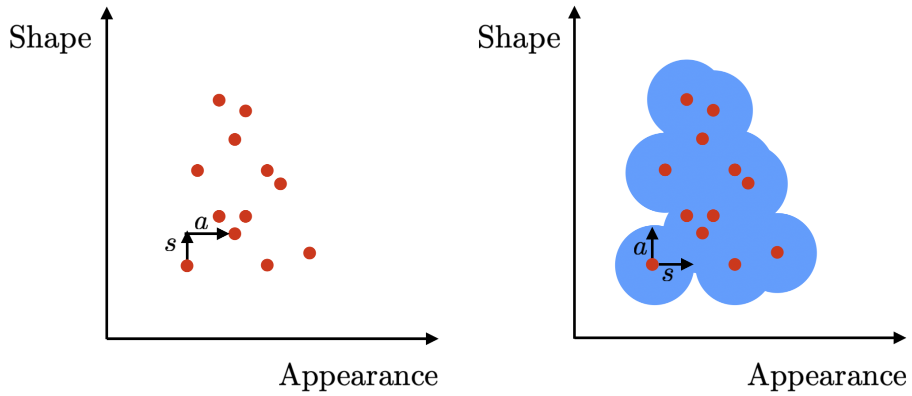
# 1 Object Shape Learning

## 1.1 Transformational Effects




(a) (b)

Figure 1.1: Effect of transformations on data distribution: (a) Data points (red) can be connected via a shape $s$ and an appearance $a$ transformation. (b) Applying transformations effectively blurs the data distribution.

In this section we discuss the effect of the transformations on learning a consistent and comprehensive representation. Since strong image transformations can make the learning curve for the algorithm too steep, we exponetially schedule the increase in magnitude, finally resulting in image changes as shown in Fig. **??**. In effect, the transformations teach the algorithm what changes in shape and appearance are. Assuming that samples from the data distribution are - showing the same object class - related via a change in shape and appearance, the transformations blur the distribution. This data augmentation is sketched in Fig. 1.1.

### 1.1.1 Spatial Transformations

We perform thin-plate spline (TPS) warps to mimick spatial transformations. These changes incorporate rotation, scaling and translation as a special case. While irreplacable for calculating the direct equivariance loss, they can result in artificial shape changes. After all, most objects - such as human beings or animals, do not warp, but articulate their parts/limbs. Natural shape changes are needed to learn a model of the objects articulation. These changes are presented in video data. Hence, for videos we enforce the reconstruction to function across different frames. This results in a much stabler performance and greater part consistency especially for highly articulated parts such as arms.

### 1.1.2 Appearance Transformations

Figure 1.2: Examples for shape and appearance transformation on CUB-200-2011. Images from the upper row relate to images directly below.

We mimick appearance changes with image transformations in color, contrast, hue and brightness. Exemplars for the combined effect of spatial and appearance transformations are shown in Fig. **??**. Especially for datasets with high intra-class appearance variance, connecting the data points via appearance changes is crucial. On Cat Head for example, without them, the method assigned different landmarks to black cats than to other-color cats. The model will incur no loss, as long as it always has to reconstruct black cats from images of black cats.

### 1.1.3 Parity

biggest failure mode of the model hard to correct obviously no loss for object images which are symmetrical under parity transformations, such as frontal view human beings. frontal and back view too similar

birds parity salsa parity Since the human body appearances in the frontal and back views are similar, we do not expect our discovered landmarks to distinguish the left and right sides of the human body, which means that a landmark at the left leg in the frontal view can locate the right leg in the back view.

solution: big change in features under parity -> salsa solution II: if object not symmetric under parity (side view bird), incorporate parity flips in equivariance loss -> problem carefully schedule this since landmarks will tend to crowd at the mirror axis otherwise. succeeded in birds!

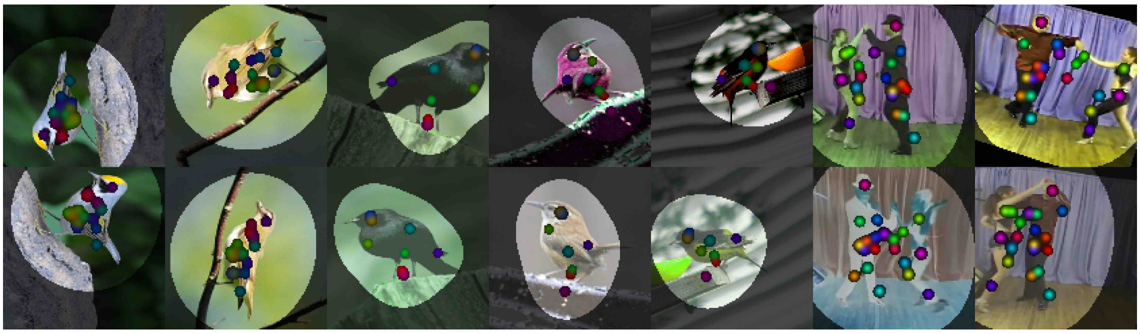


Figure 1.3: Parity changes: the images of the upper and lower row relate via the usual transformations and an additional parity flip. For the bird (1-5th column) images induced artificially, for the dancing humans (6-7th column) via sampling different frames from a video.

# 2 Bibliography