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TossingBot by Zeng et al. 2020

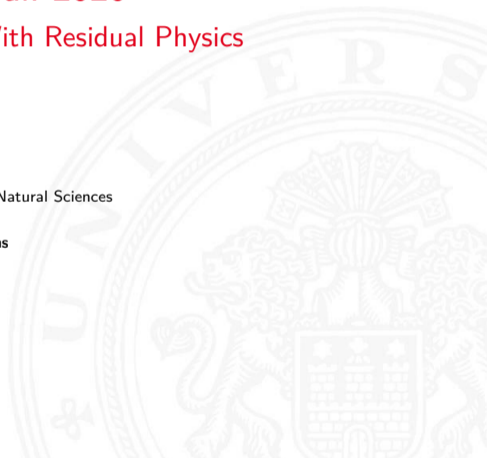
Learning to Throw Arbitrary Objects With Residual Physics



University of Hamburg
Faculty of Mathematics, Informatics and Natural Sciences
Department of Informatics

Technical Aspects of Multimodal Systems

11. Januar 2024





Outline

Motivation

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Motivation

What is TossingBot?

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Motivation

Tossing compared to Mini-Golf

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Similarities

1. Object manipulation
2. Single action
3. Dynamics estimation
4. UR5

Differences

1. Different objects - different course
2. Grasping subtask





Motivation

Projectile Trajectories and Grasping

Motivation

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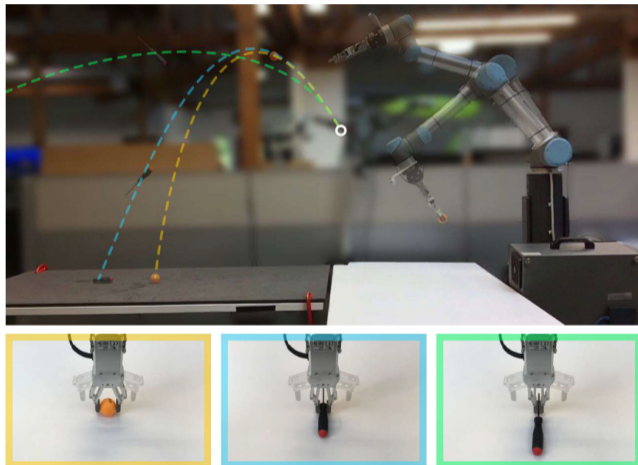
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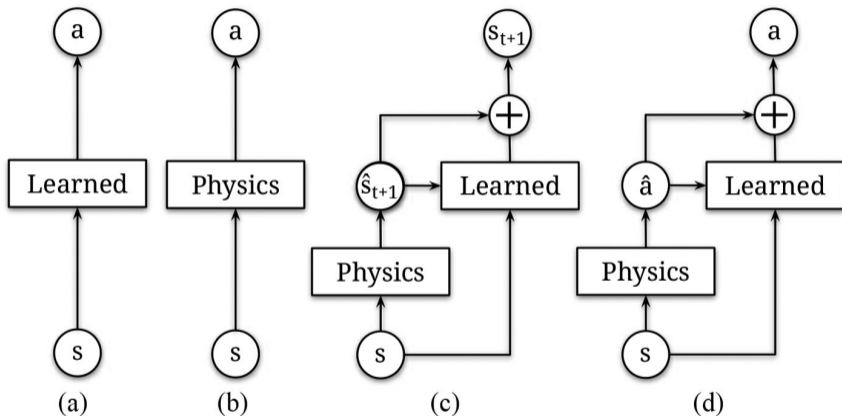
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- (a) Data-driven
- (b) Analytical
- (c) Hybrid
(predict future state)
- (d) Hybrid
(analytical + learning)



Learning Approaches

Approach

Basic Task Components

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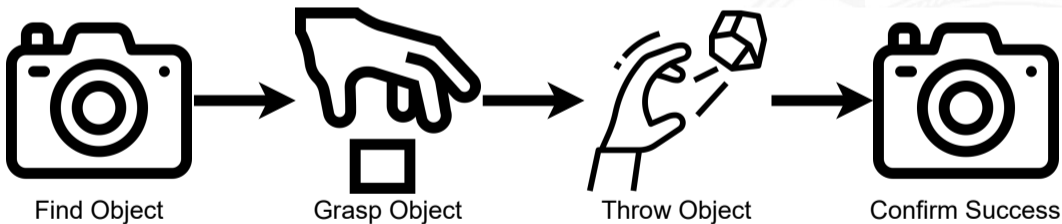
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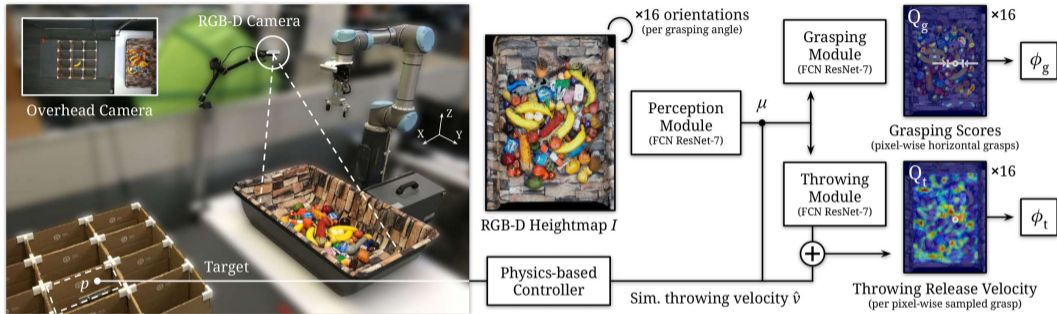
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Residual physics controller

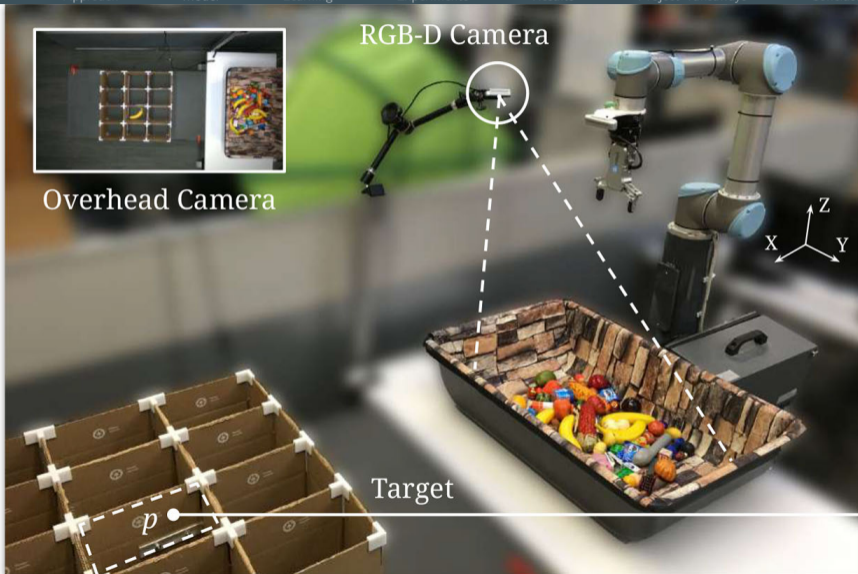
1. Analytical model for estimate of control parameter
2. Residuals for compensation of unknown dynamics



Task components of TossingBot

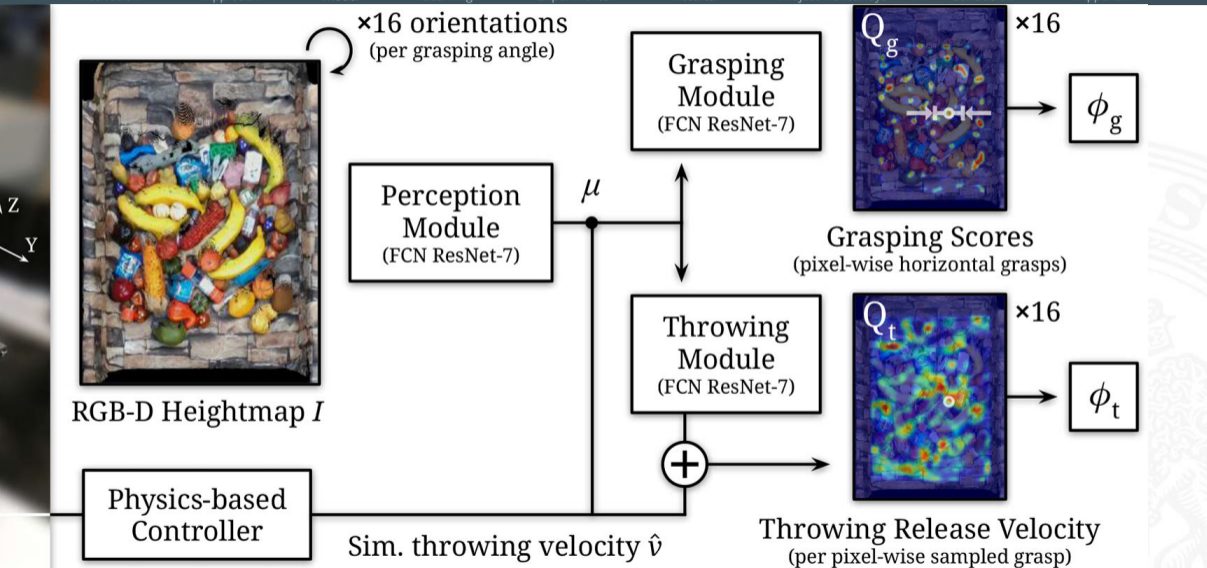


Model overview



RGB-D Heightmap

Physics-based
Controller





Grasping Primitive

- ▶ Input: $\phi_g = (x, \theta)$
- ▶ 3-D location $x = (x_x, x_y, x_z)$
- ▶ Orientation θ (around direction of gravity)

Throwing Primitive

- ▶ Endeffector trajectory
- ▶ Input: $\phi_t = (r, v)$
- ▶ Release position $r = (r_x, r_y, r_z)$
- ▶ Release velocity $v = (v_x, v_y, v_z)$
- ▶ Axis between fingers orthogonal to plane of object trajectory



Model

Perception Module

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- ▶ RGB-D heightmap
- ▶ Fixed-mounted overhead camera
- ▶ Project image onto 3-D pointcloud
- ▶ normalized

Perception Network

- ▶ Fully convolutional network ResNet-7
- ▶ convolutional layer → max pooling → residual block → max pooling → residual block → residual block
- ▶ residual block: 2 convolutional layers with bypass
- ▶ Output: spacial feature representation μ



Grasping Network

- ▶ Fully convolutional network ResNet-7
- ▶ Input: μ
- ▶ Output: probability map Q_g of grasp success
- ▶ Different grasping orientations by rotation of input heightmap
- ▶ 16 orientations
- ▶ highest probability pixel \rightarrow position and orientation
- ▶ sample efficient



Model

Throwing Module

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- ▶ Constrain release position r
 1. arial trajectory on same plane as on release
 2. fixed release distance and height to robot base
- ▶ Constrain release velocity v
 1. 45 deg upwards in direction of target p





Standard Equation of Linear Projectile Motion

$$p = r + \hat{v}t + \frac{1}{2}at^2 \quad (1)$$

Assumptions

- ▶ Grasp at CoM
- ▶ Point particle
- ▶ No drag
- ▶ Release velocity v is tossing velocity (no spin)

p : landing location

r : release position

\hat{v} : release velocity

a : acceleration ($a_z = -9.8m/s^2$)

t : time



Model

Residual Physics-Based Controller

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- ▶ Compensation for assumptions
- ▶ Residual value δ
- ▶ δ added to \hat{v}

Residual Network

- ▶ Fully convolutional network ResNet-7
- ▶ Input: μ
- ▶ Output: Q_t
- ▶ One-on-one correspondence between Q_g and Q_t
- ▶ Prediction of residual value δ_i

- ▶ All modules as one network f
- ▶ End-to-end training

y_i : Grasp success ground truth

$\bar{\delta}_i$: Residual ground truth

Loss function

$$\mathcal{L} = \mathcal{L}_g + y_i \mathcal{L}_t \quad (2)$$

- ▶ Binary cross-entropy error

$$\mathcal{L}_g = -(y_i \log q_i + (1 - y_i) \log(1 - q_i)) \quad (3)$$

- ▶ Huber loss

$$\mathcal{L}_t = \begin{cases} \frac{1}{2}(\delta_i - \bar{\delta}_i)^2, & \text{for } |\delta_i - \bar{\delta}_i| < 1 \\ |\delta_i - \bar{\delta}_i| - \frac{1}{2}, & \text{otherwise} \end{cases} \quad (4)$$



Learning Self-Supervision

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1. Capture visual input
2. Perform forward pass (get ϕ_g and ϕ_t)
3. Execute grasping
4. Execute throwing
5. Get ground truth y_i by success of throw
6. Approximate landing position \hat{p}
7. Ground truth residual $\bar{\delta}_i = \|v_{x,y}\| - \|\hat{v}_{x,y}\|_{\hat{p}}$





Experiments Simulation

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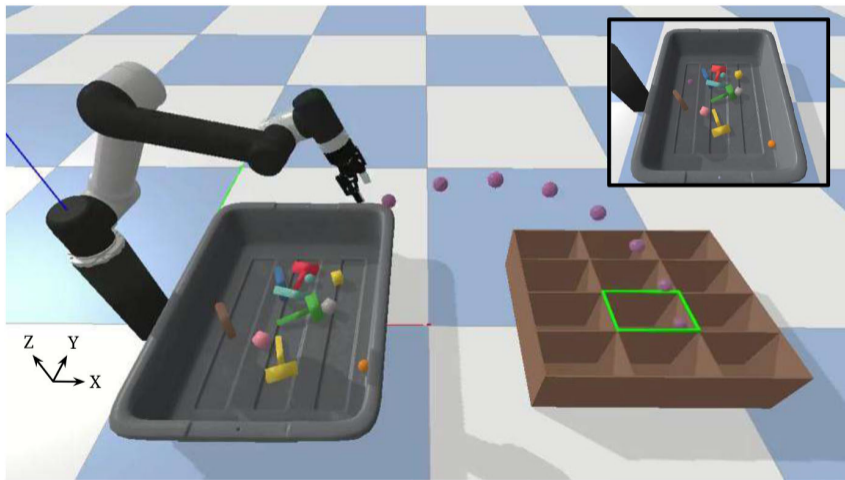
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Experiments

Objects

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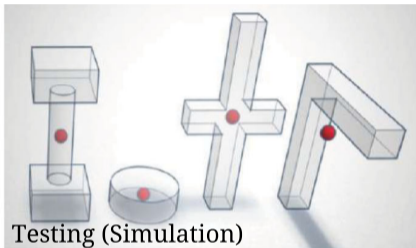
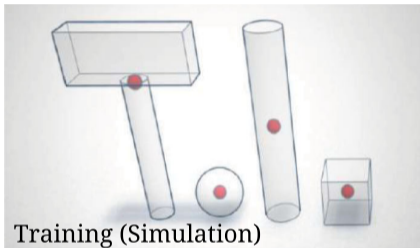
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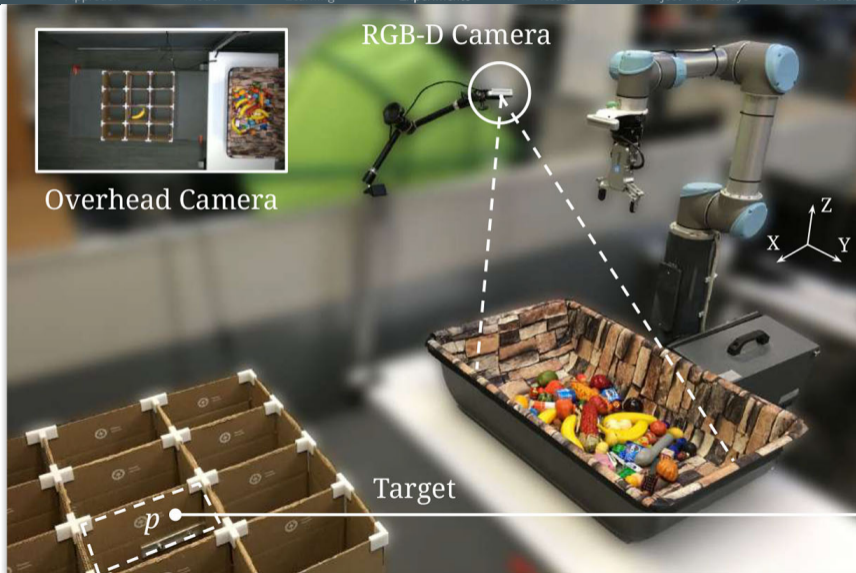
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Overhead Camera

RGB-D Camera

Target



RGB-D Heightmap

Physics-based Controller



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Method	Balls	Cubes	Rods	Hammers	Seen	Unseen
Regression	70.9	48.8	37.5	32.8	41.8	28.4
Regression-PoP	96.1	73.5	52.8	47.8	56.2	35.0
Physics-only	98.6	83.5	77.2	70.4	82.6	50.0
Residual-physics	99.6	86.3	86.4	81.2	88.6	66.5

Throwing performance simulation (Mean %)

Method	Balls	Cubes	Rods	Hammers	Seen	Unseen
Regression	99.4	99.2	89.0	87.8	95.6	69.4
Regression-PoP	99.2	98.0	89.8	87.0	96.4	70.6
Physics-only	99.4	99.2	87.6	85.2	96.6	64.0
Residual-physics	98.8	99.2	89.2	84.8	96.0	74.6

Grasping performance simulation (Mean %)



Results

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▶ <https://www.youtube.com/watch?v=f5Zn2Up2RjQ&t=04m39s>





Method	Grasping		Throwing	
	Seen	Unseen	Seen	Unseen
Human-baseline	-	-	-	80.1±10.8
Regression-PoP	83.4	75.6	54.2	52.0
Physics-only	85.7	76.4	61.3	58.5
Residual-physics	86.9	73.2	84.7	82.3

Grasping and throwing performance real (Mean %)

Method	Simulation	Real
Regression-PoP	26.5	32.7
Physics-only	79.6	62.2
Residual-physics	87.2	83.9

Throwing to unseen locations (Mean %)



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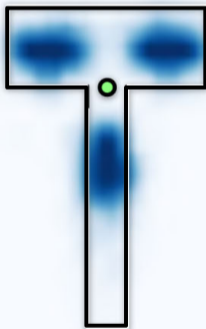
Residual Physics

(grasps supervised by gripper width)



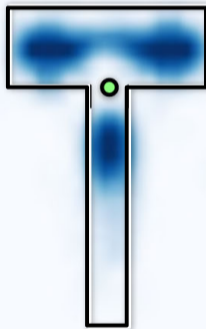
Residual Physics

(grasps supervised by throw accuracy)



Physics Only

(grasps supervised by throw accuracy)





Results

Semantics

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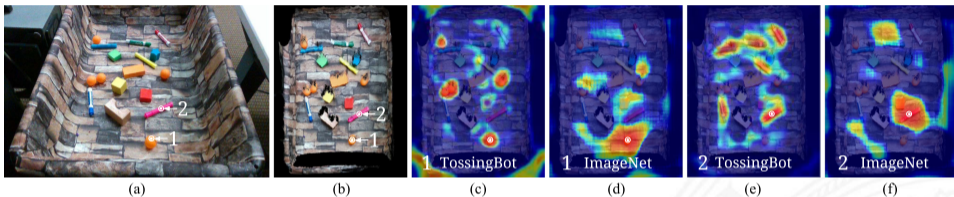
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Emerging semantics from interaction with objects

(a): Bin with objects

(b): RGB-D view

(c,e): Heatmap of pixel-wise distances

(d,f): ResNet-18 pre-trained on ImageNet



Results

Semantics

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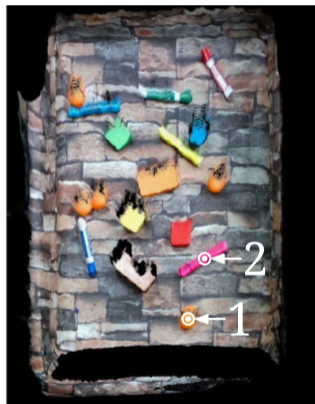
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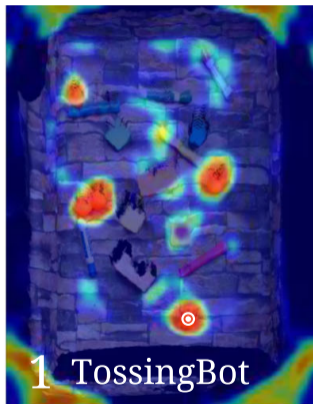
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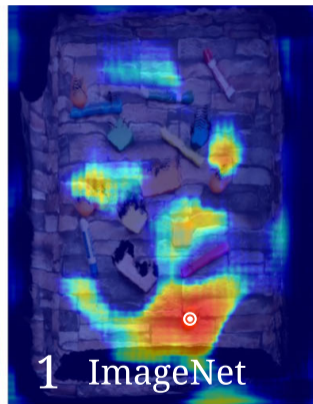
Appendix



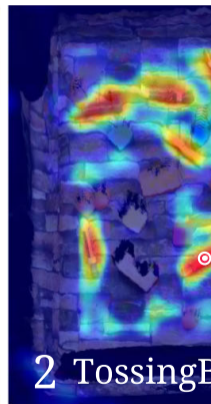
(b)



(c)



(d)



(e)



- ▶ Structure: Physics based guess and learning of residual
 1. Baseline solution
 2. Deep learning
- ▶ Motion primitive
- ▶ Training time of 14h
- ▶ Automatic reset
- ▶ ...





1. TossingBot: physics based estimate + learned residual
2. Robust grasping from downstream learning signal
3. Learning of implicit features by interaction with objects





Thank you for your attention

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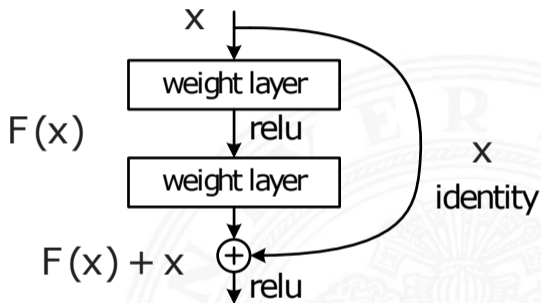
Thank you for your attention.

Are there any questions ?





- ▶ Degredation during training: saturation of accuracy \rightarrow degrading accuracy
- ▶ Shortcut connections



Residual learning: building block (He et al. 2015)



Huber Loss

$$\mathcal{L}_1(\delta, \bar{\delta}) = \begin{cases} \frac{1}{2}(\delta_i - \bar{\delta}_i)^2, & \text{for } |\delta_i - \bar{\delta}_i| < 1 \mid \text{Mean squared error for small errors} \\ |\delta_i - \bar{\delta}_i| - \frac{1}{2}, & \text{otherwise} \mid \text{Mean absolute error for large errors} \end{cases} \quad (5)$$

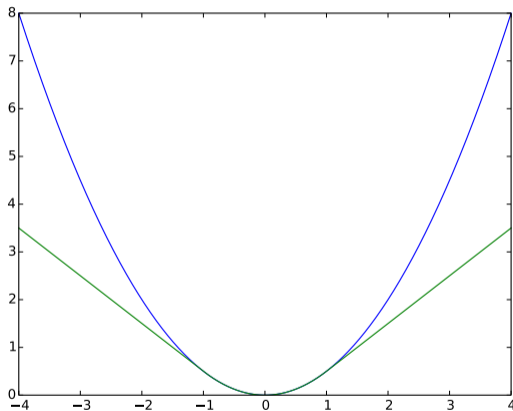
AI 2022

- ▶ Less weight on outliers compared to MSE
- ▶ Higher loss for errors below 1
- ▶ Small loss for small error

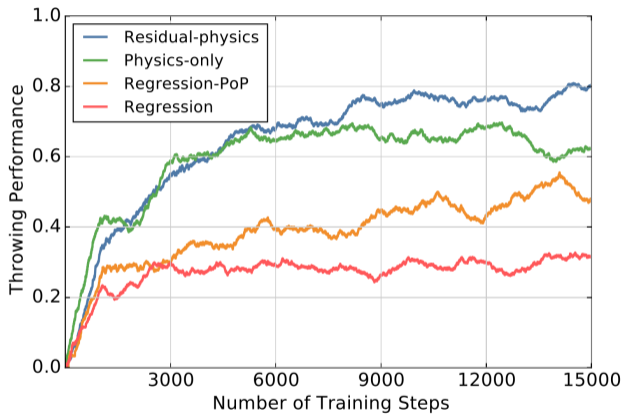


Huber Loss

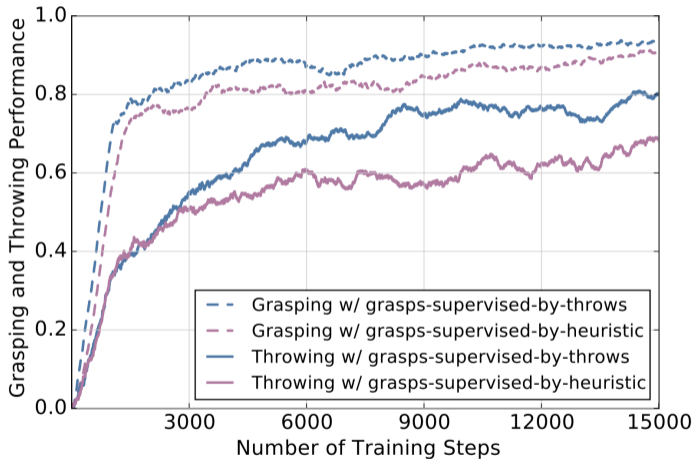
References



Huber loss (green) and mean squared error (blue) (*Huber loss 2023*)



Training performance in simulation



Grasping success in simulation

- AI, Practicus (Feb. 11, 2022).** *Understanding the 3 most common loss functions for Machine Learning Regression*. Medium. URL: <https://towardsdatascience.com/understanding-the-3-most-common-loss-functions-for-machine-learning-regression-23e0ef3e14d3> (visited on 01/10/2024).
- He, Kaiming et al. (Dec. 10, 2015).** *Deep Residual Learning for Image Recognition*. version: 1. arXiv: 1512.03385[cs]. URL: <http://arxiv.org/abs/1512.03385> (visited on 01/10/2024).
- Huber loss (Nov. 9, 2023).** In: *Wikipedia*. Page Version ID: 1184310836. URL: https://en.wikipedia.org/w/index.php?title=Huber_loss&oldid=1184310836 (visited on 01/10/2024).
- Zeng, Andy et al. (Aug. 2020).** “TossingBot: Learning to Throw Arbitrary Objects With Residual Physics”. In: *IEEE Transactions on Robotics* 36.4. Conference Name: IEEE Transactions on Robotics, pp. 1307–1319. ISSN: 1941-0468. DOI: 10.1109/TR0.2020.2988642. URL: <https://ieeexplore.ieee.org/abstract/document/9104757> (visited on 12/13/2023).



Diagram Icon Sources

References

- ▶ <https://www.flaticon.com/free-icons/camera>
- ▶ <https://www.flaticon.com/free-icons/grab>
- ▶ <https://www.flaticon.com/free-icons/throw>

