ICC: Quantifying Image Caption Concreteness for Multimodal Dataset Curation

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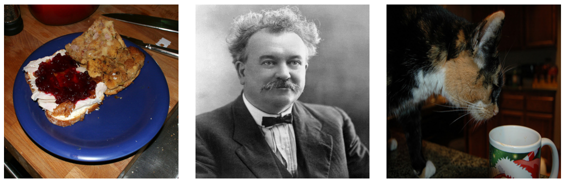
Abstract

Web-scale training on paired text-image data is becoming increasingly central to multimodal learning, but is challenged by the highly noisy nature of datasets in the wild. Standard data filtering approaches succeed in removing mismatched text-image pairs, but permit semantically related but highly abstract or subjective text. These approaches lack the fine-grained ability to isolate the *most concrete* samples that provide the strongest signal for learning in a noisy dataset. In this work, we propose a new metric, *Image Caption Concreteness (ICC)*, that evaluates caption text without an image reference to measure its concreteness and relevancy for use in multimodal learning. Our approach leverages strong foundation models for measuring visual-semantic information loss in multimodal representations. We demonstrate that this strongly correlates with human evaluation of concreteness in both single-word and sentence-level texts. Moreover, we show that curation using *ICC* complements existing approaches: It succeeds in selecting the highest quality samples from multimodal web-scale datasets to allow for efficient training in resource-constrained settings.

1 Introduction

Pre-training large vision-language models (VLMs) on web-crawled datasets consisting of image-caption pairs has become the standard practice in achieving state-of-the-art results in vision-and-language tasks such as image captioning and multimodal representation learning. However, raw web data are often noisy and contain many low-quality samples, which impair VLMs' learning in terms of quality and efficiency (Li et al., 2022; Schuhmann et al., 2022; Radenovic et al., 2023). While various factors impact data quality, we focus on *semantic* noise, characterized by analyzing the meaning of data items rather than, e.g., identifying low resolution images or quantifying token repetitions.



↑	*A sandwich sits on a small blue plate (0.96)*	*Curly-haired man with a mustache in a vintage photo (1.0)*	*A cat standing on a counter looking at a coffee cup (1.0)*
↓	*It does not look like something I would eat (0.02)*	*Talk about a bad hair day, his is frightful (0.01)*	*I cant see this image it is too dark (0.02)*

Figure 1: Given an image caption, *ICC* measures its visual concreteness. We show samples from MS-COCO (Lin et al., 2014) illustrating captions annotated by different annotators with low (↓) and high (↑) *ICC* scores. As seen above, our method successfully differentiates between concrete and abstract or subjective captions, even for high-quality datasets such as MS-COCO. This is done by quantifying visual-semantic consistency using multimodal foundation models.

Existing datasets are commonly filtered using VLMs such as CLIP (Radford et al., 2021) to identify image-text semantic misalignments (Sharma et al., 2018; Schuhmann et al., 2022), i.e. captions irrelevant to their images; using rule-based proxies such as measuring the complexity of captions via semantic parsing (Radenovic et al., 2023); or removing images that contain text that overlaps with the caption (Maini et al., 2023). However, these approaches fail to identify captions that are highly abstract and may contain subjective, non-visual information, despite being semantically aligned with the image and having a sufficiently complex grammar. Figure 1 shows examples of such image-caption pairs. A caption such as *"It does not look like something I would want to eat"* is semantically related to the image, yielding high CLIP similarity, but contains subjective details which provide a confounding signal when training VLMs (See also Figure 2). A model trained to generate such captions from images may learn to hallucinate details, e.g., liking a certain type of food

(a) *poaching still remains the biggest threat to tigers*

(b) *Wheat bread is always the healthy choice for lunchtime*

(c) *want a ring like this!*

(d) *Someone did not observe the stop sign and now it is knocked over*

Figure 2: **Examples with high CLIP similarity and low *ICC*.** We show examples from Conceptual Captions dataset (a) and (c), and COCO dataset, (b) and (d). While these captions are semantically related to the images, they are abstract or contain subjective non-visual information that, unlike *ICC*, CLIP fails to detect.

in our example, which are not visually grounded and are highly subjective. Similarly, such image-caption pairs provide a weaker signal for representation learning than images with visually-concrete captions (e.g. *"A sandwich sits on a small blue plate"*), which may impede the learning process – particularly in a resource-restricted setting where data or compute is limited.

Thus, we suggest filtering image captions by their *visual concreteness*, i.e., the degree to which a text describing a specific visual scene can be vividly imagined (unlike abstract text that may correspond to many possible visual representations or include non-visual contextual information). We show that this new dimension of textual quality enables selecting image-caption pairs that provide a strong supervision signal for vision-and-language tasks, particularly in resource-constrained settings where training directly on noisy web-scale multimodal data fails to converge to a satisfactory solution in a limited number of iterations.

We propose the *Image Caption Concreteness (ICC)* metric for quantifying the visual concreteness of image captions calculated from text alone, i.e., without an image reference. We measure concreteness using autoencoding pipelines with visual-semantic information bottlenecks. Specifically, we use a visual-bottleneck autoencoder that leverages text-to-image generative models' competence and a semantic-bottleneck autoencoder that identifies how well a large language model (LLM) recovers the input caption from its semantic CLIP embedding. As these models require costly inference through large generative models, they cannot feasibly run on a large scale; therefore, our *ICC* metric is distilled from these pipelines, enabling fast, computationally-efficient inference.

In our experiments, we demonstrate that when dealing with limited training iterations, employing *ICC* for filtering multimodal datasets leads to enhanced performance in image captioning and representation learning. Moreover, our results indicate a strong correlation between *ICC* and both single-word concreteness and caption text scores.

Stated explicitly, our contributions are as follows: (1) We propose the *ICC* metric distilled from foundation VLM models with a novel combination of autoencoding pipelines; (2) we show that *ICC* is highly correlated to human concreteness judgements of caption texts; (3) we demonstrate that *ICC* succeeds in selecting a core of samples from web-scale image-caption datasets for vision-and-language tasks, with superior downstream performance to existing multimodal filtering methods; (4) we will release our data, code, and models, anticipating the use of *ICC* for further tasks that require curation of high-quality image-caption pairs from noisy web-scale multimodal data.

2 Method

Given an image caption (of an *unseen* image), we aim to predict its degree of visual concreteness. Our underlying assumption is that more visually concrete text can be mapped to a visual representation with less information loss. Conversely, we expect that visually abstract or subjective text cannot be converted to or from a visual representation without significant information loss, since it does not clearly describe a well-defined image.

As an example, consider the text *"Wheat bread is always the healthy choice for lunchtime"* in Figure 2b. The notion of wheat bread being a healthy choice is inherently non-visual, and is unlikely to be directly encoded in a visual representation, e.g., in an image. Therefore, this information is likely to be lost in an autoencoding process that includes an image as the bottleneck, when the encoded image is decoded back to the textual modality.

We model this effect with multimodal autoencoders (Kamath et al., 2023; Yang et al., 2023). In our setting, we use multiple autoencoder components that convert text to and from visual-semantic representations using foundation VLMs, and quan-

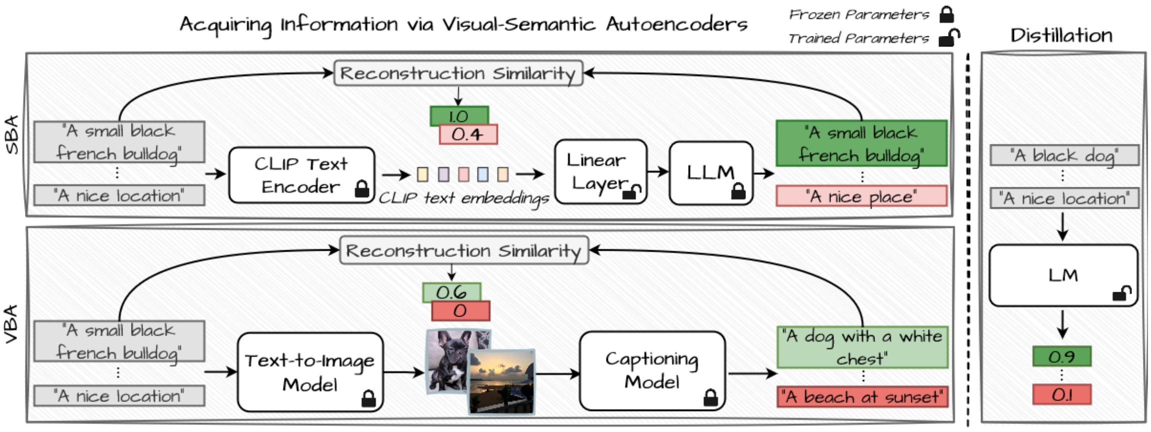


Figure 3: ***ICC* pipeline for predicting visual concreteness of image captions.** We first acquire training data using a semantic-bottleneck autoencoder (SBA, top left) and an visual-bottleneck autoencoder (VBA, bottom left). We then distill a weighted combination of their reconstruction scores into a smaller language model (LM, right), which learns to produce *ICC* scores for new text. We visualize reconstruction scores for highly concrete ("*A black dog*") and highly abstract ("*A nice location*") text. High and low scores are colored in green and red, respectively. Our final score, which combines the two pipelines, yields more accurate concreteness predictions than each of them.

tify the information loss of this process as a proxy for visual concreteness. While these autoencoders provide a strong signal, they are composed of slow, computationally-intensive large generative models making inference infeasible on a large scale. Therefore, we distill their scores into a small model which allows for an efficient calculation of the *ICC* scores.

We proceed to describe our proposed visual-bottleneck autoencoder and semantic-bottleneck autoencoder components, and their consolidated distillation into the final *ICC* metric. See Figure 3 for an overview of our full pipeline.

Visual-Bottleneck Autoencoder (VBA). Since a caption represents an image, we construct the VBA by using an image as an intermediate representation via which textual information passes. In particular, we concatenate a text-to-image model (`Stable Diffusion 2`, Ramesh et al., 2022) and a captioning model (`BLIP-2`, Li et al., 2023) as shown in Figure 3 (bottom left). This autoencoding pipeline measures text concreteness by encoding and decoding a caption, followed by measuring semantic fidelity in reconstruction using BERTScore (F1) (Zhang et al., 2019).

While the VBA pipeline is a simple and intuitive way of enforcing a visual bottleneck, it may sometimes produce sub-optimal reconstructions even for highly visual texts due to its inherently lossy nature. For example, the caption *"a small black french bulldog"* in Figure 3 may be reconstructed by the VBA from the generated image to *"a dog with a white chest"*, which is relatively semantically far from the original caption and thus results in a relatively low reconstruction score of 0.6 for a concrete caption. This stems from the dense information content of generated images, which may contain details (such as the dog's white chest) which were not mentioned explicitly in the original caption, and from the tendency of the captioning decoder to focus on different details than those used to generate the image. To alleviate this issue, we suggest next a complementary method which, while still maintaining a visual prior, also enforces a strong prior on the caption semantic information.

Semantic-bottleneck Autoencoder (SBA). Motivated by findings that CLIP embeddings encode visual information in text and particularly concreteness (Alper et al., 2023), we construct an autoencoding pipeline with CLIP text embeddings as a semantic information bottleneck, as shown in Figure 3 (top left). We extract visual information from the CLIP text embedding space by utilizing a frozen LLM (`Llama-2-7b`, Touvron et al., 2023), by training a linear layer that converts CLIP text encoder's output to inputs for the LLM. This enables more efficient training compared to fine-tuning the LLM. The training objective aims at reconstructing the input captions via a token-wise cross-entropy objective.

After training SBA over image–caption pairs, we use it for measuring text concreteness by encoding and decoding the text followed by measuring reconstruction fidelity. To measure preservation of fine-grained textual details, we quantify this fidelity via per-character edit distance (Levenshtein et al., 1966), standardized by caption length, as detailed in Appendix A.1.

This pipeline generally succeeds in reconstructing highly concrete text (such as *"A small black french bulldog"* shown in the top left part of Figure 3). However, the strong textual prior of the SBA may also leak information about abstract and subjective captions as well (e.g. the abstract caption "*A nice location*" yields a relatively high reconstruction score of 0.4), limiting its correlation with visual concreteness. Overall, the SBA and VBA provide complementary scores, where each correlates more strongly to visual concreteness in different cases. Therefore, they perform most strongly when combined together, as we explicitly verify in our ablations in Section 4. We also show qualitative examples in figures 9 and 10 in the appendix.

Optimal Score Combination. To compute the optimal combination of the two scores, we label 244 captions, sampled uniformly over VBA and SBA scores, with concreteness scores in the range 0–3. We use logistic regression to find the parameters a, b, c of $\sigma(a \cdot VBA + b \cdot SBA + c)$, where $\sigma(x) = \frac{1}{1+e^{-x}}$ is the sigmoid function, such that the output will approach 1 for concrete captions and 0 for abstract ones. We label concrete captions as captions with concreteness above the median score in the labeled dataset and abstract captions as captions with a score below this median. We visualize the annotated samples and the regression line $a \cdot VBA + b \cdot SBA + c = 0$ in Figure 4. As seen in the figure, both scores contribute to the optimal predicted concreteness score, validating the importance of using both SBA and VBA components together in our full pipeline.

***ICC* Distillation.** Using the aforementioned pipelines to quantify the concreteness at scale is not feasible, as this requires running large models (e.g., diffusion models, LLMs) with billions of parameters for many forward passes per instance (up to dozens of forward passes for the diffusion models inference and for the LLM and captioning model decoding). This requires more than 1,000 GPU hours for a dataset of 1M samples. Therefore, we assemble SBA and VBA reconstruction scores over a relatively small collection of image-caption pairs and distill their aggregated values into our final *ICC* score. This enables efficient inference that can easily run on a large scale, with over a hundred times faster inference time and much less compute required. Specifically, we train a small

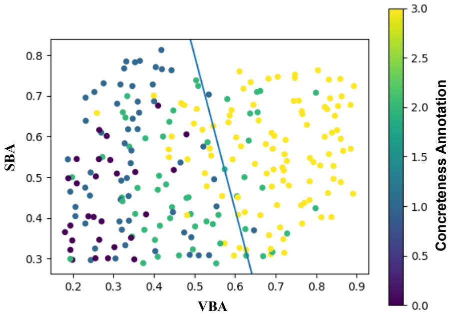


Figure 4: **Finding the Optimal Weights.** We measure the optimal combination of the two scores with respect to ground-truth concreteness annotations.

text encoder model (Liumm et al., 2019) over the optimal combination of the two score.

Implementation Details of *ICC* Construction. For the construction of our *ICC* score, we use a subset of CC3M (Sharma et al., 2018) composed of 595K image-caption pairs, introduced by Liu et al. (2023) and designed to have wider concept coverage. We take a subset of 476K samples for training the linear layer of the SBA, and train for 2 epochs with a batch size of 128 and learning rate of 2e-3 with cosine scheduling function. The remaining 118K samples are used for generating reconstruction scores through the VBA and the trained SBA. For each input caption, we generate five reconstructed captions using beam search (five beams) with the VBA's captioner and the SBA's LLM and then choose the reconstructed caption with the highest similarity to the source caption. By generating the reconstructions and measuring the reconstruction fidelities, we obtain a dataset of 118K captions and corresponding reconstruction scores. We standardize by caption length to disentangle the dependency of the reconstruction scores to the caption length (i.e., forcing the same distribution of scores for all caption lengths), as described in the appendix, and train a small language model (`DistillRoberta-Base`) over the optimal combination of the two scores as previously described, over these 118K samples with a Mean Squared Error objective. This final distilled model is used for generating the *ICC* scores.

3 Results

We turn to show *ICC*'s benefit in data curation for downstream tasks (Section 3.1), followed by its correlation to human judgement (Section 3.2).

3.1 VLM Dataset Curation

Experimental Settings We investigate the effect of *ICC* and other filtering methods for curating a core of high-quality image-caption pairs from large multimodal datasets, comparing their effects on downstream task performance – both discriminative (representation learning) and generative (image captioning). We follow similar settings as described in the Datacomp (Gadre et al., 2023) benchmark's filtering track[1], with the following modifications to model the resource-limited setting: given a training dataset comprised of $\mathcal{M}$ samples, the downstream model is constrained to train for exactly $\mathcal{N} \ll \mathcal{M}$ iterations over the filtered subset of the dataset. This contrasts with the original Datacomp setting where $\mathcal{N} = \mathcal{M}$, which requires significant compute for a web-scale dataset. Our formulation tests the ability of filtering methods to curate high-quality core subsets of such datasets. Our initial subset of LAION-400M is composed of $\mathcal{M} = 8$ million samples and we fix $\mathcal{N} = 2$ million training iterations. To verify the robustness of our method, we measure downstream performance over visually grounded benchmarks across three different sizes of filtering.

We compare to three existing filtering methods – CLIPScore (Hessel et al., 2021), Complexity and Action (CA) (Radenovic et al., 2023) using our re-implementation as there is no publicly-available code, and T-MARS (Maini et al., 2023). CA is a rule-based filtering method which aims to retain only sufficiently complex captions that also contain an action, based on semantic parsing. T-MARS filters multimodal datasets by removing samples whenever an image includes text that overlaps significantly with the caption. As opposed to these method, we focus on filtering according to the level of concreteness of image captions.

Captioning Models. In Table 1 we show quantitative results of applying *ICC* filtering on top of standard CLIP filtering over the subset of LAION-400M for training a captioning model. The captioning model used is an encoder-decoder architecture with a pretrained Swin (Liu et al., 2021) vision encoder and GPT-2 (Radford et al., 2019) text decoder. We use a batch size of 100, and learning rate of 2e-5 with a cosine scheduler. We test our approach over two standard captioning benchmarks datasets – MS-COCO (Lin et al., 2014) and NoCaps (Agrawal et al., 2019), across multiple captioning metrics. As illustrated in the table, filtering with *ICC* outperforms by a large margin the

CA	*Bathroom and bathroom remodeling ideas...*	*How to make a flower bouquet*	*Buster Posey hits a two-run home run...*
TMS	*Wholesale Best Price For White Plastic Bathroom...*	*Coffee Tabletop Decorating Ideas*	*Cleveland Indians vs. Boston Red Sox*
CLIP	*Aquariums-Aquarium of the Year - AQUARIUM OF THE YEAR*	*Dandelion Flower Gift Ideas for Kids...*	*Bryce Harper of the Toronto Blue Jays signs autographs for fans prior to the game*
ICC	*White Plastic Toilet Seat*	*White and Yellow Gerbera Flowers in a Glass Vase*	*black and white photo of a baseball player*

Figure 5: **Downsream captioning qualitative examples.** Captions generated by the model trained over *ICC*'s filtered dataset generates more concrete and accurate captions compared to models trained over dataset filtered with CA, T-MARS (TMS) and CLIP. Images are from MS-COCO dataset.

alternative filtering methods for captioning given a fixed number of desired samples and training iterations. Note that unlike other methods, *ICC* is directly aligned with the captioning objective, as a captioning model should generate visually-grounded concrete text. This can explain the large gap in performance between *ICC* and other filtering baselines. We show qualitative comparison between captioning models trained with different filtering methods in Figure 5, exemplifying how filtering with *ICC* promotes more concrete and accurate captioning.

Image-Text Representation Learning. We also perform a representation learning experiment by training a dual text and image encoder model on LAION-400M filtered with different methods. Table 2 reports text-to-image retrieval over standard held-out retrieval benchmarks, namely MS-COCO (Lin et al., 2014) and Flickr (Plummer et al., 2015). The model is initialized from pretrained vision and text encoders (`vit-base`, `BERT-Base`) (Dosovitskiy et al., 2010; Devlin et al., 2018), as suggested by Zhai et al. (2022). We use a batch size of 128, learning rate of 2e-5

[1]As opposed to the BYOD track which allows for modifying the samples, for instance by using synthetic captions.

		MS-COCO						NoCaps					
Method	**Dataset Size**	B@4	M	R	C	S	BSc	B@4	M	R	C	S	BSc
Random	100k	0.9	4.7	11.2	5	2.3	0.64	1.0	5.1	11.9	5.6	1.6	0.68
CLIP	100k	1.1	5.5	11.9	2.5	2.2	0.75	1.4	5.7	12	3	1.5	0.71
CA	100k	0.9	3.7	7.3	3.2	1.6	0.27	1.6	4.4	9.4	4.1	1.2	0.33
T-MARS	100k	1.2	4.6	10.6	5.6	2.3	0.53	1.3	4.9	11.6	6.3	1.7	0.61
ICC	100k	**10.1**	**15.4**	**35.4**	**35.8**	**10.3**	**0.9**	**12.1**	**15.8**	**35.9**	**33.3**	**6.4**	**0.9**
Random	200k	0.9	4.2	9.8	5	2.2	0.51	1	4.8	11.2	5.9	1.7	0.6
CLIP	200k	1.3	5.7	12.4	3.4	2.6	0.72	1.6	6	12.6	3.5	1.8	0.67
CA	200k	0.5	2.8	5.7	3.7	1.3	0.18	1.2	3.4	7.2	4.1	1.1	0.24
T-MARS	200k	1.1	4.6	10.7	6.5	2.4	0.5	1.7	5.4	12.3	7.8	1.9	0.6
ICC	200k	**10.0**	**15.2**	**34.6**	**35.5**	**10.4**	**0.9**	**13.1**	**15.8**	**35.2**	**34.3**	**6.7**	**0.9**
Random	500k	0.6	3.4	8.0	4.5	1.9	0.42	0.9	4.2	10.1	5.5	1.5	0.55
CLIP	500k	5.2	9.4	22	15.1	5.3	0.8	5.2	8.9	21.3	12.9	3	0.8
CA	500k	0.7	3.1	6	3.6	1.4	0.19	2.1	4.5	9.4	5.3	1.5	0.29
T-MARS	500k	0.8	3.7	8.9	5.7	2	0.42	1.2	4.7	10.8	6.5	1.7	0.65
ICC	500k	**8.3**	**13.9**	**31.4**	**30.9**	**9.7**	**0.89**	**10**	**14.2**	**31.3**	**28.2**	**6**	**0.89**

Table 1: **Captioning results for different filtered dataset sizes**. We perform evaluation of captioning models over MS-COCO and NoCaps datasets trained over different filtering schemes of the LAION-400M dataset, with varying dataset sizes. We compare the performance of *ICC* to three filtering baselines; CLIP indicates filtering by top CLIPScore, CA indicates Complexity and Action filtering and Random refers to random samples from LAION-400M. B@4, M, R, C, S and BSc denote BLEU-4, METEOR, Rouge-L, CIDEr, SPICE, and BERTScore metrics respectively. Best results are in **bold**.

with a cosine scheduling function. All other filtering methods in the table are identical to the ones in the captioning model training. As illustrated in the table, *ICC* yields superior performance for this task, showing that our method selects samples which provide better signal for downstream retrieval applications.

We note that although prior work has found filtering methods such as CLIPScore to be beneficial, we find that it fails to significantly improve (or even degrades) results in the case of selecting a small core of samples. This accords with previous work showing that applying filtering to LAION-400M with CLIP degrades the performance (Maini et al., 2023) in some of the benchmarks, likely due to high-scoring images containing literal text that overlaps with the caption.

3.2 Concreteness Correlation

Table 3 shows the correlations of different concreteness estimation methods to ground-truth concreteness scores on both single-word and sentence-level (caption) benchmarks. We compare to zero-shot probing of CLIP through Stroop probing (SP) as proposed by Alper et al. (2023). We also compare to aveCLIP (Wu and Smith, 2023), the only (to the best of our knowledge) learned metric quantifying concreteness at the sentence level, which generates multiple images from a caption and measures the average CLIP-similarity between the text and generated images. Due to its high computational cost, we only evaluate it on a statistically-significant portion of the single-word benchmark, which contains nearly 15K samples.

Correlation to Word Concreteness. We first validate our metric by measuring it on a dataset introduced by Hessel et al. (2018). This dataset is composed of 39,954 English unigrams and bigrams coupled with human-labelled concreteness scores on a scale from 1 (abstract) to 5 (concrete), averaged over annotators. To compare with prior work, we only use unigram nouns, totaling 14,562 items. As illustrated in Table 3, *ICC* significantly outperforms prior works over all correlation metrics.

Correlation to Caption Concreteness. We manually annotated concreteness scores for 200 captions from LAION-400M (Schuhmann et al., 2022), selected to cover a wider variety of levels of concreteness compared to random samples from the same dataset, by following a rule-based method. We provide further details of the sampling method used in the appendix. We emphasize

		COCO			Flickr		
Filt.	**Size**	R@1	R@5	R@10	R@1	R@5	R@10
Rand.	100k	5.0	15.4	23.3	10.6	31.5	42.6
CLIP	100k	2.1	7.5	12.4	5.7	17.1	26
CA	100k	5.2	15.8	24.1	11.3	32.2	43.8
TMS	100k	6.5	19.5	28.8	14.9	37.1	49.5
ICC	100k	**14.4**	**34.5**	**45.65**	**32.6**	**62.7**	**73.5**
Rand.	200k	9.6	25.5	36.2	21.1	48.9	61.8
CLIP	200k	6.9	10	15.8	6.9	20.9	30.9
CA	200k	8.8	24.4	35.1	20.8	48.6	61.2
TMS	200k	8.2	23	32.8	17.8	43.4	56.3
ICC	200k	**15.5**	**35.8**	**47.6**	**33.6**	**63.2**	**74.5**
Rand.	500k	8.0	22.2	32.5	17.4	42.1	55.4
CLIP	500k	5.3	16	23.9	11.5	30	42.7
CA	500k	8.2	22.6	32.4	17.0	43.3	56.7
TMS	500k	10	26.3	37.2	20.3	46.8	60.5
ICC	500k	**14.6**	**34.9**	**47.0**	**30.6**	**60.9**	**72.9**

Table 2: **Representation learning results over different filtered dataset sizes**. We perform text-to-image retrieval evaluation over MS-COCO and Flickr for different filtering schemes of LAION-400M with varying dataset sizes. We compare our performance (*ICC*) to various filtering baselines: Rand. indicates selecting random samples from LAION-400M, CLIP indicates filtering by top CLIPScore, CA indicates Complexity and Action filtering, and TMS indicates filtering with T-MARS. Best results are in **bold**.

that these captions are different from the ones used to find the optimal combinations of the VBA and SBA, thus avoiding data leakage. As seen in Table 3, *ICC* outperforms existing methods in this setting as well, by an even larger margin than that of the single-word setting.

4 Ablations

***ICC* Model Parts Ablation.** In Table 4, we ablate the effect of design choices in the *ICC* pipeline, namely different LLM sizes (Zhang et al., 2024; Geng and Liu, 2023) in the SBA pipeline and different captioning model architectures in the VBA, as well as the use of edit distance or BERTScore as the similarity measure in each pipeline, in order to justify the use of LLaMa-7B and edit distance in the SBA and BLIP2 and BERTScore in VBA. Note that we ablate the correlation to ground-truth annotations of each of the pipelines in isolation. As can be seen, increasing the size of the LLM in the SBA results in a mild increase in correlation to the ground-truth annotations. Similarly, a more capable captioning model in the VBA provide similar improvement. Moreover, we can also see that the edit distance similarity measure produces better correlation in the SBA pipeline, while BERTScore fits better in the settings of the VBA. This observation matches the intuition that the SBA reconstructs captions with more ease, benefiting from a more stringent metric for detecting abstract versus concrete reconstructions as opposed to the VBA, which should rely on a more semantic measure to properly detect abstract sentences.

	Word Conc.			Sentence Conc.		
Method	ρ	ρ_s	τ	ρ	ρ_s	τ
CLIP-SP	0.60	0.62	0.44	-0.36	-0.35	-0.27
aveCLIP	0.55	0.56	0.39	0.29	0.28	0.22
ICC	**0.75**	**0.75**	**0.55**	**0.69**	**0.67**	**0.54**

Table 3: **Concreteness evaluation on single-word and sentence-level texts.** Correlation is measured using Pearson ρ, Spearman ρ_s, and Kendall τ coefficients.

Sentence Concreteness					
Pipe	Model Part	Sim.	ρ	ρ_s	τ
SBA	TinyLLaMa-1.1B	ED	<u>0.49</u>	<u>0.43</u>	<u>0.33</u>
SBA	OpenLLaMa-3B	ED	0.48	**0.44**	**0.35**
SBA	LLaMa-2-7B	ED	**0.50**	0.42	0.31
SBA	TinyLLaMa-1.1B	BSc	0.45	0.41	0.32
SBA	OpenLLaMa-3B	BSc	0.45	0.40	0.31
SBA	LLaMa-2-7B	BSc	0.47	0.42	0.32
VBA	BLIP-Base	ED	0.47	0.41	0.32
VBA	BLIP-Large	ED	0.39	0.29	0.23
VBA	BLIP-2	ED	0.41	0.34	0.26
VBA	BLIP-Base	BSc	0.42	0.45	0.35
VBA	BLIP-Large	BSc	<u>0.54</u>	**0.48**	**0.37**
VBA	BLIP-2	BSc	**0.55**	<u>0.47</u>	**0.37**

Table 4: **Ablations over VBA and SBA Design Choices.** We ablate the effect of the LLM used in the SBA pipeline and the captioning model used in the VBA pipeline, as well as the sentence-similarity measure, on the correlation to the ground-truth concreteness annotations. Note that here we measure correlation to each model of the piplines (VBA and SBA) used in isolation. BSc and ED refer to BERTScore and edit distance respectively. We report the Pearson ρ, Spearman ρ_s, and Kendall τ correlation coefficients. Best results are in **bold**, and second-best are <u>underlined</u>

Distillation Concreteness Effect. Although the distillation procedure is necessary to make inference feasible with respect to runtime, we provide further motivation by measuring the effect of dis-

	ρ	ρ_s	τ
Before Distillation	0.60	0.53	0.42
After Distillation	**0.69**	**0.67**	**0.54**

Table 5: **Distillation Effect on Caption-Concreteness Correlation**. We show correlations to ground-truth annotated caption concreteness scores before and after distillation. The "After Distillation" row corresponds to our final *ICC* score.

	COCO		NoCaps	
Method	CIDEr	SPICE	CIDEr	SPICE
SBA	17.8	5.9	15.1	3.3
VBA	29.8	9.4	27.8	5.8
ICC	**30.9**	**9.7**	**28.2**	**6.0**

Table 6: **Score Ablations** We ablate the importance of using scores obtained from both the SBA and VBA pipelines over 200k samples filtered dataset using the different scores.

tillation on the correlation to ground-truth annotations of concreteness scores in Table 5. As can be seen, the distillation improves the correlations, providing further motivation beyond computational efficiency and simplifying the inference of our *ICC* model. We hypothesize that this improvement is due to smoothing of noisy reconstruction of the VBA and SBA by the distillation process.

Distillation Speedup. We ablate the speed-up provided by the distillation phase by running the SBA, VBA and the distilled *ICC* on the same hardware settings (an Nvidia A6000 GPU), the same batch size of 1 and the same caption samples. We find that the SBA and VBA process 0.45 and 0.2 samples per second respectively, and the distilled score processes 45 samples per second. Note that the time it would take to generate scores for our 8M subset of LAION-400M dataset is approximately 11,000 GPU hours for the VBA and 5,000 GPU hours for the SBA compared to just 50 GPU hours using the distilled *ICC*. Additionally, for a batch size of 1, the distilled model takes less than 700 MB of GPU memory compared to 13GB and 14GB for the VBA and SBA respectively.

Use of Both SBA and VBA Scores. We also conduct an ablation of the importance of using both the SBA and VBA scores for downstream captioning model training in Table 6. In the figure, we show captioning metrics (CIDEr and SPICE) of a model trained on a distilled version of each one of the scores in isolation, compared to the combined *ICC* metric which outperforms both.

5 Related Work

Evaluating Text Concreteness. Word concreteness is a topic of interest in cognitive science (Schwanenflugel, 2013), and a number of works have studied automatic prediction of word concreteness using machine learning (Hill et al., 2014; Hill and Korhonen, 2014; Hessel et al., 2018; Rabinovich et al., 2018; Charbonnier and Wartena, 2019; Alper et al., 2023). However, little attention has been paid to measuring concreteness at the sentence or string level. Most similar to us is Wu and Smith (2023), who generate multiple images for each caption and average the CLIP similarity scores over all the images to produce a sentence-level concreteness score. Other text evaluation metrics compare to reference texts (Gehrmann et al., 2023) or a reference image (Hessel et al., 2021), while we are interested in the inherent quality of text in isolation (namely, its visual concreteness).

Multimodal Dataset Curation. Due to the highly noisy nature of Internet multimodal data, prior works have filtered using approaches such as rule-based text parsing (Radenovic et al., 2023), using CLIP similarity to detect misaligned text-image pairs (Schuhmann et al., 2022), de-duplicating semantically similar content (Abbas et al., 2023), and removing samples with text that overlap with the image (Maini et al., 2023). A number of prior works have also proposed replacing or augmenting multimodal datasets with synthetic samples (Li et al., 2022, 2023; Fan et al., 2023; Lai et al., 2023; Nguyen et al., 2023). By contrast, we do not require modifying the given dataset and identify semantically infelicitous captions allowed by prior methods. Our work also contrasts with dataset distillation, which has been applied to multimodal dataset curation (Wu et al., 2023); while dataset distillation methods select samples to explicitly optimize a chosen downstream objective, we focus on the simpler and more general task of identifying samples of inherently poor quality.

6 Conclusion

We present a new metric for measuring the visual concreteness of image captions without an image reference. By leveraging strong foundation models, we quantify visual-semantic information loss and find that this highly correlates with human concreteness judgments. Our results demonstrate that *ICC* is effective at selecting a core of high-quality image-caption samples from web-scale multimodal datasets for training models in the resource-constrained setting. We foresee the use of *ICC* in additional tasks requiring the curation of web-scale multimodal data, where high-quality, visually-concrete text is needed.

Limitations

While our method manages to detect visually concrete captions well, it lacks sensitivity to grammatical structure, which might cause it to label oddly phrased captions as concrete. For instance, consider the caption: “a computer near a tree with a boy next to a table with a keyboard”. This caption is highly concrete and gets a high ICC score of 1.0. However, removing all object relations from the caption produces the following: “computer tree boy table keyboard” which results in a relatively minor decrease of the ICC score to 0.89. Such low-quality captions might have a negative impact on tasks such as image captioning where the model must learn to output grammatically correct English sentences which should ideally describe relevant fine-grained relations between entities. We hypothesize that this behavior stems from the dataset used to train the distillation model (CC3M) which is not likely to include such oddly phrased caption, and so these non-grammatical structures are not learned. We hypothesize that training over a dataset with higher caption diversity will likely alleviate this issue.

In addition, due to limited computational resources, our experiments were conducted on a relatively small scale of 8 million sample dataset. We expect that increasing the scale and the filtered dataset proportionally will result in a performance improvement in the downstream model performance. However, we leave verifying this as well as testing the effect of *ICC* filtering on other downstream tasks such as VQA and caption ranking to future work.

Finally, while our method detects and filters an important category of noise in multimodal datasets, we note that abstract captions such as those in Figure 2 may contain important information which our method discards. Future work might instead extract the relevant visual information from such captions, to avoid losing the information signal in such items. We also note that such captions often contain external or subjective information which could be of interest to tasks such as news image captioning or multimodal sentiment analysis, where external context is of interest. To identify such cases, further work might enhance the interpretability of our method to explore *why* a caption is or is not concrete.

Ethics Statement

Models trained on multimodal Internet data may inherit biases from their training data. Our method is not designed to filter potentially harmful image descriptions; moreover, such biases are also present in the models used as part of our pipeline (CLIP, generative models) and thus our model may possibly inherit or amplify these issues for downstream tasks. We anticipate further research into such biases and guidelines needed before putting these models into deployment.

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Appendix A Implementations Details

A.1 Standardizing By Caption Length

We aim to have reconstruction scores that are only dependent on the concreteness of captions and not on the length of the captions. In Figure 6, we show the distribution of the reconstruction similarities before and after standardization per caption length. We can see in Figure 6a that there is a strong dependency on caption length, which we would like to avoid.

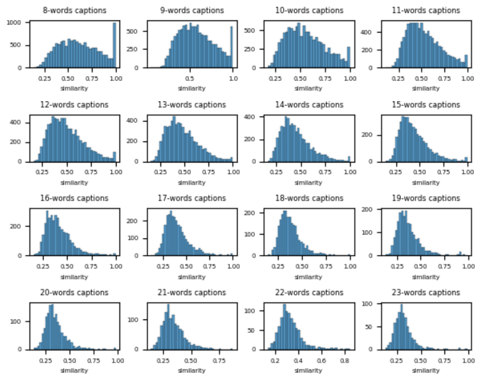
More specifically, we force the reconstruction similarity distribution to be distributed according to $\mathcal{LN}(\mu = 0.5, \sigma = 1)$, where $\mathcal{LN}$ denotes a Logit-Normal distribution. The normalization is performed by standardizing the logit of the similarities (defined by $ln(\frac{1}{1-p})$) for each caption length, and then taking the inverse logit. We can see in Figure 6b that short captions are reconstructed more easily compared to longer ones, and that normalization by caption length successfully disentangles the reconstruction scores from the caption length dependency.

A.2 *ICC* Distillation

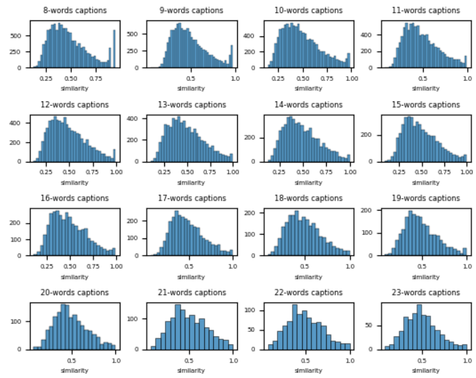
We distill the knowledge obtained by the two pipelines described in the paper in a two-stage manner. Firstly, we distill the VBA and SBA scores into two distinct DistilRoBERTa (Liumm et al., 2019) models. We then collect a small subset of 244 captions, sampled to have approximately uniform joint distribution of scores, and annotate the concreteness scores of these captions. This is showcased in Figure 4. We regress over these samples to get the optimal weights as discussed in the main paper.

A.3 Caption Concreteness Benchmark

Next we describe the data collection and annotation details for the test set used in the main paper to compute the correlations to human concreteness intuition. Our aim is to have a small, yet diverse set of samples that represent the wide diversity of possible captions. Since Laion-400M is very noisy

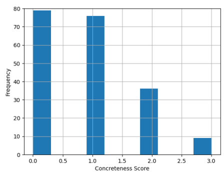


(a) Before Standardization

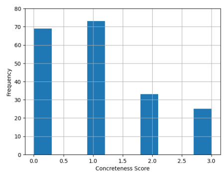


(b) After Standardization

Figure 6: **Standardizing by caption length.** We show the reconstruction similarity scores of SBA for each caption length before standardization (in 6a) and after standardization (in 6b).



(a) Random sampling



(b) Our test dataset

Figure 7: Distribution of annotated concreteness scores of 200 random samples (7a) and our test dataset (7b) sampled using rule-based methods. All samples are from LAION-400M. 0 is highly in-concrete while 3 means highly concrete caption.

and only a small portion of it includes highly concrete captions, we sample 150 items that satisfy the following rules:

- The caption must include at least 10 characters
- The caption must not contain more the 80% of capitalized words.
- The caption must include at least 2 stop words, filtered using NLTK parser (Loper and Bird, 2002).
- The ratio of stop words to all the words in a captions must not exceed 20%.

The remaining 50 samples in our dataset are selected randomly to include more "raw" captions as well. For all captions in our benchmark, we also apply NSFW filtering and make sure the caption do not include offensive or personal content. We show the distribution of concreteness scores in Figure 7 compared to a subset of random samples we annotated, with the same size. As illustrated in the figure, we were able to achieve a better coverage of highly concrete captions, more than doubling the amount of highly concrete captions, using our simple rule-based sampling. We also show all the captions in our dataset in Figure 11, sorted according to the annotated concreteness scores. The annotations are in the range 0–3, when 0 denotes highly abstract caption and 4 is a highly concrete caption.

A.4 Zero-Shot CLIP Concreteness Score

We adapt the Stroop Probing method (Alper et al., 2023) that is originally designed to assess the concreteness of words, to captions. We follow the same procedure used when measuring concreteness of words, but replace the empty slot in the prompts with a caption rather than a single word, and use only the prompts that fit the context of caption in the black spot (i.e., we don't use the captions "Alice giving the [*] to Bob" and "Bob giving the [*] to Alice" as they aren't appropriate when using a caption to replace the empty slot [*]).

A.5 aveCLIP Word Concreteness

Since aveCLIP requires generating many images per word, we found that running aveCLIP over the entire word concreteness dataset is not feasible due to runtime constraints. Therefore, we sample 150 words from the dataset, and verified that it is statistically significant by measuring the p-values of the different statistical coefficients, which were all approximately 0.

A.6 Training Hyperparameters and Additional Information

SBA. We train the linear layer of the SBA with a batch-size of 128, learning rate of 2e-3 with cosine scheduler and a warm-up ratio of 0.03, and train for a two epoch over a single Nvidia-A6000 GPU.

All other hyperparameters are set to the default of HuggingFace Trainer.

VBA Text-To-Image Hyperparameters For the image generation in VBA, we use guidance scale of 9 and 20 inference steps.

A.7 Model Checkpoints Used

We detail here all the checkpoints that were used in our experiments. All model checkpoints are taken from the Hugging Face Model Hub[2]. For the SBA, we used:

- `openai/clip-vit-large-patch14` (only the text encoder)
- `meta-llama/Llama-2-7b`

For the VBA, we used:

- `stabilityai/stable-diffusion-2`
- `Salesforce/blip2-opt-2.7b`

For the distilled model, we used:

- `distilroberta-base`

For training a captioning model, we used:

- `microsoft/swin-base-patch4 -window7-224-in22k`
- `gpt2`

For training a dual-encoder model, we used:

- `bert-base-uncased`
- `google/vit-base-patch16-224`

Appendix B Additional Experiments and Ablations

B.1 Captioning Qualitative Examples

We show in Figure 5 more examples of captions generated by captioning models trained with CA, T-MARS and *ICC* filtering. As can be seen, the model trained on the subset filtered with *ICC* generates more concrete and accurate captions, compared to CA and T-MARS filtering based model which, while generating captions which are somewhat related to the image, are highly abstract and less accurate. We use beam search of 5 for decoding in all models, including the examples shown in the main paper.

[2]https://www.huggingface.co/models

B.2 Qualitative examples Showcasing the Importance of Both Pipelines

We visually show examples of each of the scores' weaknesses and the way they compliment each other. In Figure 9, we show examples of *concrete* captions, the reconstructed captions by VBA and SBA, and the different scores of each of them. The first four rows exemplify why VBA may fail to reconstruct some concrete captions. For instance, the caption "a nurse mopping a surgeon's brow during an operation in an operation pub" was reconstructed to "two people in protective gear" which bears relatively low semantic similarity to the original caption. The main reason these cases happen is due to the inherent difficulty of reconstructing (through a captioning model) from an image the exact caption from which the image was generated, as there may be many possible such captions. In this case, the use of SBA helps determining that the caption is concrete.

In a complementary way, we show in Figure 10 examples of *abstract* captions. In this figure, the first four rows demonstrate that using SBA alone is also not enough, as it is sometimes able to reconstruct abstract captions due to the higher semantic information that is contained in the CLIP embeddings. In this scenario, VBA covers up for these failures, as it is very unlikely to reconstruct abstract text.

These qualitative examples further illustrate the benefit of using both VBA and SBA. Indeed, in both Figure 9 and 10, it can be observed that *ICC* learns to take the best of both worlds, generating low scores for abstract captions, and high scores to concrete ones in a consistent manner.

CA	*Tiger cubs playing in the rain at the Zoo of the Ozarks in Washington, D.C. on Saturday, Oct. 18*	*Coffee at the bar. I love this place! It's a great way to get away from the hustle and bustle*	*how to install window blinds in your home*	*Cambodia, the largest of all the African savannahs, is one of the most arid regions in the world.*	*Rugby World Cup 2019: The men's singles final takes place at the Ritz-Carlton in London, England, on Saturday,*
TMS	*Catching a lion in the wild is one of the most beautiful things you can do in the wild.*	*Coffee at the bar. Photo credit: Flickr userfairy.com.au. (via Flickr)*	*Door and window repair ideas for your home interior design ideas on pinterest*	*Aerial view of a wild boar in a field in Namibia, South Africa, Africa. (Photo courtesy of the Namibian Wildlife)*	*Astonishingly, there was no shortage of competition between the two-school teams at the London 2012 Olympic Games.*
CLIP	*Polar bear cubs pose for a photo with a polar bear in the background. Credit: NASA/JPL-Caltech/UCLA*	*Pizza Hut Creamy Pizza Sandwich with Bacon, Cheese, and Tomato Sauce*	*Poster for the new ""Polar Bear"" on the front of the house. It features a picture of a polar bear with the words*	*Aerial view of the world's largest crocodile in the Serengeti National Park.*	*New York Mets Fanatics Authentic 8"" x 10"" Skateboard Deck*
ICC	*Panda eating bamboo*	*A picture of a pizza box full of pizzas.*	*Outdoor Glass Window*	*Zebra at the zoo*	*A view of the tennis court from the front.*

Figure 8: More qualitative examples of captions generated by captioning models trained on datasets filtered with different filtering methods, over images from MS-COCO validation split. T-MARS is marked by TMS.

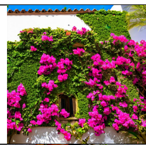
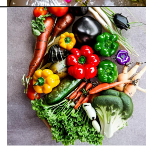
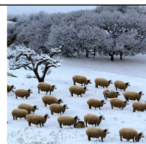
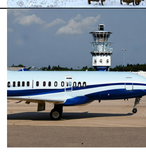
Input caption	**SBA reconstructed caption**	**VBA reconstructed caption**	**VBA bottleneck image**	**SBA**	**VBA**	***ICC***
a nurse mopping a surgeon's brow during an operation in an operation pub	a nurse wiping the brow of a surgeon during an operation in an operating room	two people in protective gear		0.77	0.25	0.72
bougainvillea climbing up the wall of a villa	bougainvillea climbing on a wall of a villa	a house covered in pink flowers		0.72	0.26	0.81
table top shot of many vegetables and mexican bugs on a table	close up shot of vegetables and bugs on a table	vegetables arranged in the shape of a human head		0.70	0.25	0.76
silhouette of a man with a gun in poses royalty	silhouette of a man holding a gun in poses royalty	a group of people silhouettes on a white background		0.82	0.26	0.93
small flock of sheep in winter snow on a hilltop	small flock of sheep in snow on a hill	a herd of sheep in the snow		0.72	0.95	1.0
small blue and white airplane parked on the ramp with a control tower in the distance	small blue and white airplane parked on the tarmac next to a control tower	a blue and white airplane parked on the tarmac		0.96	0.95	1.0
a young girl runs through a field of cabbages	a young girl runs through a field of cabbages	a girl walking through a field of cabbage		0.96	0.95	1.0
a red post box and a telephone box stand together in a village	a red telephone box and a post box stand together in a village	a red post box next to a stone wall		0.84	0.89	0.92

Figure 9: **Qualitative Examples for Highly Concrete Captions**. We demonstrate reconstructions of highly concrete captions and the final distilled *ICC* scores. We mark by red low reconstruction scores which correspond to unsuccesfull detection of the concrete captions. As illustrated above, VBA yields generally less consistent scores for concrete captions (see the text for further discussion). Nonetheless, our final distilled scores correctly identify these captions as concrete ones, obtaining high *ICC* scores over these captions.

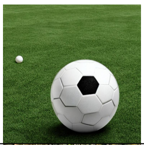
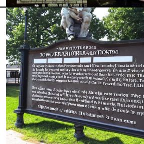
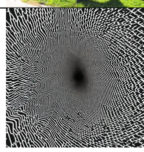
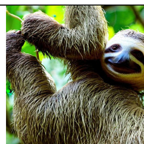
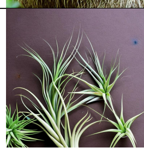
Input caption	**SBA reconstructed caption**	**VBA reconstructed caption**	**VBA bottleneck image**	**SBA**	**VBA**	***ICC***
keep an eye on the ball when it comes to investments	keep an eye on the ball when it comes to investments	a soccer ball on a green field		0.91	0.19	0.1
what 's the best thing about having a best friend of the opposite gender ?	the best thing about having a friend of the opposite gender	two young women sitting on a bench		0.89	0.16	0.1
film character : would you like to bet on these shares this christmas ?	which film character would you like to see in your shares this christmas?	santa claus, santa claus and sant		0.79	0.1	0
this is located in my home town !	this is located in my hometown!	a sign in front of a statue		0.75	0.28	0
chaotic systems are sometimes described using fractal patterns	fractals are patterns that can be found in many forms, such as chaotic systems and natural structures.	a black and white tunnel		0.22	0.19	0
on an average , the sloth travels feet a day	a sloth spends most of the day on its feet	a sloth hanging from a branch		0.17	0.27	0
get tips for biological genus , more commonly known as air plants , in your home	learn how to care for air plants, one of	a bunch of air plants on a brown surface		0.32	0.25	0
versatile and highly capable , there 's more to this tiny camera than its giant zoom	this little camera packs a big punch with its zoom lens and 2	a camera on a wooden table		0.25	0.24	0

Figure 10: **Qualitative Examples for Highly Abstract Captions**. We demonstrate reconstructions of highly abstract captions and the final distilled *ICC* scores. We mark by red captions which were reconstructed well (note that in the case of abstract captions, high scores correspond to unsuccessful detections of the abstract captions). As illustrated above, SBA yields generally less consistent scores for abstract captions (see the text for further discussion). Nonetheless, our final distilled scores correctly identify these captions as abstract ones, obtaining low *ICC* scores over these captions.

a bundt wedding cake with white chocolate dripping, evergreens, pinecones and sugar powder to imitate snow | A young boy stands in front of a wall with height measurement marks and has his hand up to show | Elderly man with a cocktail during holidays | silver soda can and glass with white background - Stock Photo | foto of wallabies - Portrait of a wallaby in the nature - JPG | Brindle pendant in light grey with copper interior | Stock photo of homemade cookies and a cup of coffe | Girl in the gym lifting up the barbell - silhouette | Young blond woman wearing a dress in the forest | A fish eye photo of people climbing high ropes | Young alligators basking in the sunlight | Couple sat by basket full of grapes | vintage book and light bulb on wood table | tree with birds and birdcages vector image | A boy volunteer with birds on his shoulders | Colorful streamers hanging from the ceiling. | A glass bowl full of yellow cream and red and orange coloured fruit on pink & white background | A Chinese man walks past a billboard for a new commercial development which reads 'Shangrila is in your mind but | Shopping bags isolated on the white background | child tying his own shoes | A spotted harrier cruising to look for food | Young girl in a party dress looking bored and unhappy | Avatars of a male and in business suits. | a stack of miso chocolate chip cookies on a white plate | Bobcat in a hollow log

foto of florida-orange - Jacksonville skyline in orange background in editable vector file - JPG | Old man cleans tables at KFC to take home leftover food for family | c1913 to 1955 tall stack of music, opera and ballet books sg | Tropical Leaf Necklace 16 | welcome to india card with famous landmarks vector image | Set of empty picture frames for your own vector | castle hotel and spa wedding photos, ceremoy and reception | Radar monitor - Aircraft radar for airport with world map... | Grey and yellow consulting or planning concept infographics set | A darkened hall filled with server racks on either side and a silhouette of a Facebook worker at the end, | 100Ducati Desmoquattro at 2009 Seattle International Motorcycle Show 2.jpg | A film still shows two panels, with green ink. On one of them, the letters RELIC can just be made | spence cabin weddings | businessman in modern office writing ghostwriter in the air | large patio roof with adjustable louvres for outdoor seating weather protection and shading | pic of gesture - vector illustration of collection of hand gestures - JPG | chubby woman eating on scale stock photo, chubby woman on the scale eating a yogurt, isolate on white by iMarin | Fisherman on a small blue and white boat with fishing net between the waves of the sea. Liguria Italy | pictures of bedroom architectural details from hgtv | EHM water ionizer and alkaline water machine factory on sale | Christopher Boffoli's photograph of a toy motorcycle rider, jumping over three toy cars and a slice of cheesecake | Pirate kids and their treasure | Incotex Benson Straight Leg Wool Trousers | QR Code for Florida Virtual School at local Shell Gas Station | Peace Love Colorectal Surgery Oval Sticker (50 pk) | moonstruck chocolates | creative eyelashes - closeup of the eye of woman with... | Simply Perfect Braided Wedges | New Years Fireworks in Seattle, 2011->2012 | 2008 Volkswagen GTI Photo | A sport fishing boat heading out of Wanchese harbor of the Outer Banks at dawn for a day of off-shore | A young beautiful girl holding a wild fox animal that was traumatized by a man and rescued by her and

Zero Zebra Safari Party Dairy-Free Chocolate Animals | The rescued soccer team members pose with a sketch of the Thai Navy SEAL diver who died while trying to | How to get a bobcat out of your window blinds | Pocket watch: technically interesting pocket watch with rare crown winding in manner of O. | I am an Aspie Girl A Book for Young Girls with Autism Spectrum Conditions by Danuta Bulhak-Paterson, Tony Attwood | Trump on etch a sketch | floor plan drawing software create your own home design easily | 1000 ideas about lake house plans on pinterest house for Basement planner online | Chanel 5, the first perfume i received as a gift. Love it! | lush greenery at National gallery of modern arts - Bangalore | A lounge room of greys and creams, black and white prints all come together to make this a relaxing and | christmas bible verses for preschoolers five scriptures about children should 664 | MAJESTIC PET PRODUCTS - Santorini Chevron Round Pet Bed - pet bed looks great in any room of your house | Sanusi under house arrest, moved to a 2-bedroom apartment without electricity & access roads (Photos | Novak Djokovic (Ser) defeated Juan Martin Del Potro (Arg) in US Open final
 Flushing Meadows 09-09-2018 US Open
 | 2013 men's the novelty original t-shirt with patterns Double-headed eagle and RUSSIA sizel xl xxl xxxl 4xl shirts free shipping | Poster of Seven Below | EFCC operatives evacuating the safe, the house where the cash was hidden and the money | closet converted into mudroom | make a closet more functional by removing doors, adding a bench at kid height, hooks | How to install an SSD in a laptop | computer tutorial | The logo of German carmaker BMW is seen on a car displayed during the annual results press conference in Munich, | Well Established and Well Equipped Butchers, Fruit and Vegetables, Frozen Seafood Plus Convenience Groceries, South London for sale | BMW Is Looking Into Gas-Powered Vehicles | summer fashion scarvesnew scarf trendswhite by scarvesCHIC on Etsy, $15.90 | Celebrating 20 years, EGEC shares declaration on the great role of geothermal energy | capricorn tattoos designs ideas and meaning tattoos for you | 25 best ideas about spice storage on spice | Julbo Eyewear - Atmo Goggle (4-8 Years Old) (Red Trans Orange Lens) Snow Goggles | The Roman temple of Jupiter is seen in the background as Lebanese youths play in the snow on January 9, | The DJI Osmo kit includes the grip, gimbal, camera and device holder for your smartphone (there is a companion app). | Miyake celebrates with his team after winning a silver medal at London 2012. | National MS Society's Katie Boothroyd, Board Member Joan Ohayon. Photo by Tony Powell. Tea Honoring Women of the Diplomatic Corps. | Top sweet and fortified wines of 2012 | there is also a small laundry with all-in-one washer and dryer | change my background how to change desktop background in windows 10 | Hand wrapping Basics - How to wrap your hands for boxing, kickboxing, and Muay Thai with long wraps | favorite colors on taupe benjamin and paint colors | Black & White Houndstooth Infinity Pocket Scarf - Travel Scarf - The Poppy Stock | looking out to the yew garden | An entrance door to transform your home for Home front entry doors | Image result for paytm with modi advertisement | Drawing notebook. never thought of including this inside a felt book, always had a separate art bag.. | how to remove a kitchen tile backsplash | ONLY - Cara Long Sleeve Shirt (Navy Blazer) Women | Tying an olive dun with mallard wings | All cold and hot rolling seamless steel pipe diameter | and when the clock strikes midnight halloween will be over | Another member said she'd tried for years to get her floor to look this clean, declaring she 'loved' the bargain | 2PCS/Set Hematite Natural Stone Bracelet1 | architectural drawings for sale unknown vintage architectural drawing for sale at 1stdibs | Prince Harry to lose honorary military titles as palace confirms exit date from royal family | Explore One 70mm Telescope | The mess I left at the end of the school year in 2015 when I couldn't unpack or move into | A pretty paper garland adds a festive touch. | Hydroponic Fodder ProFeed Growing System | Antioxidant rich RED salad with lemony dressing is delicious lunch! | Sunflowers on Saturday, when I felt called to ask David to photograph me with them since they played such a | pencil crafts for back to school and beyond | COLROVIE Culotte Leg Elegant Cami Jumpsuit Women Box Pleated Sexy V Neck Jumpsuits 2017 Fall Surplice | how to make fabric flower rosettes, tutorial | new cars with best warranty all about extended auto warranty contracts leadhub | 30 sliding barn door designs and ideas for the home With barn door wide opening | Foreign stocks for students and grannies | how to wear flat shoes to a wedding | A cartoon on the situation with languages in Ukraine cartoon. | Modest partisan differences in views of elected officials | interior design for my home minimalist interior design is maximum on style | Ebook download and read online electronic book button or icon | what do you want to know about alta motors electric street tracker | Raw Oysters are the perfect food to increase your testosterone! | Minecraft cake - Both tiers are vanilla cake with vanilla buttercream covered in fondant. The tiles are all modeling chocolate | cbd infographic why patients are leaving big pharma | the majestic elephant - one of the big 5 |

Car insurance advice: How to keep your car safe in winter weather | We only supply the tire. If there is a rim shown in the picture, it is for display purposes only. | "Steven Wright Quote: ""It's like the Wild West, the Internet. There are no rules.""" | pathandpuddle: How long do animals live? | A lack of sleep could be caused the nutrients in your diet | No time to explain. Just put on the hats and act casual. | His last at-bat, a pop fly to center field. #garrettreade #littleleague #thatsmyboy | Higher consumption of sugary beverages linked with increased risk of mortality | Words of Gymnastics Terminology w/ Monogram Drawstring Bag | Zaanse Schans, Netherlands - May 5, 2015: Tourist Visit Windmills And Rural Houses In Zaanse Schans | Losing out: BP will temporarily be locked out of lucrative deals, including contracts to supply the US military with fuel. | QuickBooks - Access | "Cranberry Chevron Rug - Deep red hues cut a rug here. The chevron is a ""go with anything"" pattern and | Bomag reports that their single direction vibratory plate compactors are great tools for contractors' day-to-day use in soil and asphalt | "Augustabernard bias-cut satin evening gown, c.1930. Label: ""Augustabernard"" with a stamped couture number on the back." | How to graduate as a successful edupreneur | garland for stairs christmas house tour decorating ideas how decorate for | This Mexican Layer Dip is easy to make and full of flavor! With layers of spicy black bean dip, homemade | what is a research process paper The term research paper may also refer to a scholarly article that contains the | Ammonia is often used in cleaning products because it reacts with grease making this easier to remove | They do not take ownership of valuable deposited with them? | Can i push out my wall to get an 8x8 bathroom leave me for Small bathroom design 5 x 8 | Making one of these wall hangings is a great way to use up old yarn ... | 6 Pack - 16 Ounce Grolsch Bottles with Easy Cap Flip Top Caps for Brewing Beer, Kombucha, Kefir, Water, Thick | Annual: The event, celebrated every year to herald good monsoon rains for increased rice harvest, prosperity and goodluck, is one | Graphic on Australia's Tasmanian Devils, rare carnivorous marsupials in a battle for survival against a contagious facial cancer. It's been | remodeling small bathroom ideas on a budget small bathroom remodel on a budget brown ceramic tile floor walk | When a 17-year-old Sharapova burst onto the scene in 2004 by winning Wimbledon, she was an immediate hit. Sure, her | The course has a convenient location in the community of Fernie. | Famous burj al arab hotel dubai 6 said to be the for Dubai world famous hotel | Among Us. (Innersloth) | Download car and vehicles decal graphics kit designs ready to print and cut for vinyl | GSM Functionality GSM Technology is a special design which can be used in conjunction with a variety of signallers depending | Kendal Town Council are calling for a bypass to solve traffic problems after Storm Desmond | Are You Am I - Faira Dress **white | interior home design also with a interior wall design also with a | One reason Millennials book cruises is the low cost - contrary to popular belief | Containers have grabbed a large share of the intermodal freight business, and here's a miniature trainload of them at the | be a donor be a hero | "Operation Surf Santa Cruz is an annual event that honors active duty military soldiers through ""an epic life-changing surfing experience.""Many | hyster h40 h forklift will not go forward or backward stuck brakes | Nominated banks roles and responsibilities under a letter of credit transaction. | Kingsbrook animal hospitals blog preferred veterinary care in two beloved basenjis kylie and cricket in a house fire in april | Example of TRAM:Cross-Domain-Solution | Skip the recycling. Use your soda cans to make bracelet cuffs instead! | They rise in quite an interesting way as well. Keep an eye on them so they don't burn, and make | "15 Thanksgiving Day Ideas for Couples. Holidays get so busy we sometimes forget our priorities. Keep your spouse at the | Tao Xiangli gets out of his homemade submarine after operating it in a lake on the outskirts of Beijing September | Professionally edit your voiceover, audiobook or podcast | "Eli struggling to find cell service ""under the biggest cell phone tower in Paris""" | Don't have time to shampoo your hair, but still want to look glam? Me too! And that's why I love | Vivid Vision for Success | Rich Karlgaard | The pistol 01 concept is a very precise and reliable sidearm! | buy a domain name | Tate Stevens - Winner of 2012 X Factor, Simon Cowell Stock Photo | Click this cover for a(n) eBook sample of Choke Point | FI Week #5 #6 #7 : Let the new digital influencers shine | Travertine is a perfect partner2 | STF has arrested the wanted accused who recruited fake teachers | SUMMER HITS 2016 Mixed by DJ Golan | Springet fra Big Business til Smaller Business (Starting Over) | Banque De Francs, French Banknote Assortment, ca. 1945-1961. | tarek christina tarek and christina el moussa s divorce affects their | Phoenix Suns are changing their perception to the basketball world | Tan Cartoon Doctor Man Carrying His - African American... | 2013 New arribal digital holly quran mp4 player wholesale price and 28 language translation(China (Mainland)) | Your spa decor should reflect your target market's preferences. | hwaseong-fortress-suwon-part-2 | Salman and Sonakshi in Dabangg 2 |

Figure 11: **Manually Annotated Captions**. The captions are sorted according to concreteness, where captions with the highest score illustrated in the top cluster and lowest at the bottom cluster. We truncate captions that are longer than 20 words, and separate captions by |.