Learning from Synthetic Animals - Supplementary Materials

Jiteng Mu*, Weichao Qiu*, Gregory Hager, Alan Yuille
Johns Hopkins University
jitengmu@jhu.edu, hager@cs.jhu.edu, {qiuwch, alan.l.yuille}@gmail.com

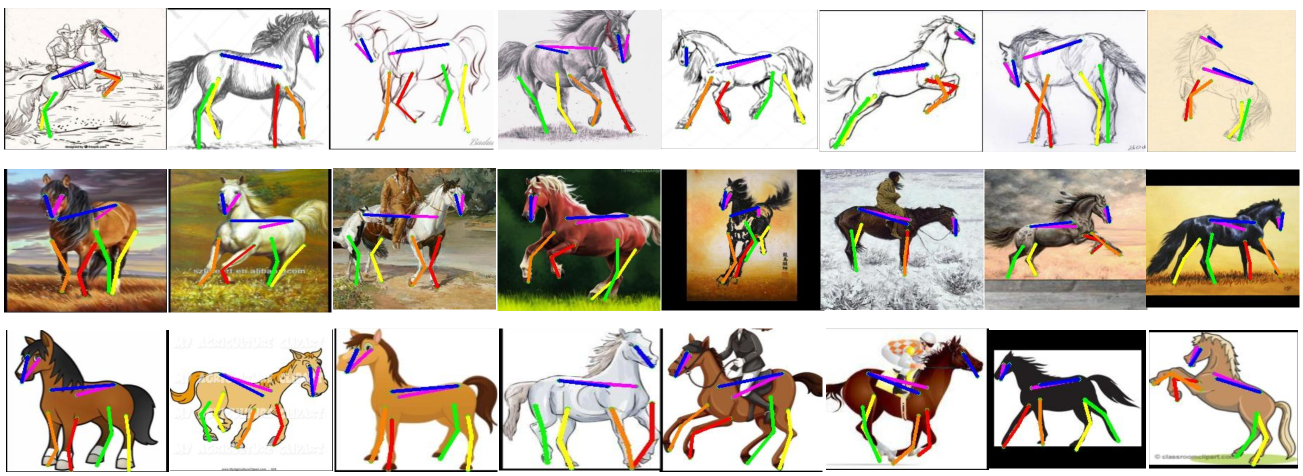

Figure 1. Visualization of 2D pose estimation of *horses* from Visual Domain Adaptation Challenge dataset(VisDA2019). From top to bottom, there are three different domains: sketch, painting, clipart. The results are generated using the CC-SSL method without using real data annotations. Best viewed in color.

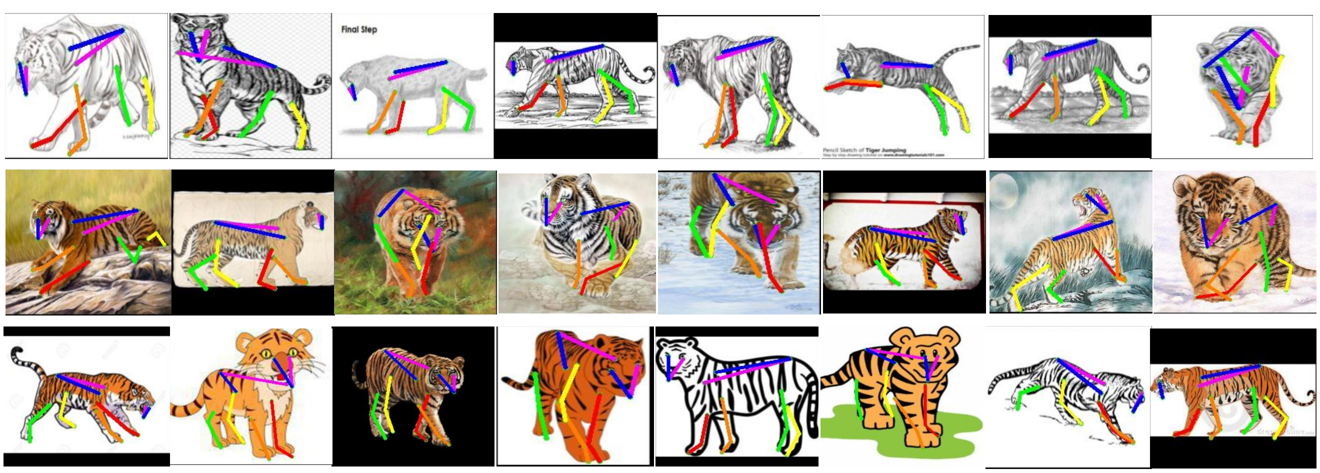

Figure 2. Visualization of 2D pose estimation of *tigers* from Visual Domain Adaptation Challenge dataset(VisDA2019). From top to bottom, there are three different domains: sketch, painting, clipart. The results are generated using the CC-SSL method without using real data annotations. Best viewed in color.

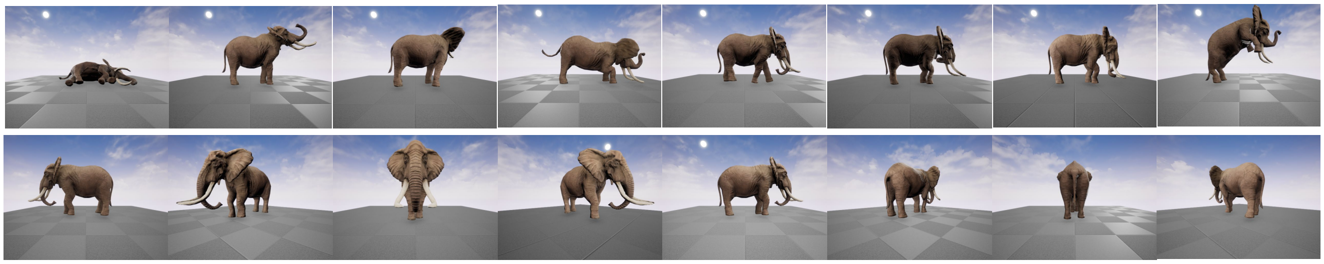

Figure 3. Synthetic data generation. We use Unreal Engine to collect rich ground truth and enable nuisance factor control. The implemented factor control includes randomizing lighting, textures, viewpoints and animal poses. Here we show random poses and viewpoints for different animals. First row shows random poses of elephants. Second row shows random viewpoints of elephants. Third row shows random poses of tigers. Fourth row shows random viewpoints of tigers. Models are from Animal Pack Ultra 2 in UE4 Marketplace. Best viewed in color.

(a) (b) (c) (d) (e) (f) (g) (h)

(i) (j) (k) (l)

Figure 4. Failure examples. (a) Failures caused by motion blur. (b)(j)(k) Failures caused by extreme poses. (c)(d)(l) Failures caused by multiple subjects. (e)(f) Failures caused by occlusion. (i) Failures caused by left-right confusion. Best viewed in color.