate that sub-selecting content words with an intermediate *skeleton prediction task denoises content* thereby leading to better human evaluation results on captioning. We also conduct an extensive analysis on multimodal discourse relations to understand the reasons for this improvement (Alikhani et al., 2020) being generation of more visible captions. (2) Scaling the large uncurated datasets to other languages is still a bottleneck. We show the *transferability of learning English skeletons* to improve caption generation in other languages – English, French, Italian, German, Spanish and Hindi. (3) The predicted skeletons qualitatively demonstrate other potential benefits, such as *controllability* of content, length, and gender via a natural language–based *interpretable* interface, which enables one to additionally interact with the generation process.

2 Related Work

Content selection from vision: There is a rich body of work in improving content selection for IC (Feng et al., 2019), mainly focused on scene graph based skeletons (Gu et al., 2019; Kim et al., 2019; Chen et al., 2020a; Yang et al., 2019). However, these annotations with objects and relations are expensive, thereby constraining the scaling up to multiple languages and diverse concepts. Our work delegates this responsibility of identifying content to the language modality by using inexpensive off the shelf tools for weak supervision.

Content selection from language: An orthogonal body of work relies on skeletons derived from language using hierarchical phrase modeling (Tan and Chan, 2016; Dai et al., 2018), semantic attention (You et al., 2016), attribute LSTM (Yao et al., 2017), skeleton based attribute filling (Wang et al., 2017), adaptively merging topic and visual information (Liu et al., 2018), multimodal flow (Li et al., 2019a) and concept guided attention (Li et al., 2019b). Note that all these prior works utilize human curated gold datasets such as COCO (Lin et al., 2014) and Flickr30k (Plummer et al., 2015) with clean coupling between captions and images. However, scaling them to large and diverse concepts is expensive. We utilize *uncurated* silver standard datasets with the advantages of richness and diversity at the cost of noisy text. Hence we show the effectiveness of a dual staged approach that denoises the captions by skeleton prediction.

Cross-lingual and controllable captions: Past work on cross-lingual captioning focused on translation (Barrault et al., 2018), fluency guidance (Lan et al., 2017), using large datasets (Yoshikawa et al., 2017) and more recently by pivoting on source language captions (Thapliyal and Soricut, 2020; Gu et al., 2018). We go a step further and pivot on the predicted English skeleton to improve multilingual captions due to the dearth of similar off the shelf tools in other languages. We qualitatively explore controlling length via skeletons which was explored before via adding length to decoder (Luo and Shakhnarovich, 2020; Cornia et al., 2019). Other controllable aspects include stylistic captions (Guo et al., 2019; Mathews et al., 2018) language (Tsutsui and Crandall, 2017) which are potential extensions to our unpaired captioning work.

Interpretable Natural language skeletons: Despite remarkable advancements of large scale end-to-end models, recent work identifies spurious correlations in the datasets that potentially leads to high performances (Geva et al., 2019; Tsuchiya, 2018). To mitigate this, researchers began dissecting intermediate components of the models with the goal of interpretability to humans (Wiegreffe and Pinter, 2019; Thorne et al., 2019; Lipton, 2018) as opposed to implicit explanation (Xu et al., 2015). Our work can also be viewed as an instance of explaining captions through skeleton predictions similar to recent works on rationalizing answer predictions for question answering (Latcinnik and Berant, 2020). We view this interpretable intermediate layer as a peek into the model predictions helping us study more subtle but crucial dataset attributes, such as gender bias and provide human-in-the-loop interventions to improve the final caption.

3 Our Approach

IC requires paired examples of images and captions ($\mathbb{I}$, $\mathbb{C}$), where $c \in \mathbb{C}$ correspond to tokens in a caption $(c_1, c_2, ..., c_m)$, which are often expensive to gather. In contrast, our approach uses intermediate skeletons as an effective way to leverage noisy, uncurated alt-text based captions to train a model to generate more visually informative captions. An

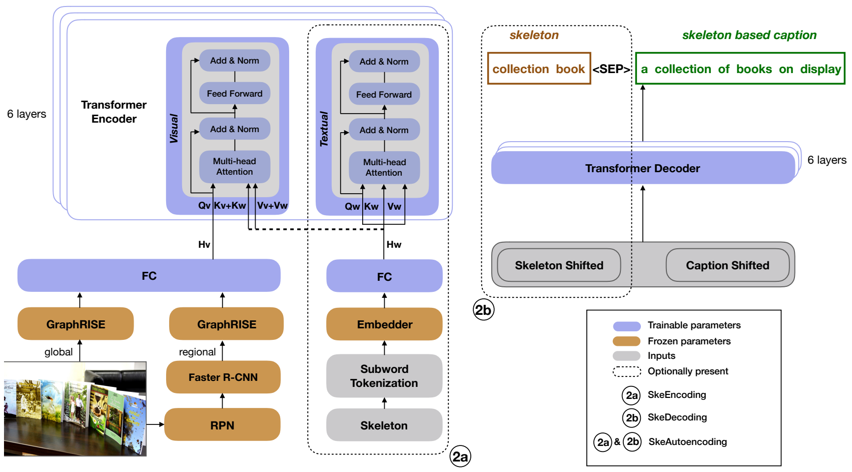


Figure 2: Model architecture of our skeleton based captioning along with *text as side attention* mechanism between visual (v) and textual (w) modalities. The skeleton is present optionally in the encoder, decoder or both based on our three approaches.

overview of both the stages is presented in Fig. 1.

3.1 Distantly Supervised Skeletons

Since gold standard skeleton words are usually not available for IC datasets, we use distant supervision to get these labels. We retrieve syntax annotations (specifically parts-of-speech (POS) and word lemmas), using the Google Cloud Natural Language API [1] over the caption texts. We use these annotations to experiment with the following four variants of skeletons.

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

2. Salient Nouns & Verbs: Saliency of nouns and verbs is determined using tf-idf scores, treating each caption as a document. For each caption, the top 2 highest scoring noun and verb tokens (lemma) are selected. This examines if saliency contributes towards effectiveness of the skeleton.

3. Nouns: This includes lemmas of all the nouns. This helps us untangle the roles of nouns vs verbs in the effectiveness of the skeleton.

4. Iteratively refined captions: Under this condition, the output of the baseline Img2Cap model serves as the 'skeleton' for the next skeleton-based captioning stage. The rationale behind this skeleton is to compare the utility of sub-selecting skeleton words based on POS in denoising caption content, compared to a full caption prediction.

We ignore skeleton tokens with a frequency of less than 50 in our training data to reduce noise. This subselection of content based on POS tags and downscaling of vocabulary helps in retaining important words as skeletons resulting in a label size of 5k.

[1]https://cloud.google.com/natural-language

3.2 Model

Baseline (Img2Cap): We adopt an encoder-decoder ($f_\theta : \mathbb{I} \rightarrow \mathbb{C}$) IC 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). Our model uses the IC framework introduced in (Changpinyo et al., 2019). Inspired by the bottom-up and top-down approach (Anderson et al., 2018), the input image $\mathbb{I}$ is represented as a bag of features, containing one global and 16 regional, fine-grained feature vectors. The regional features 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 ResNet101 (He et al., 2016) that is trained on JFT (Hinton et al., 2015) and fine-tuned on ImageNet (Russakovsky et al., 2015). We featurize both global and regional boxes using Graph-RISE (Juan et al., 2019, 2020). We make the following changes to the state of the art model (Changpinyo et al., 2019), leading to a 9-point improvement on the dev CIDEr on CC (1.00 vs. 0.91) (**improved baseline**): 1) encode the corners and the area of the bounding boxes to fuse positional information with visual features, (Lu et al., 2019a), and 2) encode each feature vector with a Linear-ReLU-LayerNorm-Linear instead of Linear embedding layer, where LayerNorm is layer normalization (Ba et al., 2016).

Dual Staged Modeling: In this approach, we introduce an intermediate natural-language interpretable skeleton $\mathbb{S}$ between $\mathbb{I}$ and $\mathbb{C}$. This $\mathbb{S}$ is composed of a sequence of lemmas, using a subset of content words $(s_1, s_2, ...s_n)$ from c, where $n < m$. This reduces the output complexity of $f_\theta : \mathbb{I} \to \mathbb{C}$ by simplifying and denoising the noisy $\mathbb{C}$ to $\mathbb{S}$. Hence, the task of IC is decomposed into the first stage of predicting skeleton concepts and the second stage of caption generation using the intermediate skeleton.

Stage 1: Skeleton Prediction (Img2Ske): The first stage ($f_\theta : \mathbb{I} \to \mathbb{S}$) is to predict one of the 4 variants of the skeleton words (from §3.1) from the images. We experiment with both classification and generation paradigm that respectively do not possess and possess linear conditioning of the predicted skeleton word on the following words. We observe that the generation based skeleton prediction results in skeleton words that co-occur in a sentence. In contrast, the classification approach predicts skeleton words relevant to an image like *person, man, singer* that do not necessarily co-occur in a caption. This is detailed in §D of Appendix.

To improve co-occurrence of the predicted skeleton words, we generate the skeleton words $\hat{\mathbb{S}}$ autoregressively where each word is conditioned on the previously predicted skeleton word. This conditional dependence models word co-occurrence more tightly as $p(\hat{\mathbb{s}}_j | I, \hat{\mathbb{s}}_{<j})$, making the skeleton a sequence of words. The model is optimized with cross-entropy loss, trained using teacher forcing. An attractive property is that the same architecture can be used to decode both the skeleton $\mathbb{S}$ and the caption $\mathbb{C}$. Moreover, the output tokens predicted in this stage are interpretable, and they are used to condition the second stage of our model.

Stage 2: Skeleton-based Caption Generation: The second stage of training uses both images and skeletons to generate captions $f_\phi : \mathbb{I}, \mathbb{S} \to \mathbb{C}$. We experiment with 3 variants of conditioning predicted skeletons via encoding, decoding and autoencoding as shown in the overall model architecture in Fig. 2. The inputs, outputs for each stage and the conditioning of attention for transformer decoder are compared in Table 1.

2a. SkeEncoding: The predicted skeleton from the previous stage is used as input to the encoder. The image encoding and skeleton embeddings are fused with a unidirectional attention mechanism, called **text-as-side** (notated as g). In other words, we use the text representation as "side information" — each transformed image feature unit can attend to other image feature units (self-attention) and text (cross-attention), but text cannot attend to image. As shown in Fig. 2, this model has the dotted box in the Transformer encoder side, with the textual query, key, value (Q_w, K_w, V_w) and the visual counterpart attending to textual or visual key and value ($K_v + K_w$, $V_v + V_w$) with a visual query (Q_v). We focus on the text-as-side attention mechanism as our preliminary results indicate that it leads to qualitatively better captions than image-text co-attention (Lu et al., 2019b).

	Stage 1		Stage 2		Conditioning
	Input	**Output**	**Input**	**Output**	
SkeEnc	$\mathbb{I}$	$\mathbb{S}'$	$\mathbb{I}$+$\mathbb{S}'$	$\mathbb{C}'$	$\hat{\mathbb{c}}^\tau \sim \prod_t Pr(\hat{\mathbb{c}}^t \vert \hat{\mathbb{c}}^{<t}, g(z_{\mathbb{I}}, \hat{\mathbb{S}}))$
SkeAE	$\mathbb{I}$	$\mathbb{S}'$	$\mathbb{I} + \mathbb{S}'$	$\mathbb{S}' + \mathbb{C}'$	$\hat{\mathbb{c}}^\tau \sim \prod_t Pr(\hat{\mathbb{c}}_k^t \vert [\hat{\mathbb{S}}; \hat{\mathbb{c}}^{<t}], g(z_{\mathbb{I}}; \hat{\mathbb{S}}))$
SkeDec	(no Stage 1)		$\mathbb{I}$	$\mathbb{S}' + \mathbb{C}'$	$\hat{\mathbb{c}}^\tau \sim \prod_t Pr(\hat{\mathbb{c}}_k^t \vert [\hat{\mathbb{S}}; \hat{\mathbb{c}}^{<t}], z_{\mathbb{I}})$

Table 1: The inputs and outputs of the different models. In iterative refinement, $\mathbb{S}'$ is replaced by $\mathbb{C}'$.

2b. SkeDecoding: The skeleton and caption are concatenated and predicted by the same decoder. This is not a two-staged model, as the model is trained to predict both skeleton and caption autoregressively. The model first predicts the skeleton words conditioned on the previously generated skeleton words, and then every token in the decoded caption attends to the entire predicted skeleton as well as the tokens of the caption decoded until that time step. The dotted box in Transformer decoder of Fig. 2 depicts this approach.

2c. SkeAE: To bring both the above models together, we simultaneously encode and decode the predicted skeleton. This brings the benefits of bidirectional attention on the input features (image and predicted skeleton words) and autoregressive attention on the re-predicted skeleton words while generating the caption. In this case, both the dotted boxes on encoder and decoder sides in Fig. 2 are active. The encoding mechanism follows the g function and the decoder prepends the caption generation task with the predicted skeleton.

4 Experiments and Results

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

4.1 Datasets

Conceptual Captions (CC): CC (Sharma et al., 2018) is a large-scale dataset of 3.3M image-caption pairs covering a large variety of processed alt-texts from the web. The focus of this work is on denoising noisy captioning datasets (web-scale, not human verified). Hence our experiments are focused on CC, which is a step closer to having large and diverse alt-texts from the web at the cost of being noisy. In contrast, other popular datasets like COCO (size 120K) (Lin et al., 2014) and Multi30k (Elliott et al., 2016) are hand-annotated by humans and contain high quality images/captions. As a resource, CC is useful both for measuring progress on large-scale automatic captioning (Sharma et al., 2018; Changpinyo et al., 2019; Alikhani et al., 2020; Thapliyal and Soricut, 2020), as well as pre-training data for a variety of vision-and-language tasks (Lu et al., 2019b; Chen et al., 2020c; Tan and Bansal, 2019; Su et al., 2020; Li et al., 2020).

Pre-processing: CC might contain a long tail of spelling errors and other typos due to the automatic curation of the data. Therefore, we perform frequency based thresholding of the skeleton words to abate this noise. We experimented with several values for this hyperparameter and selected a minimum occurrence count as 50 that provides the desired balance between noise and vocabulary size.

Multilingual CC: To demonstrate the cross lingual transferability of our skeletons, we use automatic caption translations[2] for CC, similar to the approach in (Thapliyal and Soricut, 2020). Note that the skeletons are learned from, and predicted in, English (not in the final target language), making English skeleton act as an *interlingua*. Since multilingual captions are all pivoted on English skeletons, this nullifies the requirement to 1) collect large-scale image-caption pairs in various language, and 2) have access to linguistic tools to analyze captions in each language. We perform experiments on 5 languages – French, Italian, German, Spanish and Hindi – which vary in word orders and token overlap with the English skeletons.

Conceptual Captions T2 test set: For human evaluations across *all languages*, we use T2 test set used in the Conceptual Captions Challenge[3]. It comprises of 1K out of domain images from the Open Images Dataset (Kuznetsova et al., 2020).

[2]We use the Google Cloud Translate API.
[3]http://www.conceptualcaptions.com/

	Iterative Refinement	Classification	Generation
Precision	35.75	23.22	36.66
Recall	24.29	41.31	24.30
F-score	28.92	29.73	29.23

Table 2: Performance of skeleton prediction stage. Note that for classification and generation, the skeleton type used is ‘nouns & verbs’.

Model	**CIDEr**		
Baseline (SOTA model)	0.91		(Changpinyo et al., 2019)
Impr. Img2Cap	1.00		
Impr. Img2Cap (large)	0.99		
Skeleton-based	**Skeleton Type**		
	Nouns & Verbs	**Nouns only**	**Sal. Nouns & Verbs**
SkeEncoding	0.99	0.97	0.94
SkeDecoding	0.99	0.99	0.96
SkeAE	0.99	0.96	0.94

Table 3: Automatic metrics to compare various skeleton forms. Img2Cap is the baseline (*large* version refers to 12 encoder and decoder layers). Note that these results use generation-based skeleton prediction.

4.2 Automatic Evaluation

Skeleton Prediction: The goal of this stage is to extract key skeleton words from the image. We compute precision, recall and F-score as shown in Table 2. With the same labels (skeleton: nouns & verbs), both classification and generation approaches have similar F-scores. However, precision is higher for generation and recall is higher for classification based predictions. Based on both qualitative observations and human judgements, we note that generation approach was better, which shows that a higher precision is favorable in comparison to recall for this stage. The label size (of skeletons) in Table 2 is approximately 5K.

Skeleton-based Caption Generation: We report multilingual IC performance of baseline and our dual-stage models using CIDEr in Table 3 (English) and Table 4 (multilingual). Automatic metrics for captioning are based on surface n-grams, and are not suitable to evaluate when the ground truth captions themselves are noisy. In addition, we find that CIDEr is misleading (Alikhani et al., 2020; Sharma et al., 2018; Seo et al., 2020) and does not correlate with human evaluations (§4.3).

Multilingual captioning: Note that the skeletons are always in English, trained using annotations over the original English CC dataset. Cross-lingual results on val data of Multilingual CC are presented in Table 4. In addition to the data noisiness, a reason for slightly lower performance for non-English captions is probably noisy translation

Language	Baseline	SkeEncoding	SkeDecoding	SkeAE
French	0.91	0.90	0.89	0.90
Italian	0.90	0.88	0.86	0.87
German	0.74	0.72	0.72	0.73
Spanish	0.92	0.91	0.89	0.91
Hindi	0.85	0.83	0.82	0.82

Table 4: CIDEr scores for skeleton (form: Nouns & Verbs, prediction approach: generation) conditioned caption generation for multiple languages.

Model Enc Input	CIDEr
PredSke + Img (Paired)	0.99
PredSke (Unpaired)	0.91
GtSke + Img (Paired Headroom)	4.62
GtSke (Unpaired Headroom)	4.48

Table 5: Ablations on val data for unpaired captioning.

artifacts. For example, corresponding caption in the Hindi dataset for English caption 'She is gazing at the *fall colors*' is 'वह गिरते रंगों की ओर देख रही है' (translation: She is looking at the *falling colors*.) Translation errors (such as 'fall' colors to 'falling' colors) introduce noise in the non-English datasets. Figure 3 presents an example of output multilingual captions for the baseline and our SkeAE approach.

Unpaired Image Captioning: A natural extension to our approach is for the caption generator to rely purely on predicted skeleton, and not use image features. This is a harder problem, but eliminates altogether, the need for image-caption pairs because the second stage (skeleton to caption) can be trained on a large text-only corpus. In this direction, within the scope of CC dataset, we investigate 1) with and without using image features in the second stage, 2) using ground truth skeleton (GTSke) to get an estimate of the upper bound on unpaired captioning 3) comparing the upper bound to the predicted skeleton (PredSke). These results are presented in Table 5. When image features are ignored, CIDEr drops by only 8 points when only predicted skeletons are used for caption generation compared to the baseline. This initial result shows that skeletons are a promising direction towards unpaired captioning.

4.3 Human Evaluations

Automatic metrics often have been found not to correlate well with human scores (Kilickaya et al., 2017; Alikhani et al., 2020) and do not fare well when ground truth text is noisy. So we conduct extensive human evaluations where captions for each image are evaluated both in relative preferences and absolute scale (Thapliyal and Soricut, 2020). As mentioned above, we use the T2 test set of 1000 images, each rated by 3 distinct annotators. The interface of this evaluation is displayed in Figure 4. While comparing two models side-by-side, they are randomly assigned 'A' or 'B' in the interface for each image to avoid any rater bias.

Relative Rating: For each image we ask the raters to choose the most relevant caption. Comparing Caption A to Caption B, raters can select relative options as shown 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. *Losses* are percentage of images where at least 2 out of 3 annotators voted for caption generated with Img2Cap approach. We compute *gains* in this side by side relative evaluation as $Gains_{relative}$ = Wins - Losses.

Results: Table 6 presents the human ratings for English captions using different skeletons. From this, we observe the following:

• *Dual Staging helps:* Our dual staged models with skeletons (SkeEnc, SkeDec, SkeAE) show gains compared to the improved baseline Img2Cap model. Most notably, it shows that the 'Nouns & Verbs' skeletons significantly improves SkeEncoding model attaining the most significant gain, followed by SkeAE and then SkeDecoding.

• *Subselecting content words helps:* Using the same dual staged SkeEnc model without subselecting content words in the form of iterative refinement does not show any improvement in performance, supporting the hypothesis that sub-selecting content skeleton from noisy captions improves the overall caption quality.

• *Cross-lingual skeleton transfer:* Table 7 presents our human evaluation scores for captions in other target languages. We observe gains from the skeleton-based approach for 4 out of 5 languages, and only a slight loss for the fifth language, showing the effectiveness of cross-lingual transferability of the skeleton words.

4.4 Cross-modal Discourse Coherence

To understand where the improvements quantified in Table 6 come from, we turn to the notion of discourse coherence. Alikhani et al. (2020) introduce multimodal discourse coherence relationships between image-caption pairs. For instance, a caption describing visually recognizable aspects of the image, such as 'people' or 'cake', is annotated using a *Visible* relation; in contrast, a *Meta* relation cor-

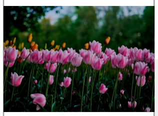
Image	Model	English	French	Italian	German	Spanish	Hindi
	**Baseline**	spring is in the air	fleurs les plus chères du monde *(meaning: most expensive flowers in the world)*	un campo di tulipani in primavera *(meaning: a field of tulips in spring)*	Frühling ist in der Luft *(meaning: spring is in the air)*	La primavera está en el aire (meaning: spring is in the air)	वसंत हवा में है *(meaning: spring is in the air)*
	SkeAE pred skeleton: 'tulip field'	pink tulips in a field	tulipes roses dans les jardins *(meaning: pink tulips in the garden)*	genere biologico in un campo *(meaning: biological genus in a field)*	ein Feld von rosa Tulpen *(meaning: a field of pink tulips)*	tulipán en un mar de tulipanes *(meaning: tulip in a sea of tulips)*	गुलाबी ट्यूलिप का एक क्षेत्र *(meaning: a field of pink tulips)*

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

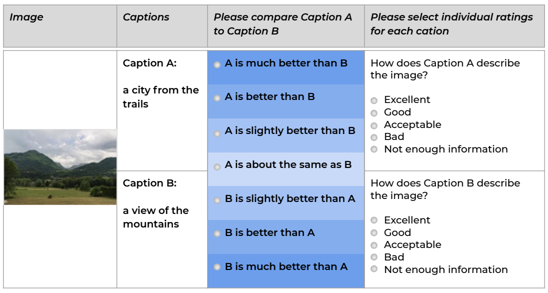


Figure 4: Human evaluation interface: We ask raters to: 1) compare the two captions (relative), 2) give ratings for each caption (absolute).

responds to a caption containing details regarding how/when/where the image was captured, such as in 'warm summer afternoon', while a *Story* relation implies that the caption 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 IC results in the generation of more captions of *Visible* type, as the intermediate skeleton predictor is trained to predict nouns and verbs from the image. To assess this effect, we train the relation classifier described in Sec. 4 of (Alikhani et al., 2020), and obtain discourse relation labels for captions generated on T2-test images, by both the baseline Img2Cap and our SkeEncoding models. Table 8 (Counts columns) quantifies the shift of relation label distribution towards the *Visible* coherence relation, confirming our hypothesis. We also study the breakdown by coherence relations using the results from our human evaluations on the English captions. Table 8 (Human Evals column) reports this breakdown, indicating that, of the 11.01% gains on human evals from Table 6, the shift from non-Visible to Visible discourse captions is associated with clear increases in preference from the human raters. This is attributable to the fact that human raters are more likely to prefer captions that are in a *Visible* relation with the image, and therefore the shift towards generating *Visible*-type captions can be positively quantified in terms of human preference.

Approach	Skeleton	Wins	Losses	Gains
SkeEncoding	Nouns & Verbs	39.34	28.33	**+11.0**
SkeAE	Nouns & Verbs	39.34	32.63	+6.7
SkeDecoding	Nouns & Verbs	34.83	34.53	+0.3
SkeEncoding	Iterative Refinement	19.62	20.52	-1.1

Table 6: Human evaluation scores of different approaches and skeletons on English (vs the Img2Cap baseline).

Language	Wins	Losses	Gains
French	31.43	29.53	**+1.9**
Italian	26.13	24.93	**+1.2**
German	35.23	33.93	**+1.3**
Spanish	34.03	34.33	-0.3
Hindi	33.13	28.63	**+4.5**

Table 7: Human evaluation results for skeleton (form: nouns & verbs, prediction approach: generation) conditioned caption generation for multiple languages.

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

Table 8: 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. Other relations with small counts are ignored in the above analysis.

5 Controllability: Qualitative Discussion

The dual-stage modeling decomposition brings forth the advantage of increased interpretability and thereby the ability to use the intermediate stage results to control the final caption. We present aspects of caption controllability by altering the skeleton to explore effects on caption length, informativeness, and gender specificity. This section discusses the utility of this dual staged model for controllability qualitatively. Instead, we present an empirical study only to semi-automatically control gender specificity in two of the languages. We plan to conduct experiments on comparison with other models (Zheng et al., 2019; Chen et al., 2020b) and automatically selecting different but relevant skeleton words in the future work.

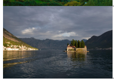
	Baseline caption	magic	peace harbour heaven	view mountain	storm darkness	house nest valley mountain
	property image # apartment for people in a picturesque village	the magic of the colours	the peace of the glorious landscape	the view from the mountains	a dark storm in the darkness	a house nestled in the valley of mountains
	a view from the water	the magic of the lakes	the peace of the river	the view from the mountains	a dark storm on the horizon	the house nestled in the valley of mountains

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.

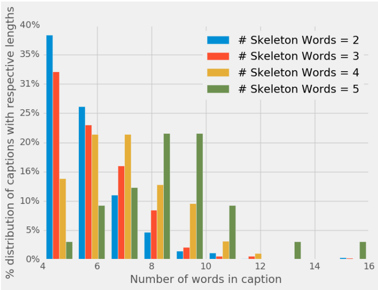


Figure 6: Quantitative relationship between the number of skeleton words and caption length.

Skeleton Words	valley (1 word)	valley mountain (2 words)	house valley mountain (3 words)	house nest valley mountain (4 words)
	the colours of the valley (5 words)	the green valley of mountains (5 words)	houses of the valley and mountains (6 words)	a house nestled in the valley of mountains (8 words)

Figure 7: Controllability: Effect of varying the number of words in the skeleton on the generated caption length.

Effect of length of skeletons on captions: For applications that limit the caption lengths due to UI restrictions, the ability to control the length is important. The length of the skeleton correlates with the number of caption words, as shown in Figure 6. For 2 or 3 skeleton words, the percentage of captions monotonically decreases with the number of caption words, with the mode at 4-word captions. Thus, for skeletons of size 2, captions of length 4 are much more frequent than captions of length 6 or 8. For longer skeletons, we see that the mode shifts to the right: with skeletons of size 5, the caption length peaks between 8 and 10 words. Fig 7 illustrates this qualitatively.

Effect on gender specificity: Current models often make embarrassing mistakes when generating captions that mention gender. The availability of a skeleton provides a direct handle for human-in-the-loop correction of such biases, at a pre-caption-generation stage. This is more robust compared to caption post-processing, especially for highly inflected languages. To illustrate this, we compare the number of times 'man' appears in the captions generated by our baseline versus our dual-stage model after automatically modifying the skeleton (replacing 'man' to the gender-neutral word 'person' in the skeleton). Over the T2 dataset, the baseline caption generates 'man' 13 times, and the automatic control mechanism via our model reduces this by 46% (to 7 occurrences) in English. In Hindi, the equivalent of 'man' (आदमी) is generated 10 times, and it is reduced to a gender neutral word (व्यक्ति) by 70% (to 3 occurrences).

Effect of guiding information through skeleton: The skeleton acts as a knob enabling the model to describe different attributes of the image. Figure 5 presents an example of how varying the skeletons for two different images affect their captions. The words highlighted in green are derived from the skeleton, the ones in blue are image-related words.

6 Conclusions

Scaling image captioning models practically mandates training on noisy and uncurated data available on web. Our works presents an approach that denoises learning from such large yet diverse web-scaled data with alt-text annotations by subselecting content as intermediate skeletons. We experimentally demonstrate that this approach improves the captions significantly in human evaluations on out-of-domain test data by converting meta and story like captions to more visually informative captions. We also demonstrate the transferability of oversimplified English skeleton words to improve captions in five other languages.

Additionally, the natural-language interpretable skeleton layer gives us an access to better control and perform human-in-the-loop corrections of model predictions. We believe that this is a promising direction towards unpaired IC and also has a strong potential for semi-automatic interventions to correct or interact with the skeletons to better guide the final captions. *Appendix G presents a broader impact of our work.*

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A Comparison of SkeEnc and SkeAE on multilingual captions

We have discussed the human evaluation scores of the SkeAE model by using *nouns and verbs* as skeletons in Table 7 in the main paper. In addition to this, we also conducted human evaluation to compare the SkeEnc model with the *nouns and verbs* skeletons in comparison to the baseline. We present this in Table 9. While there are improvements in 3 languages, the performance is also hurt in two languages. However, as we see, by comparing the performances in Table 7 and Table 9, we observe that SkeAE has a clear advantage when leveraging the English caption to improve multilingual captions. This clearly indicates that channelling the prediction of the skeleton words in conjuction with the caption itself is enabling the model decoder to attend to the previously predicted skeleton words in the same decoder.

Language	Wins	Losses	Gains
French	31.93	31.43	**+0.50**
Italian	33.13	28.32	**+4.81**
German	29.43	29.72	**-0.30**
Spanish	30.53	34.43	-3.90
Hindi	29.93	26.03	**+3.90**

Table 9: Human evaluation results on SkeEnc model for skeleton (form: nouns & verbs, prediction approach: generation) conditioned caption generation for multiple languages.

B Comparison of Classification and Generation based Skeleton Prediction

From a preliminary manual analysis, we observed that the classification based approach to skeleton prediction faces the problem of predicting words that are related but are not likely to co-occur within the same sentence in the caption. This is described in detail in points 1a and 1b of §3. To validate this observation, we conducted human evaluation of the captions generated from classification and generation based approaches relative to one another. This setup is different from the rest of the experiments in human evaluation in the paper which compare any given model relative to the baseline model. In contrast, this study is to compare the generation and classification approaches with one another. These results are presented in Table 10.

The top-8 highest scoring content words are chosen to reduce input noise for the caption generator while improving the recall of concepts. We experimented with different values for this and selected 8 to be an optimal balance between the content in the skeleton words and the noise.

Approach	Wins	Losses	Gains
Generation	39.14	30.23	**+8.91**

Table 10: Human evaluation results of comparison between the generation and classification based approaches

We observe that the generation based approach has significant gains of +8.91 over the classification based approach. Most of the prior literature uses the classification based approach to predict content or bag of concepts to assist caption generation. Our hypothesis is that this classification based model helps in end-to-end approaches where the loss from caption generation backpropagates to the classifier model as well. As opposed to this, our model decouples the prediction of the skeleton or concept words that are further used for caption generation. Hence we believe that suppressing the words that do not co-occur is important in the skeleton prediction task and the generation based approach is addressing this problem.

C Absolue Ratings

In each human evaluation experiment, we also gathered absolute ratings of each caption in addition to the relative ratings. The relative ratings are described in §4.3. We also gather absolute rating for each of the 2 captions per image. Each caption is rated as acceptable if at least 2 out of 3 annotators rate it as *acceptable*, *good* or *excellent*. $Gains_{absolute} = Accept_{our\_approach} - Accept_{baseline}$. However they are not used in this quantitative analysis. We use them only to validate the ratings such that, for example, an "Excellent" rated caption is not annotated as inferior to a "Bad" rated caption for the same image. These ratings are collected to double check the results of the relative rating as well.

These scores are presented in Table 11. The top part of the table indicate the absolute ratings in terms of Good and OK performance for multilingual captions. The second part of the table show the same scores when baseline model is compared with the corresponding model and skeleton combination. Each model i.e baseline and the proposed model in each row are rated individually (not relative to one another). The last two columns indicate the performance shift of the corresponding proposed model with respect to the baseline in each of the Good and OK categories.

Here are some of the observations from these results:

- *Better results of Dual Staged Approach:* As we can see in the last two rows (rows 8 and 9), our proposed SkeEnc and SkeAE show absolute improvements in both the categories. This further demonstrates that the proposed dual staged approach is generating better denoised captions when trained on noisy uncurated alt-text–based captions.

- *Sub-selecting content words is better:* Now that we saw the improvements with the dual staged approach, we now investigate whether sub-selecting content words is important. For this, we present comparison between rows 7 and 8. Both these models are dual staged with SkeEnc i.e encoding the predicted skeleton in the second stage. The only difference is that row 8 sub-selects all nouns and verbs to predict the skeletons whereas row 8 includes all the words from the captions to predict the skeletons. Row 8 shows better performance compared to row 7. This means that sub-selecting content words contribute to the caption generation in the second stage.

D Img2Ske: Classification based prediction

Skeleton prediction is posed as a multilabel classification problem where the prediction of a skeleton word s_i is not conditionally dependent on the prediction of another skeleton word s_j. The encoder part remains the same as the baseline followed by optimization with sigmoid cross entropy between the skeleton words $\mathbb{S}$ and image encoding $\boldsymbol{z}_{\mathbb{I}}$, which is the representation of the image from the encoder.

$$\text{Accuracy, } A = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|\mathbb{S}_i \cap \hat{\mathbb{S}}_i\right|}{\left|\mathbb{S}_i \cup \hat{\mathbb{S}}_i\right|} \tag{1}$$

The skeleton for the second stage is chosen as the ordered list of top-8 (experimentally selected) high scoring words after the softmax layer. However, conditional independence of skeleton words with

Row no.	Language	Good Baseline	Good SkeAE	OK Baseline	OK SkeAE	Gains in Good	Gains in OK
1	**French**	34.63	35.04	61.36	60.66	+0.40	-0.70
2	**Italian**	35.14	35.44	60.86	62.56	+0.30	+1.70
3	**German**	43.64	41.04	67.27	68.07	-2.60	0.80
4	**Spanish**	48.15	46.55	74.37	74.67	-1.60	+0.30
5	**Hindi**	59.96	66.17	85.99	87.99	+6.21	+2.00
Row no.	**Model**	**Good Baseline**	**Good Model**	**OK Baseline**	**OK Model**	**Gains in Good**	**Gains in OK**
6	**Unpaired**	57.36	55.06	86.48	84.28	-2.30	-2.20
7	**SkeEnc (Iterative Refinement)**	63.76	62.36	87.89	87.49	-1.40	-0.40
8	**Nouns and Verbs (SkeEnc)**	66.47	63.66	89.39	88.89	+2.81	+0.50
9	**Nouns and Verbs (SkeAE)**	51.55	56.66	79.68	83.18	+ 5.01	+3.40

Table 11: Absolute ratings in percentages in Human Evaluations.

one another ignores the co-occurrences of words 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.

Table 2 presents the precision, recall and f-scores of the generation and classification based approaches for skeleton prediction. These metrics, however are misleading because they do not account for synonyms or semantic similarity. For example, 'food', 'meal', 'lunch' and 'dinner' are all distinct labels while computing these metrics, and predicting one instead of the other get heavily penalized even though the effect on downstream caption quality would be minimal. This issue gets amplified by the fact that with CC that has a rich vocabulary with words such as electricity 'pylon' and 'tower' referring to the same concept.

E Performance drop for Spanish

While we have seen improvements in the performance on multiple languages in human evaluation (Table 6), we observed a drop in the preference for Spanish captions when we use skeletons. Given the similarity in word order between Spanish and English in comparison to Hindi, the lower performance of Spanish is an interesting result indeed. Our speculation for this is probably due to the dialect differences. The translation model that we used for Spanish is a mix of 'Spain Spanish' and 'Latin American Spanish', with Latin American Spanish dominating. The evaluation was done by raters from Spain. The dialects are sufficiently different that it would impact the absolute scores.

F Hyperparameters:

This section lists the hyperparameters used for training our models. We used BERT embeddings (Devlin et al., 2019) to initialize the words in skeletons in the SkeEnc and SkeAE models.

- *Learning rate:* We experimented with $3.2e^{-5}$, 0.5, 1, 1.5 and 2 as the learning rate. The experiments presented in the paper have the learning rate of 1. The learning rate is decayed at 0.95 decay rate with staircase strategy.

- *Number of layers:* All our models have 6 layers for encoder and decoder. We also conducted an additional experiment to check if the model complexity of the end-to-end baseline can improve the performance in comparison to our dual staged approach. To evaluate this, we doubled the number of layers where the number of transformer encoder and decoder layers are 12 each as presented in the paper as Impr Img2Cap (large) in Table 3 in Section 4.2.

- *Subtoken Vocabulary:* We experimented with 4000 and 8300 sub-token vocabularies. The experiments in the paper all have 8,300 as subtoken vocabulary size.

- *Batch size:* All our experiments include batchsize of 128 only.

- *Number of steps:* We train for a maximum of 1 million update steps.

- *Maximum Caption Length:* In the baseline and the SkeEnc models, our decoder generates a maximum words of length 36. In the SkeAE and SkeDec model, the skeleton words are prepended to the caption. So we allow the decoder to generate 72 words in these two models.

- *Warm up and decay steps:* The model is warmed up for 20 epochs and decayed for 25 epochs.

- *Embedding size:* We use embedding dimension of 512.
- *Beam size:* We perform beam search in the decoder with a beam size of 5.

Here are some of the configuration and modeling choices for training the models:

- *Attention type:* Our experiments include attention types of cross-attention and text-aside as described along with point *2a* in Section 3.
- *FRCNN Tokens:* We use 1601 tokens from the trained FRCNN.

G Broader Impact

We believe that this work has extensive impact in scaling captioning models to large and noisy datasets thereby exploiting web data and reduce manual annotation efforts. We do not foresee any immediate concerns ethically directly from our work. However, while applying this to datasets crawled from the web, offensive content should be removed. In general, we envisage researchers and practitioners to benefit from our approach especially, when expensive human annotations are not available. More broadly speaking, we also strongly believe that our approach laid blocks for future work on cross-lingually leveraging English skeletons and automatic translations to generate captions for various languages. Hence, when combined with unpaired captioning, this can especially benefit captioning in low resource languages.