
AP-10K: A Benchmark for Animal Pose Estimation in the Wild: Supplementary Material

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1 A Appendix

2 A.1 More quantitative and qualitative results

Table S1: The complete results of different models on the validation set of the SL track.

Pretraining on ImageNet	AP	AP _{.5}	AP _{.75}	AP _M	AP _L
HRNet-w32 [13]	0.738 \pm 0.006	0.958 \pm 0.004	0.808 \pm 0.007	0.592 \pm 0.074	0.743 \pm 0.006
HRNet-w48 [13]	0.744 \pm 0.004	0.959 \pm 0.002	0.807 \pm 0.006	0.589 \pm 0.042	0.748 \pm 0.003
ResNet50 [7]	0.699 \pm 0.004	0.940 \pm 0.003	0.760 \pm 0.003	0.570 \pm 0.078	0.703 \pm 0.004
ResNet101 [7]	0.698 \pm 0.002	0.943 \pm 0.002	0.754 \pm 0.007	0.543 \pm 0.070	0.702 \pm 0.001
Hourglass [10]	0.729 \pm 0.001	0.951 \pm 0.002	0.793 \pm 0.002	0.606 \pm 0.042	0.733 \pm 0.001
Training from scratch	AP	AP _{.5}	AP _{.75}	AP _M	AP _L
HRNet-w32 [13]	0.703 \pm 0.002	0.940 \pm 0.001	0.764 \pm 0.004	0.599 \pm 0.020	0.707 \pm 0.003
HRNet-w48 [13]	0.711 \pm 0.003	0.943 \pm 0.002	0.771 \pm 0.004	0.604 \pm 0.047	0.715 \pm 0.003
ResNet50 [7]	0.646 \pm 0.001	0.913 \pm 0.006	0.694 \pm 0.007	0.522 \pm 0.053	0.649 \pm 0.002
ResNet101 [7]	0.667 \pm 0.002	0.924 \pm 0.003	0.715 \pm 0.003	0.542 \pm 0.042	0.671 \pm 0.002
Hourglass [10]	0.686 \pm 0.006	0.933 \pm 0.003	0.739 \pm 0.011	0.591 \pm 0.027	0.690 \pm 0.004

3 In this Appendix, we provide the full evaluation results of HRNet-W32 [13], HRNet-w48 [13],
4 SimpleBaseline [15] with ResNet50 [7] and ResNet101 [7] and Hourglass [10] in terms of different
5 evaluation metrics on the validation set of the SL Track, as shown in Table S1. It shows that the
6 advanced network structure like HRNet [13] outperforms the other backbones on most categories in
7 terms of all evaluation metrics. It also demonstrates that pretraining on ImageNet can accelerate the
8 convergence speed and achieve a better performance than training from scratch.

9 Besides, we also present the per species results of HRNet-W32 [13] on the test set the SL Track at
10 the settings of “Pretraining on ImageNet” and “Training from scratch” in Table S2 and Table S3,
11 respectively. We also provide another test result which contains 56 animals for reference. *i.e.*,
12 Dividing Dog into Chihuahua, Collie, Dog, dalmatian and German Shepherd, dividing Cat into cat
13 and Perisian Cat and Siamese Cat. As we have mentioned in ??, Dog and Cat varies widely in
14 appearance owing to human’s cultivation for family pets.

15 Comparing Table S2 with the last rows in Table ??, Table ?? and Table ?? in the paper, where all
16 the scores represent test performance on seen species, we can find that using the same amount of
17 training data but from more diverse species can help the model learning better feature representation
18 and achieve better performance, *e.g.*, the mAP for Sheep is 0.663 *v.s.* 0.761, which is obtained by
19 the model trained only using the Bovidae family). This observation further confirms the value of our
20 AP-10K dataset.

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Table S2: Per-species results of HRNet-w32 [13] on the test set the SL Track at the setting of pretraining on ImageNet.

species	AP	AP.5	AP.75	AP(M)	AP(L)
Antelope	0.856 \pm 0.014	0.969 \pm 0.008	0.924 \pm 0.007	0.732 \pm 0.024	0.869 \pm 0.012
Argali Sheep	0.871 \pm 0.069	0.966 \pm 0.048	0.933 \pm 0.095	N/A	0.914 \pm 0.011
Bison	0.723 \pm 0.021	0.941 \pm 0.028	0.804 \pm 0.017	0.487 \pm 0.070	0.788 \pm 0.015
Buffalo	0.834 \pm 0.045	0.978 \pm 0.032	0.895 \pm 0.040	0.141 \pm 0.813	0.844 \pm 0.039
Cow	0.757 \pm 0.019	0.979 \pm 0.015	0.824 \pm 0.042	0.551 \pm 0.035	0.765 \pm 0.020
Sheep	0.761 \pm 0.011	0.959 \pm 0.015	0.833 \pm 0.010	0.598 \pm 0.154	0.769 \pm 0.008
Dog	0.771 \pm 0.013	0.962 \pm 0.006	0.836 \pm 0.003	0.129 \pm 0.803	0.772 \pm 0.011
Fox	0.780 \pm 0.002	0.943 \pm 0.025	0.843 \pm 0.014	N/A	0.780 \pm 0.002
Wolf	0.778 \pm 0.033	0.972 \pm 0.020	0.864 \pm 0.061	N/A	0.779 \pm 0.034
Beaver	0.562 \pm 0.004	0.919 \pm 0.021	0.663 \pm 0.015	0.867 \pm 0.047	0.557 \pm 0.008
Alouatta	0.784 \pm 0.038	1.000 \pm 0.000	0.924 \pm 0.061	N/A	0.784 \pm 0.038
Monkey	0.690 \pm 0.027	0.961 \pm 0.013	0.769 \pm 0.060	N/A	0.690 \pm 0.027
Noisy Night Monkey	0.765 \pm 0.026	0.960 \pm 0.000	0.803 \pm 0.068	N/A	0.777 \pm 0.040
Spider Monkey	0.602 \pm 0.046	0.871 \pm 0.024	0.627 \pm 0.072	0.300 \pm 0.920	0.600 \pm 0.048
Uakari	0.829 \pm 0.007	1.000 \pm 0.000	0.976 \pm 0.034	N/A	0.829 \pm 0.007
Deer	0.794 \pm 0.029	0.950 \pm 0.014	0.847 \pm 0.029	0.157 \pm 0.829	0.811 \pm 0.006
Moose	0.776 \pm 0.014	0.973 \pm 0.005	0.843 \pm 0.054	0.838 \pm 0.044	0.773 \pm 0.017
Hamster	0.571 \pm 0.064	0.864 \pm 0.042	0.563 \pm 0.079	0.241 \pm 0.175	0.603 \pm 0.051
Elephant	0.704 \pm 0.040	0.918 \pm 0.010	0.774 \pm 0.051	N/A	0.703 \pm 0.041
Horse	0.749 \pm 0.028	0.934 \pm 0.038	0.798 \pm 0.036	N/A	0.764 \pm 0.022
Zebra	0.755 \pm 0.026	0.921 \pm 0.013	0.775 \pm 0.041	N/A	0.764 \pm 0.019
Bobcat	0.751 \pm 0.055	0.976 \pm 0.034	0.842 \pm 0.057	N/A	0.753 \pm 0.057
Cat	0.672 \pm 0.036	0.935 \pm 0.006	0.750 \pm 0.067	N/A	0.675 \pm 0.037
Cheetah	0.735 \pm 0.029	0.936 \pm 0.010	0.800 \pm 0.026	N/A	0.769 \pm 0.032
Jaguar	0.785 \pm 0.035	0.972 \pm 0.020	0.864 \pm 0.082	0.592 \pm 0.170	0.803 \pm 0.024
King Cheetah	0.848 \pm 0.122	0.944 \pm 0.079	0.944 \pm 0.079	N/A	0.848 \pm 0.122
Leopard	0.731 \pm 0.009	0.956 \pm 0.034	0.796 \pm 0.047	N/A	0.731 \pm 0.009
Lion	0.726 \pm 0.017	0.927 \pm 0.024	0.817 \pm 0.038	N/A	0.726 \pm 0.017
Panther	0.772 \pm 0.048	0.985 \pm 0.021	0.851 \pm 0.027	0.084 \pm 0.769	0.780 \pm 0.051
Snow Leopard	0.858 \pm 0.042	1.000 \pm 0.000	0.939 \pm 0.048	0.183 \pm 0.849	0.865 \pm 0.035
Tiger	0.811 \pm 0.012	0.973 \pm 0.021	0.872 \pm 0.009	N/A	0.812 \pm 0.013
Giraffe	0.803 \pm 0.016	0.958 \pm 0.007	0.842 \pm 0.046	N/A	0.808 \pm 0.016
Hippo	0.457 \pm 0.062	0.746 \pm 0.089	0.451 \pm 0.064	0.627 \pm 0.273	0.462 \pm 0.052
Chimpanzee	0.642 \pm 0.009	0.912 \pm 0.034	0.689 \pm 0.044	0.567 \pm 0.126	0.645 \pm 0.018
Gorilla	0.753 \pm 0.010	0.950 \pm 0.029	0.881 \pm 0.038	N/A	0.753 \pm 0.010
Rabbit	0.731 \pm 0.013	0.968 \pm 0.003	0.821 \pm 0.023	N/A	0.731 \pm 0.013
Skunk	0.558 \pm 0.016	0.864 \pm 0.035	0.652 \pm 0.020	N/A	0.562 \pm 0.018
Mouse	0.640 \pm 0.015	0.954 \pm 0.033	0.717 \pm 0.036	0.123 \pm 0.796	0.640 \pm 0.013
Rat	0.650 \pm 0.031	0.929 \pm 0.015	0.729 \pm 0.052	0.200 \pm 0.849	0.652 \pm 0.030
Otter	0.559 \pm 0.017	0.909 \pm 0.031	0.582 \pm 0.050	N/A	0.559 \pm 0.017
Weasel	0.716 \pm 0.025	0.955 \pm 0.018	0.790 \pm 0.016	N/A	0.717 \pm 0.025
Raccoon	0.629 \pm 0.032	0.954 \pm 0.005	0.675 \pm 0.061	0.401 \pm 0.143	0.651 \pm 0.023
Rhino	0.819 \pm 0.021	0.980 \pm 0.000	0.892 \pm 0.048	N/A	0.819 \pm 0.021
Marmot	0.784 \pm 0.032	1.000 \pm 0.000	0.860 \pm 0.053	N/A	0.784 \pm 0.032
Squirrel	0.845 \pm 0.008	1.000 \pm 0.000	0.943 \pm 0.005	N/A	0.845 \pm 0.008
Pig	0.642 \pm 0.033	0.964 \pm 0.026	0.677 \pm 0.066	N/A	0.640 \pm 0.033
Black Bear	0.662 \pm 0.040	0.967 \pm 0.047	0.865 \pm 0.128	N/A	0.662 \pm 0.040
Brown Bear	0.617 \pm 0.029	0.940 \pm 0.011	0.660 \pm 0.051	0.067 \pm 0.759	0.620 \pm 0.026
Panda	0.583 \pm 0.008	0.912 \pm 0.020	0.607 \pm 0.082	N/A	0.583 \pm 0.009
Polar Bear	0.631 \pm 0.016	0.948 \pm 0.054	0.659 \pm 0.056	N/A	0.631 \pm 0.016

Table S3: Per-species results of HRNet-w32 [13] on the test set the SL Track at the setting of training from scratch.

species	AP	AP.5	AP.75	AP(M)	AP(L)
Antelope	0.835 \pm 0.019	0.955 \pm 0.021	0.911 \pm 0.021	0.706 \pm 0.026	0.851 \pm 0.020
Argali Sheep	0.858 \pm 0.065	0.966 \pm 0.048	0.932 \pm 0.097	N/A	0.904 \pm 0.005
Bison	0.705 \pm 0.026	0.917 \pm 0.036	0.773 \pm 0.020	0.484 \pm 0.115	0.769 \pm 0.014
Buffalo	0.810 \pm 0.044	0.973 \pm 0.039	0.870 \pm 0.060	0.136 \pm 0.806	0.818 \pm 0.043
Cow	0.733 \pm 0.018	0.962 \pm 0.017	0.810 \pm 0.009	0.571 \pm 0.091	0.742 \pm 0.018
Sheep	0.741 \pm 0.011	0.950 \pm 0.020	0.797 \pm 0.013	0.593 \pm 0.122	0.748 \pm 0.014
Dog	0.743 \pm 0.016	0.960 \pm 0.014	0.807 \pm 0.011	0.100 \pm 0.787	0.745 \pm 0.013
Fox	0.753 \pm 0.028	0.917 \pm 0.022	0.792 \pm 0.036	N/A	0.753 \pm 0.028
Wolf	0.756 \pm 0.030	0.966 \pm 0.025	0.771 \pm 0.053	N/A	0.756 \pm 0.030
Beaver	0.483 \pm 0.026	0.848 \pm 0.024	0.465 \pm 0.111	0.384 \pm 0.327	0.490 \pm 0.029
Alouatta	0.745 \pm 0.074	0.970 \pm 0.042	0.896 \pm 0.097	N/A	0.745 \pm 0.074
Monkey	0.621 \pm 0.025	0.906 \pm 0.030	0.655 \pm 0.056	N/A	0.623 \pm 0.027
Noisy Night Monkey	0.722 \pm 0.031	0.935 \pm 0.034	0.764 \pm 0.046	N/A	0.721 \pm 0.030
Spider Monkey	0.514 \pm 0.043	0.824 \pm 0.062	0.513 \pm 0.054	0.300 \pm 0.920	0.513 \pm 0.045
Uakari	0.750 \pm 0.004	1.000 \pm 0.000	0.886 \pm 0.029	N/A	0.750 \pm 0.004
Deer	0.805 \pm 0.032	0.967 \pm 0.034	0.856 \pm 0.022	0.134 \pm 0.806	0.822 \pm 0.011
Moose	0.741 \pm 0.007	0.939 \pm 0.03	0.815 \pm 0.011	0.776 \pm 0.055	0.739 \pm 0.011
Hamster	0.543 \pm 0.031	0.833 \pm 0.054	0.553 \pm 0.017	0.209 \pm 0.086	0.574 \pm 0.019
Elephant	0.664 \pm 0.035	0.881 \pm 0.051	0.725 \pm 0.064	N/A	0.662 \pm 0.037
Horse	0.759 \pm 0.033	0.928 \pm 0.043	0.802 \pm 0.025	0.023 \pm 0.731	0.765 \pm 0.033
Zebra	0.727 \pm 0.025	0.886 \pm 0.014	0.741 \pm 0.027	N/A	0.736 \pm 0.018
Bobcat	0.746 \pm 0.044	0.983 \pm 0.024	0.812 \pm 0.058	N/A	0.746 \pm 0.044
Cat	0.638 \pm 0.030	0.926 \pm 0.023	0.693 \pm 0.053	N/A	0.639 \pm 0.031
Cheetah	0.707 \pm 0.043	0.923 \pm 0.018	0.762 \pm 0.074	N/A	0.739 \pm 0.038
Jaguar	0.764 \pm 0.038	0.959 \pm 0.032	0.834 \pm 0.039	0.662 \pm 0.225	0.775 \pm 0.027
King Cheetah	0.813 \pm 0.074	0.944 \pm 0.079	0.944 \pm 0.079	N/A	0.813 \pm 0.074
Leopard	0.722 \pm 0.026	0.932 \pm 0.020	0.787 \pm 0.024	N/A	0.722 \pm 0.026
Lion	0.689 \pm 0.012	0.916 \pm 0.018	0.738 \pm 0.017	N/A	0.689 \pm 0.012
Panther	0.760 \pm 0.024	0.984 \pm 0.023	0.815 \pm 0.024	0.167 \pm 0.829	0.764 \pm 0.025
Snow Leopard	0.839 \pm 0.036	0.980 \pm 0.028	0.889 \pm 0.005	0.183 \pm 0.849	0.844 \pm 0.030
Tiger	0.764 \pm 0.018	0.971 \pm 0.024	0.828 \pm 0.026	N/A	0.764 \pm 0.018
Giraffe	0.784 \pm 0.009	0.942 \pm 0.020	0.819 \pm 0.016	N/A	0.789 \pm 0.013
Hippo	0.402 \pm 0.026	0.685 \pm 0.030	0.410 \pm 0.016	0.705 \pm 0.206	0.396 \pm 0.023
Chimpanzee	0.619 \pm 0.031	0.900 \pm 0.049	0.707 \pm 0.026	0.537 \pm 0.140	0.619 \pm 0.042
Gorilla	0.736 \pm 0.026	0.943 \pm 0.038	0.875 \pm 0.077	N/A	0.736 \pm 0.026
Rabbit	0.711 \pm 0.045	0.960 \pm 0.008	0.799 \pm 0.072	N/A	0.711 \pm 0.045
Skunk	0.499 \pm 0.039	0.830 \pm 0.079	0.514 \pm 0.054	N/A	0.504 \pm 0.041
Mouse	0.603 \pm 0.035	0.904 \pm 0.011	0.675 \pm 0.032	0.085 \pm 0.768	0.608 \pm 0.036
Rat	0.580 \pm 0.043	0.936 \pm 0.048	0.643 \pm 0.059	0.100 \pm 0.787	0.581 \pm 0.046
Otter	0.537 \pm 0.017	0.868 \pm 0.021	0.538 \pm 0.018	N/A	0.538 \pm 0.017
Weasel	0.649 \pm 0.041	0.945 \pm 0.026	0.691 \pm 0.075	N/A	0.649 \pm 0.041
Raccoon	0.585 \pm 0.028	0.940 \pm 0.009	0.590 \pm 0.113	0.363 \pm 0.124	0.601 \pm 0.026
Rhino	0.762 \pm 0.048	0.950 \pm 0.021	0.824 \pm 0.067	N/A	0.762 \pm 0.048
Marmot	0.768 \pm 0.043	1.000 \pm 0.000	0.843 \pm 0.099	N/A	0.768 \pm 0.043
Squirrel	0.849 \pm 0.022	1.000 \pm 0.000	0.962 \pm 0.027	N/A	0.849 \pm 0.022
Pig	0.612 \pm 0.045	0.907 \pm 0.049	0.648 \pm 0.057	N/A	0.610 \pm 0.045
Black Bear	0.684 \pm 0.034	0.967 \pm 0.047	0.861 \pm 0.133	N/A	0.684 \pm 0.034
Brown Bear	0.584 \pm 0.025	0.960 \pm 0.014	0.608 \pm 0.067	0.167 \pm 0.834	0.583 \pm 0.023
Panda	0.514 \pm 0.056	0.908 \pm 0.034	0.557 \pm 0.099	N/A	0.513 \pm 0.056
Polar Bear	0.619 \pm 0.016	0.928 \pm 0.028	0.650 \pm 0.021	N/A	0.619 \pm 0.016

Table S4: Per-species results of HRNet-w32 [13] on the **56 animals** test set the SL Track at the setting of pretraining on ImageNet.

species	AP	AP _{.5}	AP _{.75}	AP _M	AP _L
Antelope	0.856±0.017	0.965±0.011	0.920±0.019	0.739±0.016	0.869±0.014
Argali Sheep	0.868±0.061	0.987±0.019	0.934±0.093	N/A	0.917±0.012
Bison	0.713±0.020	0.945±0.016	0.783±0.023	0.501±0.111	0.769±0.008
Buffalo	0.825±0.050	0.973±0.026	0.899±0.049	0.113±0.796	0.837±0.043
Cow	0.764±0.023	0.993±0.009	0.828±0.047	0.663±0.052	0.770±0.025
Sheep	0.749±0.014	0.950±0.022	0.834±0.025	0.591±0.214	0.754±0.015
Chihuahua	0.760±0.021	0.982±0.025	0.851±0.042	N/A	0.760±0.021
Collie	0.775±0.026	0.973±0.021	0.877±0.053	N/A	0.775±0.026
Dalmatian	0.759±0.038	0.960±0.030	0.776±0.050	N/A	0.759±0.038
Dog	0.801±0.020	0.980±0.014	0.857±0.040	0.082±0.765	0.809±0.013
Fox	0.776±0.009	0.943±0.009	0.850±0.030	N/A	0.776±0.009
German Shepherd	0.777±0.045	0.958±0.011	0.864±0.063	N/A	0.777±0.045
Wolf	0.776±0.025	0.973±0.019	0.873±0.028	N/A	0.776±0.025
Beaver	0.564±0.046	0.868±0.047	0.623±0.128	0.585±0.300	0.565±0.045
Alouatta	0.764±0.034	1.000±0.000	0.922±0.061	N/A	0.764±0.034
Monkey	0.671±0.034	0.927±0.024	0.750±0.074	N/A	0.671±0.034
Noisy Night Monkey	0.755±0.049	0.973±0.019	0.847±0.081	N/A	0.759±0.055
Spider Monkey	0.573±0.044	0.871±0.036	0.620±0.059	0.267±0.899	0.571±0.045
Uakari	0.809±0.026	1.000±0.000	1.000±0.000	N/A	0.809±0.026
Deer	0.798±0.019	0.963±0.024	0.848±0.022	0.133±0.805	0.815±0.006
Moose	0.764±0.015	0.982±0.013	0.823±0.025	0.845±0.103	0.758±0.014
Hamster	0.595±0.036	0.875±0.044	0.628±0.078	0.288±0.133	0.626±0.040
Elephant	0.710±0.030	0.913±0.048	0.800±0.049	N/A	0.709±0.031
Horse	0.770±0.043	0.941±0.031	0.826±0.069	0.068±0.758	0.779±0.038
Zebra	0.748±0.024	0.910±0.017	0.760±0.054	N/A	0.761±0.016
Bobcat	0.765±0.043	0.983±0.024	0.845±0.022	N/A	0.768±0.046
Cat	0.697±0.052	0.962±0.008	0.807±0.086	N/A	0.697±0.052
Cheetah	0.756±0.047	0.942±0.011	0.821±0.093	N/A	0.785±0.036
Jaguar	0.793±0.041	0.984±0.011	0.866±0.080	0.638±0.195	0.809±0.029
King Cheetah	0.854±0.085	0.944±0.079	0.944±0.079	N/A	0.854±0.085
Leopard	0.760±0.005	0.983±0.024	0.850±0.017	N/A	0.760±0.005
Lion	0.716±0.022	0.922±0.008	0.787±0.016	N/A	0.716±0.022
Panther	0.794±0.037	0.983±0.024	0.914±0.037	0.184±0.837	0.796±0.038
Persian Cat	0.592±0.036	0.930±0.016	0.640±0.079	N/A	0.592±0.036
Siamese Cat	0.710±0.053	0.952±0.037	0.804±0.054	N/A	0.710±0.053
Snow Leopard	0.860±0.038	1.000±0.000	0.980±0.029	0.217±0.866	0.866±0.035
Tiger	0.810±0.014	0.979±0.015	0.858±0.019	N/A	0.810±0.014
Giraffe	0.799±0.025	0.949±0.021	0.840±0.044	N/A	0.805±0.020
Hippo	0.471±0.077	0.778±0.082	0.484±0.056	0.640±0.283	0.476±0.077
Chimpanzee	0.659±0.027	0.912±0.034	0.692±0.021	0.624±0.057	0.661±0.035
Gorilla	0.754±0.014	0.952±0.037	0.877±0.013	N/A	0.754±0.014
Rabbit	0.729±0.006	0.990±0.014	0.830±0.044	N/A	0.729±0.006
Skunk	0.576±0.033	0.874±0.044	0.651±0.046	N/A	0.580±0.035
Mouse	0.641±0.017	0.954±0.033	0.716±0.039	0.100±0.778	0.644±0.018
Rat	0.647±0.040	0.930±0.044	0.747±0.040	0.133±0.818	0.647±0.044
Otter	0.567±0.012	0.897±0.020	0.594±0.017	N/A	0.567±0.012
Weasel	0.694±0.033	0.935±0.017	0.781±0.040	N/A	0.694±0.033
Raccoon	0.649±0.041	0.972±0.021	0.759±0.035	0.433±0.128	0.673±0.035
Rhino	0.800±0.011	0.980±0.000	0.864±0.031	N/A	0.800±0.011
Marmot	0.792±0.046	0.967±0.047	0.917±0.072	N/A	0.792±0.046
Squirrel	0.863±0.008	1.000±0.000	0.953±0.013	N/A	0.863±0.008
Pig	0.645±0.040	0.928±0.050	0.706±0.039	N/A	0.644±0.040
Black Bear	0.685±0.035	1.000±0.000	0.853±0.144	N/A	0.685±0.035
Brown Bear	0.612±0.010	0.960±0.014	0.680±0.042	0.068±0.755	0.615±0.008
Panda	0.572±0.028	0.935±0.006	0.604±0.091	N/A	0.571±0.029
Polar Bear	0.623±0.001	0.931±0.053	0.654±0.015	N/A	0.623±0.001

Table S5: Per-species results of HRNet-w32 [13] on the **56 animals** test set the SL Track at the setting of training from scratch.

species	AP	AP _{.5}	AP _{.75}	AP _M	AP _L
Antelope	0.834±0.019	0.964±0.011	0.910±0.013	0.694±0.026	0.854±0.017
Argali Sheep	0.856±0.087	0.957±0.061	0.932±0.096	N/A	0.909±0.014
Bison	0.700±0.041	0.925±0.033	0.778±0.034	0.524±0.138	0.754±0.025
Buffalo	0.807±0.038	0.976±0.033	0.876±0.051	0.091±0.779	0.820±0.033
Cow	0.756±0.013	0.980±0.014	0.838±0.018	0.644±0.080	0.762±0.013
Sheep	0.749±0.013	0.958±0.024	0.831±0.019	0.616±0.160	0.755±0.013
Chihuahua	0.716±0.029	0.949±0.002	0.776±0.071	N/A	0.718±0.026
Collie	0.763±0.010	0.983±0.012	0.840±0.035	N/A	0.763±0.010
Dalmatian	0.723±0.041	0.916±0.025	0.731±0.055	N/A	0.723±0.041
Dog	0.782±0.016	0.964±0.014	0.850±0.013	0.149±0.825	0.791±0.019
Fox	0.738±0.017	0.939±0.008	0.803±0.049	N/A	0.738±0.017
German Shepherd	0.733±0.041	0.945±0.005	0.840±0.061	N/A	0.734±0.040
Wolf	0.751±0.040	0.971±0.020	0.794±0.070	N/A	0.751±0.040
Beaver	0.529±0.034	0.879±0.023	0.557±0.087	0.584±0.245	0.528±0.033
Alouatta	0.725±0.045	1.000±0.000	0.876±0.120	N/A	0.725±0.045
Monkey	0.629±0.052	0.930±0.023	0.686±0.082	N/A	0.629±0.052
Noisy Night Monkey	0.721±0.004	0.958±0.001	0.758±0.040	N/A	0.725±0.010
Spider Monkey	0.535±0.029	0.830±0.048	0.588±0.033	0.233±0.873	0.533±0.031
Uakari	0.763±0.028	1.000±0.000	0.921±0.017	N/A	0.763±0.028
Deer	0.792±0.031	0.960±0.029	0.836±0.037	0.130±0.804	0.808±0.011
Moose	0.759±0.017	0.959±0.008	0.844±0.019	0.691±0.136	0.761±0.019
Hamster	0.520±0.043	0.829±0.079	0.535±0.035	0.276±0.138	0.553±0.024
Elephant	0.672±0.038	0.883±0.031	0.772±0.051	N/A	0.671±0.040
Horse	0.757±0.015	0.935±0.022	0.785±0.008	N/A	0.768±0.012
Zebra	0.725±0.024	0.872±0.024	0.752±0.038	N/A	0.733±0.020
Bobcat	0.727±0.054	0.973±0.021	0.793±0.088	N/A	0.727±0.054
Cat	0.667±0.040	0.943±0.006	0.755±0.040	N/A	0.672±0.041
Cheetah	0.718±0.020	0.956±0.010	0.751±0.083	N/A	0.742±0.031
Jaguar	0.748±0.016	0.971±0.021	0.843±0.021	0.649±0.230	0.764±0.013
King Cheetah	0.798±0.079	0.944±0.079	0.832±0.138	N/A	0.798±0.079
Leopard	0.705±0.004	0.938±0.030	0.782±0.062	N/A	0.705±0.004
Lion	0.685±0.026	0.915±0.019	0.714±0.046	N/A	0.685±0.026
Panther	0.748±0.041	0.983±0.024	0.798±0.044	0.217±0.863	0.748±0.040
Persian Cat	0.559±0.046	0.858±0.015	0.535±0.070	N/A	0.559±0.046
Siamese Cat	0.677±0.038	0.965±0.025	0.713±0.063	N/A	0.677±0.038
Snow Leopard	0.826±0.058	1.000±0.000	0.866±0.077	0.167±0.850	0.831±0.048
Tiger	0.764±0.021	0.962±0.034	0.820±0.008	N/A	0.764±0.021
Giraffe	0.783±0.015	0.949±0.015	0.815±0.027	N/A	0.790±0.012
Hippo	0.383±0.062	0.659±0.070	0.383±0.058	0.615±0.245	0.384±0.057
Chimpanzee	0.625±0.031	0.944±0.026	0.709±0.051	0.547±0.114	0.629±0.038
Gorilla	0.736±0.029	0.942±0.036	0.836±0.058	N/A	0.736±0.029
Rabbit	0.712±0.032	0.979±0.015	0.791±0.031	N/A	0.712±0.032
Skunk	0.514±0.032	0.832±0.013	0.566±0.089	N/A	0.518±0.032
Mouse	0.608±0.032	0.928±0.030	0.657±0.090	0.124±0.795	0.607±0.032
Rat	0.588±0.079	0.935±0.058	0.623±0.128	0.133±0.806	0.586±0.083
Otter	0.537±0.021	0.889±0.037	0.516±0.048	N/A	0.537±0.021
Weasel	0.654±0.027	0.917±0.012	0.715±0.019	N/A	0.656±0.028
Raccoon	0.596±0.014	0.935±0.017	0.588±0.063	0.452±0.178	0.612±0.010
Rhino	0.773±0.043	0.945±0.033	0.854±0.076	N/A	0.773±0.043
Marmot	0.770±0.037	1.000±0.000	0.836±0.064	N/A	0.770±0.037
Squirrel	0.840±0.019	1.000±0.000	0.951±0.037	N/A	0.840±0.019
Pig	0.616±0.060	0.902±0.062	0.712±0.095	N/A	0.615±0.059
Black Bear	0.682±0.066	0.967±0.047	0.807±0.099	N/A	0.686±0.061
Brown Bear	0.589±0.022	0.973±0.005	0.621±0.050	0.101±0.779	0.589±0.022
Panda	0.525±0.033	0.921±0.024	0.498±0.081	N/A	0.524±0.033
Polar Bear	0.599±0.022	0.912±0.037	0.639±0.015	N/A	0.599±0.022

21 A.2 Motivation

22 **1. For what purpose was the dataset created? Was there a specific task in mind? Was there a**
23 **specific gap that needed to be filled? Please provide a description.**

24 **A1:** AP-10K is created to facilitate research in the area of animal pose estimation. It is important
25 to study several challenging questions in the context of more training data from diverse species are
26 available, such as 1) how about the performance of different representative human pose models on
27 the animal pose estimation task? 2) will the representation ability of a deep model benefit from
28 training on a large-scale dataset with diverse species? 3) how about the impact of pretraining, *e.g.*,
29 on the ImageNet dataset [5] or human pose estimation dataset [9], in the context of the large-scale of
30 dataset with diverse species? and 4) how about the intra- and inter-family generalization ability of
31 a model trained using data from specific species or family? However, previous datasets for animal
32 pose estimation contain limited number of animal species. Therefore, it is impossible to study these
33 questions using existing datasets as they contains at most 5 species, which is far from enough to get
34 sound conclusion. By contrast, AP-10K has 23 family and 54 species and thus can help researchers
35 to study these questions.

36 **2. Who created this dataset (e.g., which team, research group) and on behalf of which entity**
37 **(e.g., company, institution, organization)?**

38 **A2:** AP-10K is created by the authors as well as some volunteer graduate students from Xidian
39 University, including Jiarui Fan, Ziming Bai, Jinglong Zhao, Yan Liu, Yi Liu, Jiaming Li, Hanbo
40 Sun, Chong Guo, Junwei Duan, and Xinyu Wang.

41 **3. Who funded the creation of the dataset? If there is an associated grant, please provide the**
42 **name of the grantor and the grant name and number.**

43 **A3:** The creation of the dataset is founded by the Innovation Capability Support Program of Shaanxi
44 under the grant of Program No.2021TD-05 and the National Natural Science Foundation of China
45 under the grant of No.62133012, No.61936006.

46 A.3 Composition

47 **1. What do the instances that comprise the dataset represent (e.g., documents, photos, people,**
48 **countries)? Are there multiple types of instances(e.g., movies, users, and ratings; people and**
49 **interactions between them; nodes and edges)? Please provide a description.**

50 **A1:** AP-10K is comprised of images covering 54 animal species, which are categorized following
51 the taxonomic rank, *i.e.*, family and species. For each animal instance, its 17 keypoint annotations
52 are provided, including Left Eye, Right Eye, Nose, Neck, Root of Tail, Left Shoulder, Left Elbow,
53 Left Front Paw, Right Shoulder, Right Elbow, Right Front Paw, Left Hip, Left Knee, Left Back Paw,
54 Right Hip, Right Knee, Right Back Paw.

55 **2. How many instances are there in total (of each type, if appropriate)?**

56 **A2:** The AP-10K dataset contains 10,015 images and 13,028 instances with keypoint annotations.
57 Besides, AP-10K contains extra 49,643 images, where each image is only annotated with family and
58 species labels, without keypoint annotations.

59 **3. Does the dataset contain all possible instances or is it a sample (not necessarily random)**
60 **of instances from a larger set? If the dataset is a sample, then what is the larger set? Is**
61 **the sample representative of the larger set (e.g., geographic coverage)? If so, please describe**
62 **how this representativeness was validated/verified. If it is not representative of the larger set,**
63 **please describe why not (e.g., to cover a more diverse range of instances, because instances**
64 **were withheld or unavailable).**

65 **A3:** AP-10K is a real-world sample of animals, including information about their poses. It is the
66 largest dataset in the area of animal pose estimation, *e.g.*, 10× more species compared with other
67 previous datasets. Due to the diversity of real-world animal species, it is impossible to cover all
68 instances of wild animals on a single dataset. The AP-10K dataset contains 23 typical families and
69 54 species, which follows the taxonomic rank, providing a more diverse set of instances than ever
70 before and will facilitate further studies of animal pose estimation. Biological proximity exploited
71 in AP-10K may be used to help the model extend to more species in the wild.

72 **4. What data does each instance consist of? Raw data (e.g., unprocessed text or images) or**
73 **features? In either case, please provide a description.**

74 **A4:** Each instance consists of one animal with its location (bounding box), family and species labels,
75 keypoint annotations, and the unprocessed image data.

76 **5. Is there a label or target associated with each instance? If so, please provide a description.**

77 **A5:** Yes. Each target is associated with labels following the COCO-style, which contain the in-
78 stance id, image id, category information (family and species), the box area, whether is crowded or
79 not, the number of keypoints, detailed keypoints information (location and category), as well as the
80 background category.

81 **6. Is any information missing from individual instances? If so, please provide a description,**
82 **explaining why this information is missing (e.g., because it was unavailable). This does not**
83 **include intentionally removed information, but might include, e.g., redacted text.**

84 **A6:** Yes. Some instances may not have the complete keypoint annotation due to occlusion, blur, or
85 small scale, similar to those instances in the COCO human pose dataset. Therefore, the location and
86 visibility of these keypoints are marked zero following the COCO-style.

87 **7. Are relationships between individual instances made explicit (e.g., users movie ratings, so-**
88 **cial network links)? If so, please describe how these relationships are made explicit.**

89 **A7:** Yes. The instances' information are stored in the COCO-style, where the relationship between
90 instances, *e.g.*, whether two instances belong to the same category or are on the same image, can be
91 queried using the [COCO APIs](#).

92 **8. Are there recommended data splits (e.g., training, development/validation, testing)? If so,**
93 **please provide a description of these splits, explaining the rationale behind them.**

94 **A8:** Yes. We randomly split the dataset into disjoint train, validation, and test sets following the
95 ratio of 7:1:2. The splits are done within each species to keep the origin distribution.

96 **9. Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide**
97 **a description.**

98 **A9:** Although we have carefully double-check the annotations, there may be some inaccurate key-
99 point annotations, *e.g.*, small drifts in the annotation of keypoint locations. To figure out the error
100 rate of AP-10K annotations, we re-examine the annotations, and the results are available in Table [S6](#).

Table S6: Error rate in AP-10K.

Number of Images	Total keypoints	Mislabeled keypoints	Error rate
10015	130142	15	0.012%

101 **10. Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g.,**
102 **websites, tweets, other datasets)? If it links to or relies on external resources, a) are there**
103 **guarantees that they will exist, and remain constant, over time; b) are there official archival**
104 **versions of the complete dataset (i.e., including the external resources as they existed at the**
105 **time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with**
106 **any of the external resources that might apply to a future user? Please provide descriptions**
107 **of all external resources and any restrictions associated with them, as well as links or other**
108 **access points, as appropriate.**

109 **A10:** The AP-10K is comprised of the publicly available datasets, including African Wildlife [\[6\]](#),
110 Animal-Pose Dataset [\[3\]](#), Animal Image Dataset(DOG, CAT and PANDA) [\[11\]](#), Endangered An-
111 imals [\[8\]](#), IUCN Animals Dataset [\[2\]](#), Animals with Attributes 2 [\[14\]](#), Animals-5 [\[12\]](#), Animals-
112 10 [\[1\]](#), and Wild Cats [\[16\]](#). These datasets are publicly available and can be downloaded from their
113 websites, *e.g.*, the Animals-10 dataset follows the GPL v2 license while Endangered Animals fol-
114 lows the CC-BY-4.0 license. We appreciate the significant contribution of the authors to the research
115 community. Table [S7](#) shows the number of images contained in the each dataset that contribute to
116 the AP-10K dataset.

Table S7: The source dataset adopted in AP-10K.

Source Dataset	Number of Images
African Wildlife [6]	1454
Animal Image Dataset(DOG, CAT and PANDA) [11]	2753
Animal-Pose [3]	970
Animals with Attributes 2 [14]	31701
Animals-5 [12]	5110
Animals-10 [1]	14029
Endangered Animals [8]	284
IUCN Animals Dataset [2]	1689
Wild Cats [16]	1558
Internet	110

117 **11. Does the dataset contain data that might be considered confidential (e.g., data that is**
 118 **protected by legal privilege or by doctor/patient confidentiality, data that includes the content**
 119 **of individuals non-public communications)? If so, please provide a description.**

120 **A11:** No.

121 **12. Does the dataset contain data that, if viewed directly, might be offensive, insulting, threat-**
 122 **ening, or might otherwise cause anxiety? If so, please describe why.**

123 **A12:** No.

124 **A.4 Collection Process**

125 **1. How was the data associated with each instance acquired? Was the data directly observ-**
 126 **able (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly**
 127 **inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or lan-**
 128 **guage)? If data was reported by subjects or indirectly inferred/derived from other data, was**
 129 **the data validated/verified? If so, please describe how.**

130 **A1:** The data associated with each instance are directly observable, as they are stored as the common
 131 COCO format and can be easily viewed via the [COCO APIs](#).

132 **2. What mechanisms or procedures were used to collect the data (e.g., hardware apparatus**
 133 **or sensor, manual human curation, software program, software API)? How were these mecha-**
 134 **nisms or procedures validated?**

135 **A2:** The images in AP-10K come from dataset publicly available datasets described above, which
 136 can be directly downloaded from their websites.

137 **3. If the dataset is a sample from a larger set, what was the sampling strategy (e.g., determin-**
 138 **istic, probabilistic with specific sampling probabilities)?**

139 **A3:** No.

140 **4. Who was involved in the data collection process (e.g., students, crowdworkers, contractors)**
 141 **and how were they compensated (e.g., how much were crowdworkers paid)?**

142 **A4:** The first author of this paper.

143 **5. Over what timeframe was the data collected? Does this timeframe match the creation**
 144 **timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If**
 145 **not, please describe the timeframe in which the data associated with the instances was created.**

146 **A5:** It took about 1 day to collect the data and about 3 months to complete organization and annota-
 147 tion, as each participant labelled the bounding boxes and keypoints about one hour per workday.

148 **A.5 Preprocessing/cleaning/labeling**

149 **1. Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing,**
 150 **tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing**

151 **of missing values)? If so, please provide a description. If not, you may skip the remainder of**
152 **the questions in this section.**

153 **A1:** We remove replicated images by using aHash [4] to detect similar images and manually check-
154 ing. Then, images with heavy occlusion and logos are removed manually. These images are cate-
155 gorized into family and species, which are double checked by the annotators to ensure the image
156 quality of AP-10K. Next, the annotators after training start to annotate the images.

157 During training, annotators first learned about the physiognomy, body structure and distribution of
158 keypoints of the animals. Then, five images of each species were presented to annotators to annotate
159 keypoints, which were used to assess their annotation quality. Annotators with good annotation
160 quality were further trained on how to deal with the partial absence of the body due to occlusion and
161 were involved in the subsequent annotation process. Annotators were asked to annotate all visible
162 keypoints. For the occluded keypoints, they were asked to annotate keypoints whose location they
163 could estimate based on body plan, pose, and the symmetry property of the body, where the length
164 of occluded limbs or the location of occluded keypoints could be inferred from the visible limbs or
165 keypoints. Other keypoints were left unlabeled. As shown in Figure 1, the right limb of the polar
166 bear on the right could not be estimated accurately, so the annotator did not annotate it, while the
167 right limb of the panda was annotated because it could be easily estimated from their pose and the
168 symmetry property of the body.

169 To guarantee the annotation quality, we have adopted a sequential labeling strategy. Three rounds of
170 cross-check and correction are conducted with both manual check and automatic check (according
171 to specific rules, *e.g.*, keypoints belonging to an instance are in the same bounding box) to reduce
172 the possibility of mislabeling.

173 **2. Was the raw data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support**
174 **unanticipated future uses)? If so, please provide a link or other access point to the raw data.**

175 **A2:** No.

176 **3. Is the software used to preprocess/clean/label the instances available? If so, please provide**
177 **a link or other access point.**

178 **A3:** We use the open source labelling [tool](#).

179 **A.6 Uses**

180 **1. Has the dataset been used for any tasks already? If so, please provide a description.**

181 **A1:** No.

182 **2. Is there a repository that links to any or all papers or systems that use the dataset? If so,**
183 **please provide a link or other access point.**

184 **A2:** N/A.

185 **3. What (other) tasks could the dataset be used for?**

186 **A3:** AP-10K can be used for the research of animal pose estimation. Besides, it can also be used for
187 specific machine learning topics such as few-shot learning, domain generalization, self-supervised
188 learning. Please see the Discussion part in the paper.

189 **4. Is there anything about the composition of the dataset or the way it was collected and**
190 **preprocessed/cleaned/labeled that might impact future uses? For example, is there anything**
191 **that a future user might need to know to avoid uses that could result in unfair treatment of**
192 **individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms**
193 **(e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future**
194 **user could do to mitigate these undesirable harms?**

195 **A4:** No.

196 **5. Are there tasks for which the dataset should not be used? If so, please provide a description.**

197 **A5:** No.

198 **A.7 Distribution**

199 **1. Will the dataset be distributed to third parties outside of the entity (e.g., company, institu-**
200 **tion, organization) on behalf of which the dataset was created? If so, please provide a descrip-**
201 **tion.**

202 **A1:** Yes. The dataset will be made publicly available to the research community.

203 **2. How will the dataset will be distributed (e.g., tarball on website, API, GitHub)? Does the**
204 **dataset have a digital object identifier (DOI)?**

205 **A2:** It will be publicly available on the project website at [GitHub](#).

206 **3. When will the dataset be distributed?**

207 **A3:** The dataset will be distributed once the paper is accepted after peer-review.

208 **4. Will the dataset be distributed under a copyright or other intellectual property (IP) license,**
209 **and/or under applicable terms of use (ToU)? If so, please describe this license and/or ToU, and**
210 **provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or**
211 **ToU, as well as any fees associated with these restrictions.**

212 **A4:** It will be distributed under the MIT licence.

213 **5. Have any third parties imposed IP-based or other restrictions on the data associated with**
214 **the instances? If so, please describe these restrictions, and provide a link or other access point**
215 **to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with**
216 **these restrictions.**

217 **A5:** No.

218 **6. Do any export controls or other regulatory restrictions apply to the dataset or to individual**
219 **instances? If so, please describe these restrictions, and provide a link or other access point to,**
220 **or otherwise reproduce, any supporting documentation.**

221 **A6:** No.

222 **A.8 Maintenance**

223 **1. Who will be supporting/hosting/maintaining the dataset?**

224 **A1:** The authors.

225 **2. How can the owner/curator/manager of the dataset be contacted (e.g., email address)?**

226 **A2:** They can be contacted via email available on the project website.

227 **3. Is there an erratum? If so, please provide a link or other access point.**

228 **A3:** No.

229 **4. Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete in-**
230 **stances)? If so, please describe how often, by whom, and how updates will be communicated**
231 **to users (e.g., mailing list, GitHub)?**

232 **A4:** No. We have carefully double checked the annotations to reduce the labeling errors. There may
233 be a very few of labeling errors, which can be treated as noise.

234 **5. Will older versions of the dataset continue to be supported/hosted/maintained? If so, please**
235 **describe how. If not, please describe how its obsolescence will be communicated to users.**

236 **A5:** N/A.

237 **6. If others want to extend/augment/build on/contribute to the dataset, is there a mecha-**
238 **nism for them to do so? If so, please provide a description. Will these contributions be**
239 **validated/verified? If so, please describe how. If not, why not? Is there a process for com-**
240 **municating/distributing these contributions to other users? If so, please provide a description.**

241 **A6:** N/A.



Figure S1: representative examples of failures of the pose estimation in our AP-10K.

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Figure S2: Some visual examples of animal species and annotations in our AP-10K.



Figure S3: Some visual examples of animal species and annotations in our AP-10K.



Figure S4: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Antelope, Argali Sheep, Deer, Moose, and Giraffe, respectively.



Figure S5: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Bison, Buffalo, Cow, and Sheep, respectively.

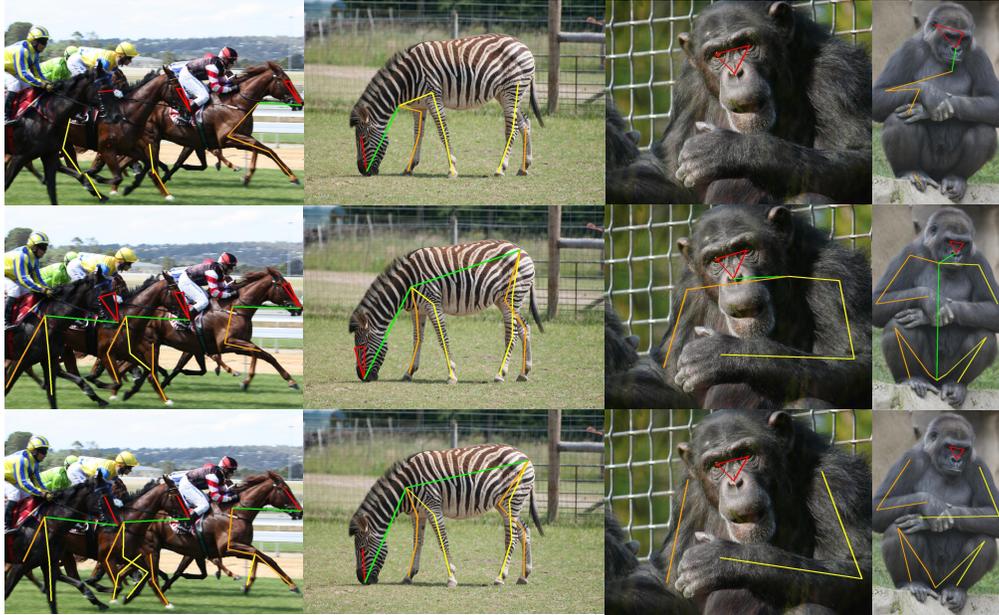


Figure S6: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Horse, Zebra, Chimpanzee, and Gorilla, respectively.

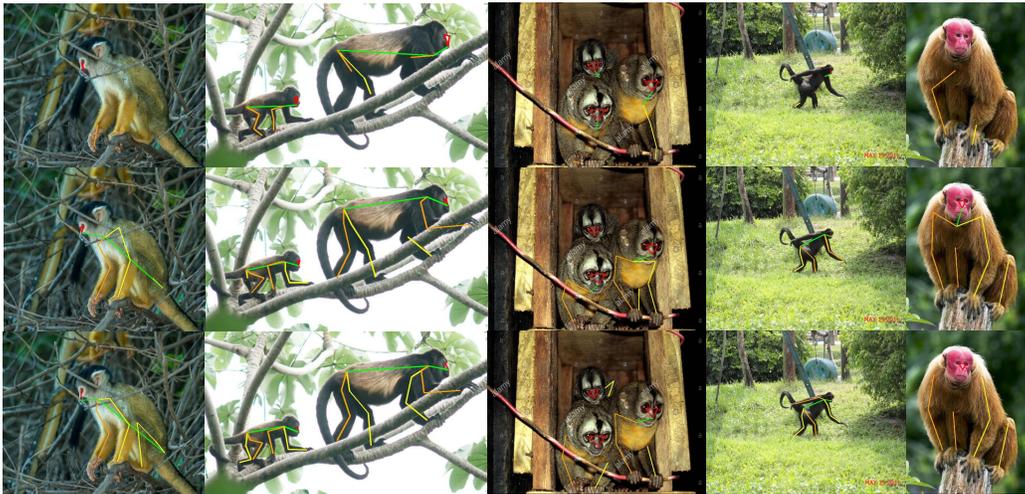


Figure S7: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Monkey, Alouatta, Noisy Night Monkey, Spider Monkey, and Uakari, respectively.

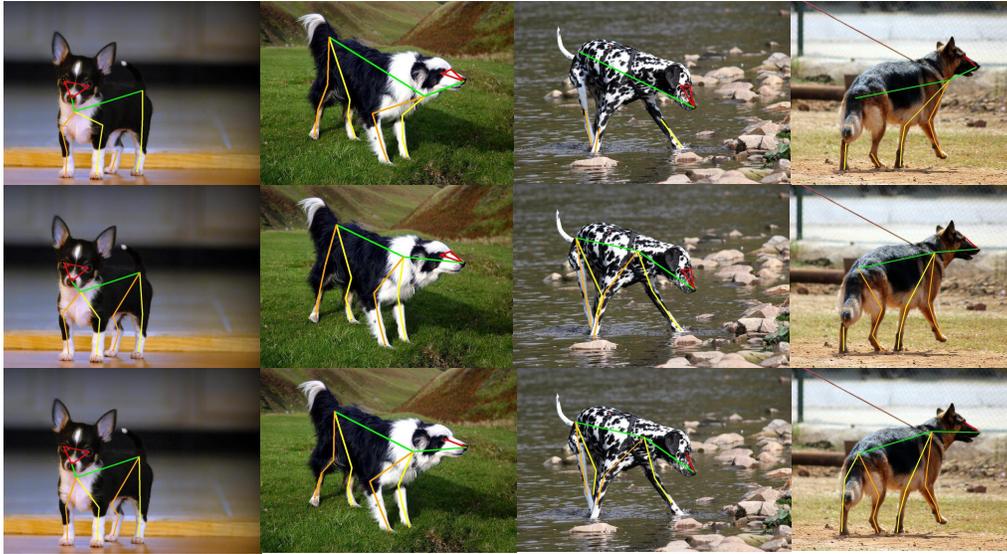


Figure S8: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Chihuahua, Collie, Dalmatian, and German Shepherd, respectively.

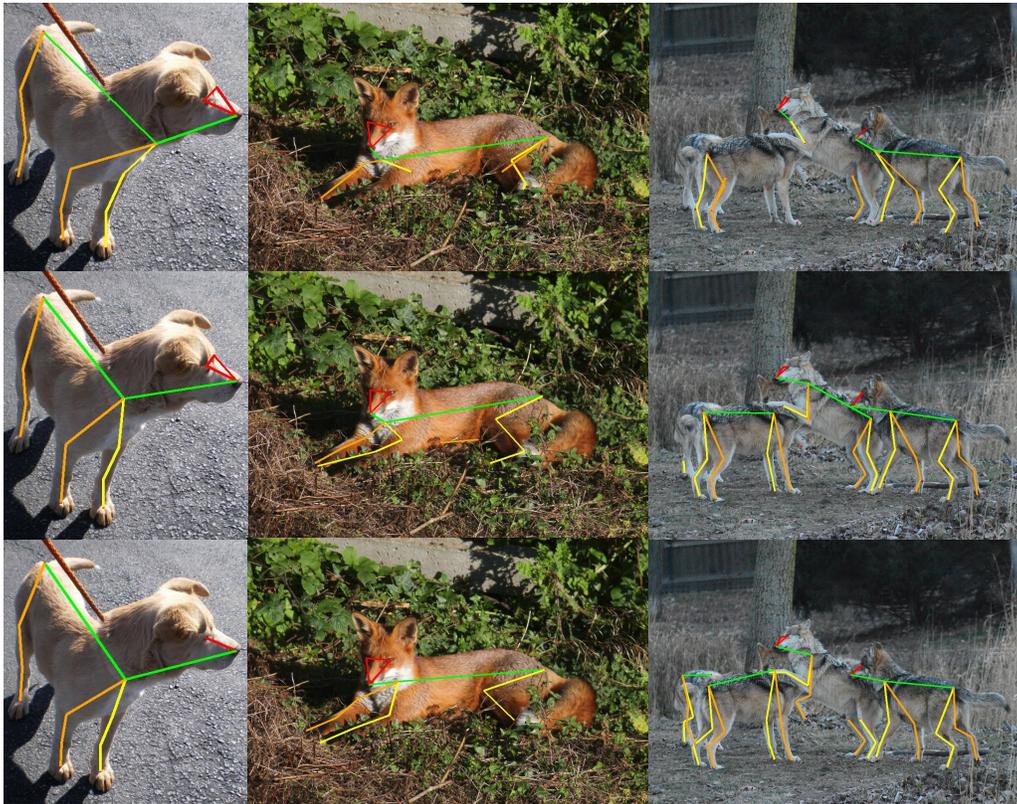


Figure S9: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataet (the second row). The ground truth poses are shown in the last row. These animals are Dog, Fox, and Wolf, respectively.

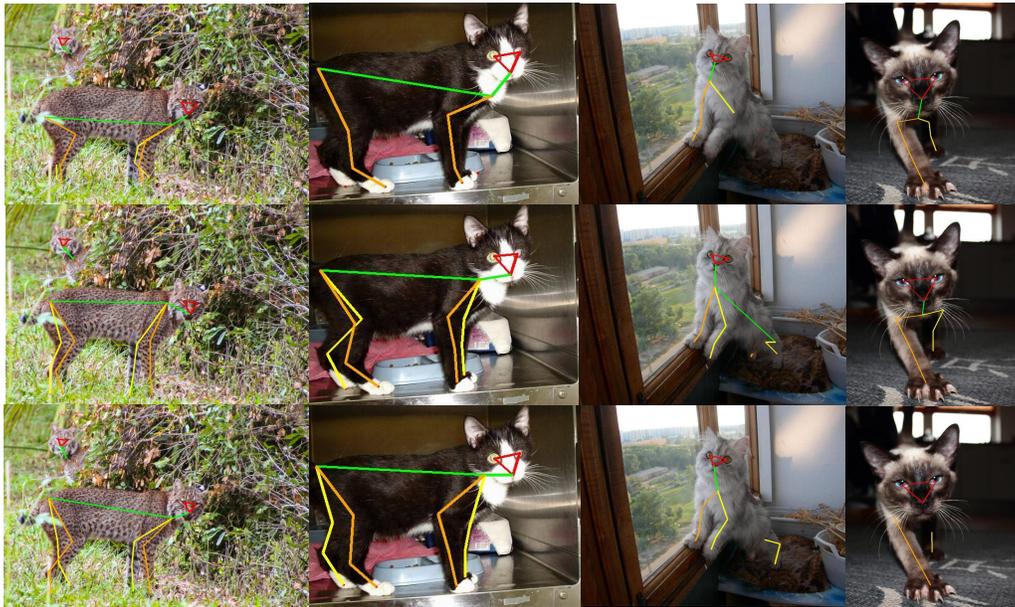


Figure S10: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Bobcat, Cat, Persian Cat, and Siamese Cat, respectively.

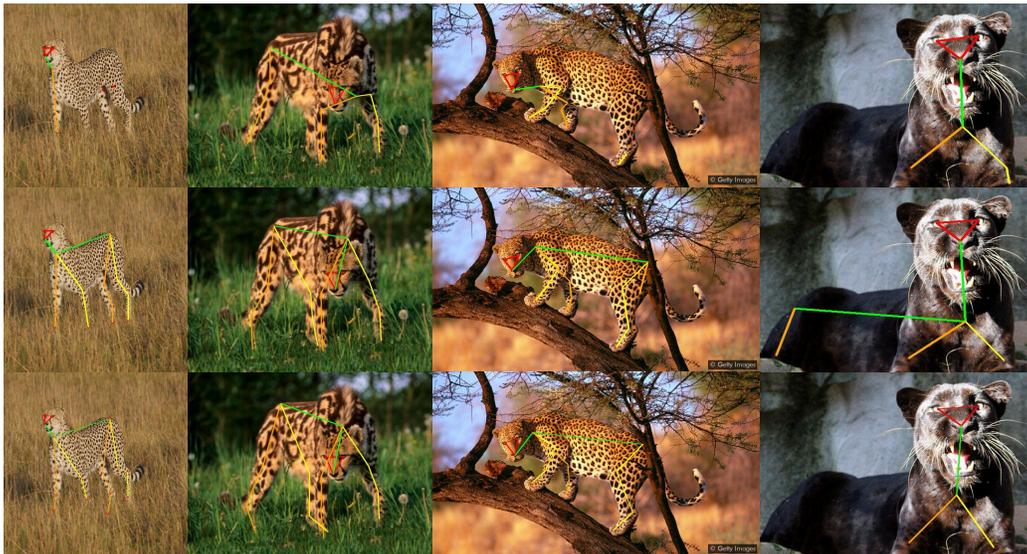


Figure S11: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Cheetah, King Cheetah, Leopard, and Panther, respectively.



Figure S12: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataet (the second row). The ground truth poses are shown in the last row. These animals are Snow Leopard, Lion, Jaguar, and Tiger, respectively.

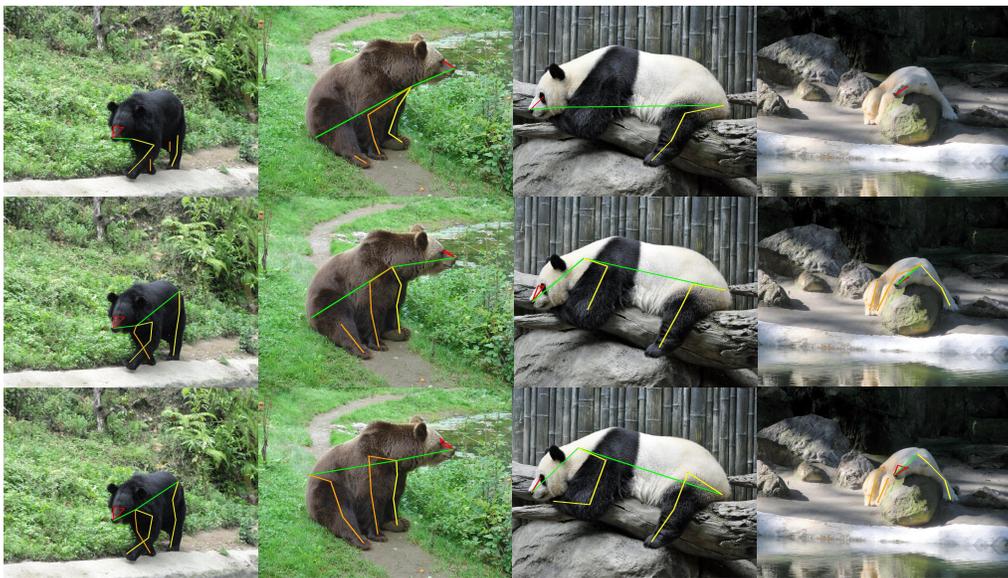


Figure S13: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataet (the second row). The ground truth poses are shown in the last row. These animals are Black Bear, Brown Bear, Panda, and Polar Bear, respectively.



Figure S14: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. Elephant, Hippo, Rhino, and Pig, respectively.

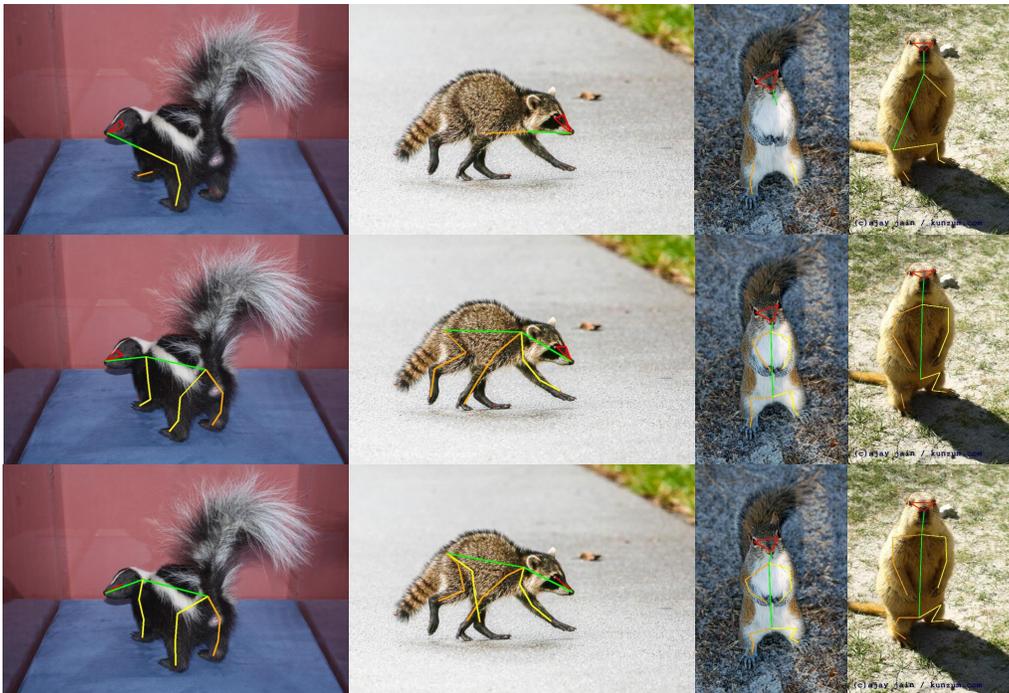


Figure S15: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Skunk, Raccoon, Squirrel, and Marmot, respectively.



Figure S16: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Beaver, Otter, and Weasel, respectively.

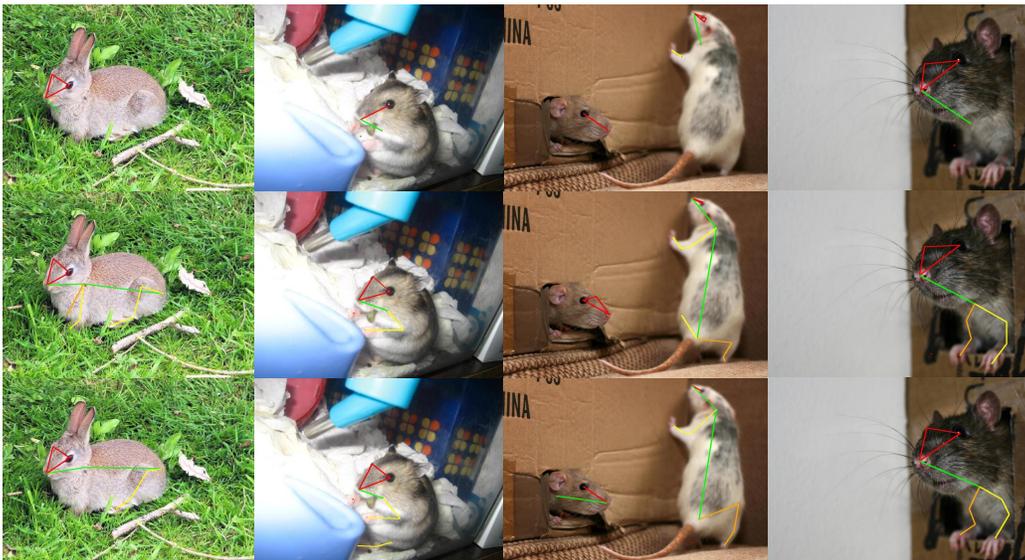


Figure S17: More qualitative results of HRNet-w32 trained on the Animal Pose dataset [3] (the first row) and our AP-10K dataset (the second row). The ground truth poses are shown in the last row. These animals are Rabbit, Hamster, Mouse, and Rat, respectively.



Figure S18: The results on video for animals in the wild.



Figure S19: The results on video for animals in the wild.

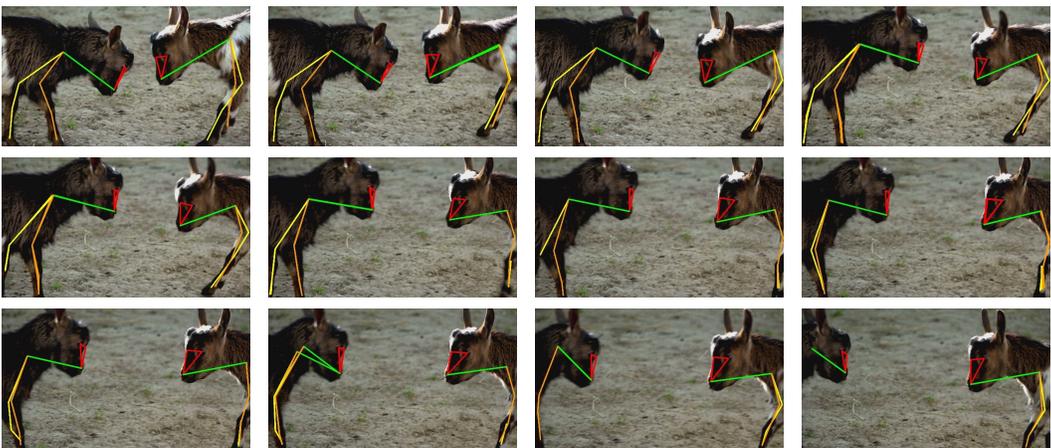


Figure S20: The results on video for animals in the wild.

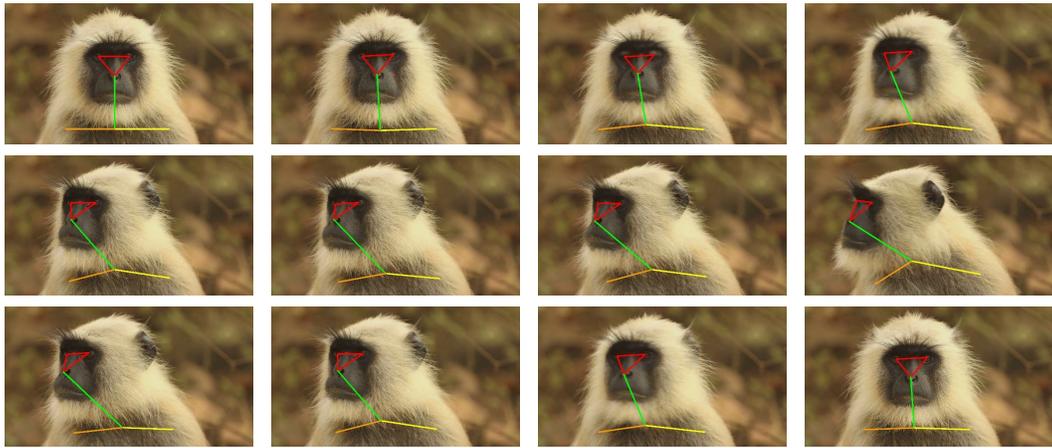


Figure S21: The results on video for animals in the wild.

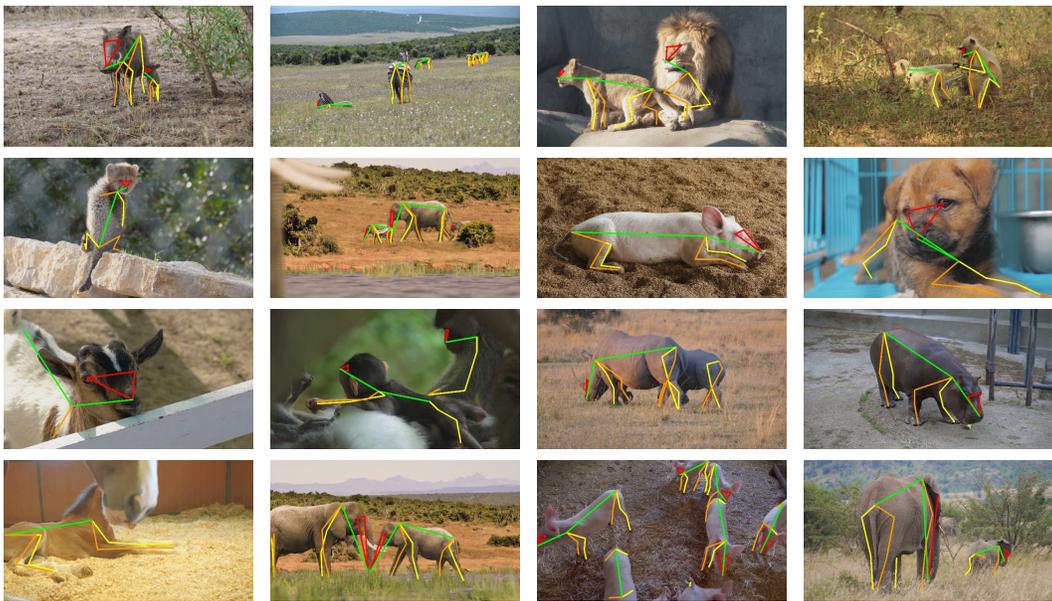


Figure S22: The results on video for animals in the wild (different scenes).