Predicting Foreground Object Ambiguity and Efficiently Crowdsourcing the Segmentation(s)

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Abstract
We propose the ambiguity problem for the foreground object segmentation task and motivate the importance of estimating and accounting for this ambiguity when designing vision systems. Specifically, we distinguish between images which lead multiple annotators to segment different foreground objects (ambiguous) versus minor inter-annotator differences of the same object. Taking images from eight widely used datasets, we crowdsource labeling the images as “ambiguous” or “not ambiguous” to segment in order to construct a new dataset we call STATIC. Using STATIC, we develop a system that automatically predicts which images are ambiguous. Experiments demonstrate the advantage of our prediction system over existing saliency-based methods on images from vision benchmarks and images taken by blind people who are trying to recognize objects in their environment. Finally, we introduce a crowdsourcing system to achieve cost savings for collecting the diversity of all valid “ground truth” foreground object segmentations by collecting extra segmentations only when ambiguity is expected. Experiments show our system eliminates up to 47% of human effort compared to existing crowdsourcing methods with no loss in capturing the diversity of ground truths.

Keywords 
Salient object detection · Segmentation · Crowdsourcing

1 Introduction
Finding the most prominent object in an image1 is a critical step for a variety of applications, such as human-robot interaction (Meger et al. 2008), image retrieval (Cheng et al. 2015), sketch-based image generation (Chen et al. 2009), and assisted recognition for blind people (Brady et al. 2013; http://www.looktel.com/recognizer, http://www.taptapseeapp.com/). For example, applications such as VizWiz Bigham et al. (2010) and TapTapSee (http://www.taptapseeapp.com/) enable a blind person to take a picture with a mobile phone and learn “what is this item?”, but these applications depend on the ability to first determine what

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1 Also, some times referred to as salient object detection (Borji et al. 2015; Cheng et al. 2015).

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One benefit of our proposed system is to inform a blind person with high precision if it is ambiguous what object (s)he is trying to recognize with existing mobile phone applications (Bigham et al. 2010, http://www.taptapseeapp.com/), empowering him/her to save the 90 s typically required with existing systems to learn this from crowd workers (Bigham et al. 2010). (b) Images shown are deemed by human judges to have an unambiguous (left) and ambiguous (right) foreground object. The two images exemplify that objects with similar boundary complexity can differ in whether they are ambiguous

Unfortunately, the aim to build machines that imitate a human’s ability to find the most prominent object introduces another problem: how to resolve disagreement that arises when multiple people perceive different foreground objects in the same image. This problem has spurred an active area of research for methods that combine multiple human annotations in an attempt to recover a single, latent object segmentation as ground truth (Biancardi et al. 2010; Cholleti et al. 2009; Warfield et al. 2004; Welinder and Perona 2010).

In this paper, rather than try to coerce multiple human inputs into a single ground truth, we instead ask, “Why and when are we observing multiple foreground object segmentations from different annotators?” We postulate that inconsistent annotations are not only a consequence of difficult tasks and imperfect human annotators, but also a consequence of inherent ambiguity. While psychology research shows humans can perceive foreground object ambiguitybrea (GarciaPerez 1989; Leopold et al. 2004), modern vision systems do not yet account for it. We aim to fill this gap. We say an image is unambiguous if it has a single, non-controversial foreground object of interest.

A central aim of our work is to disentangle the problem of foreground object recognition ambiguity from the problem of foreground object segmentation difficulty as the source of human disagreement. The two problems are only somewhat correlated. See Fig. 1b. We observe that two images that are similarly difficult (tedious, complex, etc.) to annotate need not both be ambiguous. For example, the flower (left image) and the crayons (right image) have similar boundary complexity and exhibit a large “thing” in the center of the image, yet people deem the flower image unambiguous and the crayon image ambiguous. The latter may yield segmentations showing any number of the individual crayons or the collection as a whole. Consequently, human disagreement will likely be far greater when people perceive ambiguity (e.g., crayons) than a single, unambiguous foreground object (e.g., flower).

In light of these considerations, we aim to address two key questions: (1) Given an image, can a machine be trained to predict whether multiple people would identify different foreground object segmentations? and (2) If a machine can automatically predict whether a novel image is ambiguous to people, how might this influence the way we go about obtaining its foreground annotations? In particular, can we collect annotations that are both economical and more complete by knowing when a greater number of segmentations is needed?

To answer these questions, we first introduce a crowd-labeled dataset of nearly 14,000 images, each one annotated as leading to either unambiguous or divergent manual foreground object segmentations. Included are images from seven existing computer vision benchmarks (Alpert et al. 2007; Borenstein and Ullman 2008; Everingham et al. 2010; Gulshan et al. 2010; Liu et al. 2011; Martin et al. 2001; Shotton et al. 2006) and images taken by blind people who were seeking answers to their daily visual questions with VizWiz (Bigham et al. 2010). We then demonstrate the importance of producing datasets with multiple ground truth foreground object segmentations for ambiguous images to avoid biasing algorithms to one interpretation of the truth (Sect. 3).

Next, we leverage the new dataset to develop multiple prediction systems to infer whether an image’s foreground object is ambiguous. Comparing an array of classifiers and features, we report encouraging results for solving the prediction task on both images curated from the web and from blind people (Sect. 4). Finally, building on these results, we propose a new task of “redundancy allocation” to capture diversity. The idea is to exploit our system’s ambiguity predictions to decide when multiple human-drawn foreground object annotations are necessary to capture the diversity of
opinions, versus when they would likely be redundant. In this way, we can better spend an annotation budget (Sect. 5). Our idea is distinct from prior work that spends an annotation budget to increase confidence in a latent single true annotation per image (Sheshadri and Lease 2013; Welinder and Perona 2010; Whitehill et al. 2009). Instead, we spend our budget to efficiently capture the diversity of all valid foreground object segmentations for a batch of images.

Our key contributions are the following:

- Identifying the problem of ambiguity for foreground object segmentation and demonstrating its prevalence for eight diverse datasets.
- Classification-based approach to identify which images are likely to lead to consistent foreground object segmentation results from multiple humans.
- System that efficiently captures the diversity of valid foreground object segmentations by soliciting extra manual segmentations only if an image is ambiguous.

2 Related Work

2.1 Defining Foreground Object Segmentation

The aim of foreground object segmentation is to produce a binary mask that separates pixels of the most prominent object from the background—also often referred to as salient object detection (Alpert et al. 2007; Cheng et al. 2015; Liu et al. 2011). Our focus on finding the most prominent object according to human perception is distinct from semantic segmentation where the aim is to segment regions according to a pre-defined set of object categories (Everingham et al. 2010; Lin et al. 2014; Shotton et al. 2006). Our task is also distinct from natural scene segmentation where bottom-up methods are employed to segment an image into any number of regions (Martin et al. 2001). Foreground object segmentation also differs from edge detection methods, e.g., Dollar and Zitnick (2015). To our knowledge, we are the first to propose the problem of deciding whether a single, unambiguous salient object exists in an image. Knowing whether an image shows a single, unambiguous foreground object is critical for the success of many applications, such as human-robot interaction, image retrieval, sketch-based image generation, and assisted recognition for blind people (Borji et al. 2015; Cheng et al. 2015; http://www.looktel.com/recognizer, http://www.taptapseapp.com/).

2.2 Predicting Ambiguity

Other work in computer vision explores ambiguity in relationship to language. This includes whether images lead to more or less “specific” text descriptions (Jas and Parikh 2015) and whether visual attributes permit multiple interpretations (Kovashka et al. 2014). While these prior works predict image ambiguity related to language, our work predicts image ambiguity for foreground object segmentation.

2.3 Predicting Image Segmentation Difficulty

A related, yet distinct problem in modern computer vision literature is predicting segmentation difficulty, where difficulty is commonly defined by the extent to which algorithms can produce segmentations similar to the ground truth for a given image (Jain and Grauman 2013; Kohlberger et al. 2012; Liu et al. 2011) or the time a person takes to segment an image (Vijayanarasimhan and Grauman 2011). However, what can be deemed a successful method for predicting segmentation difficulty may be a “moving target”, given the development of better algorithms and easier-to-use segmentation annotation systems. In contrast, since we aim to capture human-perceived ambiguity, our method to estimate ambiguity directly measures an intrinsic property about an image and so leads to a static “yes” or “no” outcome (rather than an evolving ranking based on the chosen algorithm or annotation system).

2.4 Predicting Image Importance

Another related, yet distinct problem is predicting image importance. The goal in such work is to identify the image within a large collection that is most representative of an object category (Berg and Berg 2009) or to identify the most noticeable semantic labels a person would use to describe an image in natural language (Berg et al. 2012; Li et al. 2017). Whereas that prior work focuses on selecting important objects/images from multiple candidates, we instead focus on determining when the most prominent object in an image is ambiguous.

2.5 Establishing Ground Truth

The status quo when creating ground truth with crowd-sourcing is to collect redundant annotations. This is because discrepancies in human-provided annotations are anticipated, whether due to crowd worker skill or bias (Sheshadri and Lease 2013; Welinder and Perona 2010; Whitehill et al. 2009); hence, the goal in prior work is to discover the single latent ground truth for each example in spite of those discrepancies. Consequently, many methods intelligently sample and fuse labels from multiple workers in an attempt to produce a final high-quality annotation (Welinder et al. 2010; Welinder and Perona 2010). In contrast, we address discrepancies that stem from ambiguity, meaning that there does not exist a single latent ground truth for each image. As such, our goal is not to gather enough annotations to wipe away anno-
tator differences (Sheshadri and Lease 2013; Welinder and Perona 2010; Whitehill et al. 2009); rather, it is to collect (just) enough annotations to capture annotator differences. Our results demonstrate this important distinction.

Our work more closely relates to the pioneering segmentation collection work by Martin et al. (2001), who collected multiple segmentations of natural scenes from independent annotators, motivated by the belief that segmentation tasks can afford multiple correct answers. Whereas Martin et al. gathered a fixed number of annotations for each image from known in-house annotators to provide a soft ground truth for image contours, we show both how to predict which images offer multiple interpretations for the foreground object segmentation problem and how to more economically collect redundant annotations from an anonymous on-line crowd.

2.6 Crowdsourcing Object Segmentation Collection

Numerous systems already collect object segmentations from online crowds, including LabelMe (Russell et al. 2008) and the MSCOCO crowdsourcing pipeline (Lin et al. 2014). These systems instruct the worker to segment as many objects as (s)he chooses (Russell et al. 2008) or as many instances of a given object category (s)he observes (Lin et al. 2014). In both cases, the aim is to efficiently segment and name all relevant objects in a given multi-object scene image. In contrast, the goal of our system is to efficiently capture the diversity of human opinions on the single, most salient object for a given image. Consequently, as commonly done in human computation systems (Liu et al. 2011; Martin et al. 2001), we collect annotations from multiple, independent annotators to avoid biasing workers. However, in contrast to these human computation systems, we automatically predict how many independent annotators to recruit to efficiently complete the task.

2.7 Blind Photography

Numerous systems have been proposed to assist blind people to take a high quality picture of an object with a mobile phone camera (Bigham et al. 2010; Jayant et al. 2011; Vázquez and Steinfeld 2014; Zhong et al. 2013; http://www.taptapseeapp.com/). Unfortunately, such systems assume a user can localize the desired object and only help the user to improve the image focus (http://www.taptapseeapp.com/), lighting (Bigham et al. 2010), or composition (Jayant et al. 2011; Vázquez and Steinfeld 2014; Zhong et al. 2013). Unlike prior work, we do not assume a user can localize the object of interest. Rather, we propose a method that can be employed to automatically alert a blind user whether an image shows a single, unambiguous object. We demonstrate the predictive advantage of our system for this task over relying on saliency-based methods (Feng et al. 2011; Zhang et al. 2015).

3 STATIC-When is There a Single Truth?

In this section, we first present our crowdsourcing dataset collection process (Sect. 3.1) to label segmentation ambiguity on images from multiple existing benchmarks. Then, we examine how the labels compare to ambiguity labels derived using multiple human-drawn segmentations (Sect. 3.2). Finally, we analyze how foreground ambiguity, as perceived by humans, influences the evaluation of segmentation algorithms (Sect. 3.3). Sections 4, 5 will introduce our ideas for a machine to predict for a novel image whether it has an ambiguous foreground object and then to efficiently collect the diversity of all valid foreground object segmentations for a batch of images.

3.1 Judging When an Image is Ambiguous

3.1.1 Crowdsourcing Strategy

The traditional method to identify human (dis)agreement is to solicit multiple people to annotate the same image and then analyze the consistency between the multiple object segmentations (Alpert et al. 2007; Liu et al. 2011; Martin et al. 2001). However, evaluating if multiple people will agree on a single, unambiguous foreground object based on multiple annotations is less direct than simply asking them what they perceive. Moreover, collecting multiple object segmentation masks is labor-intensive and costly. We instead explicitly ask an annotator to judge, for a given image, whether (s)he thinks the image segmentation task would lead to a diversity of foreground objects from multiple annotators. Our use of less costly, human judgments over evaluating annotation results aligns with existing crowdsourcing work Gilbert (2014); Shaw et al. (2011). We call our approach and our dataset a Segmentation Test for Ambiguous Truth Inferred for the Crowd (STATIC). Each image receives a binary label indicating whether it has a single, unambiguous object segmentation truth, based on human opinion.

We collect image labels from on-line crowd workers on Amazon Mechanical Turk (AMT). We designed our Human Intelligence Task (i.e., HIT) with instructions followed by the voting task (Fig. 2). We include five images per HIT. For the voting task, we ask workers the following question: “If we asked multiple people to draw the boundary of a single object in the given image, do you think all people would pick the same object?” We intentionally specify criteria that aligns with the generic object segmentation task. A crowd worker casts a vote by selecting one of two radio buttons to the right of each image to indicate “Yes” or “No.” To minimize
concerns about worker skill, we limit our pool of workers to those who previously completed at least 100 tasks and received at least a 92% approval rating. To address concerns about malicious crowd workers, we collect five predictions per image and then assign the majority vote label. We pay workers $0.02 to complete each HIT.

Our STATIC labeling approach is advantageous not only because it offers cost and time savings, but also because (1) it disentangles the segmentation ambiguity problem from the many other factors that can lead to disagreement; for example, annotator training/skill, segmentation difficulty and (2) it avoids potential biases that may arise when soliciting a small number of humans to segment objects (e.g., Fig. 7). For example, workers may annotate what is easiest to minimize segmentation effort. Our analysis in the next section (Sect. 3.2) shows our shortcut of explicitly asking workers for the ambiguity label can successfully produce high quality labels.

3.1.2 Dataset Construction

We built STATIC from eight publicly-available datasets. We include seven widely-studied computer vision segmentation benchmarks (Alpert et al. 2007; Everingham et al. 2010; Gulshan et al. 2010; Liu et al. 2011; Martin et al. 2001; Shotton et al. 2006; Borenstein and Ullman 2008) in order to study foreground object ambiguity in the context of an important practical problem of assisting blind people to take a picture of an object.

STATIC includes three computer vision benchmarks designed to contain images with a single object of interest (Alpert et al. 2007; Liu et al. 2011; Borenstein and Ullman 2008). These benchmarks were created to evaluate foreground object segmentation algorithms (Alpert et al. 2007; Borenstein and Ullman 2008) and salient object detectors (Liu et al. 2011). In particular, Weizmann (Alpert et al. 2007) contains grayscale images showing a variety of everyday objects, and Borenstein and Ullman (2008) and MSRA-B (Liu et al. 2011) consist of RGB images showing horses and a variety of everyday images respectively. As we will see below, though a single prominent object is expected in these datasets, that is not always how each image is perceived.

STATIC also includes four computer vision benchmarks that were created to evaluate algorithms for natural scene segmentation (Martin et al. 2001), interactive image segmentation (Gulshan et al. 2010), and semantic segmentation (Everingham et al. 2010; Shotton et al. 2006). A priori, we expect these datasets to offer greater ambiguity since they are not designed to contain a single object of interest. All datasets contain RGB images, with Berkeley Segmentation Dataset (Martin et al. 2001) (BSD) showing natural scenes, Interactive Image Segmentation (Gulshan et al. 2010) (IIS)
Table 1 Percentage of images in eight datasets that humans judge to not show a single, unambiguous object

| Dataset                  | # Images | # Workers | % Ambiguous images (%) |
|--------------------------|----------|-----------|------------------------|
| Horses (Borenstein and Ullman 2008) | 328      | 33        | 5 (ambiguity unexpected) |
| Weizmann (Alpert et al. 2007)     | 100      | 25        | 19 (ambiguity unexpected) |
| MSRA-B (Liu et al. 2011)         | 5000     | 128       | 25 (ambiguity unexpected) |
| IIS (Galshan et al. 2010)        | 151      | 10        | 42                     |
| VOC2012 (Everingham et al. 2010) | 2913     | 97        | 43                     |
| MSRC (Shotton et al. 2006)       | 591      | 47        | 48                     |
| BSD (Martin et al. 2001)         | 500      | 25        | 51                     |
| VizWiz (Bigham et al. 2010)      | 4163     | 25        | 64                     |

Note, only the first three datasets were explicitly created with the intention of containing a single foreground object per image. As observed, benchmarks explicitly designed for both foreground object segmentation (top three rows) and complex scenes contain a mix of ambiguous and unambiguous images showing a variety of everyday objects, and MSRC (Shotton et al. 2006) and VOC2012 (Everingham et al. 2010) showing everyday scenes of 23 and 20 object classes respectively. Again, as we will see below, even though many images have multiple objects, some have an unambiguous foreground object and some do not.

Finally, STATIC includes 4,163 randomly selected images from the VizWiz dataset (Bigham et al. 2010) that were taken by blind people with mobile phone cameras to learn answers to their visual questions. These images often are poor quality due to poor framing, poor lighting, and motion blur. Nonetheless, these images capture a real world scenario where individuals are typically trying to recognize an object in their environment. Specifically, approximately 65% of the VizWiz images were captured because a blind person wanted to either identify an object (e.g., “What is this item?”) or have an object described (e.g., “What color is this shirt?”) (Brady et al. 2013). In other words, the blind photographer typically intended to capture a single, most prominent object.

In total, STATIC includes 13,746 images; Table 1 shows the breakdown. The resulting collection includes images showing a single object, multiple objects in possibly complex scenes, or no object of interest in blurry or poorly lit images. As will be shown in the next section, this diversity of image content is valuable for training classifiers to accurately decide if an image shows a single, unambiguous object.

3.1.3 Dataset Characterization

We use the crowdsourcing strategy above to obtain human judgments about foreground object segmentation ambiguity. Table 1 summarizes the results. As observed, even benchmarks explicitly designed for foreground object segmentation (top three rows) have ambiguity for 5–25% of images. On the flip side, it is interesting to note that datasets not intentionally built for foreground object segmentation have 36–58% of images showing a single, unambiguous object. Our findings highlight that, in a wide range of datasets, some images have “well-defined” foreground object segmentation truths while others lead to a diversity of viable interpretations.

3.2 Labels: Direct Ambiguity Judgment versus Redundant Segmentations

We next investigate an important question of whether human judgments about ambiguity, as collected above, correspond to the judgments one would obtain with today’s status quo approach of collecting multiple segmentations (Alpert et al. 2007; Liu et al. 2011; Martin et al. 2001). In what follows, we term the crowd workers who declared the images as (un)ambiguous as judgers, and the annotators who manually drew segmentations as drawers.

We perform our comparison on the Weizmann benchmark (Alpert et al. 2007), since it includes three human-drawn segmentations per image for single object images. We use the hand-drawn segmentations to produce a ground truth hypothesis parallel to the one created by the judgers. Namely, we label an image as ambiguous if any drawer segments more than one object or if any pair of drawers segment the single foreground object differently (i.e., less than 50% intersection-over-union overlap).

Figure 3a shows the consistency of the two parallel labels. The matrix (left) breaks down the fraction of images receiving each label [unambiguous (U) or ambiguous (A)] by each party. Our findings demonstrate that our proposed labeling approach matches labels produced by the status quo approach for 79% of the images. Moreover, our approach achieves these high quality labels while reducing the status quo human annotation effort by over a factor of 10 (i.e., 4.7 seconds per judgement versus 50 seconds per drawing Gurari et al. 2016).

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2 We excluded all images for which the majority of three crowd workers indicated the answer to their visual question could be recognized by text in the image.
Figure 3b, c show cases where the judger and drawer labels disagree. Interestingly, the primary reason for label disagreement is because judgers predict drawer disagreement too often. We attribute the judgers’ overzealous labeling of ambiguity to judgers identifying more regularity of known causes of drawer disagreement. For example, drawers commonly disagree by segmenting at different granularity levels for the same object; e.g., while drawers disagreed whether to include the strings on the ship (Fig. 3c; bottom right corner), they did not disagree whether to segment one seed pod or both pods (Fig. 3b; bottom left corner). In addition, drawers also commonly disagree by segmenting different primary objects; e.g., while drawers disagreed whether to segment the building or traffic sign (Fig. 3c; top right corner), they did not disagree whether one would segment the water, cliff, or sky (Fig. 3b; top left corner). As exemplified in Fig. 3, the crowd judgers may be more effective in detecting plausible ambiguity than what can be revealed by a small sample size (e.g., three drawers). We further explore this issue of the appropriate sample size to detect ambiguity in Sect. 5.

### 4 Predicting Ambiguous Images

Having established a dataset of images annotated for their human-perceived ambiguity, we now turn to the question of whether ambiguity is machine learnable. We pose the task as a binary classification problem: given a novel image, can we correctly classify it as ambiguous or unambiguous using only the image content? To our knowledge, no prior work has directly addressed the problem of predicting foreground object ambiguity.

#### 4.1 Classifiers and Features

We benchmark a total of nine classifiers. We include two related saliency methods. We also train six Support Vector Machine (SVM) classifiers based on both traditional global image features and deep Convolutional Neural Network (CNN) features. Finally, inspired by the recent success...
of CNNs for image classification, we propose a *STATIC* fine-tuned CNN classifier.\(^3\)

The two existing saliency methods we benchmark are the salient object detector of Feng et al. (2011) and the salient object subitizing (SOS) method of Zhang et al. (2015). Intuitively, both should be relevant to our prediction task, since salient object strength and the number of detected salient objects should correlate with (un)ambiguity. Feng et al. (2011) system outputs a ranked list of detection subwindows. We improve its results by a refined non-maximum suppression stage, using an aggressive non-maximum suppression threshold of 0.1 to suppress overlapping detections. When a single window is returned, we use its confidence as the unambiguity score. Otherwise, we take the difference in scores of the best and second-best detections based on the intuition that a dominant salient object should “stand out” over other areas in the same image. The SOS method Zhang et al. (2015) fine-tunes the VGG16 CNN (Simonyan and Zisserman 2014) to produce a probability that the image contains (0, 1, 2, 3, or 4+) salient objects. We use the probability it returns for 1 object as the output.

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We also test six Support Vector Machine (SVM) classifiers. Three of the classifiers are trained using off-the-shelf gradient-based, global image features: GIST (Torralba et al. 2003), HOG (Dalal and Triggs 2005), and IFV (Perronnin et al. 2010). The other three are trained using the 4096-dimensional output from the last fully connected layer of three Convolutional Neural Networks (CNN): AlexNet (Krizhevsky et al. 2012), VGG16 (Simonyan and Zisserman 2014) and SOS (Zhang et al. 2015). For each of the six SVM-based classifiers, we reduce the dimensionality of the feature (GIST, HOG, IFV, AlexNet, VGG16, SOS) to 100 using PCA before applying the SVM classifier. We use degree 3 polynomial kernels, and apply fivefold cross validation to choose the SVM hyper-parameters.

Finally, we propose a *STATIC* fine-tuned CNN classifier. We fine-tune the subitizing (SOS) network to target a binary classification loss on the labeled *STATIC* training images (Jia et al. 2014). We set the starting learning rate to a moderate 0.0001 and fine-tune for 20 epochs. The subitizing features are attractive for the task at hand since intuitively an unambiguous image might be estimated to have a single salient object (recall that SOS yields a probability that the image contains one salient object).
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To recap, we benchmark nine classification pipelines, including two existing baseline models:

- **CNN-FT**: CNN classifier fine-tuned on *STATIC*.
- **SVM-GIST**: SVM on GIST.
- **SVM-HOG**: SVM on HOG.
- **SVM-IFV**: SVM on IFV.
- **SVM-AlexNet**: SVM on AlexNet CNN features.
- **SVM-VGG16**: SVM on VGG16 CNN features.
- **SVM-SOS**: SVM on the SOS fine-tuned CNN features.
- **Feng et al. (2011)**: a salient object detector.
- **SOS Zhang et al. (2015)**: a salient object subitizing (counting) method.

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4.2 Datasets
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We evaluate all classifiers on both the images coming from the 1) seven computer vision benchmarks and 2) VizWiz dataset. In doing so, we aim to learn the value of these classification systems both for high-quality, curated images from the web as well as unknown quality images collected from blind photographers with mobile phone cameras. For both sets of images, we apply a random 80/20 train/test split. We train each of our first seven classifiers in the list using the same training data. We use the remaining two methods as is. At testing, all nine models produce a probability / confidence output per image that we use to evaluate against *STATIC* ambiguity ground truth for generating precision-recall curves.

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4.3 Predictive Performance
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Figures 5a, b show the precision-recall curves for all models. Our network fine-tuned for *STATIC*, CNN-FT, achieves the best overall performance. For example, the average precision (AP) score improves over the top-performing baseline by five percentage points (i.e., 85.7% for SOS baseline versus 90.7% for CNN-FT) and over 10% points (i.e., 54.2% for Feng et al. (2011) baseline vs. 64.6% for CNN-FT) for the computer vision benchmarks and VizWiz images respectively. Our results confirm it is possible to predict whether
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Fig. 5 (a, b) Precision-recall curves and average precision scores for nine benchmark systems tested on images coming from (a) seven computer vision benchmarks and (b) blind photographers. Our STATIC fine-tuned CNN classifier (CNN-FT) outperforms SVMs trained on off-the-shelf CNN features (AlexNet, VGG16, SOS) and gradient-based features (GIST, HOG, IFV) as well as existing saliency (Feng et al. (2011)) and subitizing (SOS, Zhang et al. (2015)) methods. (c, d) Also shown are example foreground object ambiguity predictions from our deep learning system, CNN-FT, for the images coming from (c) seven computer vision benchmarks and (d) blind photographers. We show the top ten images most confidently predicted as ambiguous/unambiguous and borderline cases. See images with red boundaries for examples where the classifier predicts the wrong label. Images with a single, unambiguous object are successfully found despite the large diversity in the object’s appearance (e.g., shape, color, texture) (Color figure online).

Overall, we observe classifiers perform worse on the VizWiz images than the computer vision benchmarks; e.g., AP scores for the top-performing CNN-FT classifiers are 90.7% for computer vision benchmarks and 64.6% for a novel image contains a single, unambiguous foreground object. This is interesting because it indicates that image content alone—without external psychological cues—often carries sufficient information to gauge ambiguity.
VizWiz images. While our findings demonstrate the promise of automating the proposed prediction task, they also reveal an important, largely unsolved challenge for modern computer vision tools in handling poor quality images commonly captured by blind photographers.

Figures 5c, d show prediction results from CNN-FT. Specifically, each figure shows 10 images for four categories: confident (un)ambiguous and borderline (un)ambiguous. The borderline images highlight that the predictor often is confused by images with semi-dominant objects neighboring distractor objects. The images with the most confident “unambiguous” predictions highlight that the predictor expects human agreement in the presence of a dominant object against a consistently textured background. Interestingly, the predictor does not appear to make strong assumptions about the appearance of the foreground object, as exemplified by the dominant objects exhibiting various shapes, sizes, colors, and textures as well as being positioned in various parts of the images.

### 4.4 Predictive Cues

We apply t-SNE, a visualization technique, to the seven computer vision benchmarks in the STATIC test dataset in order to offer further insight into what our top-performing fine-tuned CNN-FT classifier learned. We leverage publicly-available code\(^4\) to create the visualization (Fig. 6). This 2D t-SNE plot places images close together that have similar learned descriptors in our CNN that is fine-tuned to target the (un)ambiguity label. Overall, we see nice trends. We see this in spite of the fact that the visualized neighbors are approximations (t-SNE embedding is stochastic and reduces dimensionality) and ambiguity scores are imperfect. Based on observed image clusters, we posit the system is picking up on a combination of low-level visual features.

First, we observe the images in the bottom left quadrant tend to capture visually similar circular objects. For example, often neighboring images share similar colored circular objects (e.g., multi-colored rock and disc in the bottom row; orange/red circular fruit in the 5th from bottom row). In addition, some image clusters also show circular objects with similar diameters (e.g., bicycle rim and water glass rim in bottom row). While the specific objects visible may vary, the features have picked up on generic properties that can lead to (un)ambiguity.

We also observe in the top left quadrant that images tend to show bikes. However, in that cluster, the classifier seems to have picked up on generic properties for separating the object category based on (un)ambiguity; i.e., the upper half is ambiguous (images with blue boundaries) and lower half is unambiguous (images with red boundaries). This suggests the classifier is learning ambiguity-specific properties for separating images rather than following object category lines. We speculate this observation explains how, in Fig. 1b, two visually similar images can lead to different labels. Specifically, humans perceive an image showing a single flower as unambiguous and an image showing a collection of crayons shaped like a flower as ambiguous. Our classifier seems to similarly be leveraging ambiguity-specific properties to detangle visually similar content and decide (un)ambiguity.

### 5 How Many Object Segmentations to Solicit?

As observed in Sect. 3, the problem of foreground object ambiguity is of immediate practical relevance for evaluating algorithms on existing object-centric datasets (Table 1). In particular, currently we lack benchmarks that include the diversity of valid foreground object segmentations for a batch of images. In this section, we propose a system to efficiently create such benchmarks. Today’s status quo is to ask \(N\) independent viewers to locate the single most prominent object in a given image (Achanta et al. 2009; Alpert et al. 2007; Borji et al. 2013; Cheng et al. 2015; Jiang et al. 2013; Liu et al. 2011).\(^5\) Commonly, a uniform number of annotations are collected for every image, ranging from as few as one segmentation per image (Cheng et al. 2015) to as many as ten (bounding box) annotations per image (Liu et al. 2011). Our aim is to capture the diversity of valid ground truths across all images without uniformly segmenting each image \(N\) times.

Our method is related but distinct from the Welinder and Perona (2010) method, which also dynamically decides the number of redundant object segmentations to collect per image. However, as discussed in Sect. 2, our goal is very different. While prior work aims to efficiently achieve a desired level of confidence in a single ground truth per image (Welinder and Perona 2010; Whitehill et al. 2009; Welinder et al. 2010), our system is designed to efficiently capture annotation diversity and so all valid ground truths per image. In fact, our method fills a gap in the literature the authors themselves report—errors for their method are concentrated on cases where “intrinsic uncertainty of the ground truth label

\(^4\) http://cs.stanford.edu/people/karpathy/cnnembed/.

\(^5\) Collecting annotations from multiple independent annotators is necessary to avoid annotator bias [e.g., Berkeley Segmentation Dataset Martin et al. 2001, MSRA Liu et al. 2011]. As discussed in Sect. 2, this is in stark contrast to dataset collection systems that solicit redundant annotations by showing each new annotator all previously-collected segmentations overlaid on the image [e.g., LabelMe (Russell et al. 2008), VOC (Everingham et al. 2010), MSCOCO (Lin et al. 2014)]. This design difference stems from different aims. While the latter aims to annotate all objects (possibly only for a pre-defined set of object categories) in an image, the former focuses on localizing all objects deemed the single most prominent object according to human perception.
Fig. 6 Images neighbor other images that share similar values in the final 4096-dimensional vector layer of the CNN. The border color for each image indicates the classification score, with blue (0) reflecting most confident ambiguous and red (1) reflecting most confident unambiguous. (Best viewed in color) (Color figure online)

is high” (Welinder and Perona 2010). Our system decides the number of human annotators to recruit based on whether the image is deemed unambiguous (single) versus ambiguous (multiple) by our STATIC ambiguity predictor.

Our system begins with exactly one human-drawn foreground object segmentation for each image. Given bounded annotation resources, the system can only request additional annotations for a subset of the images. Our goal is to capture as much of the diversity of valid foreground object segmentations as possible for the batch with the allocated human annotation budget. Our key design decisions are how to (1) allocate annotation effort and (2) quantify diversity captured by human-drawn foreground object segmentations.

5.1 Allocating Human Annotation Effort

Our system takes in a batch of $N$ images with a redundancy budget $B$ indicating the number of images to receive redundant human annotations. The system first collects one segmentation for every image. Then, the system applies our proposed prediction system discussed in Sect. 4 to every image in the batch; we use our CNN–FiT method trained on the computer vision benchmarks. Next, the system orders the $N$ images based on predicted scores from the classifier, from most confidently predicted “ambiguous” images to the most confidently “unambiguous” images. Finally, the system greedily assigns the given budget of annotation effort
for redundancy to the $B$ images predicted to reflect the greatest likelihood of ambiguity. Each image assigned to receive redundant labels is allocated a fixed number of additional human annotations.

5.2 Measuring Segmentation Diversity

We now describe our method to evaluate the segmentation diversity captured by the collection of human-drawn segmentations for a batch of images $I = \{1, \ldots, N\}$. Given the subset of images $B$ assigned to receive $A$ redundant annotations each, we compute total diversity as follows:

$$D(I) = \sum_{k \in I} d_{k0} + \sum_{j \in B} \sum_{a=1}^{A} d_{ja}$$

where $d_{k0}$ represents the diversity captured by the first annotation for the $k$-th image (defined below), $d_{ja}$ represents the diversity captured by the $a$-th redundant annotation for the $j$-th image, and $D(I)$ reflects the total annotation diversity captured for image batch $I$. The first term evaluates the diversity captured by a single segmentation per image. With no redundancy budget, the total diversity will come from this term. The second term evaluates the diversity captured by redundant annotations. When the maximum redundancy budget is available, total diversity will include the diversity captured by having redundant annotations for every image. Given a partial redundancy budget, if the ambiguity predictions were perfect, then we could safely solicit a single human-drawn segmentation on unambiguous images and extra segmentations for ambiguous images.

Our goal is to choose diversity measures that reveal when humans disagree because of ambiguity versus minor differences in boundary detail (e.g., Fig. 7, rows 2–7 vs. row 1). We chose two diversity measures that indicate for an image how different each individual’s annotation is from the

![Fig. 7](https://example.com/fig7.png)

Illustration of the measured segmentation diversity among five crowdsourced segmentations. Each example shows the raw image, diversity score derived with the weighted F-measure (Margolin et al. 2014), reference, and five crowdsourced segmentations. These illustrate how the following different levels of disagreement correlate to computed diversity scores: All Agree, Minority Disagrees, Split Opinions, and All Disagree. Diversity is often least when “All Agree” and greatest when “All Disagree”
reference segmentation. The reference segmentation represents the pixel majority vote result from multiple annotators’ segmentations. We establish each reference segmentation a priori using all the redundant crowdsourced segmentations per image. Diversity is measured as the difference of a human-drawn segmentation $S$ to the reference segmentation $R$. One measure is region-based and is computed by $1 - \text{sim}(S, R)$, where $\text{sim}$ is the weighted F-measure (Margolin et al. 2014). This measure computes the number of pixels in common between the two segmentations, using both the dependency between neighboring pixels and the location of the errors. The second measure is boundary-based and, in particular, we compute the Chamfer distance between $S$ and $R$, which indicates the distance between two shapes. For both measures, larger values reflect greater diversity.

5.3 Experimental Design

We evaluate the impact of selectively allocating human effort to create foreground object segmentations as a function of the available budget of human effort. For each budget level, we measure the total diversity resulting for the batch of images. When a system does well, the segmentation diversity captured will remain high despite using a lower budget.

We conduct our studies on 800 randomly selected images from the STATIC test set. We collect segmentations from crowd workers recruited from Amazon Mechanical Turk (AMT). We limit our pool of workers to those who previously completed at least 100 tasks and received at least a 92% approval rating. Our task includes instructions at the top of the webpage (Fig. 8a) followed by the image to segment at the bottom of the webpage (Fig. 8b). The user interface restricts the worker to exactly one object segmentation per image. We include five images per HIT and pay workers $0.10 to complete each HIT.

We compare our system to the following baselines:

- W&P-BB (Welinder and Perona 2010): An online crowdsourcing system from Welinder and Perona (2010) which decides the redundancy level per image for all images. Specifically, given a threshold, annotations are collected for an image until annotation agreement exceeds the threshold. Agreement is measured using both a confidence in the annotators’ skills and bounding box similarity. We sweep through all thresholds to create a human effort budget versus diversity curve. We use the bounding boxes of our crowdsourced segmentations.

- W&P-Seg (Welinder and Perona 2010): A system matching W&P-BB except that our crowdsourced segmentations are used directly to measure annotation agreement.

- SOS (Zhang et al. 2015): A method that predicts a confidence in whether the image contains 0, 1, 2, 3, or 4+ salient objects. Images are ordered by most confident to least confident predictions for 1 object followed by least to most confident predictions for 2, 3, 4+, and 0 objects respectively. Images ranked least confident are prioritized to receive redundancy.

- Status Quo: Images are randomly prioritized to receive redundancy.
Fig. 9 (a–d) The plots show the value of our prediction system and five baselines to allocate redundant segmentations for capturing foreground object diversity for 800 images. Results are shown based on two diversity measures: Weighted F-Measure and Chamfer Distance. Boundary conditions are (leftmost) “no redundancy per image” for all images and (rightmost) (a, b) “four redundant segmentations per image” or (c, d) “nine redundant segmentations per image” for all images. Our system outperforms existing online crowdsourcing systems (W&P Welinder and Perona (2010)) and a saliency (SOS, Zhang et al. (2015)) method. Perfect: Images are ordered by total diversity score per image, based on having all segmentations. This demonstrates the best a system could achieve.

To evaluate our approach using existing salient object detection redundancy levels, we investigate performance for two redundancy levels. First, we evaluate performance by employing the commonly-employed redundancy level of five annotations per image (e.g., MSRA-A Liu et al. 2011; Alpert et al. 2007; Martin et al. 2001; Warfield et al. 2004). We also employ the more rigorous redundancy level of ten annotations per image (i.e., MSRA-B Liu et al. 2011).

5.4 Experimental Results

Figure 9 shows the resulting human effort versus diversity curves when using all possible budget values (0, 1,…, 800 images). Our approach consistently outperforms the baselines with respect to both diversity measures for both the redundancy level of five segmentations per image (Fig. 9a, b) and ten segmentations per image (Fig. 9c, d). For example, our system accelerates the collection of ∼ 51% of the diversity by at least 27% over the four baselines (W&P–BB, W&P–Seg, SOS, Status Quo), with respect to the region-based measure (Fig. 9d). In absolute terms, this translates to eliminating over six human-hours of annotation time for 800 images, assuming a human takes approximately 54 s to segment an object (Jain and Grauman 2013). In addition, with respect to the boundary-based measure, our system accelerates the collection of ∼ 53% of the diversity by as much as 47% over the four baselines (Fig. 9d). In absolute terms, this means eliminating over eight human-hours of annotation time for 800 images. Our performance gains taper for both measures when our system has captured most of the total diversity (∼ 70%). Our findings offer promising evidence that it is possible to efficiently address the issue of image ambiguity and its effect on foreground object segmentation evaluation (discussed in Sect. 3.3) by collecting extra annotations only for images where a diversity of ground truths are expected.
We attribute our advantage over the top-performing, saliency-based predictor (i.e., SOS) to the observation that ambiguity arises for a variety of causes beyond multiple salient objects, including object granularity and occlusion (Fig. 9c). Our findings highlight a value in directly predicting whether humans will agree on a single foreground object rather than predicting the number of detected salient objects in an image.

Our method also significantly outperforms methods that predict the exact number of annotations to collect per image, i.e., the W&P baselines.6 Our results underscore that the W&P baselines tackle a distinct problem from the one tackled in this work, and in that sense our positive results are to be expected. We attribute our advantage to the fact that the W&P baselines only solicit additional segmentations if annotator disagreement is already observed between the first two segmentations. Yet, as shown in Fig. 7, one may need to collect more than two foreground object segmentations to observe diversity. Our findings highlight a value in directly predicting from an image whether humans will agree on a single foreground object rather than making inferences from observed human annotations.

Finally, as observed in Fig. 7, a different number of valid interpretations can arise due to ambiguity (e.g., 2, 3, 4, or 5 valid ground truths). This observation motivates two valuable areas for future work to achieve further savings: (1) predict the exact number of foreground object segmentations in an image and (2) target the images to the appropriate crowd workers predicted to, as a group, produce the diversity of valid outcomes without duplicates.

6 Conclusions

Our work reveals a promising, largely-untapped research problem of accounting for foreground object ambiguity to improve computer vision systems. We established a benchmark and showed segmentation algorithms are getting penalized when they produce valid results. We proposed a system that accurately predicts whether an image is ambiguous and so should have multiple ground truths, both for images in established vision benchmarks and from blind photographers. Finally, we demonstrated how to reduce human effort to collect the diversity of valid foreground object segmentations for a batch of images, improving upon existing saliency-based and online crowdsourcing methods.

We offer this work as a valuable step towards a larger community effort to build modern vision systems that account for the foreground object ambiguity that humans perceive.

One future research direction includes human computer interaction studies to explore how blind photographers prefer to integrate foreground ambiguity predictions with existing mobile phone camera applications to help them recognize objects in their environment. Future work also includes exploring how to more efficiently create salient foreground object benchmarks that include the diversity of foreground object segmentations.

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