Figures

An annotation $a \in \mathbb{R}^{h \times w}$ for object positions corresponds to a labeling of object positions $y \in \mathbb{R}^{n \times 2}$, where n is the number of objects in the image. If $y_k \in \mathbb{R}^2$ is the position of object k in the image, then we can obtain the annotation according to

$$a_{ij} = \min\left(D_{\max}, \min_k \left\| \begin{bmatrix} i \\ j \end{bmatrix} - y_k \right\|^2\right) \tag{1}$$

where $D_{\max}$ is a maximum distance threshold.

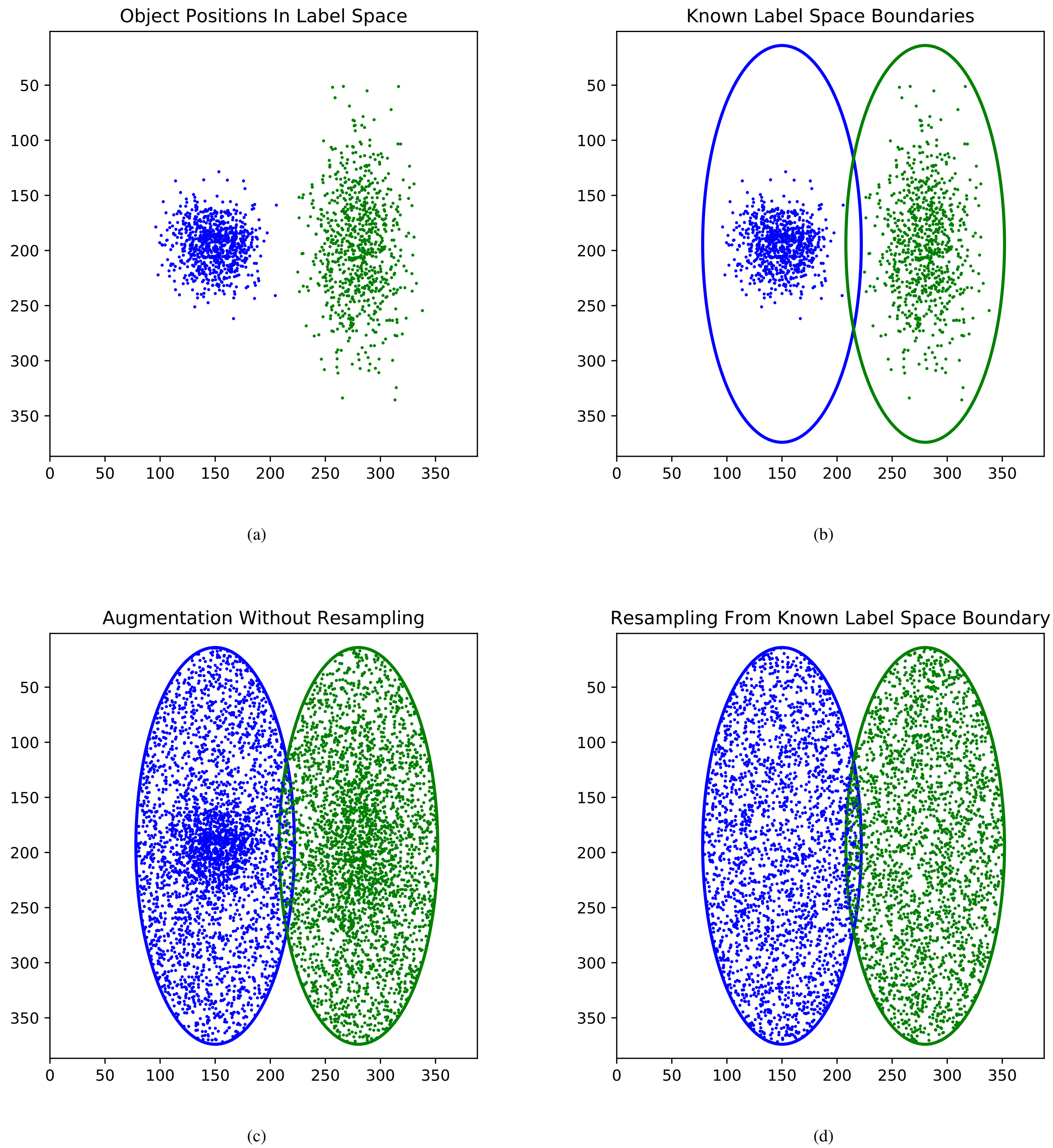

Fig. 1. For any experiment, object positions in label-space will have some natural distribution evident in the original dataset, such as in (1a). Generally, an experimenter knows absolute boundaries for each object's distribution, such as in (1b), because she imposes them during collection. To analyze object positions (or other properties) in an unbiased way, a Deep Neural Network (DNN) should be trained on images corresponding to labels from within that boundary. (1c) shows how one might select new points in label-space to generate images for, keeping all the original points. (1d) shows a resampling that keeps original points only within the desired distribution, preventing dataset bias.

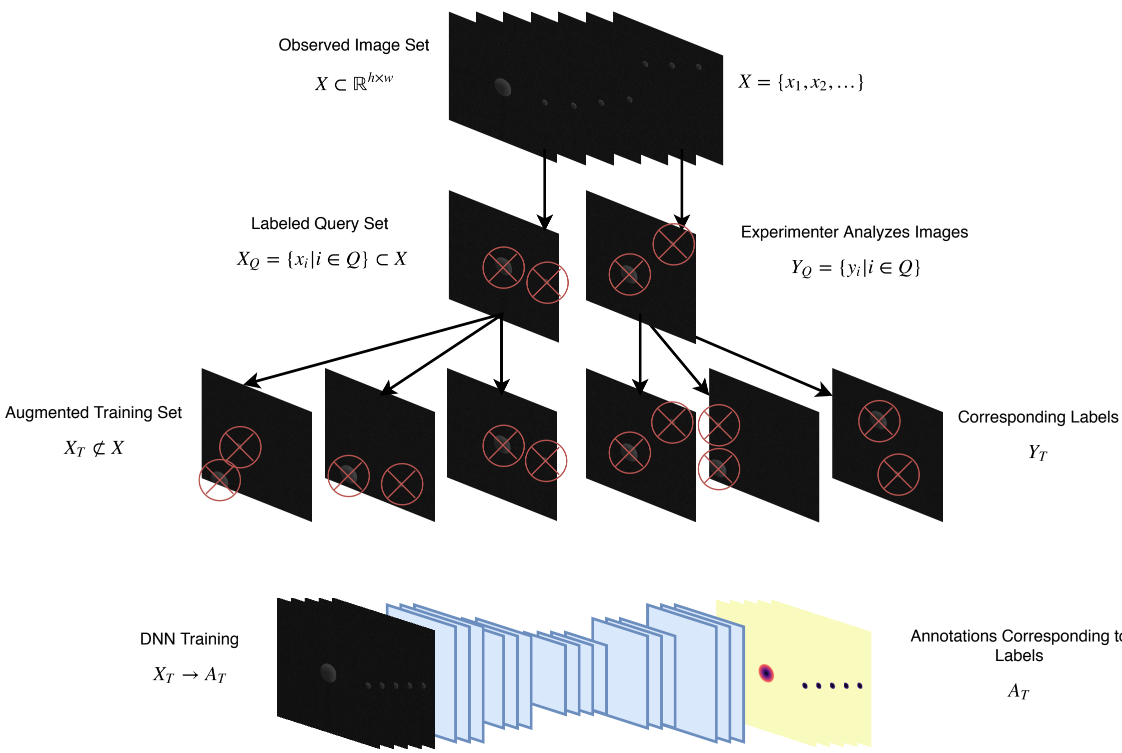

Fig. 2. Given original images observed during experiment time $X \in \mathbb{R}^{h\times w}$, a DNN-facilitated method for image analysis aims to minimize the analysis provided by an experimenter. Therefore, we select a query set X_Q of images that will most facilitate learning. For each of these images, the experimenter provides analysis which consists of labels y_i for each image (shown in red). In order to create training images X_T, we add new images by transforming elements of X_Q. For instance, we might translate image objects corresponding with new points in label-space, obtained as in Fig. (1). Training annotations A_T are obtained from Y_T according to Eq. (1), after which we train the object detection DNN on (X_T, A_T).