Surveying the Landscape of Image Captioning Evaluation: A Comprehensive Taxonomy and Novel Ensemble Method

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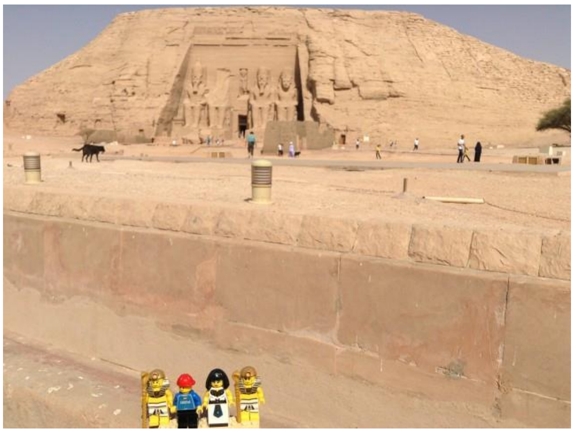
Abstract

The task of image captioning has recently been gaining popularity, and with it the complex task of evaluating the quality of image captioning models. In this work, we present the first survey and taxonomy of over 70 different image captioning metrics and their usage in hundreds of papers. We find that despite the diversity of proposed metrics, the vast majority of studies rely on only five popular metrics, which we show to be weakly correlated with human judgements. Instead, we propose ENSEMBEVAL — an ensemble of evaluation methods achieving the highest reported correlation with human judgements across 5 image captioning datasets, showing there is a lot of room for improvement by leveraging a diverse set of metrics.[1]



Lego figures in the middle of the desert
A pyramid with statues of ancient kings
Some people and a dog in front of an old monument

Figure 1: An image with various valid captions that have no overlap in content words, exemplifying some of the challenges in evaluating image captioning.

1 Introduction

Image captioning is a multi-modal task in which models generate textual captions describing an image. Evaluating the output of image captioning is challenging for several reasons. First, as in other generative tasks, multiple outputs may be valid for the same input, as illustrated in Figure 1, where different valid captions for the same image have no overlap in content words. Second, it involves bridging across modalities, requiring evaluators to compare text and images, unlike most generative tasks that only involve textual information. Attesting to the difficulty and importance of image captioning is the sheer volume of metrics proposed for this task, and their usage in hundreds of image captioning models (Figure 2).

In this work, we survey the different approaches proposed for evaluating image captioning, and provide a first taxonomy explaining over 70 metrics, which were largely developed independently of one another. Furthermore, based on our observations we devise an ensemble-based metric, ENSEMBEVAL, which achieves the highest reported correlation with human ratings.

In Section 2, we start our survey with a systematic approach to examine all relevant papers from 15 major venues in NLP, vision and machine learning between 2010 and 2024. This approach yields a body of work consisting of 71 different automatic evaluation metrics and 5 human evaluation paradigms, used in over 300 papers.

Next, we organize both automatic metrics and human evaluation in principled taxonomies (Section 3). Our taxonomy is the first to comprehensively cover all automatic metrics used in image captioning research, organized by a novel criterion: the specific property each metric aims to quantify. This enables future researchers to choose metrics based on the specific aspect their model is intended to improve. In addition, we propose the first taxonomy for human evaluation metrics, cat-

[1]Our code and data are available on github.com/uriberger/caption_evaluation.

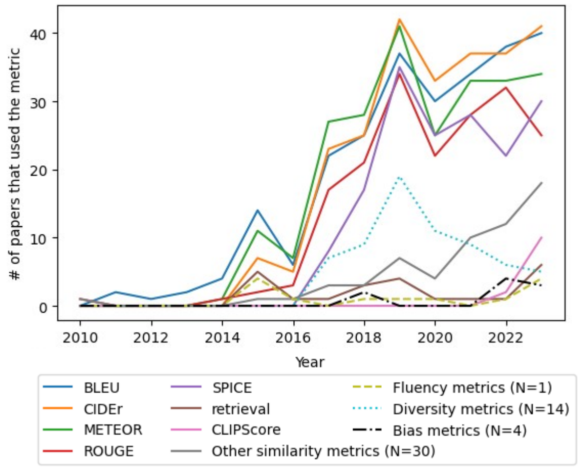


Figure 2: Metrics usage over the years. Metrics used in less than two papers are omitted.

egorizing them into groups such as comparative evaluation and scale rating evaluation.

We then survey the use of evaluation methods across a wide range of 314 papers (Section 4). Interestingly, we find that despite the wealth of different metrics proposed for the task, the vast majority of examined papers use only five simple metrics (BLEU, METEOR, ROUGE, CIDEr, SPICE), although there has been a the recent increase in the adoption of alternative metrics. Furthermore, we find that the use of human evaluation is declining in recent years and that significance and inter-annotator agreement are rarely reported.

Finally, in a series of evaluations, we show that the five most popular metrics show only a weak correlation with human ratings, whereas lesser-known metrics show a much higher correlation. This underscores the value of a systematic and comprehensive survey in identifying these lesser-known but more effective metrics. We then propose an ensemble of selected metrics, ENSEMBEVAL, optimized for diversity using a feature selection algorithm. We show that ENSEMBEVAL achieves the highest reported correlation with human ratings to date.

To recap, our contributions are twofold. First, we introduce the first comprehensive taxonomy of automatic captioning evaluation metrics, categorized by the property they assess. This will help future model developers select the most suitable metric based on the specific property they want their model to excel in. Second, our proposed ensemble approach based on this survey can be readily used as a state-of-the-art evaluation of image captioning models.

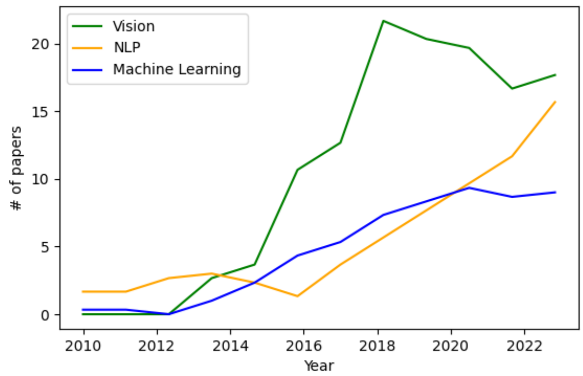


Figure 3: Annual number of image captioning papers per community, smoothed by convolving with a window size of 3 years.

Community	Conferences
NLP	AACL, ACL, CoNLL, EACL EMNLP, NAACL, TACL, *SEM
CV	CVPR, ICCV, ECCV
ML	Neurips, ICML, ICLR, AAAI

Table 1: Venues included in our review. NLP: Natural Language Processing. CV: Computer Vision. ML: Machine Learning.

2 Methodology

We perform a systematic review and gather usage statistics of metrics in conference papers on English image captioning. Overall, we examined 314 papers from 2010 to 2024, and identified 71 distinct metrics.

Venues. We focus on a large set of 15 venues spanning three distinct research communities (Table 1). Figure 3 shows the annual number of papers for each community.

Search strategy. To identify image captioning related papers within a venue, we search the venue proceedings for papers with the substrings *caption* or *description* in their titles, assuming relevant titles are likely to include variations of the phrases *image captioning* or *image descriptions*.

Filtering. Next, we manually filter out papers that we deem irrelevant to our review. Specifically, we exclude: 1) papers on other types of captioning such as video captioning; 2) papers unrelated to captioning that happen to have *caption* or *description* in their titles; 3) papers that focus on languages other than English; and 4) papers that did not conduct any experiments.

Years reviewed. We begin collecting data starting from 2024 backwards until reaching the first year with no relevant papers (2009).

Collected data. We collect two types of information. First, we intend to describe the types of metrics used in previous work. For each metric introduced or used in the papers we examined, we document its name, implementation details and the paper in which it was introduced. To the best of our knowledge, we are the first to systematically collect such a comprehensive set of metrics, as previous research has focused on a few well-known metrics (see Section 6).

Second, we seek to analyze the patterns of metrics usage. Therefore, we record which metrics were used in each examined paper.[2]

3 Taxonomy

In this section, we introduce a taxonomy of the metrics from the systematic review outlined in Section 2. This work is novel in two respects: we are the first to comprehensively include all metrics proposed and used in previous studies, rather than focusing on a limited set of well-known metrics. Second, we are the first to describe a taxonomy for human evaluation methods.

3.1 Automatic Evaluation

The release of large benchmarks like MSCOCO (Lin et al., 2014) has made manual evaluation of captioning models impractical. Hence, automatic tools for assessing generated captions have been developed, and some tools from other text generation tasks have been adapted for the image captioning task.

We turn to describing the various automatic evaluation methods. We categorize metrics based on the specific property they aim to evaluate.[3] The taxonomy is presented visually in Figure 4.

3.1.1 Relation with Ground-Truth

The largest and most widely used class of automatic methods use a ground-truth source (either a reference caption or the image) as a basis for evaluating the candidate. We categorize these methods based on the relation they examine (similarity/extrinsic) and the nature of the ground-truth (reference, image, both) they use.

Similarity to reference. Early automatic methods, still the most common today, compare the candidate caption to a reference caption.

Lexical similarity: Some metrics compare the candidate and reference captions at the word level using a straightforward textual comparison, most naïvely using exact match (Kang et al., 2023). More advanced methods include computing n-gram overlap (*BLEU*: Papineni et al. 2002, *NIST*: Doddington 2002, *ROUGE*: Lin 2004, *METEOR*: Banerjee and Lavie 2005), n-gram TF-IDF (*CIDEr*: Vedantam et al. 2015, *CIDEr-r*: Oliveira dos Santos et al. 2021), and calculating minimal edits to match the reference (*TER*, Snover et al., 2006). Other metrics include the number of reference words in the candidate (*Rword*, Cho et al., 2022) and semantic comparisons including synonyms (*CHAIR*, Rohrbach et al., 2018). Finally, some studies measure the precision and recall of specific word categories, including parts of speech (e.g., *Exact noun/verb overlap* Chan et al., 2023a), objects (Wang et al., 2021c) and named entities (common in news image captioning, e.g., Zhang and Wan, 2023).

Phrase-level semantic similarity: Others compare the semantics of sentence elements, most commonly using phrase embeddings, either with context (*BERTScore*: Zhang et al. 2019, *BERTScore++*: Yi et al. 2020) or without (*WMD*: Kusner et al. 2015, *NW*: Cornia et al. 2019a, *SSD*: Takmaz et al. 2020, *SemSim*: Nag Chowdhury et al. 2021, *Fuzzy noun/verb overlap*: Chan et al. 2023a). *VILBERTScore* (Lee et al., 2020) enriches phrase embeddings by injecting visual information. The SPICE family (*SPICE*: Anderson et al. 2016, *SPICE-U*: Wang et al. 2020d) compares the components of scene graphs of the candidate and reference captions. *ALOHa* (Petryk et al., 2024) prompts Large Language Models (LLMs) to identify object phrases in both candidate and references and computes the similarity of these phrases' embeddings.

Sentence-level similarity: Some metrics compare semantics at the sentence level. *MP-NetScore* (Black et al., 2024a) compares sentence level embeddings. Others (*CLAIR*: Chan

[2] We only document metrics that were used in the main body of the paper, omitting metrics used in the Appendix.

[3] One metric (Yngve score, Liu et al., 2019a) could not fit into any of the proposed categories, while another (Nubia) is assigned to two categories.

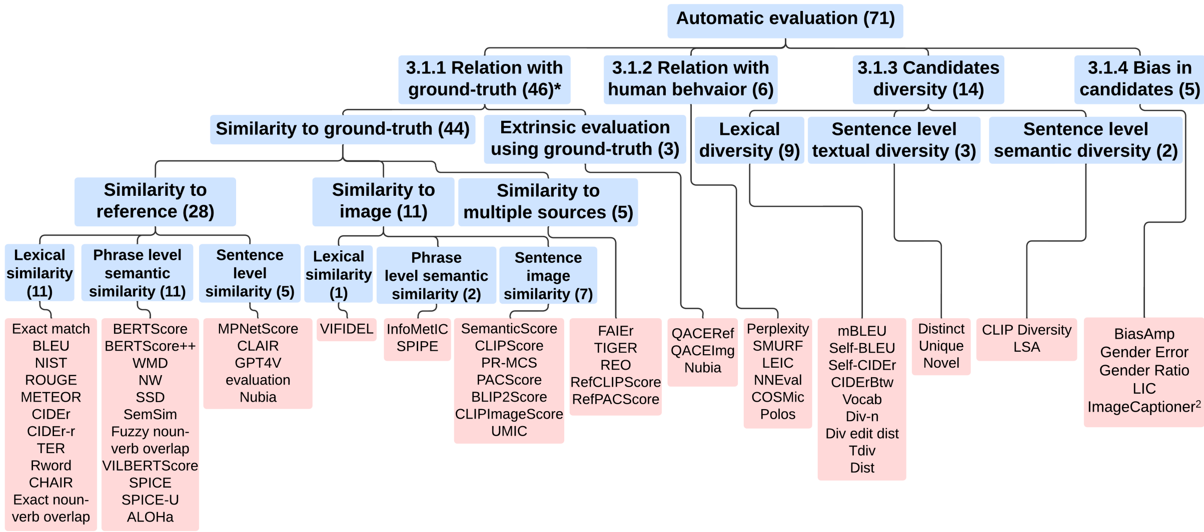


Figure 4: A taxonomy of automatic metrics for image evaluation. For each category, we indicate the number of metrics within that category in parentheses. Top categories are preceded by the relevant section number. Categories are in blue, metrics in red. * – Nubia is assigned to two distinct categories under *Relation with ground-truth*.

et al. 2023b, *GPT4V evaluation*: Ge et al. 2024a) prompt LLMs to compare the candidate and reference caption. *Nubia* (Kane et al., 2020) explicitly trains a model to evaluate sentence similarity.

Extracted information similarity: In specific domains (e.g., medical image captioning), it is common to extract relevant information from both the reference and candidate captions for comparison (e.g., a list of diseases from the captions in clinical image captioning, Nishino et al., 2022).

Similarity to image. Recent work suggests comparing the candidate caption to the image instead of a reference caption. These metrics are also known as reference-free metrics.

Lexical similarity: *VIFIDEL* (Madhyastha et al., 2019) compares object phrases in the candidate with names of objects identified in the image.

Phrase-level semantic similarity: *InfoMetIC* (Hu et al., 2023a) compares text and visual token embeddings. *SPIPE* (Xie et al., 2022) is a variation of SPICE where the scene graphs of the candidate and image are compared.

Sentence-image similarity: Several recent works embeded sentences and images in a joint visual-textual space and computed the similarity of candidate-image embeddings (*Semantic Score*: Dognin et al. 2019, *CLIPScore*: Hessel et al. 2021, *PR-MCS*: Kim et al. 2023, *PAC-Score*: Sarto et al. 2023, *BLIP2Score*: Zeng et al. 2024a). *CLIPImageScore* (Ge et al., 2024a) use text-to-image methods to generate an image based on the candidate and computes the embedding similarity between this generated image and the original image. *UMIC* (Lee et al., 2021b) explicitly trains models to predict similarity of candidate caption and image.

Retrieval-based methods: A popular evaluation protocol involves using text-to-image retrieval on the test set (e.g., Kornblith et al., 2023). In this setting, a candidate caption is matched with each image in the test set using an image-text matching model (most commonly CLIP), and the images are ranked by their matching score with the candidate. Then, recall@n is applied as the evaluation metric, with typical values for n being 1, 5, and 10.

Similarity to multiple sources. Some methods use both the image and reference captions as sources for comparison. *FAIEr* (Wang et al., 2021b) compares the candidate scene graph with a fusion of the image and reference scene graphs. *TIGER* (Jiang et al., 2019b) and *REO* (Jiang et al., 2019a) compare the candidate-image joint embedding vector with the reference-image joint embedding vector. *RefCLIPScore* (Hessel et al., 2021) and *RefPACScore* (Sarto et al., 2023) compute the harmonic mean of candidate-image similarity with candidate-reference similarity.

Extrinsic evaluation using ground-truth. Several NLP tasks focus on understanding the relation between two input sources. Some metrics use models trained for this task with the candidate and a ground-truth source as the inputs.

Question generation and question answering. Lee et al. (2021a) generate questions from the candidate and score it by how well a question-answering model answers using the reference caption (*QACERef*) or the image (*QACEImg*).

Natural language Inference (NLI). Nubia (Kane et al., 2020) use NLI models with the reference as the premise and the candidate as the hypothesis.

3.1.2 Relation With Human Behavior

The primary aim of captioning systems developed in recent years is to imitate human behavior, both in the text they generate and in the evaluation process. Metrics in this category strive to explicitly assess these properties.

Candidate fluency. Some works (e.g., Ou et al., 2023) evaluate the candidate's *perplexity* by employing an off-the-shelf large language model (commonly GPT-2, Radford et al., 2019) to compute the probability of the candidate's tokens. *SMURF* (Feinglass and Yang, 2021) computes the activation flow through a Transformer model self-attention layers, assumed to increase when the candidate differs greatly from typical captions.

Is the candidate human-like? *LEIC* (Cui et al., 2018) and *NNEval* (Sharif et al., 2018) measure how likely the candidate is to deceive a model that discriminates between human-generated and machine-generated sentences.

Human rating prediction. *COSMic* (Inan et al., 2021) and *Polos* (Wada et al., 2024) explicitly train a model to predict human scores.

3.1.3 Candidate Diversity

Several methods measure the diversity of generated captions. All assume a set of generated captions S for which diversity is measured, where S can either consist of candidates for the entire test set, a set of similar images or a single image.

Lexical diversity: While some works use lexical similarity methods such as BLEU (*mBLEU*: Shetty et al. 2017, *self-BLEU*: Zhu et al. 2018) and CIDEr (*Self-CIDEr*: Wang and Chan 2019, *CIDErBtw*: Wang et al. 2020a) on pairs of captions from S, others specifically designed methods to measure lexical diversity in S (*Vocab*: Shetty et al. 2017, *Div-n*: Shetty et al. 2017, *diversity edit distance*: Dai et al. 2018a, *Tdiv*: Liu et al. 2019a, *Dist*: Liu et al. 2019a).

Sentence-level textual diversity: Other methods compute the percentage of distinct candidates in S (*Distinct*, AKA *Unique*, Wang et al., 2017a), or the percentage of sentences not seen in the training set (*Novel*, Wang et al., 2017a).

Sentence-level semantic diversity: Recent methods propose to compare the semantics of candidates as an indicator for diversity. *LSA* (Wang and Chan, 2019) computes a matrix K where $K_{i,j}$ is the dot-product between the bag-of-words vectors of captions i, j in S, and calculates the singular vector decomposition (SVD) of K. *CLIP diversity* (Li et al., 2023b) computes the similarity of the CLIP embeddings of captions in S.

3.1.4 Bias in Candidates

Various metrics have been proposed to quantify the extent of bias evident in captioning models. *BiasAmp* (Zhao et al., 2017) measures the amplification of bias by the model compared to the training set by comparing the correlation between predefined attributes and activities (e.g., female-cooking) in model- and human-generated captions. Hendricks et al. (2018) introduce two metrics: *Gender error*, which assumes that images are labeled as male or female and calculates the number of gender misclassified words in the candidates, and *Gender ratio*, which defines male or female sentences based on the inclusion of predefined gender-related words and computes the ratio of male candidates to female candidates. Others measure bias amplification by training models to predict protected attributes given a caption (*LIC*, Hirota et al., 2022) or an image-caption pair (*ImageCaptioner*^{2}, Abdelrahman et al., 2024), and computing the difference between accuracies when training on candidates versus references.

3.2 Human Evaluation

While automatic evaluation offers clear benefits in terms of scale and consistency, it still serves as a surrogate for human evaluation. To ensure that the improvements shown by automatic methods are genuine, many image captioning studies also apply human evaluation methods to a subset of the data. Here, we categorize various frameworks for human evaluation.

Scale rating. Several studies direct human participants to evaluate candidates on a discrete scale based on various attributes, such as relevance (Maeda et al., 2023), fluency (Wu et al., 2023b) and descriptiveness (Yue et al., 2023).

Comparative. A different approach presents pairs of captions to human participants and asks them to decide which one is better without knowing their source. Early studies compared candidates to references (Kuznetsova et al., 2014; Yatskar et al., 2014), while recent research compares candidates with captions generated by baseline models (Tanaka et al., 2024; Ge et al., 2024a).

Yes/no questions. Certain studies involve human participants answering yes/no questions such as whether the candidate exhibits human-like qualities (Yao et al., 2019) or describes all the objects in the image (Chen et al., 2022).

Retrieval. Another popular approach is to ask participants to perform text-to-image retrieval given the candidate caption (Wang and Chan, 2019; Ou et al., 2023).

Answer questions using the candidate. Nie et al. (2020) prompts participants with questions and requires them to answer using the candidate provided, without showing the images.

4 Metrics Usage Analysis

In this section, we analyze the data from Section 2 to identify usage patterns and present the main findings, excluding 2024 as the data was collected before the year ended. Appendix B lists metric usage for all 314 reviewed papers.

4.1 Automatic Evaluation

A set of 5 metrics dominates. Figure 2 displays the number of papers using different metrics each year. Given the large number of metrics identified (71), we only plot usage for the seven most common metrics, clustering all other metrics by the categories from Section 3. Metrics used by no more than one paper are omitted.

The figure shows that since 2015, five metrics – BLEU, CIDEr, METEOR, ROUGE, and SPICE (henceforth, the five dominant metrics) – have been used substantially more frequently than all other metrics. This trend has begun to shift in recent years, with an increase in the use of other metrics starting from 2020. Notably, four of the dominant metrics (all except SPICE) are lexical similarity metrics, criticized for failing to capture semantic similarity (Giménez and Màrquez, 2007), and none consider the image during evaluation.

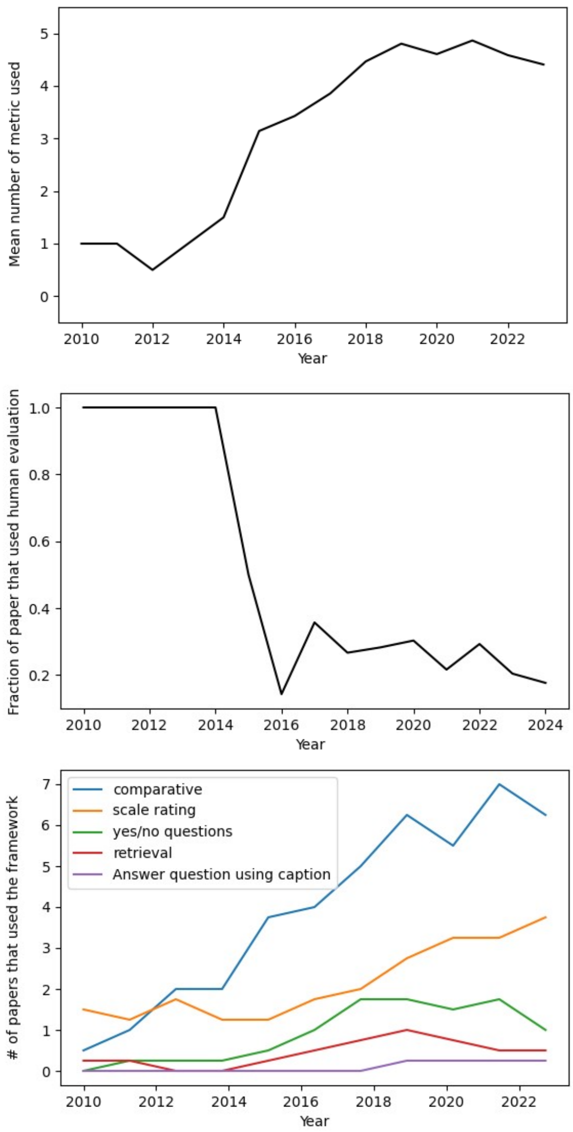


Figure 5: Metrics usage analysis plots. Top: Mean number of metrics used per paper each year. Center: Fraction of papers that performed human evaluation each year. Bottom: Human evaluation frameworks usage over the years, smoothed by convolving with a window size of four years.

The number of metrics per paper has settled at 4-5. Figure 5 (top) shows the mean number of metrics used per paper each year. There is a gradual increase until the mean number reached approximately 4.5 in 2019, remaining in the range of 4-5 since then.

4.2 Human Evaluation

Human evaluation usage is decreasing. Figure 5 (center) shows the fraction of papers with human evaluation each year. From 2010 to 2014, all papers conducted human evaluation. However, the publication of large image-caption datasets made this more challenging, and beginning at 2015 (a year after MSCOCO's release) there has been a general decline in the use of human evaluation, likely due to improvements in automatic evaluation metrics.

Comparative is the most common human framework. Figure 5 (bottom) presents the number of papers using each human evaluation framework per year. The comparative framework is most frequently used, closely followed by scale rating.

Significance and agreement are rarely reported. Out of the 94 papers that used human evaluation (29.9% of the papers we documented), only 19 reported significance. Reporting significance is crucial in human evaluation because, in most cases, only a small subset of the test set is assessed due to the high cost of human labor. Moreover, the results may be unreliable if the annotator agreement is low; however, only 6 of these 94 papers reported annotator agreement.

5 Experiments

Following previous work (Anderson et al., 2016; Hessel et al., 2021), we use correlation with human ratings as an indicator of metric quality. While inspired by previous work, our experiments include metrics not studied previously.

5.1 Experimental Setup

Datasets. We experiment with the following 7 human rating datasets.

Flickr8k-Expert and Flickr8k-CF (Hodosh et al., 2013) include human ratings for captions on the 1000 images of the Flickr8k test set. The captions are human-generated captions selected from the test set, where each image is associated with a set of captions (not necessarily initially generated for that image). Flickr8k-Expert includes 5,822 captions rated by a small and controlled group of native English speakers on a scale from 1 to 4. Flickr8k-CF comprises 47,830 captions, each rated by three or more crowd-sourced workers using a binary label (describes/doesn't describe the image). For each caption, we take the percentage of positive ratings as the final ground truth score.

Composite (Aditya et al., 2015) includes 11,985 human ratings for captions of 3,925 images from Flickr8k, Flickr30k and MSCOCO. Each image is paired with two model-generated and one original reference captions. Each caption is rated for correctness and thoroughness on a scale from 1 to 5. Following previous studies (Anderson et al., 2016), we use the correctness rating (also termed "relevance" in some prior research) as the score.

THumB (Kasai et al., 2022) features human ratings of captions for 500 images sourced from MSCOCO. Each image is associated with four model-generated and one original reference captions. Ratings cover various dimensions, such as precision, recall, and an overall score. We take the overall score as the score for this caption.

Polaris (Wada et al., 2024) contains 131,020 human ratings for captions generated for 13,691 images from MSCOCO and nocaps (Agrawal et al., 2019). The captions were generated by 10 different models. The dataset is partitioned into training, validation and test sets.

Pascal50S (Vedantam et al., 2015) contains 4000 pairs of candidate captions for images from the Pascal Sentence dataset (Rashtchian et al., 2010), evenly distributed across four categories: both captions are human-generated for the image (HC), both are human-generated but only one corresponds to the image (HI), one is human-generated while the other is machine-generated (HM), both are machine-generated (MM). Each pair has 48 human judgments indicating which of the two candidates is more similar to a reference caption. Following previous work (Hessel et al., 2021) we take the majority vote for each candidate pair (ties are broken randomly) and randomly select 5 references out of the available 48 for reference-based metrics.

The Reformulations dataset (introduced in a work currently under review) includes model-generated captions for 1,405 images from MSCOCO and Flickr30k, along with human-generated reformulations, i.e., corrected versions of the captions (if any errors exist). Evaluation metrics are expected to favor the caption after human correction. The dataset contains 5,208 caption-reformulation pairs; we omit 864 pairs where the reformulation is identical to the caption.

More details on the version we used for each dataset can be found in Appendix A.1.

Metrics selection. We now select the metrics to be evaluated out of the 71 identified metrics. First, we exclude bias metrics, as bias is not captured by the human ratings datasets. Next, we filter out all

Metric	Category	Coef
BLIP2Score	Image similarity	0.83
Polos	Human rating prediction	0.82
PACScore	Image similarity	0.29
Exact NO	Lexical similarity	0.08
BLEU1	Lexical similarity	0.07
Fuzzy VO	Phrase semantic similarity	0.02
BLEU4	Lexical similarity	0.02
CIDEr	Lexical similarity	-0.02
ROUGE	Lexical similarity	-0.07
RefCLIPScore	Multiple source similarity	-0.16

Table 2: Metrics selected by the feature selection algorithm to predict human ratings, along with their categories and linear regression coefficients.

metrics that receive multiple candidates as input (such as diversity metrics), as the human ratings are provided for a single candidate. Finally, we exclude all metrics that rely on a closed model API access (CLAIR, GPT4V evaluation, ALOHa), focusing on publicly accessible evaluation methods.

After filtering, 56 metrics remain. To ensure fair comparison, we conduct all the experiments for each metric ourselves, even if previous studies have reported results for this metric. Due to the effort required and the scope of this study, we focus on metrics frequently employed in image captioning research. Specifically, we select metrics used in at least two papers per year on average since their publication.[4] This narrows our selection to 20 metrics.[5] For details on the implementation of each metric, refer to Appendix A.2.

5.2 ENSEMBEVAL: An Ensemble of Evaluation Methods

We now examine whether a more diverse evaluation method, incorporating multiple existing metrics, outperforms individual metrics. We propose an ensemble approach we name ENSEMBEVAL, using a linear combination of these metrics.

Due to strong correlations among certain metrics, using all metrics in the ensemble might create redundancy. Therefore, we employ a sequential feature selection algorithm to identify a subset of metrics that accurately predict human ratings. At each step, the algorithm adds the best metric to the ensemble based on the cross-validation score of a linear regression estimator of human ratings. The process stops when the estimator's score does not increase by at least ε. We use the Polaris train set[6] for selecting the metrics and the validation set to determine the optimal ε value (0.0001).

Next, we find the metrics coefficients by training a linear regression model to predict human ratings, again using the Polaris train dataset. More details on our feature selection and linear regression procedures can be found in Appendix A.3.

Table 2 displays the selected metrics, their taxonomy categories, and their linear regression coefficients. The metrics span different categories, indicating that predicting human ratings could benefit from using different types of metrics. Interestingly, some metrics received a negative coefficient, most notably RefCLIPScore which is widely regarded as highly correlated with human ratings (Kasai et al., 2022).

Considering the frequent use of the five dominant metrics in prior research, we include an ensemble of these metrics (the dominant ensemble) as a baseline. As before, we determine the coefficients for this ensemble using linear regression.

5.3 Correlation with Human Ratings

We now compute the correlation between metric scores and human ratings across all datasets containing human ratings (all but Pascal50S and the Reformulations datasets).[7] We follow previous work (Anderson et al., 2016; Hessel et al., 2021; Kasai et al., 2022; Wada et al., 2024) and use Kendall-C correlation for Flickr8k-Expert, Composite and Polaris, Kendall-B correlation for Flickr8k-CF and Pearson correlation for THumB.

Table 3 presents the results. We omit results for five metrics[8] that were proposed ad hoc in an experiment (rather than in a dedicated paper) and showed weak performance. We will now discuss the findings derived from this data.

An ensemble improves over individual metrics. Our proposed ENSEMBEVAL achieves state-of-the-art results across all datasets, indicating that

[4]Not including the publication year and 2024.

[5]BLEU1, BLEU2, BLEU3, BLEU4, BLIP2Score, CIDEr, CLIPImageScore, CLIPScore, Exact noun overlap (NO), Exact verb overlap (VO), Fuzzy noun overlap (NO), Fuzzy verb overlap (VO), METEOR, MPNetScore, PACScore, ROUGE, RefCLIPScore, RefPACScore, SPICE, Polos. We omit two metrics for which we could not obtain a full implementation: PR-MCS and InfoMetIC.

[6]This is the only human rating dataset that is split into train/val/test.

[7]For Polaris we use the test set.

[8]CLIPImageScore, Exact NO, Exact VO, Fuzzy NO, Fuzzy VO.

Metric	Flickr8k (Expert)	Flickr8k (CF)	Composite	THumB	Polaris
BLEU4	30.8	16.9	30.6	10.4	46.2
BLEU3	31.5	17.0	30.9	11.8	46.6
BLEU2	32.5	17.9	31.1	15.8	47.1
BLEU1	32.3	17.9	31.4	19.5	45.4
ROUGE	32.3	19.9	32.5	18.7	46.2
METEOR	41.8	22.3	39.0	18.5	51.2
CIDEr	43.9	24.6	37.5	22.4	52.1
Dominant ensemble	43.7	23.3	38.5	23.1	52.3
SPICE	44.9	24.4	40.4	21.0	50.9
CLIPScore	51.4	34.4	53.8	31.9	51.5
PACScore	54.3	36.0	55.7	31.4	52.4
MPNetScore	54.7	35.3	54.7	40.4	53.6
RefCLIPScore	53.0	36.4	55.4	40.7	54.1
RefPACScore	55.9	37.6	57.3	42.4	55.2
BLIP2Score	52.5	36.7	61.5	44.9	53.7
Polos	56.4	37.8	58.0	43.4	57.8
EnsembEval (ours)	**58.5**	**38.7**	**61.7**	**46.6**	**58.8**
Δ from 2nd	+2.1	+0.9	+0.2	+1.7	+1.0

Table 3: Correlation with human ratings across different datasets. The best performing metric is in bold. Metrics are sorted by their average score.

integrating various aspects of caption quality yields a more "human-like" score.

Dominant metrics are weaker than recent alternatives. The five dominant metrics, as well as their ensemble, exhibit weaker correlations with human ratings compared to other metrics. Moreover, BLEU4, the most common BLEU variation, shows the weakest correlation with human ratings.

Lesser-known metrics prove to be valuable. While some metrics were introduced in dedicated papers, others were proposed ad hoc in the experiments section. Previous studies comparing metrics performance have only discussed the former, missing strong correlations with human ratings observed with ad hoc metrics like MPNetScore and BLIP2Score. This underscores the importance of a systematic review of all relevant papers.

5.4 Accuracy on Pairwise Comparison

We also perform a pairwise comparison task on the Pascal50S and Reformulations datasets to assess metrics' accuracy in assigning a higher score to the human-preferred candidate in each pair. For Pascal50S, we use majority vote to indicate human preference and report the mean and standard deviation across five random instances of tie-breaking and reference selection. For Reformulations, we consider the reformulated caption as preferred.

The results are presented in Table 4. EnsembEval attained the highest score on the Reformulations dataset, as well as when comparing human-generated to machine-generated captions in Pascal 50 (HM). In all other cases MPNetScore and BLIP2Score performed best. As noted earlier, these metrics were absent from previous studies since they weren't introduced in dedicated papers.

6 Related Work

6.1 Image Captioning Surveys

To the best of our knowledge, no previous work has exclusively surveyed image captioning evaluation methods. However, most image captioning surveys include a dedicated section for automatic evaluation methods, typically mentioning the five dominant metrics along with one or two additional ones (e.g., Hossain et al., 2019; Liu et al., 2019b; Ghandi et al., 2023; Sharma and Padha, 2023).

A few studies (Stefanini et al., 2022; Xu et al., 2023) provide a more detailed taxonomy of automatic metrics. Our work differs from them in two ways: First, we conduct a systematic review to gather all metric usage, identifying strong metrics not covered previously (as discussed in Section 5.3). Second, while these studies group metrics into loosely defined categories (e.g., "standard" metrics), we clearly define our categorization criteria based on the properties each metric

Metric	Pascal50S HC	HI	HM	MM	Mean	Reformulations
BLEU4	59.8 ± 0.7	92.3 ± 0.7	85.6 ± 0.5	57.3 ± 1.2	73.7 ± 0.5	49.8
BLEU3	60.6 ± 0.9	93.0 ± 0.7	88.1 ± 0.5	57.6 ± 1.0	74.8 ± 0.6	51.8
ROUGE	63.1 ± 0.8	95.2 ± 0.6	91.9 ± 0.3	60.3 ± 1.0	77.6 ± 0.4	53.1
BLEU2	62.9 ± 1.7	94.0 ± 0.4	90.1 ± 0.2	58.6 ± 1.0	76.4 ± 0.7	54.9
BLEU1	62.8 ± 1.3	95.1 ± 0.5	91.5 ± 0.4	59.8 ± 0.7	77.3 ± 0.2	56.0
CIDEr	65.6 ± 1.7	98.0 ± 0.4	90.9 ± 0.3	64.9 ± 1.1	79.8 ± 0.4	54.3
SPICE	61.2 ± 1.9	94.3 ± 0.7	85.5 ± 0.7	49.5 ± 0.7	72.6 ± 0.7	67.6
METEOR	64.4 ± 1.7	97.6 ± 0.4	94.1 ± 0.8	65.3 ± 0.9	80.4 ± 0.6	66.3
Dominant ensemble	65.5 ± 1.7	97.7 ± 0.3	93.0 ± 0.5	68.0 ± 0.7	81.1 ± 0.6	66.0
RefPACScore	67.6 ± 0.7	99.6 ± 0.1	96.0 ± 0.2	75.7 ± 0.6	84.7 ± 0.3	73.3
RefCLIPScore	64.1 ± 1.2	99.6 ± 0.1	95.8 ± 0.4	72.9 ± 0.6	83.1 ± 0.4	74.9
BLIP2Score	60.5 ± 0.2	$\mathbf{99.8 \pm 0.0}$	96.3 ± 0.0	71.2 ± 0.5	82.0 ± 0.1	76.1
Polos	69.5 ± 1.2	99.6 ± 0.0	97.0 ± 0.3	78.5 ± 0.6	86.1 ± 0.1	73.0
MPNetScore	$\mathbf{71.9 \pm 0.6}$	99.8 ± 0.1	96.3 ± 0.5	$\mathbf{79.0 \pm 0.6}$	$\mathbf{86.7 \pm 0.2}$	72.7
PACScore	60.4 ± 0.1	99.3 ± 0.0	96.8 ± 0.0	72.9 ± 0.4	82.4 ± 0.1	77.2
CLIPScore	56.1 ± 0.2	99.3 ± 0.0	96.3 ± 0.0	71.2 ± 0.4	80.7 ± 0.1	80.8
EnsembEval (ours)	68.7 ± 0.6	99.8 ± 0.1	$\mathbf{98.3 \pm 0.3}$	77.3 ± 0.3	86.0 ± 0.2	**81.4**

Table 4: Accuracy in pairwise comparison. In Pascal50S we report mean and standard deviation across five random instances of tie-breaking and reference selection. HC: both captions are human-generated for the image, HI: both are human-generated but only one corresponds to the image, HM: one caption is human-generated while the other is machine-generated, MM: both captions are machine-generated. In each dataset, best scoring metric is in bold. Metrics are sorted by their average score.

aims to measure.

We are also the first to develop a taxonomy for human evaluation frameworks. Before our study, Bernardi et al. (2016) discussed human evaluation but only mentioned the scale rating framework.

Prior to our study, Staniūtė and Šešok (2019) reported metric usage from selected papers; however, they manually selected popular papers rather than identifying them systematically. Similar to our work, two studies (Sharma, 2021; Al-Shamayleh et al., 2024) systematically identify image captioning papers and report metric usage. However, they cover much fewer papers (79 and 41, respectively) and metrics (3 and 8, respectively), and do not report trends or provide in-depth analysis.

6.2 Image Captioning Metrics Analysis

Several previous studies have analyzed the effectiveness of image captioning metrics. Hodosh et al. (2013) compare BLEU and ROUGE scores to human ratings and find that these metrics fall short in measuring content quality. Elliott and Keller (2014) compute the correlation of lexical similarity metrics with human ratings and find that METEOR had the strongest correlation. Kilickaya et al. (2017) compare the five dominant metrics and WMD, finding that n-gram based metrics exhibit lower performance than SPICE and WMD.

Recently, as reference-free metrics like CLIPScore gain prominence, there has been growing criticism directed at this line of research. Deutsch et al. (2022) argue that reference-free metrics can be exploited at test time to find outputs that maximize their scores. Ahmadi and Agrawal (2024) find these metrics sensitive to visual grounding errors but not to caption implausibility. Ma et al. (2024b) show that optimizing for reference-free metrics leads to unreadable captions.

7 Conclusion

We conducted a comprehensive survey of image captioning evaluation methods, finding that the vast majority of papers use only 5 metrics which are weakly correlated with human judgment. Instead, we propose EnsembEval, which leverages a diverse set of metrics in a data-driven manner to achieve state-of-the-art results.

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A Experiments: Additional Information

A.1 Datasets

Flickr8k. We use the official version of the Flickr8k dataset.[9] We follow previous work (Anderson et al., 2016; Hessel et al., 2021) when handling references that are also included in the candidate set: in Flickr8k-Expert we remove these sentences from the candidate set (158 examples), and in Flickr8k-CF we remove these sentences from the reference set.

Composite. We use the official version of the Composite dataset.[10] While previous work mentioned that there are three candidates per image and a single score per candidate, we find that the dataset contains four candidates per image for MSCOCO and Flickr30k, and two scores per candidate (correctness and throughness). We find that results from prior work was most closely replicated when we discarded the fourth candidate when one exists and used the correctness score as the total score. Also, following Hessel et al. (2021) we remove sentences that appear both as references and as candidates from the reference set.

THumB. We use the official version of the THumB dataset.[11] Following the practice in other datasets, we remove sentences that appear both as references and as candidates from the reference set.

Polaris. We use the HuggingFace version of the Polaris dataset.[12]

Pascal50S. The link to download the official version of the dataset in the CIDEr blog post[13] seems to be broken; we thank (REMOVED FOR ANONIMYZATION) for providing us with the original files.

A.2 Metrics implementations.

The five dominant metrics. For the five most dominant metrics we use the pycocoevalcap implementation.[14]

Exact/fuzzy noun/verb overlap. We use an implementation[15] provided to us by the author.

CLIPImageScore. Since no implementation is provided by the authors, we implement the metric ourselves. We use the SD-XL 1.0-base model[16] to generate the image based on the candidate.

(Ref) CLIP and PAC Score, Polos. We use the official implementations.[17] [18] [19]

BLIP2Score. Since no implementation is provided by the authors, we implement the metric ourselves. We use the BLIP2 image-text-matching model from the LAVIS package (Li et al., 2023a).

MPNetScore. Since no implementation is provided by the authors, we implement the metric ourselves. We use the all-mpnet-base-v2 model.[20]

A.3 Feature Selection and Linear Regression

We use the scikit-learn[21] implementations of feature selection and linear regression. We use forward-selection in feature selection.

[9] www.kaggle.com/datasets/dibyansudiptiman/flickr-8k
[10] imagesdg.wordpress.com/image-to-scene-description-graph
[11] github.com/jungokasai/THumB
[12] huggingface.co/datasets/yuwd/Polaris
[13] vrama91.github.io/cider/
[14] pypi.org/project/pycocoevalcap
[15] github.com/DavidMChan/caption-by-committee/blob/main/cbc/metrics/content_score.py
[16] huggingface.co/stabilityai/stable-diffusion-xl-base-1.0
[17] github.com/jmhessel/clipscore
[18] github.com/aimagelab/pacscore
[19] github.com/keio-smilab24/Polos
[20] huggingface.co/sentence-transformers/all-mpnet-base-v2
[21] scikit-learn.org/stable

A.4 Reproducibility Issues

In our experiments in Section 5.3 we tried our best to replicate the results reported by previous studies. We now describe the cases where we were enable to. We compare our results to Hessel et al. (2021), Kasai et al. (2022), Sarto et al. (2023), Hu et al. (2023a) and Wada et al. (2024).

The five dominant metrics. Across some of the datasets, we found small differences between our values and previous reported values, no larger than 0.2. One exception is the THumB dataset, where prior work (Kasai et al., 2022; Hu et al., 2023a) report no digits after the decimal point, so the differences are no larger than 1.0, except for BLEU4, where the difference was larger because the authors used the sacrebleu implemenation while we used the pycocoevalcap implementation, consistent with the common practice in image captioning.

(Ref) CLIP and PAC Score. Across all datasets our results are identical to those previous reported. One exception is the Polaris dataset, where our results for these metrics differed from those of Wada et al. (2024). Since we used the HuggingFace version of the dataset and the official implementations for these metrics, we assume this discrepancy results from the authors using a more preliminary version of the dataset.

B Metric Usage Records

We now list all the papers we examined and the metric categories they used. Abbreviations: LexSim: Lexical similarity, RefPhSim: Candidate-reference phrase semantic similarity, RefSenSim: Candidate-reference sentence-level similarity, InfoSim: Extracted information similarity, ImPhSim: Candidate-image phrase-level semantic similarity, SenImSim: Sentence-image similarity, Ret: Retrieval-based methods, MulSim: Candidate-multiple source similarity, Flu: Fluency, Div: Diversity, Yngve: Yngve score, Bias: Bias.

2024. *NLP* Yang et al. (2024): LexSim, RefPhSim, Bias, Ramos et al. (2024): LexSim, Tanaka et al. (2024): Div, Qu et al. (2024): LexSim, Li et al. (2024b): LexSim, SenImSim

Vision Ge et al. (2024b): RefSenSim, SenImSim, Huang et al. (2024): LexSim, RefPhSim, Zeng et al. (2024b): LexSim, RefPhSim, SenImSim, Li et al. (2024a): LexSim, RefPhSim

Machine Learning Ma et al. (2024c): LexSim, RefPhSim, Black et al. (2024b): LexSim, RefSenSim, Liu et al. (2024): LexSim, RefPhSim, Ma et al. (2024a): LexSim, Qi et al. (2024): LexSim, Qiu et al. (2024): LexSim, RefPhSim, Wang et al. (2024): LexSim, RefPhSim, Fu et al. (2024): LexSim, RefPhSim

2023. *NLP* Wang et al. (2023c): LexSim, RefPhSim, Qiu et al. (2023): LexSim, RefPhSim, SenImSim, Hwang and Shwartz (2023): LexSim, RefPhSim, Chan et al. (2023a): LexSim, RefPhSim, Ret, Maeda et al. (2023): LexSim, RefPhSim, SenImSim, MulSim, Yang et al. (2023d): LexSim, RefPhSim, Mohamed et al. (2023): LexSim, Wu et al. (2023b): LexSim, Yang et al. (2023a): LexSim, RefPhSim, Yang et al. (2023b): LexSim, RefPhSim, Rajakumar Kalarani et al. (2023): LexSim, Ramos et al. (2023b): LexSim, Ou et al. (2023): Flu, Zhang and Wan (2023): LexSim, Bielawski and VanRullen (2023): LexSim, Anagnostopoulou et al. (2023): LexSim, Zhao et al. (2023): LexSim, RefPhSim, Ramos et al. (2023a): LexSim, RefPhSim, Zhou and Long (2023): LexSim, RefPhSim, Flu

Vision Wu et al. (2023a): LexSim, Li et al. (2023b): Flu, Div, Kornblith et al. (2023): LexSim, SenImSim, Ret, MulSim, Hu et al. (2023b): LexSim, RefPhSim, Tu et al. (2023): LexSim, RefPhSim, Fei et al. (2023a): LexSim, RefPhSim, Fan et al. (2023): LexSim, RefPhSim, Kang et al. (2023): LexSim, RefPhSim, SenImSim, Ret, Barraco et al. (2023): LexSim, RefPhSim, SenImSim, MulSim, Hu et al. (2023b): LexSim, RefPhSim, Chen et al. (2023b): LexSim, Dessì et al. (2023): LexSim, RefPhSim, Vo et al. (2023): LexSim, RefPhSim, SenImSim, Ret, MulSim, Luo et al. (2023a): LexSim, RefPhSim, Zeng et al. (2023): LexSim, RefPhSim, SenImSim, MulSim, Div, Kuo and Kira (2023): LexSim, RefPhSim, Chen et al. (2023a): LexSim, Ramos et al. (2023c): LexSim, RefPhSim, Hirota et al. (2023): LexSim, RefPhSim, SenImSim, Bias, Ren et al. (2023): LexSim, RefPhSim

Machine Learning Yang et al. (2023c): LexSim, Yue et al. (2023): SenImSim, Ret, Flu, Div, Luo et al. (2023b): SenImSim, Ret, Zheng and Yu (2023): LexSim, Li et al. (2023c): LexSim, RefPhSim, Fei et al. (2023b): LexSim, RefPhSim, Zhong et al. (2023): LexSim, RefPhSim, Nguyen et al. (2023): LexSim, RefPhSim, Wang et al. (2023b): LexSim, RefPhSim, Wang et al. (2023a): LexSim, RefPhSim

2022. *NLP* Gao et al. (2022): LexSim, Div, Zhang et al. (2022a): LexSim, RefPhSim, Mirchandani et al. (2022): LexSim, Nukrai et al. (2022): LexSim, Zhou et al. (2022): LexSim, Zhao et al. (2022): LexSim, RefPhSim, Nishino et al. (2022): LexSim, RefPhSim, InfoSim, Cafagna et al. (2022): LexSim, RefPhSim, Cho et al. (2022): LexSim, RefPhSim, SenImSim, Ret, MulSim, Pantazopoulos et al. (2022): LexSim, RefPhSim, Xu et al. (2022): LexSim, Guo et al. (2022): LexSim

Vision Jiao et al. (2022): LexSim, Wang et al. (2022b): LexSim, RefPhSim, Ruta et al. (2022): LexSim, Wang et al. (2022c): LexSim, RefPhSim, Nguyen et al. (2022): LexSim, RefPhSim, Meng et al. (2022): LexSim, RefPhSim, Chen et al. (2022): LexSim, Hirota et al. (2022): LexSim, Bias, Cai et al. (2022): LexSim, Wu et al. (2022): LexSim, RefPhSim, Chen et al. (2022): LexSim, Yuan et al. (2022): LexSim, Li et al. (2022): LexSim, RefPhSim, Fei et al. (2022): LexSim, RefPhSim, Liu et al. (2022): LexSim, RefPhSim, Vo et al. (2022): LexSim, RefPhSim, Mohamed et al. (2022): LexSim, Fang et al. (2022): LexSim, RefPhSim, Hu et al. (2022): LexSim, RefPhSim, Kuo and Kira (2022): LexSim, RefPhSim, Mavroudi and Vidal (2022): LexSim, RefPhSim

Machine Learning Yang et al. (2022): LexSim, RefPhSim, Yang et al. (2022): LexSim, RefPhSim, SenImSim, Div, Xie et al. (2022): ImPhSim, Fei (2022): LexSim, RefPhSim, Zhang et al. (2022b): LexSim, RefPhSim, Div, Yao et al. (2022): LexSim, Wang et al. (2022a): LexSim, RefPhSim, Feng et al. (2022): LexSim, RefPhSim, Flu

2021. *NLP* Yang et al. (2021c): LexSim, Liu et al. (2021): LexSim, Tu et al. (2021a): LexSim, RefPhSim, Chen et al. (2021a): LexSim, Shi et al. (2021b): LexSim, RefPhSim, Div, Ng et al. (2021): LexSim, RefPhSim, Div, Yan et al. (2021): LexSim, Shi et al. (2021c): LexSim, RefPhSim, Ret, Tu et al. (2021b): LexSim, RefPhSim, Bugliarello and Elliott (2021): LexSim, RefPhSim, Wang et al. (2021c): LexSim, RefPhSim, Honda et al. (2021): LexSim, RefPhSim, Nag Chowdhury et al. (2021): LexSim, RefPhSim, Ahsan et al. (2021): LexSim, RefPhSim, Zhong and Miyao (2021): LexSim, RefPhSim, Nagasawa et al. (2021): LexSim, RefPhSim

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