You Only Annotate Once.

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Why I believe in learning with little supervision. The Perspective from Human Vision.

- Human infants learn vision without direct supervision. And, despite a few recent claims, the human visual system remains the gold standard for general purpose vision.
- There is an enormous literature on how infants learn vision. Different visual abilities arise at different times in a stereotyped sequence.
- Infants learn by actively interacting with and exploring the world. They are not merely passive acceptors of stimuli. They are more like tiny scientists who understand the world by performing experiments and seeking causal explanations for phenomena.

Arterberry and Kellman. “Development of Perception in Infancy” (2016).
Gopnik et al. “The Scientist in the Crib”. (2000)

The Perspective from Computer Vision

- The current evaluation paradigm for computer vision assumes finite annotated datasets which are balanced for training and testing.
- This is limited for several reasons:
- (1) It is hard/impossible to provide annotations for many visual tasks. This biases researchers to work on problems for which annotated datasets exist. My students say "we can't work on this problem because there isn't an annotated dataset". *Fortunately my wife writes an unsupervised algorithm to solve the problem.*
- (2) In real world situations, balanced training and testing datasets do not exist and it is impractical to create them.
- (3) Current datasets are finite-sized, of necessity, and fail to capture the complexity of the real world. They are biased and contain corner cases ("almost everything is a corner case" – professional annotator).
- (4) Fundamentally, the world is combinatorially complex.

A.L. Yuille and C. Liu. "Deep Networks: What Have They Ever Done for Vision?". IJCV. 2020.

To a New Evaluation Paradigm

- We need to move towards a new paradigm where we separate learning/training.
- *We should train with very little annotated data (rest of talk).*
- We should test over an infinite set of images by studying the worst cases and allowing our "worst enemy" to test our algorithm. An *Adversarial Examiner* who adaptively selects a sequence of test images to probe the weaknesses of your algorithm. *Don't test an algorithm on random samples. Would a professor test students by asking them random questions?*
- M. Shu, C. Liu, W. Qiu, & A.L. Yuille. Identifying Model Weakness with Adversarial Examiner. AAAI. 2020.

Learning to Parse Animals with Weak Prior Knowledge: “You Only Annotate Once”.

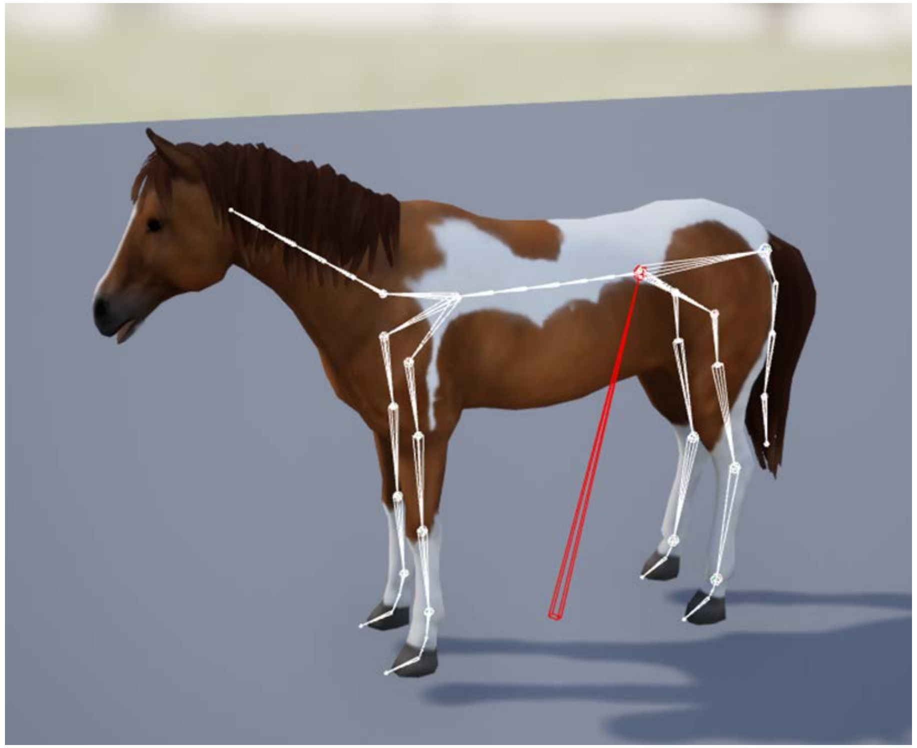
- Infants play with toys.
- An infant can play with a toy horse, or a toy dog.
- The infant can explore what geometric configurations it can take (without breaking) and identify the key-points where it bends.
- The infant can see the toy horse from different viewpoints and under different lighting conditions.
- The infant can paint the horse, or smear food on it, to see how the appearance changes.
- In short, the infant can build a computer graphics model of the horse. The infant has “annotated a horse once”.
- How can this help the infant detect and parse real world horses?

You Only Annotate Once

- Key ideas:
- (I) Take a computer graphics model of a horse, or tiger, and annotate its key-point. You only annotate once.
- (II) Generate a large set of simulated images (with key-points known) with diversity of viewpoint, pose, lighting, texture appearance, and of background.
- (III) Train a model for detecting key-points on these simulated images.
- *But these images are not very realistic and are of a single horse only. Their performance at key-point detection is weak on real images.*
- (IV) Retrain the key-point detection using self-supervised learning on real images of horses including videos.
- *Performance is now much better.*
- *Jiteng Mu, Weichao Qiu, et al. CVPR (oral). 2020.*

Animal Parsing

- Annotate Key Points of a Synthetic Animal. Goal: parse real animal.
- J. Mu, W. Qiu, et al. CVPR. 2020.

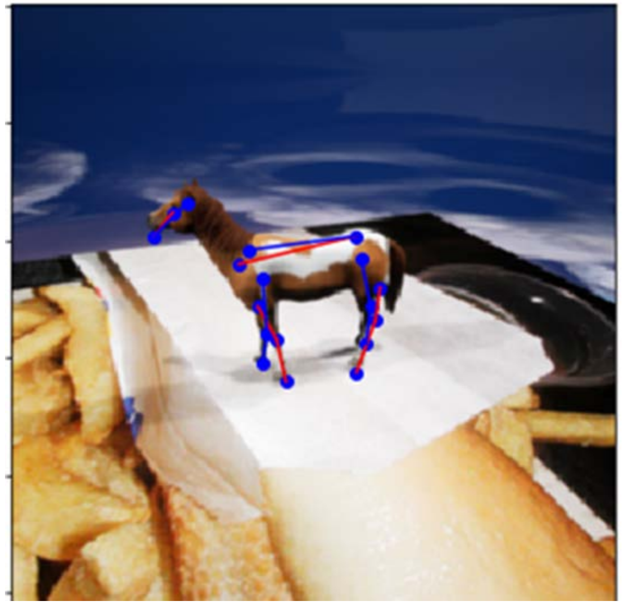


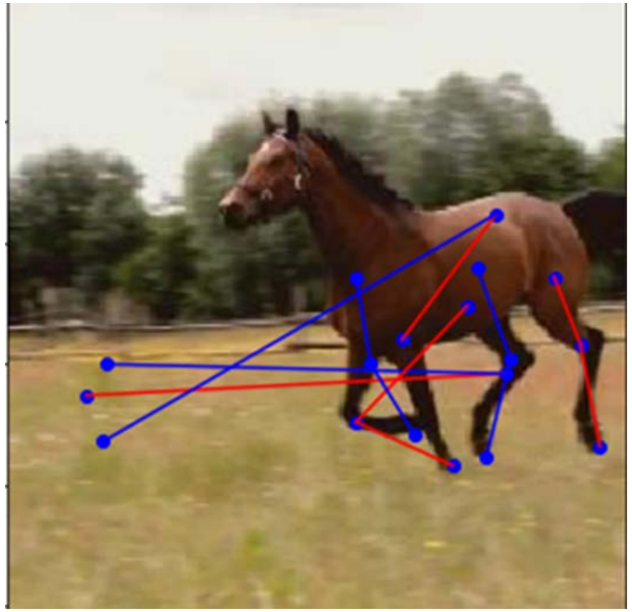
History of this project

- Stage 1: Use synthetic data as if it was real data (naïve). *Failed due to the big domain gap between synthetic and real images.*
- Stage 2: Use diversity to help solve the domain gap. *Success by combining diversity with learning from simulation.*
- Stage 3: Use properties of synthetic data to scale up to multiple objects and multiple tasks. *Very fast, by exploiting the synthetic annotations.*

Stage 1: Naïve Strategy does not work

- Train using synthetic data only.
- Works well on synthetic data, but very badly on real data (technically – the deep network features are too different).





How to Improve Performance?

- Try better synthetic data?
- Buy more realistic (expensive) models and make realistic backgrounds?

- This is intuitive, but we could not get it to work.

- Results are terrible. By contrast, Training with Real Data gives (78.98 PCK@0.05 for keypoint detection)

$599 Image source: turbosquid.com $799

Stage 2: Realism versus Diversity tradeoff

- These realistic synthetic models are expensive.
- *They lack diversity – only one horse, only one tiger.*

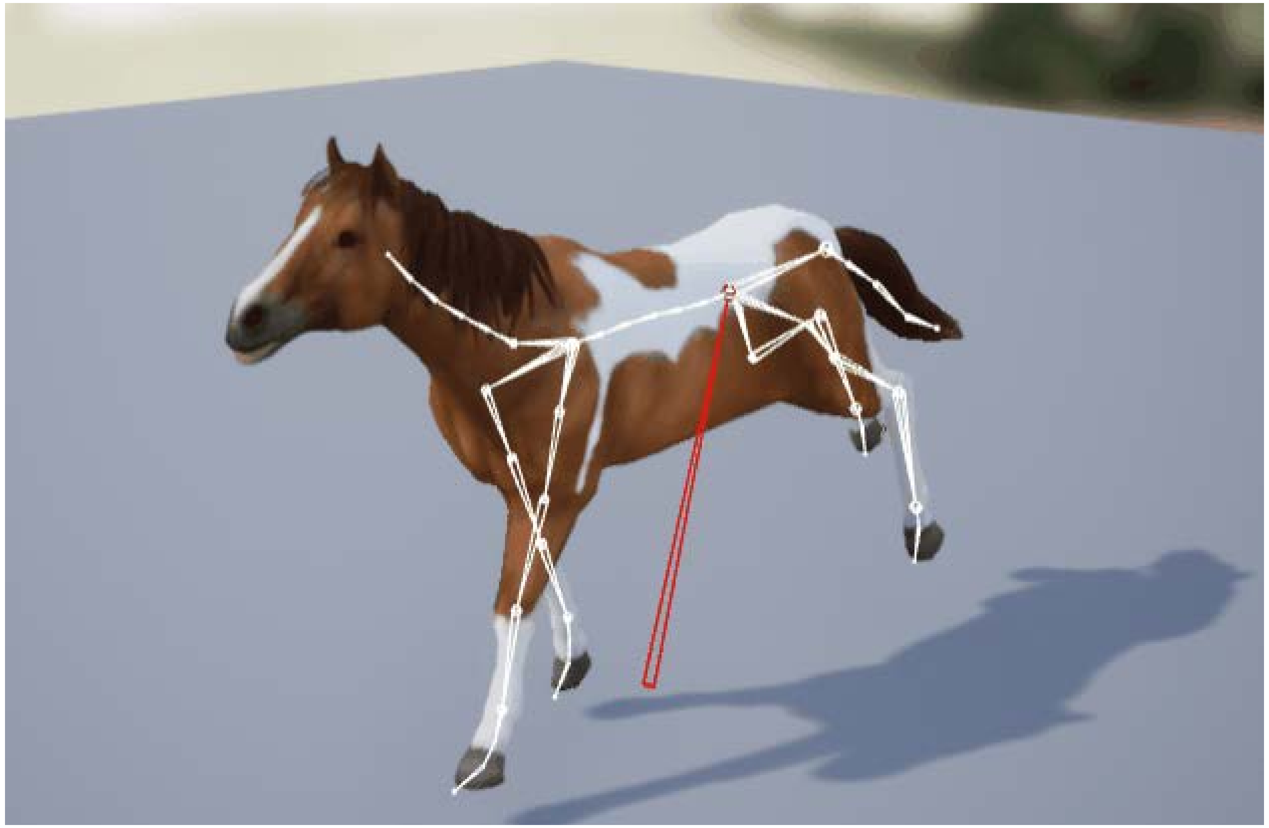
- Instead:
- *(I) Increase diversity by randomizing texture, lighting, background. (25.33 PCK@0.05)*
- *(II) Data augmentation – adding Gaussian noise, rotating the images. (60.85 PCK@0.05)*
- Recall Training with Real Data achieves 78.98 PCK@0.05.

How to improve performance?

- Training with Real Only (78.98)
- Better Data
  - More realistic model, realistic background (intuitive, but not work)
  - Texture Randomization (25.33)
  - Data Augmentation, rotation, gaussian noise (60.84)
- Better Training
  - Domain adaptation
    - *synthetic +unlabeled real data, adversarial training (62.33)*
    - *synthetic +unlabeled real data, semi-supervised training (70.77)* *No real annotations!*

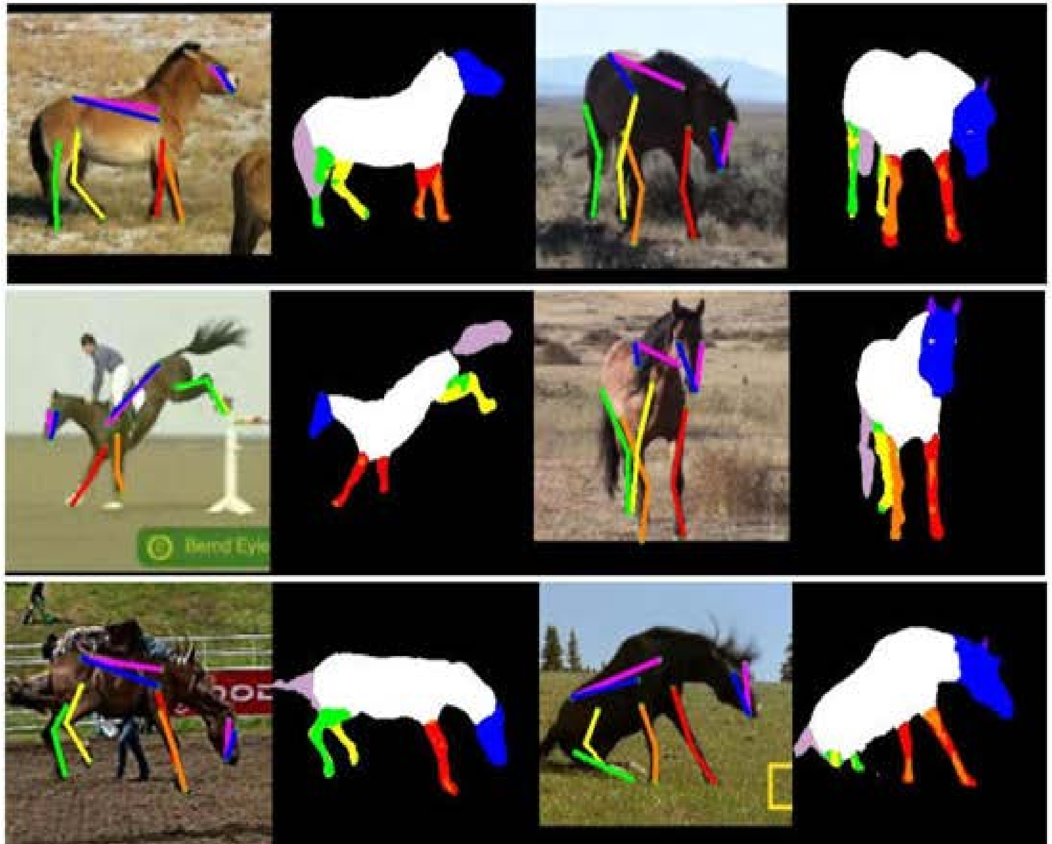
    - synthetic +labeled real data, (82.43 > 78.98) *Combining real with synthetic does best.*

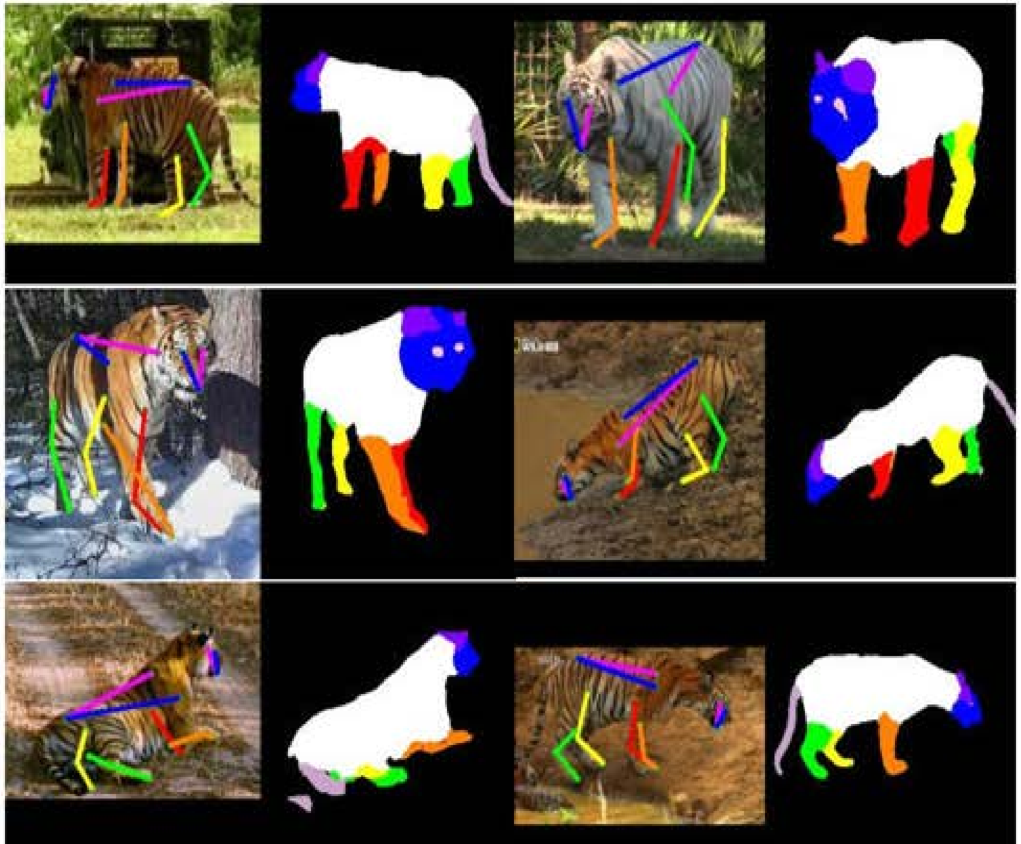
An animal keypoint video



Stage 3: Scale Up –extend to new tasks.

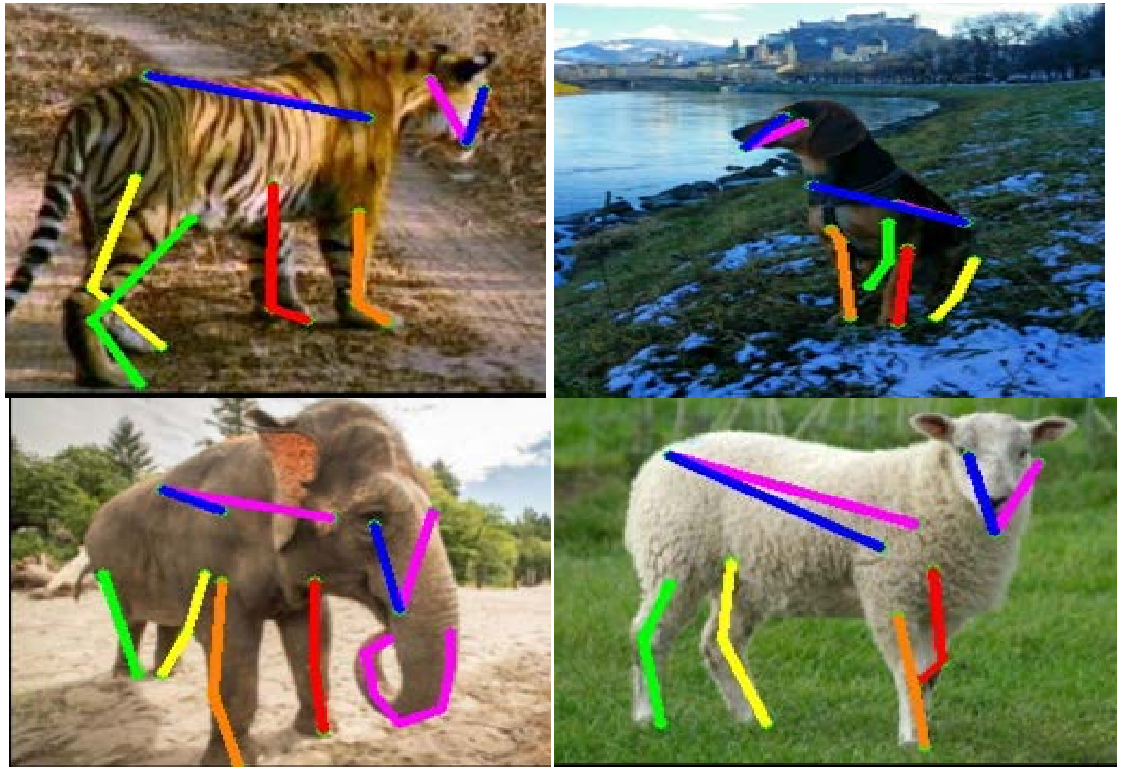
New Visual Task: Part Segmentation: Identify head, torso, legs, tails.
Same diversity plus learning strategy.





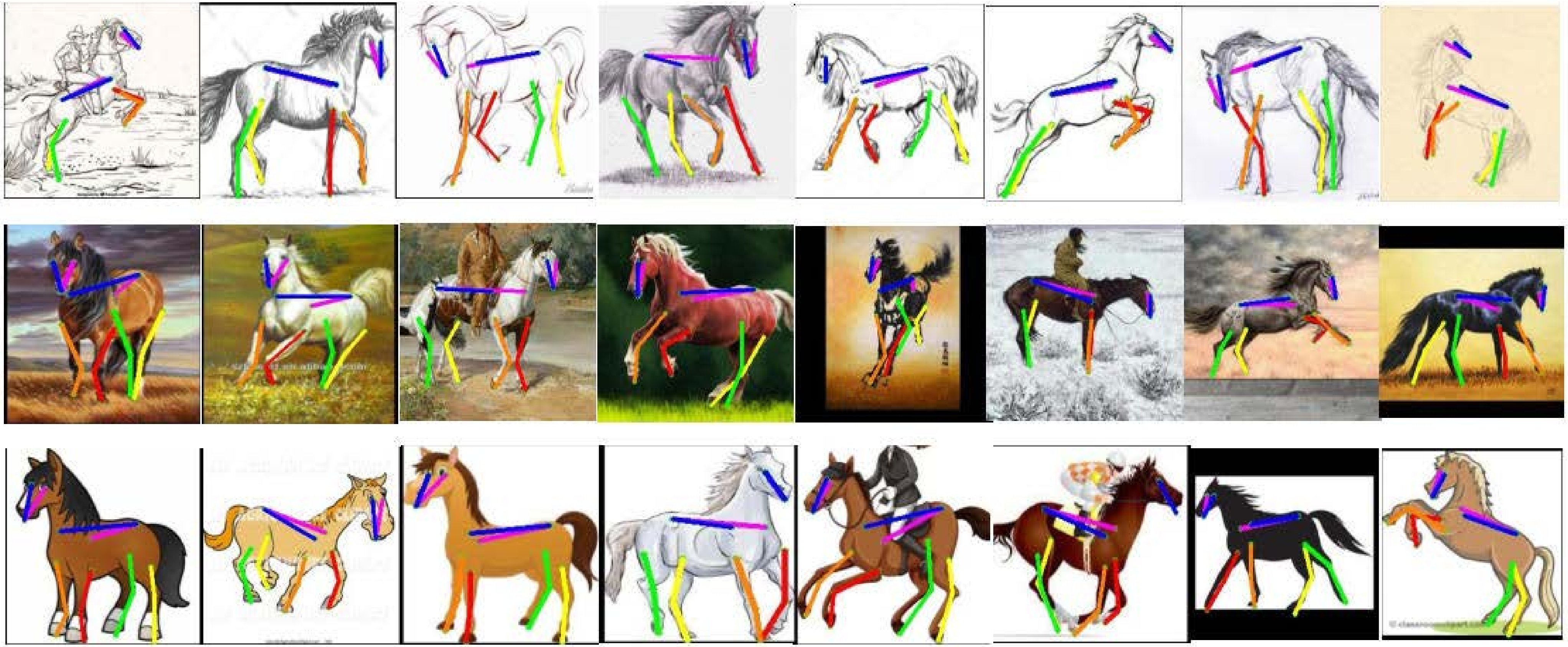
Scale Up -- extend to more categories

You only annotate once (for each object category) but same diversity and learning strategies still apply.



Scale Up: extend to domain generalization

Better Domain Generalization



Conclusion

- *Learning with weak supervision is not only very important. It is also possible and practical.*
- Learning to Parse Animals with Weak Prior Knowledge – You Only Annotate Once.
- *To approach human level performance, the computer vision community needs to move to a paradigm where we use limited annotations to train but are tested for our worst case performance on an infinite set (by our worst enemy).*
- Human infant learning, and human visual abilities, are great motivations for the next wave of computer vision.

References

- ***Human Infant Learning:***
- M.E. Arterberry & P.J. Kellman. “Development of Perception in Infancy: The Cradle of Knowledge Revisited”, Oxford University Press, 2016.
- A. Gopnik, A. N. Meltzoff, P. K. Kuhl. “The Scientist in the Crib: What Early Learning Tells Us About the Mind”. William Morrow Paperbacks, 2000.
- ***Learning by Prior Models. You Only Annotate Once:***
- *Jiteng Mu, Weichao Qiu, Gregory Hager, Alan Yuille. “Learning from Synthetic Animals”. CVPR (oral). 2020.*
- *See this paper for related references.*

- ***Need for New Testing Paradigm:***
- *Shu, Michelle, Chenxi Liu*, Weichao Qiu, and Alan Yuille. "Identifying Model Weakness with Adversarial Examiner." In AAAI. 2020.*
- *Yuille, Alan L., and Chenxi Liu. "Deep Nets: What have they ever done for Vision?." arXiv preprint arXiv:1805.04025 (2018).*