Learning to Find Common Objects Across Image Collections

Amirreza Shaban∗1, Amir Rahimi∗2, Shray Bansal1, Stephen Gould2, Byron Boots1, and Richard Hartley2

1Georgia Tech, {amirreza, sbansal34, bboots}@gatech.edu,
2ACRV, ANU Canberra, {amir.rahimi, stephen.gould, richard.hartley}@anu.edu.au

Abstract

We address the problem of finding a set of images containing a common, but unknown, object category from a collection of image proposals. Our formulation assumes that we are given a collection of bags where each bag is a set of image proposals. Our goal is to select one image from each bag such that the selected images are of the same object category. We model the selection as an energy minimization problem with unary and pairwise potential functions. Inspired by recent few-shot learning algorithms, we propose an approach to learn the potential functions directly from the data. Furthermore, we propose a fast and simple greedy inference algorithm for energy minimization. We evaluate our approach on few-shot common object recognition and object co-localization tasks. Our experiments show that learning the pairwise and unary terms greatly improves the performance of the model over several well-known methods for these tasks. The proposed greedy optimization algorithm achieves performance comparable to state-of-the-art structured inference algorithms while being ∼10 times faster. The code is publicly available on https://github.com/haamoon/finding_common_object.

1. Introduction

We address the problem of finding a set of images containing a common, but unknown, object category from a collection of image proposals. The input is a collection of bags, each containing several images from multiple classes. A bag is labelled as positive if it contains at least one image from the common object class and negative if none of the images in the bag is from the common object class. The goal is to find an instance of the common object in each positive bag.

Several computer vision problems, including co-

 segmentation, co-localization, and unsupervised video object tracking and segmentation have been formulated in this way [1, 2, 3, 4, 5]. In the co-localization problem, Figure 1, each bag contains many cropped image regions from one image and these bags are labelled as positive or negative based on the presence of the common object. The goal is to identify proposals (regions), one per positive bag (image) that contain the common object. We designed our approach to address the general problem of finding common objects from positive bags and have evaluated it on two problems: few-shot common object recognition and object co-localization.

Weakly supervised classification methods like multiple-instance learning (MIL) [6] can be used to solve this type of problems, but they require many training bags to learn new concepts. Meta-learning techniques [7] [8] [9] have
been shown to reduce the need for training instances in few-shot learning. They do this by transferring knowledge from datasets of similar tasks so that classifiers can be trained with only a small set of examples from new unseen classes [10]. Unfortunately, these methods require full supervision for the new classes. Motivated by their success, we leverage meta-learning to reduce the need for large training sets for the weakly supervised domain.

We model the problem of finding common objects as minimizing the energy of a graphical model. Each node of the graphical model represents a positive bag and minimizing the energy function corresponds to finding one image in each positive bag that contains the common object. The energy minimization problem uses unary and pairwise potential functions, where unary potentials represent the relation of the image to the images in the negative bag and the pairwise potentials represent the relation of an image pair from two positive bags. We adopt the relation network [11], which is successfully used in few-shot recognition to predict the relation of image pairs as our pairwise potentials. We propose a new algorithm that uses the relation of an image to all of the images in the negative bag to provide our unary potentials. Although graphical models have been used for MIL problems [12, 13], our method is different in that it uses a learning-based approach, inspired by meta-learning, to increase the generalization power of potential functions to novel classes.

Any general purpose structured inference method [14, 15, 16] could be used to minimize the energy of the proposed graphical model. While significantly outperforming several MIL baselines, these algorithms suffer from a slow inference step when the number of instances in each bag is large. Further exacerbating the problem, the common object recognition task can be part of a larger pipeline, e.g., training a weakly supervised few-shot object detector, which might require millions of iterations of the inference to achieve good performance. To address this issue, we propose a greedy search algorithm for finding the common object based on the following observation: the common object for the complete problem is a common object in any subset of the bags as well. For example, in Figure 1, a cake is the common object in the four bags, but it is also one of the common objects in any subset of positive bags. Our greedy method uses this property to restrict the search space for the optimal solution to the set of candidates that are a solution to a subset of bags. We introduce an efficient bottom-up algorithm that can be implemented as a simple neural network which finds common objects in a set of positive bags with a single forward pass.

We make the following contributions. (1) Introduce a method to transfer knowledge from large-scale strongly supervised datasets by learning pairwise and unary potentials and demonstrate the superiority of this learned relation metric to earlier MIL approaches on two problems. (2) Propose a specialized fast greedy algorithm for structured inference and show that this method achieves performance comparable to the state-of-the-art inference methods while requiring less computational time.

2. Related Work

Multiple instance learning (MIL) [17, 18] methods have been used for learning weakly supervised tasks such as object localization (WSOL) [19, 20, 21, 22]. In a standard MIL framework, instance labels in each positive bag are treated as hidden variables with the constraint that at least one of them should be positive. MI-SVM and mi-SVM [23] are two popular methods for MIL, and have been widely adapted for many weakly supervised computer vision problems, achieving state-of-the-art results in many different applications [17, 24]. In these methods, images in each bag inherit the label of the bag and an SVM is trained to classify images. The trained SVM is used to relabel the instances and this process is repeated until the labels remain stable. While mi-SVM uses all the instances in positive bags, in MI-SVM only the image with the highest score in each positive bag is used for training.

Co-saliency [25, 5], co-segmentation [1, 2, 26], and co-localization [27] methods have the same kind of output as WSOL methods. Similar to standard MIL algorithms, some of these methods rely on a relatively large training set for learning novel classes [27, 28]. The main difference between these methods and WSOL methods is that they usually do not utilize negative examples [1, 27, 28]. Negative examples in our method are optional and could be used to improve the results of the co-localization task.

Our approach is related to weakly supervised methods that make use of auxiliary fully-labelled data to accelerate the learning of new categories [29, 30, 31, 32, 33]. Since visual classes share many visual characteristics, knowledge from fully-labelled source classes is used to learn from the weakly-labelled target classes. The general approach is to use the labelled dataset to learn an embedding function for image proposals and use MI-SVM to classify instances of the weakly labelled dataset in this space [29, 30, 31]. We show that learning a scoring function to compare images in the embedded space significantly improves the performance of this approach, especially when few positive images are available. Rochan et al. [32] propose a method to transfer knowledge from a set of familiar objects to localize new objects in a collection of weakly supervised images. Their method uses semantic information encoded in word vectors for knowledge transfer. In contrast, our method uses the similarity between tasks in training and testing and does not rely solely on a given semantic relationship between the familiar and new classes. Deselaers et al. [33] transfer objectness scores from source classes and incorporate them into
3. Problem Setup and Notation

We consider a set \( \mathcal{I} \) with a binary relation \( R \). The elements of the set are called images in our work for simplicity of exposition. A relation \( R \) is simply a subset of \( \mathcal{I} \times \mathcal{I} \):

\[
R(e_1, e_2) = \begin{cases} 
+1, & \text{if } (e_1, e_2) \in R \text{ i.e. inputs are related} \\
-1, & \text{otherwise.}
\end{cases}
\]

A bag is a set of images, thus, a subset of \( \mathcal{I} \). We will be concerned with collections of bags, \( \mathcal{V} = \{v_1, v_2, \ldots, v_N\} \). We say that a collection \( \mathcal{V} = \{v_1, \ldots, v_N\} \) is positive if it is possible to select images, one from each bag, so that they are all related in pairs.

Given a collection, \( \mathcal{V} \) and an optional additional bag \( \bar{v} \) that we designate as negative\(^1\), the task is to output a selection of images \( O = (e_1, \ldots, e_N) \), one for each positive bag \( v_i \), where \( e_i \) is from positive bag \( v_i \), such that the images are pairwise related, i.e., \( R(e_i, e_j) = 1 \) and that not all images are pairwise related to any image in the negative bag, i.e., \( \exists e_i \in O \) such that \( \forall e \in \bar{v}, R(e_i, e) = -1 \).

3.1. Constructing \( R \) From Image Labels

We are interested in cases where each of the images \( e \in \mathcal{I} \) has a single latent (unknown) label \( c_e \in \{c_\varnothing\} \cup \mathcal{C} \) where \( c_\varnothing \) is the background class and \( \mathcal{C} \) is the set of foreground classes. Two images \( e_1 \) and \( e_2 \) are related if their labels are the same and belong to a foreground class i.e. \( c_{e_1} = c_{e_2} \in \mathcal{C} \). For example, (cropped) images may be labelled according to the foreground object they contain. In this case, two images \( (e_1, e_2) \), both containing a “cake” are related, \( R(e_1, e_2) = 1 \). Whereas two images \( (e_3, e_4) \) that are not of the same foreground object category are unrelated, \( R(e_3, e_4) = -1 \).

3.2. Training and Test Splits

For a dataset \( \mathcal{D} \subseteq \mathcal{I} \), we use the notation \( \mathcal{W} \sim \mathcal{D} \) to indicate that a random collection \( \mathcal{W} = (\mathcal{V}, \bar{v}) \) is drawn from the dataset. We define the sampling strategy in the implementation details for each dataset. During training, algorithms have access to a dataset \( \mathcal{D}_{\text{train}} \) and corresponding ground-truth relation. We construct the relation for the training dataset based on a set of foreground classes \( \mathcal{C}_{\text{train}} \) as described above.

Methods are evaluated on samples from a test dataset \( \mathcal{W} \sim \mathcal{D}_{\text{test}} \). There are no images in common between the training and test datasets. Moreover, the set of foreground classes \( \mathcal{C}_{\text{test}} \) used to construct the relation for the test dataset is different to the set of foreground classes used during training, i.e., \( \mathcal{C}_{\text{test}} \cap \mathcal{C}_{\text{train}} = \emptyset \). At test time we only know whether a bag is positive or negative with respect to a collection. The groundtruth relation (i.e., foreground class) is unknown to the model and only used for evaluating the performance of the model.

4. Pairwise Relation Module

The proposed method relies on an algorithm to estimate the relation of an input image pair \((e_1, e_2)\). One common approach is to learn an embedding function and use a fixed distance metric to compare the input pairs in the embedded space. In this approach, the learning happens only in the embedding function. Relation Network \(^1\) extends this by jointly learning the embedding function and a comparator. The network consists of embedding and relation modules. The embedding module learns a joint feature embedding (into \( \mathbb{R}^d \)) for the input pair of images \( C(e_1, e_2) \) and the relation module learns a mapping \( g : \mathbb{R}^d \rightarrow \mathbb{R} \), mapping the embedded feature to the relation score \( r_{\phi}(e_1, e_2) = g(C(e_1, e_2)) \) where \( \phi \) denotes the parameters of the embedding and scoring functions combined. We adopt the relation module from the Relation Network due to its simplicity and success in few-shot learning. However, any other method which computes the relation between image pairs could be used in our method.

As we need to evaluate the relation of many image pairs, our goal is to keep the model for the embedding and scoring functions as simple as possible. The feature embedding function \( C(\cdot, \cdot) : \mathcal{I} \times \mathcal{I} \rightarrow \mathbb{R}^d \) consists of feature concatenation and a single linear layer with gated activation \(^2\) and skip connections. Let \( f_1 \) and \( f_2 \) be features in \( \mathbb{R}^d \) extracted from images \( e_1 \) and \( e_2 \) by a CNN feature extraction module. Let \( f = [f_1, f_2] \) be the concatenation of feature pairs. The embedding function is defined as:

\[
C(e_1, e_2) = \tanh(W_1 f + b_1) \cdot \sigma(W_2 f + b_2) + \frac{1}{2}(f_1 + f_2),
\]

\(^1\)There is no point in having more than one negative bag in a collection since its purpose is simply to provide a set of images that are not compatible with the positive bags, in the sense described.

\(^2\)We adopt the notation used in Relation Network paper \(^1\)
where $W_1, W_2 \in \mathbb{R}^{d \times 2d}$ and vectors $b_1, b_2 \in \mathbb{R}^d$ are the parameters of the feature embedding module and $\text{tanh}(\cdot)$ and $\sigma(\cdot)$ are hyperbolic tangent and sigmoid activation functions respectively, applied componentwise to vectors in $\mathbb{R}^d$. Then, we use a linear layer to map these features into relation score i.e., $r_{\theta}(e_1, e_2) = w^T C(e_1, e_2) + b$, where $w \in \mathbb{R}^d$ and $b \in \mathbb{R}$. We found in practice that using gated activation in the embedding module improves the performance over a simple ReLU, whereas adding more layers does not affect the performance. We note that the effectiveness of gated activation has also been shown in other work [37].

5. Proposed Method

We pose the problem of finding the common object as finding a selection $O$ that minimizes an energy function. Our energy function is defined as sum of potential functions as follows:

$$ E(O | \mathcal{V}, \bar{v}) = \sum_{e_i \in O} \psi^P(e_i) + \sum_{e_i \in O} \sum_{j > i} \psi^U(e_i, e_j), \quad (3) $$

in which $\psi^P(\cdot, \cdot)$ and $\psi^U(\cdot)$ are pairwise and unary potential functions with parameters $\theta$ and $\beta$ and hyperparameter $\eta \geq 0$ controls the importance of unary potentials. The pairwise potential function is learned so that it encourages choosing pairs that are related to each other. The unary potential is chosen so it minimizes when its input is not related to the images in the negative bag. In this way, the overall energy is minimized when images in $O$ are related to each other and unrelated to images in the negative bag.

We first present the method for learning the pairwise and unary potential functions. Next, we propose a greedy searching algorithm that uses the following structure in this problem to optimize the energy function: the common object of the complete problem is a common object in any subset of the positive bags as well. In this model, we search for the optimal solution by evaluating the objective for selections that were optimal for smaller subproblems.

5.1. Learning Potential Functions

The pairwise potential function is defined as the negative of the output of the relation module: $\psi^P(e_i, e_j) = -r_{\theta}(e_i, e_j)$ so it has a lower energy for related pairs. For a sampled collection $\mathcal{V}$ the episode loss is written as a binary logistic regression loss

$$ L^P = \frac{1}{NP} \sum_{(e_i,e_j) \sim \mathcal{V}} \log \left( 1 + \exp(-R(e_i, e_j) r_{\theta}(e_i, e_j)) \right) $$

where the sum is over all the pairs in the collection, $NP$ is the total number of such pairs, and relation $R(\cdot, \cdot)$ defined in Eq (1) provides the groundtruth labels.

The unary potential $\psi^U(e_i)$ is constructed by comparing image $e_i$ with images in the negative bag $\bar{v}$. Let the vector $u(e_i)$ be the estimated relation between image $e_i$ and all the images in $\bar{v}$ i.e. $u(e_i)_j = r_{\beta}(e_i, \bar{e}_j)$ where $\bar{e}_j$ is the $j$-th image in the negative bag. By definition, the unary energy for an image $e_i$ should be high if at least one of the values in $u(e_i)$ is high. In other words, $e_i$ is related to $\bar{v}$ if it is related to at least one image in $\bar{v}$. This suggests the use of $\max(u(e_i))$ as the unary energy potential. However, depending on the class distribution of images in the negative bag, an image $e_i$ which is not from the common object class could be related to more than just one image from the negative bag. In this case, using the average relation to the few mostly related elements in $u(e_i)$ might help to reduce the noise in the estimation and works better than a simple max operator. This motivates us to use a soft notion of max operator in which we use a weighted average of the relations in which higher relation values get a higher weight

$$ \psi^U_{\beta, \nu}(e_i) = \text{softmax}(\nu u(e_i))^T u(e_i) \quad (4) $$

where $\nu$ controls how smoothly the weights change with respect to the input relation values and

$$ \text{softmax}(\nu u(e_i)) = \text{vec} \left( \frac{\exp(\nu u(e_i)_k)}{\sum_m \exp(\nu u(e_i)_m)} \right)_{k=1}^B \quad (5) $$

where $B$ is the total number of images in the negative bag. Observe that for $\nu = 0$ we have the mean value of $u(e_i)$ and it converges to the max operator as $\nu \to +\infty$. We let the algorithm learn a balanced value for parameter $\nu$ in a data-driven way.

For a sampled collection $\mathcal{W} = (\mathcal{V}, \bar{v})$, the episode loss for the unary potential is defined as a binary logistic regression loss

$$ L^U = \frac{1}{NU} \sum_{e \in \mathcal{V}} \sum_{e \in \mathcal{V}} \log \left( 1 + \exp(-R(e, \bar{v}) \psi^U_{\beta, \nu}(e)) \right) \quad (6) $$

where we use an extended definition of the relation function where $R(e, \bar{v}) = \max_{e_i \in \bar{v}} R(e, e_i)$ and $NU$ is the total number of unary potentials in the collection. By optimizing this loss, we learn a potential function that has higher value if $e$ is related to one example in the negative bag. Note that in Eq (5) selection of unary potentials with high values are discouraged.

Parameters of the unary and pairwise potential functions are learned by optimizing the sum of the presented loss functions over randomly sampled problems from the training set

$$ L = \mathbb{E}_{\mathcal{W} \sim \mathcal{D}_{\text{train}}} \left( L^U + L^P \right) + \lambda \|\theta\|^2 + \lambda \|\beta\|^2. \quad (7) $$

Although both unary and pairwise potential functions are using the relation network with an identical architecture,
their input class distribution is different since one is comparing images in positive bags and one is comparing between images in positive and negative bags. Thus, sharing their parameters decreases overall performance.

5.2. Inference

Finding an optimal selection $O$ that minimizes the energy function defined in Eq. (3) is NP-hard and thus not feasible to compute exactly. Loopy belief propagation [18], TRWS [15], and AStar [16], are among the many algorithms used for approximate energy minimization. We propose an alternative approach specifically designed for solving our optimization problem.

Our approach is designed to decompose the overall problem into smaller subproblems, solve them, and combine their solutions to find a solution to the overall problem. This is based on the observation that a solution to the overall problem will also be a valid solution to any of the subproblems. Let $\mathcal{V}(p, q) = \{v_p, v_{p+1}, ..., v_q\}$ be a subset of $\mathcal{V}$. Then, a subproblem refers to finding a set of common object proposals $\mathcal{B}$ for $\mathcal{V}(p, q)$ with low energy values. Energy value for a selection $O_{p,q} \in \mathcal{B}$ is defined as sum of all pairwise and unary potentials in the subproblem, similar to how the energy function is defined for the overall problem in Eq. (3).

The problem decomposition starts at the root and divides it into two disjoint subproblems recursively continues dividing each into two subproblems until each subproblem only contains a single bag $v_i$. If $N = 2^Z$, then this can be represented as a full binary tree where each node represents a subproblem. Let $N_l^i$ be the $i$-th node at level $l$. Then root node $N_1^{Z}$ represents the overall problem, nodes $N_l^i$ at any given level $l$ represent disjoint subproblems of the same size, and the leaf nodes, $N_0^i$, at level 0 of the tree each represent a subproblem with only one positive bag $v_i$.

The computation starts at the lowest level (leaf nodes) where the set of solution proposals is simply all the images in the bag. At the next level each node combines the solution proposals from its child nodes and prunes them to compute solution proposals for its own subproblem, which in turn is used as input to nodes at the next level and so on until we reach the root node, which is the output for the optimization. The joining procedure used to combine the solution of two nodes is described next.

Joining: Node $i$ at level $l$ receives as input solution proposals $B_{2^l-1}^{i}$ and $B_{2^l-1}^{i}$ from its child nodes $N_{2^l-1}^{i}$ and $N_{2^l-1}^{i}$. The joining operation simply concatenates every possible selection from the first set with every possible selection in the second set and forms a set of selection proposals $X_l^i$ for the subproblem

$$X_l^i = \{O|O = [O', O'] \forall O' \in B_{2^l-1}^{i}, O' \in B_{2^l-1}^{i}\}$$

This is without loss of generality since zero padding could be used if the number of positive bags is not a power of 2.

| Algorithm 1: Greedy Optimization Algorithm |
|--------------------------------------------|
| **Input:** $\mathcal{V} = \{v_1, ..., v_N\}$ and $\overline{v}$, $N = 2^Z$  |
| **Output:** Selection $O = (e_1, ..., e_N)$  |
| $B_0^i = v_i$ $\forall i \in [1, \ldots, N]$ |
| $E_0^i(O_{i,i}) = \eta e_{i}^{\beta}$ of $e_i$ $\forall e_i \in B_0^i$, $i \in [1, \ldots, N]$ |
| for $l \leftarrow 1$ to $2^Z$ do  |
| | for $i \leftarrow 1$ to $2^{Z-l}$ do  |
| | $X_l^i \leftarrow B_{2^l-1} \times B_{2^l-1}$ (joining)  |
| | Update Energy Values According to Eq. (9)  |
| | $B_l^i \leftarrow Z_k(X_l^i)$ (pruning)  |
| return $O \in B_2^1$ with the minimum energy |

where $[..]$ concatenates two selection sequences. We denote the joining operation by the Cartesian product notation $\times$ i.e. $X_l^i = B_{2^l-1}^{i} \times B_{2^l-1}^{i}$.

Pruning: Due to the Cartesian product used to generate $X_l^i$, the number of proposal selections grows exponentially as we ascend the tree. Also, not all the generated proposals contain a common object. Therefore, we use a pruning algorithm $B_l^i = Z_k(X_l^i)$ that picks the $k$ selections with the lowest energy values. The energy values for each subproblem can also be efficiently computed from bottom to top. At the lowest level, the energy for each selection is the unary potential from Eq. (4),

$$E_i^0(O_{i,i}) = \eta e_{i}^{\beta} \forall e_i \in B_0^i = v_i, \quad (8)$$

Note that selection $O_{i,i} = (e_i)$ consists of only one image. After the leaves, energy in other nodes can be computed recursively. Let $O \in X_1^l$ is formed by joining two selection proposals $O' \in B_{2^l-1}$ and $O' \in B_{2^l-1}$. The energy function $E_l^i(O)$ can be factorized as

$$E_i^l(O) = E_{2^l-1}^i(O') + E_{2^l-1}^i(O') + P(O', O') \quad (9)$$

where $P(\ldots)$, according to the graph structure, is the sum of all pairwise potentials between two joining subproblems and computed on the fly.

Algorithm 1 summarizes the method. A good value of $k$ in the pruning method depends on the ambiguity of the task. It is possible to construct an adversarial example that needs all possible proposals at the root node to find the optimal solution. However, in practice, we found that $k$ does not need to be large to achieve good performance. Importantly, unlike other methods, this algorithm does not necessarily compute all of the pairwise potentials. For example, if an object class only appears in a small subproblem, the images of that class will get removed by nodes whose subproblem size is large enough. Thus, in the next level of the tree, the pairwise potentials between those images and other images would no longer be required. In general, the number of pairwise potentials computed depends on both the value of...
and the dataset. We observed only a small fraction of the total pairwise potentials were required in our experiments.

6. Experiments

In this section, we evaluate the proposed algorithm on few-shot common object recognition and co-localization tasks. For each task, we first pre-train a CNN feature extractor module on the training set and use it with fixed weights to extract features from images for all the methods.

For learning pairwise and unary potentials, stochastic gradient descent with gradual learning rate decay schedule is used to minimize the loss function in Eq (3). The complete framework (“Ours” in the tables) uses greedy optimization method described in Algorithm 1. The optimal value of $\eta$ in Eq (3) is found using grid search. In all experiments, a maximum of 300 top selection proposals are kept in the greedy algorithm.

All experiments are done on a single Nvidia GTX 2080 GPU and an AMD Ryzen Threadripper 1920X CPU with 12 Cores (24 Threads) and 4GHz frequency. In the next sections, we first review the baseline methods and then present the results for each task.

6.1. Baseline Methods

We compare our greedy optimization algorithm to ASTar [10] which is used for object co-segmentation [11] and the faster TRWS [15] which is used for inference on MIL problems [12, 33]. We use a highly efficient parallel implementation of these algorithms [38].

SVM based MIL. We report the results of the three well-known MI-SVM, mi-SVM [23] and sbMIL [39] methods using publicly available source code [24]. The sbMIL method is specially designed to deal with sparse positive bags. The RBF and linear kernel are chosen as they work better on few-shot common object recognition and co-localization respectively. Grid search is performed in order to select the hyperparameters.

Attention based deep MIL. Along with the SVM based methods, the results of the more recent attention based deep learning MIL method [40] (ATNMIL) is presented on our benchmarks. After training the model, we select the image proposal with the maximum attention weight from each positive bag.

6.2. Few-shot Common Object Recognition

In this task, bags are constructed by sampling images from the miniImageNet dataset [10]. To construct bags, we first randomly select $M$ classes out of all the possible classes $C$. One of these is selected to be the target and the rest are considered non-target classes. Then, each positive bag is constructed by randomly sampling one image from the target class and $B - 1$ images from the target and non-target classes. The negative bag is built by sampling $\bar{B}$ examples from non-target classes. For output selection $O$, we measure the success rate which is equal to the percentage of $e \in O$ that belong to the target class. We compute the expected value of success rate for 1000 randomly sampled problems and report the mean and 95% confidence interval of the evaluation metric.

miniImageNet is a benchmark in few-shot learning. We use it as a proof of concept for comparison of different design choices without requiring large scale training and performance evaluations. The dataset contains 60,000 images of size $84 \times 84$ from 100 classes. We experiment on the standard split of 64, 16 and 20 classes for training, validation and testing, respectively [24].

For the CNN feature extractor module, a Wide Residual Network (WRN) [41] with depth 28 and width factor 10 is pre-trained on the training split. The $d = 640$ dimensional output of global average pooling layer of the pre-trained network is provided as input to all the methods.

We vary the number of bags as well as their sizes. We select the number of positive bags $N \in \{4, 8, 16\}$, the size of each positive bag $B \in \{5, 10\}$, and the size of negative bag $\bar{B} \in \{10, 20\}$. The number of classes $M$ to sample from in each episode changes the difficulty of the task. We randomly choose $M$ between 5 and 15 when $B = 5$, and between 10 and 20 when $B = 10$ for each problem.

The results in Table 1 show our method outperforms ATNMIL and SVM based approaches for all version of the problem. To test the importance of learning the unary and pairwise potentials, we construct a baseline that uses cosine similarity to compute the relation between pairs while keeping the rest of the algorithm identical. The performance gap between our method and the baseline shows that the relation learning method, apart from structured inference formulation, plays an important role in boosting the performance.

Average total (potentials computation + inference) runtime versus accuracy plot of different energy minimization methods on different settings is shown in Figure 2. Even on this small scale problem, the greedy optimization is faster on average while its accuracy is on par with other inference methods. See the supplementary material for complete numerical results.

6.3. Co-Localization

We evaluate on the co-localization problem to illustrate the benefits of the methods discussed in the paper on a real world and large scale dataset. In this task, each bag is constructed by extracting region proposals from one image and a selection $O$ represents one bounding box from each image. To select images of each problem, we first randomly

We also use negative of Euclidean distance measure for the relation but it shows inferior performance.
We train the algorithm on a split of COCO 2017 [45] dataset with 63 seen classes and evaluate on the remaining 17 unseen classes. The resulting dataset contains 111,085 and 8,245 images in the training and test set respectively. To evaluate the performance of the trained algorithm on a larger set of unseen classes we also test on validation set of ILSVRC2013 detection [46]. This dataset has originally 200 classes but only 148 classes do not have overlap with the classes that were used for training. The final dataset, after removing coco seen classes, contains 12,544 images from 148 unseen classes. The dataset creation method is explained in the supplementary material in more detail.

For the CNN feature extractor module, we pre-train a Faster-RCNN detector [47] on the training dataset which has only seen classes. For each bag, top $B = 300$ region proposals with the highest objectness scores are kept. The output of the second stage feature extractor is used in all methods.

Table 2 illustrates the quantitative results on COCO and ImageNet datasets with 8 positive and 8 negative images.

Our method works considerably better than other strong MIL baselines. Qualitative results of our method compared with other MIL based approaches are illustrated in Figure 3. Our method selects the correct object even when the target object is not salient. More qualitative results are presented in the supplementary material.

To see the effect of unary and pairwise potentials separately, we provide results for two new variants for structured inference based methods: (i) Unary Only: where the common object proposal in each bag is selected using only the information in negative bags without seeing the elements in other bags, and (ii) Pairwise Only: where the negative bag information is ignored in each problem. The results show that the pairwise potentials contribute more to the final results. This is not surprising since negative images only help when they contain an object which is also appearing in positive images which, given the number of classes we are sampling from, has a low chance. Interestingly, by using the learned unary potentials alone we could get comparable results to the MIL baselines. The results in Table 2 show that different inference algorithms have very similar performance. However, as it is shown in Figure 4 the greedy optimization algorithm is much faster. Note that our method requires to compute only 15% out of all pairwise potentials in average. One may argue that the pairs can be forwarded on multiple GPUs in parallel and this reduces the forward time. However, our greedy inference method can also take advantage of multiple GPUs since the nodes at each level are data independent.

6.4. Ablation Study

In order to evaluate the effectiveness of our proposed unary potential function, we devise the following experiment. In the few-shot common object recognition task with inferior results to MI-SVM.
Figure 3. Qualitative results on COCO dataset. Each row shows positive bags of a sampled collection. Negative bags are not shown. Note that the first image in the first two rows are identical but the target object is different. Last row shows a failure case of our algorithm. While cup is the target object, our method finds plant in the second image. This might be due to the fact that pot (which has visual similarities to cup) and plant are labelled as one class in the training dataset. Note that “dog”, “cake” and “cup” are samples from unseen classes. Selected regions are tagged with method names. Ground-truth target bounding box is shown in green with tag “GT”.

Figure 4. Forward and inference time (in sec.) on COCO.

Table 4. 5-way, 1-shot, classification accuracy with 95% confidence interval on miniImageNet test set.

| Method     | Accuracy (%) |
|------------|--------------|
| adaResNet  | 56.88 ± 0.62 |
| SNAIL      | 55.71 ± 0.99 |
| Gidaris et al. | 55.45 ± 0.89 |
| TADAM      | 58.50 ± 0.30 |
| Qiao et al. | 59.60 ± 0.41 |
| Ours-ReLU  | 56.43 ± 0.79 |
| Ours-Gated | 57.80 ± 0.77 |

$N = 8$ positive bags, $\bar{B} = 10$ negative images, and $B = 5$, we train the unary potentials with four different settings: (1) SOFTMAX: Unary potential function with the learned $\nu$ described in Section 5.1 (2) MAX: $\nu \rightarrow +\infty$, (3) MEAN: $\nu = 0$, and (4) No Unary: the model without using negative bag information. The pairwise potential function is kept identical in all the methods. The performance of our methods on the described settings are presented in Table 3. The results show the superiority of the learned weighted similarity to other strategies.

Next, we evaluate the quality of the learned pairwise relations $r(e_1, e_2)$ by using them for the task of one-shot image recognition [10] on miniImageNet and compare it to the other state-of-the-art methods. In each episode of a one-shot 5-way problem, 5 classes are randomly chosen from the set of possible classes and one image is sampled from each class. This mini-training set is used to predict the label of a new query image which is sampled from one of the 5 classes. The performance is the accuracy of the method to predict the correct label averaged over many sampled episodes. All of these models are trained with a variant of deep residual networks [41, 53]. Note that unlike other methods, the model in [52] is trained on validation+training meta-sets.

At each episode, we use the learned relation function to score the similarity between the query image and all the images in the mini training set. The predicted label for the query image is simply the label of the image in mini training set which has the highest relation value to the query image. We compute the accuracy of the predictions of our pairwise potentials on test classes of minImageNet and compare it with current state-of-the-art few-shot methods in Table 4. We also provide comparison of gated activation function and a simplified ReLU activation in our architecture. Although our method is not trained directly for the task of one-shot learning, it achieves competitive results to the previous methods which are specifically trained for the task. Also, gated activation outperforms ReLU for this task.

7. Conclusion

In this paper, we introduce a method for learning to find a common object among small image collections which is constructed by learning unary and pairwise terms in an structured output prediction framework. Moreover, we pro-
pose a simple greedy inference algorithm that uses the structure of the problem to solve the task at hand without requiring computation of all pairwise terms. Our experiments on two challenging tasks illustrate that transferring knowledge from seen classes is favourable to other fine-tuning based weakly supervised methods in low data regimes. In addition, our greedy inference algorithm is comparable to the two well-known structured inference algorithms for this task while requiring significantly less computation.

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A. Co-Localization: COCO Dataset Creation and Faster-RCNN Training

COCO dataset has 80 classes in total. We take the same 17 unseen classes which is used in zero-shot object detection paper [Ref1] and keep remaining 63 classes for training. The training set is constructed using the images in COCO 2017 train set which contain at least one object from the seen classes. The COCO test set, is built by combining the unused images of the train set and images in COCO validation set which contain at least one object from the unseen classes. Similar to [Ref1], to avoid training the network to classify unseen objects as background, we remove objects from unseen classes from the training images using their groundtruth segmentation masks.

We use Tensorflow object-detection API for pre-training the Faster-RCNN feature extraction module [Ref4]. To speed up pre-training, training images are resized down to $336 \times 336$ pixels and ResNet-50 [53] is used as the backbone feature extractor. All layer weights are initialized with variance scaling initialization [Ref2] and biases are set to zero initially. An additional linear layer which maps the $2048$ dimensional output of second stage feature extractor to a $d = 640$ dimensional feature vector is added to the network. We did this to have the dimension of the feature space the same as few-shot common object recognition experiment. We pre-train the feature extractor on four GPUs with batch size of $12$ for $600k$ iterations. The $d = 640$ dimensional features are used as input to all of the methods in our experiments.

B. Hyperparameter Tuning

In the few-shot common object recognition task, we use grid search on the validation set to tune the hyperparameters of all the methods. To ensure that the structured inference methods optimize the same objective function, we find $\eta$ for the TRWS method and use the same value in AStar and greedy energy functions. For the few-shot common object recognition task value of $\eta$ is shown in Table 5 for each setting.

In the Co-Localization experiments, the results of the best performing hyperparameters is reported for all the methods. $\eta = 0.5$ and $\eta = 0.7$ is used in COCO and ImageNet experiments respectively.

C. Structured Inference Methods Comparison

The numerical results which are used to generate Figure 2 of the paper are shown in Table 5. The success rate of the greedy method is on par with the other inference algorithms. From the optimization point of view it is also important to see the mean energy value for the top selection of each method. These results are shown in Table 6 and Table 7 for few-shot common object recognition and co-localization experiments respectively. While AStart and TRWS achieve lower energy values for this problems, the success rate of the methods are comparable. This suggests that finding an approximate solution for the minimization problem is sufficient for achieving high success rate.

| $B$ | $N$ | TRWS | AStar | Greedy (Ours) |
|-----|-----|------|-------|--------------|
| 4   | 0   | 64.55 ± 1.54 (0.0) | 64.33 ± 1.54 (0.0) | 64.19 ± 1.54 (0.0) |
| 8   | 0   | 64.55 ± 1.54 (0.0) | 64.19 ± 1.54 (0.0) | 64.01 ± 1.54 (0.0) |
| 16  | 0   | 64.55 ± 1.54 (0.0) | 64.01 ± 1.54 (0.0) | 63.82 ± 1.54 (0.0) |

Table 5. Success rate of different energy minimization algorithms on miniImageNet. These numbers were used to generate Figure 2 in the paper. Value of the parameter $\eta$ is shown in the parenthesis for each experiment. See section 6.2 and Table 7 for the detailed problem setup.

D. Sharing Parameters of Unary and Pairwise Relation Modules

As it is discussed in section 5.1, both unary and pairwise potential functions use the relation module with an identical architecture. However, since the input class distribution is different for these functions, we choose not to share their parameters. We conduct an experiment to see the effect of parameter sharing in few-shot common object recognition task with $B = 5$, $N = 8$, and $B = 10$. As Table 7 shows, the success rate for this setting is $72.49 \pm 0.98\%$ without parameter sharing.
### Table 6. Expected energy for different inference methods. Lower energy is better.

| Method | \( N \) = 4 | \( N \) = 8 | \( N \) = 16 |
|--------|--------------|--------------|--------------|
| TRWS   | 2.929179     | -4.416873    | -12.602217   |
| AStar  | 2.908970     | -4.429455    | -4.529052    |
| Greedy | 2.908970     | -4.51543     | -4.529052    |

| Method | \( B = 10 \) | COCO         | ImageNet     |
|--------|--------------|--------------|--------------|
| TRWS   | -28.485636   | -28.630786   |
| AStar  | -28.487422   | -28.631678   |
| Greedy | -27.246355   | -25.496649   |

### Table 7. Mean energy on COCO and ImageNet with 8 positive and 8 negative images. Lower energy is better.

However, when the unary and pairwise are trained with shared relation module parameters, the performance degrades to 69.35 ± 1.01%.

**E. More Qualitative Results**

Qualitative results on ImageNet dataset are illustrated in Figure 5. Figure 6 shows the complete qualitative results presented in the paper with the negative images on COCO dataset.

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Figure 5. Qualitative results on ImageNet dataset. In each problem, the first row and the second row show positive and negative images respectively. While different methods work as good in easier images with one object, the greedy method performs better in harder examples with multiple objects in each image. Selected regions are tagged with method names. Ground-truth target bounding box is shown in green with tag “GT”.
Figure 6. Qualitative results on COCO. Complete version of the results shown in Figure 3 of the paper with negative images. In the first problem, class “Person” does not appear in the negative images. This could explain why “Unary Only” method detects people in the first problem.