TossingBot: Learning to Throw Arbitrary Objects with Residual Physics

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Outline

What robots can do

- Pick (Grasp)
- Place
- Move
- Push
- Interact with humans
- ...

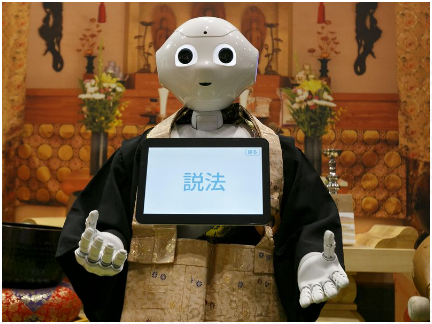


Figure: Robot conducting Buddhist funeral [Mat]

[SK16]

… and toss

- Zheng et al. presented TossingBot in 2019
- End-to-end formalism for grasping and throwing
- Deployed to an UR5 robot

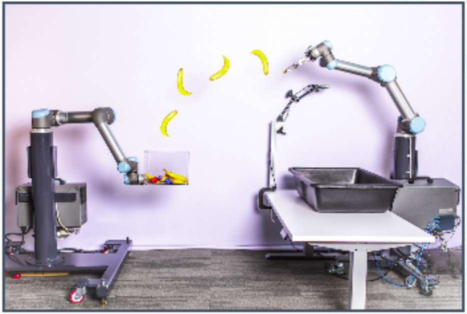


Figure: UR5 throws a banana [Zen19]

Paper:

TossingBot: Learning to Throw Arbitrary Objects with Residual Physics [Zen+19]

- Developed at *Google AI* and the *Princeton University*
- by Andy Zhang
- Other contributors from Columbia University and the MIT
- Best Systems Paper Award, Robotics Science and Systems (2019)

Characteristics:

- (Self-) supervised learning
- Trial and error learning
- Main components:
  - Deep Neural Networks
  - Physics controller
- Key aspects:
  - Joint learning of grasping and throwing policies
  - Residual learning of throw release velocities

Motivation (cont.)

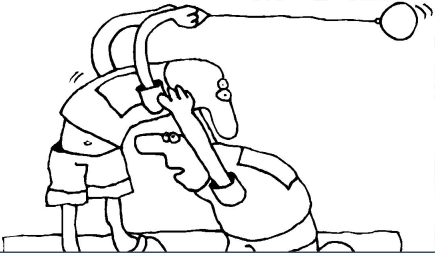
- Not the only tossing approach

Benefits

- **Exploit dynamics** to increase robot's capabilities
- **Extends** the **operation radius**
- **Increase** the **frequency** for pick and place
- Can outperform humans

Challenges

- Acquisition of reliable **pre-throw conditions**
  - e.g grasp of the object
- Handling of **object-centric properties**
  - e.g. mass distribution, friction and shape
- and **dynamics**
  - e.g. aero-dynamics [Gra]



Basics

Self Supervised Learning

- Supervised learning example: Support Vector Machines
- Efforts manual labeling
- (Too) many possibilities for an object to grasp
- Human notions are biased by semantics
- Datasets are restricted in quantity and quality
  $\longrightarrow$ overfitting

[PG16]

Self Supervised Learning (cont.)

- Self-supervised learning tends to limit human involvement
- Task is framed into special form to predict only subset of information
- All information has been provided by the input
- Self-generating its labels

[PG16; Wen19]

Self Supervised Learning (cont.)

- Trial and error training obtains ground truth labels y_i *and* $\bar{\delta}_i$
- At each training step a visual input is fed into the network
- Grasping and throwing parameters are predicted
- Ground truth grasp success label y_i generated either
  - by gripper distance threshold or
  - by throwing success (target hit)

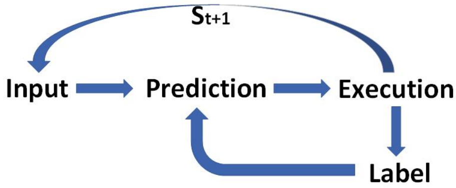


Figure: Training circle

Self Supervised Learning (cont.)

- After throw the landing location is measured
- Landing location p and release velocity v is sampled
- Ground truth residual label $\bar{\delta_i}$ is obtained by $\|v_{x,y}\| - \|\hat{v}_{x,y}\|_{\bar{p}}$
- Training environment is independently reset by the robot

Figure: Reset training environment [Zen19]

Joint Learning of Policies

- DNN[1] maps from visual observations to control parameters:
  - Likelihood of grasping success
  - Throwing release velocities
- Grasping directly supervised by throw accuracy
- Throws directly conditioned on specific grasps
- Stable grasps $\Longleftrightarrow$ predictable throws and throwing velocities

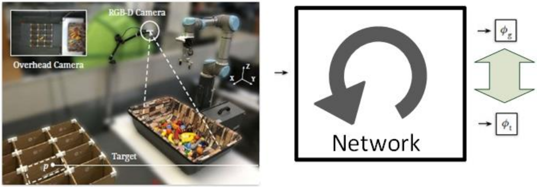


Figure: DNN black box [Zen+19]

[1] Deep Neural Network

Learning of release velocities

- Physics controller predict throw velocities $\hat{v}$
- Based on ideal ballistic motion
- Residual δ is (learned) corrective factor
- Final release velocity: $v = \hat{v} + \delta$

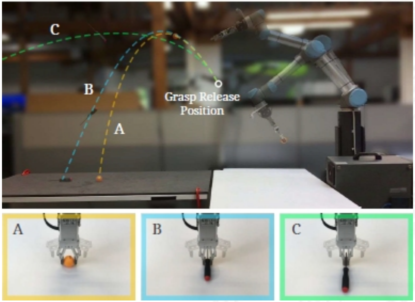


Figure: Different projectile trajectories [Zen+19]

Methods

Network

- Neural Network: $f(I, p)$ [2]
- Output: Prediction of parameters ϕ_g and ϕ_t
- Parameters used by grasping and throwing motion primitives
- Objective: Optimize parameter prediction for a hit

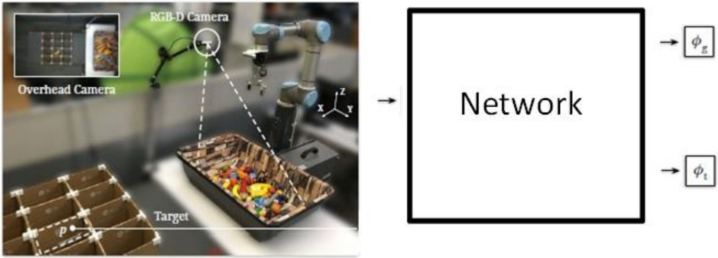


Figure: DNN black box [Zen+19]

[2] I = visual observation, p = landing location

- Input: RGB-D heightmap **I**
- Output: Spatial feature representation μ
- Used by grasping and throwing module

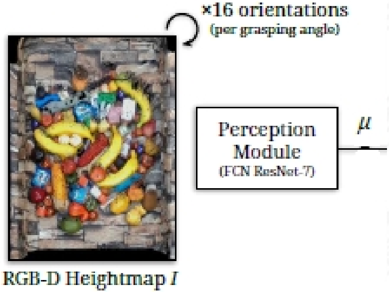


Figure: Input to perception module [Zen+19]

Grasping Module

- Outputs a probability map Q_g (grasping scores)
- Each pixel value represents probability of grasping success
- Input heightmap is rotated 16 x
- Pixel with highest probability determine ϕ_g
- Grasping primitive takes $\phi_g = (x, \theta)$
  where x = pixel location, θ = rotation angle

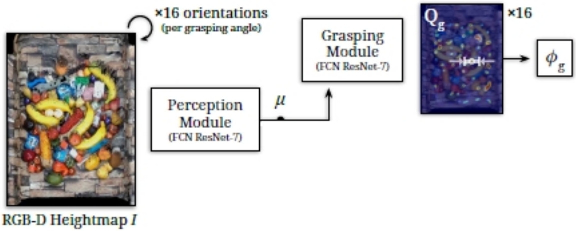


Figure: Grasping module [Zen+19]

Throwing Process

- Predict release position r of throwing primitive
  - Distance $\sqrt{r_x^2 + r_y^2}$ for point of release to base is fixed
- Predict release velocity v of throwing primitive
  - Throw release angle θ constrained to $45°$
  - Only $\|v_{x,y}\|$ is unknown

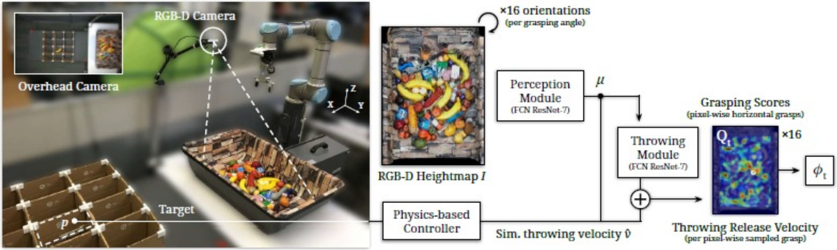


Figure: Throwing process [Zen+19]

Physics-Based Controller

- Physic based controller predicts $\|\hat{v}_{x,y}\|$
- Assume a grasp on the center of mass of the object
- Analytically solves back for $\hat{v}$ given p and r

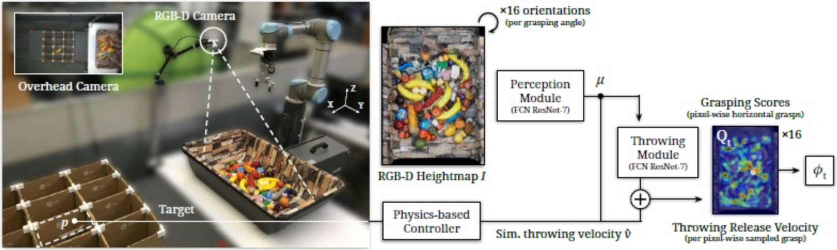


Figure: Throwing process [Zen+19]

Throwing Module

- Output is an image Q_t
- Each pixel holds prediction for residual value δ_i
- δ_i added on top of $\|\hat{v}_{x,y}\|$
- Final release velocity: $\|v_{x,y}\| = \|\hat{v}_{x,y}\| + \delta$
- Throwing primitive takes $\phi_t = (r, v)$

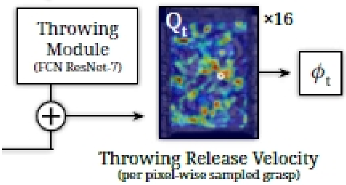


Figure: Throwing module [Zen+19]

Conditioning

- Release velocity $\hat{v}$ is also feed in the grasping and throwing network
- μ concatenated with k-channel image where each pixel holds value of $\hat{v}$
- Conditions the grasping and throwing predictions on $\hat{v}$
- Supervising grasps by accuracy of throws leads to better grasps

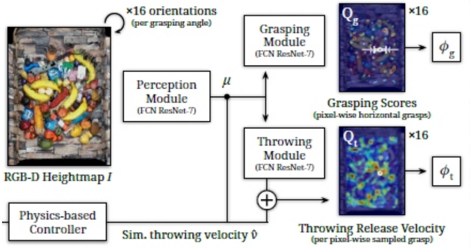


Figure: Release velocity feed [Zen+19]

Full Network

- Self-supervision from trial and error
- Tracking ground truth landing position of thrown objects
- Not a single network that maps states to actions
- Four modules that provide intermediate (differentiable) results
- Output are factors that does not directly control the actuator
- Complex systems are hard to control

[Gla17]

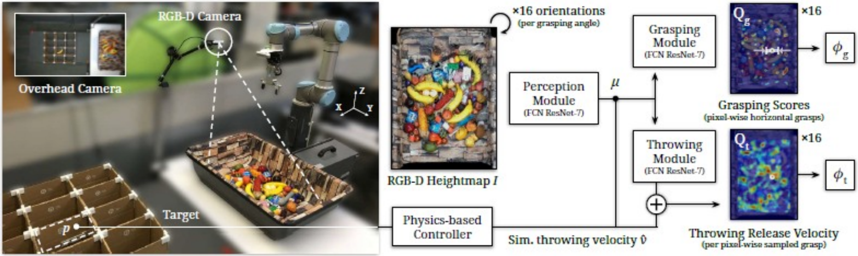


Figure: Overview [Zen+19]

Results

Experimental Setup

- Evaluation metrics
  - Grasping success (% rate of succesfull grasps)
  - Throwing success (% rate of target hits)
- 12 various objects are grasped and thrown
- Target are 12 boxes outside kinematic range
- Real world: UR5 robot with RG2 gripper

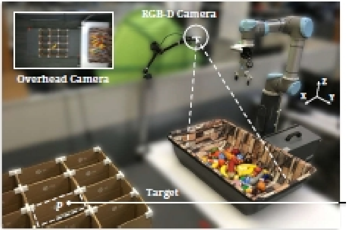


Figure: Workspace [Zen+19]

Figure: RG2 gripper [Onr]

Simulation

- 8 different objects (4 seen, 4 unseen), 12 in total
- Varying center of mass (CoM)
- Simulated environment does not account for aerodynamics
- Real world experiments are conducted

TABLE I
THROWING PERFORMANCE IN SIMULATION (MEAN %)

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**

TABLE II
GRASPING PERFORMANCE IN 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

Figure: [Zen+19]

Real World

- 15,000 steps training, 1,000 steps testing
- Average grasping and throwing success rates

TABLE III
GRASPING AND THROWING PERFORMANCE IN REAL (MEAN %)

	Grasping		Throwing	
Method	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**

TABLE IV
PICKING SPEED VS STATE-OF-THE-ART SYSTEMS

System	Mean Picks Per Hour (MPPH)
Cartman [24]	120
Dex-Net 2.0 [20]	250
FC-GQ-CNN [27]	296
Dex-Net 4.0 [21]	312
TossingBot (w/ Placing)	432
TossingBot (w/ Throwing)	**514**

Figure: [Zen+19]

Performance

- Residual physics outperforms by learning residual throwing velocities
- Compensate for for grasping offsets from objects CoM

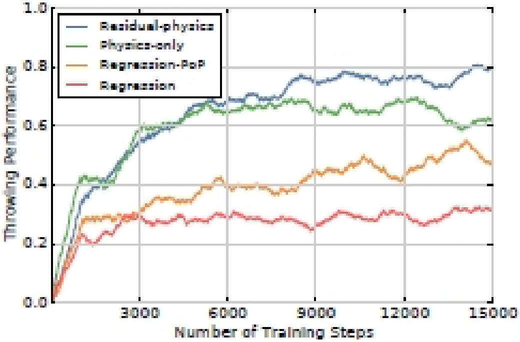


Figure: Throwing performance on hammers[Zen+19]

- 2 variants of grasp success label y_i
- Grasping supervised by throwing yields best throwing results
- Supervised grasps are more restricted, resulting in more dexterous throws

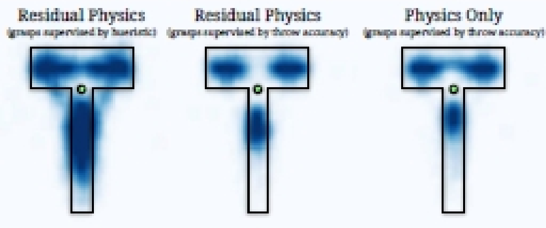


Figure: Histograms of succesfull grasps[Zen+19]

Conclusion

Conclusion

- Paper provides new perspectives on throwing
  - Relationship of throwing to grasping
  - Throwing correlates with grasp quality
  - Learning by combining physics with trial and error
  - Synergies between grasping and throwing is exploited
- *Residual Physics* leverage advantages of physic based controllers while maintaining the capacity to account for dynamics
- Generalization via analytic models
- Data-driven residual corrects the real world projectile velocity

Thank you for your attention!

Questions?

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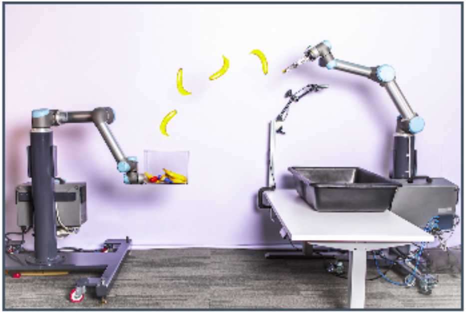
[Wen19] Lilian Weng. *Self-Supervised Representation Learning*. 2019. URL: https://lilianweng.github.io/lil-log/2019/11/10/self-supervised-learning.html (Retrieved 05/23/2020).

[Zen+19] Andy Zeng et al. "TossingBot: Learning to Throw Arbitrary Objects with Residual Physics". In: (2019). DOI: 10.15607/rss.2019.xv.004. arXiv: 1903.11239.

[Zen19] Andy Zeng. *TossingBot: Learning to Throw Arbitrary Objects with Residual Physics*. 2019. URL: https://tossingbot.cs.princeton.edu/ (Retrieved 05/23/2020).

Video

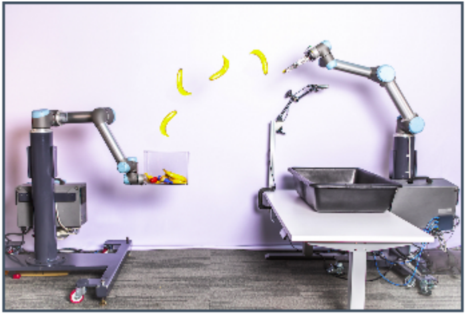


Ballistics [Zen19]

Appendix - Future Work

- Train networks to predict motions that account for fragile objects
- Explore additional sensing modalities such as force-torque
- How should robots learn semantics of the visual world?
- Classic computer vision: predefined semantics using manually constructed class categories
- Here: Implicitly learn object-level semantics from physical interactions

Video



[Zen19]

Appendix - Loss Function

- Loss function for network training:
  - Binary cross-entropy error $\mathcal{L}_g$ from predictions of grasping success
  - Huber-loss $\mathcal{L}_t$ from its regression of δ_i for throwing

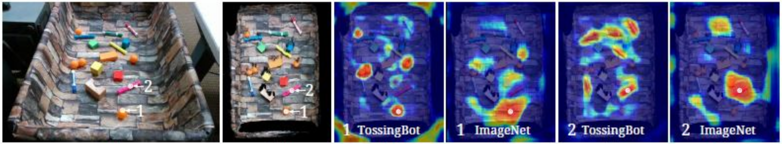
$$(1) \quad \mathcal{L} = \mathcal{L}_g + y_i \mathcal{L}_t$$

$$(2) \quad \mathcal{L}_g = -(y_i \log q_i + (1 - y_i) \log(1 - q_i))$$

$$(3) \quad \mathcal{L}_t = \begin{cases} \frac{1}{2}(\delta_i - \bar{\delta}_i)^2, \ for \ |\delta_i - \bar{\delta}_i| < 1, \\ |\delta_i - \bar{\delta}_i| - \frac{1}{2}, otherwise \end{cases}$$

where y_i is the binary ground truth grasp success label, q_i and $\bar{\delta}_i$ are the predicted values and $\bar{\delta}_i$ is the ground truth residual label

Appendix (cont.)



(a) (b) (c) (d) (e) (f)

Fig. 10. **Emerging semantics from interaction.** Visualizing pixel-wise deep features μ learned by TossingBot (c,e) overlaid on the input heightmap image (b) generated from an RGB-D side-view (a) of a bin of objects. (c) shows a heatmap of pixel-wise feature distances (hotter = smaller distance) from the feature vector of a query pixel on a ping pong ball (labeled 1). Likewise, (e) shows a heatmap of pixel-wise feature distances from the feature vector of a query pixel on a pink marker pen (labeled 2). These visualizations show that TossingBot learns features that distinguish object categories from each other without explicit supervision (*i.e.*, only task-level grasping and throwing). For reference, the same visualization technique is used on deep features generated by a ResNet-18 pre-trained on ImageNet (d,f).

Figure: [Zen+19]

Appendix (cont.) - Image Projection

- Capture RGB-D image from fixed mount camera
- Project data onto 3D-point cloud
- Orthographical back-projection in gravity direction
- color and height-from-bottom channels
- normalization allows sharing of learned convolutional filters

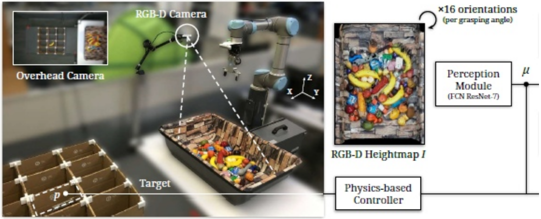


Figure: Projection [Zen+19]

Appendix (cont.) - Gripper Modalities

- Top-down parallel yaw grasp centered at $x = (x_x, x_y, x_z)$
- Oriented θ° around gravity direction
- Gripper approaches x until middle point of finger tips meets x
- Gripper closes and lifts upwards
- Planning by stable, collision-free IK-solver

Appendix (cont.) - Release Position

- Derive release position r from landing location p
- Assume: aerial trajectory is linear on xy-horizontal plane and in the v_x, v_y direction
- Neglect orthogonal aerodynamic forces
- Parallel aerodynamic forces are compensated
- Making all release positions accessible by robot
- Constants: $r_z = 0.04$ m and distance to base $\sqrt{r_x^2 + r_y^2} = 0.7$ m in sim, 0.02m and 0.76 m in reality
- Constraint: $(r_{x,y} - p_{x,y}) x v_{x,y} = 0$

Appendix (cont.) - Physics controller

- Physics based controller provides a closed form solution
- Generalizes well to new landing locations
- Serves as consistent approximation for $\hat{v}$
- Simplified model
- Neglects aerodynamic drag
- Gripper release velocity does not directly determine projectile velocity
- Centripetal forces

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

Appendix (cont.) Example Calculation

- UR5 joint speed: $\frac{180^\circ}{s} \Rightarrow \omega = \frac{\pi}{s}$
- Length of lower arm: $\approx 0.49m$
- Peripheral speed: $v = \frac{pi}{s} \cdot 0.49m \approx 1.54\frac{m}{s}$
- Ballistic equation projectile range: $x = v_0 \cdot \cos\theta \cdot t$
- Ballistic equation ToF[3]: $t = \frac{2 \cdot v_0 \cdot \sin\theta}{g}$
- Throwing angle $\theta =$ impact angle $= 45^\circ$

$$x = \frac{2 \cdot (v_0)^2 \cdot \sin(2 \cdot \theta)}{2 \cdot g} = \frac{2 \cdot (1.54\frac{m}{s})^2 \cdot \sin 90}{2 \cdot 9.81\frac{m}{s^2}} \approx 0.24m$$

[3] Time-of-Flight

Appendix (cont.) - Learning of release velocities

Ballistic calculation:

- Ballistic equation projectile range: $x = \hat{v} \cdot \cos\theta \cdot t$
- Ballistic equation ToF[4]: $t = \frac{2 \cdot v_0 \cdot \sin\theta}{g}$
- Throwing angle θ = impact angle

$$\hat{v} = \sqrt{\frac{x \cdot g}{\sin(2 \cdot \theta)}} \tag{2}$$

e.g. $\sqrt{\frac{0.24m \cdot 9.81\frac{m}{s^2}}{\sin(2 \cdot 45)}} \approx 1.53\frac{m}{s}$ throwing velocity

[NAS]

[4] Time-of-Flight

Appendix (cont.) - Learning of release velocities

- fixed throwing release height r_z
- fixed release distance from robot base origin c_d
- release vel. angled 45° upwards
- landing location p $= (p_x, p_y, p_z)$
- release position r is fixed at $c_d = 0.76$m and r_z at constant height $c_h = 0.02$m
- Release vel. magnitude $\|v\|$

Ballistic calculation:

$$\theta = \arctan(\frac{p_y}{p_x})$$

$$r_x = c_d \sin\theta$$

$$r_y = c_d \cos\theta$$

$$\|v\| = \sqrt{\frac{a(p_x^2 + p_y^2)}{r_z - p_z - \sqrt{p_x^2 + p_y^2}}}$$

Appendix (cont.) - Self Supervised Learning

- Pinto and Gupta [PG16] emphasized benefits of large-scale datasets
- Introduced large robot dataset
- Limit human involvement
- Execute trial and error grasps
- Image patch of grasp feed to CNN
- Output is the likelihood of the grasp

[PG16]

Appendix (cont.) - Self Supervised Learning

- Trained model is used for next grasping stage
- Execute grasp along the predicted output
- Grasps are evaluated by gripper's force sensor
- Correct grasp modalities are reinforced

[PG16]

Appendix (cont.) - Self Supervised Learning

- better utilizing unlabelled data, while learning in a supervised learning manner
- framing a supervised learning task in a special form to predict only a subset of information using the rest
- all the information needed, both inputs and labels, has been provided. This is known as self-supervised learning.
- self-generated labels
- To make use of this much larger amount of unlabeled data, one way is to set the learning objectives properly so as to get supervision from the data itself.
- The self-supervised task, also known as pretext task, guides us to a supervised loss function.

[Wen19]

Appendix (cont.)

Algorithm 1 System Pipeline

```
Initialize robot.
Initialize policy with model f.
Initialize replay buffer.
while step i < N and not terminate do
    I^i = robot.CaptureState()
    p^i = robot.SelectTarget()
    φ_g^i, φ_t^i = f.Inference(I^i, p^i)
    while robot.is_grasping do
        f.ExperienceReplay(buffer)
    y^{i-1} = robot.CheckGraspSuccess()
    robot.ExecuteThrow(φ_t^{i-1}, p^{i-1})        ▷ asynchronous
    while robot.is_throwing do
        f.ExperienceReplay(buffer)
    robot.ExecuteGrasp(φ_g^i)                     ▷ asynchronous
    p̄^{i-1} = robot.TrackLanding()
    buffer.SaveData(I^{i-1}, p^{i-1}, φ_g^{i-1}, φ_t^{i-1}, y^{i-1}, p̄^{i-1})
    i = i + 1
```

Figure: Ideal ballistic equations [Zen+19]

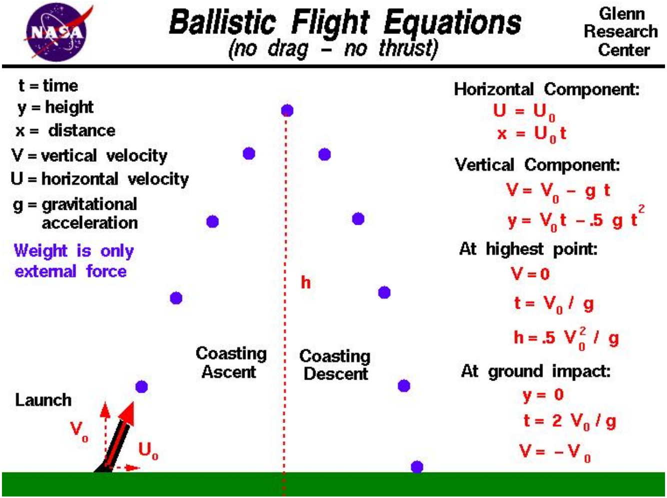


Figure: Ideal ballistic equations [NAS]

Appendix (cont.)

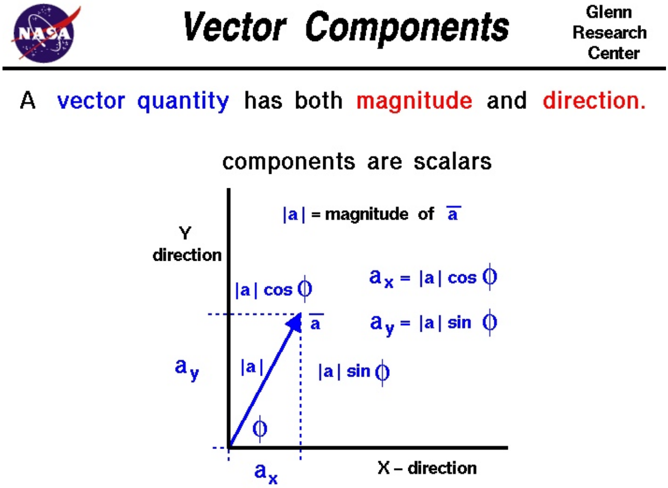


Figure: Vector components [NAS]

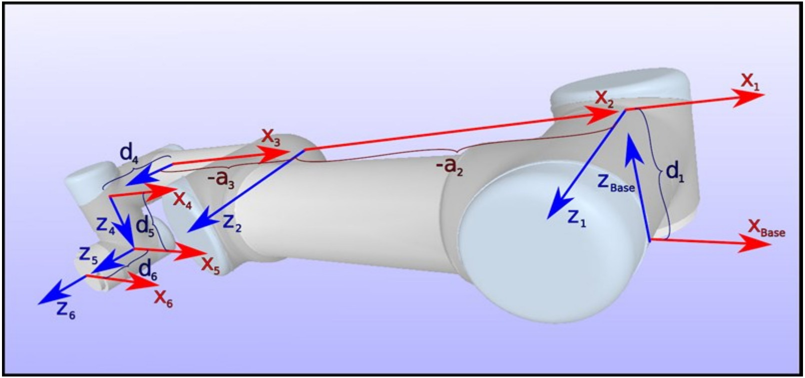


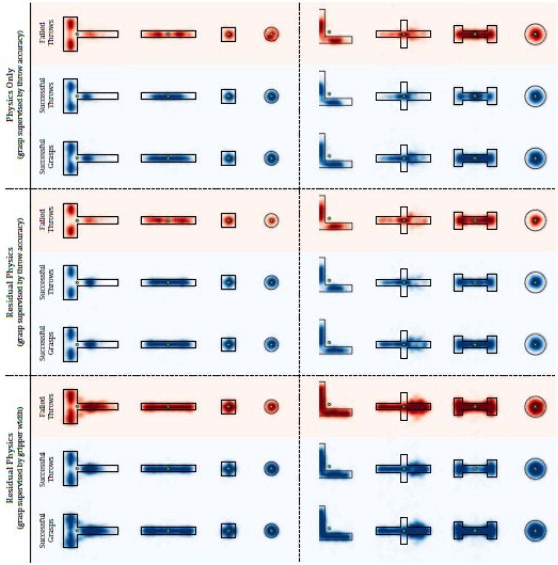
Figure: Denavit–Hartenberg parameters of UR robots [Uni18]

Appendix (cont.)

UR5e							
Kinematics	theta [rad]	a [m]	d [m]	alpha [rad]	**Dynamics**	Mass [kg]	Center of Mass [m]
Joint 1	0	0	0.1625	π/2	Link 1	3.761	[0, -0.02561, 0.00193]
Joint 2	0	-0.425	0	0	Link 2	8.058	[0.2125, 0, 0.11336]
Joint 3	0	-0.3922	0	0	Link 3	2.846	[0.15, 0.0, 0.0265]
Joint 4	0	0	0.1333	π/2	Link 4	1.37	[0, -0.0018, 0.01634]
Joint 5	0	0	0.0997	-π/2	Link 5	1.3	[0, 0.0018,0.01634]
Joint 6	0	0	0.0996	0	Link 6	0.365	[0, 0, -0.001159]

Figure: UR5 Technical specifications [Uni16]

Appendix (cont.)



Appendix (cont.)

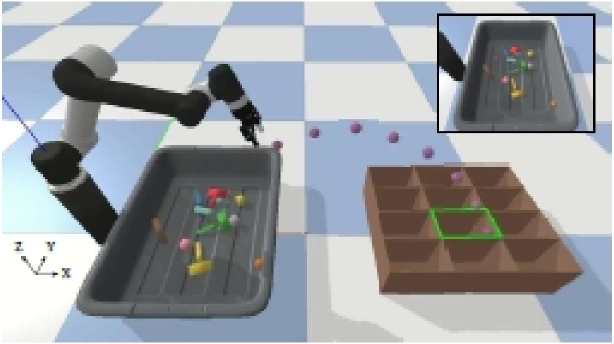
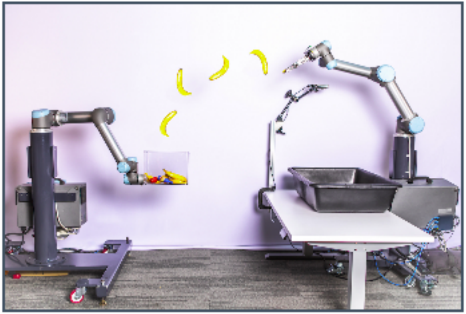


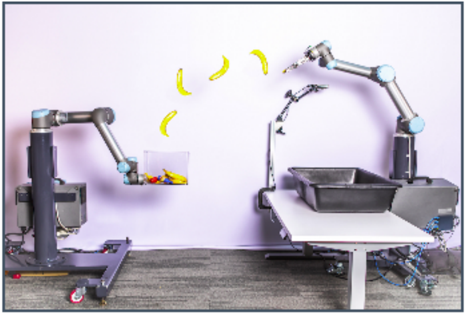
Figure: PyBullet simulation [Zen+19]

Video



[Zen19]

Video



[Zen19]