Learning in Robotics

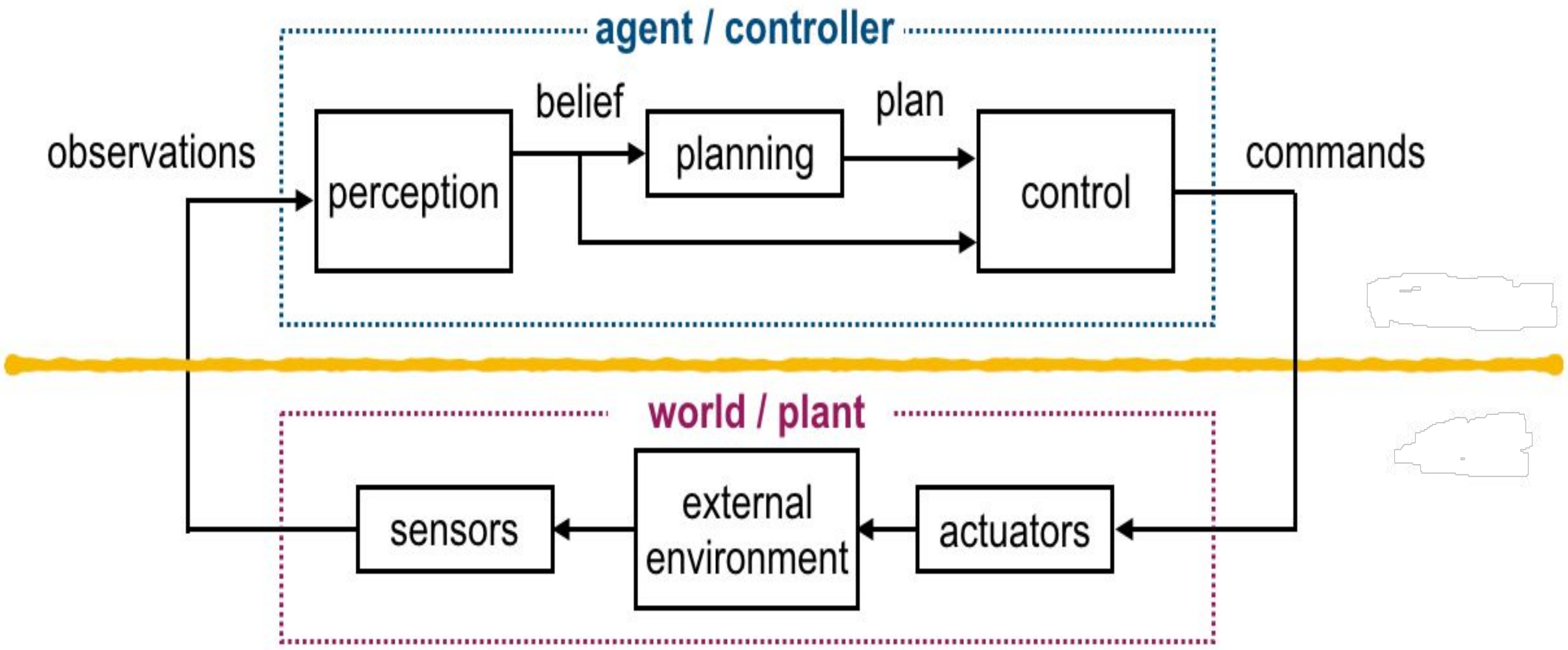
Adane Letta, PhD

December 2024

Outline

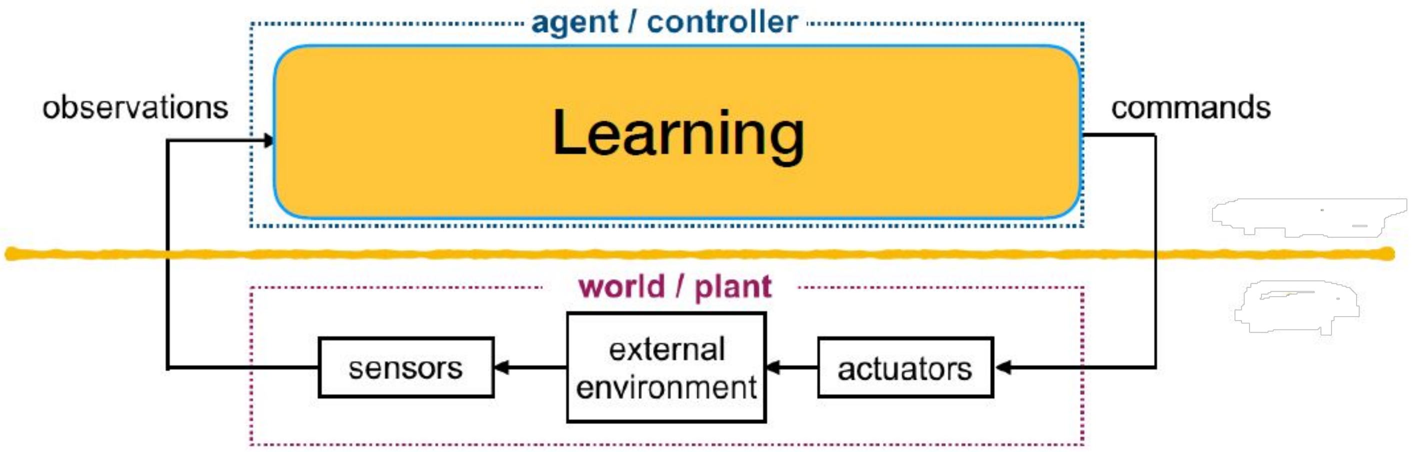
- Supervised, unsupervised, and reinforcement learning for robotics
- Policy learning and imitation learning
- Multi-agent systems and learning in robotic swarms

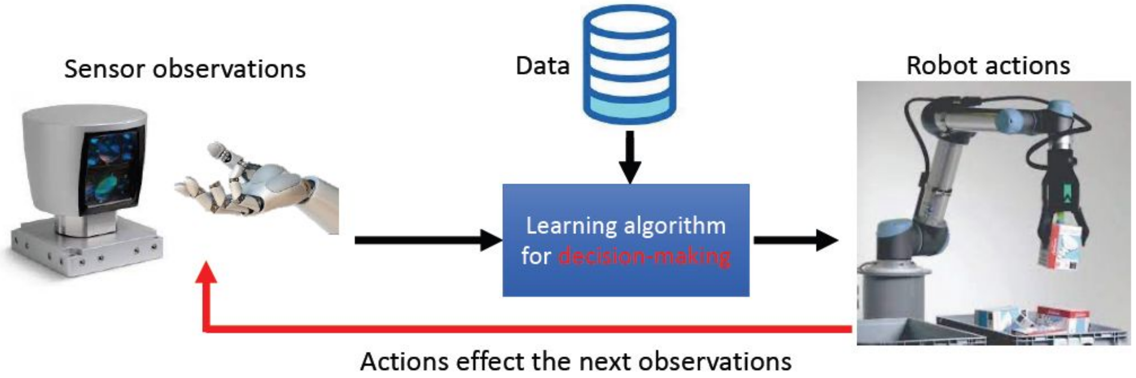
Learning In Robotics: Introduction



Ack: Julian Zilly, Machine Learning in Robotics

Learning In Robotics: Introduction





- Learning to make sequential decisions in the physical world
    - The current action/decision influences the next state

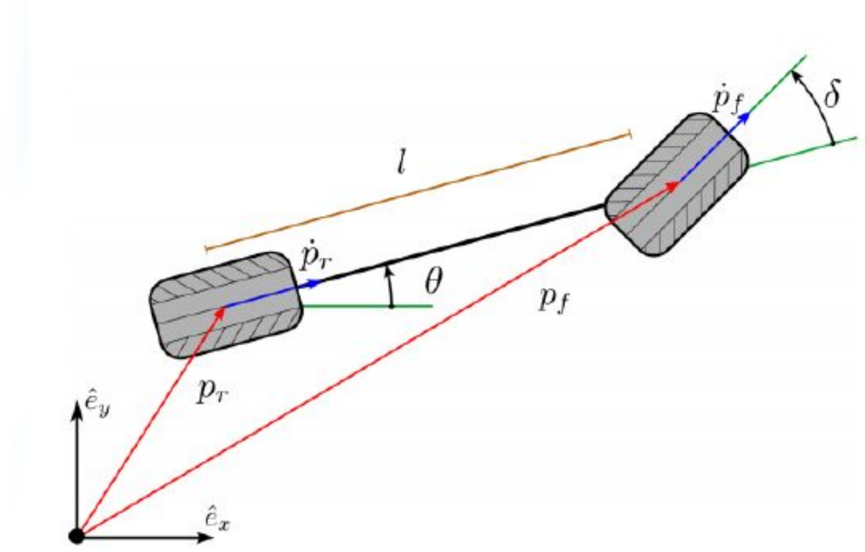
Ack: Guanya Shi. Carnege Mellon University

Why Learning?

When should I use model-based or data-driven approaches?

Detect cats

Predict movement



- We do not know how to model everything
- But we often have data to approximate the relationship

Why should robots Learn?

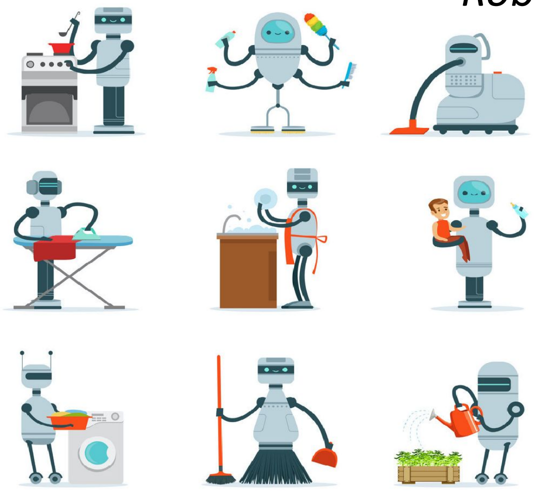
- We cannot model everything a robot needs to “know”
- The world changes - making models obsolete
- Robots can learn counterintuitive strategies (RL)
- We need robots to explore and learn by themselves if they are to be useful in complex scenarios

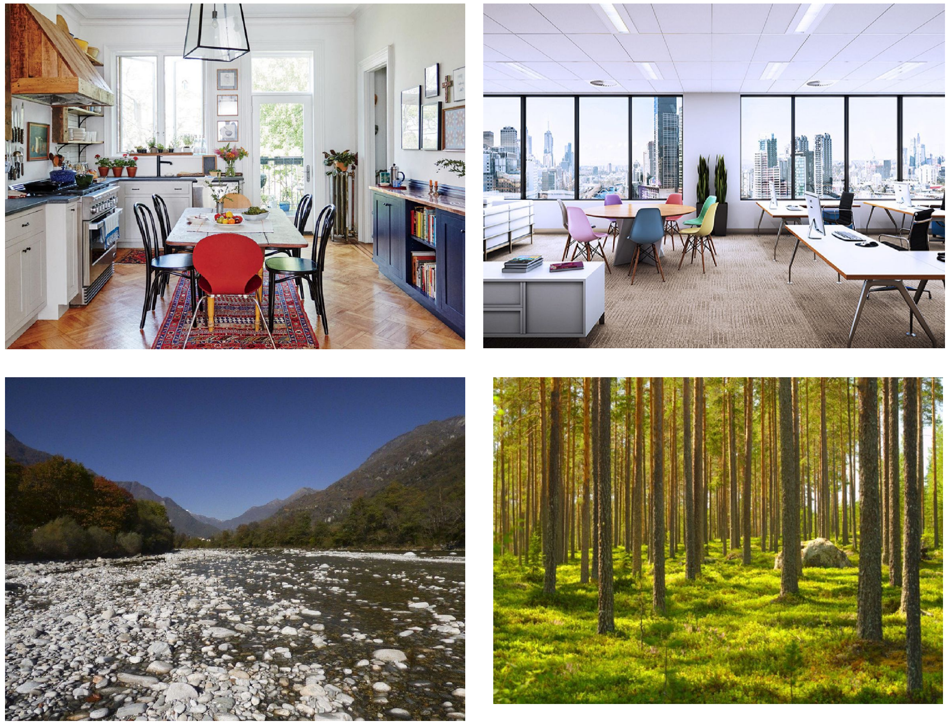
- Robot learning plays a fundamental role in enabling robots to autonomously acquire skills, adapt to dynamic environments, and perform complex tasks.

What is the Goal of “Robot Learning”?

- Ultimate goal: Build general-purpose embodied intelligence by learning to make sequential decisions in the physical world

Robots that can do thousands of tasks in thousands of environments





“It is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to *perception* and *mobility*.” (Hans, 1988)

Robot Learning & Data

- Learning: Data-driven and improve from data

- Data increases the “upper bound” of algorithm, computation, and hardware

- Challenges (compared to other AI or machine learning domains):
  - Where is the data from?
  - How to use the data?

Learning Algorithms

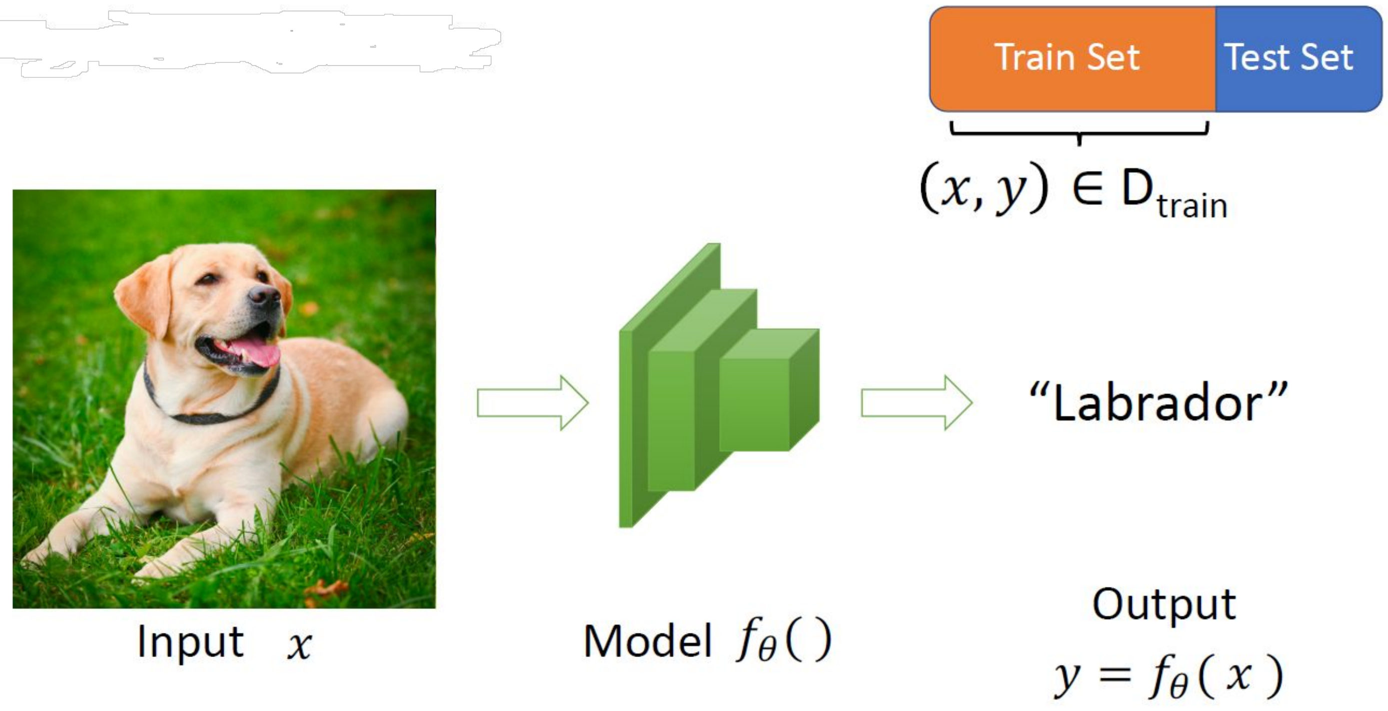
- The field of robotics has undergone a transformative evolution
- Transitioning from
  - Static and rule-based machines
  - Adaptive and intelligent entities capable of learning from their experiences and interactions with the world.

Learning Algorithms: Supervised Learning

- Supervised learning involves training robots using labeled data, where the algorithm learns to map input data to desired outputs.
- Useful for tasks like image recognition and object manipulation, where the robot can generalize from the provided examples to handle new, similar situations.

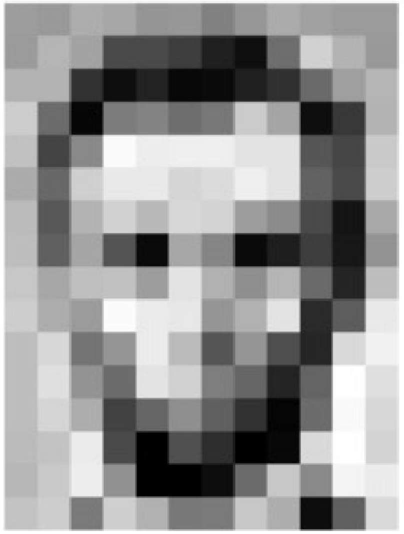
- Learn a function f: $X \rightarrow Y$ from an input space X (observations) to an output space Y (targets), using a set of labeled examples $D_{train} = (x_1, y_1) \dots . (x_n, y_n)$

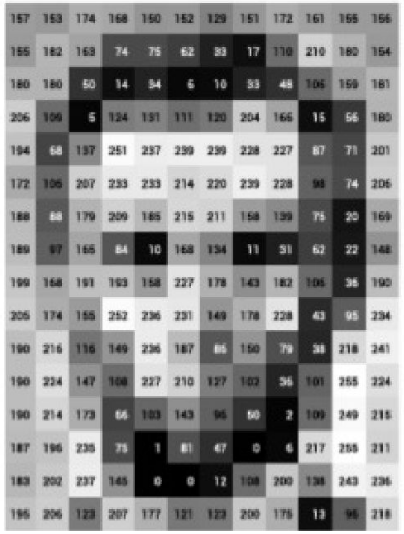
- "Generalization": Ideally, such learned function ! will perform well on the test data, example: image classification



Learning Algorithms: Supervised Learning

- What we see and what a computer sees?

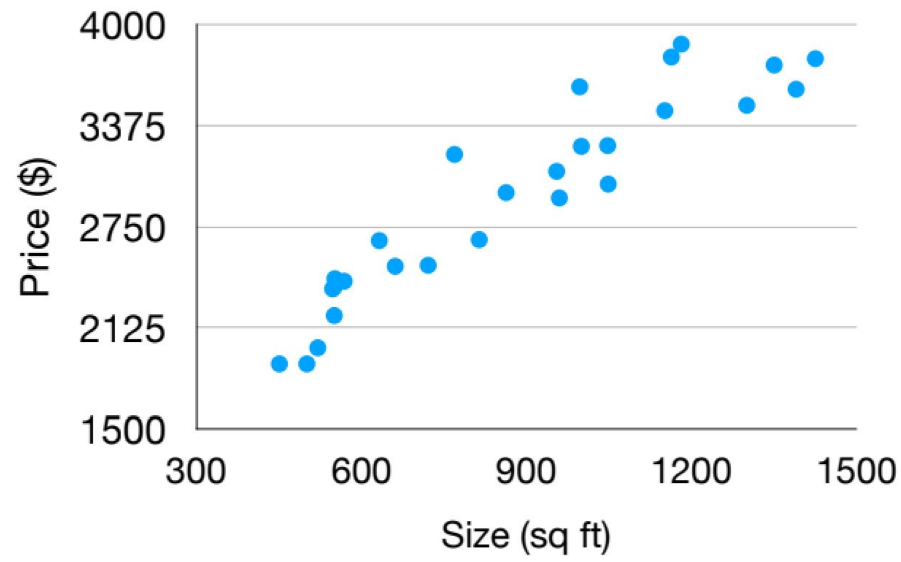




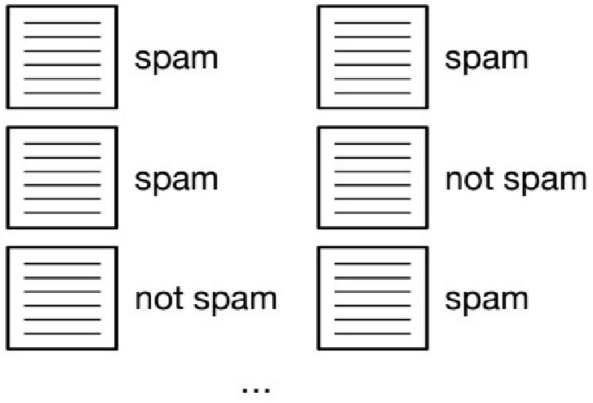
157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

- It is why we need learning! To extract pattern from “complex” data.

Supervised Learning Problems



Regression: predict real values $Y = R \text{ or } R^n$



Classification: predict a class y from a fixed finite set

Machine learning foundations

- Training data

- Model/architecture: refers to the mathematical framework and computational structure used to process input data, learn from it, and make predictions or decisions based on it.

- Loss: used in machine learning to measure the difference between a model's predictions and the actual target values.

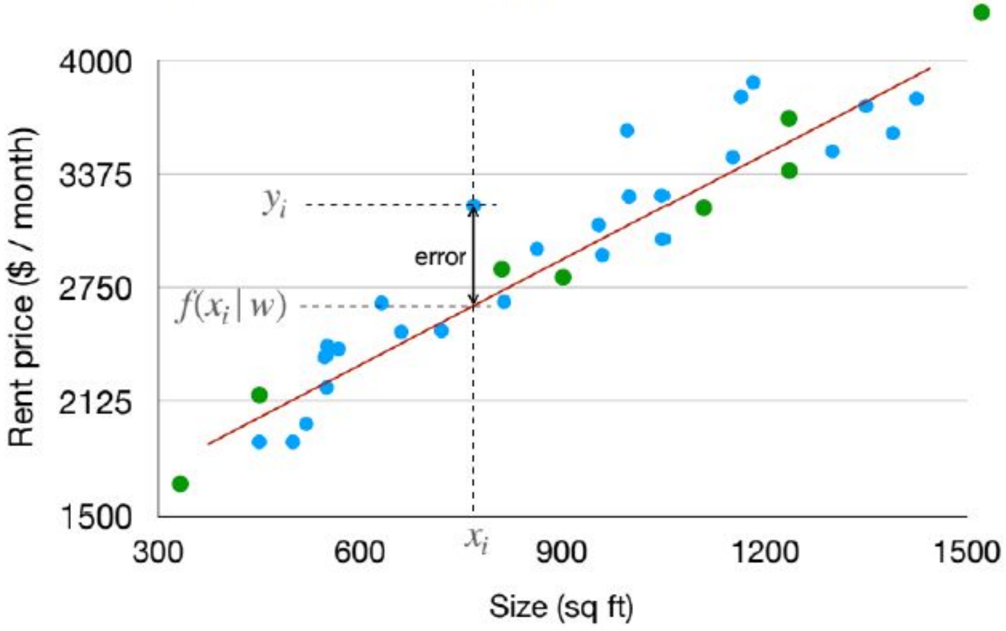
- Learning objective: refers to the specific goal or target that the model aims to achieve during the training process.

Machine learning foundations

- Generalization: model's ability to perform well on new, unseen data that it has not encountered during training.
- Overfitting: a model learns the training data too well and to the extent that it performs poorly on new, unseen data.
- Underfitting: a model is too simple to capture the underlying patterns in the data--- it performs poorly on both the training data and unseen data, failing to make accurate predictions or provide meaningful insights.
- Optimization: in machine learning refers to the process of adjusting the parameters of a model (e.g., weights and biases) to minimize or maximize a specific objective function, often the loss function.

Example: Linear Regression

D_{train}: blue dots; D_{test}: green dots



- ❑ **Loss**: squared loss $L(y, y') = (y - y')^2$
- ❑ **Learning objective**:

$$\underset{w}{\operatorname{argmin}} L_N(w) = \sum_{i \in D_{\text{train}}} L(y_i, f(x_i|w))$$

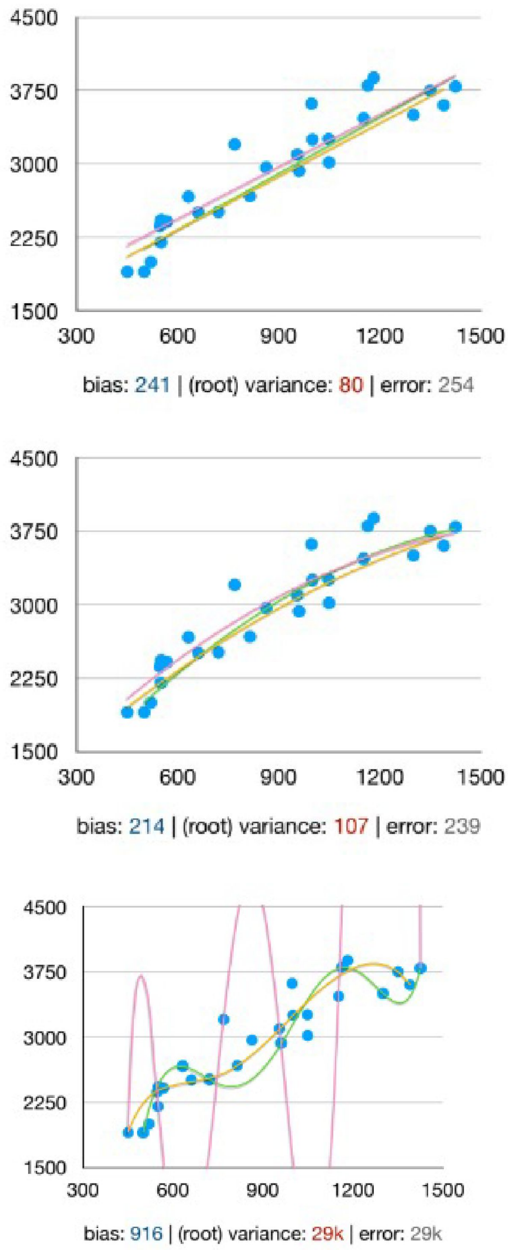
- ❑ **Overfitting**: test error >> training error
- ❑ **Underfitting**: test and training error are similar and both high
- ❑ **Optimization**: optimize the learning objective
  - Closed-form solution $w = (X^\top X)^{-1} X^\top Y$
  - Gradient descent: $w \leftarrow w - \eta \nabla_w L_N(w)$
  - SGD:

$$w \leftarrow w - \eta \nabla_w \sum_{i \in \text{Batch}} L(y_i, f(x_i|w))$$

Model Selection and Validation Set

- How do we choose from these models and tune hyper-parameters such as learning rates?
- We only have training dataset – cannot measure the true test error
- The key principle of machine learning: "Test and train conditions must match"

- Split the original dataset into a training set and a validation set
- Train model on the training set
- Evaluate on the validation set to *estimate* the test error
- Can also do this procedure in a k-fold way (split the original data into k equal parts)

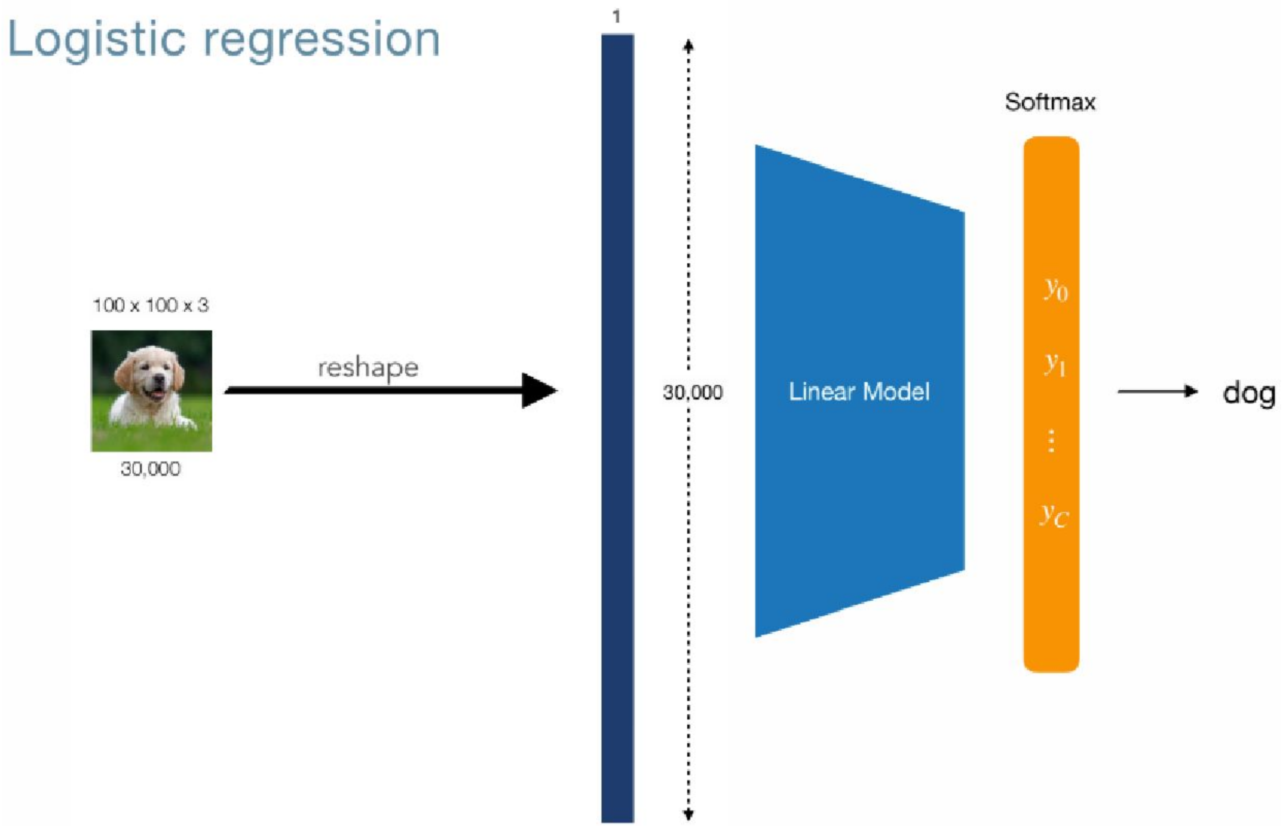


Supervised Learning in Robotics

- Training dataset: $Dtrain = (x_1, y_1) \dots . (x_n, y_n)$
- y can be many things!
    - Dynamics (model-based control and RL)
    - Action (imitation learning)
- How to generate y and how to use it are more important!

Supervised Learning in Robotics: Deep Learning

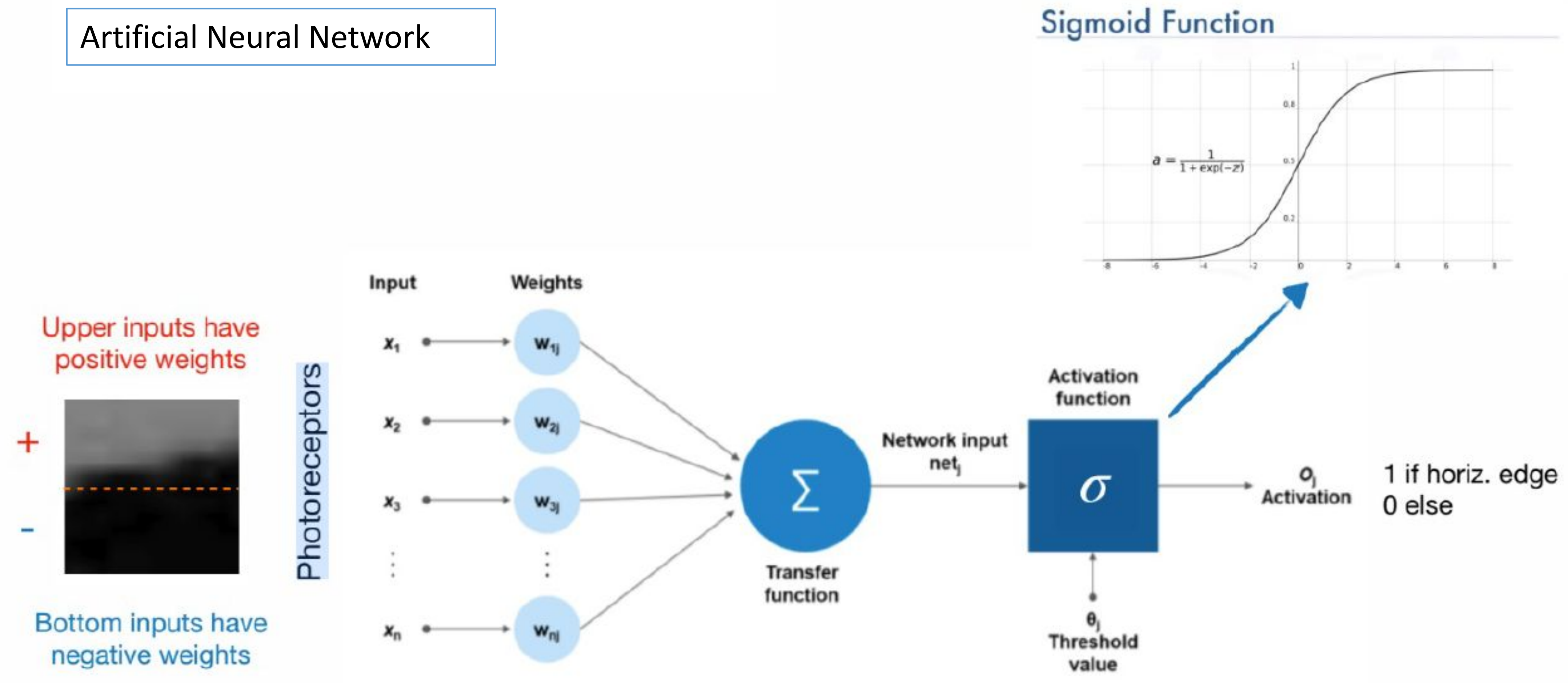
- Logistic regression for image classification: Does it work?



In images individual features (pixels) are not meaningful. What matters is the relation between pixels!

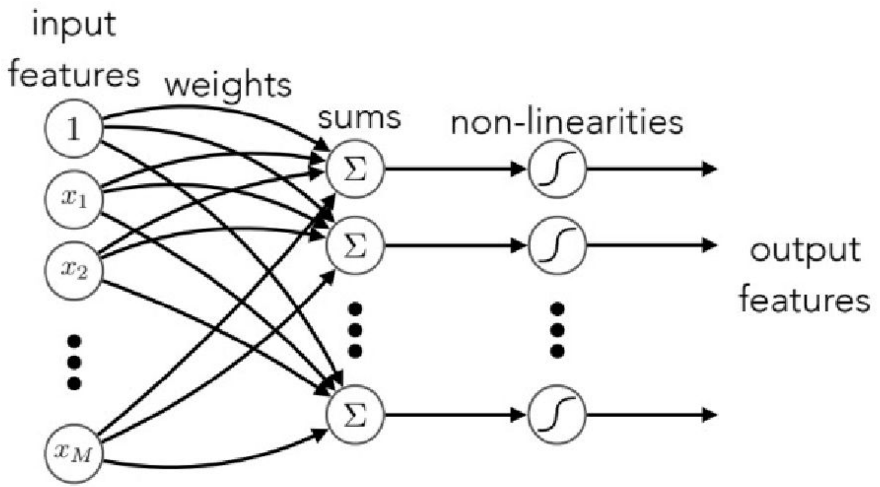
- Example: to recognize a person we need to look at parts and relation between parts

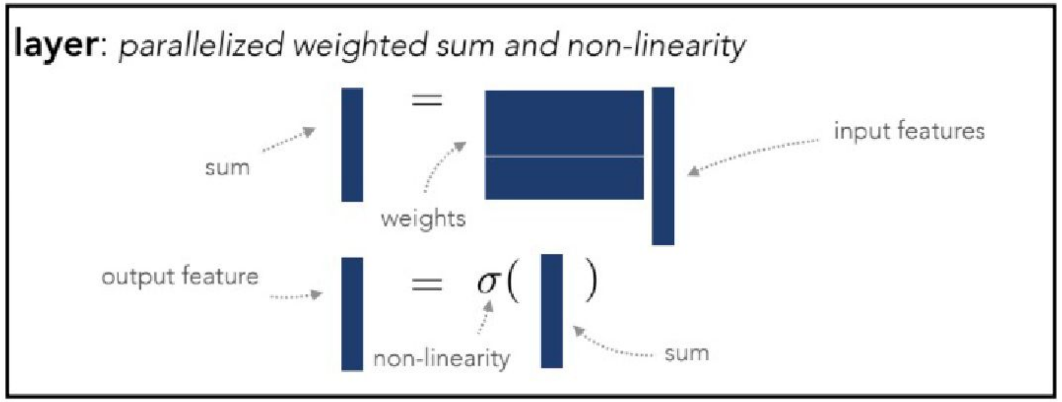
Supervised Learning in Robotics: Deep Learning



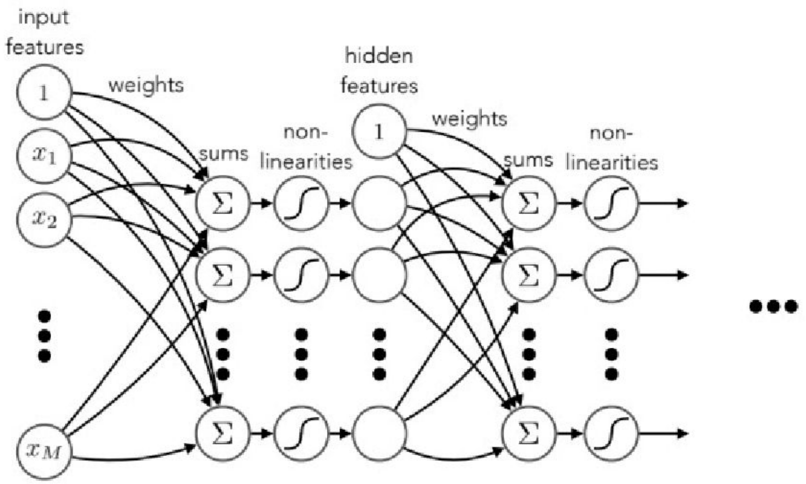
Supervised Learning in Robotics: Deep Learning

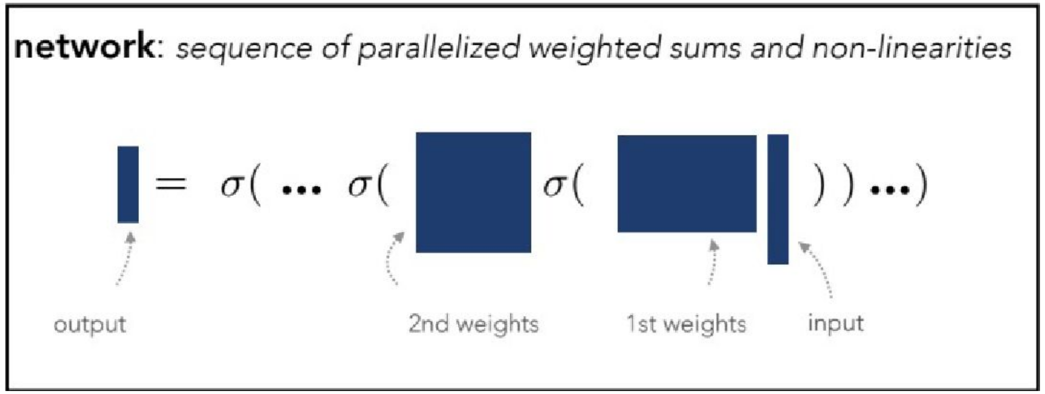
One layer ANN





Multilayer ANN

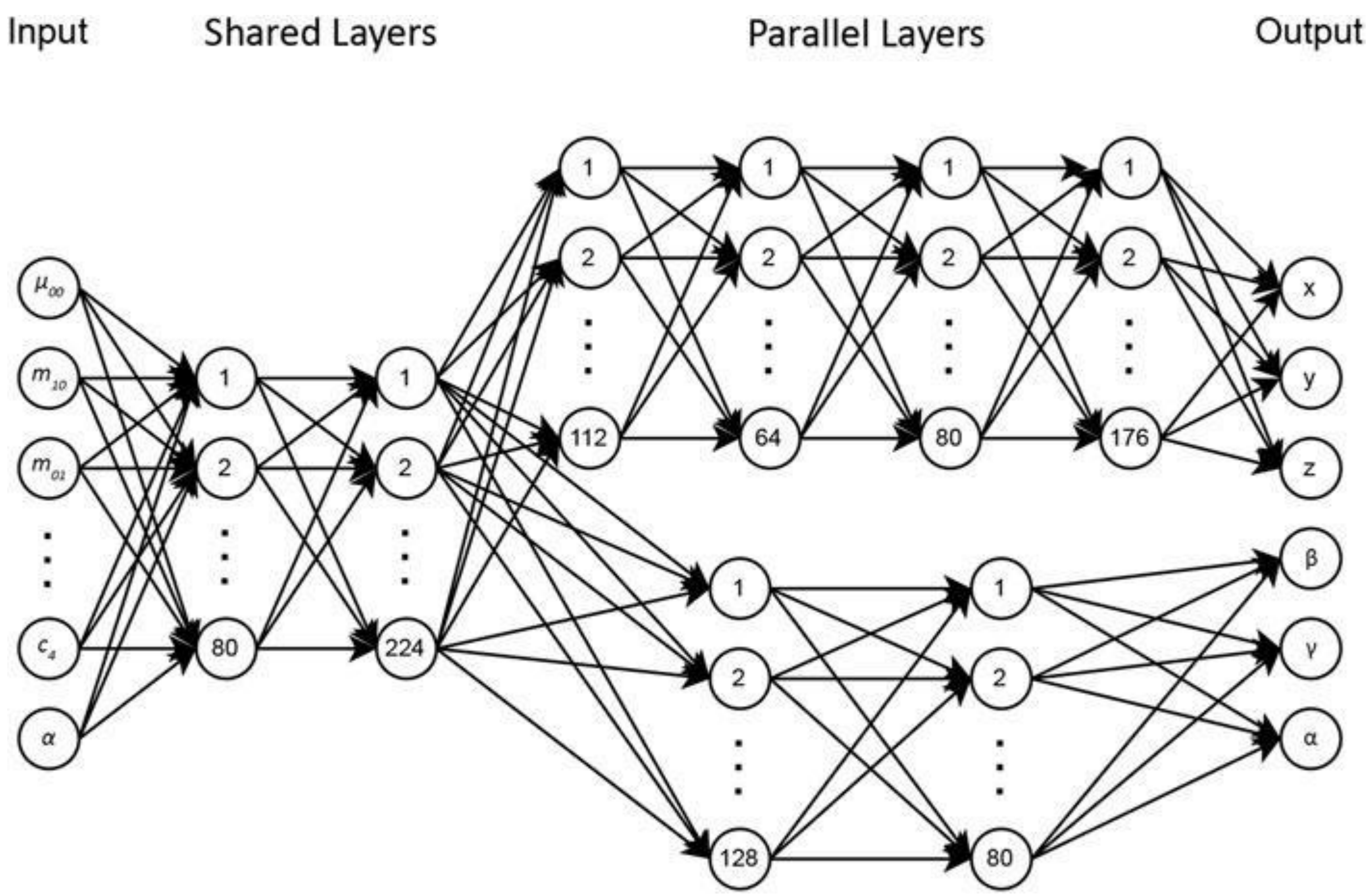




Supervised Learning in Robotics: Deep Learning

- The success of deep learning in computer vision has inspired some applications in robotics.
- Challenges
  - Robots must perform a wide range of tasks, and it is often time-consuming or even infeasible to code completely new learning algorithms and features for each task.
  - Robots must handle a huge amount of variety in the real world, which is difficult for many learning algorithms to handle.
  - Time is at a premium in most robotic applications, so learning algorithms must lend themselves to fast inference to be useful for robotic applications.
- DNN benefits
  - Generality due to its non-linearity
  - Feature learning
  - Parallelism
  - Multimodal -- multiple modalities of input data, such as audio and video, text and image data

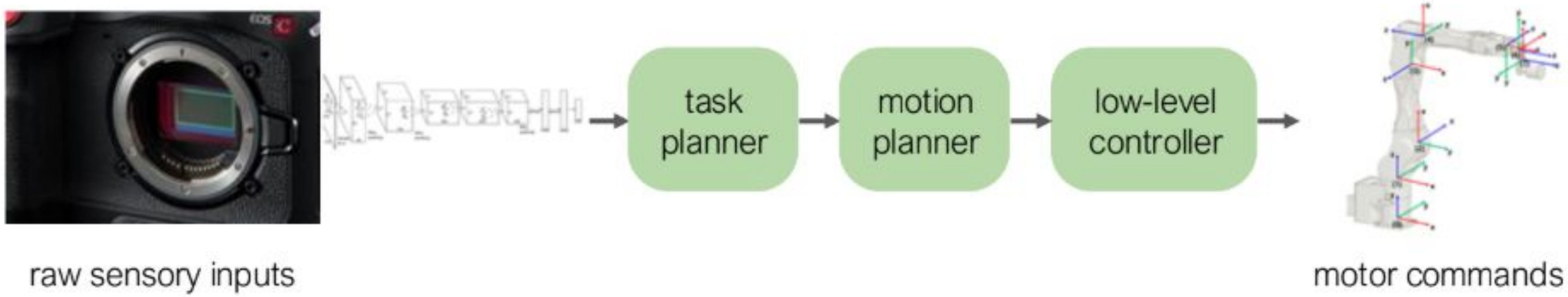
Supervised Learning in Robotics: Deep Learning

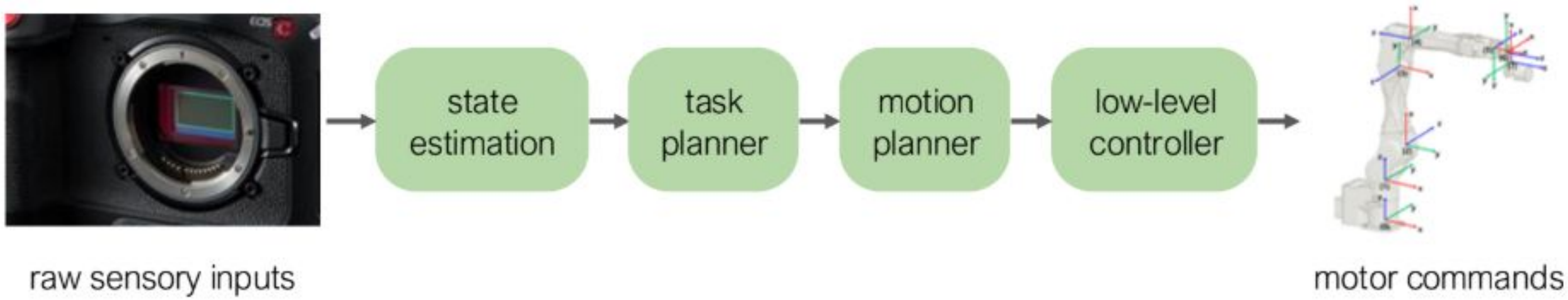


- Hyperparameter tuning:
- Activation Functions
- Batch Size
- Learning Rate
- Optimizers

Shayan et al., 2024. Deep neural network-based robotic visual servoing for satellite target tracking

Supervised Learning in Robotics: Deep Learning





Supervised Learning in Robotics: Deep Generative Models in Robotics

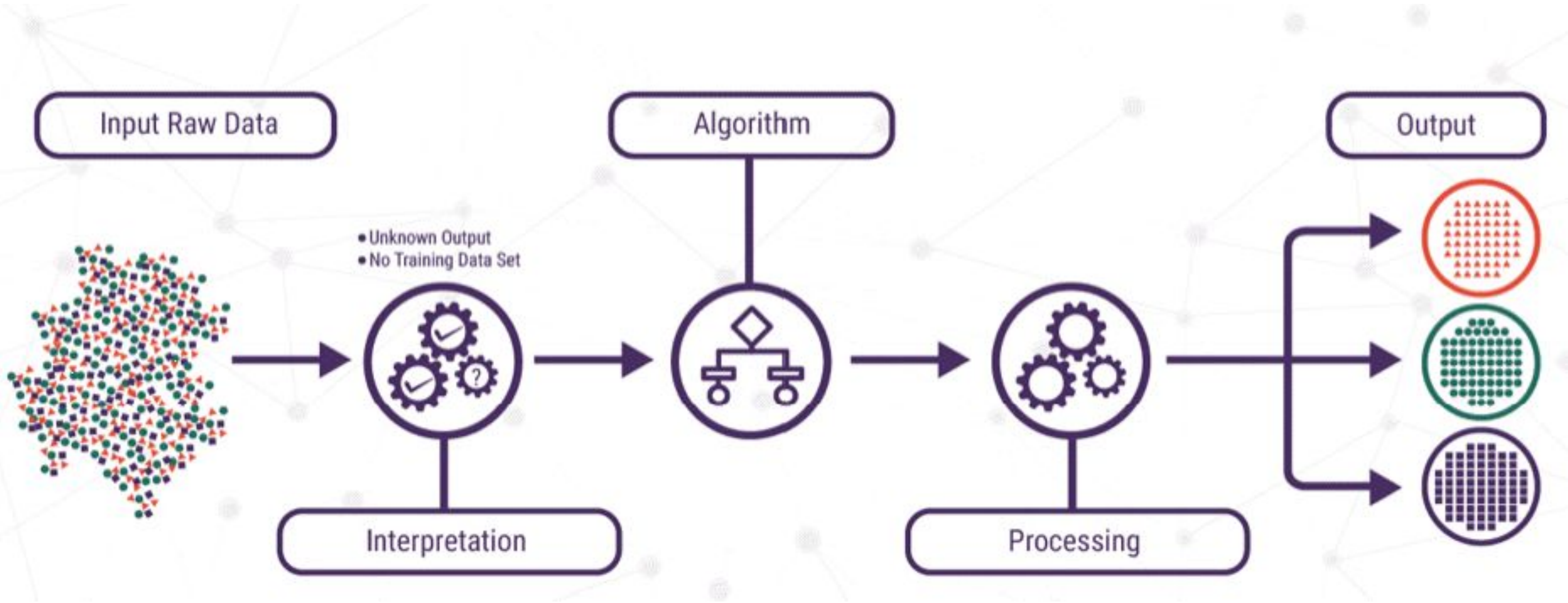
- Motion Planning and Control
  - Can simulate possible trajectories and motions for a robot.
- Perception and Sensor Fusion
  - Robots equipped with multiple sensors (e.g., cameras, LiDAR, and tactile sensors) use generative models to infer missing or noisy data.
- Human-Robot Interaction
  - Generative models are used to predict and simulate human actions, emotions, or intentions for more natural interactions.
- Grasping and Object Manipulation
  - Generative models can predict grasping strategies or generate 3D object reconstructions for manipulation tasks.

Generative Models in Robotics

- Variational Autoencoders
- Generative Adversarial Networks
- Diffusion Models
- Hidden Markov Models (HMMs)

Learning Algorithms: Unsupervised Learning

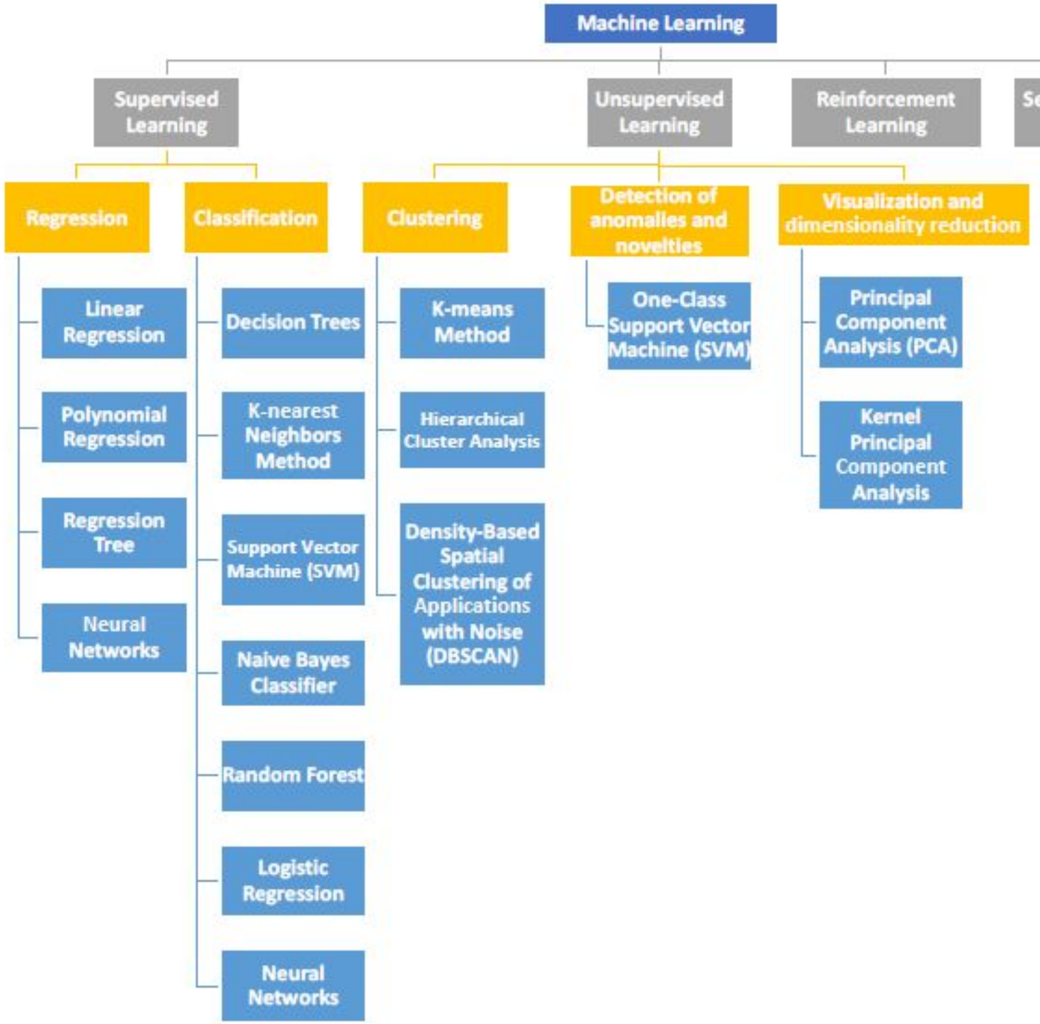
- **Definition** (Unsupervised Learning)**.** Given a collection of n data points (x1, . . . , xn), the unsupervised learning problem is to find patterns in the data.



Learning Algorithms: Unsupervised Learning

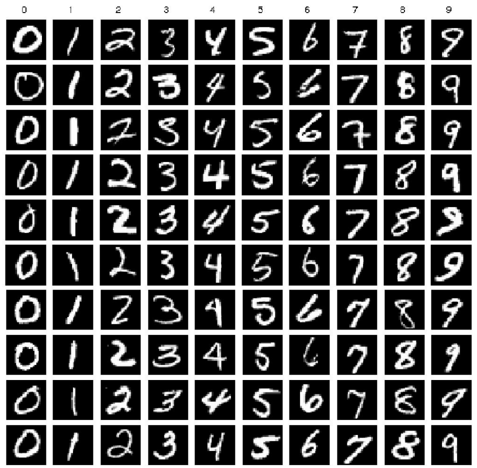
- There is a large class of models which can learn from unlabeled data.
- Unsupervised learning is a branch of machine learning which only uses unlabeled data.
- Key goals:
  - Learn the structure of data: learn if the data consists of clusters, or if it can be represented in a lower dimension.
  - Learn the probability distribution of data: By learning the probability distribution where the training data came from, it is possible to generate synthetic data which is "similar" to real data.
  - Learn a representation for data: We can learn a representation that is useful in solving other tasks later by reducing the need for labeled examples for classification.

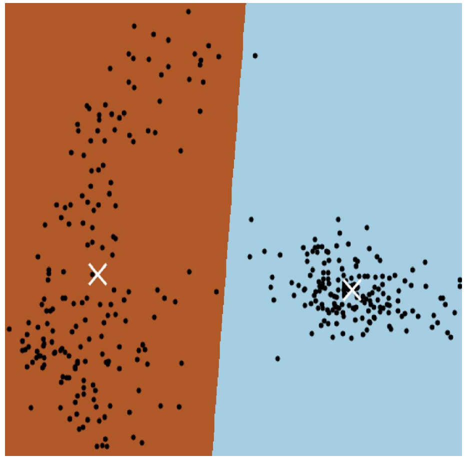
Learning Algorithms: Unsupervised Learning



Learning Algorithms: Unsupervised Learning

- Clustering: Learn the structure of data
  - K-means performs centroid-based clustering groups similar sensor readings





2D visualization of the k-means clusters differentiating between the digits “1” and “0” (right).

- A “good” **cluster** is a subset of points which are closer to each other than to all other points in the dataset.

- A “good” **cluster** is a subset of points which are closer to the **mean** of their own cluster than to the mean of other clusters.

Maintain clusters $C_1, C_2, \ldots, C_k$
For each cluster C_i, find the mean $\vec{\mathbf{y}}_i$
Initialize new clusters $C'_i \leftarrow \emptyset$
for $\vec{\mathbf{x}} \in \mathcal{D}$ **do**
 $i_x = \arg\min_i \|\vec{\mathbf{x}} - \vec{\mathbf{y}}_i\|_2$
 $C'_{i_x} \leftarrow C'_{i_x} \cup \{\vec{\mathbf{x}}\}$
end for
Update clusters $C_i \leftarrow C'_i$

Learning Algorithms: Unsupervised Learning

- Dimensionality Reduction:
  - Dimensionality reduction reduces the number of features or variables in data while preserving its essential information, allowing robots to compress sensor data or map environments.

  - Dimensionality reduction techniques
    - Principal Component Analysis maximizes variance through linear transformation compresses data

Unsupervised Learning in Robotics

- Robots are becoming more capable and versatile, but they still face many challenges in adapting to new and complex environments.
- The increasing diversity and complexity of such open environments have necessitated a renewed focus on unsupervised machine learning from large volumes of unstructured and unlabeled data
- One way to enhance their autonomy and performance is to use unsupervised learning… can facilitate downstream tasks such as perception, navigation, manipulation, or communication.
- Recent developments in autonomous robotics highlight the significance of unsupervised machine learning for skill transfer… help robots generate novel behaviors and solutions that are not predefined by human programmers, which can increase their creativity and flexibility.
- Autonomous robots use sensory–motor capabilities to interact independently within an open environment.

Robots employing unsupervised learning can identify similarities, group data, and uncover hidden insights, making it valuable for tasks such as environment exploration and data clustering.

Applications of Unsupervised Learning in Robotics

Perception and Object Recognition

- Robots use unsupervised learning to analyze sensor data (e.g., images, LiDAR scans) and identify patterns.
- Techniques like clustering and dimensionality reduction help robots recognize objects without prior labeling.

- Example: Autonomous robots categorizing objects in a cluttered environment.

Anomaly Detection

- Robots employ unsupervised learning models to detect deviations from normal behavior in processes or systems.

- Example: Identifying unexpected obstacles or equipment malfunctions in industrial robots.

Applications of Unsupervised Learning in Robotics

Behavioral Learning

- Unsupervised learning allows robots to observe and mimic human behaviors or actions by recognizing patterns.
- Example: Collaborative robots (cobots) learning human workflows in manufacturing.

Environment Mapping

- Robots can build detailed 3D maps of their surroundings using unsupervised learning techniques like SLAM (Simultaneous Localization and Mapping).
- Example: Autonomous vehicles generating maps of urban areas.

Feature Extraction for Control Systems

- Robots extract meaningful features from high-dimensional sensor data, which improves control and decision-making.
- Example: UAVs (unmanned aerial vehicles) identifying features of terrain for navigation.

Unsupervised Learning in Robotics

- Unsupervised learning is useful for robot navigation when there is no clear or correct way to perform a task, and when there is a lot of unlabeled data available.

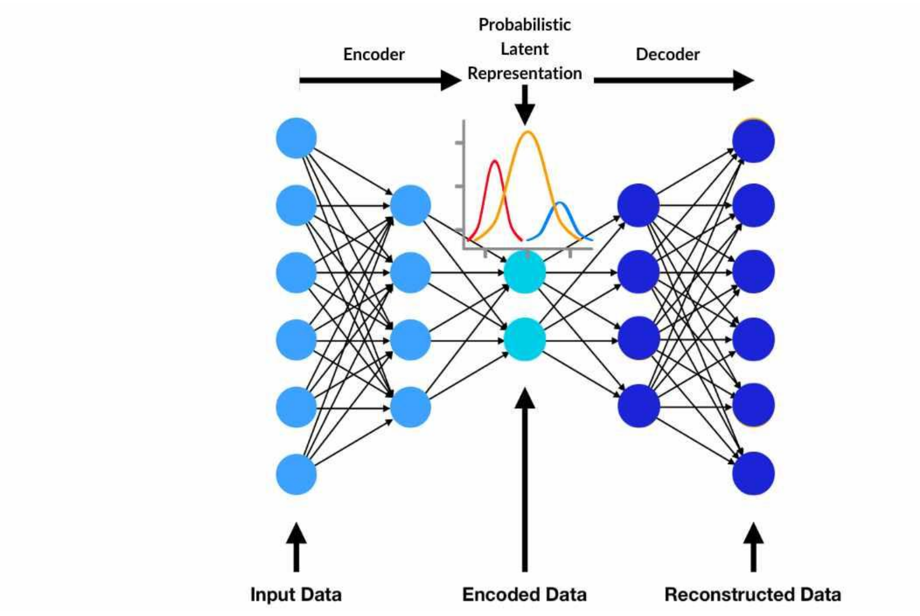
- However, unsupervised learning also has some challenges, such as:
  - Evaluation: is the process of measuring the quality and performance of a machine learning model
    - Can be difficult for unsupervised learning because there is no clear or objective criterion to judge the results.
  - Interpretation: is the process of understanding the meaning and significance of a machine learning model
    - Can be challenging because there is no explicit or intuitive explanation for the patterns and structures that the model finds.
  - Coordination: is the process of aligning and collaborating with other agents or systems
    - Can be problematic for unsupervised learning because there is no common or consistent framework or protocol to communicate or exchange information.

Self-Supervised Learning

- Self-supervised learning falls between supervised and unsupervised learning.
- Models learn from unlabeled data with the goal of generating classified outputs.
- This makes it possible to perform a sort of supervised learning without actually having labeled data.
- Self-supervised learning has drawn massive attention for its excellent data efficiency and generalization ability.
- Recent self-supervised learning models include frameworks such as Pre-trained Language Models (PTM), Generative Adversarial Networks (GAN), Autoencoder and its extensions, Deep Infomax, and Contrastive Coding.

Self-Supervised Learning: Algorithms

- Autoencoders
  - The autoencoder model is trained to encode the input data into a low-dimensional representation and then decode it back to the original input.
  - The objective is to minimize the difference between the input and the reconstructed output.



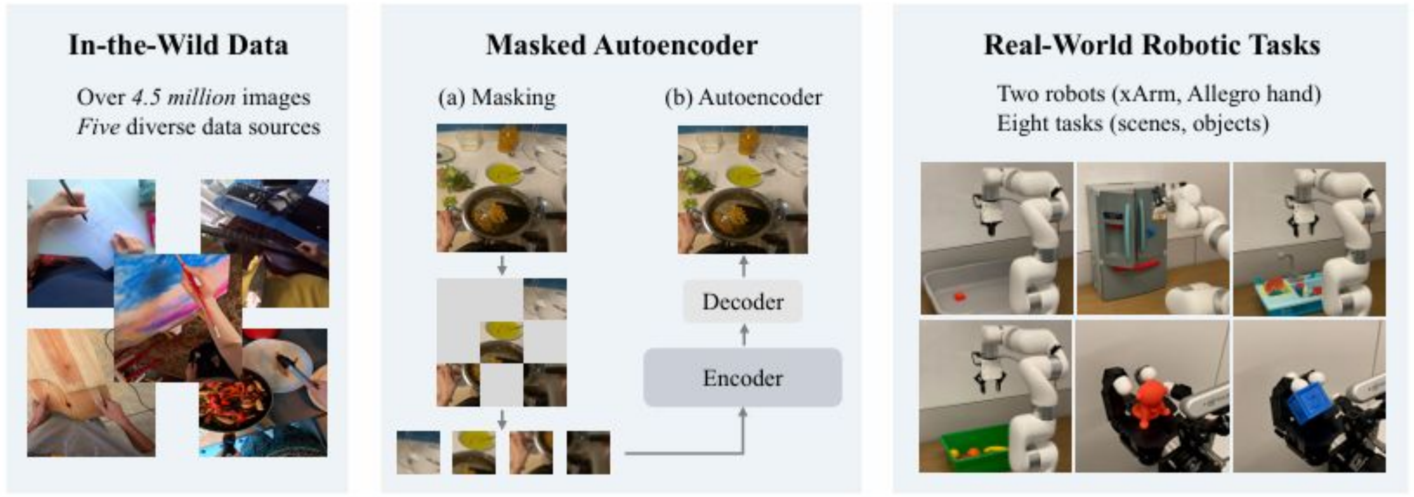
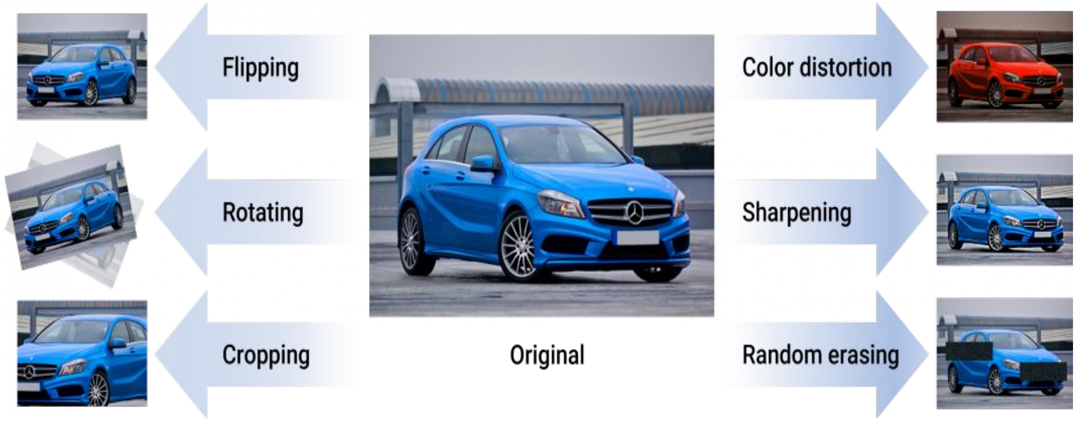


Figure 1: **Real-world robot learning with masked visual pre-training.** We learn visual representations from a massive collection of Internet and egocentric data. We pre-train representations with masked image modeling, freeze the encoder, and learn control policies for robotic tasks on top.

Radosavovic (2022): Real-World Robot Learning with Masked Visual Pre-training

Self-Supervised Learning: Algorithms

- Simple Contrastive Learning (SimCLR)
  - Simple framework for contrastive learning of visual representations
  - Maximizes the agreement between different augmentations of the same image.



Examples of image augmentations

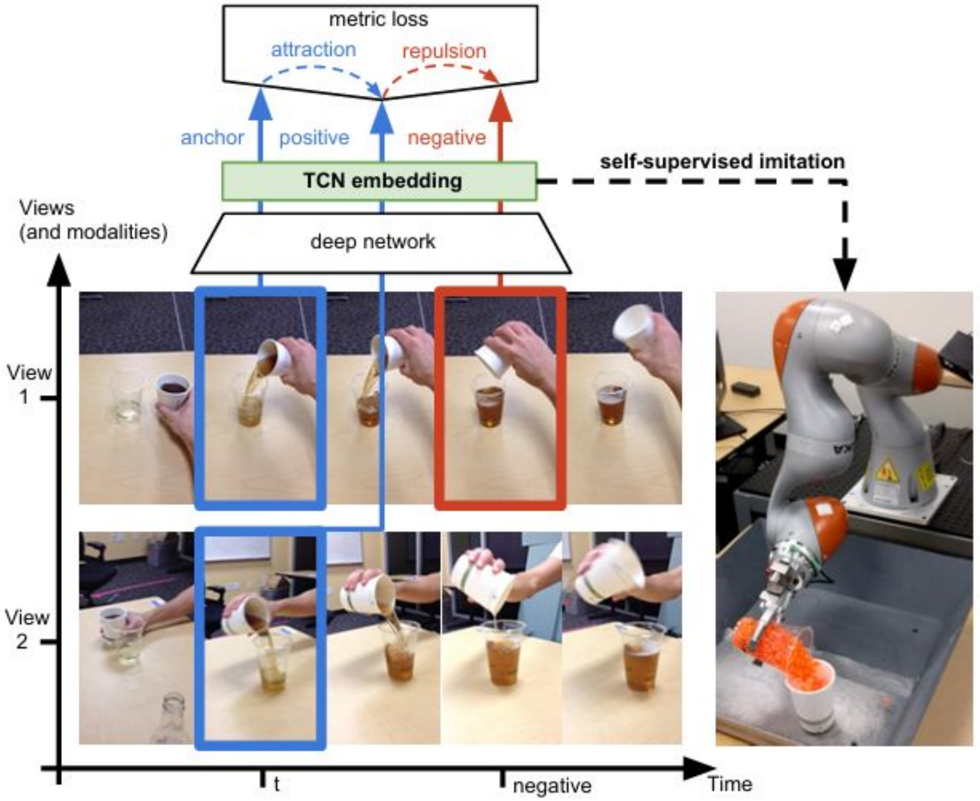
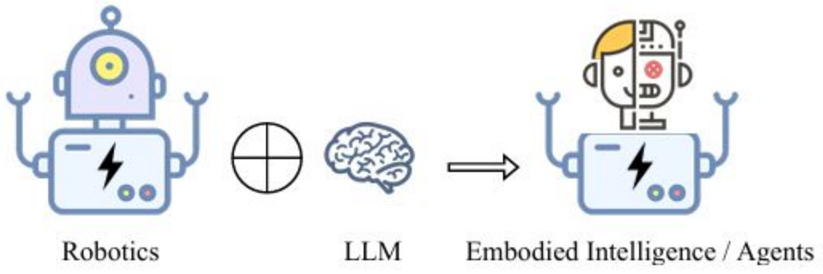


Fig. 1: **Time-Contrastive Networks (TCN):** Anchor and positive images taken from simultaneous viewpoints are encouraged to be close in the embedding space, while distant from negative images taken from a different time in the same sequence. The model trains itself by trying to answer the following questions simultaneously: What is common between the different-looking blue frames? What is different between the similar-looking red and blue frames? The resulting embedding can be used for self-supervised robotics in general, but can also naturally handle 3rd-person imitation.

Sermanet et al. (2024): Time-Contrastive Networks: Self-Supervised Learning from Video

Self-Supervised Learning: Algorithms

- Pre-trained Language Models (PTM)
  - Used for NLP, where the machine learning model is trained on large amounts of text data to predict missing words or masked tokens.
  - Often used for language modeling, text classification, and question-answering systems.



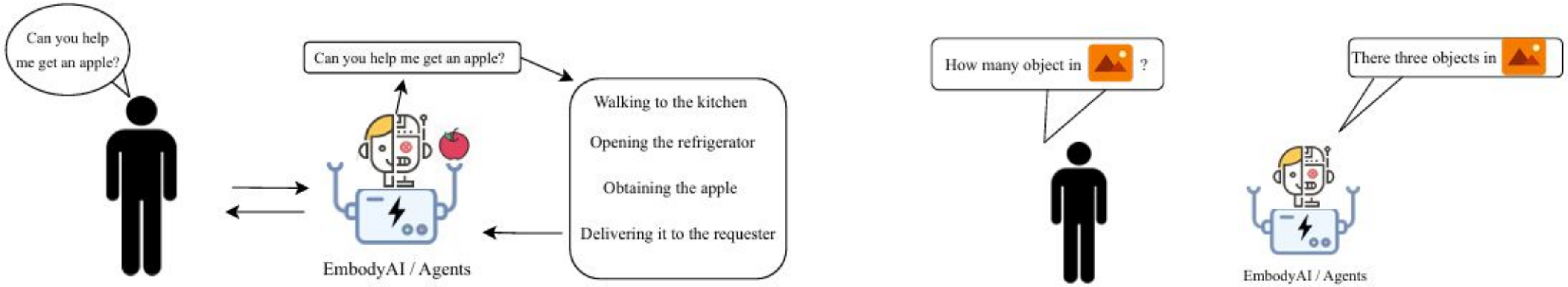
Robotics based on LLM.

Self-Supervised Learning: Algorithms

Pre-trained Language Models

LLMs for robot in recent years

Year	LLM-based robotics	Description
2022	PaLM-SayCan	PaLM-SayCan can function as the physical embodiment of LLM, utilizing LLM's semantic capabilities to process natural language instructions. Enabling robots to execute tasks assigned by humans through the value function.
2023	PaLM-E	PaLM-E boasts an LLM capable of integrating continuous sensory information from the real world, effectively bridging the gap between language and perception.
2023	LM-Nav	LM-Nav was developed, exploiting the advantages of language to facilitate effective communication between users and robots. The LM-Nav system comprises three components: a vision-navigation model (VNM); a vision language model (VLM); and a large language model (LLM).
2023	Expedition A1	Expedition A1, developed by AGIBot, embodies the company's commitment to seamlessly integrating advanced AI into robotics and fostering harmonious collaboration between humans and machines.



(a) Task decomposition.

(b) Multi-modal sentences in PaLM-E.

Zeng (2023): Large Language Models for Robotics: A Survey

Self-Supervised Learning: Algorithms

- Generative Models
  - Learn to generate new data points that are similar to the training data.
  - One popular example is Generative Adversarial Networks (GANs).
    - GANs consist of a generator producing synthetic data points and a discriminator distinguishing between synthetic and real data points.

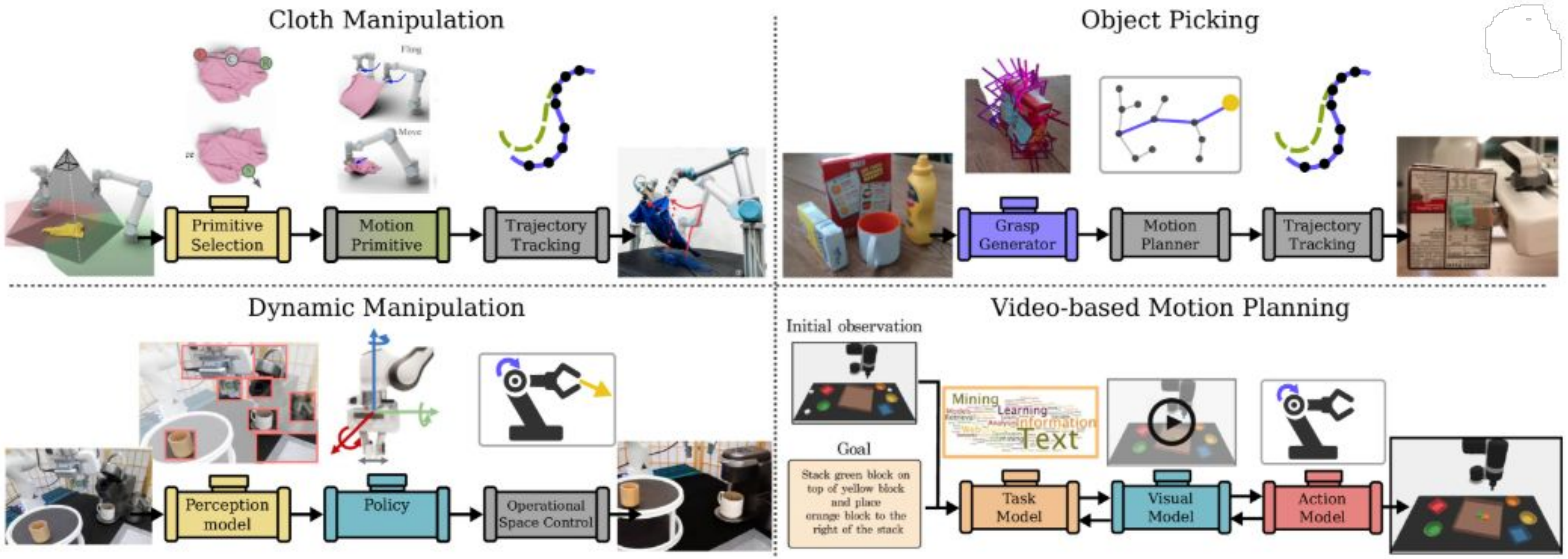


Figure 7: Visual representation of different approaches to apply DGM in robotics tasks. Colored: Learned models, Grey: Predefined models. **(a)** Cloth Manipulation. Given a set of motion primitives, an Action Value Map selects the primitive and the parameters of the primitive [43]. **(b)** Object Picking. An SE(3) pose generative model generates a target pose to grasp an object and a motion planner generates the path to reach the grasp [5]. **(c)** Visuo-Motor Policy. Given an image as input, a visuomotor policy generates end-effector actions. Then, an Operational Space Controller maps the action to the configuration space [147]. **(d)** Video Planning. A LLM generates a plan in text. The text generates a video of the substeps. Then, a goal-conditioned policy generates robot actions conditioned on generated images [127].

Urain et al. (2024) Deep Generative Models in Robotics: A Survey on Learning from Multimodal Demonstrations

Self-Supervised Learning: Examples

- Example #1: Motion and Depth Estimation: a self-supervised learning technique used to predict motion and depth from video frames. This is an example of how self-supervised learning is used for training autonomous vehicles to navigate and avoid obstacles based on real-time video.

- Example #2: Audio Recognition: a self-supervised learning technique where the model is trained to recognize spoken words or musical notes. This technique is useful for training speech recognition and music recommendation systems.

- Example #3: Cross-modal Retrieval: a self-supervised learning technique where the model is trained to retrieve semantically similar objects across different modalities, such as images and text. This technique is useful for training recommender systems and search engines.

Gaundez (2023): Self-Supervised Learning: Everything You Need to Know (2024)

Self-Supervised Learning

Advantages of self-supervised learning	Disadvantages of self-supervised learning
Requires less labeled data than supervised learning	Can require more computation and resources
Enables learning from unlabeled data, which is more abundant and easier to acquire in some cases	Pretext tasks can be challenging to formulate and may require expert knowledge
Can recognize new concepts after seeing only a few labeled examples	May not perform as well as supervised learning on some tasks
Resistant to adversarial machine learning attacks	May suffer from overfitting and generalization errors on some tasks
Can be used in a wide range of applications, including computer vision, natural language processing, and speech recognition	Some applications may still require large labeled datasets
Enables the development of more efficient and generalizable models	

Learning Taxonomy

- Supervised Learning– "Teacher" provides required response to inputs. Desired behaviour known. "Costly"
- Unsupervised Learning– Learner looks for patterns in inputs. No "right" answer
- Reinforcement Learning– Learner not told which actions to take, but gets reward/punishment from environment and adjusts/learns the action to pick next time.

Learning Algorithms: Reinforcement Learning

- Reinforcement learning is learning what to do—how to map situations to actions—so as to maximize a numerical reward signal.
- The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them.
- In the most interesting and challenging cases, actions may affect not only the reward but also the next situation and, through that, all subsequent rewards.
- These two characteristics—trial-and-error search and delayed reward—are the two most important distinguishing features of reinforcement learning.

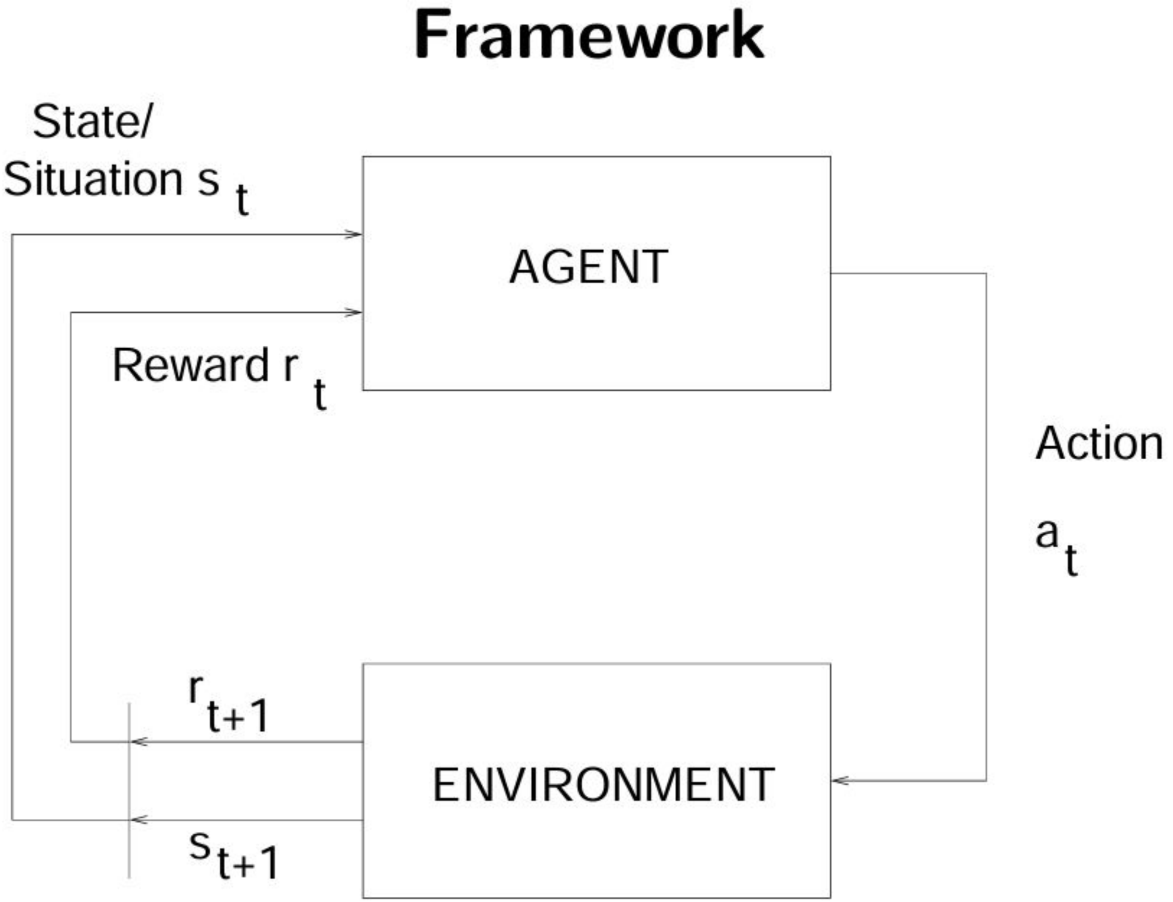
Learning Algorithms: Reinforcement Learning

- Takes inspiration from behavioral psychology, where robots learn through trial and error.

- By receiving feedback in the form of rewards or penalties, a robot's algorithm gradually improves its decision-making abilities.

- Enabled robots to master complex tasks like playing games, navigating through intricate environments, and even manipulating delicate objects.

Learning Algorithms: Reinforcement Learning



Learning Algorithms: Reinforcement Learning

General Reinforcement Learning Algorithm

1. Initialise learner's internal state (e.g. Q values, other statistics)

2. Do for a long time

   - Observe current world state s
   - Choose action a using the policy
   - Execute action a
   - Let r be immediate reward, s' new world state
   - Update internal state based on s, a, r, s', previous internal state

3. Output a policy based on, e.g. learnt Q values and follow it

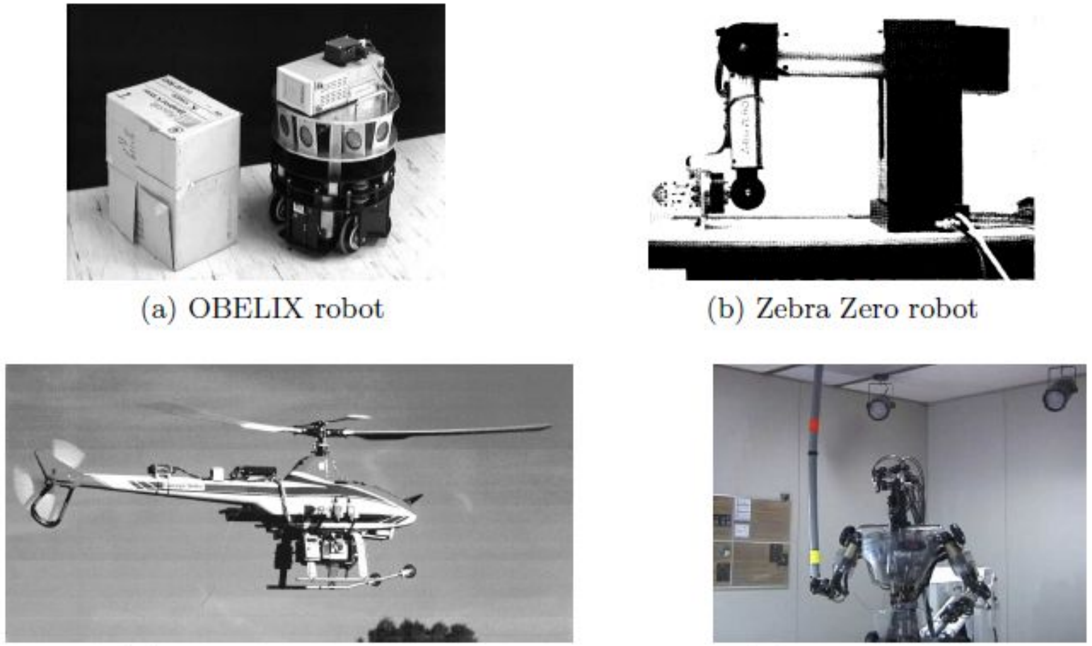
Learning Algorithms: Reinforcement Learning

Requirements for an RL Algorithm

We need:

- Decision on what constitutes an internal state
- Decision on what constitutes a world state
- Sensing of a world state
- Action-choice mechanism (policy) based usually on
- an evaluation (of current world and internal state) function
- A means of executing the action
- A way of updating the internal state

Learning Algorithms: Reinforcement Learning



(a) OBELIX robot

(b) Zebra Zero robot

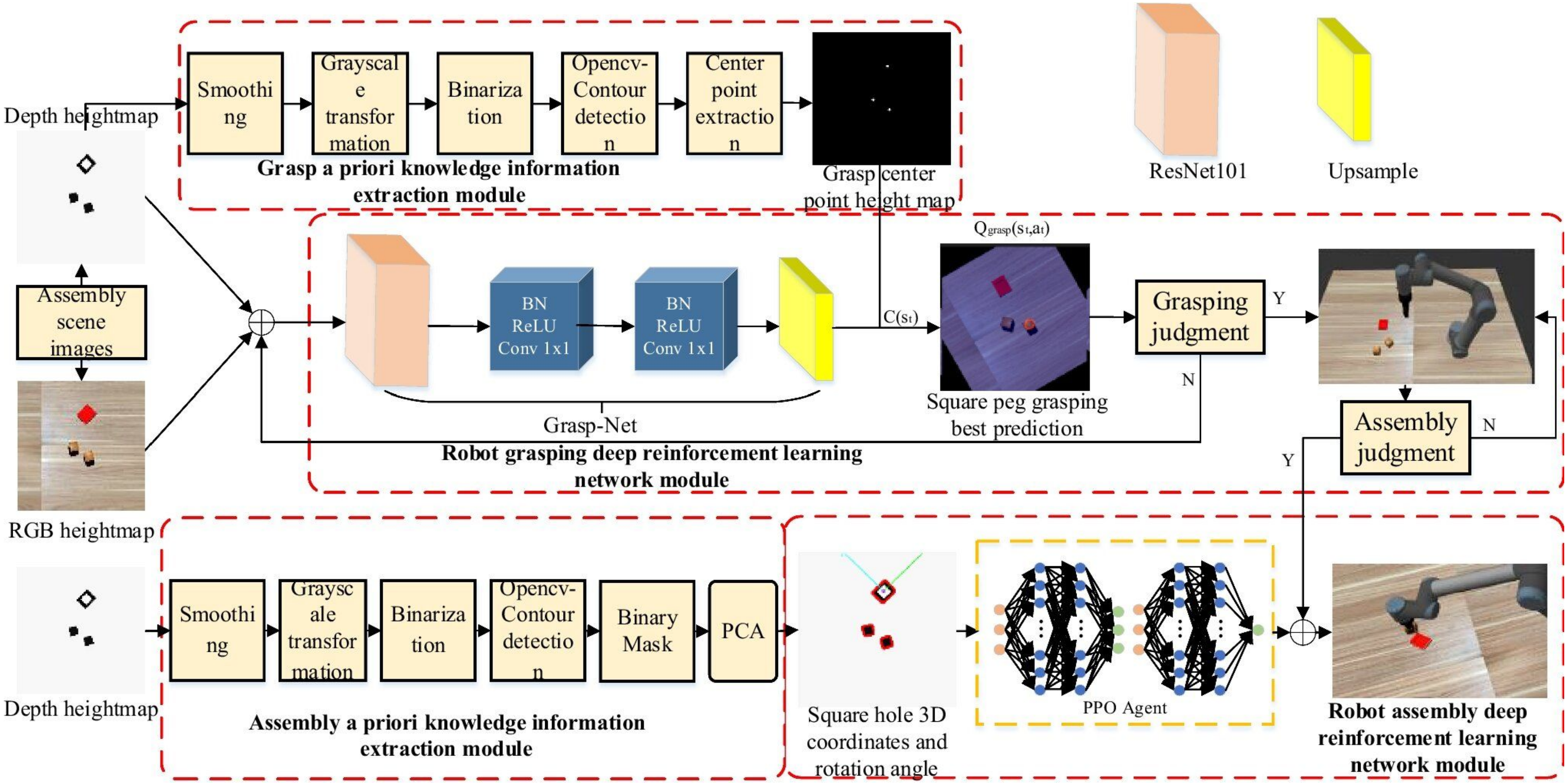
(c) Autonomous helicopter

(d) Sarcos humanoid DB

This figure illustrates a small sample of robots with behaviors that were reinforcement
learned.

Kober et al. (), Reinforcement Learning in Robotics: A survey

Learning Algorithms: Reinforcement Learning



Fadelli (2024): A deep reinforcement learning approach to enhance autonomous robotic grasping and assembly

Learning Algorithms: Reinforcement Learning

- One of the challenges that arise in reinforcement learning, and not in other kinds of learning, is the tradeoff between exploration and exploitation.

- The agent has to exploit what it has already experienced in order to obtain reward, but it also has to explore in order to make better action selections in the future.

- To obtain a lot of reward, a reinforcement learning agent must prefer actions that it has tried in the past and found to be effective in producing reward.

Learning Algorithms: Reinforcement Learning

- Examples

1. A master chess player makes a move. The choice is informed both by planning-anticipating possible replies and counterreplies—and by immediate, intuitive judgments of the desirability of particular positions and moves.

2. An adaptive controller adjusts parameters of a petroleum refinery's operation in real time. The controller optimizes the yield/cost/quality trade-o↵ on the basis of specified marginal costs without sticking strictly to the set points originally suggested by engineers.

3. A mobile robot decides whether it should enter a new room in search of more trash to collect or start trying to find its way back to its battery recharging station. It makes its decision based on the current charge level of its battery and how quickly and easily it has been able to find the recharger in the past.

Learning Algorithms: Reinforcement Learning

- Challenges
  - *Sample Efficiency: training robots using reinforcement learning often requires a substantial number of interactions with the environment.*
  - *Safety and Robustness: Ensuring the safety of robotic systems trained with reinforcement learning is a paramount concern.*
  - *Exploration-Exploitation Tradeoff: Striking the right balance between exploration and exploitation is a fundamental challenge in reinforcement learning.*

Learning Algorithms: Reinforcement Learning

- Challenges
  - *Robust Perception:* Reinforcement learning relies heavily on accurate perception of the environment
  - *Long-term Planning and Memory*: Long-term planning and memory retention pose challenges for reinforcement learning algorithms, as they need to handle temporal dependencies and account for delayed consequences.
  - *Scalability to Complex Tasks:* As robotic applications become more complex, scalability becomes a challenge for reinforcement learning.