On the use of Cortical Magnification and Saccades as Biological Proxies for Data Augmentation

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Abstract

Self-supervised learning is a strong way to learn useful representations from the bulk of natural data. It's suggested to be responsible for building the visual representation in humans, but the specific objective and algorithm are unknown. Currently, most self-supervised methods encourage the system to learn an invariant representation of different transformations of the same image in contrast to those of other images. However, such transformations are generally non-biologically plausible, and often consist of contrived perceptual schemes such as random cropping and color jittering. In this paper, we attempt to reconfigure these augmentations to be more biologically or perceptually plausible while still conferring the same benefits for encouraging a good representation. Critically, we find that random cropping can be substituted by cortical magnification, and saccade-like sampling of the image could also assist the representation learning. The feasibility of these transformations suggests a potential way that biological visual systems could implement self-supervision. Further, they break the widely accepted spatially-uniform processing assumption used in many computer vision algorithms, suggesting a role for spatially-adaptive computation in humans and machines alike.

1 Introduction

It has long been suggested that the human visual system is tuned not solely via supervised learning, but also with the assistance of innate inductive biases and more recently self-supervised learning schemes. If so, how might we approximate the powerful self-supervised learning in biological vision? One place to begin is the recent progress in self-supervised learning in machine vision.

Recent years have seen great advances of self-supervised learning (Chen et al., 2020a; Grill et al., 2020) and their implications to machine vision (Geirhos et al., 2020) and human vision (Konkle & Alvarez, 2020; Orhan et al., 2020b). One common theme in these methods is to encourage the learned representation to be invariant to certain augmentations. These transformations are manually picked, and their effects differ greatly in encouraging a good visual representation(Chen et al., 2020a). Random crop and color jittering have been shown empirically to be an *optimal* transformation in the sense that using them within a contrastive framework yields both high in-distribution generalization and robustness to common corruptions (Hendrycks et al., 2019; Naseer et al., 2020).

The triumph of the general principle of learning invariant representation and the success of the specific transforms of random crop and color jittering, suggest that biological visual system may also evolve to leverage the same objective for self-supervised learning. In other words, to generate invariant representations against augmentations may be one goal our visual system used to train itself in order to learn object recognition. If so, what could be the augmentations the visual system learns to be invariant against? Two biological processes appear to be relevant: 1) the spatially-varying

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resolution (foveation) at the retina (Anstis, 1974); and 2) the active sampling procedure *(saccades)* which happen naturally three times per second (Eckstein, 2011; Traver & Bernardino, 2010). The combination of the two processes creates a frequently changing retinal input to our visual system, while our perception of the world stays stable. It's a reasonable objective to encourage the high level visual representation to stay stable across views of the environment. Indeed, there is neurobiological evidence that higher visual cortices have longer time constants than lower visual cortex, suggesting a more stable representation of natural input (Chaudhuri et al., 2015). Thus we hypothesize that these foveation-based transformations and saccade-like active sampling mechanisms may be the natural augmentations that biological visual systems learn to be invariant against, forming a counterpart to the random crops in the self-supervised learning framework for computer vision.

Indeed, recent work has suggested a functional goal of the adaptive multi-resolution nature of the primate retina – mainly tailored towards achieving scale invariance (Poggio et al., 2014; Han et al., 2020), adversarial robustness (Luo et al., 2015; Reddy et al., 2020; Jonnalagadda et al., 2021) and o.o.d generalization (Deza & Konkle, 2020). Thus given these hints of a representational goal of foveation – that go beyond computational efficiency – we hypothesize that it could possibly give rise to similar or better effects in terms of generalization than its non-biologically plausible counter-parts (*i.e.* random cropping and color jittering) within a self-supervised framework.

In this work, we want to test these natural augmentations computationally, *i.e.* jointly implement foveation and saccades as augmentations under a self-supervised learning framework, and then compare it against their engineered counter-part augmentations like random crops. Altogether, this work provides a proof of concepts of whether it's possible to leverage these natural augmentations to learn good visual representations without semantic labels.

2 Methods

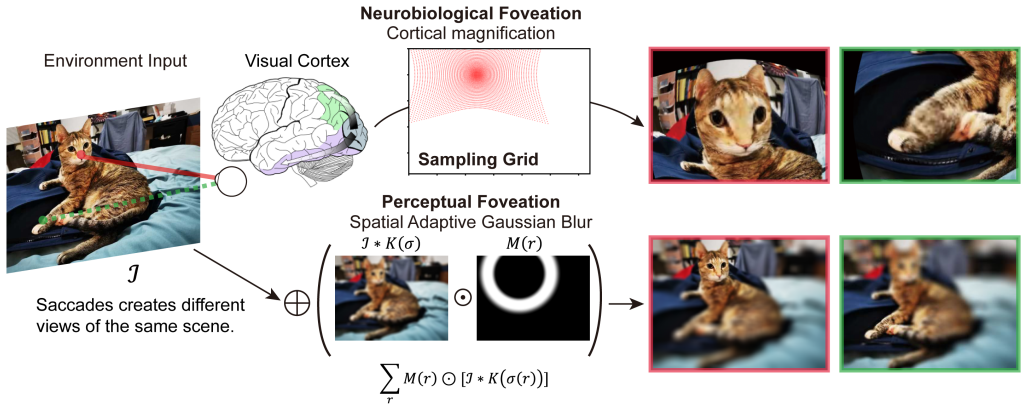

Figure 1: **Foveation Transform**. The upper row shows foveation as magnification, which models the cortical representation of an image. We implemented this operation by sampling from a warped grid around the fixation point. The lower row shows foveation as adaptive blur, which models the perception. It's implemented by blending images blurred by different kernels with different masks.

Our natural augmentation pipeline consists of a saccade (selection of fixation point) and a foveation transform (emphasizing visual information around the fixation).

We implement saccades as sampling multiple **fixation points** on the same image. These fixation points $p = (x, y)$ are generated by i.i.d. sampling either from a uniform distribution over the center part of the image, or from a gaze probability distribution over the image. In our implementation, we pre-computed the saliency maps S of all images with the FastSal model (Hu & McGuinness, 2021) pre-trained on the SALICON dataset (Jiang et al., 2015). This saliency map is interpreted as the unnormalized log-density of the gaze probability on the image. We continuously tune the effect of the saliency information by changing a "temperature" parameter T of the sampling density.

$$P[x, y] \propto \exp(\frac{S[x, y] - \max(S)}{T})$$

Higher temperature will tune down the effect of saliency and approximate a uniform distribution over the image, closer to the original sampler. Lower temperature will amplify the effect of saliency, resulting in a focused, low-entropy sampling of high saliency part of the object (Fig.2E).

Next, for foveation, we define foveation as spatially-adaptive (non-uniform) processing of the image (Eckstein, 2011; Bajcsy et al., 2018). We identified at least two approaches to implement foveation as a transform of the images, one inspired by our perception, the other inspired by the structure of the visual cortical map (Fig.1). We compared both of them in our experiments.

Foveation as Spatial-Varying Blur This approach is inspired by our visual perception of the world: when we fixate our gaze, our perception of the visual periphery seems lower resolution than the central field of view. To approximate this phenomena, people have used spatial varying blur (Geisler & Perry, 1998; Pramod et al., 2018; Malkin et al., 2020) or texture-based distortions (Freeman & Simoncelli, 2011; Rosenholtz et al., 2012; Deza et al., 2017; Wallis et al., 2019; Kaplanyan et al., 2019) to transform an image such that it matches our perception of it. The extent of distortion or Gaussian blur changes as a function of the eccentricity.

We implemented this foveation transform $\mathcal{F}$ as classically done in Geisler & Perry (1998), and also Pramod et al. (2018); Malkin et al. (2020): Given a fixation point, the pixels in the image are divided into belts of similar eccentricity, represented by masks M_i (Deza & Eckstein, 2016); and the image is convolved with Gaussian kernels of different standard deviation σ_i, corresponding to the degree of blur at different eccentricity; finally, these blurred images $I * K(\sigma_i)$ are blended into one with the belt-shape masks (Fig.1).

$$\mathcal{F}(I) = \sum_{i}^{N_b} M_i \cdot [I * K(\sigma_i)], \quad \sum_{i}^{N_b} M_i[i,j] = 1$$

This was implemented using simple operations in computer vision (convolution, pixel-wise multiplication and addition) such that it could be an efficient step in the augmentation pipeline during training. The standard deviation of the blur kernel is a linear function of the eccentricity $\sigma_i = Ke_i$; besides, the pixels within eccentricity e_o is not blurred, corresponding to the foveal vision. So, there are two parameters: the size of foveal area (ratio of unblurred pixels) $fov\ area$, and the linear coefficient K of kernel size with respect to eccentricity. For more details, see Sec.A.1.

Foveation as Cortical Magnification In contrast, this approach is inspired by the structure of retinotopic maps on the visual cortex: due to the difference density of retina ganglion cells in central and peripheral vision(Wässle et al., 1989), the size of the cortex corresponding to the same size of retinal image varies as a function of eccentricity(Van Essen et al., 1984). Thus, we can think of the image in cortical coordinates as a warped version of the corresponding retinal image (Fig.1). When our eyes move around on a scene, the cortical "image" will magnify different parts depending on the fixation points; and the viewing distance will affect the magnification factor. If we assume CNN as a model of cortical visual processing, then the cortical magnified views of an image is a reasonable transformation to use in representation learning (Bashivan et al., 2019).

Classically, the cortical magnification factor is an inverse function of the eccentricity, (Harvey & Dumoulin, 2011). Additionally, here we assume the CMF is constant close to fovea since the data there is usually lacking.

$$CMF(r) = \begin{cases} C & r < r_{fov} \\ \frac{C(r+r_{fov})}{r+K} & r \geq r_{fov} \end{cases}$$

Here, we transform the retinal eccentricity to cortical radial distance by integrating the reciprocal of the cortical magnification function. Thus we get the retinal eccentricity $e(r)$ as a linear (foveal) or quadratic (peripheral) function of cortical radius r.

$$e(r) = \int_0^r \frac{1}{CMF(\rho)} d\rho = \frac{1}{C} \begin{cases} r; & r < r_{fov} \\ \frac{(r+K)^2}{2(r_{fov}+K)} + \frac{r_{fov}-K}{2}; & r \geq r_{fov} \end{cases}$$

We assume an isotropic transform from retinal images to cortical images, so we can use this radial transform to build the 2d change of coordinates $(r, \theta) \mapsto (e(r), \theta)$. We note that the constant $1/C$ controls the scaling of the map, which affects the image area covered by the sampling grid. Thus we use the **cover ratio** as the control parameter in experiments. Besides, parameter r_{fov} controls the area of linear sampling while K controls the degree of distortion in the periphery, which are manually tuned and fixed ($r_{fov} = 20, K = 20$).

3 Experiments and Results

We adapted the framework of SimCLRv2 (Chen et al., 2020b), and used STL-10 dataset (96 pixel resolution) as our test bed to evaluate the effectiveness of the proposed transforms. ResNet18 models (He et al., 2016) were trained with the default setting of SimCLR (see A.2) on the unlabeled set (100K images) of the STL-10 dataset. We evaluated the quality of representation through training by linear probes: For every 5 epochs, we froze the model and trained a linear classifier from its representation vector to the labels using the training set (500 images$\times$ 10 classes), and then evaluated this linear classifier on the testing set (800 images$\times$ 10 classes). The train set and test accuracy and the evolution of them across training process is reported as our major evaluation criterion. (Note that on this dataset, linear evaluation of a random visual representation (randomly initialized ResNet18) can already achieve around 50% training accuracy and 39% test accuracy.) We also take note on another statistics, top-1 simclr accuracy, the accuracy of the self-supervised learning task. This is the success rate of distinguishing views of the same image from those of different images; in our setting when batch size is 256 this is the accuracy of a 511-way classification. We interpret this statistic as the intrinsic difficulty of the augmentation.

In the following experiments, we kept the common augmentations in place: random horizontal flip, random color jittering, and randomly turning images into gray scale. With blur, we refer to the spatial uniform blur of the image.

Experiment 1: Foveation as Adaptive Blur First, we tested if the foveation as adaptive blur could substitute random crops as a natural alternative. In this experiment, fixation points are uniformly sampled. We found that, using either foveation or uniform blur without random crop, the SimCLR training failed: the final test accuracy (36.8-39.0%) is close to or even worse than that of random networks (39.0%) (Tab. 1). Using foveation in addition to random crop will result in similar representation quality (77.8-78.3%) as the baseline using blur (80.6%). Note that without random crop, SimCLR accuracy is saturated. We found that after a few epochs this saturated objective no longer guides the learning of representation ; in other words, with variations only in color and resolution but not space, learning the equivalence of different views of same image is trivial for CNN. In this regard, "moving" the image with respect to the field of view of the CNN seems necessary towards learning a good representation.

crop	**fov**	**blur**	**fov area**	train	test	SimCLR
✓$*$		✓		86.6	80.5	78.1
✓†		✓		86.5	80.8	74.3
✓		✓		86.6	80.7	79.2
✓	✓		[0.01, 0.1]	84.4	78.2	78.6
✓	✓		[0.01, 0.5]	84.1	78.3	78.9
✓	✓		[0.1, 0.5]	83.6	77.8	79.0
	✓		[0.01, 0.1]	40.4	38.4	100.0
	✓		[0.01, 0.5]	39.6	36.8	100.0
	✓		[0.1, 0.5]	41.0	39.0	100.0
		✓		38.0	35.0	99.7

Table 1: **Performance of Foveation as Blur Augmentation**. **Crop** denotes the random resized crop augmentation guided by pre-computed saliency maps; with the exceptions: $*$ used the original crop, † used flat saliency map. **Fov** refers to foveation as blur transform. Train, test accuracy at 96 epochs and the exponential moving averaged ($\alpha = 0.6$) SimCLR objective accuracy at 99 epochs are reported, same below.

crop	**magn**	**blur**	cover ratio	train	test	SimCLR
✓		✓		85.2	79.7	84.8
	✓	✓	[0.01, 0.35]	84.8	79.0	57.3
	✓	✓	[0.05, 0.35]	84.9	79.1	66.7
	✓	✓	[0.05, 0.7]	82.8	76.8	83.0
	✓	✓	[0.01, 1.5]	78.5	72.0	87.9

Table 2: **Performance of Foveation as Magnification Augmentation**. Here **crop** denotes the original random resized crop. **Magn** denotes the foveation as magnification transform. Statistics of row 1 and 3 are averaged across 9 runs while the rest are averaged across 2 runs.

Experiment 2: Foveation as Magnification Next, we tested if foveation as magnification could replace random crop. We found that, magnification transform can substitute the effect of random crop, with all other augmentations in place. We performed rough parameter tuning for the cortical magnification transform, and picked the best performing parameter (Tab. 2). We replicated the magnification transform and the random crop baseline $N = 9$ times and compared their representation quality. The test set accuracy for magnification transforms is $79.07 \pm 0.21\%$ (mean$\pm$std) while that for the random crop group is $79.72 \pm 0.23\%$. The 95% confidence interval of their difference is [-0.887, -0.477]%, which is a significant but negligible difference in terms of overall accuracy, suggesting proper magnification is a biologically-plausible alternative to the random crop.

Experiment 3: Random Crops Guided by Saliency Maps After finding the biological plausible equivalent of random crops, we moved on to test the effect of different models of saccade, i.e. the sampling distribution of the center of views. Specifically, we manipulated the temperature of the sampling, which controls the entropy of the fixation distribution. We found that with lower temperature, the accuracy for SimCLR objective can also saturate (97.4% for 0.01 temperature or 93.9% for 0.1 temperature, Fig.2A) However, the linear evaluated accuracy either on training set or test set decreased as the temperature became too low (Fig.2B). In the other extreme, high enough temperature will eliminate the effect of saliency map, and bring the test accuracy and SimCLR accuracy closer to the uniform sampling baseline. In between, there was a sweet spot at which the saliency guided sampling could improve the quality of learned representation: when temperature was in the range $[0.3, 4.5]$, the test accuracy increased about 0.3%-0.7%.

Experiment 4: Foveation as Magnification Guided by Saliency Maps Similar to experiment 3, we also performed saliency guided sampling for the magnification transform and examined the effect of sampling temperature. The results showed a similar trend as that in experiment 3 (Fig.2 C,D): sampling temperature has a U-shaped effect on the quality of learnt representation, with the optimal temperature falling in the range $[0.3, 1.5]$.

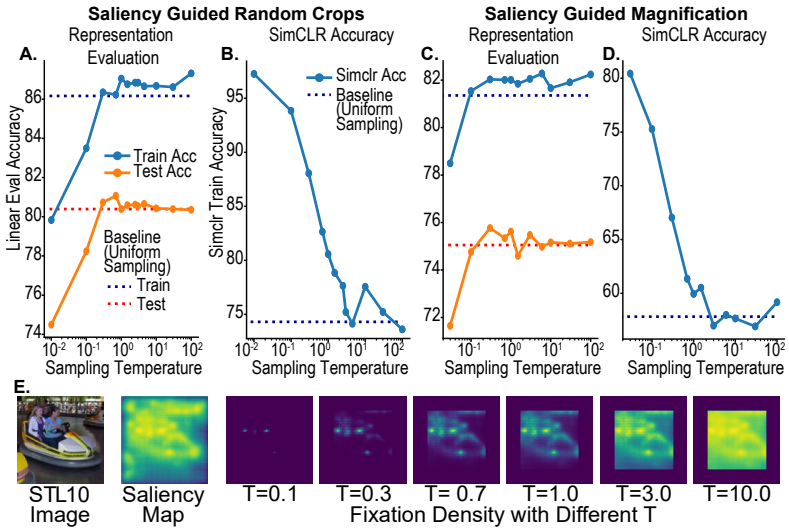

Figure 2: **Effect of sampling temperature on training and feature quality**. For **random crops** with different temperature (Exp 3), **A.** Linear evaluation of the representation quality as a function of temperature, uniform sampling baselines are showed in dashed lines; **B.** Final accuracy for SimCLR objective as a function of temperature. In the same format, **C.D.** show the effect of temperature, for **foveation as magnification** (Exp 4). **E.** Sample from STL-10, its saliency map and the fixation densities corresponding to different temperatures.

4 Discussion

Our results showed that foveation as spatially varying blur of the image *per se* is not a particularly strong mode of data augmentation, and its effect is comparable to uniform Gaussian blurring of the image. Reframing random crop as cortical magnification, however, provides both a biologically plausible method of data augmentation and similarly robust benefits to training. Furthermore, random sampling of the fixation points (via crops; Exp 3) based on pre-trained saliency information has a small but reasonable effect on the learned representation. Overall, finding these pattern of results are encouraging despite not including temporal dynamics (Akbas & Eckstein, 2017), inhibition-of-return or actual human fixation data (Koehler et al., 2014). Broadly, we think this computational framework should set the stage to further incorporate these and other factors in additional analysis where perceptual dimensions such as adversarial robustness and o.o. d generalization can be tested.

Altogether, this work presented a first step into finding parity between classically used transformations in computer vision, with biologically motivated computations that occur in human visual cortex. As previously discussed, future work should focus on incorporating the temporal nature of visual perception within a contrastive framework and comparing these learned representations with real human fixation data. Such directions have been growing in popularity as modern datasets have been tracking infant visual behavior (Sullivan et al., 2020; Orhan et al., 2020a). We think these datasets and approaches may provide an excellent first step for creating more 'infant'-like self-supervised learning regimes to gradually close the gap between human and machine perception. Finally, our results suggest a symbiotic motivation to continue to find biologically-plausible transformations for modern computer vision training pipelines rather than relying on hand-engineered heuristics.

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A Appendix

A.1 Implementation Details for Foveation as Blur Transform

The equations to generate the belts around fovea are borrowed from Equ. 1,3 in Deza & Eckstein (2016). It reads

$$f(x) = \begin{cases} \cos^2(\pi(x + \frac{1}{4})); & \text{if } -\frac{3}{4} \leq x \leq -\frac{1}{4} \\ 1; & \text{if } -\frac{1}{4} \leq x \leq \frac{1}{4} \\ 1 - \cos^2(\pi(x - \frac{3}{4})); & \text{if } \frac{1}{4} \leq x \leq \frac{3}{4} \\ 0; & \text{otherwise} \end{cases}$$

$$g_n(e) = f(\frac{\log(e) - [\log(e_0) + w_e(n+1)]}{w_e});\ w_e = \frac{\log(e_r) - \log(e_0)}{N_e}$$

The belt shaped masks are generated by passing the eccentricity (distance to fixation point (x, y)) of each pixel into $g_n(e)$ function

$$M_n[i, j] = g_n(\sqrt{(i-x)^2 + (j-y)^2})$$

A.2 Hyperparameters for SimCLR Training

For the model, we used the ResNet-18 architecture, with 512 dimension representation space and a 1 hidden-layer MLP as projection head. We used 256 dimension projection space for calculating the SimCLR loss. For the SimCLR objective, 2 views are generated per image and the soft-max temperature for the view classification is set as 0.07.

For training, Adam optimizer is used with an initial learning rate 0.0003 and a Cosine Annealing schedule (Loshchilov & Hutter, 2016), while the weight decay was set as 0.0001. All experiments were conducted with single GPU training (TeslaV100 32G), using batch size 256. Training terminates at 100 epochs, which usually took 3-6 hrs for one run.

A.3 Training Process of Foveation as Blur Augmentations

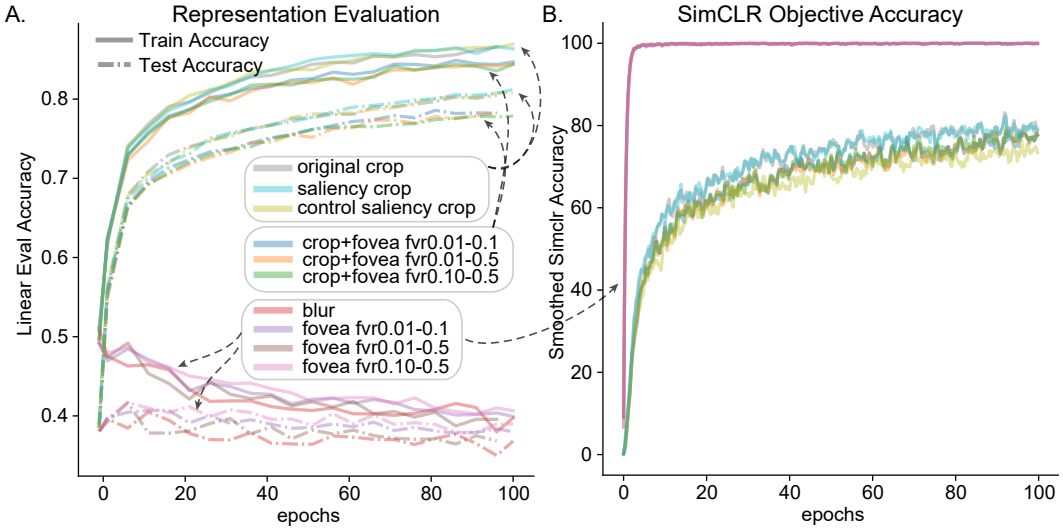

Figure 3: **Evolution of representation quality and SimCLR objective during training of Experiment 1**. **A.** Linear probe evaluation of the representation throughout training, training and test accuracy are showed in solid and dashed lines. **B.** SimCLR Accuracy through out training. The experiments are categorized to three groups: with crops, with crop+foveation, and with foveation/blur only. The SimCLR accuracy saturated rapidly for all runs without random crops, and their representation quality stopped improving or even degraded.

A.4 Distribution of Augmented Images

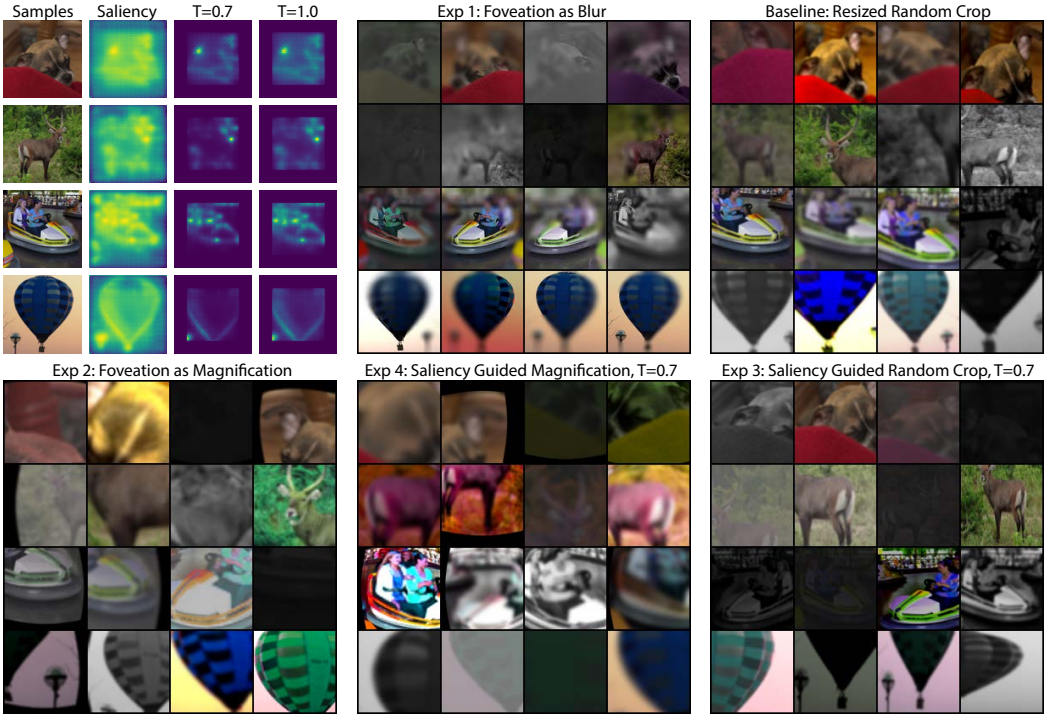

Figure 4: **Distribution of Augmented Images in Experiments**. Four images sampled from STL-10 unlabeled set are showed as example, the corresponding saliency map and fixation densities are showed on their side. We visualize four views for each images for each training setting: Foveation as blur, without crop; Baseline setting, resized random crops; Foveation as Magnification, without crop; saliency guided sampling for magnification; saliency guided sampling for random crops. The variation and focus of each augmentation pipeline could be seen from this comparison.