“Show me the cup”: Reference with Continuous Representations

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Abstract

One of the most basic functions of language is to refer to objects in a shared scene. Modeling reference with continuous representations is challenging because it requires individuation, i.e., tracking and distinguishing an arbitrary number of referents. We introduce a neural network model that, given a definite description and a set of objects represented by natural images, points to the intended object if the expression has a unique referent, or indicates a failure, if it does not. The model, directly trained on reference acts, is competitive with a pipeline manually engineered to perform the same task, both when referents are purely visual, and when they are characterized by a combination of visual and linguistic properties.

1 Introduction

Humans use language to talk about the world, and one of its most basic functions is to refer to objects (Russell, 1905). This makes reference one of the fundamental devices to ground linguistic symbols in extralinguistic reality (Harnad, 1990). ¹ For successful reference, the speaker must choose an expression allowing the hearer to pick the right referent. For instance, assume that Adam and Barbara are in the context of Figure 1, and consider the dialogues in (1).

(1)  Adam: Can you please give me...  
    a.  ...the mug?  
       Barbara: Sure.
    b.  ...the pencil?  
       Barbara (searching): Ahem, I can’t see any pencil here...  
    c.  ...the book?  
       Barbara: Sorry, which one?

In dialogue (1-a), reference is successful. It fails in (1-b) and (1-c), but for different reasons: in (1-b), the word “pencil” does not apply to any object in the scene; in (1-c), the use of singular “the” implies that Adam refers to a unique object, while the scene contains three matching objects. These examples show how reference involves both characterization mechanisms that capture object properties, mainly through the use of content words (e.g. “mug” vs. “pencil”), and individuation mechanisms, prominently encoded in function words and morphology (e.g., “the” vs. “some”, singular vs. plural), which allow us to track and distinguish referents.

¹We ignore the thorny philosophical issues of reference, such as its relationship to reality. For an overview and references (no pun intended), see Reimer and Michaelson (2014).
dividuation. The converse holds for logics-based approaches (Bos et al., 2004).

In this paper, we propose a neural network model aimed at both aspects of reference, and that can be trained directly on reference acts. Just like in the typical reference scenario, the model works across modalities, looking for the referent of a verbal expression in the visual world, or in a setting in which entities are characterized by joint visual and linguistic information. The model, Point-or-Protest (PoP), behaves like Barbara: It identifies (points to) the image that corresponds to a given linguistic expression, or protests in case of reference failure. While the model is generic and could be extended to other reference types, our starting point in this paper is reference to (concrete) entities using single-entity denoting noun phrases (as in (1)). This case clearly illustrates the joint workings of characterization (reference requires recognizing the right sort of entity in the scene) and individuation (reference succeeds only if there is exactly one entity of the right kind: in (1), Barbara cannot simply recognize the presence of some “pencil mass”, but she must check that there is only one pencil to unambiguously refer to). We show, in two experiments, that PoP is competitive with a state-of-the-art pipeline requiring specific heuristics.2

2 We will make our code and data available.

2 Models

Point-or-Protest Point-or-Protest (PoP) is a feed-forward neural network learning from examples how to react to successful and failed reference acts.3 Given a variable-length sequence of objects depicted in images (possibly coupled with other information characterizing them, e.g., verbal attributes) and a natural language query, PoP must either point to the object denoted by the query, returning its index in the sequence, or protest if the query phrase is not an appropriate referring expression. The PoP architecture builds an “entity array” whose entries are vectors storing information about the objects in the scene, and uses similarity-based reasoning about the vectors in the array and the query to decide its response. We currently focus on singular definite article semantics, as in (1), with failure if there is no possible referent (missing-referent anomaly) or if there is more than one (multiple-referent anomaly). We discussed above the linguistic appeal of this case. From a machine-learning perspective, one-entity individuation requires a non-linear separation of the anomalous reference acts (0 or more than 1) from the felicitous ones.

We use the diagram in Figure 2 to introduce PoP. In this example, the input set contains a harrier and two cups, with the corresponding linguistic query being cup.4 PoP should thus raise the anomaly flag.

The linguistic query is first mapped to a dense space by using pre-compiled cbow embeddings, whereas images are mapped to vector representations by passing them through a pre-trained convolutional neural network (cnn), and extracting the activation patterns in one of the top layers of the network (see Section 4 for further details). If the input consists of objects with linguistic attributes, we simply concatenate the corresponding cnn and cbow vectors to get their input representation, and analogously we concatenate cbow vectors to represent multi-word linguistic phrases. Conceptually, using cbow embeddings means that the listener we model already possesses large amounts of unembodied knowledge about word meaning, as gathered from linguistic co-occurrence patterns independently of reference. This assumption is unrealistic, and we abandon it with the TRPoP model described below.

PoP maps the input object representations in the sequence to an array of entity vectors by applying a linear transformation. The corresponding mapping matrix V is shared across objects, as the position of objects in the input sequence is arbitrary, and PoP should not learn associations between objects and specific sequence slots (e.g., from the Figure 2 example, it should not learn to associate cups with positions 2 and 3 in general). Each vector in the entity array corresponds to one input object. In parallel, PoP maps the linguistic expression to a “query” vector through a separate linear transformation L. The query vector lives in the same space as the entity vectors to enable pairwise similarity computations. We can thus interpret the matrices V and L as map-

3 For neural network design and training see, e.g., Nielsen (2015).

4 We do not enter the determiner in the query, since it does not vary across data points: our setup is equivalent to always having “the” in the input. The network learns the intended semantics through training.
PoP also needs to assess whether the reference act was felicitous. The cumulative “similarity mass” across entity vectors should provide the network with good evidence to reason about anomaly. For the specific aim of modeling singular reference, the network should discover that, when cumulative similarity is too low or too high, the reference is not appropriate for the current sequence: in the first case, because no object matches the query; in the second, because there is more than one object that matches the query. More precisely, along the “anomaly pathway” shown in grey in Figure 2, we first pass the similarity vector through a nonlinearity $\psi$ to sharpen the contrasts, particularly zeroing out low similarities. For example, a ReLU transformation might set all low similarities to 0, making it easier to detect anomalies: in Figure 2, the whitening of the harrier similarity cell is meant to suggest this process. We then sum across all values in the resulting vector, obtaining a cumulative similarity score. We concatenate it with the cardinality of the input sequence and feed them, via a linear transformation $A_i$, to a vector of “anomaly sensor” cells. Cardinality enables the model to take the number of inputs into account when assessing the cumulative similarity score: the same score that looks suspiciously high for two objects is bound to be low for ten objects. More specifically, through cardinality the model can compare the average similarity to arbitrary thresholds, and subsets of anomaly sensor cells can learn different thresholds to pick up anomalies (the presence of multiple anomaly sensor cells allows the model to pick up “non-linear” patterns, such as the one for single-entity reference we are addressing here). Their output is linearly combined via matrix $A_o$ into a single value. The latter is passed through nonlinearity $\phi$, that is bounding the anomaly score to approximate a discrete yes/no response.

We finally concatenate the similarity profile with the cell containing the anomaly score, and pass the resulting vector through a softmax nonlinearity ($\pi$). The model output for an input sequence of $n$ objects will thus contain a probability distribution over $n+1$ indices. We take the index with the maximum value for this distribution as PoP’s response: if it
is one of the first $n$ indices, then PoP “pointed” at the corresponding object, whereas if PoP assigned maximum probability to the $n + 1$ th cell, that means that it “protested”. In the figure diagram, PoP has correctly raised the anomaly flag. We train PoP by backpropagating the error of the log-likelihood cost function when comparing its output (either the index of the correct object, or the anomaly flag) with the ground truth for the training reference acts.

**Pipeline**  As a strong competitor, we implemented a method that performs our task by manual pipelining of a set of separately trained/tuned components. The Pipeline first induces a set of multimodal embeddings by optimizing similarities between matched pairs of queries and objects, compared to random confounders. It uses a max-margin cost function forcing query representations to be (much) more similar to the objects they denote than to irrelevant ones. This has been shown to produce excellent multimodal embeddings (Frome et al., 2013; Lazaridou et al., 2015a; Weston et al., 2011). Once these embeddings have been separately trained, the model computes similarities between the query and each of the objects in each referential act in our test sets, picking the object with largest similarity as candidate object to point at. Then, two separately-tuned heuristics are used to catch anomalous acts: Missing reference is predicted if no query-object similarity is above an (optimized) threshold. Multiple reference is guessed if the difference between the two largest similarities is below another optimized threshold.

**Convolutional Neural Network**  Since PoP uses input image embeddings based on a pre-trained convolutional neural network (CNN), we also test a model matching the categorical labels produced by the same CNN for the input images against the query. For the example of Figure 2, it would pass each of the images through the full CNN, obtaining 3 labels. We take a lax approach to label matching, in which the model scores a hit even when, e.g., the gold label is a substring of the model-predicted one. Anomaly detection is straightforward (although again implemented ad hoc): CNN deems a reference act anomalous if no produced label matches the query, or if more than one does. Thus, the CNN would be successful if it predicted a synonym of *cup* for both image 2 and 3.

**Tabula Rasa PoP**  Through the cbow vectors, PoP can rely on pre-acquired text-induced word similarity knowledge. The assumption that word meanings are first learned separately, purely from language statistics, and then fine-tuned in the referential setup, is unrealistic. Ideally, we would want a model that learns word representations in parallel from reference acts and language statistics. For the time being, we consider instead the other extreme, where word representations are entirely induced from the reference acts during training. The “Tabula Rasa” PoP model (TRPoP) is identical to the one in Figure 2, except that input query representations (and attributes in the Object+Attribute setup explained below) are one-hot vectors. This model will thus induce distributed representations from scratch when estimating the weights of matrices $L$ and $V$. Such representations will then depend entirely on the role of words as queries or attributes in the referential acts we model.

## 3 Data

We test our model in two experiments, for each of which we have automatically created a large-scale dataset. Both datasets contain 40,000 sequences for training, 5,000 for validation and 10,000 for testing, each with 15% missing-referent and 15% multi-referent anomalies. The sequences are of varying length, from 2 to 5 candidate referents. The supplementary materials contain the algorithms used to generate the datasets as well as detailed statistics.

**Object-Only Experiment.**  Our first experiment represents a base case of reference, namely matching noun phrases consisting of single nouns with visually represented entities. Figure 3 shows two examples. The objects and images are sampled uniformly at random from a set of 2,000 objects and 50 ImageNet images per object, itself sampled from a larger dataset used in Lazaridou et al. (2015b). As the examples show, we use natural objects and images, which makes the task very challenging (even humans might wonder which image in the second row depicts a *darling*). We generate data with an algorithm sampling sets of sequences with uniform distributions over sequence lengths (2 to 5) and indices of the queried object within a sequence.

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^5http://imagenet.stanford.edu/
**Object+Attribute Experiment.** Our second experiment, illustrated in Figure 4, goes one step further in testing the model’s individuation capabilities. In the scene from Section 1, imagine that Adam points to the book on top and says “I recommend this book”. This linguistically conveyed information will be associated to Barbara’s representation of the entity, together with its visual features. Crucially, it can be used to identify the first book if later on Adam asks her “Can you bring the book I recommended?” We test this situation in a simplified form. Each referent is associated with both an image and a linguistically-expressed attribute, more specifically a verb (the only word class from which we could sample a sufficient number of attributes with the characteristics outlined below). The query and the sequence items are all pairs like spend:bill, where we interpret the attribute analogously to an object relative clause, that is, a bill that is being spent (we ignore tense for simplicity).

We restrict the attributes under consideration for each object to the 500 highest-associated syntactic neighbors of the object according to the DM resource (Baroni and Lenci, 2010), such that the attributes be compatible with the objects (to exclude nonsensical combinations such as repair:dog). Of these, we retain only verbs taking the target item as direct object, in line with the “relative clause” interpretation sketched above. Moreover, we focus on (relatively) abstract verbs, for two reasons. First, a concrete verb is more likely than an abstract one to have strong visual correlates that do not match what is actually depicted in an image (cf. groom:dog vs. like:dog). Second, successful reference routinely mixes concrete and abstract cues (e.g., a noun referring to a concrete object combined with a modifier recording an event associated to it: the book I lent you), and we are interested in simulating this scenario. We thus filter verbs through the concreteness norms of Brysbaert et al. (2014), retaining only those with a concreteness score of at most 2.5 (on a 1–5 scale).

The object-attribute structure of the stimuli in this experiment also enables us to introduce challenging confounders into the sequences – namely, pairs that share either the attribute or the object with the query. For each sequence, we start by picking an attribute-object query. Given the query, we generate two more compatible attributes for the query object, and alternative objects compatible to these attributes as well as the initial attribute. Starting from all attribute-object combinations, we randomly drop as many as necessary to obtain the final sequences of 2 to 5 items. A consequence of this design is that the objects within sequences tend to be somewhat related since they share compatible attributes, and vice versa. The first sequence in Fig. 4 illustrates the effect: For the query
object bartender, we generate the confounder object soldier, connected through the attributes instruct and inform. The full sequence also includes the confounder object emperor, not shown in the figure.

4 Experiments

Method PoP and Pipeline’s input word representations are 400-dimensional cbow embeddings from Baroni et al. (2014), trained on about 2.8 billion tokens of unannotated text. These models, as well as TRPoP, use 4096-dimensional vectors as input visual representations, which are produced by passing images through the pre-trained VGG 19-layer CNN of Simonyan and Zisserman (2015) (trained on the ILSVRC-2012 data), and extracting the corresponding activations on the topmost fully connected layer.6 The same pre-trained network was used to generate the labels of our CNN competitor model. The parameters of PoP/TRPoP and of the Pipeline max-margin embeddings are estimated by online stochastic gradient descent on the training portions of the two datasets. For Pipeline, we extract all possible pairs of positive and negative query-object tuples from each reference act in the relevant training data. Details on model hyperparameter tuning are in the supplementary material. We consider three baselines for both experiments. Random assigns all labels randomly. Majority assigns the most frequent output label, namely anomaly, accounting for 30% of the sequences (the non-anomalous labels are distributed among predicted indices). Probability randomly assigns labels based on their relative frequency in the training data.

Experiment 1: Object-Only Results are reported on the left-hand side of Table 1. Besides overall accuracy (Total), we show accuracy itemized by successful reference acts (Pointing), missing-referent (MissRef) and multiple-referent anomalies (MultRef).

(TR)PoP and Pipeline are clearly above the baselines (Majority and Probability reach deceptively high anomaly-detection scores by over-raising the anomaly flag, at the cost of pointing performance). PoP’s absolute performance is close to that of the manually-crafted Pipeline. By jointly learning to point and handling anomalies in reference acts, PoP loses some performance in pointing, but in exchange it does better on anomaly detection. As could be expected, MissRef is more difficult than MultRef for all three models. Interestingly, TRPoP, which does not rely on pre-trained word embeddings, performs comparably to PoP (but it requires more than twice as many epochs to converge, see supplementary materials). This suggests that useful representations of word meaning can be learned solely from examples of successful and failed reference acts.

CNN performance is barely above baseline, and, like Majority and Probability, it trivially reaches high performance on anomaly cases because it raises the anomaly flag whenever it fails to produce the name of the target object (and it rarely produces the right label). For instance, in the first example in Figure 3, CNN can get a hit as long as it doesn’t produce “cup”. As for its extremely low pointing performance, note that CNN, unlike PoP, cannot make reasonable pointing guesses for objects it did not see during training. The large performance asymmetry between these two models sharing the same visual processing network shows that PoP generalizes well beyond the knowledge it inherited from this pre-trained network. Importantly, PoP reasons about similarity in multimodal space, rather than assigning hard labels. For example, the CNN, when presented with an image associated to the out-of-training query academician, tags it as academic gown – not unreasonably but incorrectly. PoP points to the correct slot because its multimodal academician query vector is most similar to the correct entity vector than to the other candidates, with no need to perform explicit label matching. Intriguingly, even when considering the subset of test data that CNN is trained on, we still observe an asymmetry: CNN reaches 58% accuracy, while PoP’s performance is at 67%. This suggests that reference-based training has fine-tuned better representations also for the objects the CNN was explicitly trained for.

Experiment 2: Object+Attribute Results are shown on the right side of Table 1. CNN is not tested here, as it does not handle attributes. PoP’s results are slightly higher than in the previous experiment, while those of TRPoP and Pipeline are slightly lower, such that now PoP is clearly above them. The three models are exploiting both visual and verbal information, as shown by their comparison to two additional.

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6We use the MatConvNet toolkit, http://www.vlfeat.org/matconvnet/
### Table 1: Results

|                | Exp 1: Object Only                  | Exp 2: Object+Attribute                  |
|----------------|------------------------------------|-----------------------------------------|
|                | Total | Pointing | MissRef | MultRef | Total | Pointing | MissRef | MultRef |
| PoP            | 66    | 71       | 57      | 51      | 69    | 77       | 57      | 46      |
| TRPoP          | 65    | 70       | 58      | 44      | 62    | 70       | 38      | 48      |
| Pipeline       | 67    | 75       | 51      | 45      | 65    | 74       | 37      | 55      |
| CNN            | 35    | 9        | 100     | 94      | -     | -        | -       | -       |
| Random         | 17    | 17       | 17      | 17      | 17    | 17       | 17      | 17      |
| Majority       | 30    | 0        | 100     | 100     | 30    | 0        | 100     | 100     |
| Probability    | 22    | 18       | 30      | 30      | 22    | 18       | 30      | 30      |
| AttrRandom     | -     | -        | -       | -       | -     | 47       | 16      | 0       |
| ImgShuffle     | -     | -        | -       | -       | 50    | 58       | 31      | 32      |

Figure of merit is percentage accuracy. See text for details.

baselines, shown at the bottom of the table. AttrRandom randomly picks one of the objects that shares the attribute with the query, if any, and raises the anomaly flag otherwise. This baseline has, by construction, 0% accuracy on MultRef anomalies, and it performs at random in MissRef detection. However, even in the pointing case, its performance is still well below that of the models. ImgShuffle is a variant of PoP trained after shuffling image vectors, so that each image ID is (consistently) associated with the CNN representation of another image (mostly depicting objects that do not match the image label). The only reliable signal that this baseline can then exploit is attribute information. Again, its performance is clearly below that of the models.

As for anomaly handling, while PoP still finds MissRef easier than MultRef, this time TRPoP and Pipeline actually perform worse on MissRef. Comparing the MissRef cases in which the models failed to raise the anomaly flag, we observe that Pipeline and TRPoP wrongly pointed to an entity sharing the query attribute much more often than PoP (943 and 883 vs. 629). They are thus over-relying on matching attributes, assigning too high a similarity to pairs that are simply sharing the verbal attribute. This also explains their higher performance on MultRef: Attribute sharing makes both repeated referents very similar to the query, triggering the relevant heuristic. Thus, PoP seems better at integrating verbal and visual cues than them. Compared to TRPoP, PoP has an important prior in the semantics encoded in its pre-trained word embeddings, which helps it discover systematic relations between words and objects while keeping the attribute information apart from that of the head noun. Compared to Pipeline, by jointly learning to point and to spot anomalies, it might be able to attain a better balance between visual and verbal information.

To conclude, our model PoP and its variant TRPoP can learn to refer directly from examples. While PoP is not clearly superior to Pipeline, it has a fundamental advantage: It learns to refer in one integrated architecture. Pipeline (as well as CNN) learns to characterize objects (e.g., to recognize cups as referents for “cup”), but uses an ad hoc strategy, needing a manually coded heuristic, to simulate individualizing capabilities (distinguishing cases where there are several or no cups). As soon as the referential setup gets more complex, as in the Object+Attribute experiment in which visual and verbal information need to be combined, the heuristics break down.

### 5 Related work

**Modeling.** The PoP model “reasons” about the similarity between a query and a set of candidates in vector space, akin to soft attention mechanisms in recent neural network architectures (Bahdanau et al., 2015; Xu et al., 2015). While attention is standardly used to retrieve auxiliary information when producing an output, we directly expose the similarity vector as (part of the) output, in order to obtain a model that learns to point robustly across input sequence orders and lengths. The idea of exposing an attention mechanism functioning as a pointer over the input has recently been employed by Vinyals et al. (2015) in the context of sequence-to-sequence RNNs. PoP’s
entity array emulates traditional memory locations within a fully differentiable architecture. This is akin to the memory vectors of the recently proposed Memory Networks framework (Sukhbaatar et al., 2015; Weston et al., 2015). However, the Memory Networks array has fixed size, whereas our entity array adapts to input object cardinality.

**Multimodal reference resolution.** Our task is a special case of reference resolution. Various studies in this area have proposed multimodal approaches jointly handling vision and language (Gorniak and Roy, 2004; Larsson, 2015; Matuszek et al., 2014; Steels and Belpaeme, 2005, a.o.). These papers focus on aspects of the resolution process we are not currently addressing, such as full compositionality or gesture, but they work with very limited perceptual input, such as simple shapes and colours. Probably the most relevant study in this area is the one by Kennington and Schlangen (2015). They consider visual scenes with more objects than our sequences, but more limited in nature (tables with 36 puzzle pieces). They handle spatial relations and flexible compositionality. However, they must train a separate classifier for each word in their set, which means that their method can’t process unseen words, and would probably perform badly for words that are not observed frequently enough during training. Moreover, they do not present an integrated architecture for the whole resolution process, as we do, but separate components that are manually combined. Crucially, they assume referring expressions are always felicitous. We are not aware of prior work that, like our Object+Attribute setup, considers referents disambiguated by a mixture of perceptual and verbally-expressed abstract properties.

**Referring expression generation and other related work.** The task of referring expression generation (Krahmer and van Deemter, 2012) has recently received new impulses from the study of multimodal language/vision scenarios. The task is converse to ours: given a scene, generate the optimal linguistic expression to pick out a given referent. The focus is generally on considerably more complex (but artificial or heavily controlled) scenes than our sequences, and correspondingly on linguistically more complex referring expressions. Some recent efforts collect and analyze large corpora of referring expressions for multimodal tasks (Kazemzadeh et al., 2014; Tily and Piantadosi, 2009). A method to generate unambiguous referring expressions for objects in natural images has been recently proposed by Mao et al. (2016). Our task is more distantly related to visual question answering (Geman et al., 2015; Malinowski and Fritz, 2014; Ren et al., 2015), in the sense that we model one specific type of question that could easily be asked about an image. Even more generally, our approach fits into the multimodal distributional semantics paradigm. See Baroni (2016) for a discussion of how the problem of reference is addressed in that line of work. There is of course a large body of work on modeling reference with symbolic/logical methods (Abbott, 2010), that provides the framework for our problem, but is not directly relevant to our empirical aims. Our task can finally also be seen as a special case of the much broader problem of content-based image retrieval (Datta et al., 2008).

**6 Conclusion and outlook**

PoP is a neural network model that, given a linguistic expression and a set of objects represented by natural images, either resolves reference by pointing to the object denoted by the expression, or flags the reference act as anomalous if the linguistic expression is not adequate. The model is competitive with a pipeline manually engineered to perform the same task. PoP successfully accounts for characterization because it is able to relate entity properties (visual, and linguistically conveyed) to linguistic expressions, via its distributed representations. It has some individuating capabilities because it builds entity representations and reasons about them.

Although our experiments concentrated on singular definite descriptions (“show me THE cup”), the PoP architecture is general enough that should be able, given appropriate training data, to learn to respond to other reference acts, e.g., corresponding to all X or many X (Sorodoc et al., 2016). We intend to pursue this direction in future work. We also intend to progressively remove various artificial characteristics of our simulations, such as the fact that our sequences do not form natural scenes,
and that our linguistic expressions are very limited. Most importantly, we are currently assuming one-to-one mapping between images and entity vectors. In real-life reference, however, possible referents might re-appear or be mentioned at different times and in different places, and we might, over time, acquire further knowledge characterizing them. PoP must thus eventually be able to learn when to initialize a new entity vector (thus maintaining distinct, individuated representations of the entities in ongoing discourse), and when to update an existing one with new information (furthering the characterization of the entity). Recent work on fully differentiable architectures controlling discrete data structures that can grow and shrink, such as stacks (Joulin and Mikolov, 2015), should make such extensions feasible.

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This supplementary file formally defines the algorithms for the creation of the two datasets we use (Sections 1 and 2), provides statistics on the final datasets (Section 3) and on hyperparameter tuning (Section 4).

1 Data Creation for the Object-Only Dataset (Experiment 1)

The process to generate an object sequence is shown in Algorithm 1. We start with an empty sequence and sample the length of the sequence uniformly at random from the permitted sequence lengths (l. 2). We fill the sequence with objects and images sampled uniformly at random (l. 4/5). We assume, without loss of generality, that the object that we will query for, $q$, is the first one (l. 6). Then we sample whether the current sequence should be an anomaly (l. 7). If it should be a missing-anomaly (i.e., no matches for the query), we overwrite the target object and image with a new random draw from the pool (l. 9/10). If we decide to turn it into a multiple-anomaly (i.e., with multiple matches for the query), we randomly select another position in the sequence and overwrite it with the query object and a new image (l. 12/13). Finally, we shuffle the sequence so that the query is assigned a random position (l. 14).

2 Data Creation for the Object+Attribute Dataset (Experiment 2)

Figure 1 shows the intuition for sampling the Object+Attribute dataset. Arrows indicate compatibility constraints in sampling. We start from the query pair (object 1 – attribute 1). Then we sample two more attributes that are both compatible with object 1. Finally, we sample two more objects that are compatible both with the original attribute 1 and one of the two attributes.

Algorithm 2 defines the sampling procedure formally. We sample the first triple randomly (l. 2). Then we sample two two compatible attributes for this object (l. 3), and one more object for each attribute (l. 4). This yields a set of six confounders (l. 5–10). After sampling the length of the final sequence $l$ (l. 11), we build the sequence from the first triple and $l − 1$ confounders (l. 12–13), with the first triple as query (l. 14). The treatment of the anomalies is exactly as before.
### Table 1: Statistics on Object-Only and Object+Attribute datasets. O: object, A: attribute, I: image.

|                     | Train set avg. frequency | Test set avg. frequency | unseen in test set (%) |
|---------------------|--------------------------|-------------------------|------------------------|
|                     | O     | O+I   | O+A  | O+A+I | O     | O+I   | O+A  | O+A+I | O     | O+I   | O+A  | O+A+I |
| Object-Only         | 90.0  | 2.0   | –    | –     | 22.5  | 1.2   | –    | 23.1  | 0.0   | 23.1  | –    | –     |
| Object+Attribute    | 90.9  | 2.2   | 8.2  | 1.1   | 23.1  | 1.3   | 2.7  | 1.0   | 0.0   | 20.2  | 0.9  | 82.9  |

#### Algorithm 2 Creation of Object+Attribute dataset

**Input:** Sequence length interval $[i \geq 2, j]$; Set of objects $O = \{o_1, \ldots, o_n\}$, sets of associated images $I(o)$ and associated abstract attributes $A(o)$ for each object $o$; probability of missing-anomalies $P_0$; probability of multiple-anomalies $P_m$.

**Output:** $\langle$ object-attribute query $q$, object-image-attribute sequence $S$$\rangle$

```plaintext
1: $S \leftarrow \emptyset$, $S_c \leftarrow \emptyset$
2: $o_1 \sim O$, $a_1 \sim A(o_1)$, $i_1 \sim I(o_1)$
3: $a_2, a_3 \sim A(o_1)$ so that $a_1 \neq a_2 \neq a_3$
4: $o_2 \sim A^{-1}(m_2)$, $o_3 \sim A^{-1}(m_3)$
5: $S_c[1] \leftarrow \langle o_2, o_1, i \sim I(o_1) \rangle$
6: $S_c[2] \leftarrow \langle o_1, o_2, i \sim I(o_2) \rangle$
7: $S_c[3] \leftarrow \langle o_2, o_2, i \sim I(o_2) \rangle$
8: $S_c[4] \leftarrow \langle o_3, o_1, i \sim I(o_1) \rangle$
9: $S_c[5] \leftarrow \langle o_1, o_3, i \sim I(o_3) \rangle$
10: $S_c[6] \leftarrow \langle o_3, o_3, i \sim I(o_3) \rangle$
11: $i \sim U(i, j)$
12: $S[1] \leftarrow \langle o_1, o_2, i_1 \rangle$
13: $S[2..j] \leftarrow$ sample candidates from $S_c$ w.o. replacement
14: $q \leftarrow S[1]$
15: $r_0 \sim \text{Bern}(p_0)$, $r_m \sim \text{Bern}(p_0 + p_m)$
16: **if** $r_0$ **then**
17: $o' \sim O$, $a' \sim A(o)$, $i' \sim I(o)$ so that $\langle o', a' \rangle \neq q$
18: $S[0] \leftarrow \langle a', o', i \rangle$
19: **else if** $r_m$ **then**
20: $i \sim U(1, l)$
21: $S[l] \leftarrow \langle a, o, i' \rangle$ where $S[1] = \langle a, o, i \rangle$, $i' \sim I(o)$
22: **shuffle**$(S)$
```

### 3 Statistics on the Datasets

Table 1 shows statistics on the dataset. The first line covers the Object-Only dataset. Objects occur on average 90 times in the train portion of Object-Only, specific images only twice; the numbers for the test set are commensurately lower. While all objects in the test set are seen during training, 23% of the images are not. Due to the creation by random sampling, a minimal number of sequences is repeated (5 sequences occur twice in the training set, 1 four times) and shared between training and validation set (1 sequence). All other sequences occur just once.

The second line covers the Object+Attribute dataset. The average frequencies for objects and object images mirror those in Object-Only quite closely. The new columns on object-attribute (O+A) and object-attribute-image (O+A+I) combinations show that object-attribute combinations occur relatively infrequently (each object is paired with many attributes) but that the combination is considerably restricted (almost no combinations are new in the test set). The full entity representations (object-attribute-image triples), however, are very infrequent (average frequency just above 1), and more than 80% of these are unseen in the test set. A single sequence occurs twice in the test set, all others once; one sequence is shared between train and test.

### 4 Hyperparameter Tuning

We tuned the following hyperparameters on the Object-Only validation set and re-used them for Object+Attribute without further tuning (except for the Pipeline heuristics’ thresholds). Chosen values are given in parentheses.

- **PoP**: multimodal embedding size (300), anomaly sensor size (100), nonlinearities $\psi$ (relu) and $\phi$ (sigmoid), learning rate (0.09), epoch count (14).
• **TRPoP**: same settings, except epoch count (36).

• **Pipeline**: multimodal embedding size (300), margin size (0.5), learning rate (0.09), maximum similarity threshold (0.1 for Object-Only, 0.4 for Object+Attribute), top-two similarity difference threshold (0.05 and 0.07).

Momentum was set to 0.09, learning rate decay to 1E-4 for all models, based on informal preliminary experimentation.