# *Learning to Parse Object from Virtual Data: "You only annotate once".*

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# *Parsing: Beyond Humans*

- Almost all work on object parsing has been done on humans.
- This is because there exist many annotated datasets of humans – with 2D joints annotated and also 3D positions. This has resulted in effective algorithms methods for detecting 2D joints and estimating their3D structure.
- Do we need large datasets with joints labeled for  other animals?
- Instead we can use *computer graphics models* of animals (e.g., horses and tigers) to give training data for joints. Then perform *domain transfer* by *self-supervision* to obtain models that work on real world images.
- Jiteng Mu et al. CVPR. 2020. Oral Presentation.

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$599 Image source: turbosquid.com $799

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# *The Value of Simulated Data*

- ***Simulated data can help, but there are three important findings.***
- It is important to do *domain adaptation* **–** e.g., adversarial training. Combining synthetic with real data naively works poorly.
- It is better to have *diverse stimuli* (texture, lighting, data augmentation) than realistic synthetic stimuli.
- You *can annotate many properties of the synthetic object* – e.g., part positions, key-points, and 3D structure. You only need to annotate the synthetic model and then you can render it with different viewpoints, poses, texture, lighting, noise, etc. “You only annotate once”.

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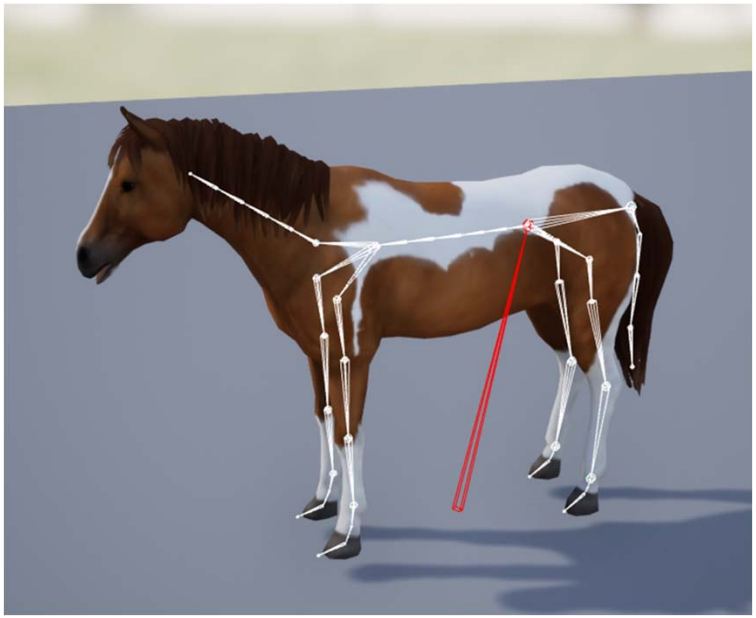
# Illustration: Animal Parsing

- Annotate Joints of a Synthetic Animal.  Goal: parse real animal.
- J. Mu et al. CVPR. 2020.



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# History of this project

- Stage 1: Use synthetic data as if it was real data (naïve). *Failed due to the big domain gap between real and synthetic stimuli.*
- Stage 2: Use diversity of lighting/viewpoint/texture/background 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. *Possible by exploiting the synthetic annotations.*

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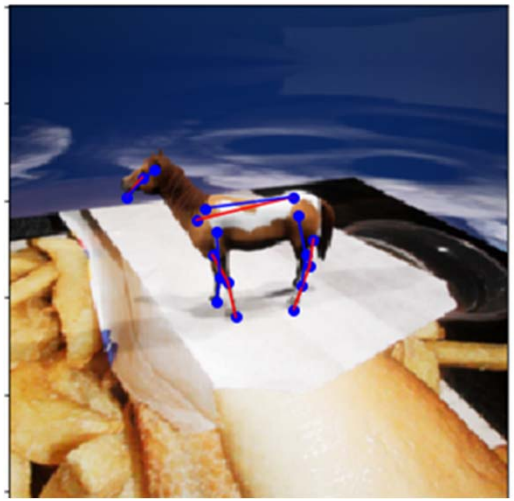
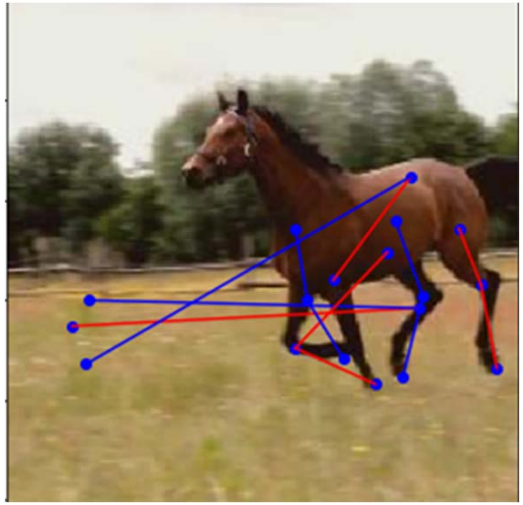
# Stage 1: Naïve Strategy does not work

- Train using synthetic data only(left image).
- Works well on synthetic data, but very badly on real data (right image).
- (The deep network features are too different in real and synthetic).





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# How to Improve Performance?

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

- This is intuitive, but does not work well.

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

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# 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.

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# How to improve performance?

- Training with Real Only (78.98)
- Train with diverse synthetic data:
  - More realistic model, realistic background (intuitive, but not work)
  - Texture Randomization (25.33)
  - Data Augmentation, rotation, gaussian noise (60.84)
- Add self-supervised training on real data:
  - 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.*

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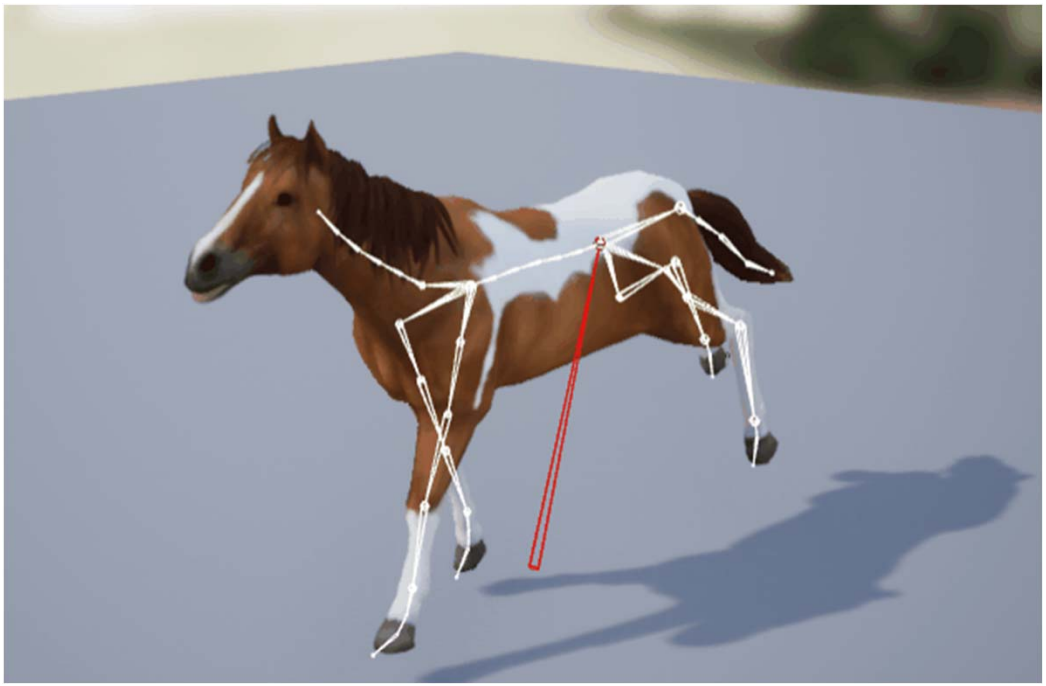
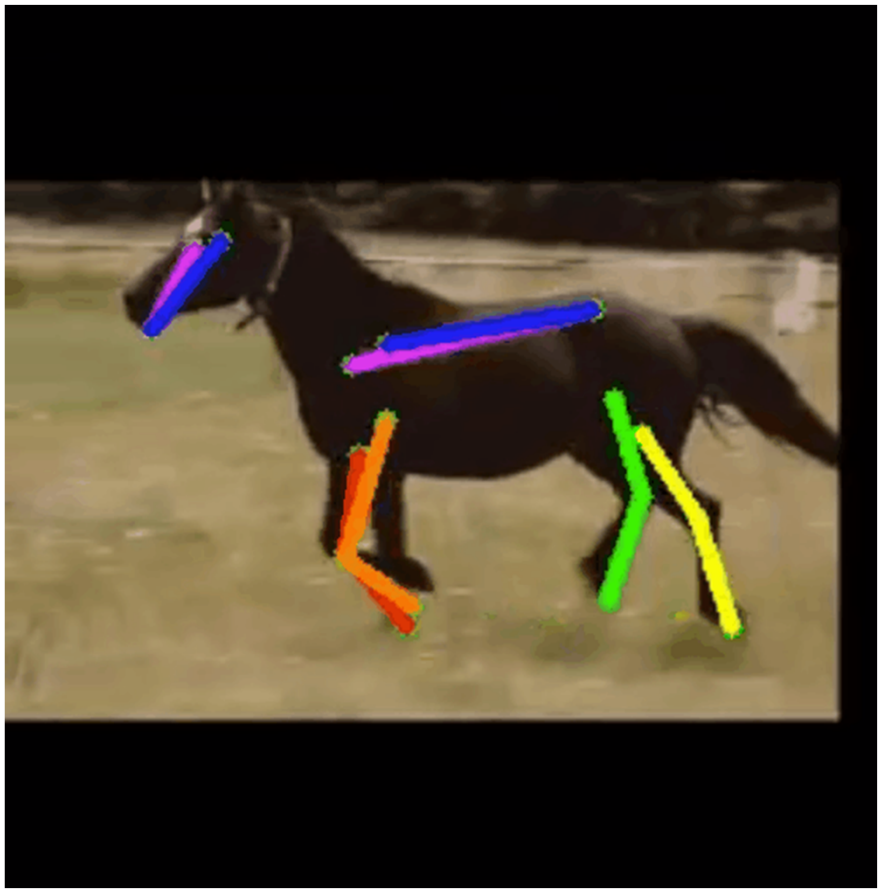
# Animal keypoint video (2)





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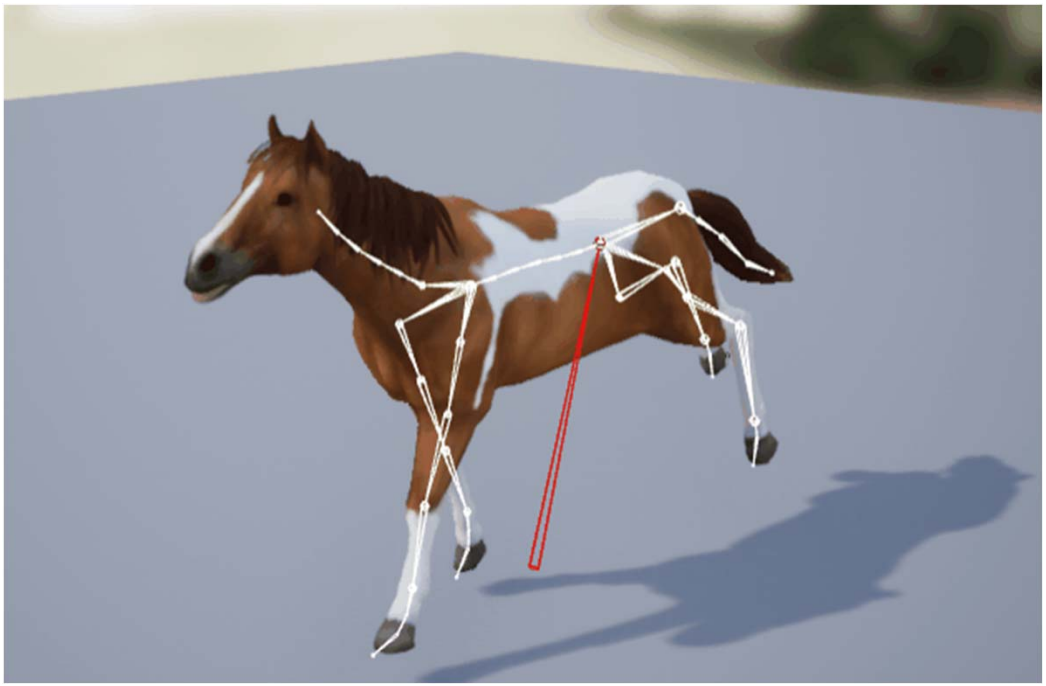

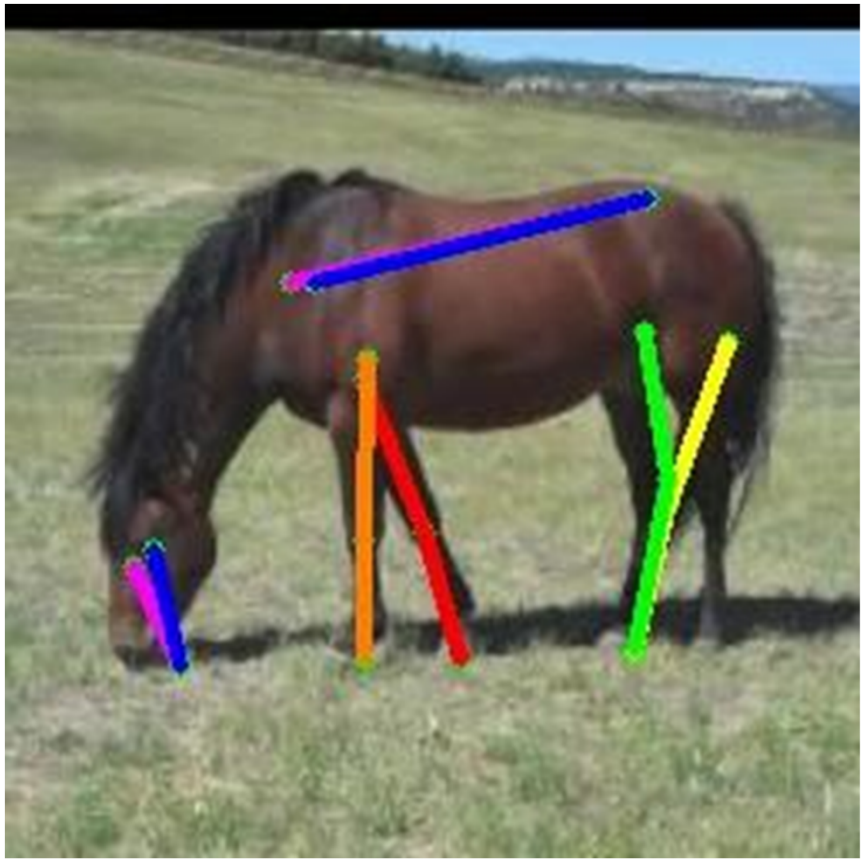

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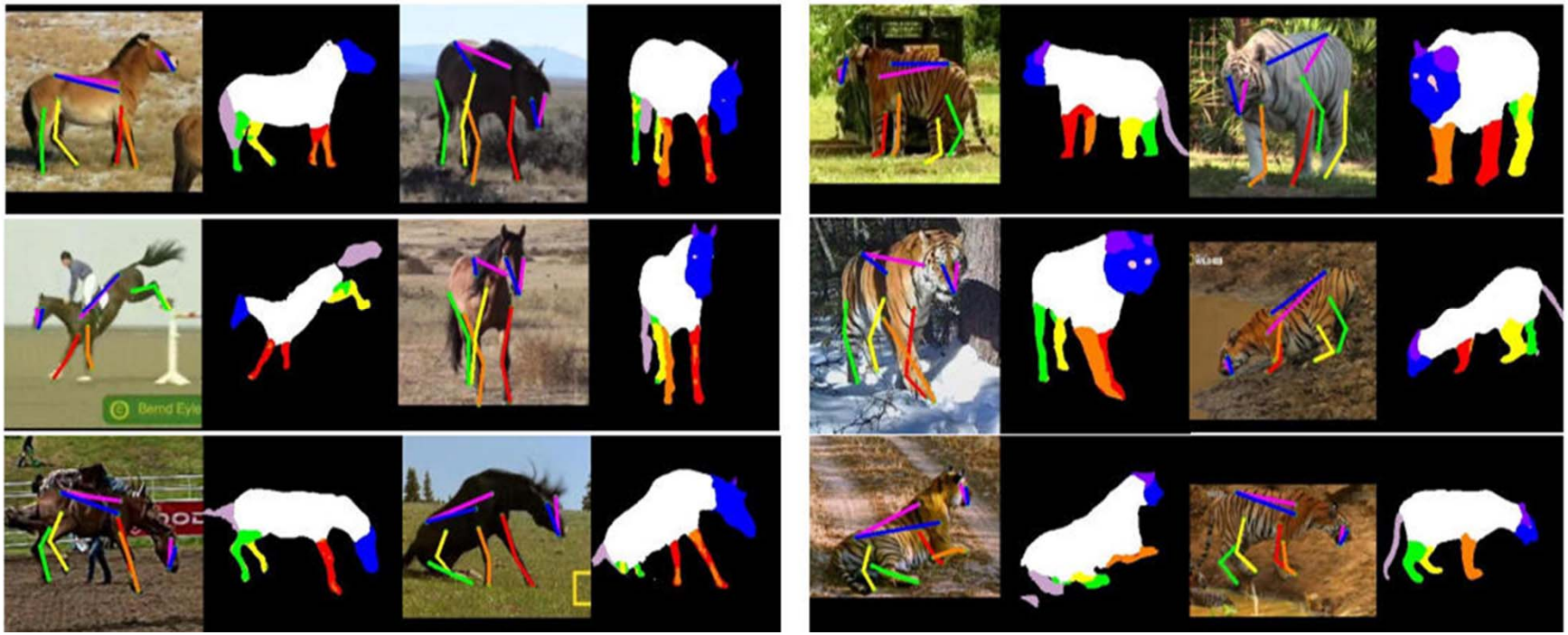
# Stage 3: Scale Up –extend to new tasks.

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



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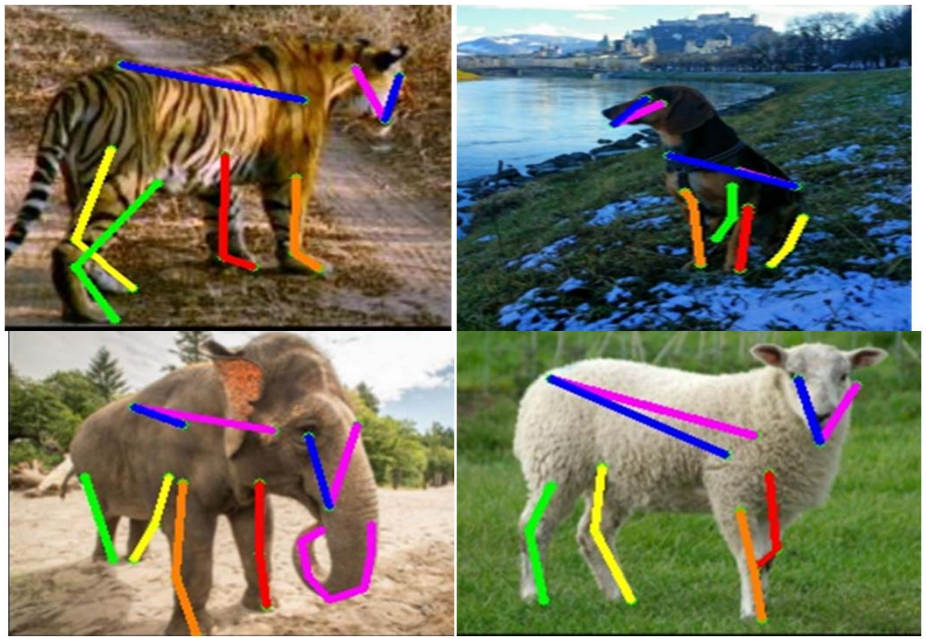
# Scale Up -- extend to more categories

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



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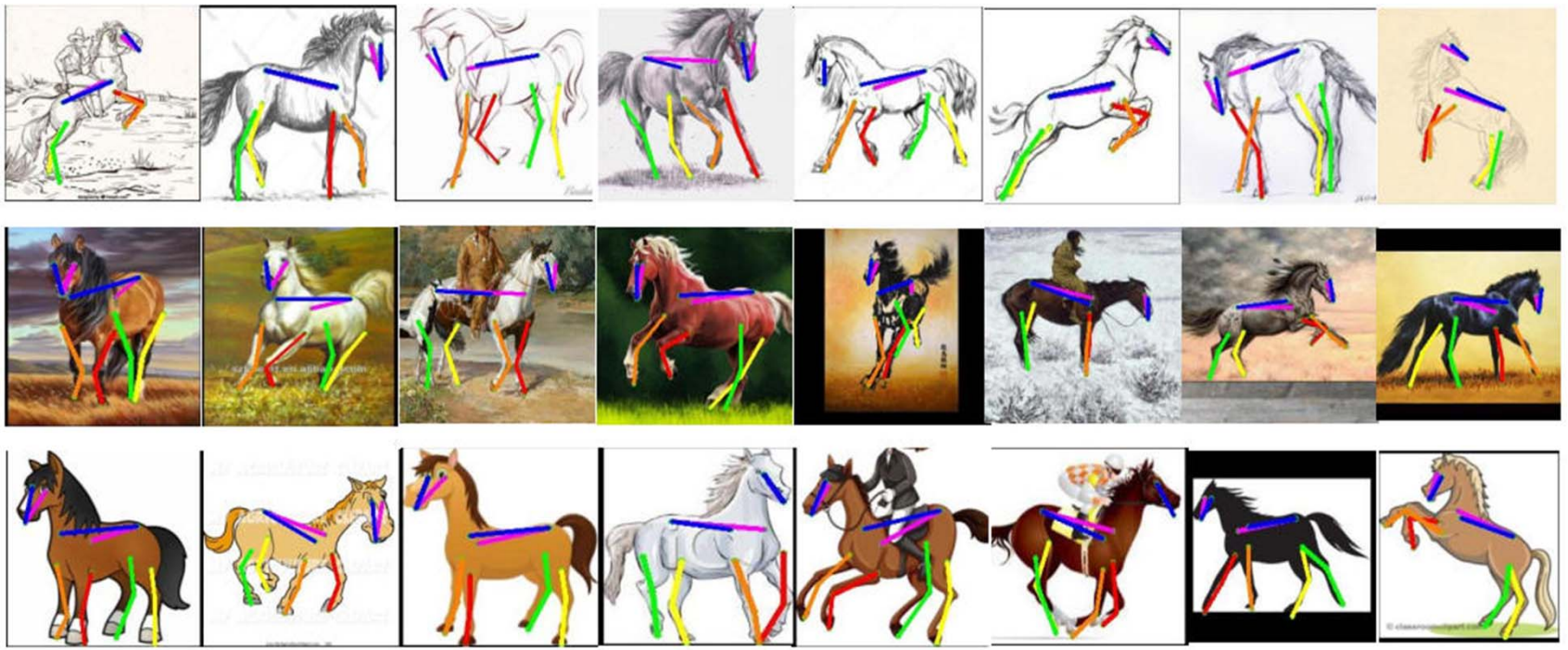
# Scale Up: extend to different domains.

Better Domain Generalization: line drawings, pictures.



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# Recap: History of this project

- Stage 1: Use synthetic data as if it was real data (naïve). *Failed due to the big domain gap between real and synthetic.*
- Stage 2: Use diversity to help solve the domain gap. *Success by combining diversity with self-supervision on real data.*
- Stage 3: Use properties of synthetic data to scale up to multiple objects and multiple domains. *Exploit the synthetic annotations.*

- *It took months to go from Stage 1 to Stage 2. It took weeks to go from Stage 2 to Stage 3.*

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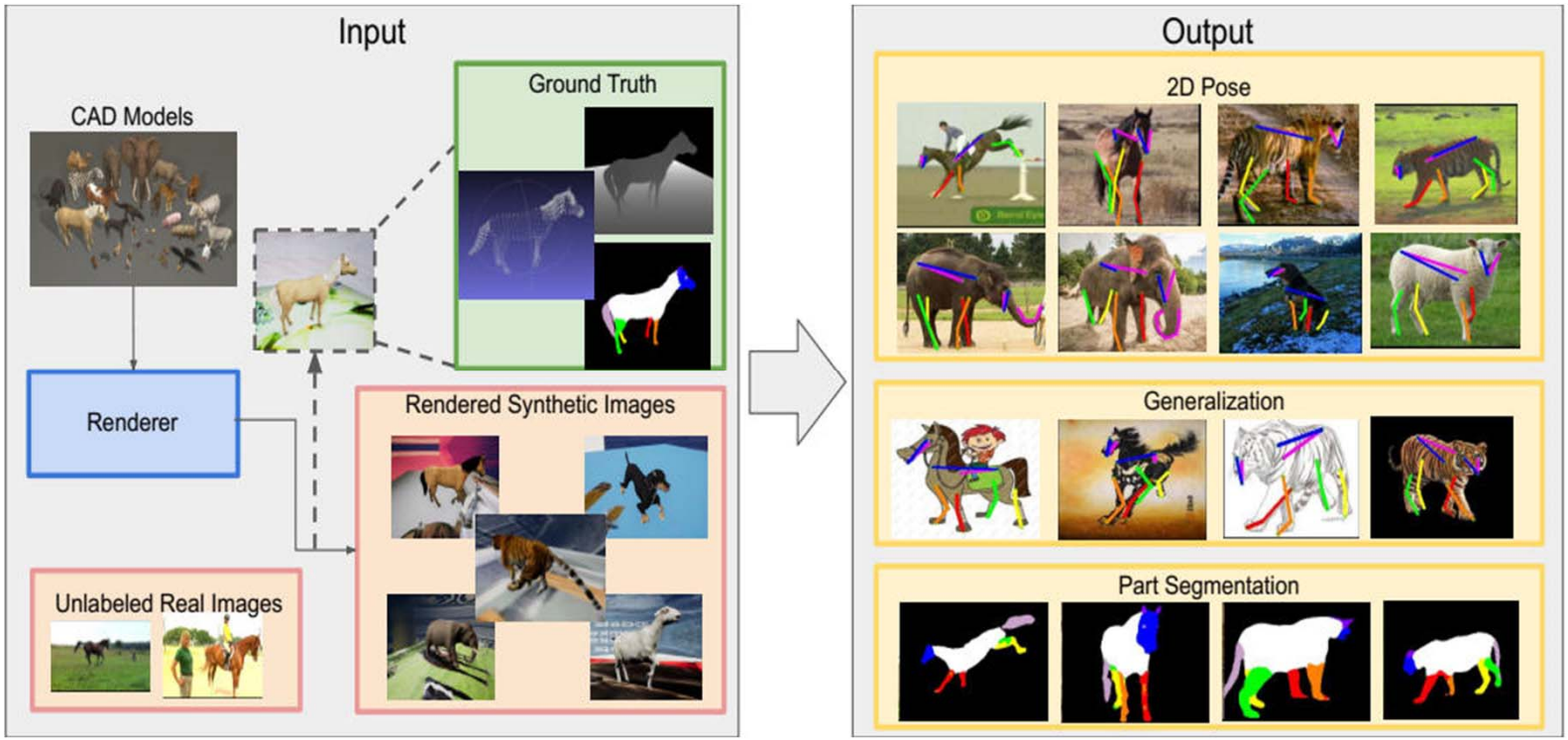
# Conclusion

- ***Synthetic Data is very helpful but have three messages:***
- (1) Diversity of Synthetic Data is required. Synthetic alone is not realistic enough.
- (2) Domain Adaptation is required. Self-supervised learning.
- (3) Rich annotations on synthetic data: “you only annotate once”.

# Backup Slides

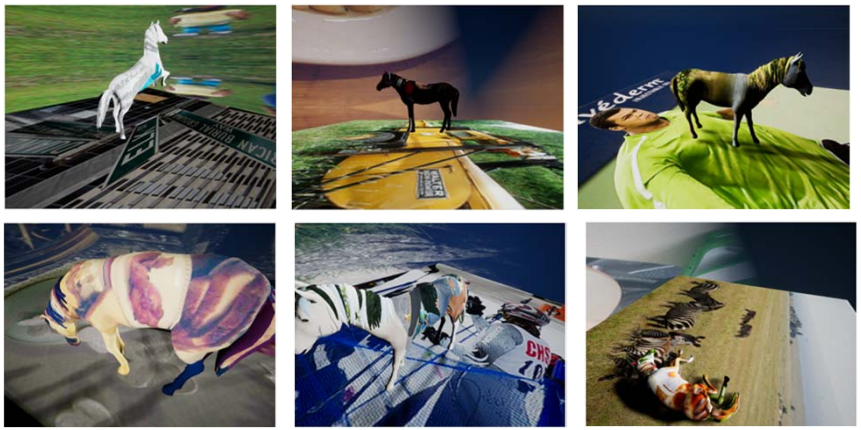
# Synthetic Animal Project



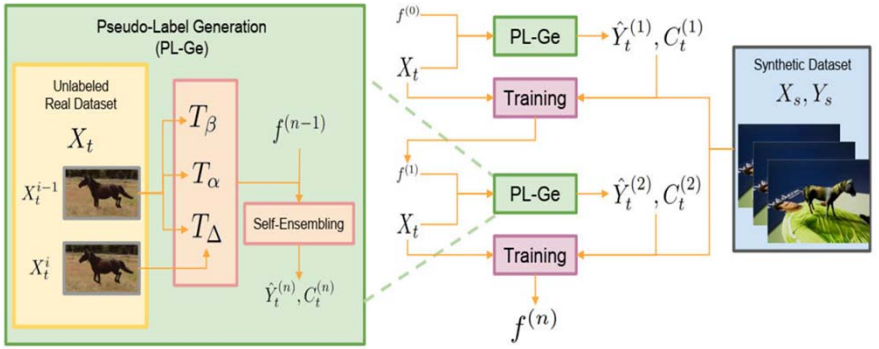

J Mu et al. ‘Learning from Synthetic Animals’. CVPR 2020.

# From Stage 1 to Stage 2: Diversity + Adaptation

## Domain Randomization



## Domain Adaptation

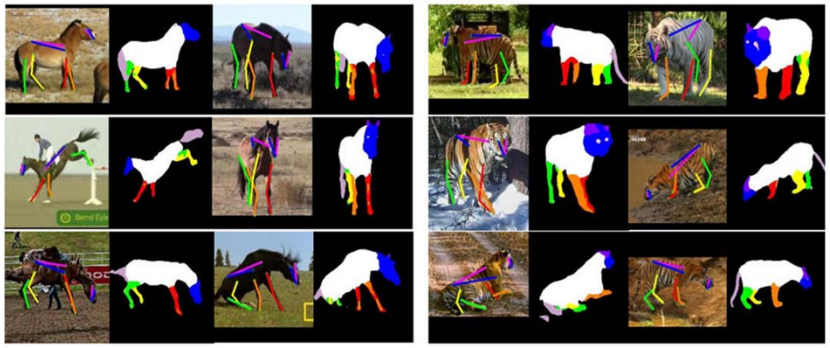



| | Horse Accuracy | | | | | | | | Tiger Accuracy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Eye | Chin | Shoulder | Hip | Elbow | Knee | Hoove | Mean | Eye | Chin | Shoulder | Hip | Elbow | Knee | Hoove | Mean | |
| *synthetic + real* | | | | | | | | | | | | | | | | | |
| Real | 79.04 | 89.71 | **71.38** | 91.78 | 82.85 | 80.80 | 72.76 | 78.98 | **96.77** | 93.68 | 65.90 | 94.99 | 67.64 | 80.25 | 81.72 | 81.99 | Stage 1 |
| CC-SSL-R | **89.39** | **92.01** | 69.05 | **92.28** | **86.39** | **83.72** | **76.89** | **82.43** | 95.72 | **96.32** | **74.41** | **91.64** | **71.25** | **82.37** | **82.73** | **84.00** | Stage 2 |
| *synthetic only* | | | | | | | | | | | | | | | | | |
| Syn | 46.08 | 53.86 | 20.46 | 32.53 | 20.20 | 24.20 | 17.45 | 25.33 | 23.45 | 27.88 | 14.26 | 52.99 | 17.32 | 16.27 | 19.29 | 21.17 | Stage 1 |
| CycleGAN [45] | 70.73 | 84.46 | 56.97 | 69.30 | 52.94 | 49.91 | 35.95 | 51.86 | 71.80 | 62.49 | 29.77 | 61.22 | 36.16 | 37.48 | 40.59 | 46.47 | |
| BDL [26] | 74.37 | 86.53 | 64.43 | 75.65 | 63.04 | 60.18 | 51.96 | 62.33 | 77.46 | 65.28 | 36.23 | 62.33 | 35.81 | 45.95 | 54.39 | 52.26 | |
| CyCADA [16] | 67.57 | 84.77 | 56.92 | 76.75 | 55.47 | 48.72 | 43.08 | 55.57 | 75.17 | 69.64 | 35.04 | 65.41 | 38.40 | 42.89 | 48.90 | 51.48 | |
| CC-SSL | **84.60** | **90.26** | **69.69** | **85.89** | **68.58** | **68.73** | **61.33** | **70.77** | **96.75** | **90.46** | **44.84** | **77.61** | **55.82** | **42.85** | **64.55** | **64.14** | Stage 2 |

# Stage 3: More gains?

1. stage 2 Vs stage 3 = 4 months Vs 3 weeks
2. More categories? More annotation format? Better domain generalization?

Segmentation Masks



More categories

Domain Generalization

| | Horse | | | | | | Tiger | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Visible Kpts Accuracy | | | Full Kpts Accuracy | | | Visible Kpts Accuracy | | | Full Kpts Accuracy | | |
| | Sketch | Painting | Clipart | Sketch | Painting | Clipart | Sketch | Painting | Clipart | Sketch | Painting | Clipart |
| Real | 65.37 | 64.45 | 64.43 | 61.28 | 58.19 | 60.49 | 48.10 | 61.48 | 53.36 | 46.23 | 53.14 | 50.92 |
| CC-SSL | 72.29 | 73.71 | **73.47** | **70.31** | **71.56** | **72.24** | 53.34 | 55.78 | 59.34 | 52.64 | 48.42 | 54.66 |
| CC-SSL-R | **73.25** | **74.56** | 71.78 | 67.82 | 65.15 | 65.87 | **54.94** | **68.12** | **63.47** | **53.43** | **58.66** | **59.29** |