CAN WE LEARN TO SIM?

HENRIQUE TELES MAIA

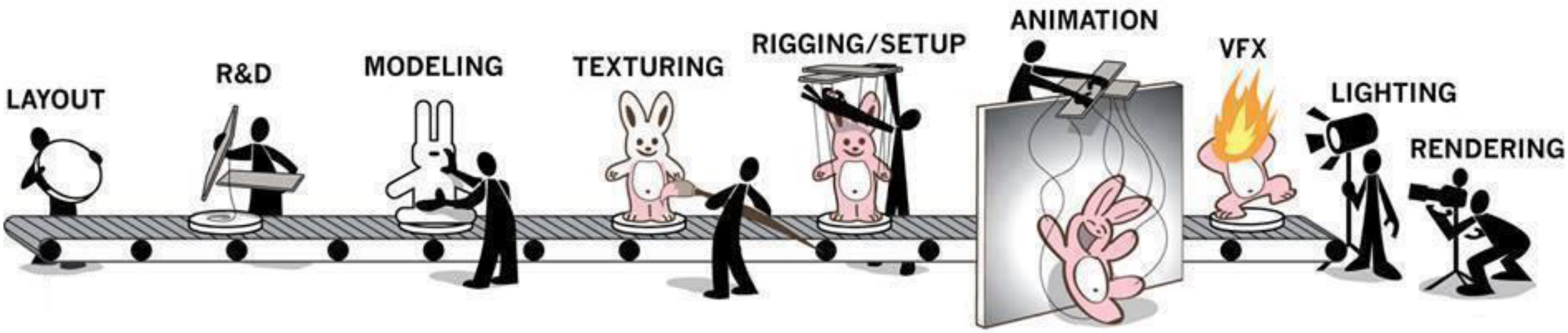
MACHINE LEARNING IN GRAPHICS

hours / days

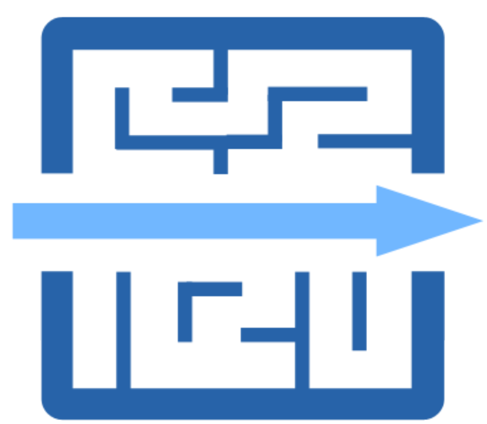

Full Simulatio


Online Reduced Simulation Results, ~51 minutes, 56x speedup

MACHINE LEARNING IN GRAPHICS



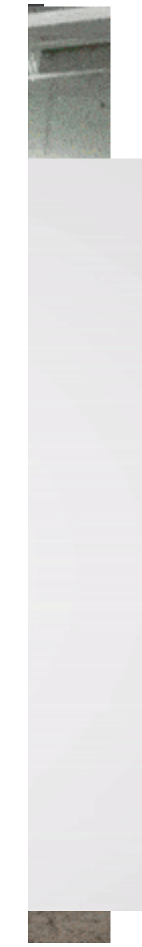

speed


simplicity


visual quality


robustness

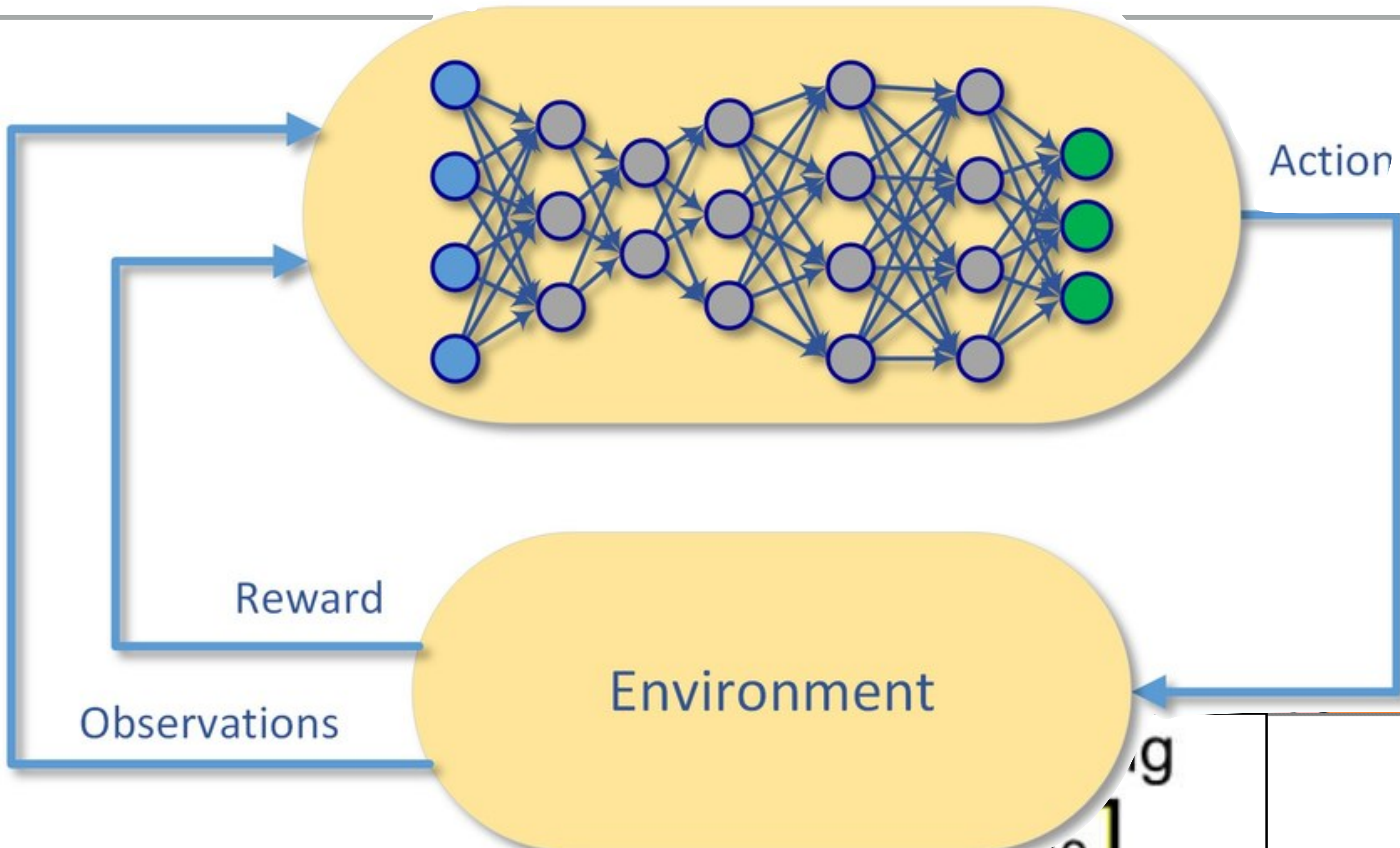
OUTLINE

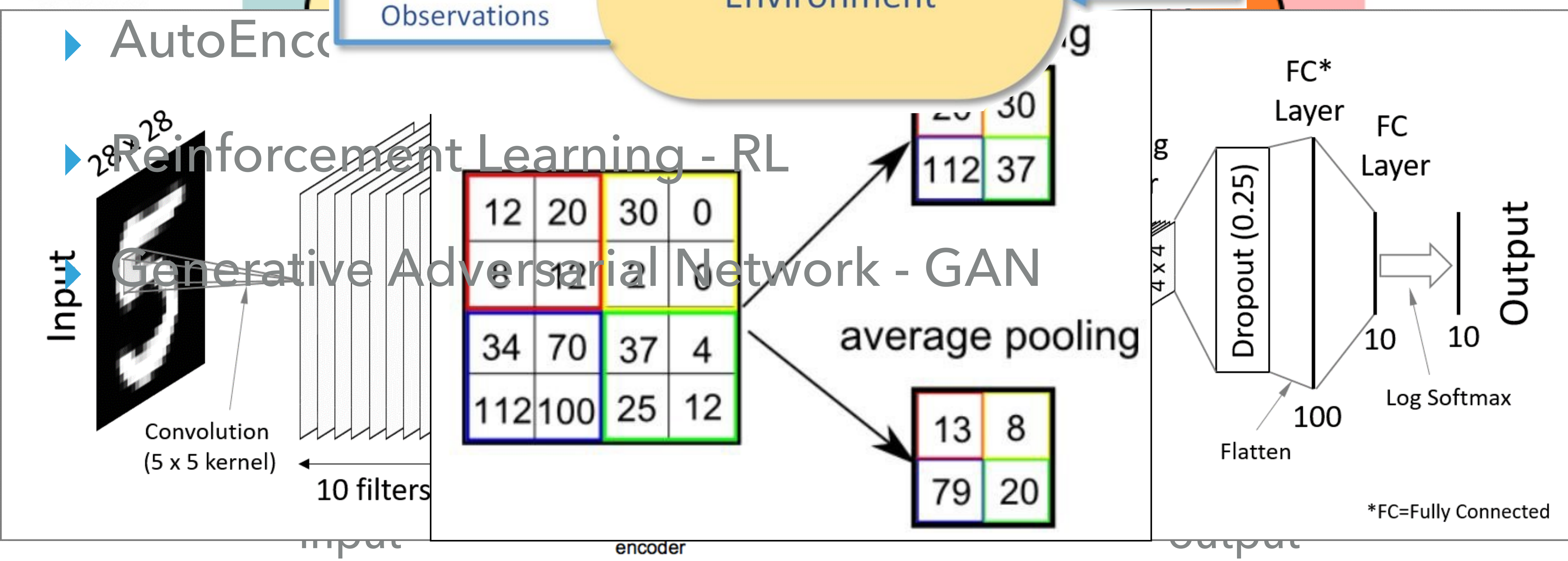


- ML for use in Production
- 3D Modeling
- Robotic Control Schemes
- Virtual Character Control
- Learning for Deformable Simulations
- Fluid Simulation
- Where is it not yet?

FLAVORS OF

- Neural N
- Convolut
- AutoEnc
- Reinforcement Learning - RL
- Generative Adversarial Network - GAN





OUTLINE

- **ML for use in Production**
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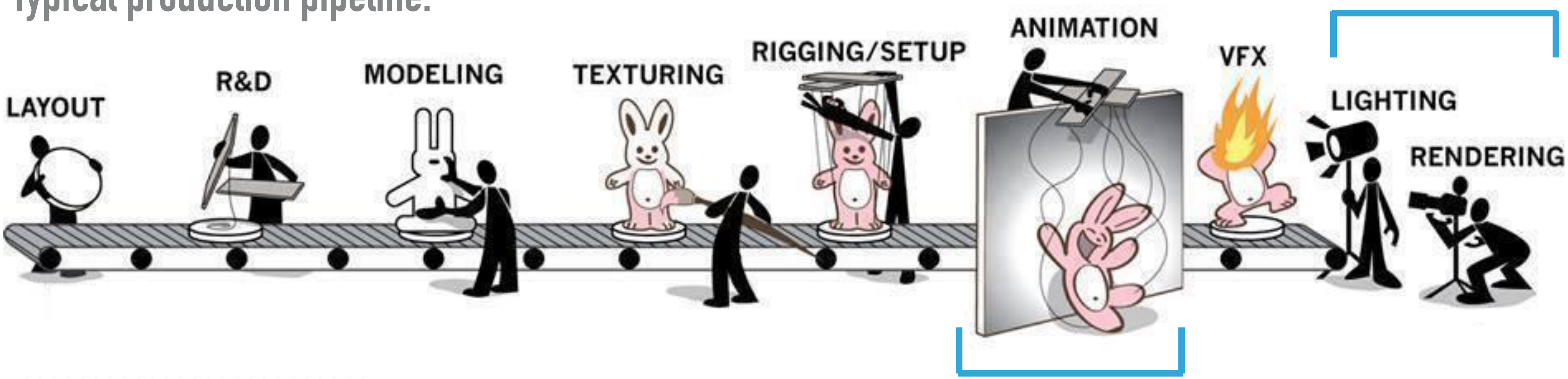
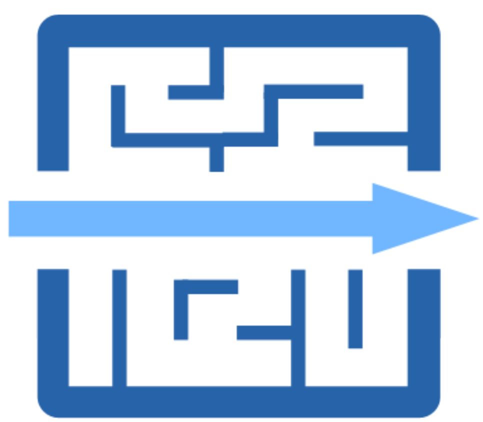
ML IN PRODUCTION

Typical production pipeline:



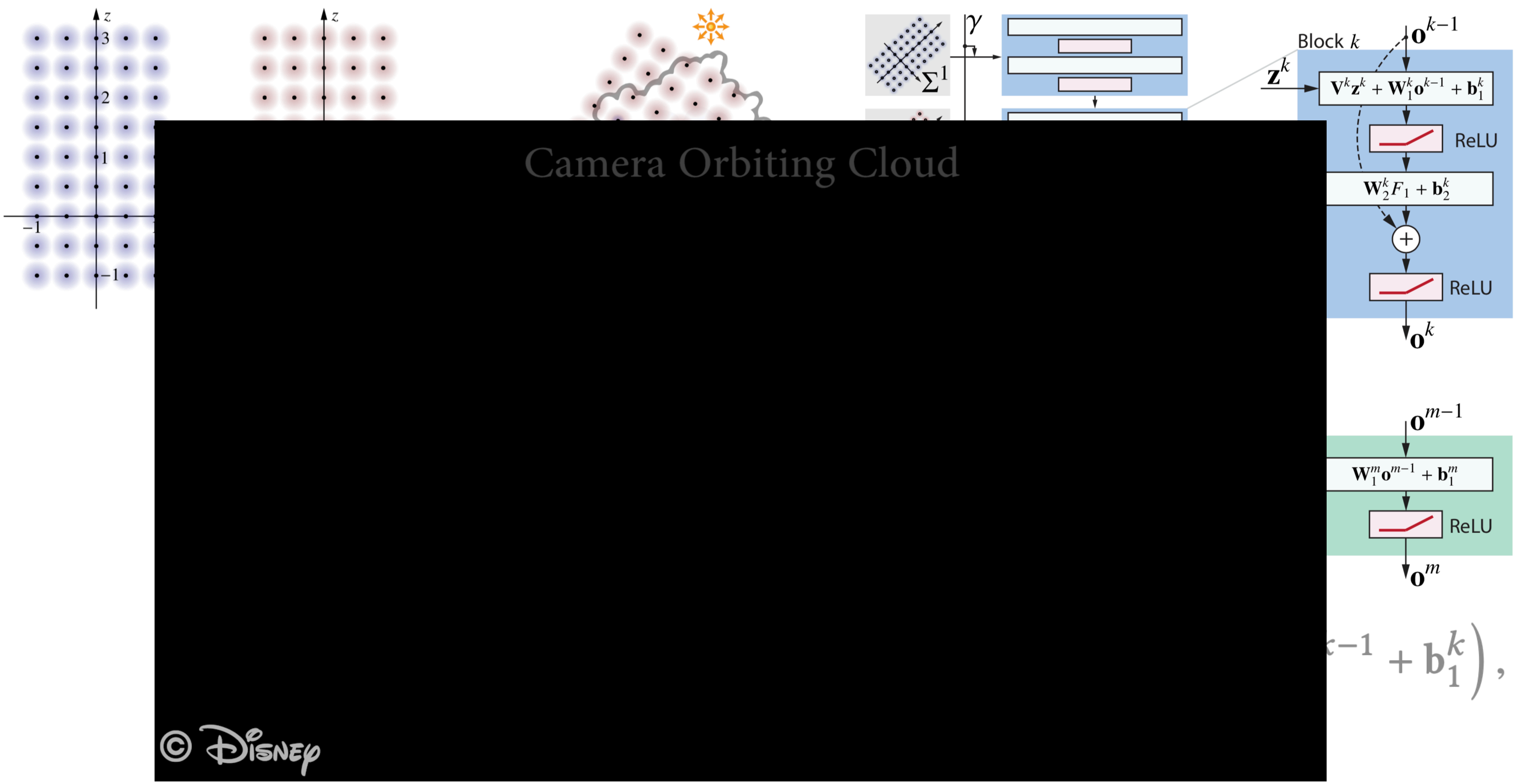
speed



visual quality

RADIANCE PREDICTION

Kallweit et al (2017)

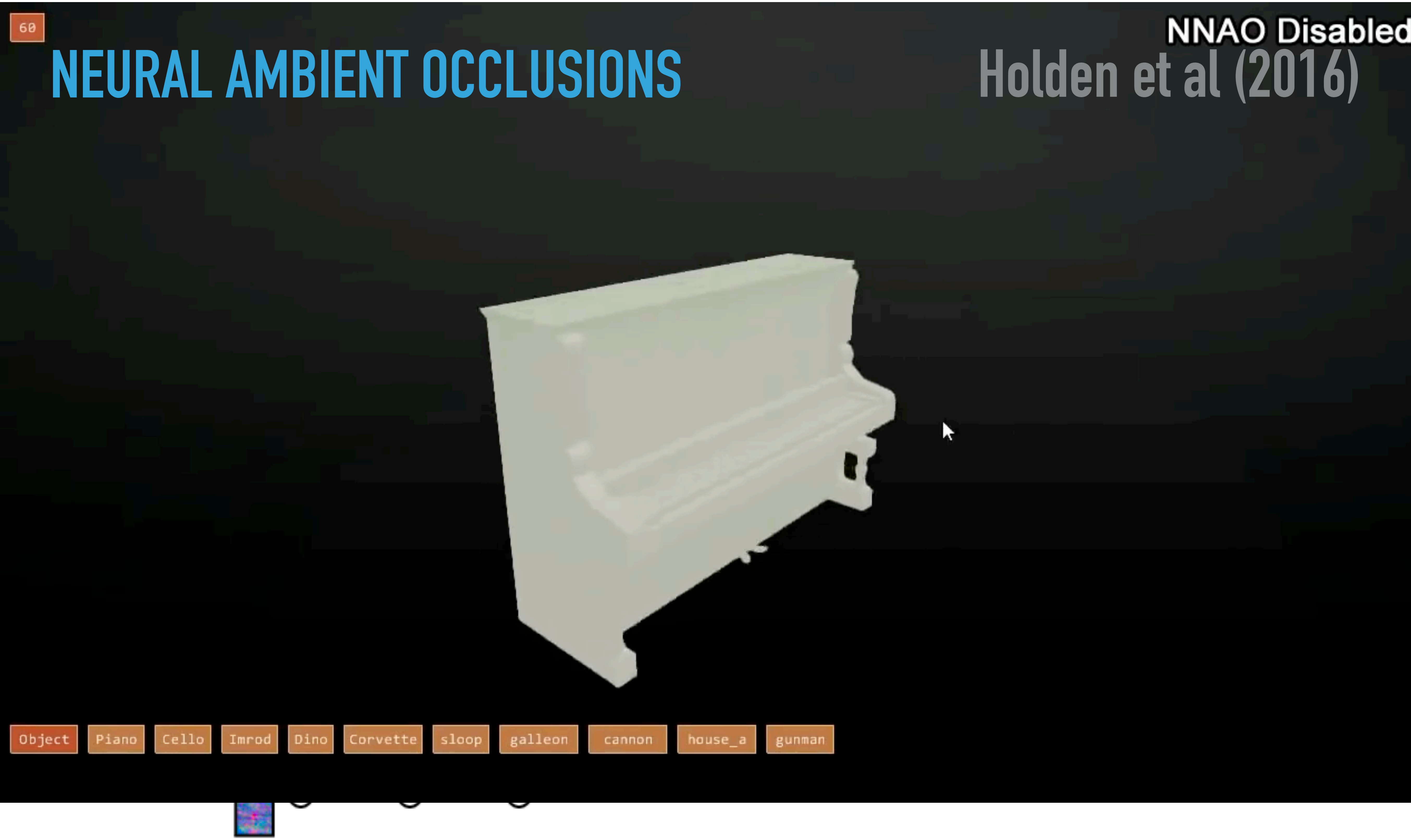


$$\mathbf{o}^k = f\left(F_2^k + \mathbf{o}^{k-1}\right),$$

Simon Kallweit, Thomas Muller, Brian McWilliams, Markus Gross, Jan Novak

NEURAL AMBIENT OCCLUSIONS

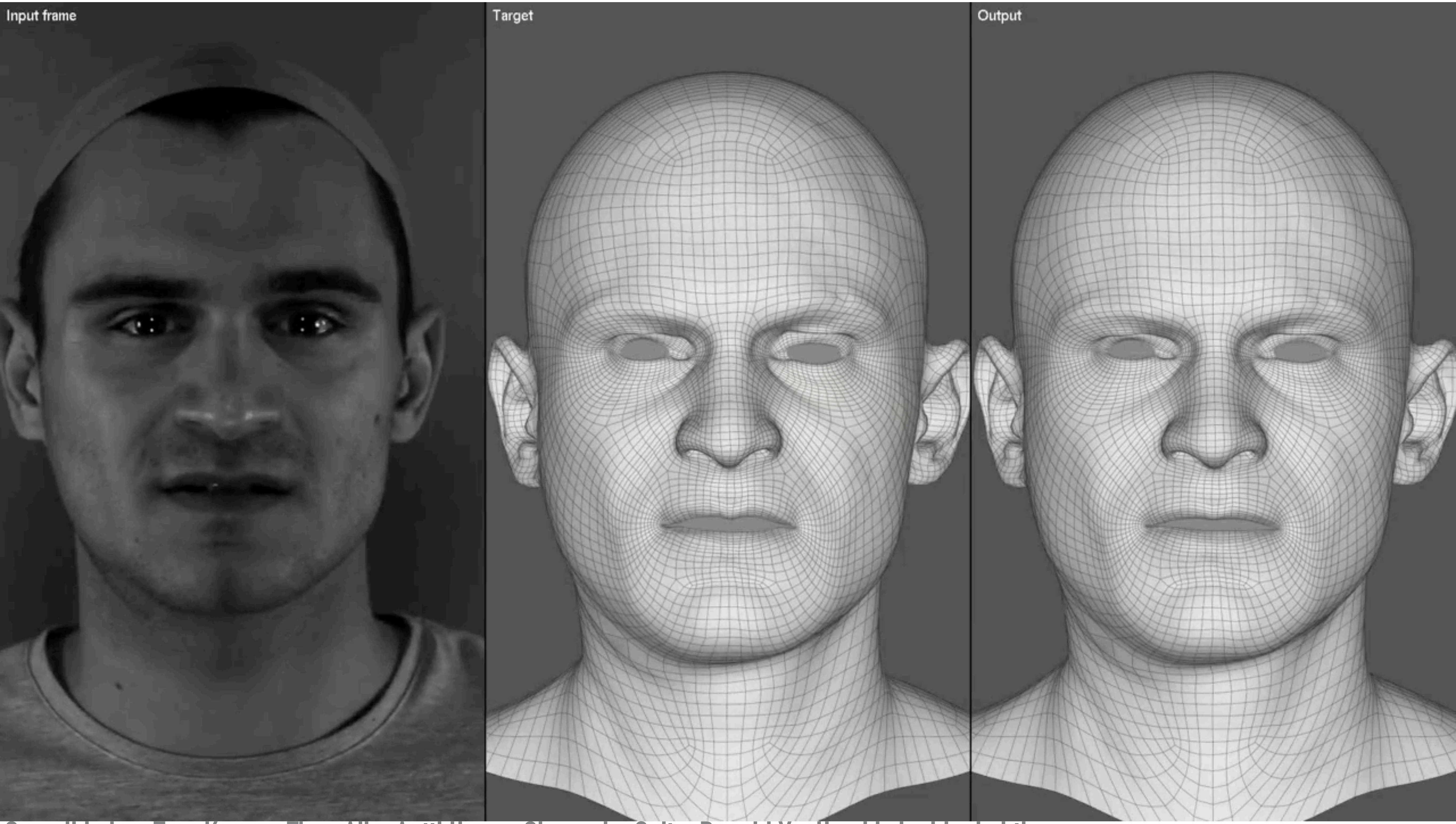
Holden et al (2016)



Daniel Holden, Jun Saito, Taku Komura

RETARGETING PERFORMANCE CAPTURE

Laine et al (2017)



Samuli Laine, Tero Karras, Timo Aila, Antti Herva, Shunsuke Saito, Ronald Yu, Hao Li, Jaakko Lehtinen

PRODUCTION & ML

	Net Type	Contribution	Limitations
Kallweit et al (2017)	NN	highly accurate and significantly faster	train new net for every type of cloud
Holden et al (2016)	CNN	higher sampling rate for AO than existing methods	new net required depending on scale of features
Laine et al (2017)	CNN	fully automated pipeline replaces manual work	-per user calibration -requires expensive capture setup

- **Outperform previous methods**
- **but are limited to privileged data**

OUTLINE

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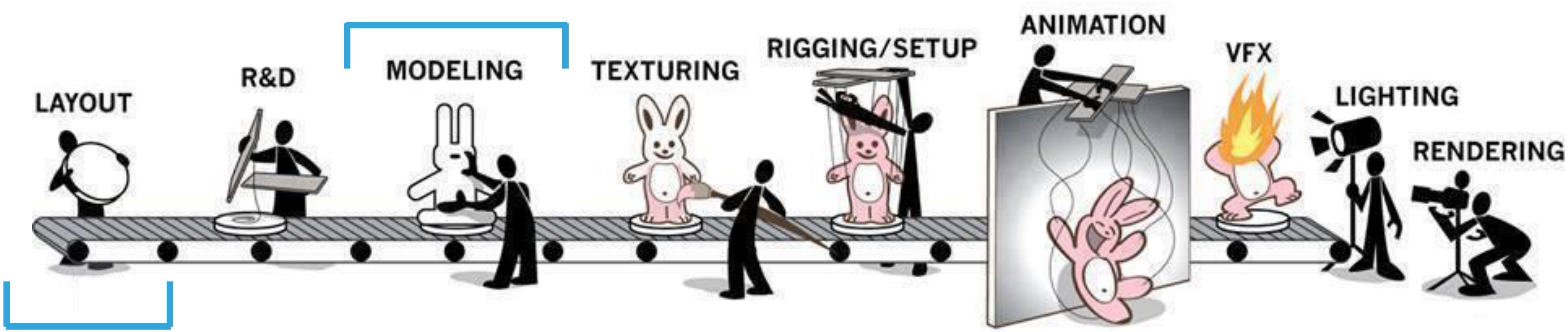
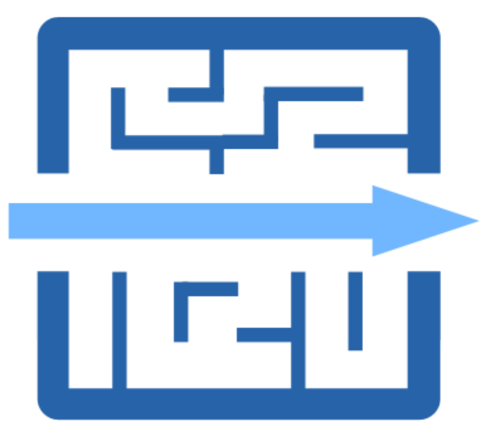
3D MODELING WITH ML



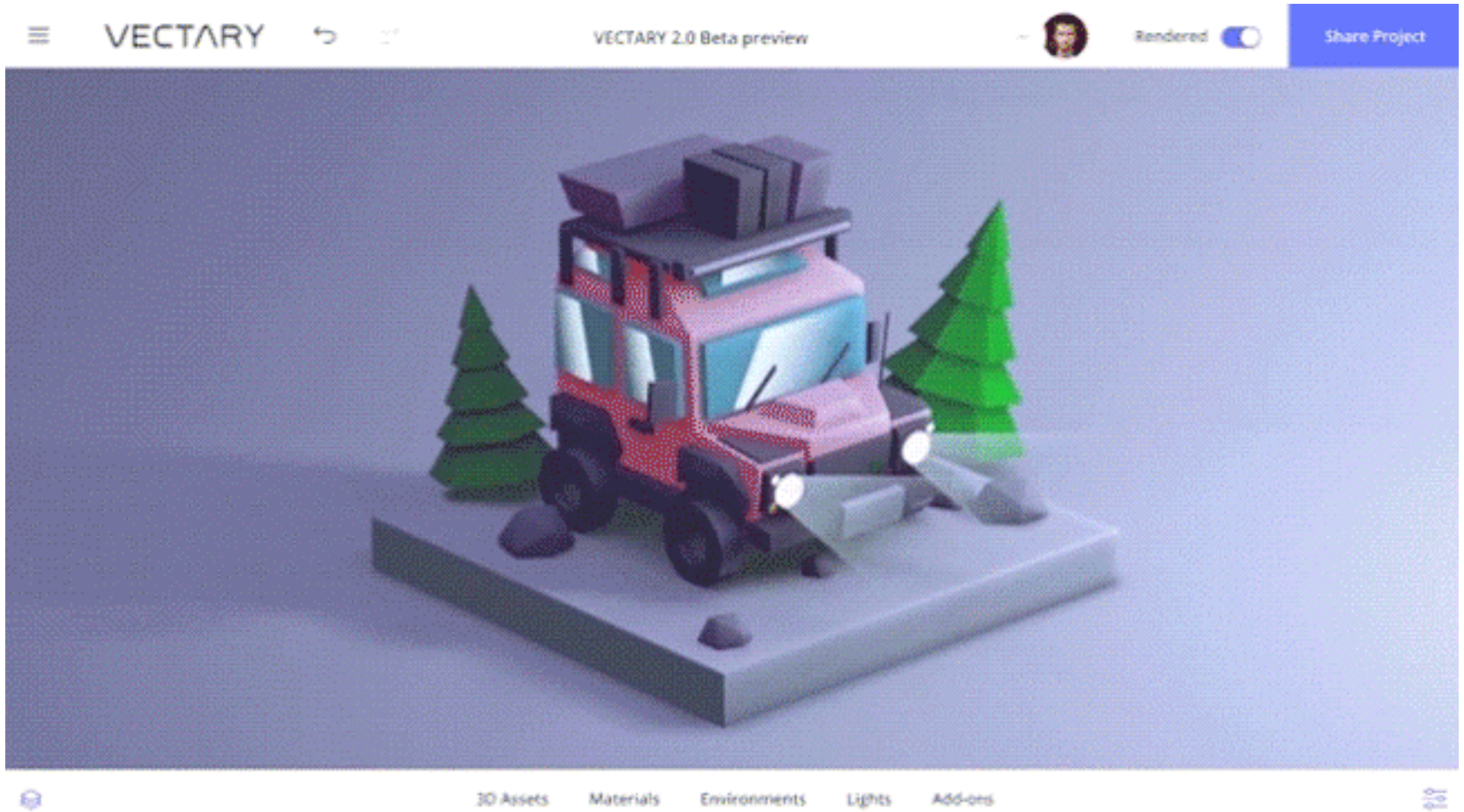


simplicity

robustness

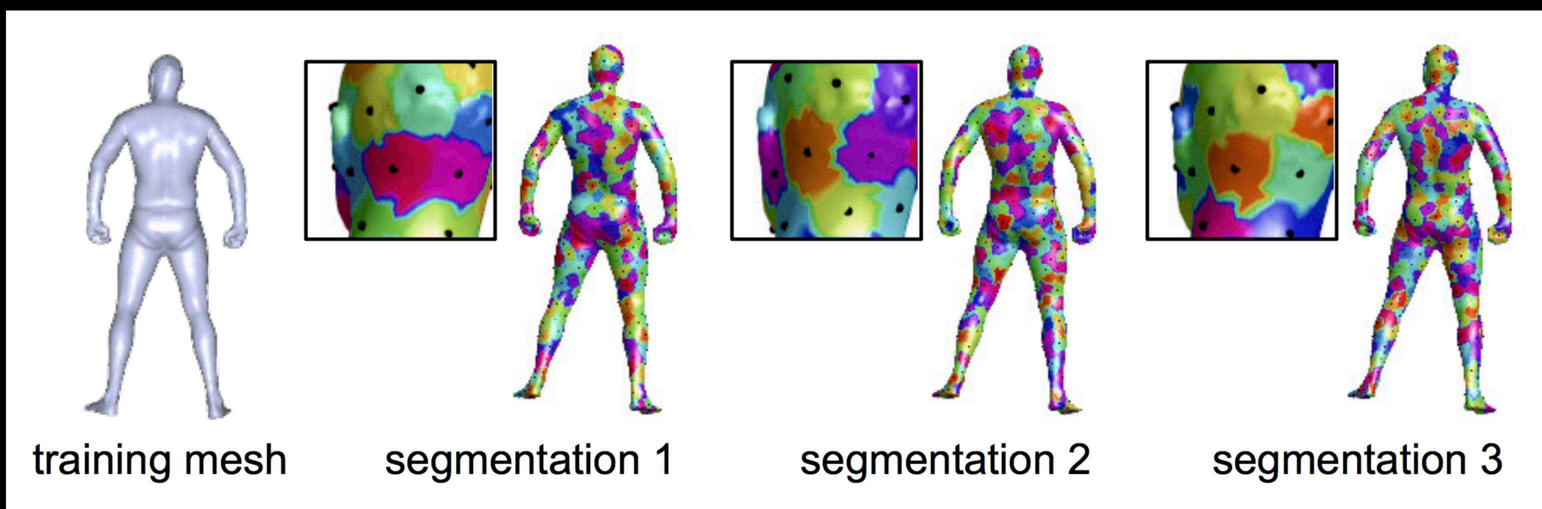
3D MODELING WITH ML

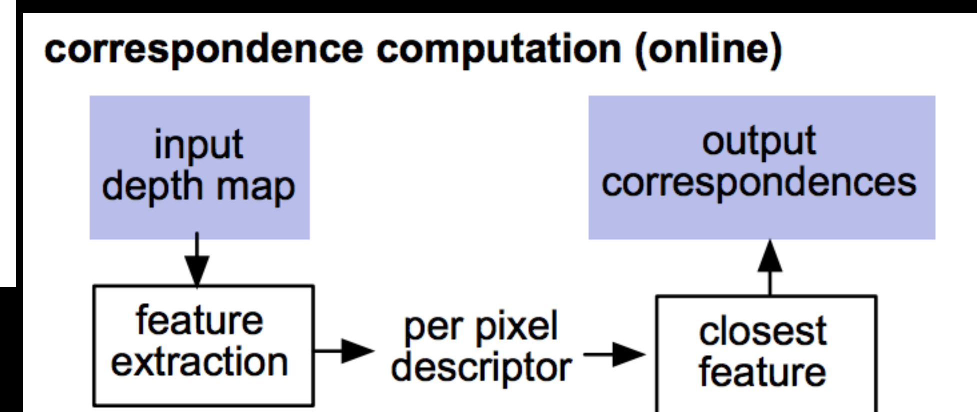
- How do we acquire our shapes and models?
- How do we structure and layout our shapes into a scene?
- How do we process our shapes?



STITCHING SCANS

Wei et al (2016)





Results

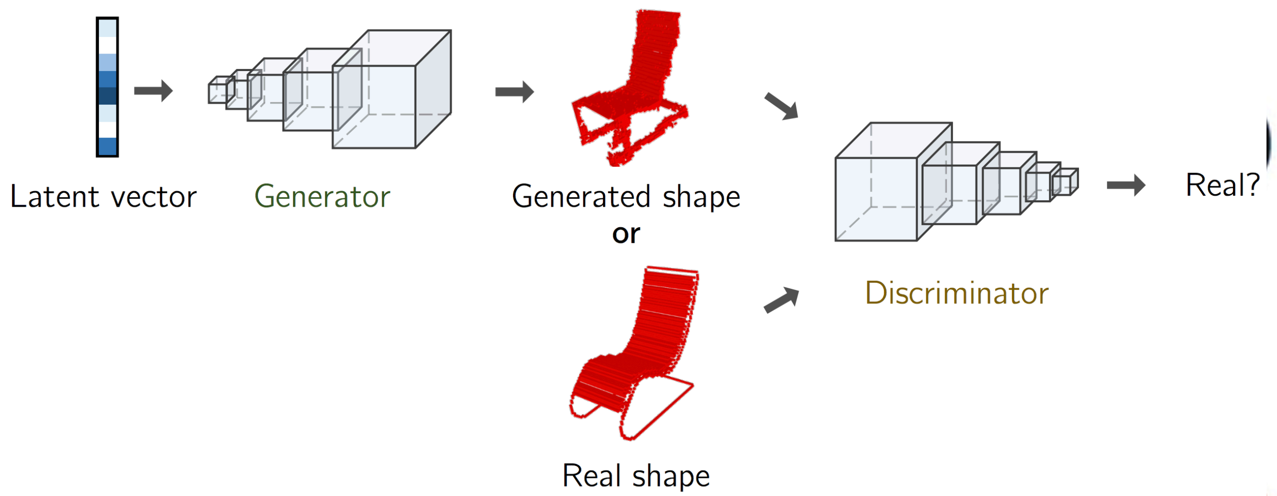
full-to-partial correspondences

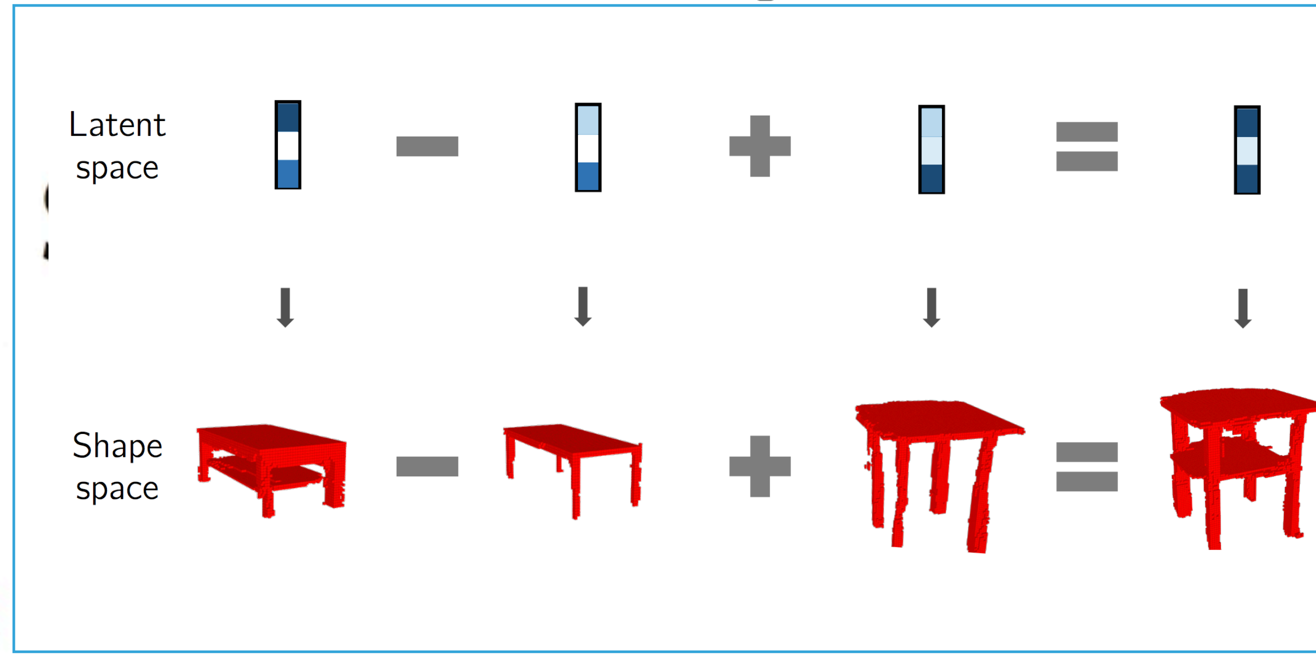
- f depends only on pixel location on body
  - irrespective of pose, clothing, view angle, or body shape
- ||f(p)-f(q)|| is small when p and q are nearby, and large for distant points

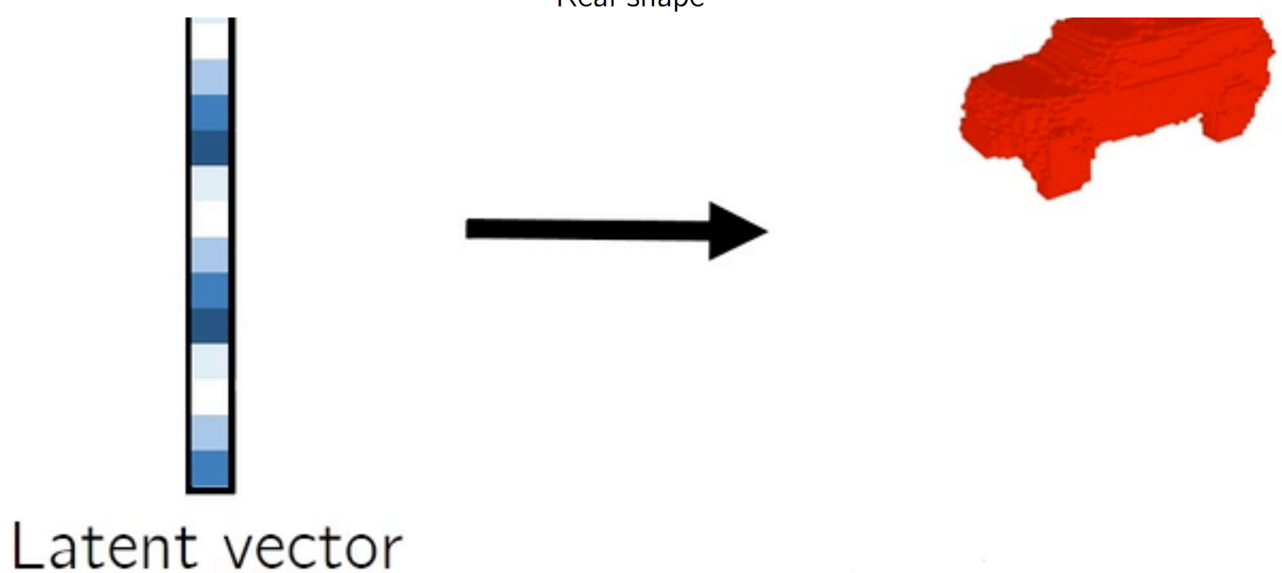
Lingyu Wei, Qixing Huang, Doygu Ceylan, Etienne Vouga, Hao Li

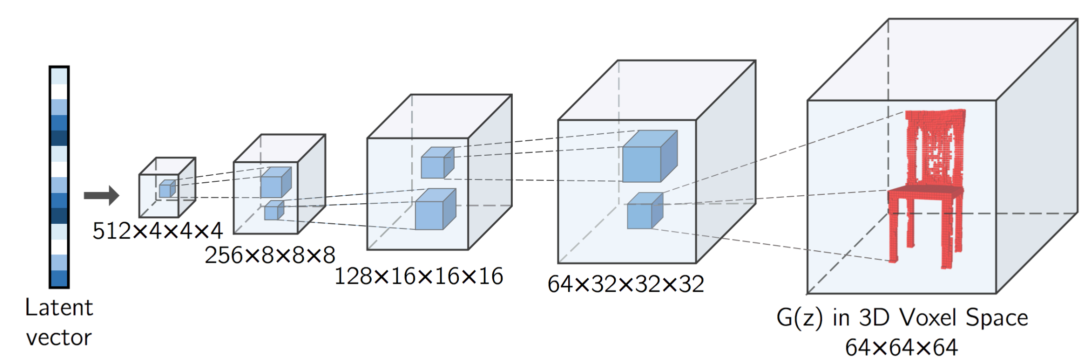
EXPLORING 3D SHAPE-SPACE

Wu & Zhang et al (2016)







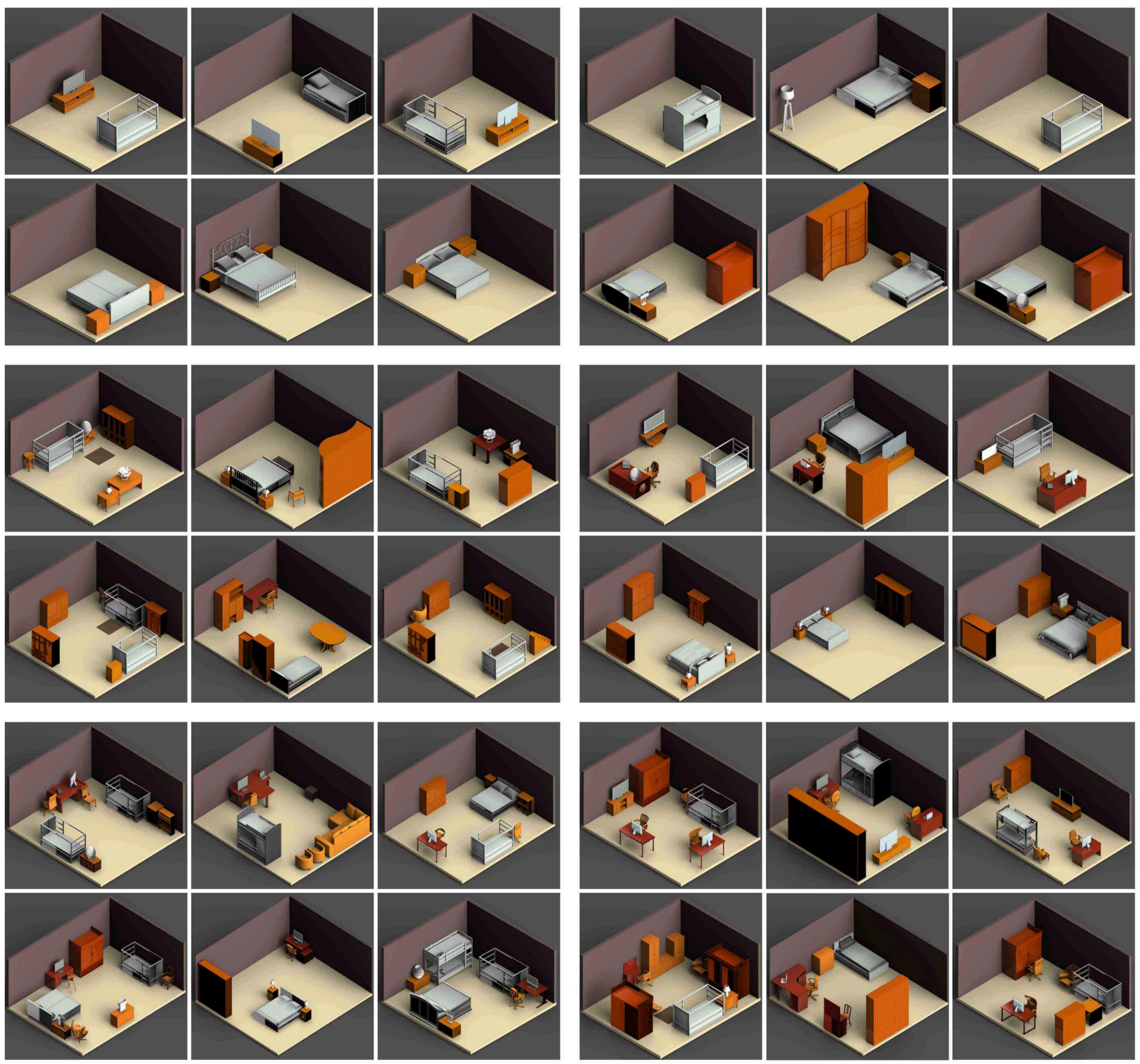


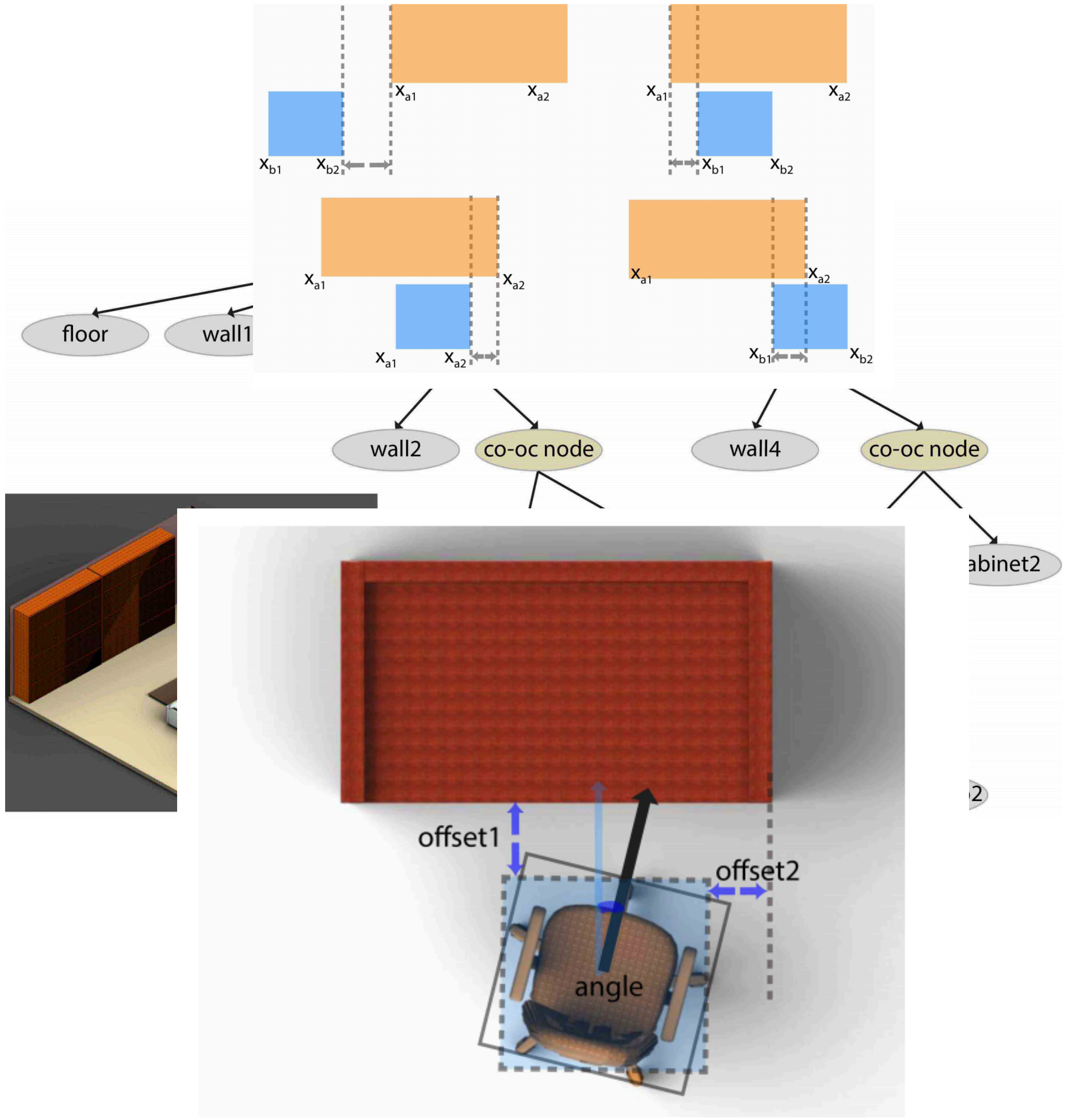
In this work, we build a model to generate 3D shapes from latent vectors.

Jiajun Wu, Chengkai Zhang, Tianfan Xue, William Freeman, Joshua Tenenbaum

EXPLORING 3D SCENE HIERARCHIES

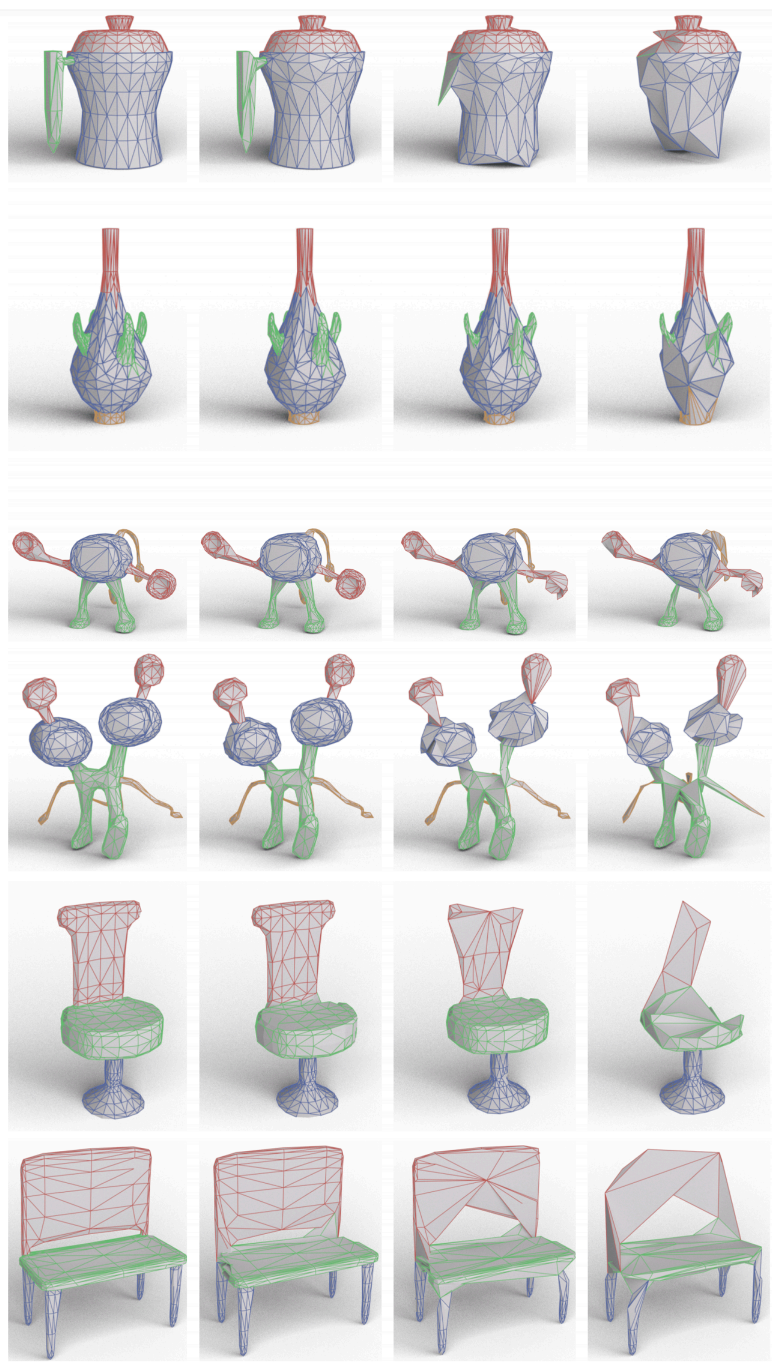
Li et al (2019)

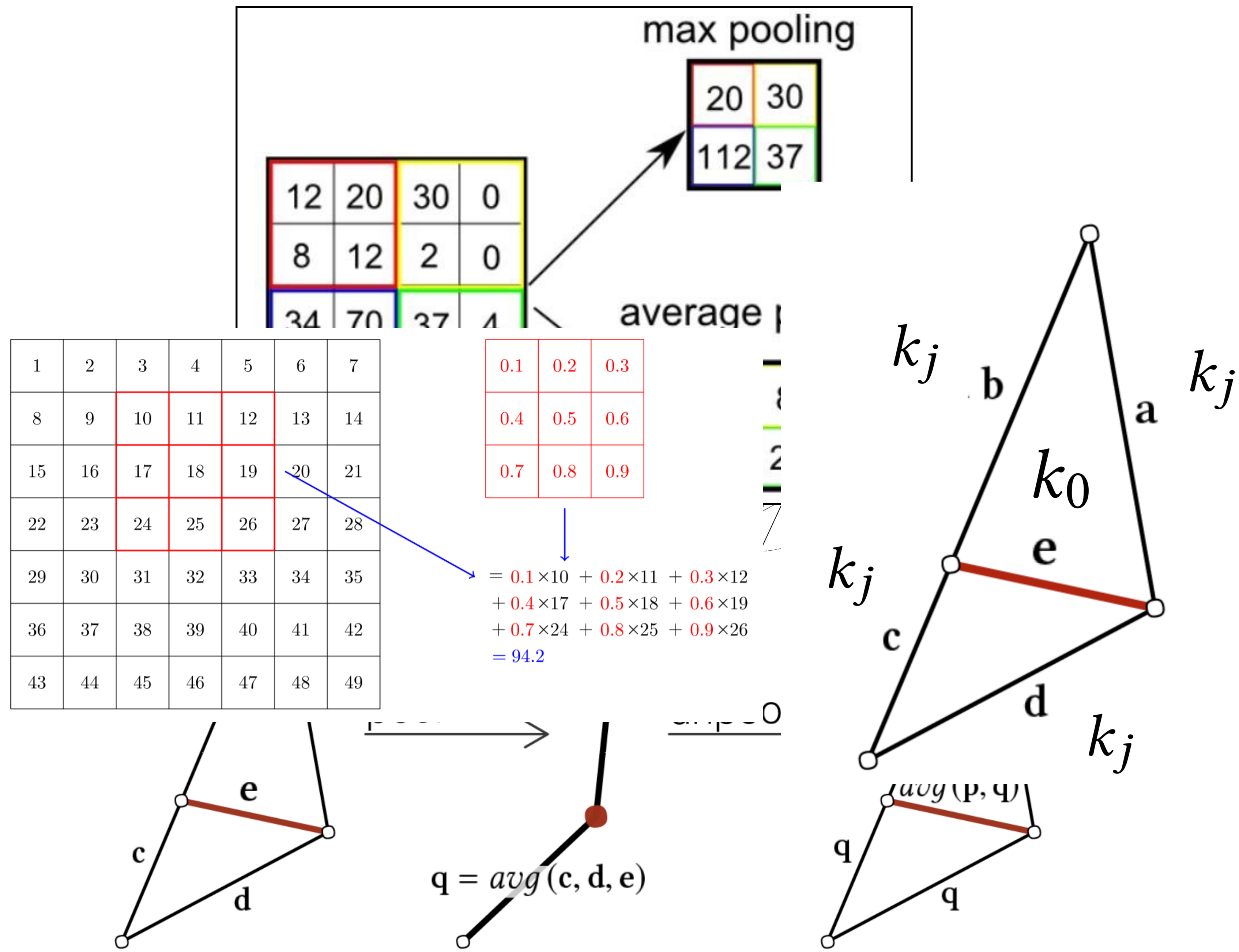




Manyi Li, Akshay Patil, Kai Xu, Siddhartha Chaudhuri, Owais Khan, Ariel Shamir, Changhe Tu, Baoquan Chen, Daniel Cohen-Or, Hao Zhang

EXTENDING CONVOLUTIONS TO MESHES Hanocka et al (2019)





Rana Hanocka, Amir Hertz, Noa Fish, Raja Giryes, Shachar Fleishman, Daniel Cohen-Or

COMPARISON OF PREVIOUSLY SEEN METHODS

	Net Type	Contribution	Limitations
Wei et al (2016)	CNN	scan correspondence in seconds	new clothing and poses require new net (250 hours train)
Wu & Zhang et al (2016)	GAN	shape generation, interpolation, and arithmetic	complexity limited by voxel-grid resolution
Li et al (2019)	AE	sample/search new scene layouts	limited by complexity of node descriptors
Hanocka et al (2019)	CNN	ability to view mesh as an image	Requires expensive priority queue updates

New applications of ML to 3D models

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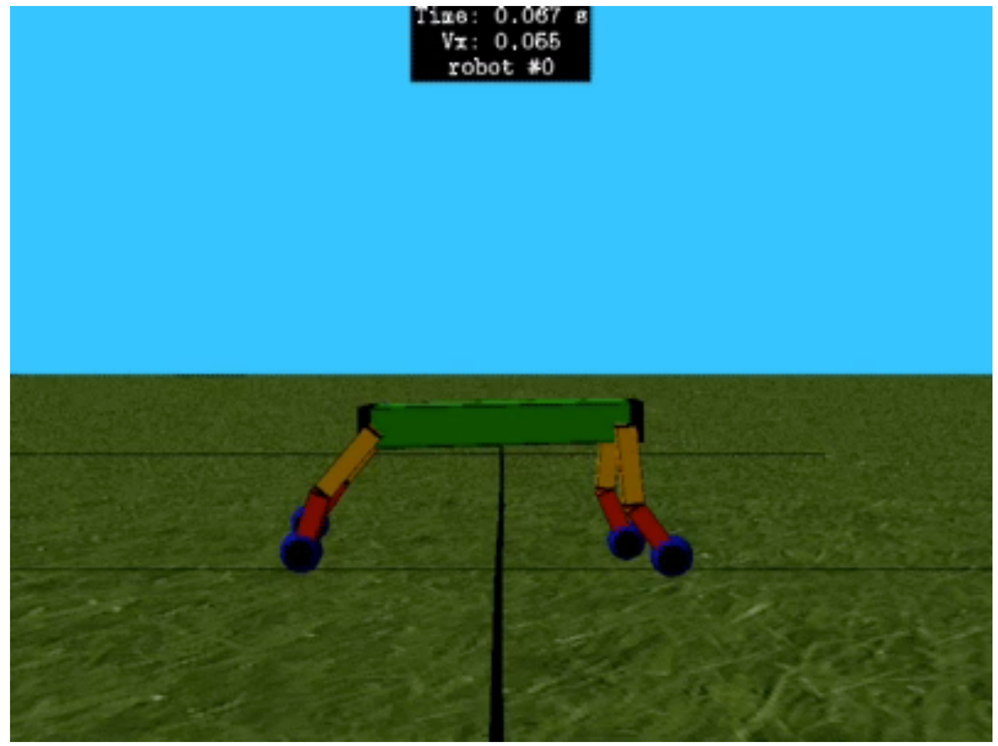
ROBOTICS CONTROL SCHEMES

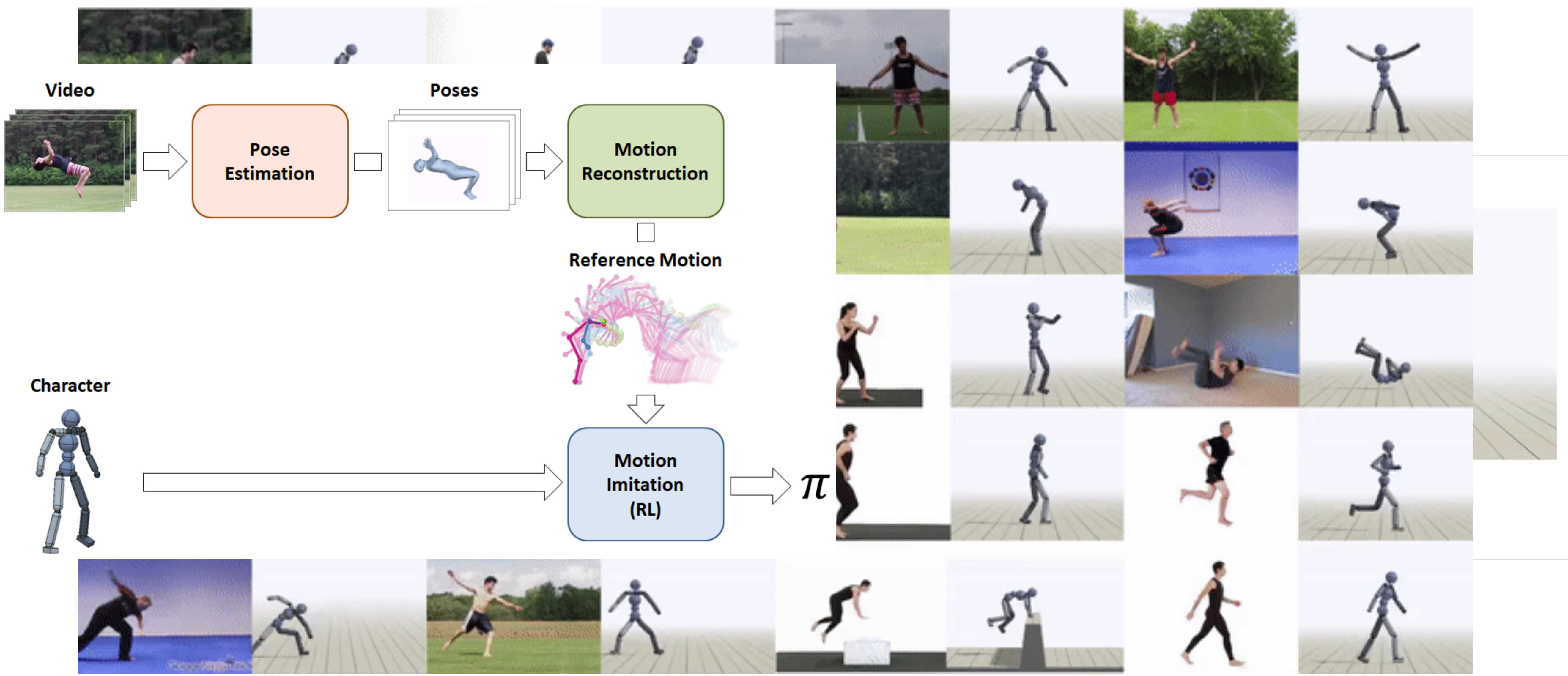


Reward

Action: {Stay, Move}

PHYSICAL SKILLS FROM VIDEOS

Peng et al (2018a)

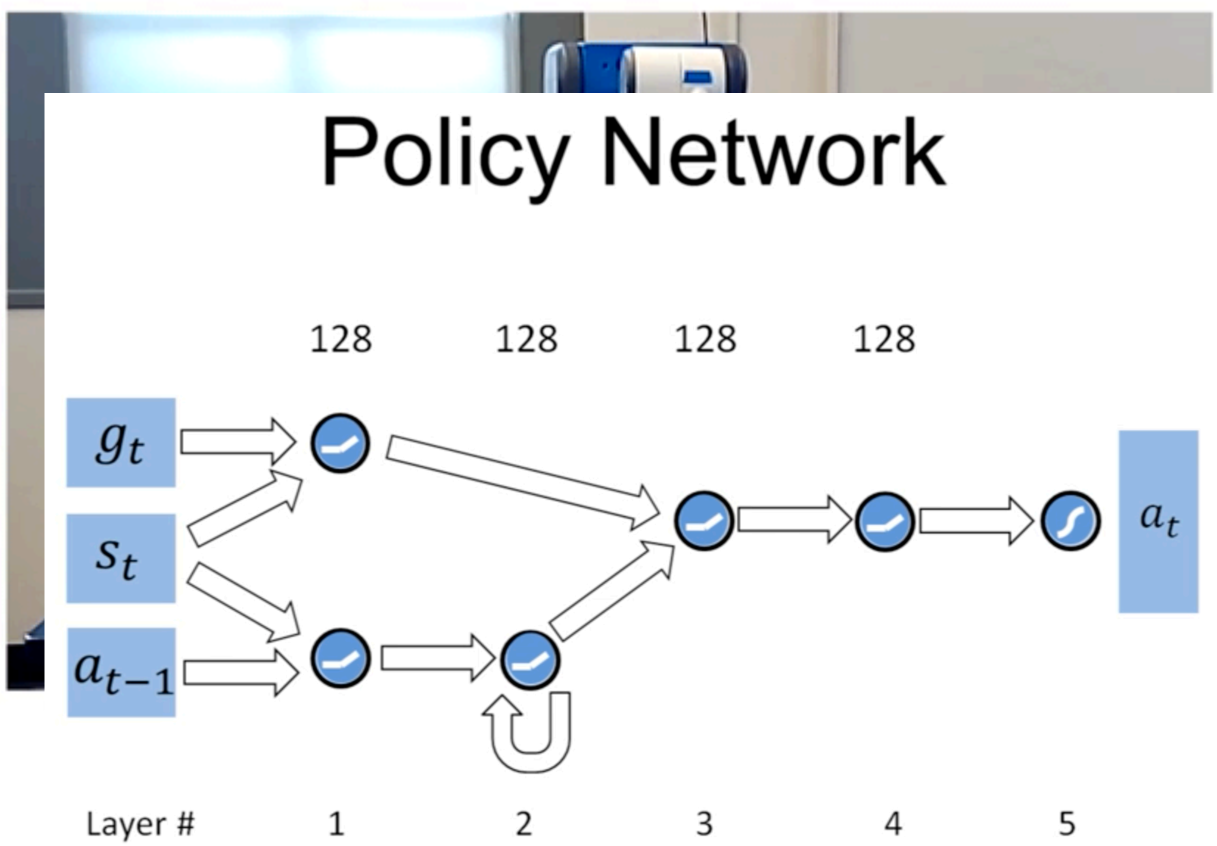


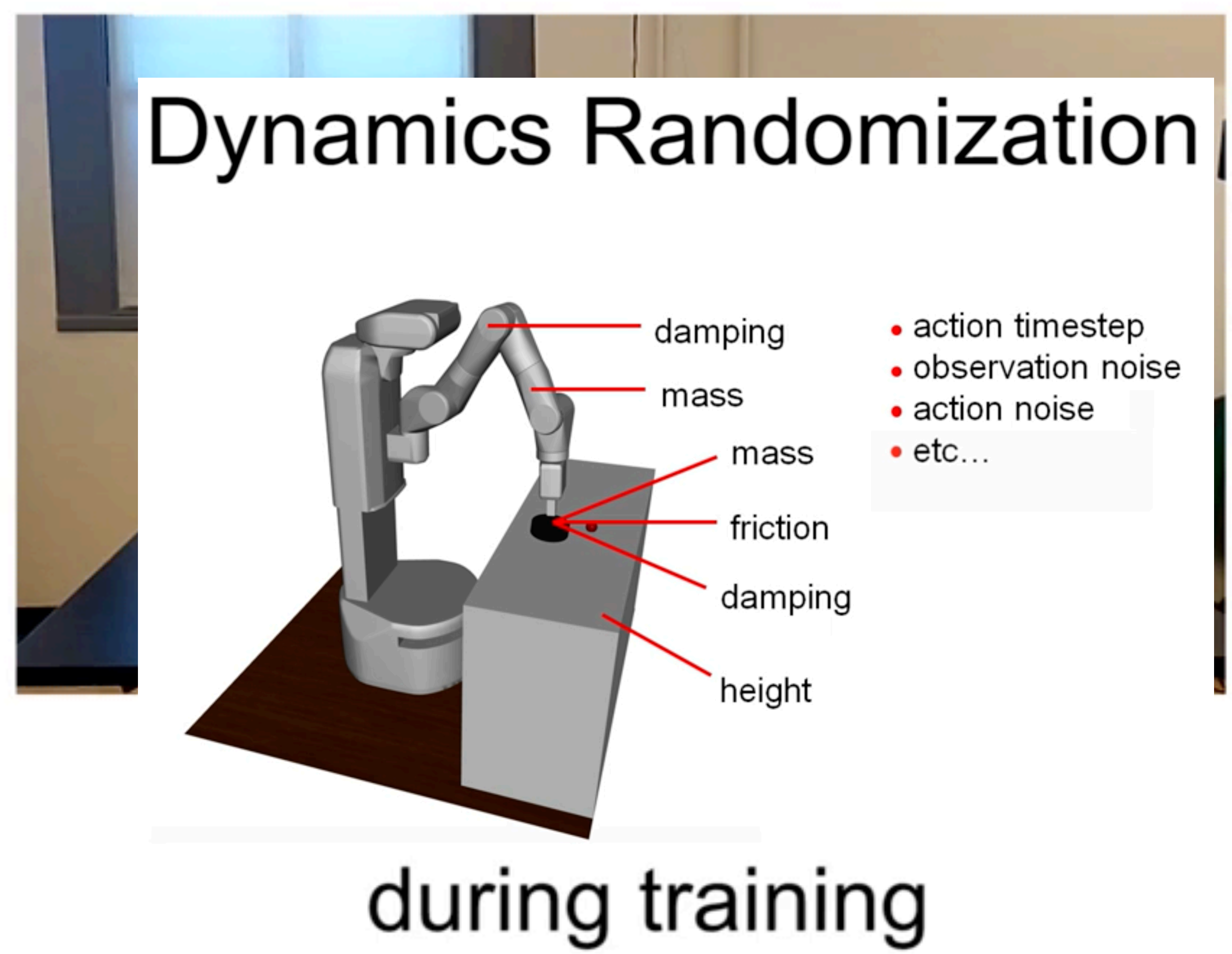
Xue Bin Peng, Anglo Kanazawa, Jitendra Malik, Pieter Abbeel, Sergey Levine

DYNAMICS RANDOMIZATION

Peng et al (2018b)

Comparisons





Xue Bin Peng, Marcin Andrychowicz, Wojciech Zaremba, Pieter Abbeel

ROBOTICS CONTROL SCHEMES

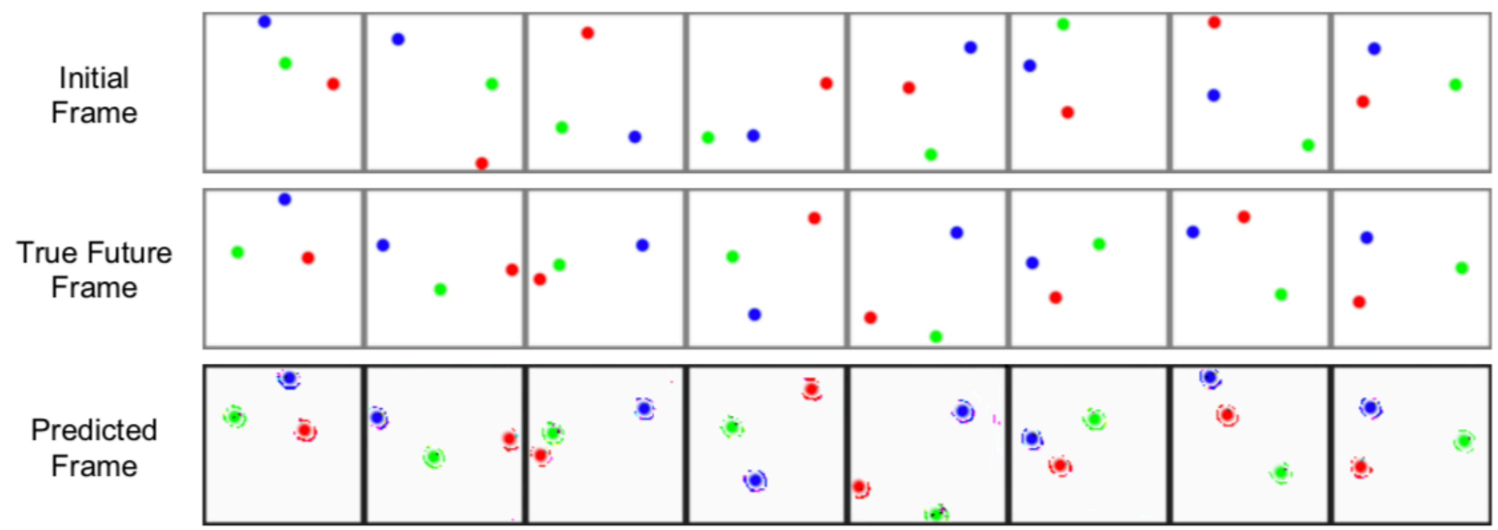
what if we could trace gradients through our environment?

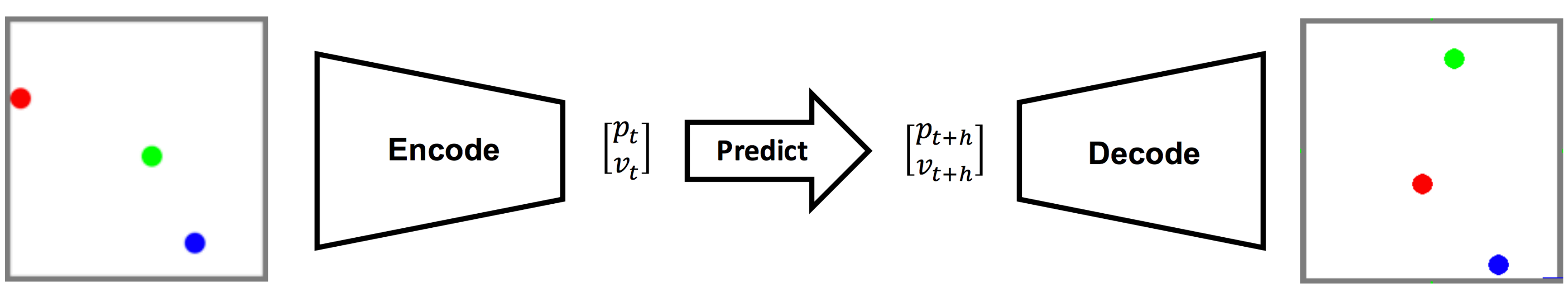
Reward

Action: {Stay, Move}

LEARNING FROM FRAMES

Belbute-Peres et al (2018)

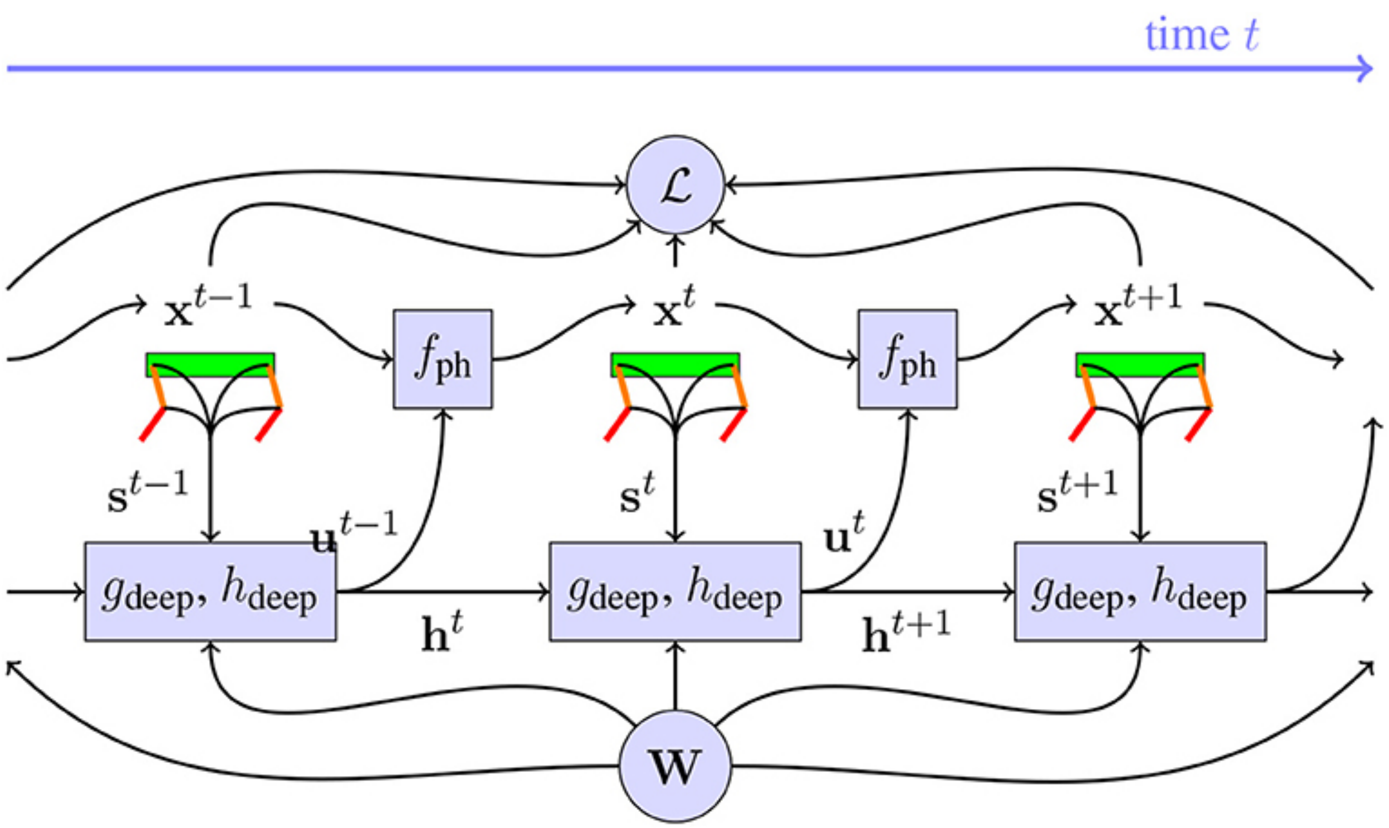


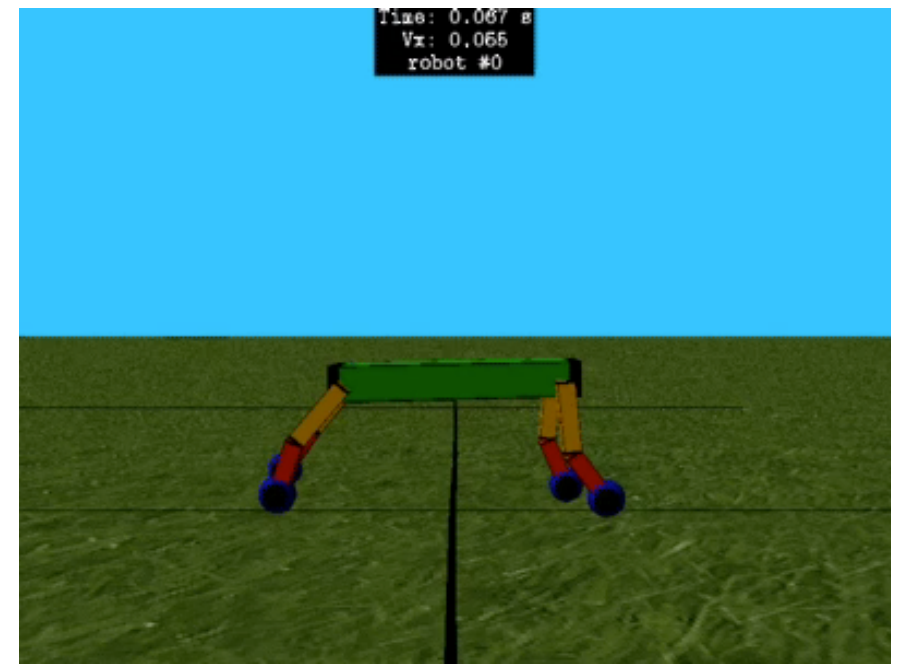


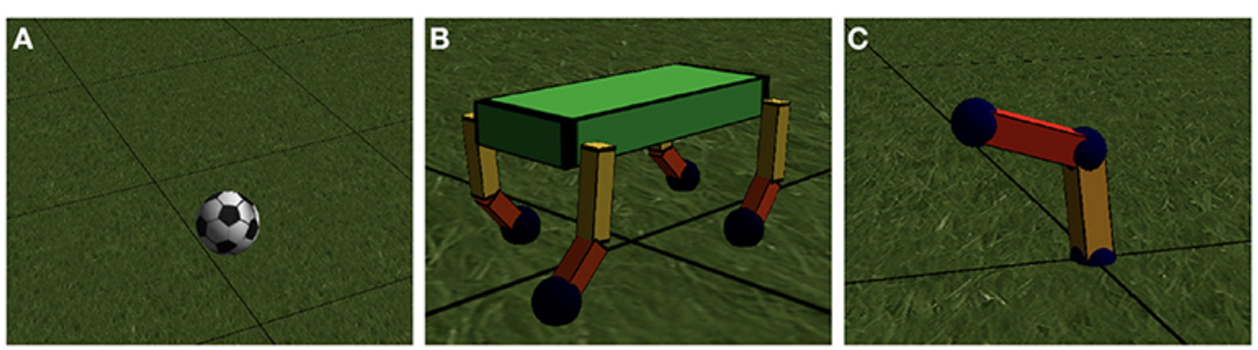
Filipe de A. Belbute-PEres, Kevin A. Smith, Kelsey R. Allen, Joshua Tenenbaum, J. Zico Kolter

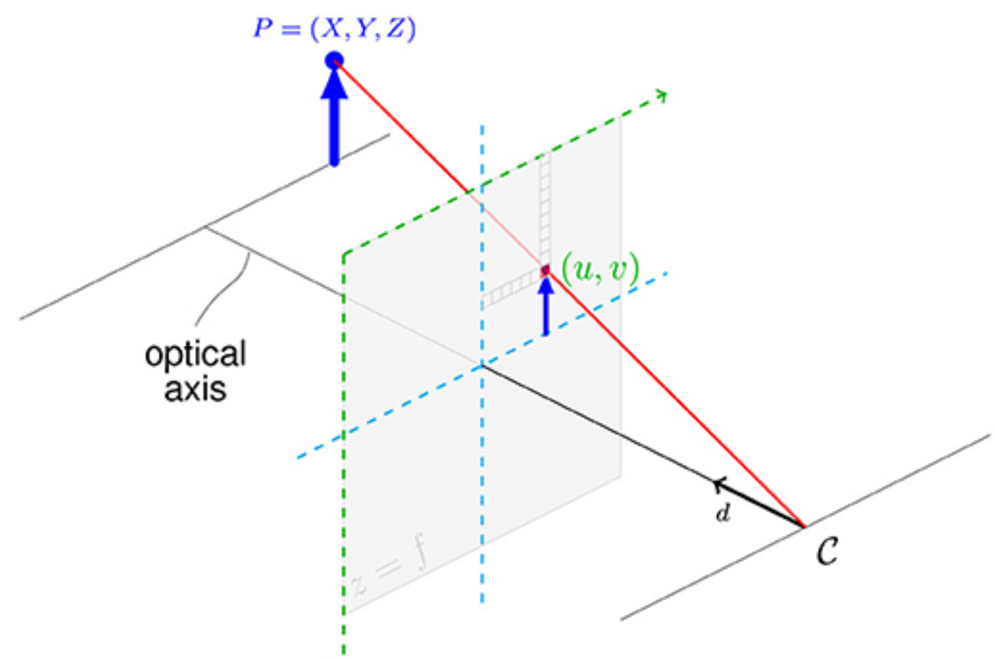
DIFFERENTIABLE PHYSICS ENGINE

Degrave et al (2019)





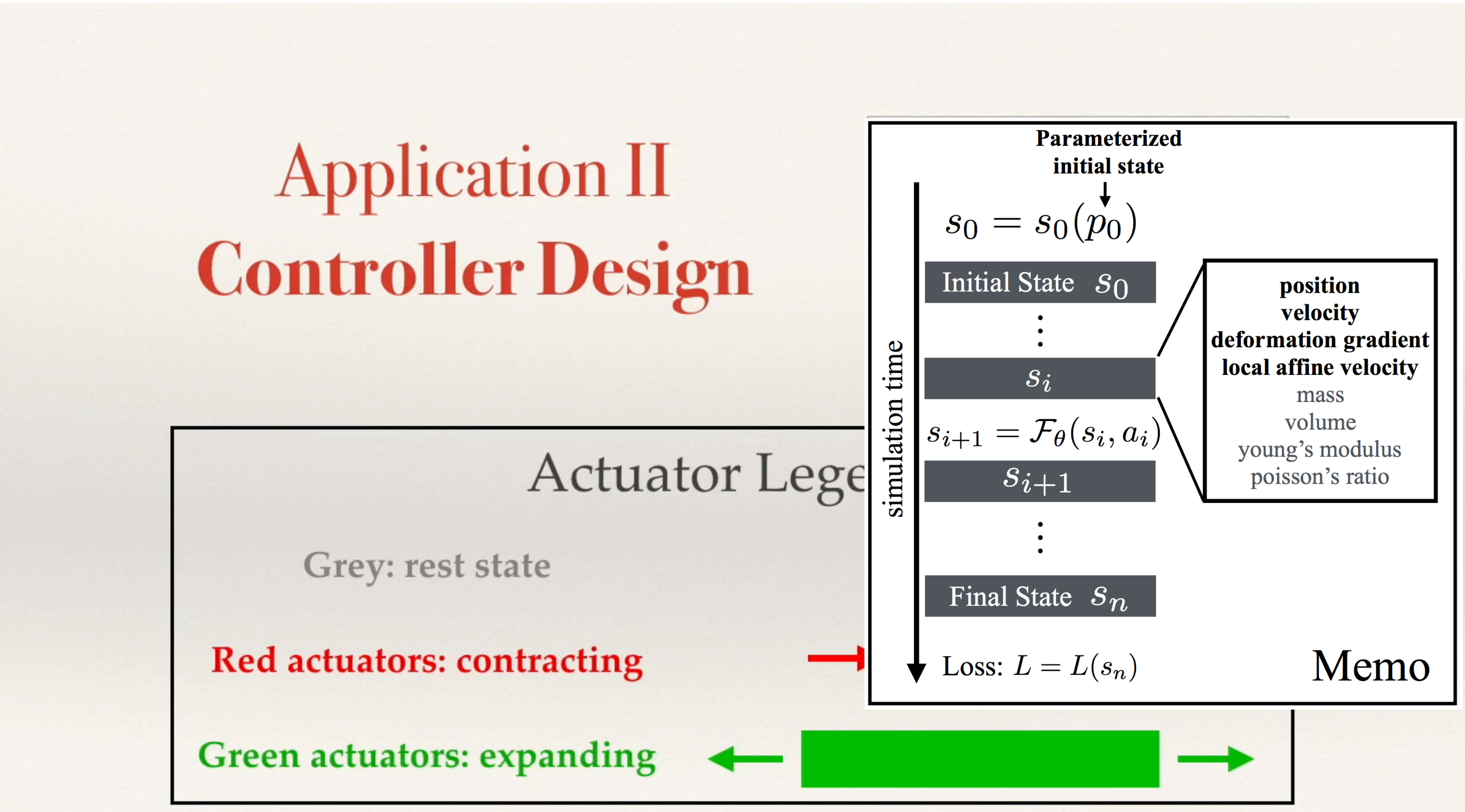




Joans Degrave, Michiel Hermans, Joni Dambre, Francis Wyffels

ML-MLS-MPM FOR SOFT ROBOTICS

Hu et al (2019)



Yuanming Hu, Jiancheng Liu, Andrew Spielberg, Joshua Tenenbaum, William Freeman, Daniela Rus, Wojciech Matusik

COMPARISON OF PREVIOUSLY SEEN METHODS

	Net Type	Contribution	Limitations
Peng et al (2018a)	RL	teach agents from wealth of videos	unable to reproduce fast motions
Peng et al (2018b)	RL	key insight on closing 'reality gap'	evaluated on limited tasks
Belbute-Peres et al (2018)	AE	handles contact	2D RB simulations
Degrave et al (2019)	RL	3D PD control scenarios	limited motions and no contact
Hu et al (2019)	RL	3D soft robotics	limited motions/ tasks

- **often try to simulate the entire pipeline,**
- **unnatural behavior arises that satisfies the goal**

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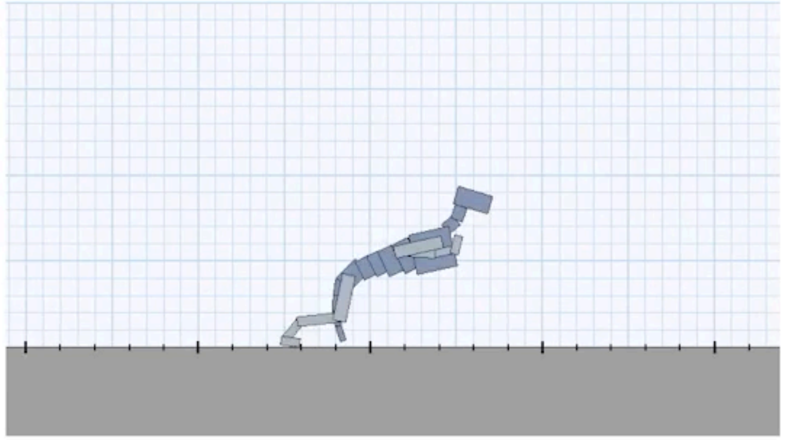
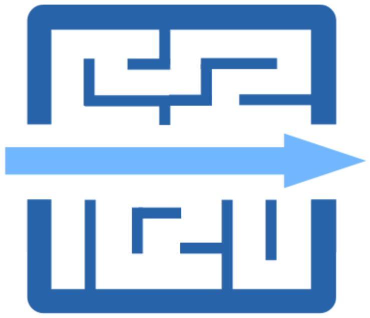
MOTIVATE SUBCATEGORY WITH EXAMPLE/QUESTIONS

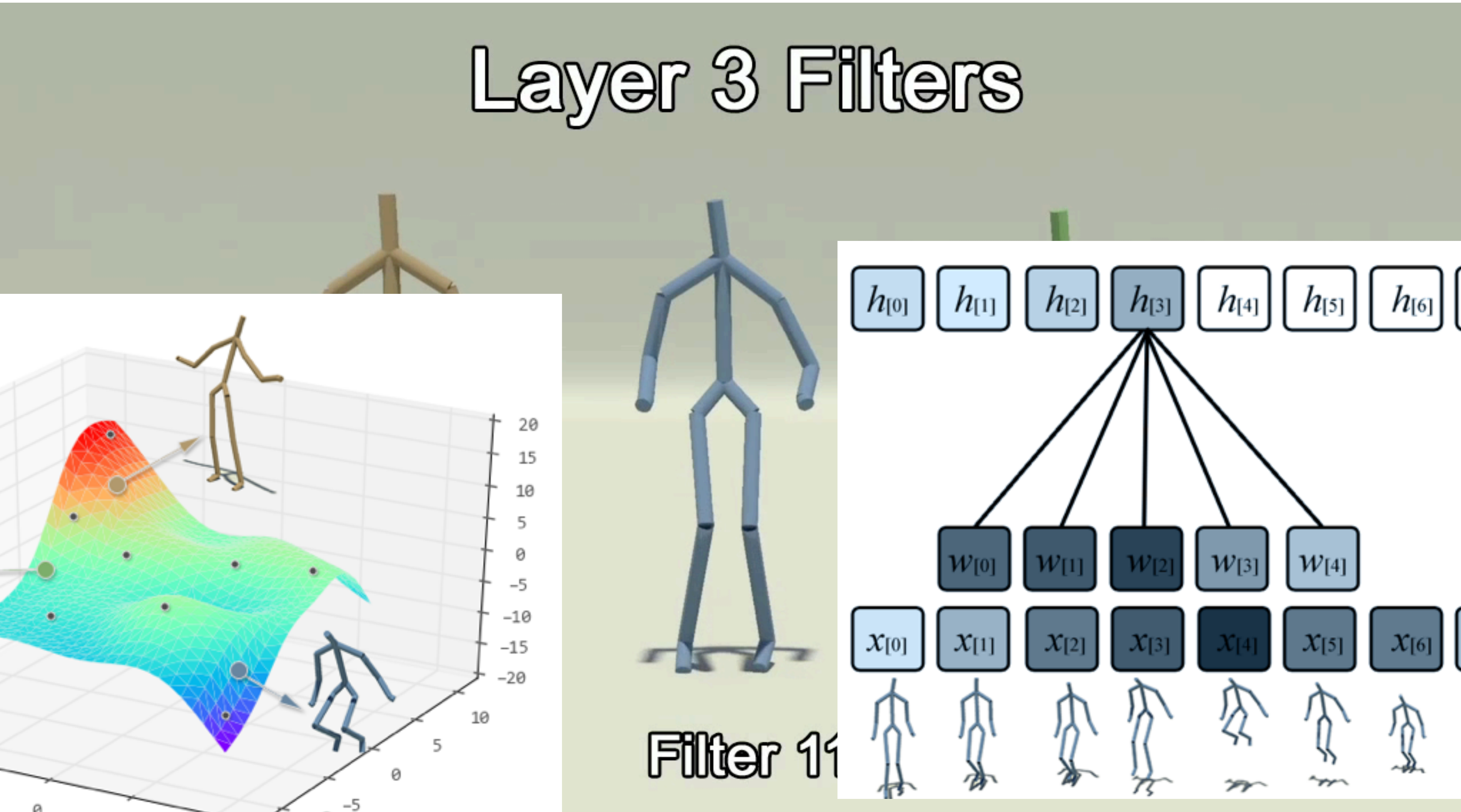


Reference



LEARNING MOTION MANIFOLDS

Holden et al (2015)



Daniel Holden, Jun Saito, Taku Komura, Thomas Joyce

LEARNING CONTROL FRAGMENTS

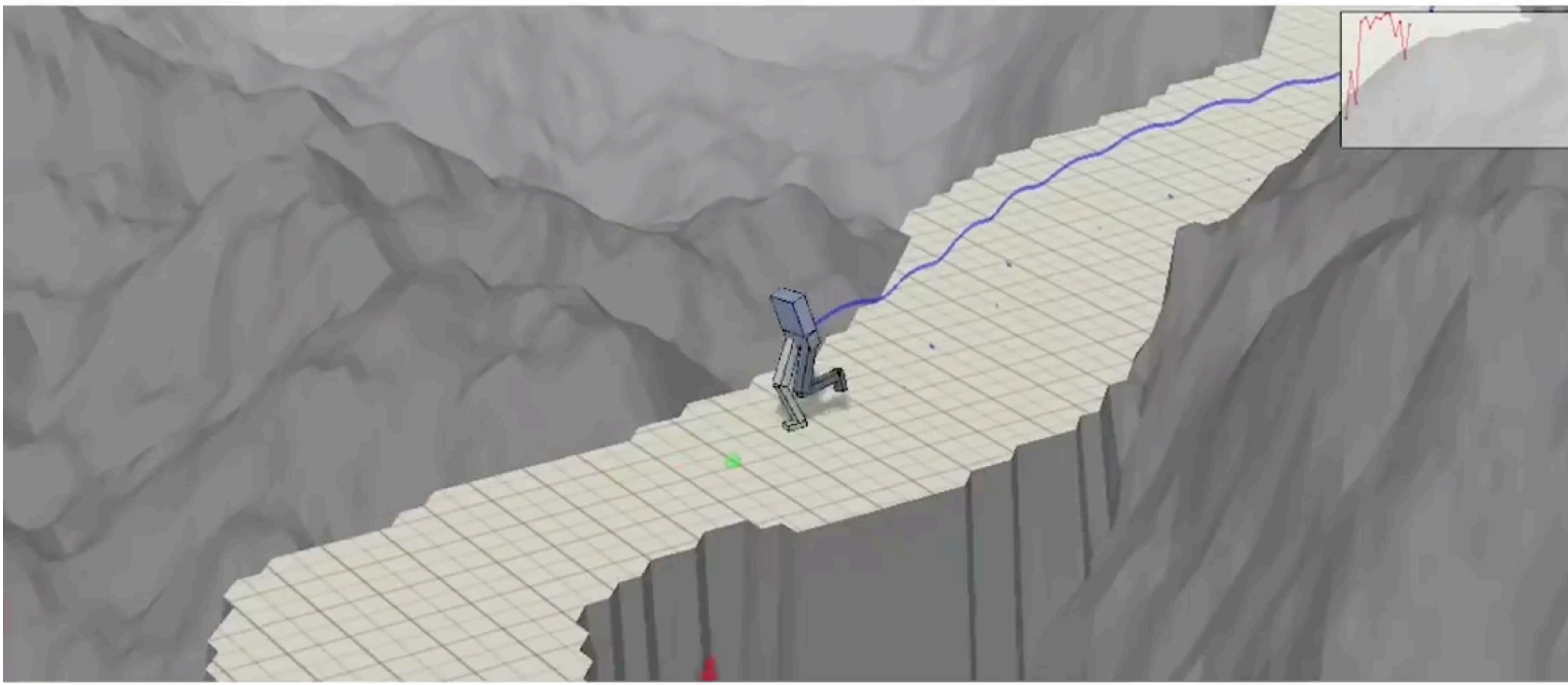
Liu & Hodgins (2017)

Libin Liu, Jessica Hodgins

DYNAMIC LOCOMOTION

Peng et al (2017)

Path Following (Run)

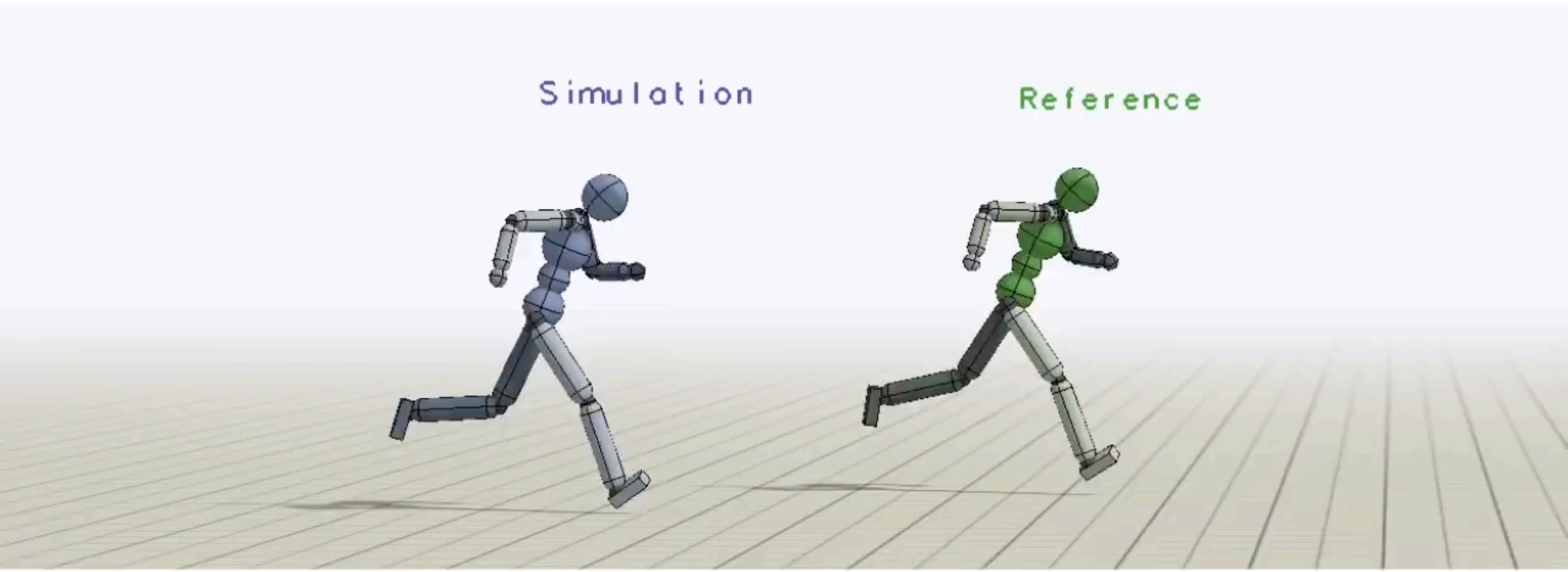


Xue

MIMICKING CHARACTER SKILLS

Peng et al (2018c)

Humanoid: Run

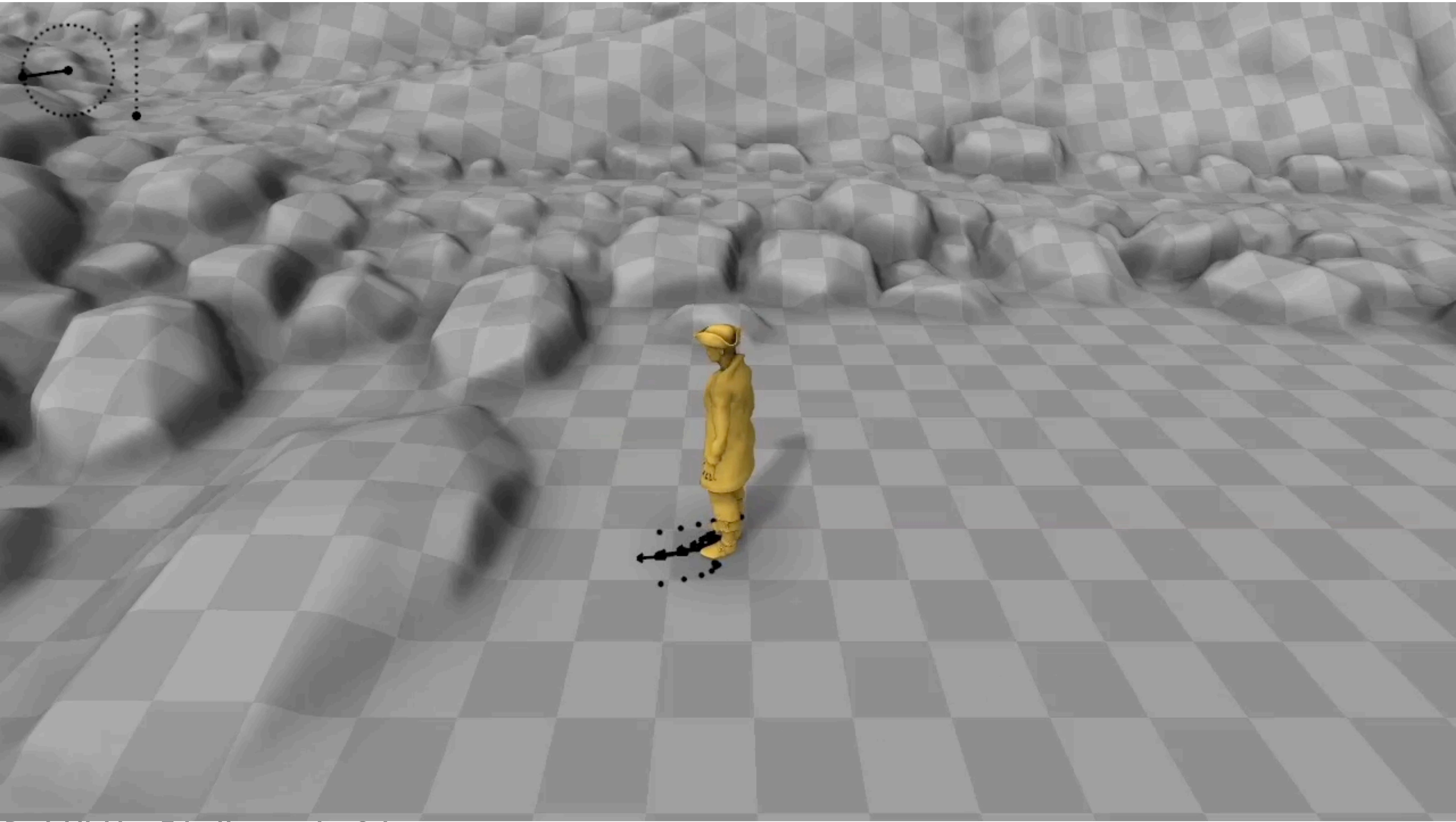


Policy trained to imitate a running clip.

Xue Bin PEng, Pieter Abbeel, Sergey Levine, Michiel Van De Panne

PHASE-FUNCTIONED NETS

Holden et al (2017)



Daniel Holden, Taku Komura, Jun Saito

COMPARISON OF PREVIOUSLY SEEN METHODS

	Net Type	Contribution	Limitations
Holden et al (2015)	CNN & AE	fix corrupt/missing data, motion interp	random joint lengths and ground contact
Liu & Hodgins (2017)	RL	highly dynamic balance behaviors	cannot handle complex environ.
Peng et al (2017)	RL	no ref motion clips needed	training two networks
Peng et al (2018c)	RL	smooth motions from clips	several days of training per skill
Holden et al (2017)	NN	adaptive smooth motions	undesirable extrapolations

- **virtual control tasks are naturally suited for ML**
- **difficulty generalizing across agents/motions**

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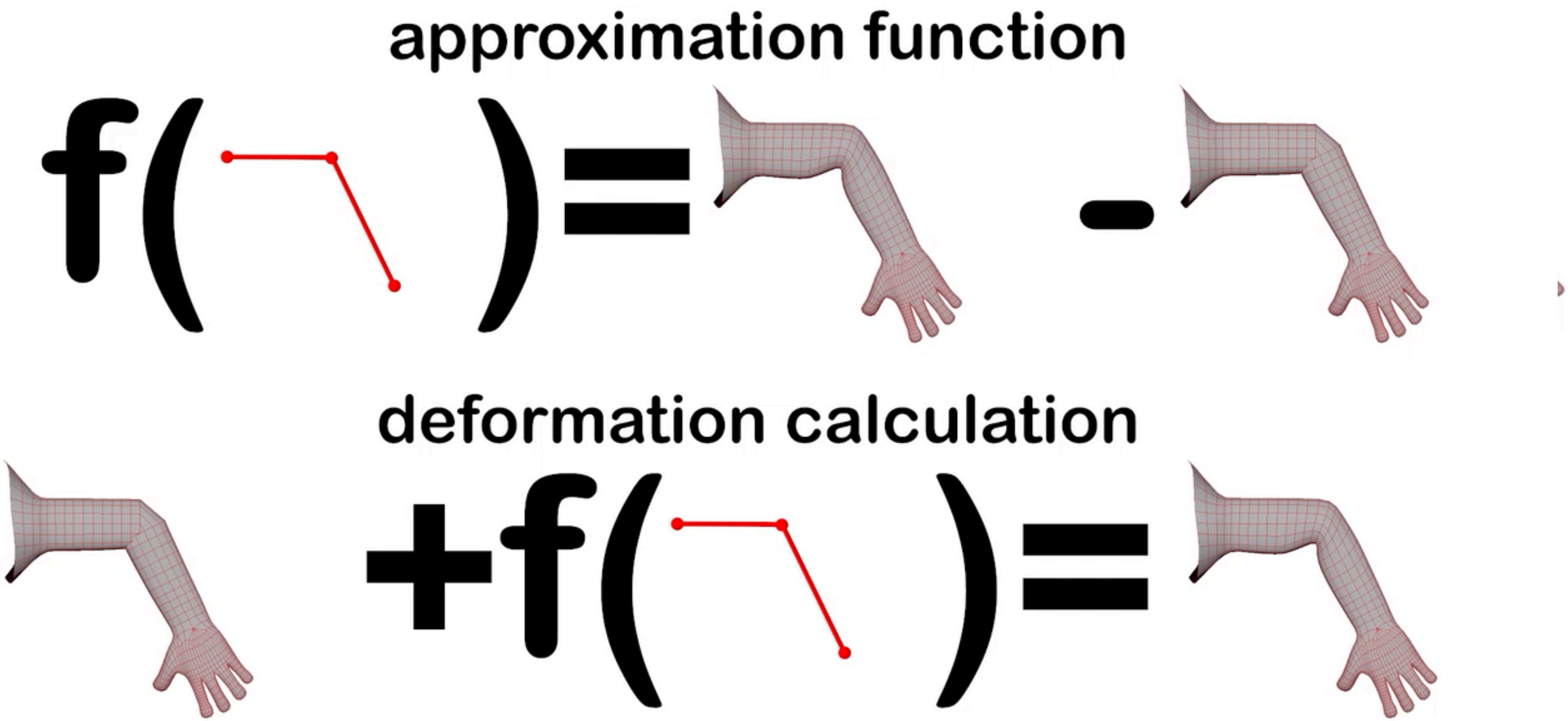
DEEP NONLINEAR BLEND SKINNING

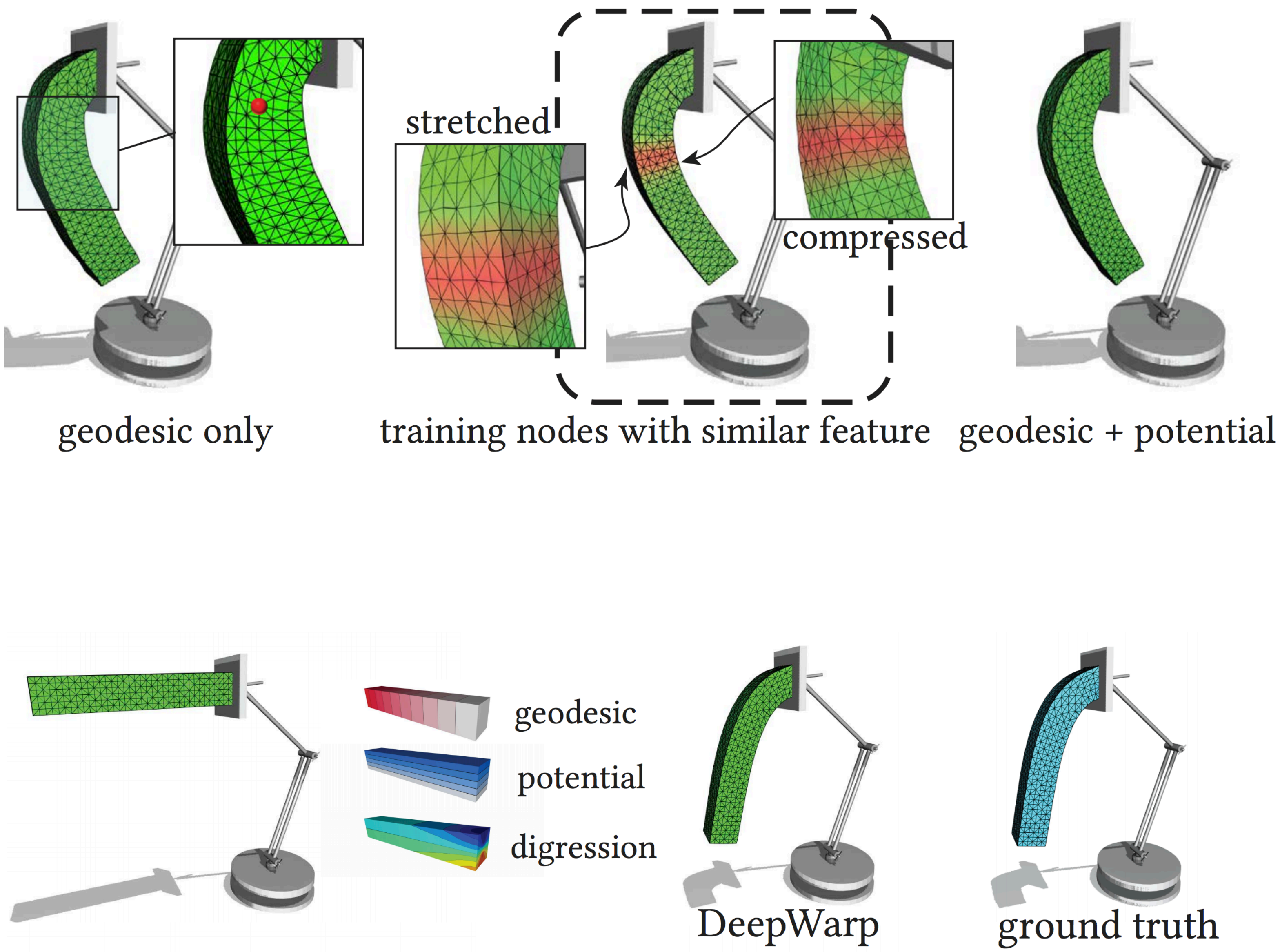
Bailey et al (2018)

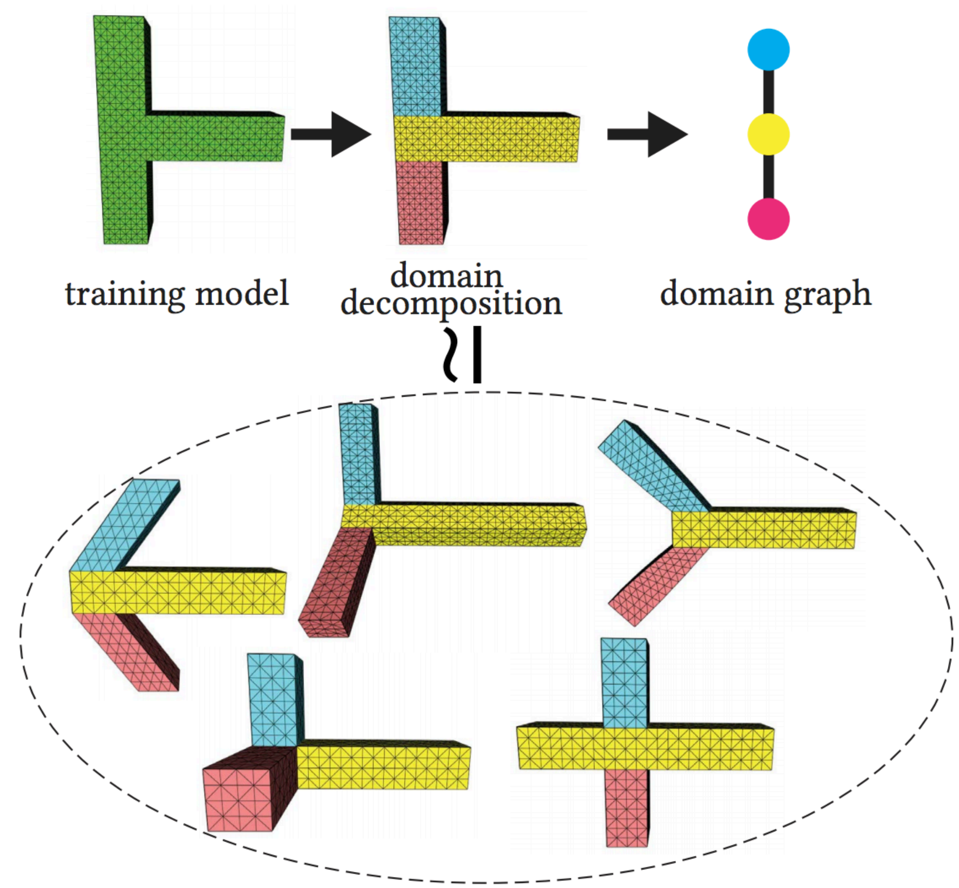


Stephen Bailey, Dave Otte, Paul Dilorenzo, James Obrien

REUSABLE NONLINEAR DISPLACEMENTS

Luo et al (2018)

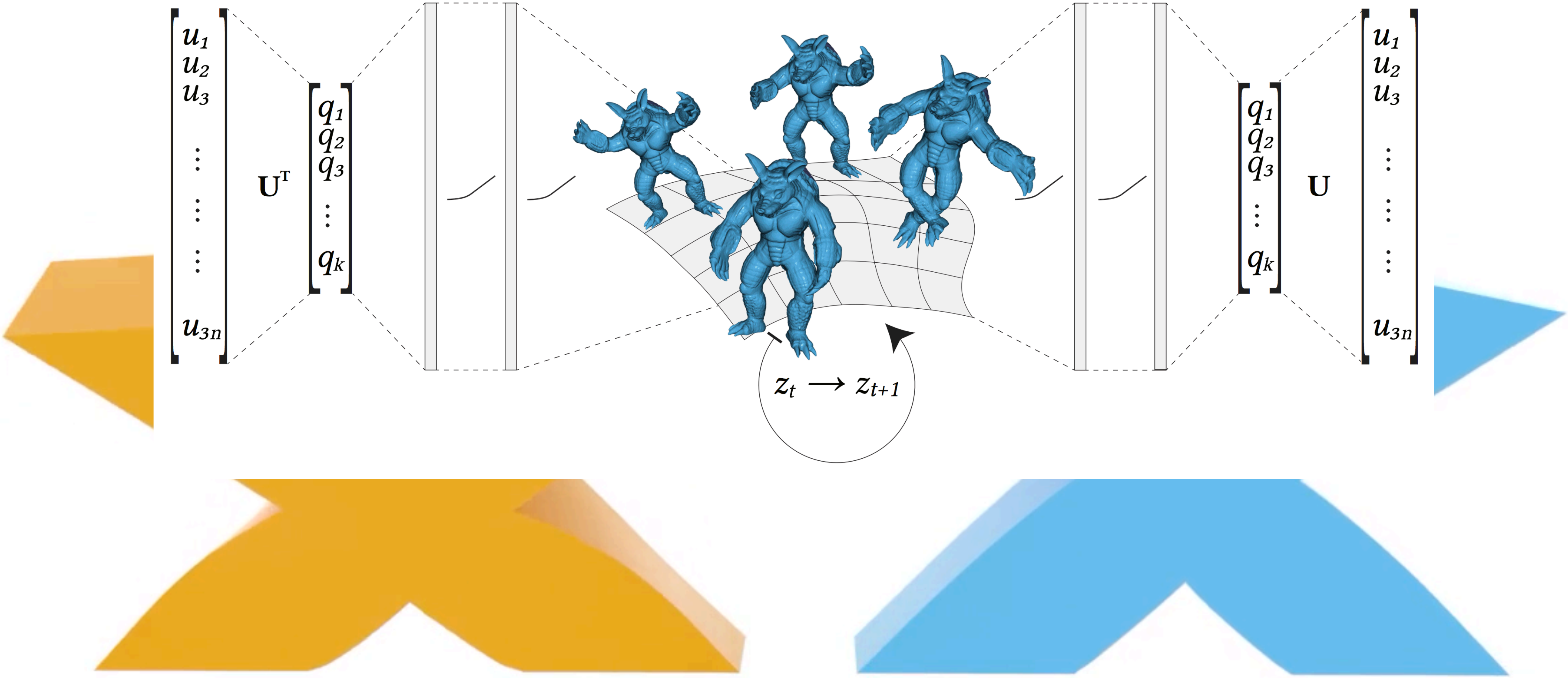




Ran Luo, Tianjin Shao, Juamin Wang, Weiwei Xu, Kun Zhou, Yin Yang

REDUCED DEFORMABLE ELASTICA

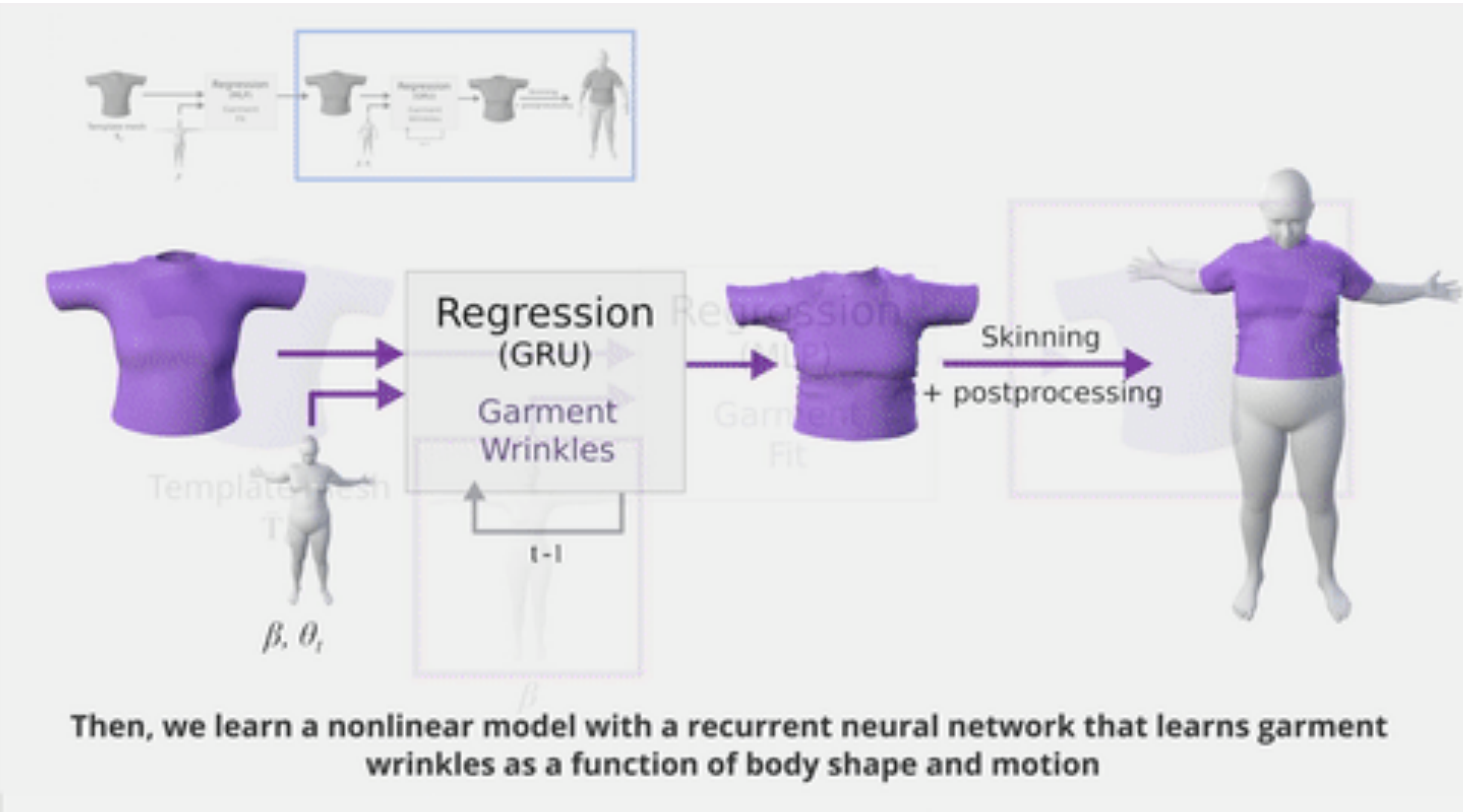
Fulton et al (2019)



6 dof PCA vs 6 dof Autoencoder

Lawson Fulton, Vismay Modi, David Duvenaud, David Levin, Alec Jacobson

LEARNING GARMENT FIT & WRINKLES Santesteban et al (2019)



Igor Santesteban, Miguel A. Otaduy, Dan Casas

COMPARISON OF PREVIOUSLY SEEN METHODS

	Net Type	Contribution	Limitations
Bailey et al (2018)	NN	mobile real-time skinning on large meshes	large dataset required
Luo et al (2018)	NN	extrapolate a simple model to complex shapes	difficulties with contacts and extrapolation
Fulton et al (2019)	AE	unsupervised model reduction	modest improvements, trouble extrapolating
Santesteban et al (2019)	NN	virtual try-on of new shape and pose in milliseconds	smooths high frequency wrinkles

- **fast approximations**
- **challenges with unseen deformations**

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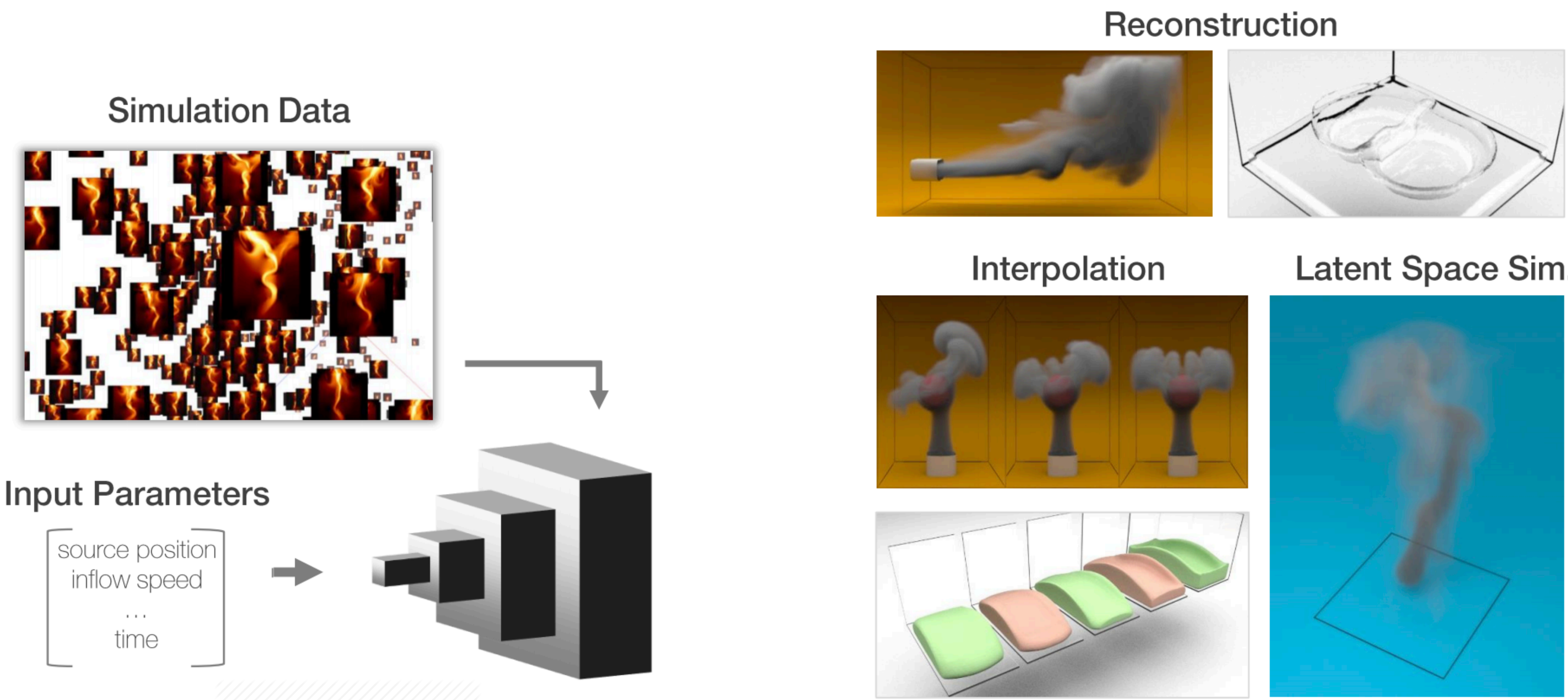
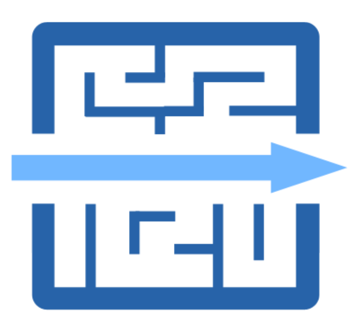
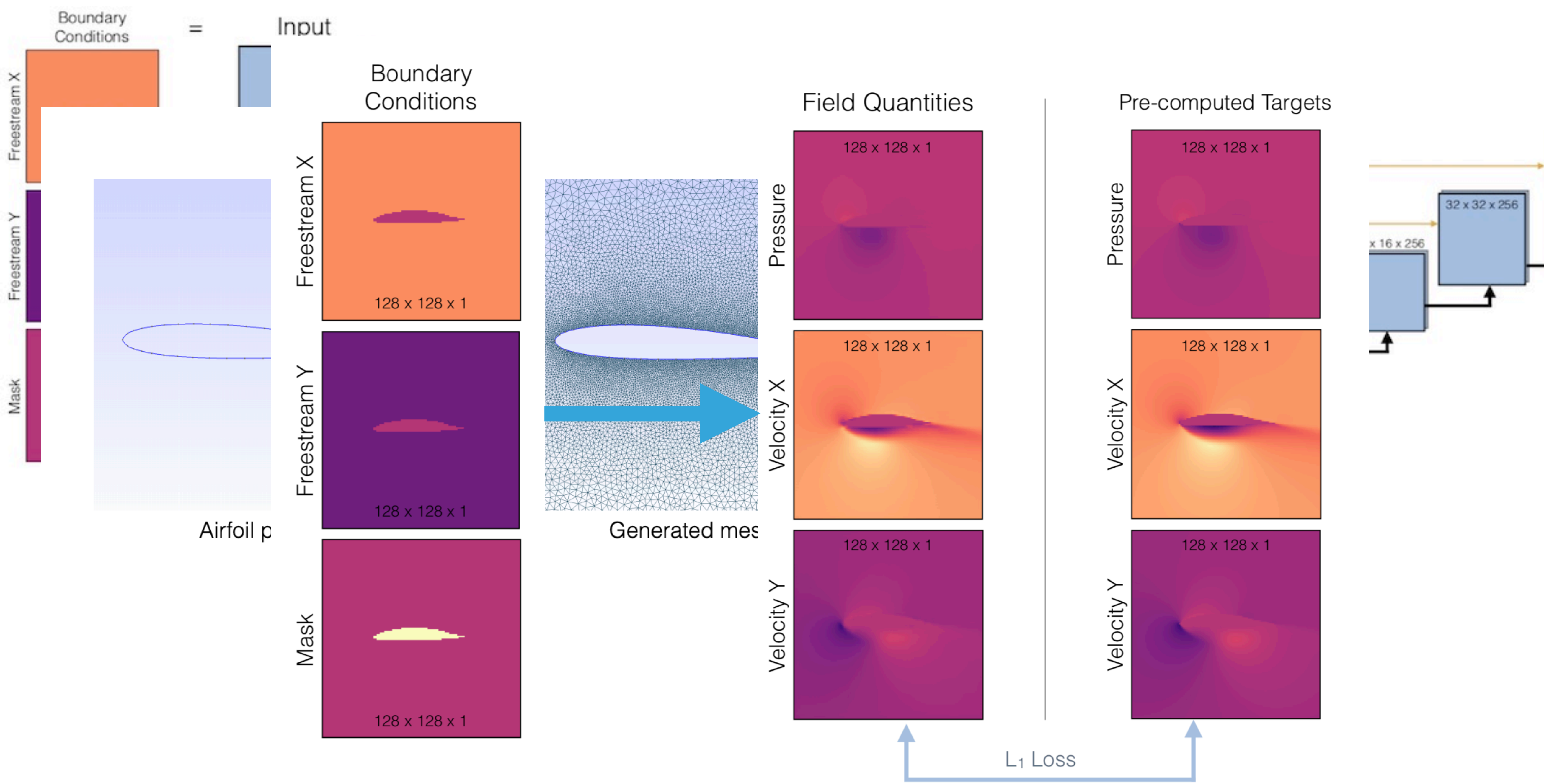




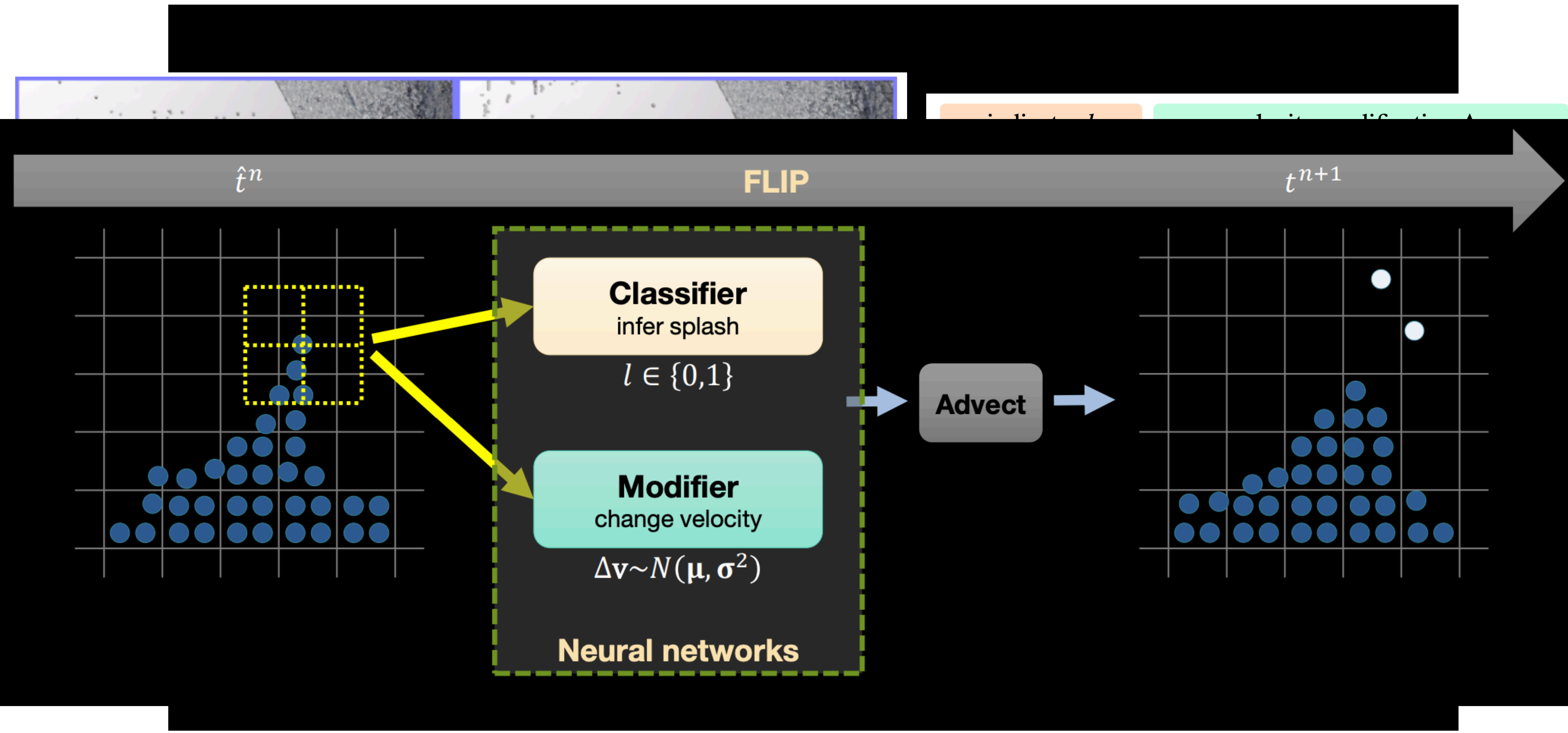
REYNOLDS-AVERAGED AIRFOIL FLOWS Thuerey et al (2019)



N Thuerey, K. Weissenow, L. Prantl, Xiangyu Hu

AUGMENTING SPLASHES

Um et al (2017)



Kiwon Um, Xiangyu Hu, Nils Thuerey

AUGMENTING SMOKE

Xie et al (2018)

You Xie, Erik Franz, Mengyu Chu, Nils Thuerey

SMOKE SYNTHESIS

Chu & Thuerey (2017)

Mengyu Chu, Nils Thuerey

COMPARISON OF PREVIOUSLY SEEN METHODS

	Net Type	Contribution	Limitations
Thuerey et al (2019)	CNN	quick airfoil/flow evaluation in 2D	not yet accurate enough for engineering use
Um et al (2017)	CNN	added splashing effects with little overhead	no interactions between splash particles
Xie et al (2018)	GAN	space-time coherent GAN	fixed resolution difference from low to high
Chu & Thuerey (2017)	CNN	quick upsampling of smoke from database examples	memory intensive and no physical guarantees

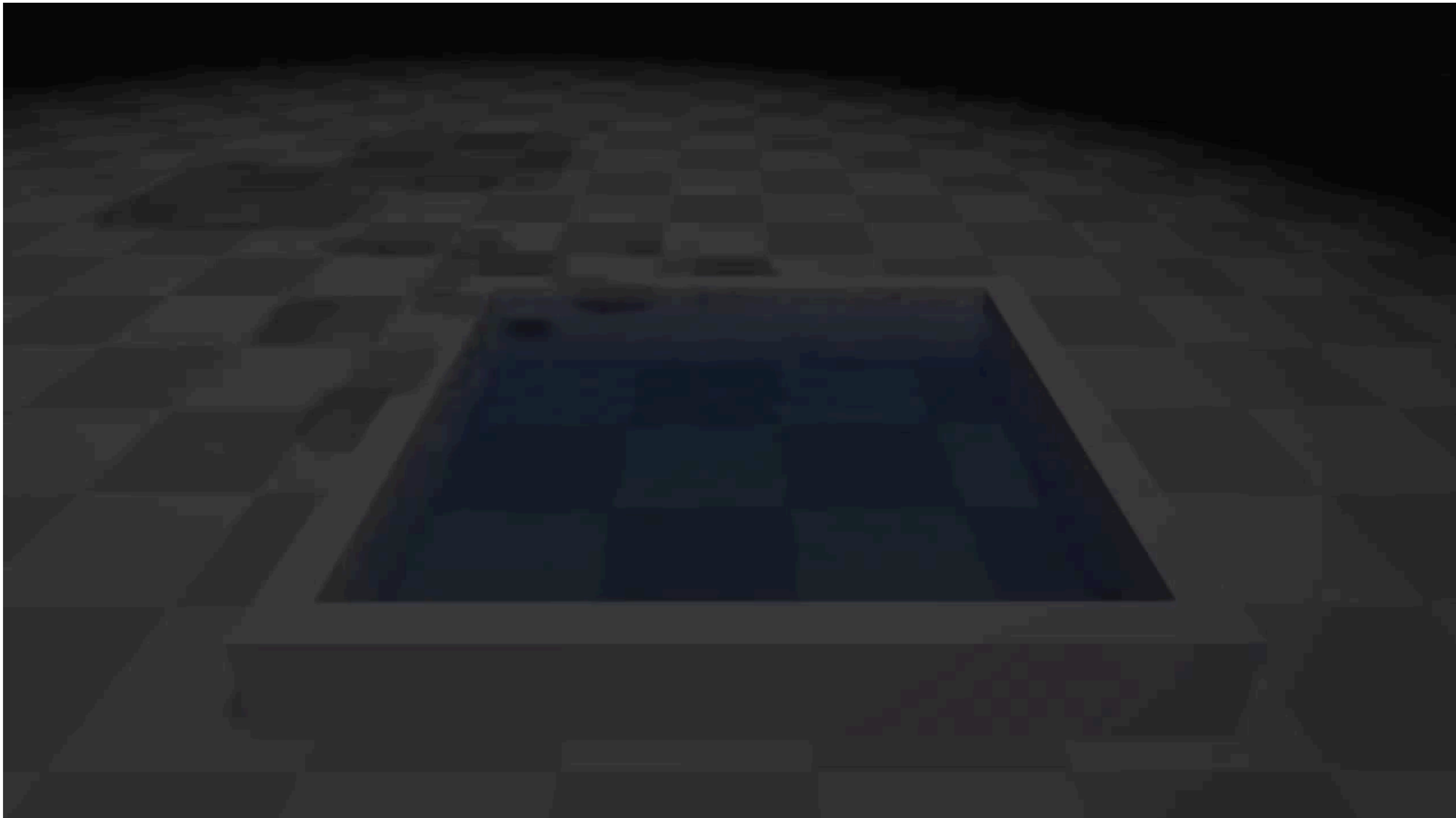
- **heavily dependent on grid resolution**
- **pairing black boxes with physics**

CONCLUSION

- What did we learn already?
  - small networks are often enough
  - understanding the underlying physics is key
  - learn nonlinear effects and couple with linear physics
  - ML provides an overall faster approach to approximations we already concede

UNIFIED PARTICLE PHYSICS

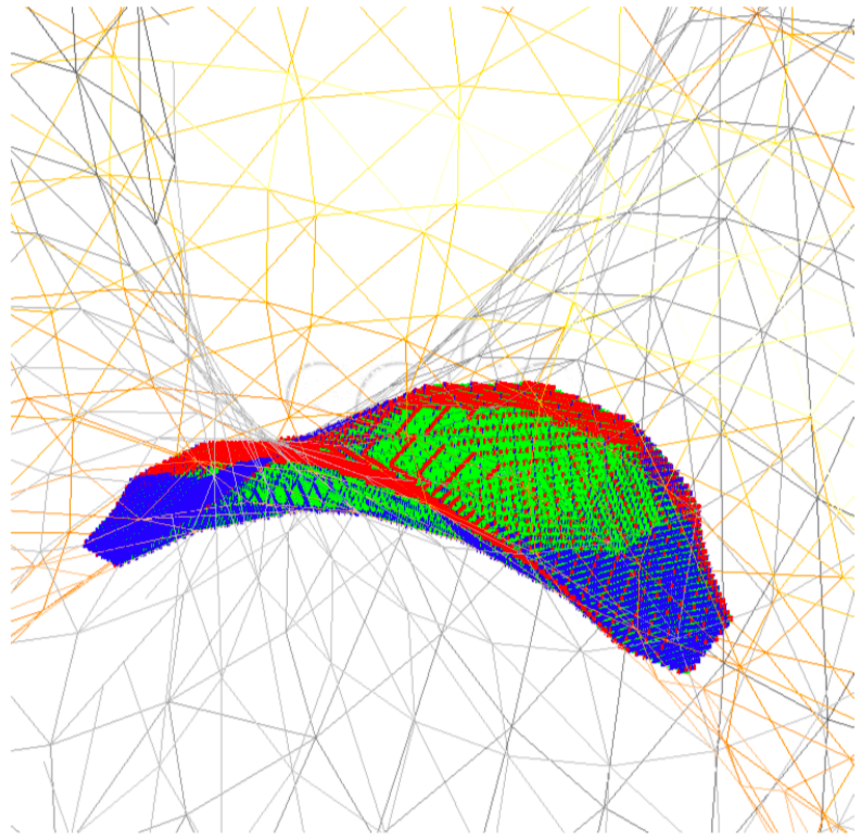
Macklin et al (2014)

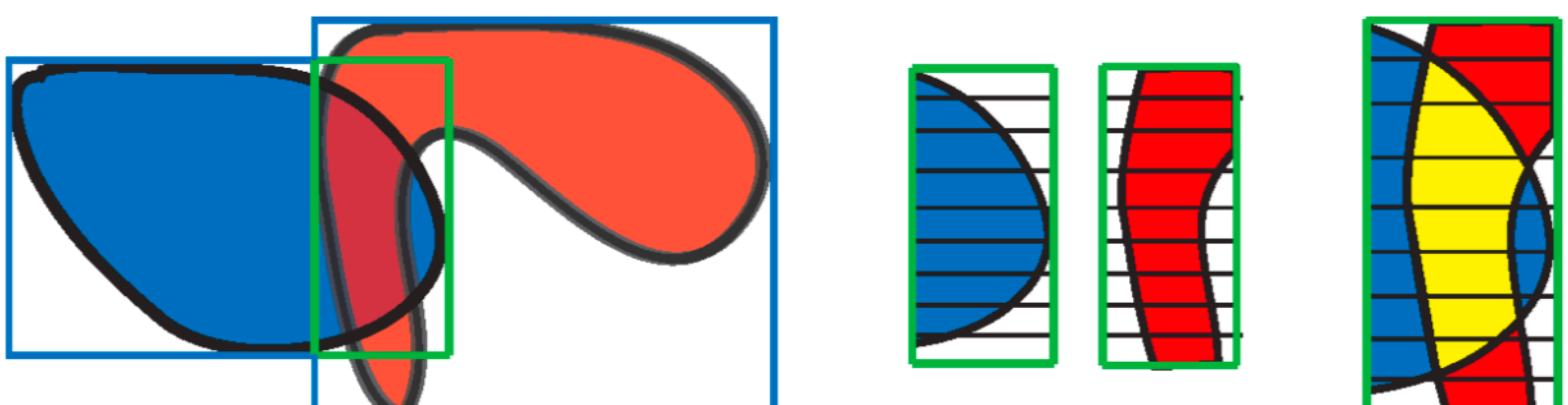


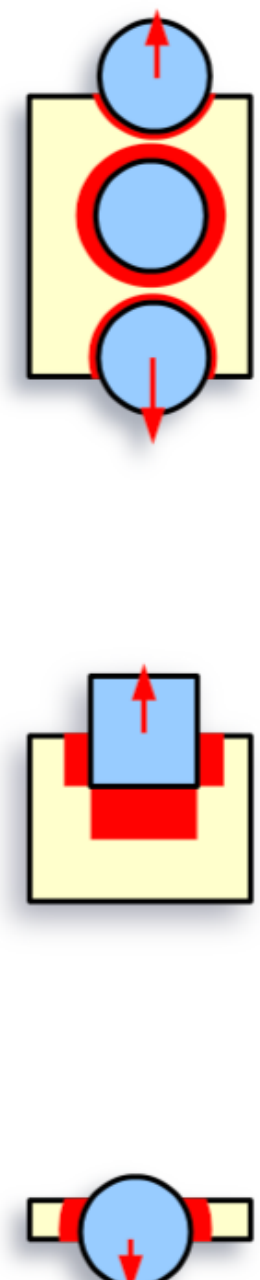
Miles Macklin, Matthias Muller, Nuttapong Chentanez, Tae-Yong Kim

IMAGE-BASED COLLISIONS

Faure et al (2008)



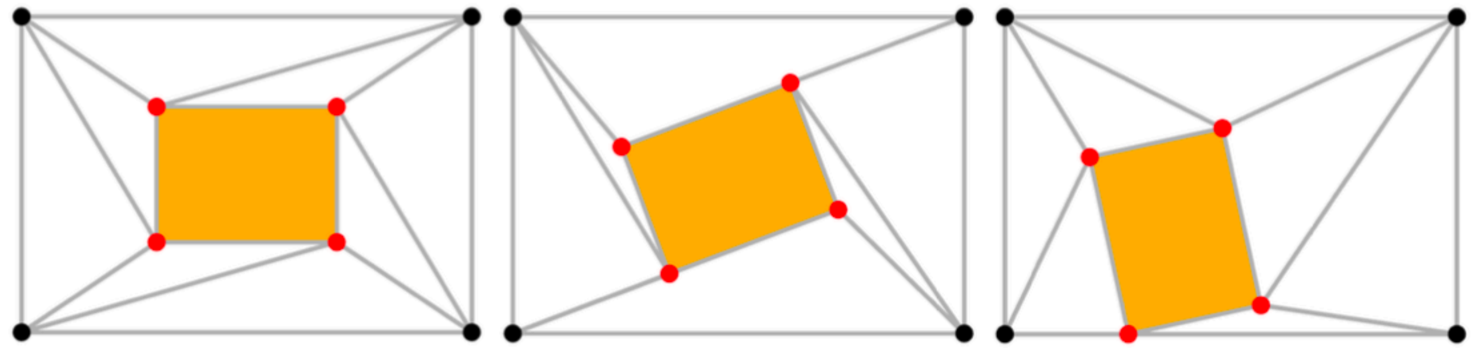


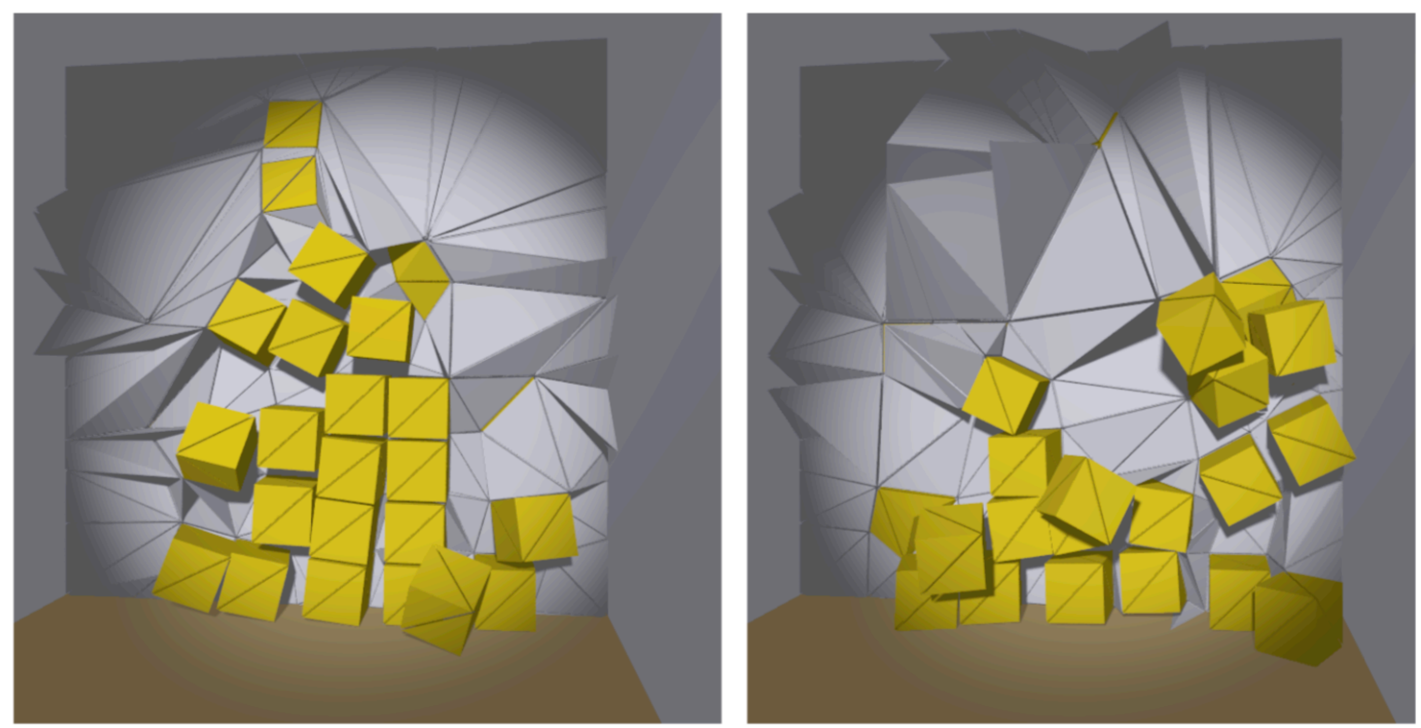


Francois Faure, Sebastien Barbier, Jeremie Allard, Florent Falipou

AIR-MESH COLLISION BUFFERS

Muller et al (2015)





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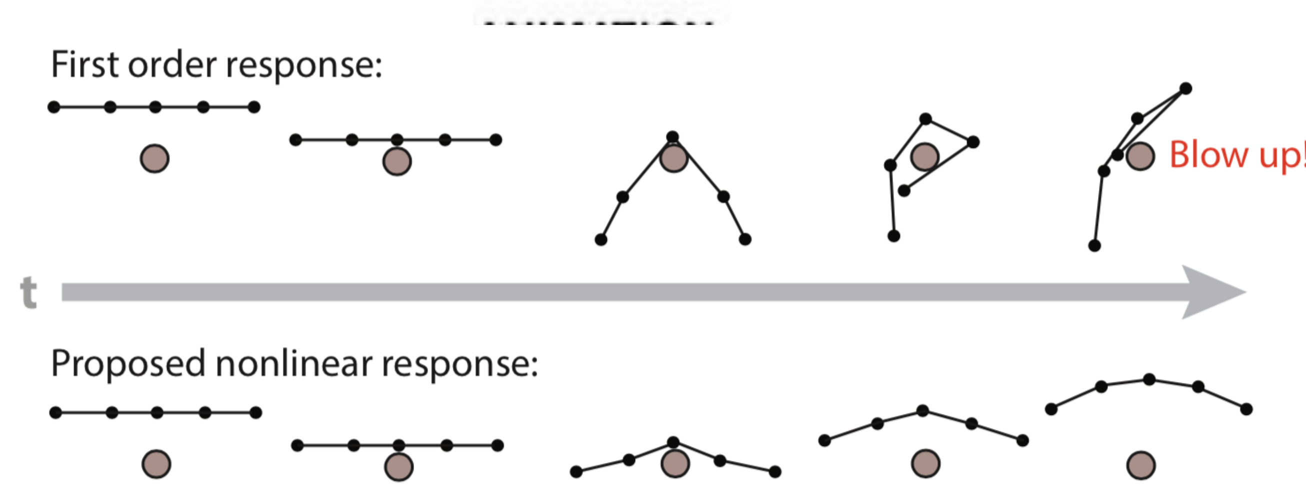
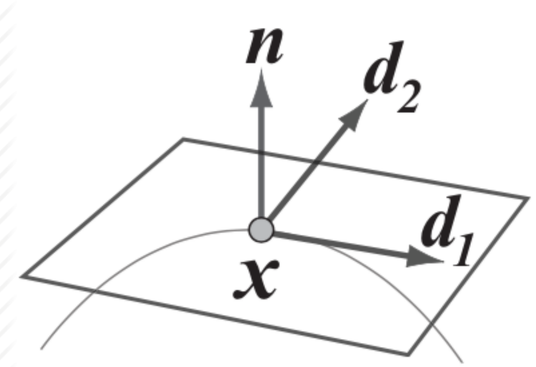
LOOKING AHEAD

Algorithm 1 Simulation Loop

for all particles i **do**
  apply forces $\mathbf{v}_i \Leftarrow \mathbf{v}_i + \Delta t \mathbf{f}_{ext}(\mathbf{x}_i)$
  predict position $\mathbf{x}_i^* \Leftarrow \mathbf{x}_i + \Delta t \mathbf{v}_i$
  apply mass scaling $m_i^* = m_i e^{-kh(\mathbf{x}_i^*)}$
end for
for all particles i **do**
  find neighboring particles $N_i(\mathbf{x}_i^*)$
  find solid contacts
end for
while $iter < stabilizationIterations$ **do**
  $\Delta\mathbf{x} \Leftarrow \mathbf{0}$, $n \Leftarrow 0$
  solve contact constraints for $\Delta\mathbf{x}$, n
  update $\mathbf{x}_i \Leftarrow \mathbf{x}_i + \Delta\mathbf{x}/n$
  update $\mathbf{x}^* \Leftarrow \mathbf{x}^* + \Delta\mathbf{x}/n$
end while
while $iter < solverIterations$ **do**
  for each constraint group G **do**
    $\Delta\mathbf{x} \Leftarrow \mathbf{0}$, $n \Leftarrow 0$
    solve all constraints in G for $\Delta\mathbf{x}$, n
    update $\mathbf{x}^* \Leftarrow \mathbf{x}^* + \Delta\mathbf{x}/n$
  end for
end while
for all particles i **do**
  update velocity $\mathbf{v}_i \Leftarrow \frac{1}{\Delta t}(\mathbf{x}_i^* - \mathbf{x}_i)$
  advect diffuse particles
  apply internal forces $\mathbf{f}_{drag}, \mathbf{f}_{vort}$
  update positions $\mathbf{x}_i \Leftarrow \mathbf{x}_i^*$ or apply sleeping
end for





THANK YOU

QUESTIONS?

TECHNICAL DETAILS

BACKUP SLIDES

[AUTHOR & YEAR]

- one slide for each paper
- all the difficult relevant technical details