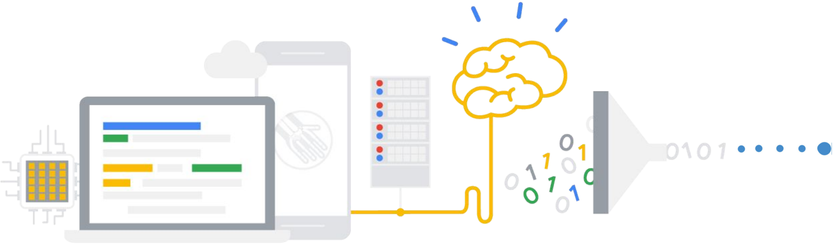
Cerberus: A Multi-Headed Derenderer

Boyang Deng, Simon Kornblith, and Geoffrey Hinton

Google Brain, Toronto

Google AI



Modeling objects in images

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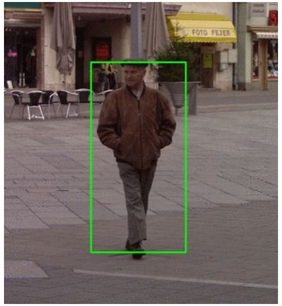

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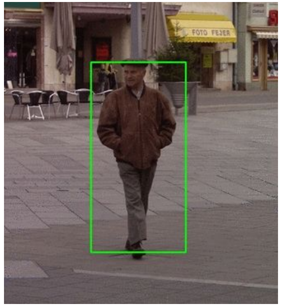

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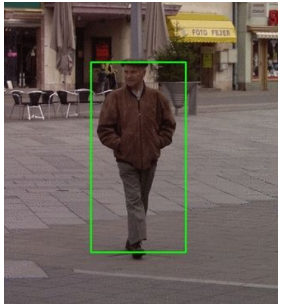

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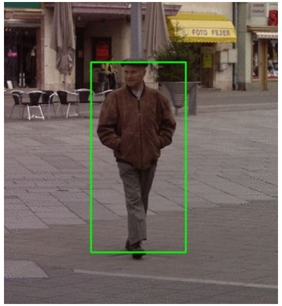
- And …… this is a 3D Vision workshop.



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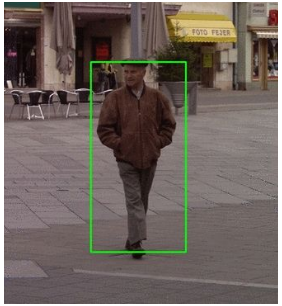

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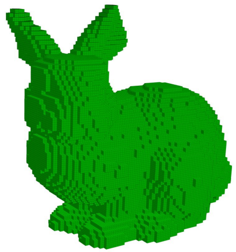

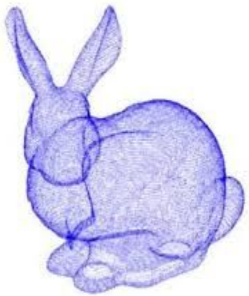

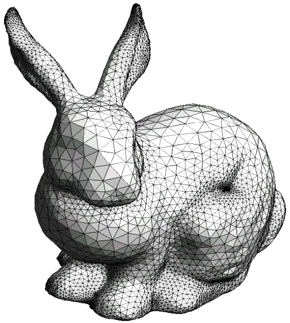

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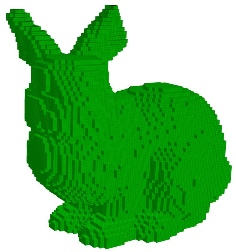

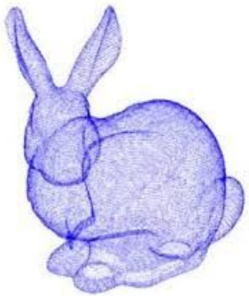

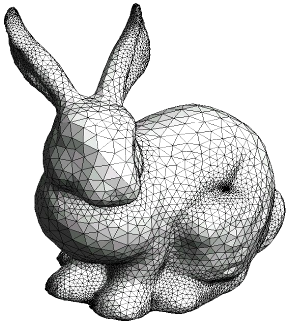

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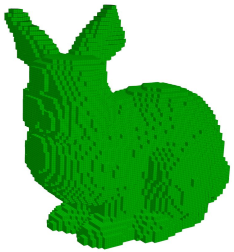

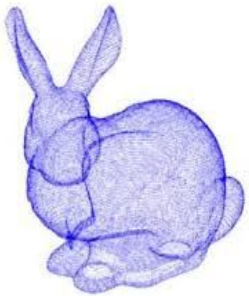

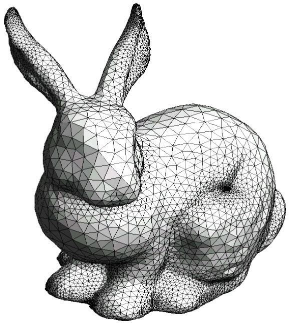

Modeling objects in images

1. 2D Representation? Not Enough.

2. 3D Representation?

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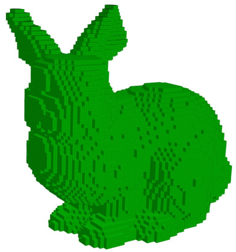
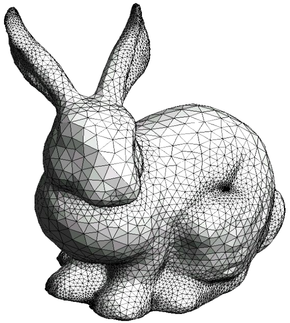
- Friendly to re-rendering under novel scenes. Thanks to Graphics.
- Which one to use? Voxel, point cloud, or mesh.





Modeling objects in images

1. 2D Representation? Not Enough.
2. 3D Representation?

- We choose mesh.
    - Compact compared to voxel.
    - Fast rasterization -> Plug a differentiable renderer in training -> <u>**No 3D supervision**</u>.

Modeling object in images

1. 2D Representation? Not Enough.

2. 3D Representation? Mesh.

3. Mesh for Articulated Bodies

- Previous methods[1, 2] use a **single mesh** with fixed topology.
- Articulated bodies have poses, i.e. relative locations and orientations of parts.

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- Articulated bodies have poses, i.e. relative locations and orientations of parts.
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  - Solution: **A Part-based Model**.

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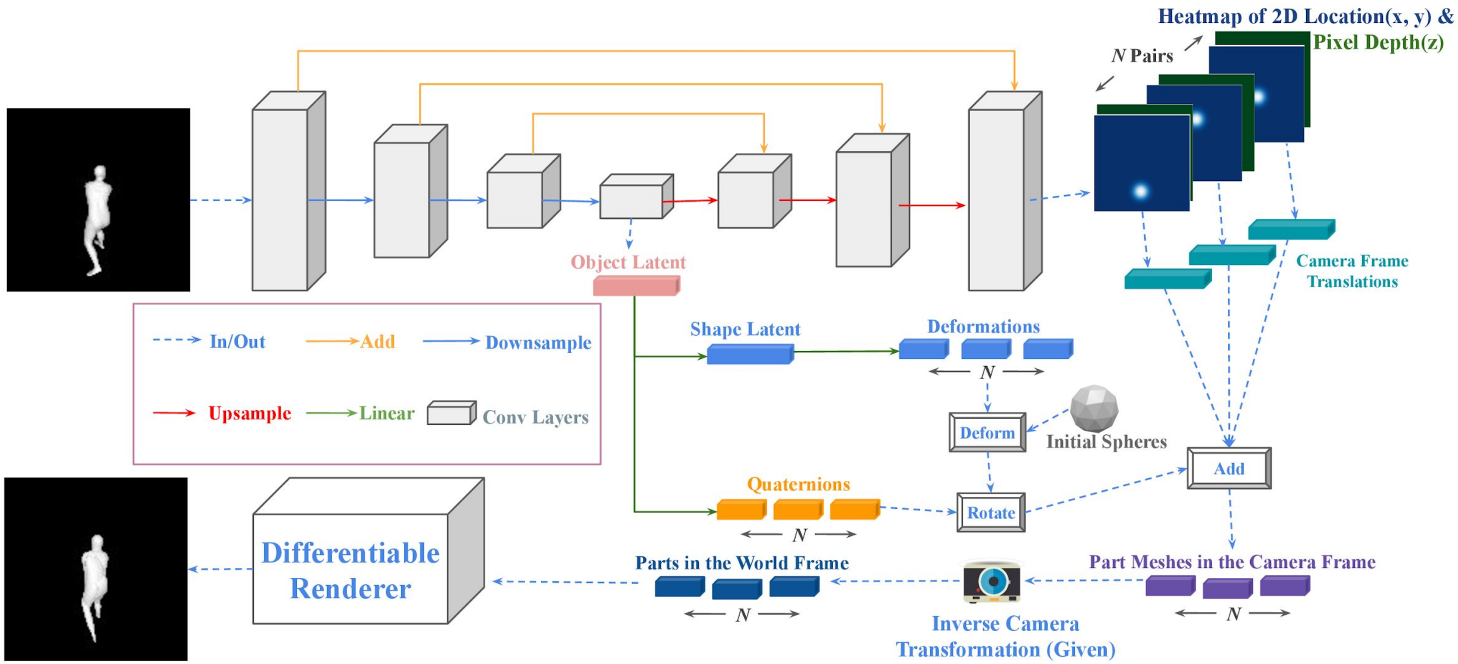

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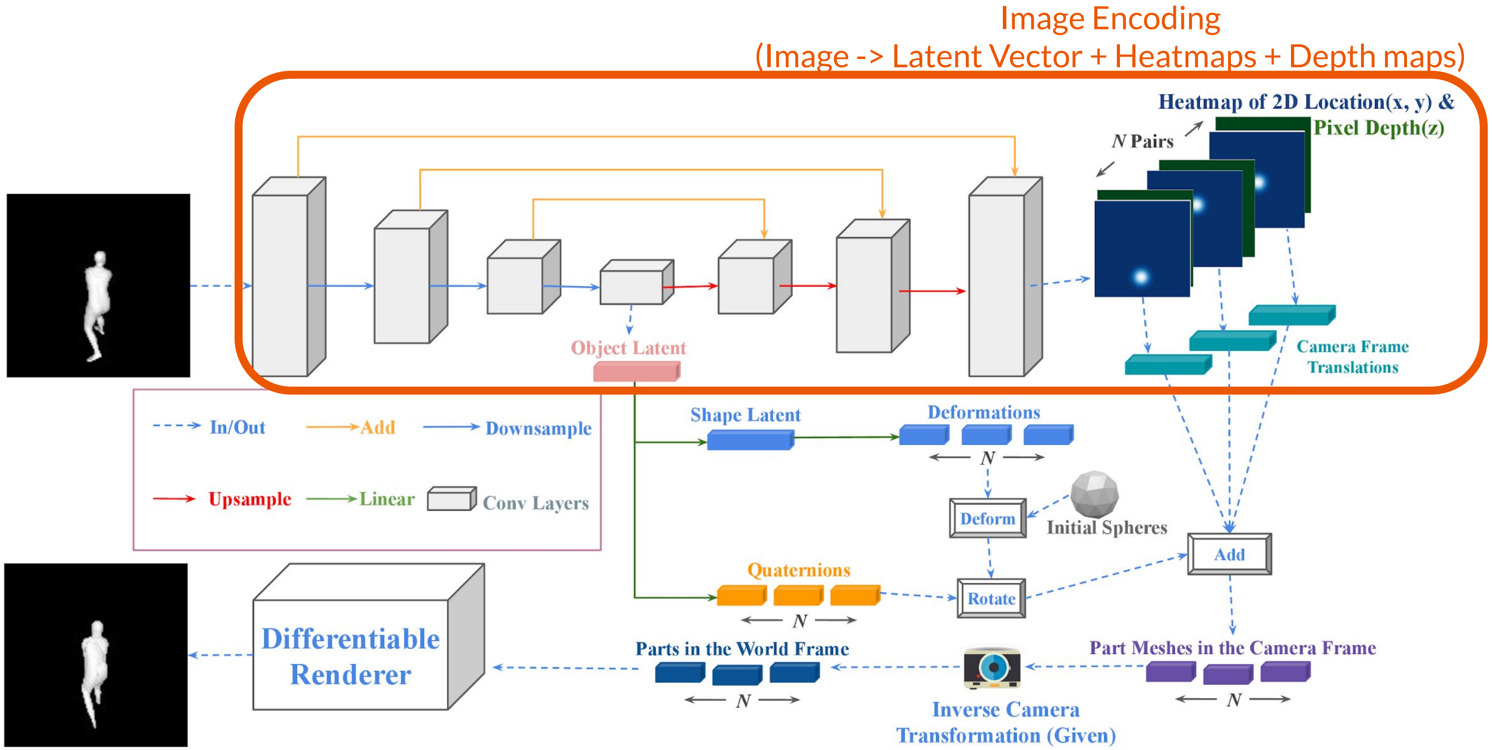

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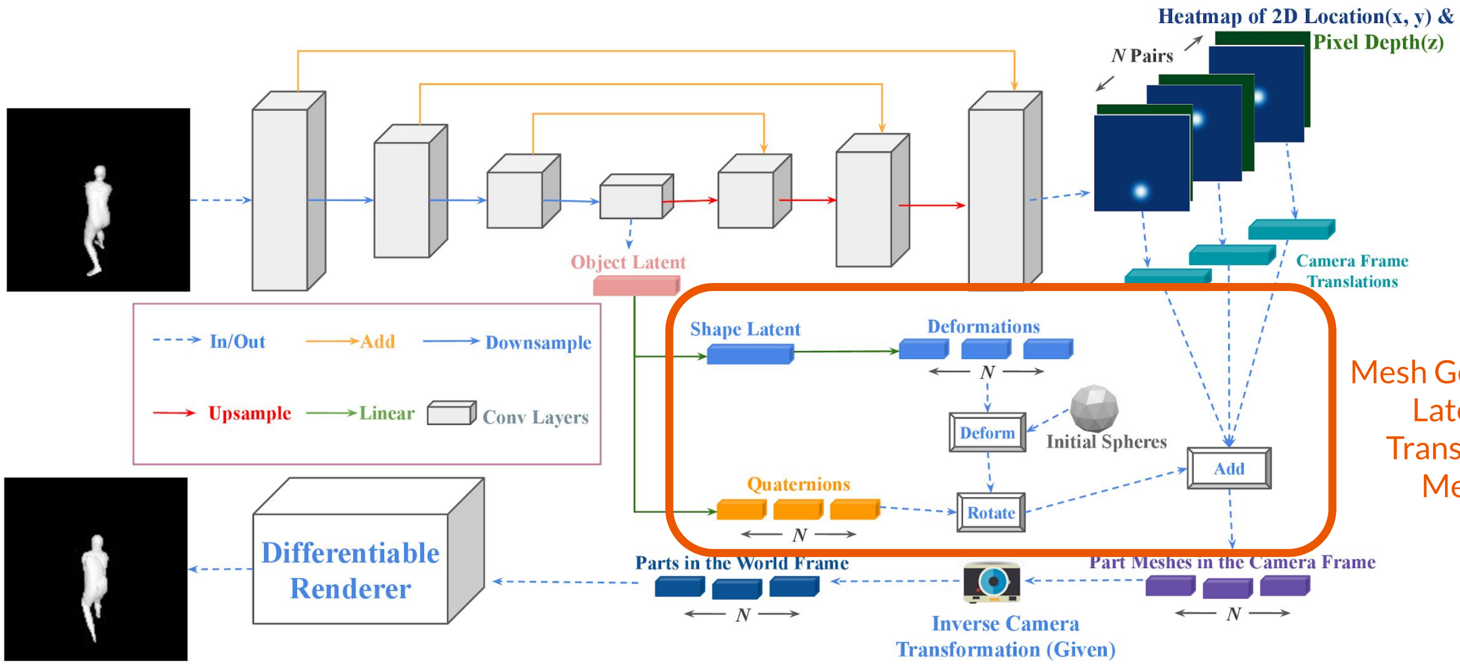

Mesh Generation: Latent -> Transformed Meshes

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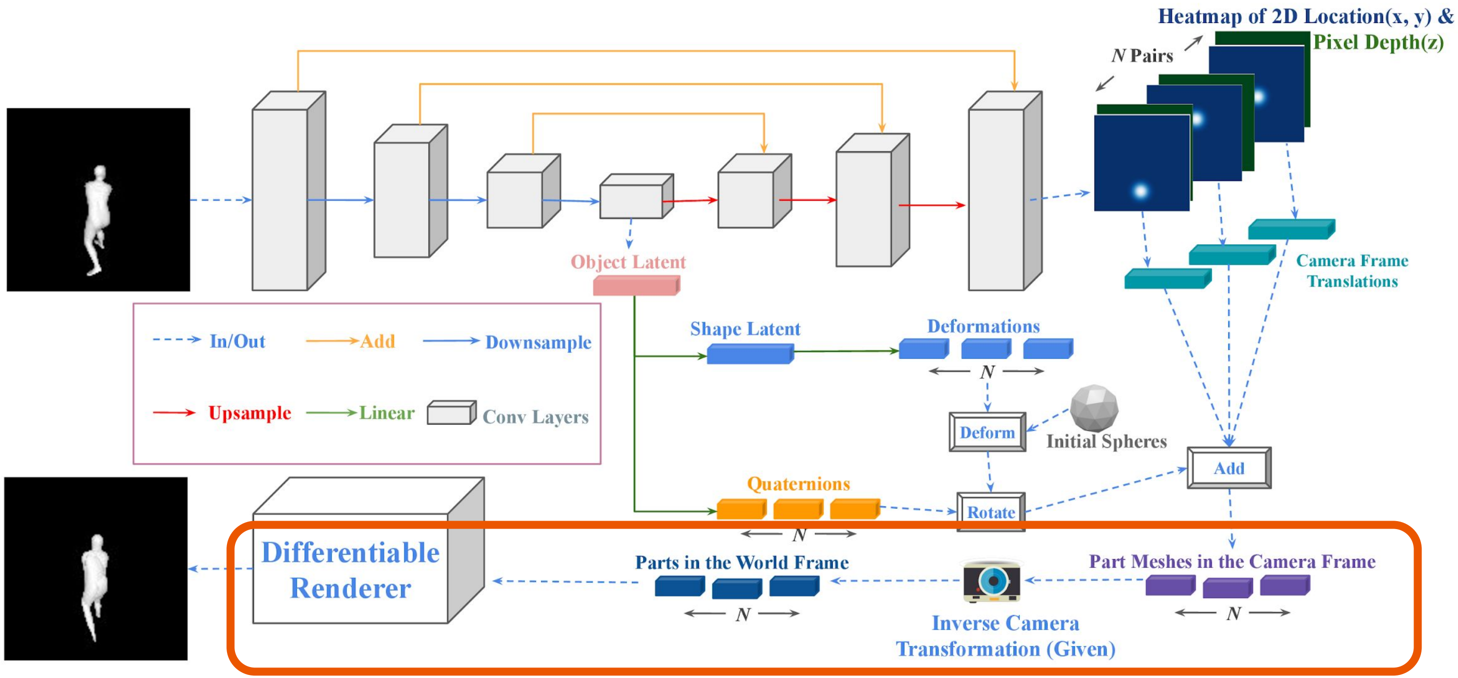

Differentiable Mesh Rendering

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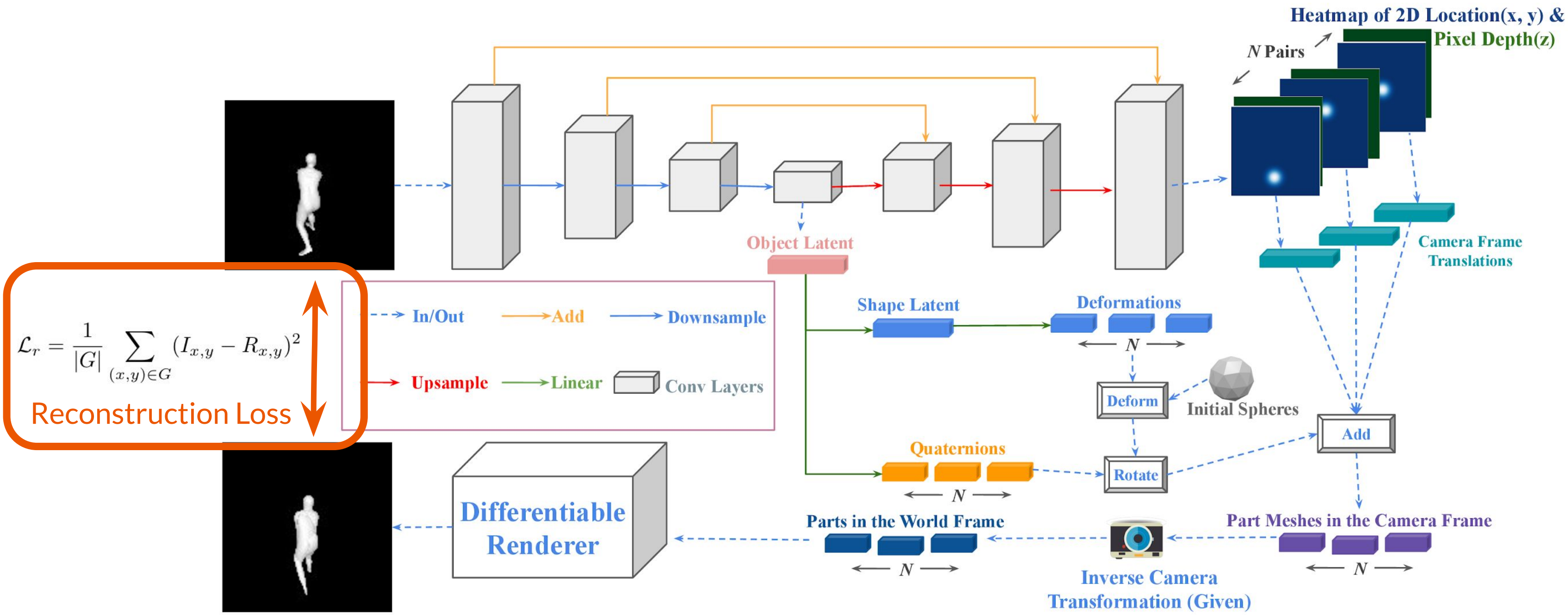

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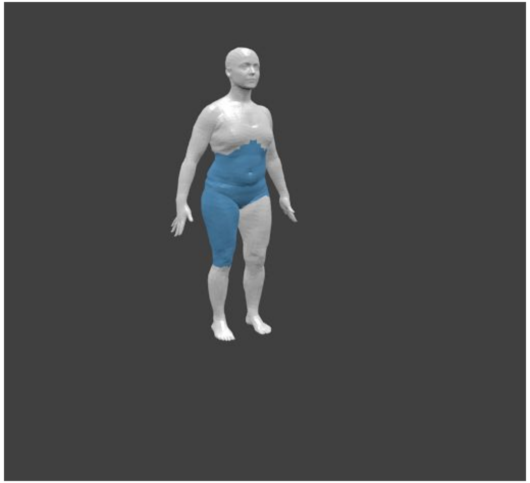
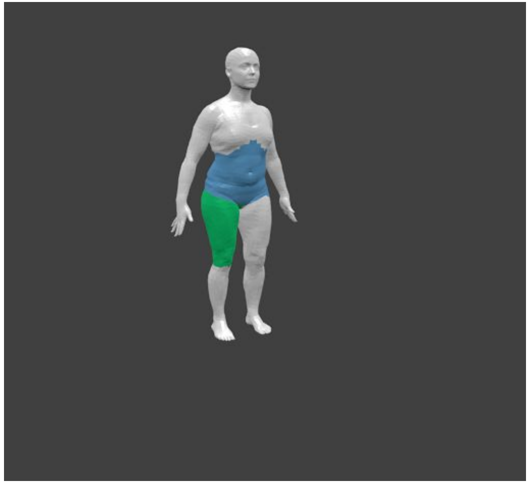
- Can we learn parts without part annotations? **Yes.**
- Let's rethink the properties of parts.

How to learn parts?

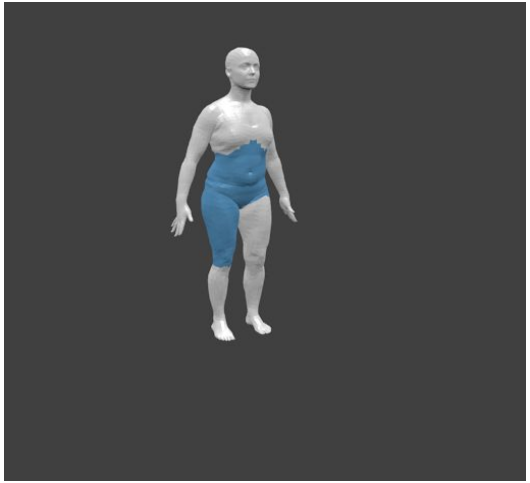


Part Split No.1



Part Split No.2

How to learn parts?



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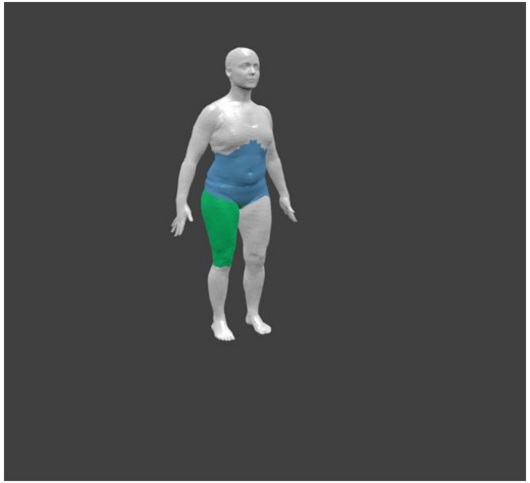
Why?



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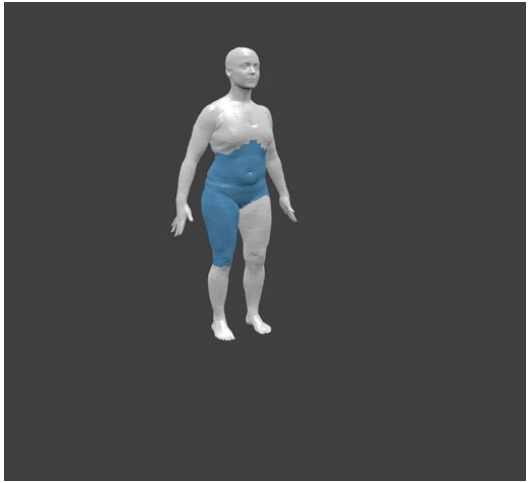

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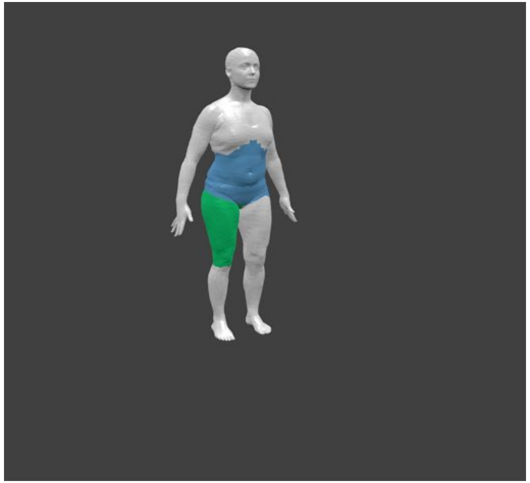
Pose Consistency



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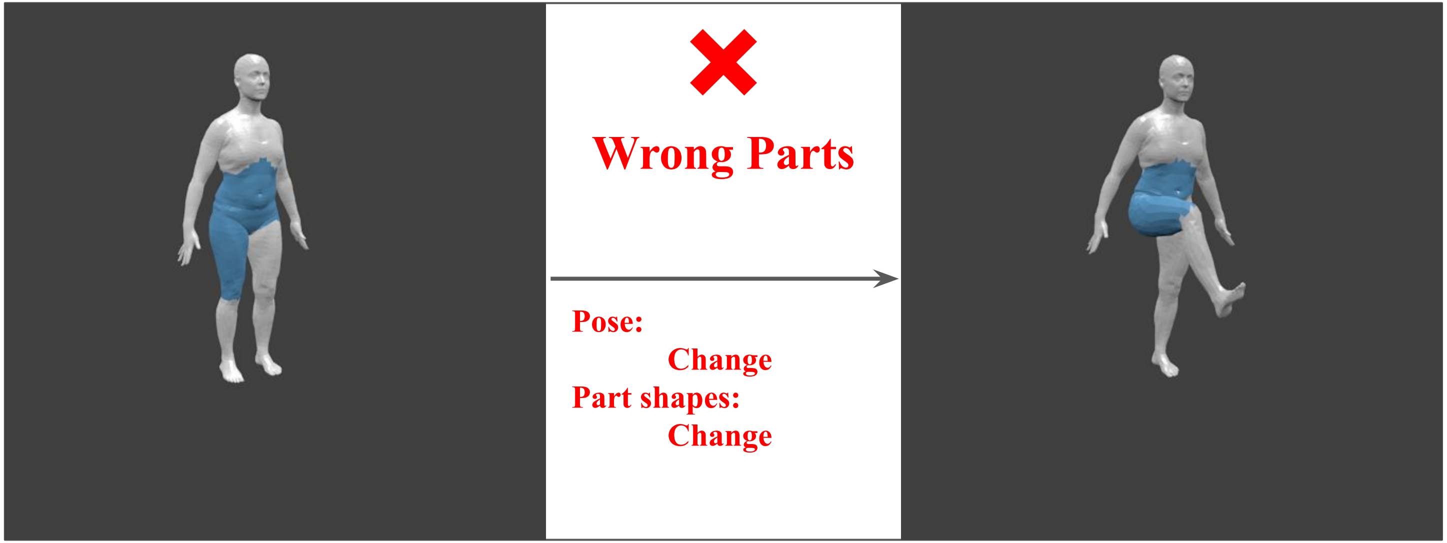

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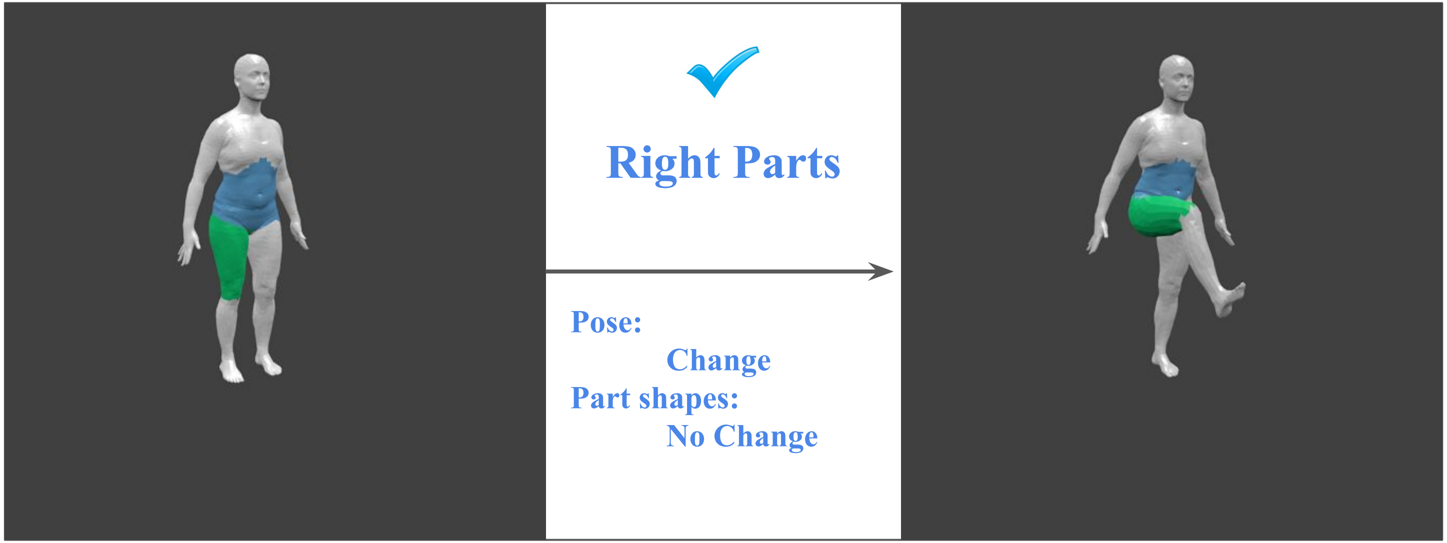
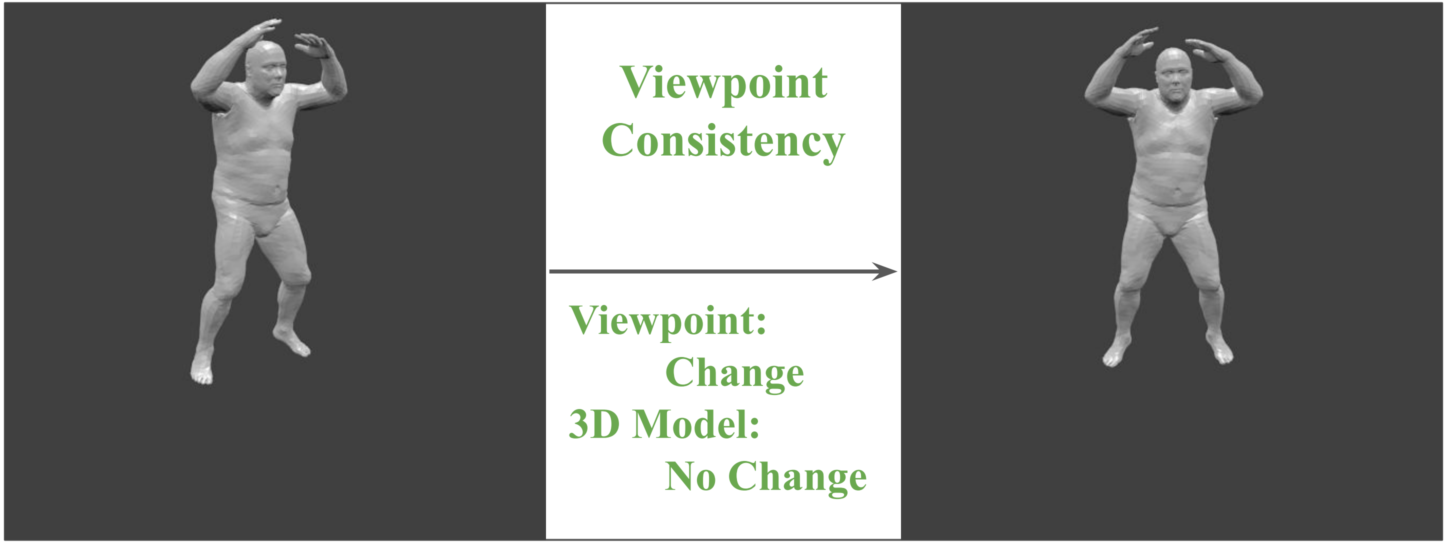


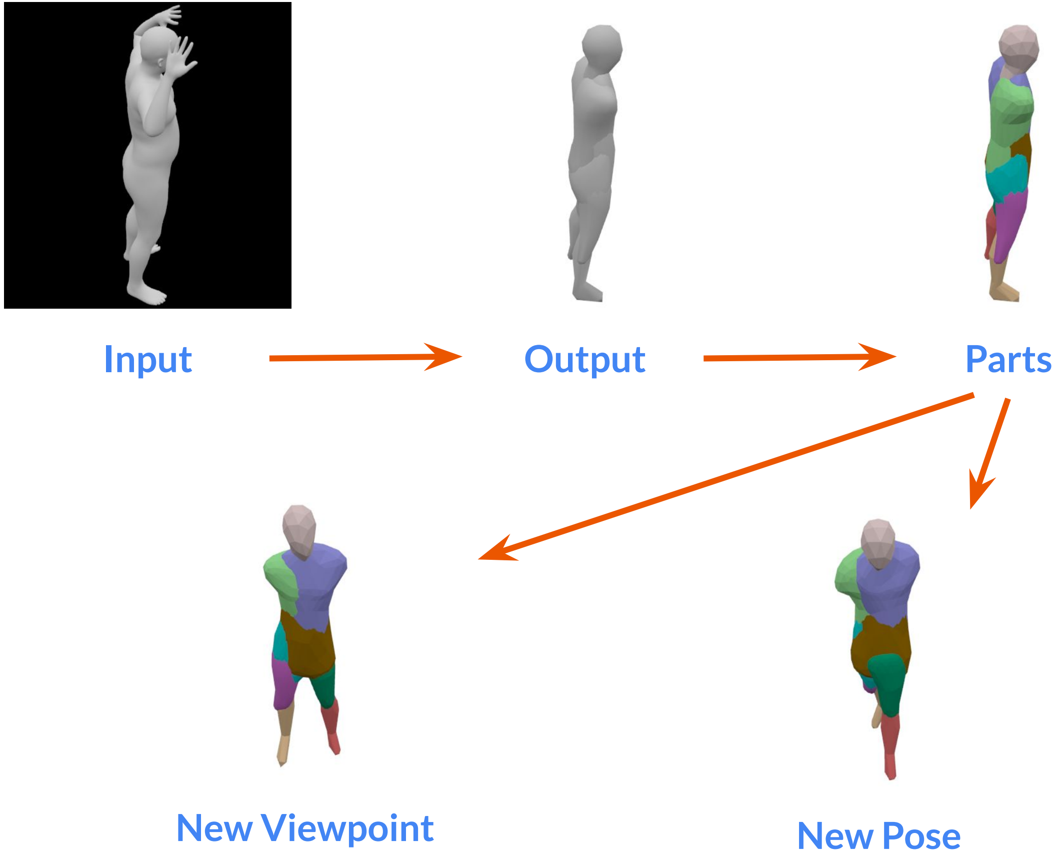
Part Split No.2

Another consistency



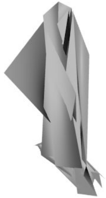
Viewpoint Consistency

Results



Results: Human Dataset*

Input



NMR

NMRs

NMRr

Ours

Our Parts

Our Turn

- NMR is Neural Mesh Renderer.
- NMRs is NMR with smooth loss.
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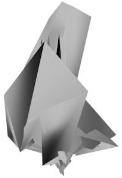

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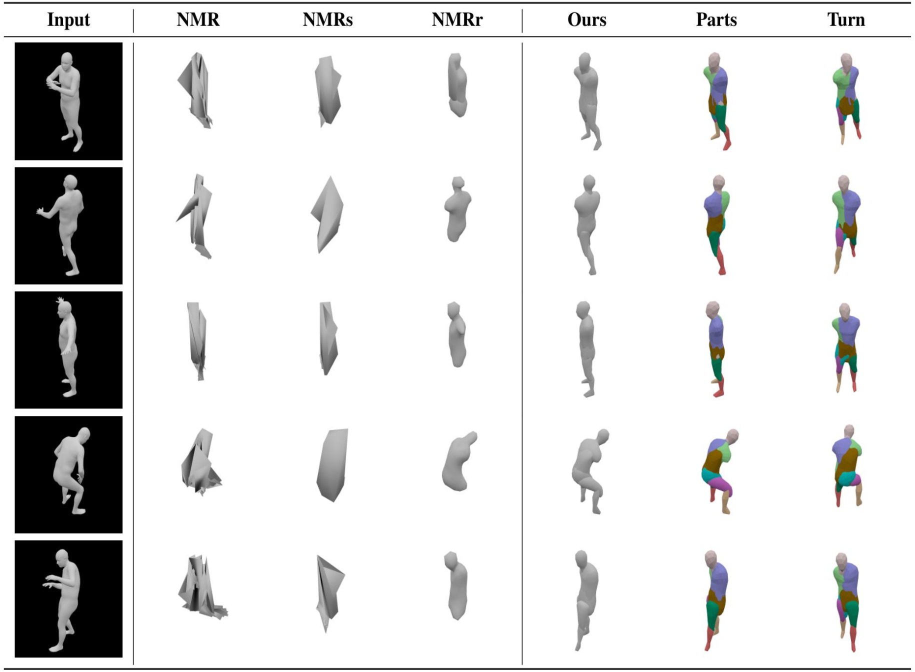
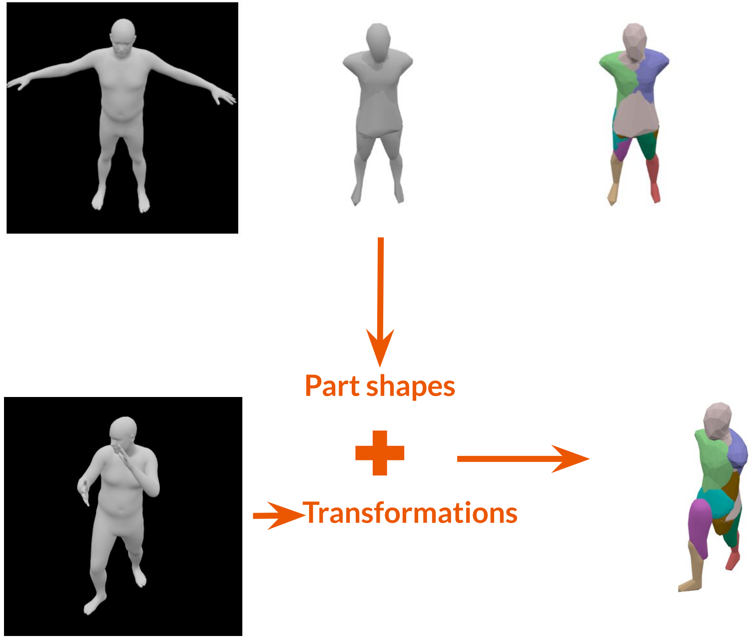


Model	Human	Human Hard	Animal
NMR	0.2596	-	0.3000
NMRs	0.2233	-	0.2574
NMRr	0.3084	-	0.3201
Cerberus	0.4970	**0.4728**	**0.4255**
Free Cerberus	**0.5099**	0.4365	0.4196

- Free Cerberus is Cerberus without pose consistency.
- Cerberus is better than baselines both quantitatively and qualitatively.

Results: Evaluate parts quantitatively



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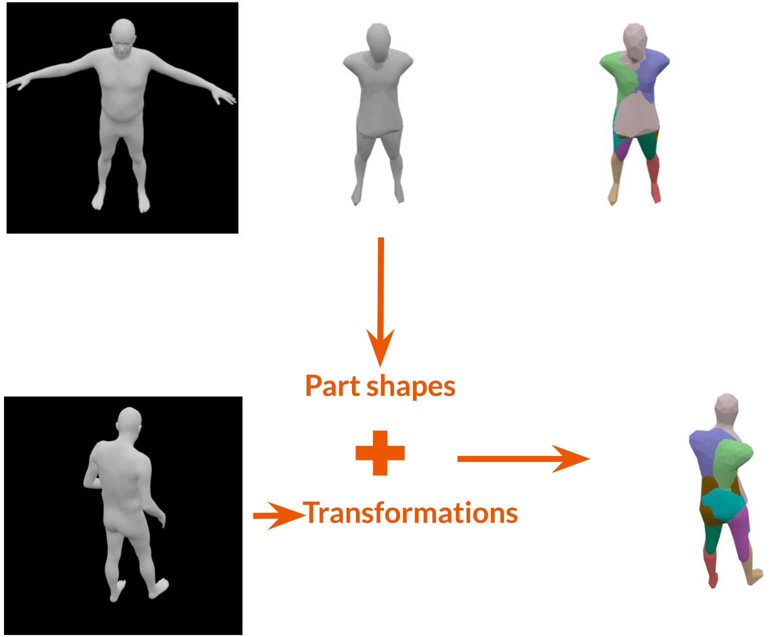

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Results: Animal Dataset* (Higher Shape Variance)

(a) Cougar

(b) Deer

(c) Tiger

(d) Hippo

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- **Cerberus is consistently better than baseline methods.**

*The dataset is credit to SMAL from MPII.

Summary

- We present Cerberus, a 3D perception framework for articulated bodies.
- We present consistency constraints for learning parts without part supervision.
- Cerberus, trained with the proposed constraints, outperforms baselines on both standard and hard tests.

Thank you for listening!