

Who are you referring to? Coreference resolution in image narrations

Arushi Goel¹, Basura Fernando², Frank Keller¹, and Hakan Bilen¹

¹School of Informatics, University of Edinburgh, UK

²Institute of High-Performance Computing, Agency for Science, Technology and Research, Singapore.

Abstract

Coreference resolution aims to identify words and phrases which refer to the same entity in a text, a core task in natural language processing. In this paper, we extend this task to resolving coreferences in long-form narrations of visual scenes. First, we introduce a new dataset with annotated coreference chains and their bounding boxes, as most existing image-text datasets only contain short sentences without coreferring expressions or labeled chains. We propose a new technique that learns to identify coreference chains using weak supervision, only from image-text pairs and a regularization using prior linguistic knowledge. Our model yields large performance gains over several strong baselines in resolving coreferences. We also show that coreference resolution helps improve grounding narratives in images.

1. Introduction

Consider the image paired with the long-form description in Figure 1, an example from the Localized Narratives [47]. Can you tell whether *the woman* who is wearing spectacles refers to *a person* or *another woman* in the text? We are remarkably good at identifying referring expressions (or mentions) and determining which of them corefer to the same entity, a task that we regularly perform when we read text or engage in conversations. The text-only version of this problem is known as coreference resolution (CR) [29, 30, 57], a core task in natural language processing (NLP) with a large literature. While solving text-only CR requires a very good understanding of the syntactic and semantic properties of the language, the visual version of CR shown in the example also demands an understanding of the visual scene. In our example, a language model has to figure out that *a person* can be a woman, has hands, and correctly match it with *her [hand]* and *the woman*, but not with *another woman*. However, a language model alone cannot answer whether *the woman* refers to *a person* or *the woman*. This can only be disambiguated after visually inspecting which of the two *is wearing spectacles*.



In the image we can see there is *a person* who is standing and holding cardboard sheets in *her* hand and *she* is wearing ash colour jacket and there is *another woman* sitting and at the back on the table there are wine bottles and cardboard boxes and books and *the woman* is wearing spectacles.

Figure 1: Coreference resolution from an image and narration pair. Each highlighted block of text is referred to as a *mention*. The mentions in the same color corefer to the same entity, and belong to the same coreference chain.

Text-only CR has been a crucial component for a range of NLP applications including question answering [28, 14], sentiment analysis [6, 43], summarization [19, 54] and machine translation [40, 4, 63]. Most text-only CR methods are either rule-based [29, 49] using heuristics such as pronoun match or exact match based on part of speech tagging, or are learned on large annotated text datasets from domains such as news text or Wikipedia articles [5, 31, 30, 21]. State-of-the-art methods [30, 21] fail to resolve coreferences correctly in image narrations for a few reasons. First, CR in image narrations often require image understanding (see Fig. 1). Neural networks trained on text datasets [48, 9] suffer from poor transferability and a significant performance drop when applied to image narrations because of domain shift. Image narrations are unstructured and can be noisy, unlike the well-edited text used during training (such as news or Wikipedia). Moreover, standard image-text datasets [34, 26, 8, 46] only contain short descriptions with very few or no cases of coreference, thus, are not suitable for training text-only CR models.

Some prior work have looked at visual CR for specific tasks. [50] and [53] link character mentions in TV shows or movie descriptions to character occurrences in videos. More recently, the Who’s Waldo dataset [13] links person names in the caption to their occurrence in the image. However, these methods rely on a limited set of object categories and referring expression types (see Table 3 discussed below), require annotated training data and therefore cannot

be applied to long-form unconstrained image narrations that include open-world object categories and multiple types of referring expressions such as pronouns (*she*), common nouns (*another woman*), or proper nouns (*Peter*).

In this paper, we look at *the problem of CR in image narrations*, *i.e.*, resolving the coreference of mentions in narrative text that is paired with an image. As the prior benchmarks in this domain are limited to either a small vocabulary of objects or specific referring expression types, we introduce a new dataset, Coreferenced Image Narratives, *CIN* which augments the rich long-form narrations in the existing Localized Narratives dataset [47]. We add coreference chain annotations and ground each chain by linking it to a bounding box in the corresponding image.

Manually annotating the whole dataset [47] is expensive, hence these annotations are provided only for evaluation and are not available for training. To cope with this setting, we propose a weakly supervised CR method that learns to predict coreference chains from only paired image-text data. Our key idea is to learn the linking of the mentions to image regions in a joint multi-modal embedding space and use the links to form coreference chains during training. To this end, we propose a multimodal pipeline that represents each modality (image regions, text mentions and also mouse traces, additionally provided by [47]) with a modality-specific encoder and then exploit the cross-modal correlations between them to resolve coreference. Finally, inspired by the rule-based CR [29], we incorporate linguistic rules into our learning formulation in a principled way. We report extensive experiments on *CIN* and demonstrate that our method brings significant improvements in CR and in weakly supervised narrative grounding, a form of disambiguation that has been underexplored in visual grounding¹.

To summarize our contributions, we introduce (1) the new task of resolving coreferences in multimodal long-form textual descriptions (narrations), (2) a new dataset, *CIN*, that enables the evaluation of coreference chains in text and the localization of bounding boxes in images, which is provided with multiple baselines and detailed analysis for future work, (3) a new method that learns to resolve coreferences while jointly grounding them from weak supervision and exploiting linguistic knowledge, (4) a rigorous experimental evaluation showing significant improvement over the prior work not only in CR but also in weakly supervised grounding of complex phrases in narrative text.

2. Related Work

Text-only CR in NLP has a long history of rule-based and machine learning-based approaches. Early methods [20, 49] used hand-engineered rules to parse dependency trees,

¹Our code and dataset is available at <https://github.com/VICO-UoE/CIN>.

which outperformed all learning-based methods at the time. Recently, neural network methods [62, 61, 12, 21, 30] have achieved significant performance gains. The key idea is to identify all mentions in a document using a parser and then learn a distribution over all the possible antecedents for each mention. SpanBERT [21] uses a span-based masked prediction objective for pre-training and shows improvements on the downstream task of CR. Stolfo *et al.* [55], on the other hand, transfer the pre-trained representations using rules for CR. It is worth noting that all these learning-based approaches either require large pretraining data or training data annotated with gold standard (ground-truth) coreference chains, such as OntoNotes [48] or PreCo [9].

Visual CR includes learning to associate people or characters mentioned in the text with images or videos [50, 53, 13]. Kong *et al.* [24] exploit CR to relate texts to 3D scenes. Another direction is to resolve coreferences in visual dialog [25] for developing better question-answering systems. Unlike these works, we focus on learning coreferences from long unconstrained image narrations using weak supervision. A related group of work [64, 66, 33, 16] aims to ground phrases in image parts. In visual phrase grounding [64, 35, 10, 65, 16, 22, 32], the main objective is to localize a single image region given a textual query. These models are trained on visual grounding datasets such as ReferItGame [23], Flickr30K Entities [46], or RefCOCO [65]. However, due to short captions, the grounding of text boils down to mostly salient objects in images. In contrast, grounding narrations which aim at capturing all image regions is significantly more challenging and cannot be effectively solved with those prior methods.

Weakly supervised grounding, learning to ground from image-text pairs only, has recently been used in [37, 39, 38, 36, 59] for referring expression grounding. These methods use phrase reconstruction from visual region features as a training signal. Other methods [60, 18, 15] use contrastive learning by creating many negative queries (based on word replacement) or by mining negative image regions for a given query. Wang *et al.* [60] is a strong method in this domain, hence we establish it as a baseline in our experiments. Liu *et al.* [39] parses sentences to scene graphs for capturing visual relation between mentions to improve phrase grounding. However, this cannot be directly applied to our task, as parsing scene graphs from narrations are typically very noisy and incomplete. Wang *et al.* [59] learns/predicts object class labels from the object detector during training and inference respectively. Due to the open-vocabulary setting in our dataset, we directly rely on predictions from the detector and use them as features to avoid the complexity of open-vocabulary object detection. Furthermore, we show in Sec. 5 that grounding is useful to anchor mentions but it is not sufficient to resolve coreferences without prior linguistic knowledge. Thus, our method also employs contrastive

learning but for learning CR from weak supervision.

3. Coreferenced Image Narratives

Our CIN dataset contains 1880 images from the Localized Narratives dataset [47] that come with long-form text descriptions (narrations) and mouse traces. These images are originally a subset of the test and validation set of the Flickr30k dataset [46]. We annotated this subset with coreference chains and bounding boxes in the image that are linked with the textual coreference chains, and use them only for validation and testing. Note that we also include singletons (*i.e.*, coreference chains of length one). Fig. 1 shows an example image from CIN.

Annotation procedure. The annotation involved three steps: (1) marking the mentions (sequences of words) that refer to a localized region in the image, (2) identifying coreference chains for the marked mentions, including (a) pronominal words such as *him* or *who* that are used to refer to other mentions, (b) mentions that refer to the same entity (*e.g.*, *a lady* and *that person*), and (c) mentions that do not have any links (*e.g.* *another woman*), (3) drawing bounding boxes in the image for the coreference chains/mentions identified in steps (1) and (2). We created an annotation interface based on LabelStudio [1], an HTML-based tool that allows us to combine text, image, and bounding box annotation. More details are provided in the supplementary material.

Dataset	#noun phrases	#pronouns	#coreference chains	#bounding boxes
Flickr30k Entities [46]	15,252	×	×	17,234
RefCOCO [65]	10,668	×	×	10,668
CIN (Ours)	19,587	1,659	3,310	21,246

Table 1: Statistics of relevant noun phrases, pronouns, coreference chains and bounding boxes on Flickr30k Entities [46], RefCOCO [65] and CIN.

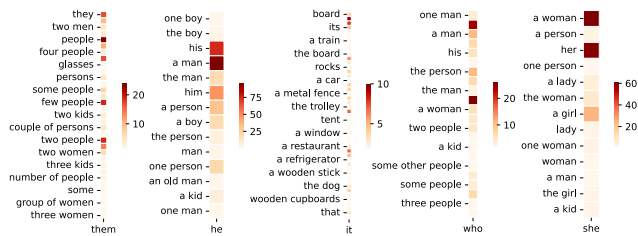


Figure 2: Numbers of mentions as part of the coreference chain for pronouns *them*, *he*, *it*, *who*, *she* in CIN.

Dataset statistics. We split the 1880 images in the dataset into a test and validation set using the pre-defined split of [46]. More specifically, we have 1000 images in the test set and 880 images in the validation set. It is important to note

that the narrations have a lot of first-person pronouns such as *I can see . . .*. We specifically instruct the annotators to exclude such mentions that are not a part of any coreference chain and at the same time cannot be grounded on the image. We elaborate more on the filtering process for these mentions in the supplementary material.

Overall, the dataset has 19,587 noun phrase mentions, 1,659 pronouns, 3,310 coreference chains and 21,246 bounding boxes. In Table 1, we compare the statistics of CIN with the test/val splits of other related datasets. In Fig. 2, we show the distribution over the frequency and types of mention such as *a metal fence* or *few people* that are referred to using a particular pronoun (*them*, *he*, *it*, *who* and *she*). There is a huge diversity in (1) the categories of the mentions and (2) how many times they form a part of the coreference chain.

In Tab. 2, we also report the frequency of the top-6 mentions for each pronoun category to check the diversity of pronoun words in the dataset.

he	she	who	them	it
a man (0.28)	a woman (0.33)	a person (0.18)	people (0.11)	a board (0.06)
his (0.21)	her (0.32)	one person (0.16)	few people (0.08)	a dog (0.05)
him (0.13)	a girl (0.13)	a man (0.07)	two people (0.08)	a building (0.04)
a person (0.09)	the woman (0.04)	the person (0.07)	they (0.08)	which (0.04)
one person (0.06)	a lady (0.03)	him (0.04)	a few people (0.08)	a wall (0.04)
a boy (0.06)	a person (0.02)	her (0.04)	their (0.06)	a vehicle (0.03)

Table 2: Frequency of top-N mentions for each pronoun category.

Comparison to existing CR datasets. In Table 3, we compare our proposed CIN dataset to other CR datasets. This comparison shows that most of the other datasets are either from a restricted domain (*shopping*, *indoor scenes*, *etc.*), have limited mention types referring to either only *people* or *limited object categories*, or do not cover all possible referring expression types such as common nouns (*a person*) and pronouns (*he*).

Dataset	Modality	Domain	Object categories	Referring expression types
NYU-RGBD v2 [24]	Images	Indoor home scenes	Household objects	Common nouns
SIMMC 2.0 [17]	Images	Shopping	Clothing	Common nouns
MPH-MD [53]	Videos	Movies	People	Proper names, Pronouns
Who's Waldo [13]	Images	WikiMedia	People	Proper names
CIN (Ours)	Images	Open-world	General objects	Common nouns and Pronouns

Table 3: Comparison to existing datasets.

4. Method

4.1. Text-only CR

Given a sentence containing a set of mentions (*i.e.*, referential words or phrases), the task of CR is to identify which mentions refer to the same entity. This is fundamentally a clustering problem [57]. In this work, we use an off-the-shelf NLP parser [2] to obtain the mentions. Formally, let

$S = \{m_1, m_2, \dots, m_{|S|}\}$ denote a sentence with $|S|$ mentions, where each mention m contains a sequence of words, $\{w_1, w_2, \dots, w_{|m|}\}$. We assign a label y_{ij} to each mention pair (m_i, m_j) , which is set to 1 when the pair refers to the same entity, and to -1 otherwise. We wish to learn a compatibility function, a deep network f that scores high if a pair refers to the same entity, and low otherwise.

Given a training set D that contains $|D|$ sentences with their corresponding labels, one can learn f by optimizing a binary cross-entropy loss:

$$\min_f \sum_{S \in D} \sum_{i=0}^{|S|-1} \sum_{j=i+1}^{|S|} \log(y_{ij}(\sigma(f(m_i, m_j))) - \frac{1}{2}) + \frac{1}{2} \quad (1)$$

where σ is the sigmoid function. Note that prior methods [29, 30, 21] require large labeled datasets for training and are limited to only a single modality, text. These methods typically also combine the learning with fixed rules based on recency and grammatical principles [29].

4.2. CR in image narrations

Problem definition. Next, we extend the text-only CR to image-text data in the absence of coreference labels. Let (I, S) denote an image-text pair where S describes an image I as illustrated in Figure 1, and assume that coreference labels for mention pairs are not present. As in Sec. 4.1, our goal is to identify the mentions that refer to the same entity in an image-text pair. Each image is defined by $|I|$ regions $I = \{r_1, r_2, \dots, r_{|I|}\}$ which are obtained by running the pre-trained object detector (trained on the COCO [34] and Visual Genome [26] dataset) in [52] on the image. Each region r is described by its bounding box coordinates \mathbf{b} , the text embedding for the detected object category \mathbf{o} , and the visual features \mathbf{v} . More details are provided in Section 4.3.

Weak supervision. We use ‘weak supervision’ to refer to a setting where no coreference label for mention pairs and no grounding of mentions (*i.e.*, bounding boxes are not linked to phrases in the text) are available. Moreover, in contrast to the output space of the object detector (a restricted set of object categories), the sentences describing our images come from the unconstrained vocabulary. Hence, an object instance in a sentence can be referred to with a synonym or may not even be present in the object detector vocabulary [34, 27]. Finally, the object detector can only output *category-level* labels and hence cannot localize object instances based on the more specific *instance-level* descriptions provided by the sentences. For instance in Figure 1, *a person* and *the woman* both are labeled as *person* by the object detector.

In addition to image and text, we explore the use of an auxiliary modality, mouse trace segments provided in [47]. Each mouse trace includes a sequence of 2D points over time that relate to a region in the image when de-

scribing the scene. As the text in Localized Narratives is a transcription of the speech of the annotators, the mouse traces are synced with spoken words, which we denote as $T = \{t_1, t_2, \dots, t_{|T|}\}$ where $|T| = |S|$. These features are stacked with textual features (see Section 4.3).

In the weakly supervised setting, the key challenge is to replace the coreference label supervision with an alternative one. We hypothesize that each mention in a coreferring pair corresponds to (approximately) the same image region, and it is possible to learn a joint image-text space which is sufficiently rich to capture such correlations. Concretely, let $g(m, r)$ denote an auxiliary function that is instantiated as a deep network and outputs a score for the mention m being located at region r in image I . This grounding score for each mention can be converted into probability values by normalizing them over all regions in the image:

$$\bar{g}(m, r) = \frac{\exp(g(m, r))}{\sum_{r' \in I} \exp(g(m, r'))}. \quad (2)$$

The compatibility function f can be defined as a sum product of a pair’s grounding probabilities over all regions:

$$f(m, m') = \sum_{r \in I} \bar{g}(m, r) \bar{g}(m', r). \quad (3)$$

In words, mention pairs with similar region correlations yield bigger compatibility scores and are hence more likely to corefer to each other. The key idea is that we employ the grounding for mentions as anchors to relate coreferring mentions (*e.g.*, *a person* and *the woman*). At test time, we compute $f(m, m')$ for all the pairs and threshold them to predict their pairwise coreference labels.

As no ground-truth bounding box for each mention is available for learning the grounding g , we pose grounding as a weakly supervised localization task as in [18, 60]. To this end, we impute the missing bounding boxes by taking the highest scoring region for a given mention m at each training iteration:

$$r_m = \arg \max_{r \in I} g(m, r). \quad (4)$$

Then we use r_m as the pseudo-truth to learn g as following:

$$\min_g \sum_{(I, S) \in D} \sum_{m \in S} -\log \left(\frac{\exp(g(m, r_m))}{\sum_{I' \in D \setminus I} \exp(g(m, r'_m))} \right) \quad (5)$$

where $r'_m = \arg \max_{r \in I'} g(m, r)$ is the highest scoring region in image I' for mention m . For each mention, we treat the highest scoring region in the original image as positive and other highest scoring regions across different images as negatives, and optimize g for discriminating between the two. However, as the denominator requires computing g

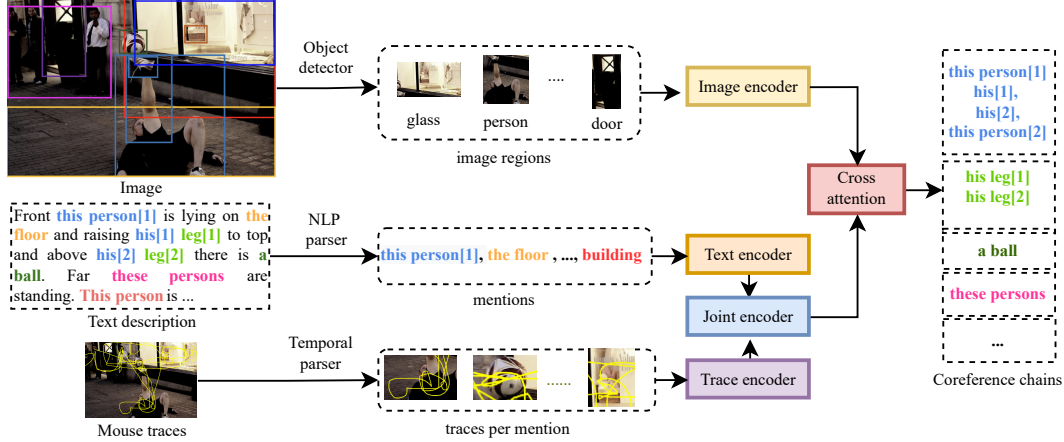


Figure 3: Overview of our pipeline. Our model encodes the image regions obtained from an object detector using the image encoder. We parse text mentions and mouse traces from the sentence description, which are then encoded using a text and trace encoder respectively. Finally, a joint text-trace encoder learns a joint embedding for text and traces. A cross-attention module attends to the words given an image region and then we compute the joint probability of the paired mentions, thus forming coreference chains.

over all training samples at each iteration, which is not computationally feasible, we instead sample the negatives only from the randomly sampled minibatch.

Linguistic constraints. Learning the associations between textual and visual features helps with disambiguating corefering mentions, especially when mentions contain visually salient and discriminative features. However, resolving coreferences when it comes to pronouns (*e.g.*, *her*, *their*) or ambiguous phrases (*e.g.*, *one man* or *another man*) remains challenging. To address such cases, we propose to incorporate a regularizer into the compatibility function $f(m, m')$ based on various linguistic priors. Concretely, we construct a look-up table for each mention pair $q(m, m')$ based on the following set of rules [29]:

- (a) **Exact String Match.** Two mentions corefer if they exactly match and are noun phrases (not pronouns).
- (b) **Pronoun Resolution.** Based on the part-of-speech tags for the mentions, we set $q(m, m')$ to 1 if m is a pronoun and m' is the antecedent noun that occurs before the pronoun.
- (c) **Distance between mentions.** Smaller distance is more likely to indicate coreference since mentions occur close together if they refer to the same entity.
- (d) **Last word match.** In certain cases, the entire phrases might not match but only the last word of the phrases.
- (e) **Overlap between mentions.** If two mentions have one or more overlapping words, then they are likely to corefer.

Finally, we include $q(m, m')$ as a regularizer in Eq. (5):

$$\min_g \sum_{(I, S) \in D} \sum_{m \in S} \left(-\log \left(\frac{\exp(g(m, r_m))}{\sum_{I' \in D \setminus I} \exp(g(m, r_{m'}))} \right) + \lambda \sum_{m' \in S} \|f(m, m') - q(m, m')\|_F^2 \right) \quad (6)$$

where λ is a scalar weight for the Frobenius norm term. Note that f is a function of g (see Eq. (3)). We show in Section 6 that incorporating this term results in steady and significant improvements in CR performance.

4.3. Network modules

Our model (illustrated in Figure 3) consists of an image encoder e_i and text encoder e_t to extract visual and linguistic information respectively, and a cross-attention module a for their fusion.

Image encoder e_i takes in a d_r -dimensional vector for each region r that consists of a vector consisting of bounding box coordinates $\mathbf{b} \in R^4$, text embedding for the detected object category $\mathbf{o} \in R^{d_o}$ and visual features $\mathbf{v} \in R^{d_v}$. The regions are extracted from a pre-trained object detector [52] for the given image I . The image encoder applies a nonlinear transformation to this vector to obtain a d -dimensional embedding for each region r .

Text encoder e_t takes in the multiple mentions from a parsed multi-sentence image description S produced by an NLP parser [2] and outputs a d -dimensional embedding for each word in the parsed mentions. Note that the parser does not only extract nouns but also pronouns as mentions.

Mouse trace encoder e_m takes in the mouse traces for each mention parsed above after it is preprocessed into a 5D vector of coordinates and area, $(x_{\min}, x_{\max}, y_{\min}, y_{\max}, \text{area})$ [44] and outputs a d_m -dimensional embedding. In [7, 47], mouse trace embeddings have been exploited for image retrieval, however, we use them to resolve coreferences. We concatenate each mention embedding extracted from e_t with the mouse trace encoding e_m , denoted as e_{tm} and ap-

ply additional nonlinear transformations (Joint encoder in Fig. 3) before feeding into the cross-attention module.

Cross-attention module a takes in the joint text-trace embeddings for all the words in each mention and returns a d -dimensional vector for each m by taking a weighted average of them based on their correlations with the image regions. Concretely, in this module, we first compute the correlation between each word w (or joint word-mouse trace) and all regions, take the highest correlation over the regions through an auxiliary function \bar{a} :

$$\bar{a}(w) = \max_{r \in I} \left(\frac{\exp(e_{tm}(w) \cdot e_i(r))}{\sum_{r' \in I} \exp(e_{tm}(w) \cdot e_i(r'))} \right) \quad (7)$$

where \cdot is dot product. The transformation can be interpreted as probability of word w being present in image I . Then we compute a weighted average of the word embeddings for each mention m :

$$a(m) = \sum_{w \in m} \bar{a}(w) e_{tm}(w). \quad (8)$$

Similarly, $a(m)$ can be seen as probability of mention m being present in image I .

Scoring function $g(m, r)$ can be written as a dot product between the output of the attention module and region embeddings:

$$g(m, r) = a(m) \cdot e_i(r). \quad (9)$$

While taking a dot product between the two embeddings seemingly ignores the correlation between text and image data, the region embedding $e_i(r)$ encodes the semantic information about the detected object category in addition to other visual features and hence results in a high score only when the mention and region are semantically close. Further implementation details about the modules can be found in Section 5 and the supplementary.

5. Experiments

We train our models on the Flickr30k subset of the Localized Narratives [47] which consists of 30k image-narration pairs, and evaluate on the proposed CIN dataset, which contains 1000/880 pairs for test/val respectively.

Evaluation metrics. To evaluate the CR performance, we use the standard link-based metrics MUC [58] and BLANC [51]:²

(a) **MUC F-measure** counts the coreference links (pairs of mentions) common to the predicted chain R and the ground-truth chain K by computing MUC-R (recall) and MUC-P (precision).

(b) **BLANC** measures the precision (BLANC-P) and recall (BLANC-R) between the ground-truth and predicted coreference links and also between non-coreferent links.

(c) **Narrative grounding.** For evaluating narrative grounding in images, we consider a prediction to be correct if the IoU (Intersection over Union) between the predicted bounding box and the ground truth box is larger than 0.5 [60, 18]. We report percentage accuracy for evaluating narrative grounding for both noun phrases and pronouns. Further details about the metrics is in the supplementary material.

Inputs and modules. For the image modeling, we extract bounding box regions, visual features and object class labels using the Faster-RCNN object detector [52]. For the text modeling, we use Glove embeddings [45] to encode the object class labels and the mentions from the textual branch. For the mouse traces, we follow [47] and extract the trace for each word in the sentence and then convert it into bounding box coordinates for the initial representation. The model discussed in Sec. 4 referred to as ‘Ours’ in Sec. 6 uses the transformer backbone for the image, text and trace encoders (more details in supplementary).

Baselines. We consider the following baselines to fairly compare and evaluate our proposed method:

(a) **Text-only CR:** For all these methods, we directly evaluate the coreference chains using the narration only without the image. (1) *Rule-based* [29]: In this method, a multi-sieve rule based system is used to find mentions in the sentence and the coreference chains, (2) *Neural-Coref* [30]: Instead of rules, this method is trained end-to-end using a neural network on a large corpus of wikipedia data to detect mentions and coreferences, and (3) *Similarity-based*: We compute cosine similarity between mentions using Glove word features and threshold them to get coreference chains.

(b) **Visual-text models:** The baselines discussed below are not trained for CR and hence we post-process their output in order to evaluate for CR. (1) VisualBert [56], UNITER [11] and VinVL [67] are vision- language models trained on image-caption data and fine-tuned on downstream tasks such as VQA, NLVR. To test it for CR, we compute the cosine similarity for the multi-modal mention embeddings in a zero-shot way. (2) *GLIP* [32]: GLIP is trained on large-scale image-text paired data with bounding box annotations and shows improvement in object detection and visual phrase grounding. To evaluate it for CR, we predict bounding boxes for the mentions in the narrations from GLIP. If the IoU overlap between the mentions is greater than 0.7, then we consider them to form a coreference chain, (3) *MAF[†]* [60]: MAF is a weakly supervised phrase grounding method, originally trained on the Flickr30k-Entities [46]. We train this model on narrations data and evaluate CR by computing Eq. (3). (4) *MAF++*: We retrain the MAF[†] model on the narrations with our reg-

²Refer to [30, 42] for a more detailed discussion of CR metrics.

Method	Text	Image	MT	MUC-R	MUC-P	MUC-F1	BLANC-R	BLANC-P	BLANC-F1
Rule-Based [29]	✓	✗	✗	5.6	10.13	6.4	3.3	4.1	4.9
Neural-Coref [30]	✓	✗	✗	0.11	0.17	0.13	1.59	36.99	3.23
Similarity-based	✓	✗	✗	7.07	14.43	9.06	37.48	65.17	45.98
GLIP [32]	✓	✓	✗	0.13	0.12	0.12	21.71	61.40	31.66
VisualBERT [56]	✓	✓	✗	18.17	6.08	8.06	23.90	44.07	22.38
UNITER [11]	✓	✓	✗	16.92	7.15	8.83	27.64	55.30	29.20
VinVL [67]	✓	✓	✗	16.76	8.60	9.75	34.56	58.07	36.56
MAF [†] [60]	✓	✓	✗	25.86	10.18	13.21	37.68	61.14	38.17
MAF++	✓	✓	✗	19.07	15.62	15.65	41.25	65.04	47.21
Ours	✓	✓	✗	22.07	17.10	17.58	42.72	65.92	48.29
	✓	✓	✓	24.87	18.34	19.19	43.81	66.35	48.53

Table 4: CR performance on CIN dataset. *MT* denotes mouse trace and [†] denotes our trained model.

ularization term. Architecturally our method differs from the MAF[†] in two aspects: i) we employ a transformer to encode visual and text features unlike the MLP in theirs and ii) we attend to the mouse traces when present (not present in MAF) and word features jointly whereas they directly compute the similarity function.

6. Results

Coreference resolution. In Table 4, we report the CR performance of the baselines and our method. Our method significantly outperforms all the text-only and vision-text baselines on all the metrics. The text-only CR baselines in the first three rows fail to effectively resolve coreferences from narrations. It is important to note that a relatively high number in BLANC scores (compared to MUC) occurs because this measure also counts non-coreferent links (*i.e.* mentions that are not paired with anything), whereas MUC only measures pairs that are resolved.

The rule-based method [29] uses exact match noun phrases, pronoun-noun matches, and the distance between mentions as hard constraints. It achieves low scores on all metrics and especially on BLANC. The reason for this is the limitation of the rule-based heuristics: For instance, in long narrations, if a pronoun such as *she* occurs farther to its referent (*e.g.* *the woman*) than the predefined distance, it will not form a coreference chain. In contrast, as we apply rules as a soft constraint, we are able to make more flexible decisions from our method. Neural-Coref [30], a deep network on a pre-trained large-corpus of labeled CR data, obtains low scores on CIN for both MUC and BLANC. This is due to the large domain gap between the source and target data as well as the ambiguity in resolving the mentions without visual cues. Similar observations are made when pre-trained CR methods are applied to other domains such as biomedical text [41] or social media [3]. Lastly, the similarity-based baseline performs poorly, as the utilized off-the-shelf word vectors are not trained to cluster

corefering mentions. The relatively high scores on BLANC are due to the frequent non-coreferents in our narratives. This kind of approach clusters words with similar meanings together *e.g.* *woman* and *another woman* (both representing female entities) or *he* and *she* (both pronouns).

Next, we compare our method to the visual grounding baselines that use both image and text input. Our method also outperforms these baselines: Though GLIP is pre-trained on large-scale data with ground-truth boxes for each object in captions, these captions are usually short and do not contain multiple mentions of entities, unlike in our data. Hence GLIP acts more like an object detector, fails to link corefering pairs (low MUC scores) and merely identifies singletons (higher BLANC scores). While it is nontrivial to finetune GLIP on our data without groundtruth boxes, we finetuned MAF on our data, as its training does not require groundtruth boxes; we denote this as MAF[†]. This is the strongest baseline on our task, as training it on narrations including the pronouns reduces the domain gap and enables it to resolve coreferences well. However, this method obtains low precision by incorrectly linking visually similar mentions (that do not belong together) such as *trees*, *plant*, *flowers*. When the training is regularized with the linguistic priors from our method, denoted as MAF++, its performance significantly improves on both MUC and BLANC. The constraint helps to push away the negative mentions (*trees*, *plant*, etc.) and encourages the model to learn unique embeddings for them. Due to the self-attention in the transformer architectures, Ours without mouse traces (MT) achieves better performance than MAF++, a simple MLP baseline. The performance difference between our method without using mouse traces and MAF++ can be explained by the better architecture described previously. Finally, our method achieves the best performance gains in CR thanks to the mouse traces and improved architecture over MAF.

Ablation on mouse traces In Table 4, we also analyze the contribution of modeling mouse traces (second last row). Adding the mouse traces improves performance on CR

MT	Regularization	CR						Grounding
		MUC-R	MUC-P	MUC-F1	BLANC-R	BLANC-P	BLANC-F1	Acc (%)
✗	✗	21.84	12.29	14.09	40.15	62.82	43.69	25.97
✓	✗	20.19	15.79	16.26	41.91	65.42	47.82	26.75
✓	L1	20.76	15.47	16.05	41.73	64.94	47.09	27.65
✓	MSE	21.58	16.40	17.00	42.19	65.37	47.60	28.50
✗	Frobenius Norm	22.07	17.10	17.58	42.72	65.92	48.29	28.31
✓		24.87	18.34	19.19	43.81	66.35	48.53	29.36

Table 5: Ablation study with different regularizer types and with/without mouse traces.

across all metrics. We hypothesize that the mouse traces provide a strong discriminative location prior to the textual mentions, which helps the model to learn a better compatibility score. To visualize qualitatively, consider the example in Figure 3, the same mention *this person* points to two different visual regions – one with the person holding the ball and the other person standing next to the door. In such cases, mouse traces provide a strong signal for disambiguation. But in many cases, mouse traces are noisy and can link mentions that are very close to each other in the image, referring to two different regions. In the above example, mouse traces for *these persons* and *this person* have a significant overlap and hence act as a noisy prior. Therefore, without the visual/image region features, it is very challenging to address the problem with mouse traces alone.

Narrative grounding Not only does our method show performance gains on CR but also outperforms the baselines on another challenging task of narrative grounding. Table 6 compares results from our methods and baselines. We directly compare with the weakly supervised method for a fair comparison. MAF[†] [60] is originally evaluated on the Flickr30k-Entities [46] dataset where the textual descriptions are significantly shorter (*i.e.* single sentence) than the image narrations in our dataset. The performance of MAF on our dataset is significantly lower (21% vs 61% on Flickr30k-Entities), which indicates that narrative grounding is a challenge in itself and cannot be addressed off-the-shelf by phrase grounding methods. When trained with the regularizer, the localization performance improves for both nouns and pronouns with our method and MAF++. With the help of regularization, the model learns to attend to different regions of the image for semantically similar mentions as they might be two separate entities (*e.g.* *five people* and *the people* in Fig. 4).

Further ablations. In Table 5, we start by exploring the impact of training using our proposed architecture without incorporating mouse traces and the regularizer. This leads to a decrease in both coreference (CR) and grounding performance. Although the model manages to capture certain coreference links, it also generates a noticeable number of

Method	Reg	Noun Phrases	Pronouns	Overall
MAF [†] [60]	✗	21.60	18.31	20.91
MAF++	✓	25.58	22.36	24.91
Ours	✗	27.62	23.46	26.75
	✓	30.27	25.96	29.36

Table 6: Grounding accuracy (%) for noun phrases and pronouns and the overall accuracy on the CIN dataset.

incorrect associations (resulting in lower precision scores, row 1) when compared to the model trained with mouse traces (row 2).

In subsequent rows, we investigate the effects of using different regularizers during training. Notably, using the Frobenius norm as a constraint brings improvements in performance, in contrast to using L1 and mean squared error (MSE) regularizers. This improvement can be attributed to the Frobenius norm’s ability to impose a more solid constraint on the learned coreference matrix. It’s important to note that the final row in the table corresponds to our proposed model, which combines mouse traces and the Frobenius norm regularizer (MT+Frobenius norm).

Attention	CR		Grounding
	MUC-F1	BLANC-F1	Acc(%)
Average	17.02	48.26	28.83
Cross attention	19.19	48.53	29.36

Table 7: Our method with/without cross attention.

In Tab. 7, we compare the performance of our final method under two settings: (1) directly averaging the word features or (2) attending over the words by using the image as the query as discussed in Sec. 4. The MUC-F1 and narrative grounding scores are 17.02 and 28.83 respectively for the (1) setting and 19.19 and 29.36 respectively for the (2) setting. Both the narrative grounding accuracy and the coreference evaluation get a boost in performance for visually aware word features. More often than not, the word phrases are relatively short (*e.g.*, *the machine*) and hence the model does not always learn to disambiguate better with attention for the grounding. On the other hand, this technique

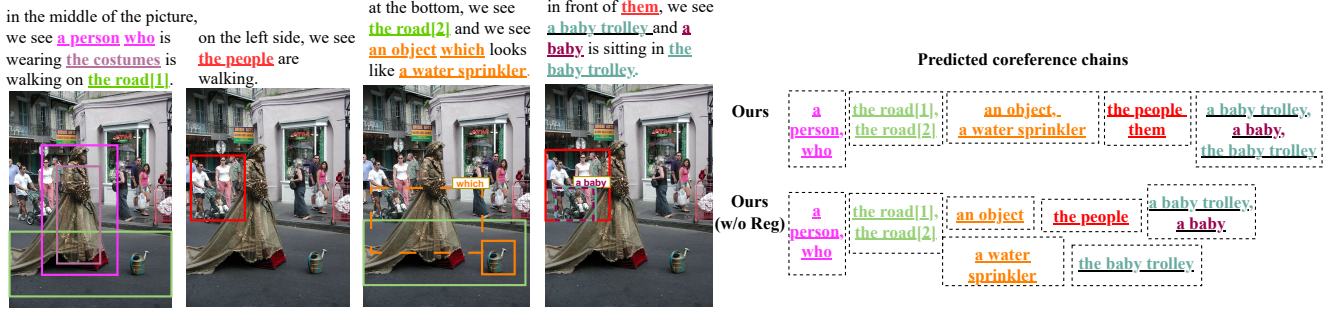


Figure 4: Qualitative results of predictions on the CIN dataset. The colored mentions in the text indicate the ground truth coreference chains. The solid and dotted bounding boxes on the image denote the correct and incorrect grounding respectively for our proposed method. We also show the predicted coreference chains for our final method with and without regularizer.

is especially useful for CR because the flow of visual information to the word features acts as a prior to cluster mentions that refer to the same region but with are referred to with different mentions/entities in the text (*e.g. the machine and an equipment*).

Qualitative results Figure 4 qualitatively analyzes CR and narrative grounding. We visualize the narrative grounding results from our proposed method on the images. The model correctly resolves and localizes phrases such as *a person, who, the people, them* and *a baby trolley, the baby trolley*. Whereas, the model fails to ground and chain the instance *a baby*. It is interesting to note that our model pairs *an object* and *water sprinkler*, thereby resolving ambiguity in what *the object* might refer to. But it fails to add *which* to this coreference chain. Moreover, without the language regularizer, our method fails to link *them* to *the people*. It is very hard to learn coreferences for these pronouns as they come with a weak language prior and hence are difficult for the model to disambiguate. Our model (without regularization) misses the referring expression of *the baby trolley* to refer to the instance of the trolley before. With the help of rules (*e.g. last token match*), we can resolve these pairs more often than not. Hence, we clearly show the challenging problem of coreferences we are dealing with and indicate the great potential for developing models with strong contextual reasoning.

7. Conclusion

We introduced a novel task of resolving coreferences in image narrations, clustering mention pairs referring to the same entity. For benchmarking and enabling the progress, we introduce a dataset – CIN – that contains images with narrations annotated with coreference chains and their grounding in the images. We formulate the problem of learning CR by using weak supervision from image-text pairs to disambiguate coreference chains and linguistic priors to avoid learning grammatically wrong chains.

We demonstrate strong experimental results in multiple settings. In the future, we plan to address the noise induced by the language rules during learning and also reduce the errors coming from the mouse traces. We hope that our proposed task definition, dataset, and the weakly supervised method will advance the research in multi-modal understanding.

Acknowledgement: AG is supported by the Armeane Choksi Scholarship and HB is supported by the EPSRC programme grant Visual AI EP/T028572/1 and HB and FK are supported by Edinburgh Laboratory for Integrated Artificial Intelligence (ELIAD). This research/project is supported by the National Research Foundation, Singapore, under its NRF Fellowship (Award NRF-NRFF14-2022-0001). We thank the anonymous reviewers for their constructive feedback.

References

- [1] Labelstudio. <https://labelstud.io/>. 3
- [2] Spacy. <https://spacy.io/>. 3, 5
- [3] Berfin Aktaş, Veronika Solopova, Annalena Kohnert, and Manfred Stede. Adapting coreference resolution to twitter conversations. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2454–2460, 2020. 7
- [4] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014. 1
- [5] Eric Bengtson and Dan Roth. Understanding the value of features for coreference resolution. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, pages 294–303, 2008. 1
- [6] Erik Cambria, Dipankar Das, Sivaji Bandyopadhyay, Antonio Feraco, et al. A practical guide to sentiment analysis. 2017. 1
- [7] Soravit Changpinyo, Jordi Pont-Tuset, Vittorio Ferrari, and Radu Soricut. Telling the what while pointing to the where: Multimodal queries for image retrieval. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 12136–12146, 2021. 5

- [8] Soravit Changpinyo, Piyush Sharma, Nan Ding, and Radu Soricut. Conceptual 12m: Pushing web-scale image-text pre-training to recognize long-tail visual concepts. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3558–3568, 2021. 1
- [9] Hong Chen, Zhenhua Fan, Hao Lu, Alan L Yuille, and Shu Rong. Preco: A large-scale dataset in preschool vocabulary for coreference resolution. *arXiv preprint arXiv:1810.09807*, 2018. 1, 2
- [10] Kan Chen, Rama Kovvuri, and Ram Nevatia. Query-guided regression network with context policy for phrase grounding. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 824–832, 2017. 2
- [11] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. Uniter: Universal image-text representation learning. In *European conference on computer vision*, pages 104–120. Springer, 2020. 6, 7
- [12] Kevin Clark and Christopher D Manning. Improving coreference resolution by learning entity-level distributed representations. *arXiv preprint arXiv:1606.01323*, 2016. 2
- [13] Yuqing Cui, Apoorv Khandelwal, Yoav Artzi, Noah Snavely, and Hadar Averbuch-Elor. Who’s waldo? linking people across text and images. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1374–1384, 2021. 1, 2, 3
- [14] Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José MF Moura, Devi Parikh, and Dhruv Batra. Visual dialog. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 326–335, 2017. 1
- [15] Samyak Datta, Karan Sikka, Anirban Roy, Karuna Ahuja, Devi Parikh, and Ajay Divakaran. Align2ground: Weakly supervised phrase grounding guided by image-caption alignment. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2601–2610, 2019. 2
- [16] Jiajun Deng, Zhengyuan Yang, Tianlang Chen, Wengang Zhou, and Houqiang Li. Transvg: End-to-end visual grounding with transformers. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1769–1779, 2021. 2
- [17] Danfeng Guo, Arpit Gupta, Sanchit Agarwal, Jiun-Yu Kao, Shuyang Gao, Arijit Biswas, Chien-Wei Lin, Tagyoung Chung, and Mohit Bansal. Gravl-bert: Graphical visual-linguistic representations for multimodal coreference resolution. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 285–297, 2022. 3
- [18] Tanmay Gupta, Arash Vahdat, Gal Chechik, Xiaodong Yang, Jan Kautz, and Derek Hoiem. Contrastive learning for weakly supervised phrase grounding. In *European Conference on Computer Vision*, pages 752–768. Springer, 2020. 2, 4, 6
- [19] Vishal Gupta and Gurpreet Singh Lehal. A survey of text summarization extractive techniques. *Journal of emerging technologies in web intelligence*, 2(3):258–268, 2010. 1
- [20] Jerry R Hobbs. Resolving pronoun references. *Lingua*, 44(4):311–338, 1978. 2
- [21] Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S Weld, Luke Zettlemoyer, and Omer Levy. Spanbert: Improving pre-training by representing and predicting spans. *Transactions of the Association for Computational Linguistics*, 8:64–77, 2020. 1, 2, 4
- [22] Aishwarya Kamath, Mannat Singh, Yann LeCun, Gabriel Synnaeve, Ishan Misra, and Nicolas Carion. Mdetrm: Modulated detection for end-to-end multi-modal understanding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1780–1790, 2021. 2
- [23] Sahar Kazemzadeh, Vicente Ordonez, Mark Matten, and Tamara Berg. Referitgame: Referring to objects in photographs of natural scenes. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 787–798, 2014. 2
- [24] Chen Kong, Dahua Lin, Mohit Bansal, Raquel Urtasun, and Sanja Fidler. What are you talking about? text-to-image coreference. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3558–3565, 2014. 2, 3
- [25] Satwik Kottur, José MF Moura, Devi Parikh, Dhruv Batra, and Marcus Rohrbach. Visual coreference resolution in visual dialog using neural module networks. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 153–169, 2018. 2
- [26] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *International journal of computer vision*, 123(1):32–73, 2017. 1, 4
- [27] Alina Kuznetsova, Hassan Rom, Neil Alldrin, Jasper Uijlings, Ivan Krasin, Jordi Pont-Tuset, Shahab Kamali, Stefan Popov, Matteo Mallocci, Alexander Kolesnikov, et al. The open images dataset v4. *International Journal of Computer Vision*, 128(7):1956–1981, 2020. 4
- [28] Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. Natural questions: a benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:453–466, 2019. 1
- [29] Heeyoung Lee, Yves Peirsman, Angel Chang, Nathanael Chambers, Mihai Surdeanu, and Dan Jurafsky. Stanford’s multi-pass sieve coreference resolution system at the conll-2011 shared task. In *Proceedings of the fifteenth conference on computational natural language learning: Shared task*, pages 28–34, 2011. 1, 2, 4, 5, 6, 7
- [30] Kenton Lee, Luheng He, Mike Lewis, and Luke Zettlemoyer. End-to-end neural coreference resolution. *arXiv preprint arXiv:1707.07045*, 2017. 1, 2, 4, 6, 7
- [31] Kenton Lee, Luheng He, and Luke Zettlemoyer. Higher-order coreference resolution with coarse-to-fine inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 687–692, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. 1

- [32] Liunian Harold Li, Pengchuan Zhang, Haotian Zhang, Jianwei Yang, Chunyuan Li, Yiwu Zhong, Lijuan Wang, Lu Yuan, Lei Zhang, Jenq-Neng Hwang, et al. Grounded language-image pre-training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10965–10975, 2022. 2, 6, 7
- [33] Muchen Li and Leonid Sigal. Referring transformer: A one-step approach to multi-task visual grounding. *Advances in Neural Information Processing Systems*, 34:19652–19664, 2021. 2
- [34] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer, 2014. 1, 4
- [35] Daqing Liu, Hanwang Zhang, Feng Wu, and Zheng-Jun Zha. Learning to assemble neural module tree networks for visual grounding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4673–4682, 2019. 2
- [36] Xuejing Liu, Liang Li, Shuhui Wang, Zheng-Jun Zha, Zechao Li, Qi Tian, and Qingming Huang. Entity-enhanced adaptive reconstruction network for weakly supervised referring expression grounding. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2022. 2
- [37] Xuejing Liu, Liang Li, Shuhui Wang, Zheng-Jun Zha, Dechao Meng, and Qingming Huang. Adaptive reconstruction network for weakly supervised referring expression grounding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2611–2620, 2019. 2
- [38] Xuejing Liu, Liang Li, Shuhui Wang, Zheng-Jun Zha, Li Su, and Qingming Huang. Knowledge-guided pairwise reconstruction network for weakly supervised referring expression grounding. In *Proceedings of the 27th ACM International Conference on Multimedia*, pages 539–547, 2019. 2
- [39] Yongfei Liu, Bo Wan, Lin Ma, and Xuming He. Relation-aware instance refinement for weakly supervised visual grounding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 5612–5621, 2021. 2
- [40] Adam Lopez. Statistical machine translation. *ACM Computing Surveys (CSUR)*, 40(3):1–49, 2008. 1
- [41] Pengcheng Lu and Massimo Poesio. Coreference resolution for the biomedical domain: A survey. *arXiv preprint arXiv:2109.12424*, 2021. 7
- [42] Xiaoqiang Luo and Sameer Pradhan. Evaluation metrics. In *Anaphora Resolution*, pages 141–163. Springer, 2016. 6
- [43] Walaa Medhat, Ahmed Hassan, and Hoda Korashy. Sentiment analysis algorithms and applications: A survey. *Ain Shams engineering journal*, 5(4):1093–1113, 2014. 1
- [44] Zihang Meng, Licheng Yu, Ning Zhang, Tamara L Berg, Babak Damavandi, Vikas Singh, and Amy Bearman. Connecting what to say with where to look by modeling human attention traces. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12679–12688, 2021. 5
- [45] Jeffrey Pennington, Richard Socher, and Christopher D Manning. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543, 2014. 6
- [46] Bryan A Plummer, Liwei Wang, Chris M Cervantes, Juan C Caicedo, Julia Hockenmaier, and Svetlana Lazebnik. Flickr30k entities: Collecting region-to-phrase correspondences for richer image-to-sentence models. In *Proceedings of the IEEE international conference on computer vision*, pages 2641–2649, 2015. 1, 2, 3, 6, 8
- [47] Jordi Pont-Tuset, Jasper Uijlings, Soravit Changpinyo, Radu Soricut, and Vittorio Ferrari. Connecting vision and language with localized narratives. In *European conference on computer vision*, pages 647–664. Springer, 2020. 1, 2, 3, 4, 5, 6
- [48] Sameer Pradhan, Alessandro Moschitti, Nianwen Xue, Olga Uryupina, and Yuchen Zhang. Conll-2012 shared task: Modeling multilingual unrestricted coreference in ontonotes. In *Joint Conference on EMNLP and CoNLL-Shared Task*, pages 1–40, 2012. 1, 2
- [49] Karthik Raghunathan, Heeyoung Lee, Sudarshan Rangarajan, Nathanael Chambers, Mihai Surdeanu, Dan Jurafsky, and Christopher D Manning. A multi-pass sieve for coreference resolution. In *Proceedings of the 2010 conference on empirical methods in natural language processing*, pages 492–501, 2010. 1, 2
- [50] Vignesh Ramanathan, Armand Joulin, Percy Liang, and Li Fei-Fei. Linking people in videos with “their” names using coreference resolution. In *European conference on computer vision*, pages 95–110. Springer, 2014. 1, 2
- [51] Marta Recasens and Eduard Hovy. Blanc: Implementing the rand index for coreference evaluation. *Natural language engineering*, 17(4):485–510, 2011. 6
- [52] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems*, 28, 2015. 4, 5, 6
- [53] Anna Rohrbach, Marcus Rohrbach, Siyu Tang, Seong Joon Oh, and Bernt Schiele. Generating descriptions with grounded and co-referenced people. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4979–4989, 2017. 1, 2, 3
- [54] Tian Shi, Yaser Keneshloo, Naren Ramakrishnan, and Chandan K Reddy. Neural abstractive text summarization with sequence-to-sequence models. *ACM Transactions on Data Science*, 2(1):1–37, 2021. 1
- [55] Alessandro Stolfo, Chris Tanner, Vikram Gupta, and Mrinmaya Sachan. A simple unsupervised approach for coreference resolution using rule-based weak supervision. In *Proceedings of the 11th Joint Conference on Lexical and Computational Semantics*, pages 79–88, 2022. 2
- [56] Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. Vi-bert: Pre-training of generic visual-linguistic representations. *arXiv preprint arXiv:1908.08530*, 2019. 6, 7
- [57] Rhea Sukthanker, Soujanya Poria, Erik Cambria, and Ramkumar Thirunavukarasu. Anaphora and coreference resolution: A review. *Information Fusion*, 59:139–162, 2020. 1, 3

- [58] Marc Vilain, John D Burger, John Aberdeen, Dennis Connolly, and Lynette Hirschman. A model-theoretic coreference scoring scheme. In *Sixth Message Understanding Conference (MUC-6): Proceedings of a Conference Held in Columbia, Maryland, November 6-8, 1995*, 1995. 6
- [59] Liwei Wang, Jing Huang, Yin Li, Kun Xu, Zhengyuan Yang, and Dong Yu. Improving weakly supervised visual grounding by contrastive knowledge distillation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 14090–14100, 2021. 2
- [60] Qinxin Wang, Hao Tan, Sheng Shen, Michael W Mahoney, and Zhewei Yao. Maf: Multimodal alignment framework for weakly-supervised phrase grounding. *arXiv preprint arXiv:2010.05379*, 2020. 2, 4, 6, 7, 8
- [61] Sam Wiseman, Alexander M Rush, and Stuart M Shieber. Learning global features for coreference resolution. *arXiv preprint arXiv:1604.03035*, 2016. 2
- [62] Sam Joshua Wiseman, Alexander Matthew Rush, Stuart Merrill Shieber, and Jason Weston. Learning anaphoricity and antecedent ranking features for coreference resolution. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. Association for Computational Linguistics, 2015. 2
- [63] Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. Google’s neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*, 2016. 1
- [64] Licheng Yu, Zhe Lin, Xiaohui Shen, Jimei Yang, Xin Lu, Mohit Bansal, and Tamara L Berg. Mattnet: Modular attention network for referring expression comprehension. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1307–1315, 2018. 2
- [65] Licheng Yu, Patrick Poirson, Shan Yang, Alexander C Berg, and Tamara L Berg. Modeling context in referring expressions. In *European Conference on Computer Vision*, pages 69–85. Springer, 2016. 2, 3
- [66] Zhou Yu, Jun Yu, Chenchao Xiang, Zhou Zhao, Qi Tian, and Dacheng Tao. Rethinking diversified and discriminative proposal generation for visual grounding. *arXiv preprint arXiv:1805.03508*, 2018. 2
- [67] Pengchuan Zhang, Xiujun Li, Xiaowei Hu, Jianwei Yang, Lei Zhang, Lijuan Wang, Yejin Choi, and Jianfeng Gao. Vinvl: Revisiting visual representations in vision-language models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 5579–5588, 2021. 6, 7