Artifice: Generalized Object Detection in Laboratory Images

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Together with large training sets, Deep Neural Networks (DNNs) have enabled a wide range of advancements in Computer Vision tasks, especially with regard to object detection in real-world images. Object detection for laboratory images, on the other hand, presents challenges unlike more traditional vision tasks. First, experiments exhibit a scarcity of labelled data, a problem which we address through active learning and data augmentation. Second, scientific experiments involve inherent constraints, such as a natural law or governing principle, which the experimenter intends to observe. Although this quality seems advantageous for data augmentation, it threatens to undermine the scientific rigor of DNNs for laboratory tasks. In this progress report, we describe our ongoing effort toward training and verification of DNNs which are agnostic to inherent constraints while.

1 Introduction

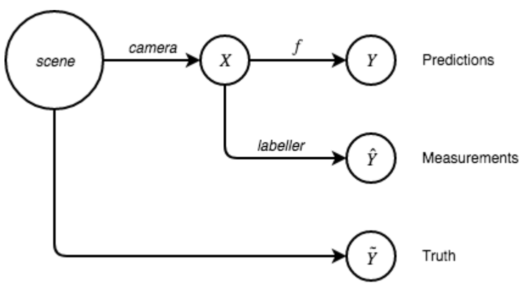
Recent advances in compute power have allowed neural networks to grow in both size and complexity, tackling increasingly sophisticated tasks with applications including facial recognition and self-driving. However, this success relies on the availability of very large, well-labeled datasets like ImageNet [1] or COCO [2], which facilitate supervised training. Although "real-world" applications

2 Method

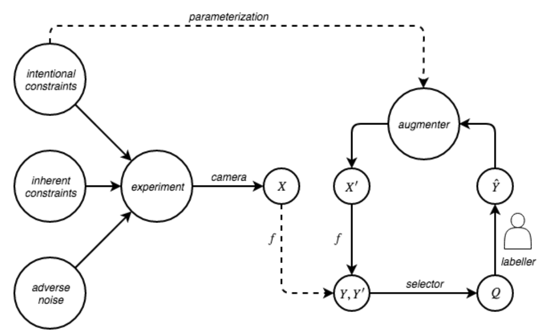
References

[1] Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. "ImageNet: A Large-Scale Hierarchical Image Database". p. 8.

[2] Lin, T.-Y., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J., Perona, P., Ramanan, D., Zitnick, C. L., and Dollr, P., 2014. "Microsoft COCO: Common Objects in Context". *arXiv:1405.0312 [cs]*, May. arXiv: 1405.0312.



(a) Traditional dependency graph



(b) Artifice's dependency graph

Fig. 1: For a traditional vision task (**a**), a camera converts real-world *scenes* into an unlabeled dataset X. These scenes have actual attributes $\tilde{Y}$ which a *labeller* records as the "ground truth" or "measurement" Y. A classifier or regression model f, trained on (X,Y), produces predictions $\hat{Y}$.
Artifice's dependency graph (**b**), specialized for object detection in laboratory images, distinguishes between two types of constraints. *Imposed constraints*, such as physical boundaries, are known to the experimenter, but *inherent constraints*, such as a physical law, are the subject of hypothesis. *Adverse noise*, including lighting changes or object deformation, also influences the experiment. In (**b**), the augmented dataset X is continually updated by the Training Cycle. A *selector* chooses the query set $Q \subseteq X'$ based on existing predictions $\hat{Y}$. A *labeler* produces imperfect ground truth Y, which enables the *augmenter* to intelligently update the dataset X', incorporating imposed constraints. Here, dashed lines represent single instance connections, such as instantiating $X' \leftarrow X$, rather than continual dependency throughout the Training Cycle.