Sentence Directed Video Object Codetection

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Abstract—We tackle the problem of video object codetection by leveraging the weak semantic constraint implied by sentences that describe the video content. Unlike most existing work that focuses on codetecting large objects which are usually salient both in size and appearance, we can codetected objects that are small or medium sized. Our method assumes no human pose or depth information such as is required by the most recent state-of-the-art method. We employ weak semantic constraint on the codetection process by pairing the video with sentences. Although the semantic information is usually simple and weak, it can greatly boost the performance of our codetection framework by reducing the search space of the hypothesized object detections. Our experiment demonstrates an average IoU score of 0.423 on a new challenging dataset which contains 15 object classes and 150 videos with 12,509 frames in total, and an average IoU score of 0.373 on a subset of an existing dataset, originally intended for activity recognition, which contains 5 object classes and 75 videos with 8,854 frames in total.

Index Terms—video, object codetection, sentences

1 INTRODUCTION

In this paper, we address the problem of codetecting objects with bounding boxes from a set of videos, without any pretrained object detectors. The codetection problem is typically approached by selecting one out of many object proposals per image or frame that maximizes a combination of the confidence scores associated with the selected proposals and the similarity scores between proposal pairs. While much prior work focuses on codetecting objects in still images (e.g., [7, 25, 39, 42]), little prior work [22, 34, 35, 40, 41] attempts to codetect objects in video. In both lines of work, most [7, 22, 25, 34, 39, 42] assume that the objects to be codetected are salient, both in size and appearance, and located in the center of the field of view. Thus they easily “pop out.” As a result, prior methods succeed with a small number of object proposals in each image or frame. Tang et al. [42] and Joulin et al. [22] used approximately 10 to 20 proposals per image, while Lee and Grauman [25] used 50 proposals per image. Limiting codetection to objects in the center of the field of view allowed Prest et al. [34] to prune the search space by penalizing proposals in contact with the image perimeter. Moreover, under these constraints, the confidence score associated with proposals is a reliable measure of salience and a good indicator of which image regions constitute potential objects [39]. In prior work, the proposal confidence dominates the overall scoring process and the similarity measure only serves to refine the confidence. In contrast, Srikantha and Gall [41] attempt to codetect small to medium sized objects in video, without the above simplifying assumptions. However, in order to search through the larger resulting object proposal space, they avail themselves of human pose and depth information to prune the search space. It should also be noted that all these codetection methods, whether for images or video, codetect only one common object at a time: different object classes are codetected independently.

The confidence score of a proposal can be a poor indicator of whether a proposal denotes a salient object, especially when objects are occluded, the lighting is poor, or motion blur exists (e.g., see Figure 1). Salient objects can have low confidence score while nonsalient objects or image regions that do not correspond to objects can have high confidence score. Thus our scoring function does not use the confidence scores produced by the proposal generation mechanism. Moreover, our method does not rely on human pose and depth information, which is not always available. Human pose can be difficult to estimate reliably when a person is only partially visible or is self-occluded [3], as is the case with most of our videos.

We avail ourselves of a different source of constraint on the codetection problem. In videos depicting human interaction with objects to be codetected, descriptions of such activity can impart weak spatial or motion constraint either on a single object or among multiple objects of interest. For example, if the video depicts a “pick up” event, some object should have an upward displacement during this process, which should be detectable even if it is small. This motion constraint will reliably differentiate the object which is being picked up from other stationary background objects. It is weak because it might not totally resolve the ambiguity; other image regions might satisfy this constraint, perhaps due to noise. Similarly, if we know object A is on the left of object B, then the detection search for object A will weakly affect the detection search for object B, and vice versa. To this end, we extract spatio-temporal constraints from sentences that describe the videos and then impose these constraints on the codetection process to find the most salient collections of objects that satisfy these constraints. Even though the constraints implied by a single sentence are usually weak, when accumulated across a set of videos and sentences, they together will greatly prune the detection search space. We call this process sentence directed video object codetection. It can be viewed as the inverse of video captioning/description [5, 14, 17] where object evidence (detections or other visual features) is first produced by pretrained detectors and then sentences are generated given the object appearance and movement.
Generally speaking, we extract a set of predicates from each sentence and formulate each predicate around a set of primitive functions. The predicates may be verbs (e.g., CARRIED and ROTATED), spatial-relation prepositions (e.g., TO THE LEFT OF and ABOVE), motion prepositions (e.g., AWAY FROM and TOWARDS), or adverbs (e.g., QUICKLY and SLOWLY). The sentential predicates are applied to the candidate object proposals as arguments, allowing an overall predicate score to be computed that indicates how well these candidate object proposals satisfy the sentence semantics. We add this predicate score into the codetection framework, on top of the original similarity score, to guide the optimization. To the best of our knowledge, this is the first work that uses sentences to guide generic video object codetection. To summarize, our approach differs from the indicated prior work in the following ways:

(a) Our method can codetect small or medium sized non-salient objects which can be located anywhere in the field of view.
(b) Our method does not require or assume human pose or depth information.
(c) Our method can codetect multiple objects simultaneously. These objects can be either moving in the foreground or stationary in the background.
(d) Our method allows fast object movement and motion blur. Such is not exhibited in prior work.
(e) Our method leverages sentence semantics to help codetection.

We evaluate our approach on two different datasets. The first is a new dataset that contains 15 distinct object classes and 150 video clips with a total of 12,509 frames. The second is a subset of CAD-120 [24], a dataset originally intended for activity recognition, that contains 5 distinct object classes and 75 video clips with a total of 8,854 frames. Our approach achieves an average IoU (Intersection-over-Union) score of 0.423 on the former and 0.373 on the latter. It yields an average detection accuracy of 0.7 to 0.8 on the former and 0.423 on the latter. It yields an average overall detection accuracy of 0.7 to 0.8 on the former and 0.373 on the latter. It yields an average overall detection accuracy of 0.7 to 0.8 on the former and 0.373 on the latter.

3 Sentence Directed Codetection

Our sentence-directed codetection approach is illustrated in Figure 2. The input is a set of videos paired with human-elicted sentences, one sentence per video. A collection of object-candidate generators and video-tracking methods are applied to each video to obtain a pool of object proposals. Object instances and predicates are extracted from the paired sentence. Given multiple such video-sentence pairs, a graph is formed where object instances serve as vertices and similarities between object instances and predicates linking object instances in a sentence serve as edges. Finally, Belief

1. For clarity, in the remainder of this paper, we refer to object proposals for a single frame as object candidates, while we refer to object tubes or tracks across a video as object proposals.
Propagation is applied to this graph to jointly infer object codetections.

### 3.1 Sentence Semantics

Our main contribution is exploiting sentence semantics to help the codetection process. We use a conjunction of predicates to represent (a portion of) the semantics of a sentence. Object instances in a sentence fill the arguments of the predicates in that sentence. An object instance that fills the arguments of multiple predicates is said to be coreferenced. For a coreferenced object instance, only one track is codetected. For example, a sentence like “the person put the mouthwash into the sink near the cabbage” implies the following conjunction of predicates:

\[
\text{DOWN}(\text{mouthwash}) \land \text{NEAR}(\text{mouthwash}, \text{cabbage})
\]

In this case, \textit{mouthwash} is coreferenced by the predicates \text{DOWN} (fills the sole argument) and \text{NEAR} (fills the first argument). Thus only one \text{mouthwash} track will be produced, simultaneously constrained by the two predicates (Figure 2, blue track).

In principle, one could map sentences to conjunctions of our predicates using standard semantic parsing techniques [12, 45]. However, modern semantic parsers are domain specific, and employ machine-learning methods to train a semantic parser for a specific domain. No existing semantic parser has been trained on our domain. Training a new semantic parser requires a parallel corpus of sentences paired with intended semantic representations. Modern semantic parsers are trained with corpora like PropBank [31] that have tens of thousands of manually annotated sentences. Gathering such a large training corpus would be overkill for our experiments that involve only a few hundred sentences, especially since such is not our focus or contribution. Thus like Lin et al. [26], Kong et al. [23], and Plummer et al. [33], we employ simpler handwritten rules to fully automate the semantic parsing process for our limited corpus. Nothing, in principle, precludes using a machine-trained semantic parser in its place.

Our semantic parser employs seven steps.

1. Spelling errors are corrected with Ispell.
2. The NLTK parser is used to obtain the POS tags for each word in the sentence.
3. POS tagging errors are corrected by a postprocessing step with a small set of rules (Table 1a).
4. Words with a specified set of POS tags are eliminated.
5. NLTK is used to lemmatize all nouns and verbs.
6. Synonyms are conflated by mapping phrases to a smaller set of nouns and verbs using a small set of rules (Table 1b).
7. A small set of rules map the resulting word strings to predicates (Table 1c).

The entire process is fully automatic and implemented in less than two pages of Python code.

The rules employed by the last step of the above process generate a \textit{weak} semantic representation, containing only those predicates that are relevant to our codetec-tion process. For example, for the phrase “\textit{into the sink}” in the above sentence, it is beyond our interest to detect the object \textit{sink}. Thus our predefined rules generate \text{DOWN}(\text{mouthwash}) instead of \text{INTO}(\text{mouthwash}, \text{sink}). Also,
although a more detailed semantic representation for this sentence would include \texttt{put(person, mouthwash)}, we simplify this two-argument predicate to a one-argument predicate \texttt{MOVE(mouthwash)}, since we do not attempt to code- tect people. To ensure that we do not introduce surplus semantics, the generated predicates always implies a weaker constraint than the original sentence.

Each predicate is formulated around a set of primitive functions on the arguments of the predicate. The primitive functions produce scores indicating how well the arguments satisfy the constraint. The aggregate score over the functions constitutes the predicate score. Table 2 shows the complete list of our 24 predicates and the scores they compute. The function \texttt{medOptFlow(p)} computes the median of the average optical flow magnitude within the detections for the proposal \( p \). The functions \( x(p^{(t)}) \) and \( y(p^{(t)}) \) return the \( x \)- and \( y \)-coordinates of the center of \( p^{(t)} \), normalized by the frame width and height, respectively. The function \( \text{distLessThan}(x, a) \) is defined as \( \log(1/(1 + \exp(-b(x - a)))) \), where we set \( b = -20 \) in the experiment. Similarly, the function \( \text{distGreaterThan}(x, a) \) is defined as \( \text{distLessThan}(-x, -a) \). The function \( \text{distOverlap}(p_1, p_2) \) computes the distance between the centers of \( p_1 \) and \( p_2 \), also normalized by the frame size. The function \( \text{smaller}(p_1, p_2) \) returns 0 if the size of \( p_1 \) is smaller than that of \( p_2 \), and \( -\infty \) otherwise. The function \( \text{tempCoher}(p) \) evaluates whether the position of proposal \( p \) changes during the video, by checking the position offsets between every two frames. A higher \( \text{tempCoher} \) score indicates that \( p \) is more likely to be stationary in the video. The function \( \text{rotAngle}(p^{(t)}) \) computes the current rotated angle of the object inside \( p^{(t)} \) by looking back 1 second (30 frames). We extract SIFT features \[27\] for both \( p^{(t)} \) and \( p^{(t-30)} \) and match them to estimate the similarity transformation matrix, from which the angle can be computed. Finally the function \( \text{hasRotation}(\alpha, \beta) \) computes the rotation log-likelihood given angle \( \alpha \) through the von Mises distribution for which we set the location \( \mu = \beta \) and the concentration \( \kappa = 4 \).

### 3.2 Generating Object Proposals

We first generate \( N \) object candidates for each video frame. We use EdgeBoxes \[46\] to obtain the \( \frac{N}{2} \) top-ranking object candidates and MCG \[4\] to obtain the other half, filtering out candidates larger than \( \frac{1}{20} \) of the video-frame size to focus on small and medium-sized objects. This yields \( NT \) object candidates for a video with \( T \) frames. We then generate \( K \) object proposals from these \( NT \) candidates. To obtain object proposals with object candidates of consistent appearance and spatial location, one would nominally require that \( K \ll NT \). To circumvent this, we first randomly sample a frame \( t \) from the video with probability proportional to the averaged magnitude of optical flow \[15\] within that frame. Then, we sample an object candidate from the \( N \) candidates in frame \( t \). To decide whether the object is moving or not, we sample from \{\text{MOVING,STATIONARY}\} with distribution \( \{\frac{1}{2}, \frac{1}{2}\} \). We sample a \text{MOVING} object candidate with probability proportional to the average flow magnitude within the candidate. Similarly, we sample a \text{STATIONARY} object candidate with probability inversely proportional to the average flow magnitude within the candidate. The sampled candidate is then propagated (tracked) bidirectionally to the start and the end of the video. We use the CamShift algorithm \[9\] to track both \text{MOVING} and \text{STATIONARY} objects, allowing the size of \text{MOVING} objects to change during the process, but requiring the size of \text{STATIONARY} objects to remain constant. \text{STATIONARY} objects are tracked to account for noise or occlusion that manifests as small motion or change in size. We track \text{MOVING} objects in HSV color space and \text{STATIONARY} objects in RGB color space. We do not use optical-flow-based tracking methods since these methods suffer from drift when objects move quickly.
the distances are linearly scaled to $[0,1]$ and converted to log similarity scores. Finally, the similarity between two proposals $p_1$ and $p_2$ is taken to be:

$$g(p_1, p_2) = \frac{\text{median}}{m} \left( \left( b_{1}^{m} - b_{2}^{m} \right) \right)$$

### 3.4 Joint Inference

We extract object instances (see all 15 classes for our new dataset and all 5 classes for our subset of CAD-120 in Section 4) from the sentences and model them as vertices in a graph. Each vertex $v$ can be assigned one of the $K$ proposals in the video that is paired with the sentence in which the vertex occurs. The score of assigning a proposal $k_v$ to a vertex $v$ is taken to be the unary predicate score $h_v(k_v)$ computed from the sentence (if such exists, or otherwise 0). We construct an edge between every two vertices $v$ and $u$ that belong to the same object class. We denote this class membership relation as $(v,u) \in C$. The score of this edge $(v,u)$, when the proposal $k_v$ is assigned to vertex $v$ and the proposal $k_u$ is assigned to vertex $u$, is taken to be the similarity score $g_{v,u}(k_v, k_u)$ between the two proposals, as described in Section 3.3. Similarly, we also construct an edge between two vertices $v$ and $u$ that are arguments of the same predicate. We denote this predicate membership relation as $(v, u) \in P$. The score of this edge $(v,u)$, when the proposal $k_v$ is assigned to vertex $v$ and the proposal $k_u$ is assigned to vertex $u$, is taken to be the predicate score $h_{v,u}(k_v, k_u)$ between the two proposals, as described in Section 3.3. Our problem, then, is to select a proposal for each vertex that maximizes the joint score on this graph, i.e., solving the following optimization problem:

$$\max_{k} \sum_{v} h_v(k_v) + \sum_{(v,u) \in C} g_{v,u}(k_v, k_u) + \sum_{(v,u) \in P} h_{v,u}(k_v, k_u)$$

where $k$ is the collection of the selected proposals for all the vertices. Note that the unary and binary scores are equally weighted in the above objective function. This discrete inference problem on graphical models can be solved approximately by Belief Propagation [32]. In the experiment, we use the OpenGM [2] implementation to find the approximate solution.

### 4 Experiment

Our method can only be applied to datasets with the following properties:

I) It can only be applied to video that depicts motion and changing spatial relations between objects.

II) It can only be applied to video, not images, because it relies on such motion and changing spatial relations.

III) The video must be paired with sentences that describe that motion and those changing spatial relations. Some existing image and video corpora are paired with sentences that do not describe such.

IV) The objects to be codetected must be detectable by existing object proposal methods.

V) There must be different clips that all involve different instances of the same object class participating in the described activity. This is necessary to support codetection.
Most existing datasets do not meet the above criteria and are thus ill suited to our approach. We evaluate on two specific datasets that are suited. Most existing methods require properties that our datasets lack. For example, Srikantha and Gall [41] require depth and human pose information. Others, such as Prest et al. [34], Schulter et al. [40], Joulin et al. [22], and Ramanathan et al. [35] do not make code available. Thus neither can one run our method on existing datasets or existing methods on our datasets.

It is not possible to compare our method to existing image codetection methods or evaluate on existing image codetection datasets, or any existing image captioning datasets, because they lack properties I, II, and III. Further, it is not possible to compare our method to existing video codetection methods or existing video codetection datasets. Schulter et al. [40] and Ramanathan et al. [35] address different problems with datasets that are highly specific to those problems and are thus incomparable. The dataset used by Prest et al. [34] and Joulin et al. [22] lacks properties I and III. Srikantha and Gall [41] evaluate on three datasets: ETHZ-activity [16], CAD-120, and MPII-cooking [38]. Two of the three, namely ETHZ-activity and MPII-cooking, lack properties II and III. Srikantha and Gall [41] rely on depth and human pose information to overcome the lack of property IV. Moreover, the kinds of activity depicted in ETHZ-activity and MPII-cooking cannot easily be formulated in terms of descriptions of object motion and changing spatial relations. We do apply our method to a subset of CAD-120. However, because we do not use depth and human pose information, we only consider that subset of CAD-120 that satisfies property IV. Srikantha and Gall [41] apply their method to a different subject, rendering their results incomparable with ours. Moreover, we use incompatible sources of information: we use sentences but they do not; they use depth and human pose but we do not. This is impossible to perform an apples-to-apples comparison, even on the common subset.

There exist a large number of video datasets that are not used for codetection but rather are used for others purposes like activity recognition and video captioning. Sentential annotation is available for some of these, like MPII-cooking, M-VAD [43], and MPII-MD [37]. However, the vast majority of the clips in M-VAD (48,986 clips annotated with sentences) and MPII-MD (68,337 clips annotated with sentences) do not satisfy properties I and IV. We searched the sentential annotations from each of these two corpora for all instances of twelve common English verbs that represent the kinds of verbs whose that describe motion and changing spatial relations between object.

We further examined ten sentences for each verb from each corpus, together with the corresponding video clips, and found that only ten out of the 240 examined satisfied properties II and IV. Moreover, none of these ten suitable video clips satisfied property IV. Further, of the twelve classes (AnswerPhone, DriveCar, Eat, FightPerson, GetOutCar, HandShake, HugPerson, Kiss, Run, SitDown, SitUp, and StandUp) in the Hollywood 2 dataset [29], only four (AnswerPhone, DriveCar, GetOutCar, and Eat) satisfy property IV. Of these, three classes (AnswerPhone, DriveCar, and GetOutCar) always depict a single object class, and thus are ill suited for codetecting anything but the two fixed classes phone and car. The one remaining class (Eat) fails to satisfy property IV. This same situation occurs with essentially all standard datasets used for activity recognition, like UCF Sports [36].

| Scene | New, codetection set | Subset of CAD-120, codetection set |
|-------|----------------------|----------------------------------|
| 1     | 2                    | 3                                |
| 4     | 5                    | 6                                |
| 7     | 8                    | 9                                |
| 10    | 11                   | 12                               |

TABLE 3

The experimental setup of the 10 codetection sets for our new dataset and the 5 codetection sets for our subset of CAD-120.

Fig. 3. Examples of the 15 object classes to be codetected in our new dataset and the 5 object classes to be codetected in our subset of CAD-120. From left to right: the object classes in our new dataset, bowl, box, bucket, cabbage, coffee grinder, cooler, cup, gas can, juice, ketchup, milk, mouthwash, pineapple, squash, and watering pot, and the object classes in our subset of CAD-120, bowl, cereal, cup, jug, and microwave.
The standard sources of naturally occurring video for corpora used within the computer-vision community are Hollywood movies and YouTube video clips. However, Hollywood movies, in general, mostly involve dialog among actors, or generic scenery and backgrounds. At best, only small portions of most Hollywood movies satisfy property [I] and such rarely is reflected in the dialog or script, thus failing to satisfy property [III]. We attempted to gather a codetection corpus from YouTube. But again, about a dozen students searching YouTube for depictions of about a dozen common English verbs, examining hundreds of hits, found that fewer than 1% satisfied property [I] and non satisfied property [V]. Thus it is only feasible to evaluate our method on video that has been filmed to expressly satisfy properties [I] and [V].

While existing datasets within the computer-vision community do not satisfy properties [I] and [V], we believe that these properties are nonetheless reflective of the natural world. In the real world, people interact with everyday objects (in their kitchen, basement, driveway, and many similar location) all of the time. It is just that people don’t usually record such video, let alone make Hollywood movies about it or post it on YouTube. Further, people rarely describe such in naturally occurring text in movie scripts or in text uploaded to YouTube. Yet, children—and even adults—probably learn names of newly observed objects by observing people in their environment interacting with those objects in the context of dialog about such. Thus we believe that our problem, and our datasets, are a natural reflection of the kinds of learning that people employ to learn to recognize newly named objects.

### 4.1 Datasets

We evaluate our method on two datasets that do satisfy these properties. The first is a newly collected dataset, filmed to expressly satisfy properties [I] and [V]. This dataset was filmed in 6 different scenes (four in the kitchen, one in the basement, and one outside the garage) of a house. The lighting conditions vary greatly across the different scenes, with the basement scene the darkest, the kitchen scene exhibiting modest lighting, and the garage scene the brightest. Within each scene, the lighting often varies across different video regions. We assigned 5 actors (four adults and one child) with 15 distinct everyday objects (bowl, box, bucket, cabbage, coffee grinder, cooler, cup, gas can, juice, ketchup, milk, mouthwash, pineapple, squash, and watering pot, see Figure 3), and had them perform different actions which involve interaction with these objects. No special instructions were given requiring that the actors move slowly or that the objects not be occluded. The actors often are partially outside the field of view. Note that the dataset used by Srikantha and Gall [31] does not exhibit this property. Indeed, their method employs human pose which requires that the human be sufficiently visible to estimate such. The filming was performed using a normal consumer camera that introduces motion blur on the objects when the actors move quickly. We downsampled the filmed videos to 768 × 432 and divided them into 150 short video clips, each clip depicting a specific event lasting between 2 and 6 seconds at 30 fps. The 150 video clips constitute a total of 12,509 frames.

The second dataset is a subset of of CAD-120. Many of the 120 clips in CAD-120 depict sequences of actions. We divide these clips into subclips, each containing one action. We discard those that fail to satisfy any of the properties [I] or [V] leaving 75 clips. These clips have spatial resolution 640 × 480, each clip depicting a specific event lasting between 3 and 5 seconds at 30 fps. The 75 video clips constitute a total of 8,854 frames, and contain 5 distinct object classes, namely bowl, cereal, cup, jug, and microwave.

### 4.2 Experimental Setup

We employed Amazon Mechanical Turk (AMT) to obtain three distinct sentences, by three different workers, for each video clip. For each video clip, resulting in 450 sentences for the our new dataset and 225 sentences for our subset of CAD-120. AMT annotators were simply instructed to provide a single sentence for each video clip that described the primary activity depicted taking place with objects from a common list of object classes that occur in the entire dataset. The collected sentences were all converted to the predicates in Table 2 using the methods of Section 3.1. We processed each of the two datasets three times, each time using a different set of sentences produced by different workers; each sentence was used in exactly one run of the experiment. Furthermore, we divided each corpus into codetection set, each set containing a small subset of the video-sentence pairs. (For our new dataset, some pairs were reused in different codetection sets. For CAD-120, each pair was used in exactly one codetection set.) Some codetection sets contained only videos filmed in the same background, while others contained a mix of videos filmed in different backgrounds. (The backgrounds in each codetection set for our new dataset are summarized in Table 3 where K, B, and G denote kitchen, basement, and garage, respectively.) This rules out the possibility of codetecting objects by simple background modeling (e.g., background subtraction).

Codetection sets were processed independently, each with a distinct graphical model. Table 3 contains the number of video-sentence pairs and the number of vertices in the resulting graphical model for each codetection set of each corpus.

We compared the resulting codetections against human annotation. Human-annotated boxes around objects are provided with CAD-120. For our new dataset, these were obtained with AMT. We obtained five bounding-box annotations for each target object in each video frame. We asked annotators to annotate the referent of a specific highlighted word in the sentence associated with the video containing that frame. Thus the annotation reflects the semantic constraint implied by the sentences. This resulted in 5 × 289 = 1445 human annotated tracks. To measure how well codetections match human annotation, we use the IoU, namely the ratio of the area of the intersection of two bounding boxes to the area of their union. The object codetection problem exhibits inherent ambiguity: different codackers tend to annotate different parts of an object or make different decisions whether to include surrounding background regions when the object is partially occluded.
To quantify such ambiguity, we computed intercoder agreement between the human annotators for our datasets. We computed \( \frac{24}{2} = 10 \) IoU scores for all box pairs produced by the 5 annotators in every frame and averaged them over the entire dataset, obtaining an overall human-human IoU of 0.72.

We found no publicly available implementations of existing video object codetection methods \([22, 34, 35, 40, 41]\), thus for comparison we employ four variants of our method that alternatively disable different scores in our codetection framework. These variants help one understand the relative importance of different components of the framework. Together with our full method, they are summarized below:

| Parameter | Flow score? | Similarity score? | Sentence score? |
|-----------|-------------|------------------|-----------------|
| SIM       | no          | yes              | yes             |
| FLOW      | yes         | yes              | no              |
| SENT      | yes         | partial          | yes             |
| SIM+FLOW  | yes         | yes              | yes             |
| SIM+SENT  | yes         | yes              | yes             |

Note that SIM uses the similarity measure but no sentential information. This method is similar to prior video codetection methods that employ similarity and the proposal confidence score output by proposal generation methods to perform codetection. When the proposal confidence score is not discriminative, as is the case with our datasets, the prior methods degrade to SIM. FLOW exploits only binary movement information from the sentence indicating which objects are probably moving and which are probably not (i.e., using only the functions medFlMg and tempCoher in Table 2) without similarity or any other sentence semantics (thus “partial” in the table). SIM+FLOW adds the similarity score on top of FLOW. SENT uses all possible sentence semantics but no similarity measure. SIM+SENT is our full method that employs all scores. All the above variants were applied to each run of each codetection set of each dataset. Except for the changes indicated in the above table, all other parameters were kept constant across all such runs, thus resulting in an apples-to-apples comparison of the results. In particular, \( N = 500, K = 240, M = 20, \) and \( L = 15 \) (see Section 3 for details).

4.3 Results

We quantitatively evaluate our full method and all of the variants by computing IOU\(_{\text{frame}}\), IOU\(_{\text{object}}\), IOU\(_{\text{set}}\), and IOU\(_{\text{dataset}}\) for each dataset as follows. Given an output box for an object in a video frame, and the corresponding set of annotated bounding boxes (five boxes for our new dataset and a single box for CAD-120), we compute IoU scores between the output box and the annotated ones, and take the averaged IoU score as IOU\(_{\text{frame}}\). Then IOU\(_{\text{object}}\) is computed as the average of IOU\(_{\text{frame}}\) over the output object track. Then, IOU\(_{\text{set}}\) is computed as the average of IOU\(_{\text{object}}\) over all the object instances in a codetection set. Then, IOU\(_{\text{set}}\) is computed as the average of IOU\(_{\text{object}}\) over all runs of all codetection sets for a dataset.

We compute IOU\(_{\text{set}}\) for each variant on each run of each codetection set in each dataset as shown in Figure 4. The first

5. Both datasets, including videos, sentences, and bounding-box annotations, are available at [http://upplysingaoflun.ecn.purdue.edu/~qobi/cccp/sentence-codetection.html](http://upplysingaoflun.ecn.purdue.edu/~qobi/cccp/sentence-codetection.html)

6. [http://upplysingaoflun.ecn.purdue.edu/~qobi/cccp/sentence-codetection.html](http://upplysingaoflun.ecn.purdue.edu/~qobi/cccp/sentence-codetection.html)
strates that natural language, when combined with typical computer-vision problems, could provide the capability of high-level reasoning that yields better solutions to these problems.

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Fig. 6. Examples of the 15 codetected object classes in our new dataset (top) and the 5 codetected object classes in our subset of CAD-120 (bottom). Note that in some examples the objects are occluded, rotated, poorly lit, or blurred due to motion, but they are still successfully codetected. (For demonstration purposes, the original output detections are slightly enlarged to include the surrounding context; zoom in on the screen for the best view).
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