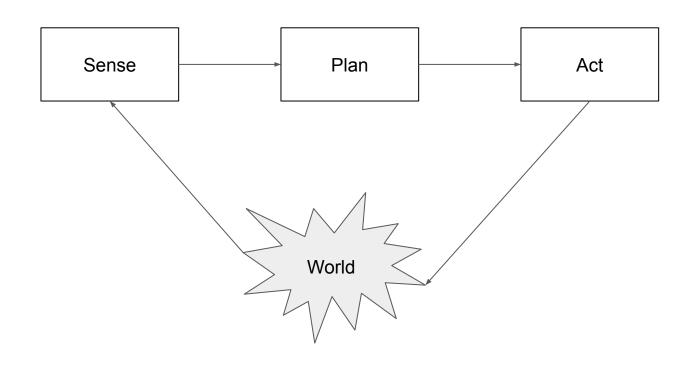
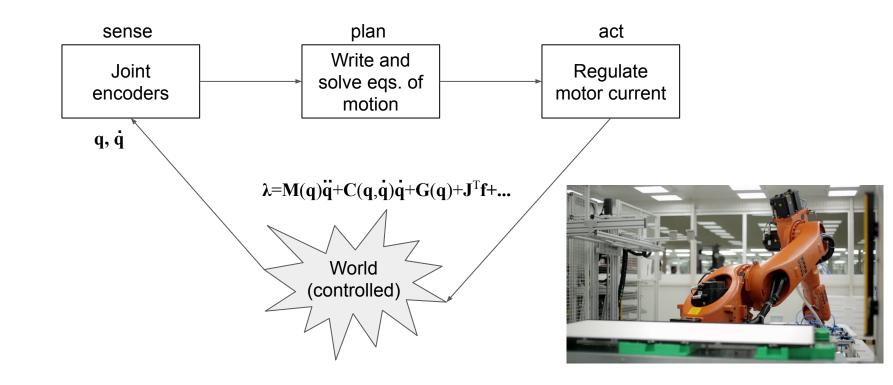
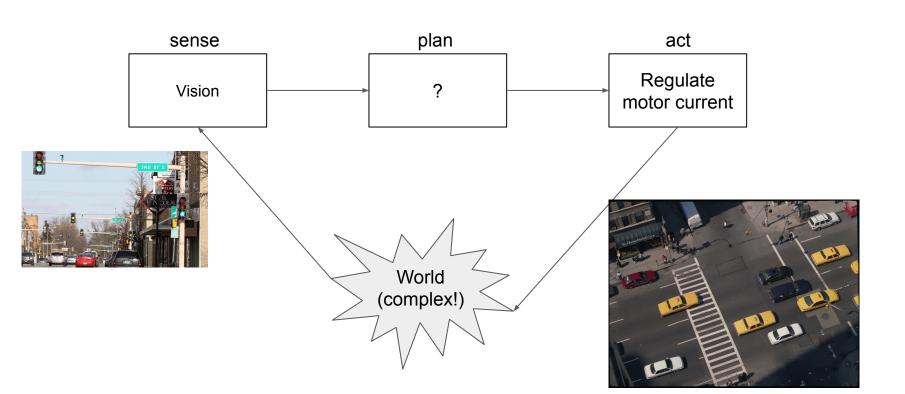
MECS 6616

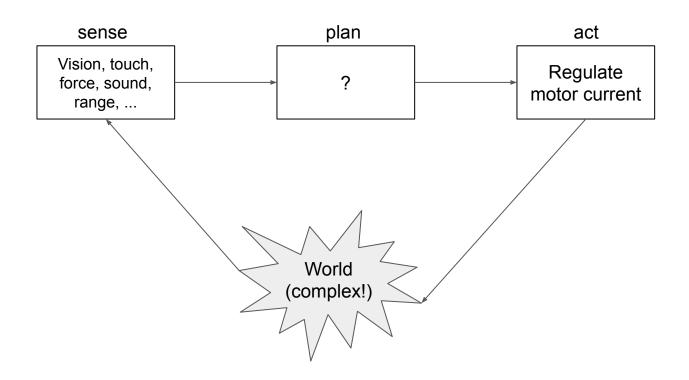
Robot Learning

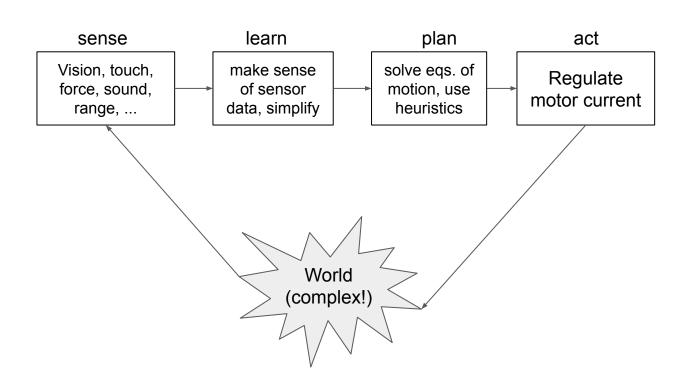
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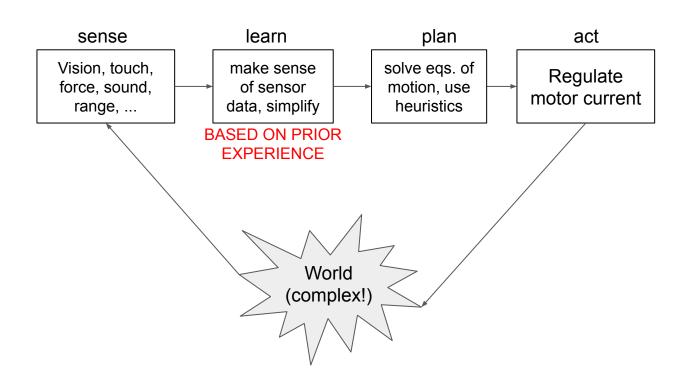








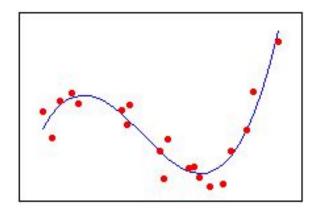




What is Machine Learning?

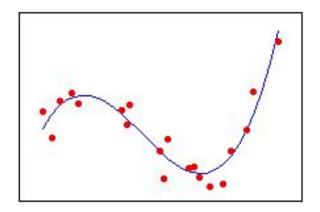


Option A: magic
You put in your problem and out
comes the answer, and you don't
need to write down a single
equation about your robot.

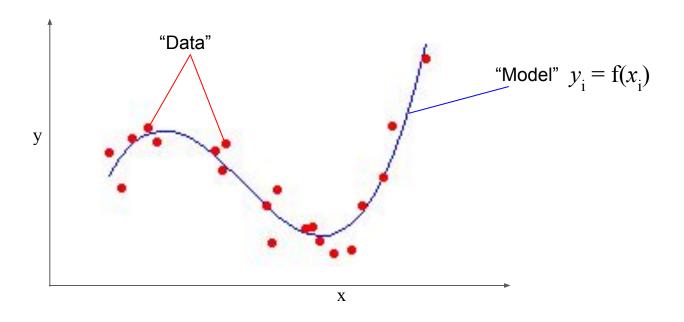


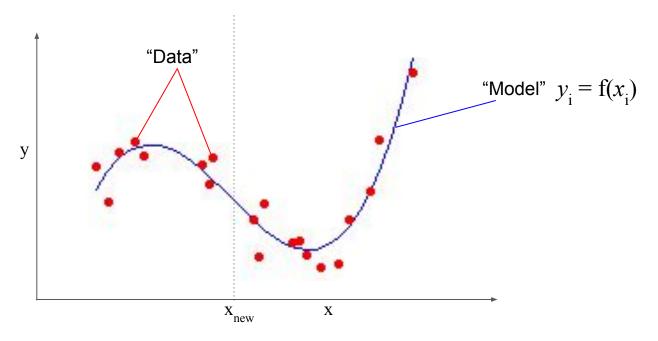
Option B: statistical estimation You fit curves to points.

What is Machine Learning? Unfortunately:

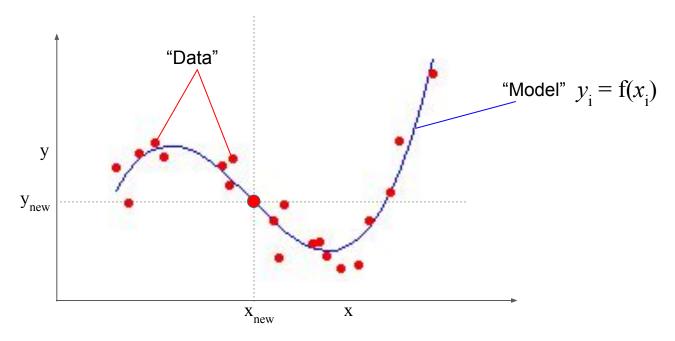


Option B: statistical estimation You fit curves to points.

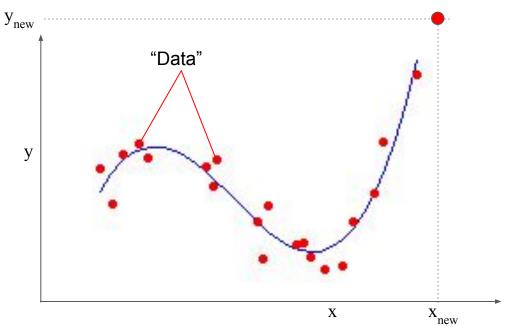




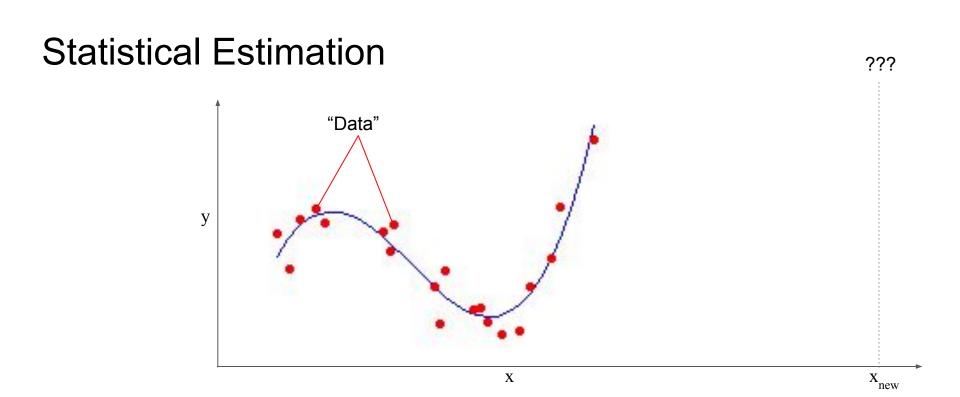
Interpolation



Interpolation



Extrapolation



Extrapolation

Broadest ML Problem Categorization

- Unsupervised
- Supervised

X	\subset	\Re^{d1}
Λ	$\overline{}$	JU

Find some **structure** in the data you are given, **simplify**

 \mathbf{X}_1

Clustering:

x₂

Find a number of discrete classes, or clusters:

• • •

 $\mathbf{c}_{1}, \, \mathbf{c}_{2}, \, ..., \, \mathbf{c}_{k}, \, \, k << n$

 \mathbf{X}_{n}

Assign each point to a cluster $\mathbf{x}_{k} \subseteq \mathbf{c}_{i}$ ("belongs" to \mathbf{c}_{i})

Minimize "distance" between points and their cluster

rundamen	tal Unsupervised ML Pro	bolems			
$\mathbf{x} \subset \Re^{\mathrm{d}1}$	Find some structure in the data you are given, simplify				
\mathbf{x}_1	Clustering:	Dimensionality redu			
\mathbf{x}_2	Find a number of discrete classes, or clusters:	Express each data pousing fewer variables			
 X _n	$\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k, \mathbf{k} << \mathbf{n}$	$\mathbf{x}_{i} \sim f(\mathbf{y}_{i}), \mathbf{y}_{i} \subseteq \Re^{d2}, d2$			
n	Assign each point to a cluster $\mathbf{x}_{\mathrm{k}} \subseteq \mathbf{c}_{\mathrm{i}}$ ("belongs" to \mathbf{c}_{i})	Minimize information			

Minimize "distance" between points and their cluster

Dimensionality reduction:

Express each data point using fewer variables

 $\mathbf{x}_{i} \sim f(\mathbf{y}_{i}), \, \mathbf{y}_{i} \subseteq \Re^{d2}, \, d2 < d1$

Minimize information loss:

 $\|\mathbf{x}_i - \mathbf{f}(\mathbf{y}_i)\|$

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$$\mathbf{x} \subset \Re^{d1}, \mathbf{y} \subset \Re^{d2}$$

$$\mathbf{x}_1 \rightarrow \mathbf{y}_1$$

$$\mathbf{x}_2 \rightarrow \mathbf{y}_2$$

...

$$\mathbf{x}_{n} \rightarrow \mathbf{y}_{n}$$

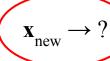
$$\mathbf{x} \subset \Re^{d1}, \mathbf{y} \subset \Re^{d2}$$

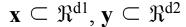
$$\mathbf{x}_1 \rightarrow \mathbf{y}_1$$

$$\mathbf{x}_2 \rightarrow \mathbf{y}_2$$

. . .

$$\mathbf{x}_{n} \rightarrow \mathbf{y}_{n}$$





$\mathbf{x}_1 \rightarrow \mathbf{y}_1$

$$\mathbf{x}_2 \rightarrow \mathbf{y}_2$$

. . .

$\mathbf{x}_{n} \rightarrow \mathbf{y}_{n}$



Classification:

$$d2 = 1$$

 $y \subseteq \{c_1, c_2, ..., c_k\}$

y is **discrete**

y_i tells you what class x_i belongs to

X	\subset	\Re^{d1}	, y	\subset	\Re^{d2}

$$\mathbf{x}_1 \rightarrow \mathbf{y}_1$$

$$\mathbf{x}_2 \rightarrow \mathbf{y}_2$$

_ _ _

$$\mathbf{x}_{n} \rightarrow \mathbf{y}_{n}$$



Classification:

$$d2 = 1$$

$$y \subseteq \{c_1, c_2, ..., c_k\}$$

y is discrete

 \boldsymbol{y}_i tells you what class \boldsymbol{x}_i belongs to

Regression:

$$y \subset \Re^{d2}$$

y is **continuous** (potentially multi-dimensional)

 \boldsymbol{x}_i is being **mapped** to point \boldsymbol{y}_i in a different space

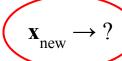
$$\mathbf{x} \subset \Re^{d1}, \mathbf{y} \subset \Re^{d2}$$

$$\mathbf{x}_1 \rightarrow \mathbf{y}_1$$

$$\mathbf{x}_2 \rightarrow \mathbf{y}_2$$

. . .

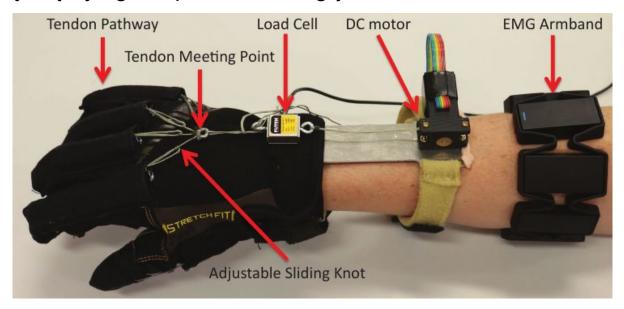
$$\mathbf{x}_{n} \rightarrow \mathbf{y}_{n}$$



Classification:

$$\mathbf{x} = [\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_8]^T$$

 $\mathbf{y} = \{\text{"trying to open", "relaxing"}\}$



$$\mathbf{x} \subset \Re^{d1}, \mathbf{y} \subset \Re^{d2}$$

$$\mathbf{x}_1 \rightarrow \mathbf{y}_1$$

$$\mathbf{x}_2 \rightarrow \mathbf{y}_2$$

. . .

$$\mathbf{x}_{n} \to \mathbf{y}_{n}$$

$$\mathbf{x}_{new} \to ?$$

Regression:

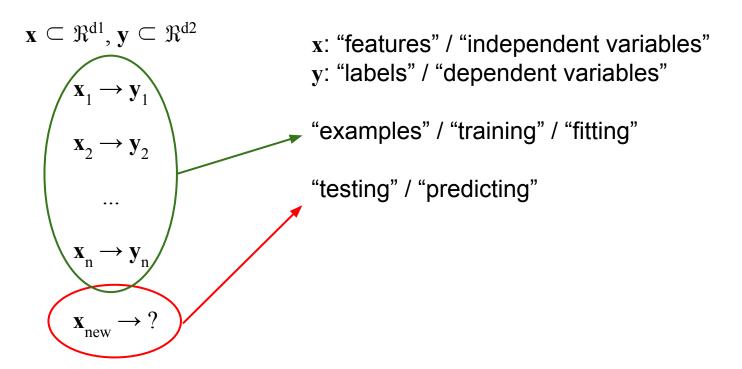
$$\mathbf{x} = [s_1, s_2, \dots, s_5]^{\mathrm{T}}$$

$$\mathbf{y} = [l_a, l_b]^T$$



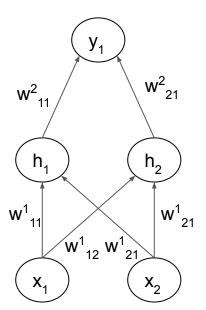


Nomenclature



Neural Networks

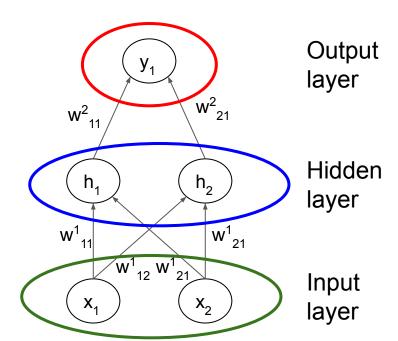
- $\bullet \quad \mathbf{h}_{\mathbf{i}} = \mathbf{f}(\ \underline{\Sigma}\mathbf{x}_{\mathbf{j}}\ \mathbf{w}^{1}_{\ \mathbf{j}\mathbf{i}})$
- $\bullet \quad y_i = \sum h_i w_{ii}^2$
- Training the network: finding $\boldsymbol{w}^k_{\ ij}$ Done via backpropagation algorithm



"Fully connected"

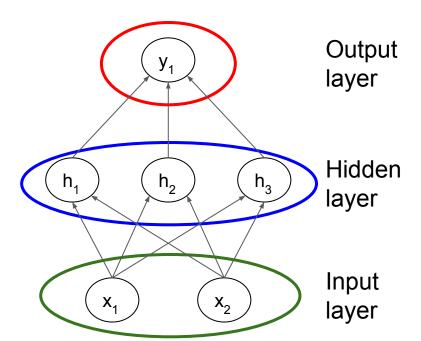
Neural Networks

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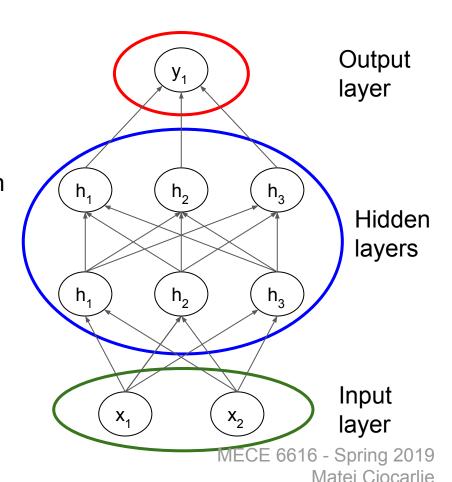
Neural Networks

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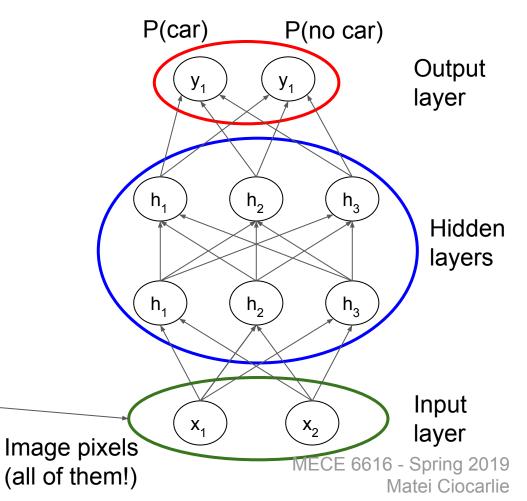


Deep Learning

- Deep Neural Network (DNN): more than one hidden layer
- Even two hidden layers make for incredibly powerful approximators even for highly non-linear functions
- Hidden layers can have different sizes
- Enabled by:
 - better training (backprop)
 - massively parallel computers (GPUs)



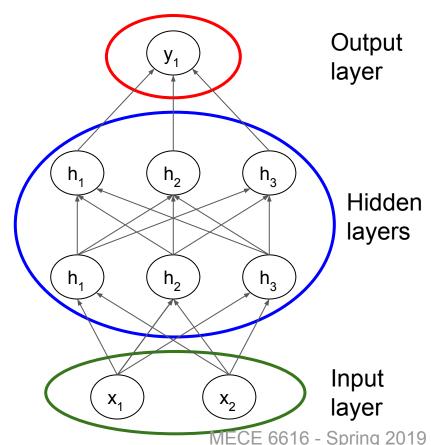
Deep Neural Networks





Deep Neural Networks

- "Network engineering": setting the number and dimensions of the hidden layers
- Qualitative characteristics:
 - for some problems, they easily outperform anything else
 - very hard to model and analyze quantitatively, to get a sense for what makes them "tick"
 - need large amounts of data to train



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What Could I Be Learning?

- Input: sensor data
 - Semantic meaning of my sensor data
- Input sensor data plus action
 - What will happen next?
 - How "good" is this action?
 - O What action should I take?

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Learning Dynamic Models

- time enters the picture denoted by subscript t
- system state: $\mathbf{x}_{_{\mathrm{f}}} \subset \Re^{\mathrm{d}1}$
- action / command: $\mathbf{a}_{t} \subseteq \Re^{d2}$
- model of system dynamics:
 - $\circ \quad \mathbf{x}_{t+1} = \mathbf{f}(\mathbf{x}_t, \, \mathbf{a}_t)$
 - shorthand: dynamic(s) model, forward model

Learning Dynamic Models

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- model of system dynamics:
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 - shorthand: dynamic(s) model, forward model
- "model-based": $f(x_{t}, a_{t})$ is an analytical function written by the roboticist
- "learning-based": $f(x_1, a_1)$ is learned from data, standard regression problem:

$$(\mathbf{x}_{t}, \mathbf{a}_{t}) \rightarrow \mathbf{x}_{t+1}$$

Learning Dynamic Models

model of system dynamics:

$$\circ \quad \mathbf{x}_{t+1} = \mathbf{f}(\mathbf{x}_t, \, \mathbf{a}_t)$$

- "learning-based": $f(x_1, a_2)$ is learned from data, standard regression problem
- why learn dynamic models?
 - can use many non-learning techniques derived over the years that require the existence of one

What Could I Be Learning?

- Input: sensor data
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Reinforcement Learning

Conceptually very different from supervised / unsupervised learning.

- system state: $\mathbf{x}_{t} \subseteq \Re^{d1}$ known
- action / command: $\mathbf{a}_{_{\mathbf{r}}} \subset \Re^{\mathrm{d}2}$ controllable
- dynamics / forward model:
 - o deterministic: $\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{a}_t)$
 - o stochastic: $P(\mathbf{x}_{t+1} \mid \mathbf{x}_t, \mathbf{a}_t) = f(\mathbf{x}_t, \mathbf{a}_t)$
 - could be known (model-based RL) or unknown (model-free RL)
- reward: $r(x_1, a_2)$ known
- goal: learn a policy that maximizes expected reward
 - o deterministic: $\mathbf{a}_{t} = \Pi(\mathbf{x}_{t})$
 - o stochastic: $P(\mathbf{a}_{t} | \mathbf{x}_{t}) = \Pi(\mathbf{a}_{t}, \mathbf{x}_{t})$

Reinforcement Learning

Conceptually very different from supervised / unsupervised learning.

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 - o deterministic: $\mathbf{a}_{t} = \Pi(\mathbf{x}_{t})$
 - o stochastic: $P(\mathbf{a}_{t} \mid \mathbf{x}_{t}) = \Pi(\mathbf{a}_{t}, \mathbf{x}_{t})$
- robot is never told "how to do something", only if what it did is good or bad
- many algorithms:
 - Q-learning
 - policy gradient
 - 0 ..

Key questions:

 What kind of a problem is it? Clustering, dimensionality reduction, regression, classification, policy.

Key questions:

- What kind of a problem is it? Clustering, dimensionality reduction.
- What are the features? How do I get a feature vector $\mathbf{x} \subset \mathbb{R}^{d1}$ from my data?

Key questions:

- What kind of a problem is it? Regression, classification.
- What are the features? How do I get a feature vector $\mathbf{x} \subseteq \Re^{d1}$ from my data?
- What are the labels? How do I express what I care about as $y \subseteq \Re^{d2}$?
- Where does my training data come from? It needs to be labeled with "ground truth".

Key questions:

- What kind of a problem is it? Policy
- What is my state space? It needs to be known for training and testing.
- What is my action space? It needs to contain things I can control.
- What is my reward function? I need to have access to a reward signal, either by computing it, or from an oracle.

For all problems:

- What algorithm/model is being used?
 - "fit" my data well
 - run in reasonable time on my problem size
 - have low training loss
- How are the results tested?
 - what is the performance on the testing data?
 - what is the relationship between training and testing data?
 - <u>is testing data predictive of deployment?</u>

Course Structure

- Components (roughly 7-10 lectures each):
 - Part 1: Dimensionality reduction, classification and regression
 - Part 2: Deep Learning and learning in Computer Vision
 - Part 3: Reinforcement learning

Lectures

- theoretical concept presentation (in moderate depth)
- discussion of papers in Robotics using these concepts

Course Structure

- 3 Programming Projects: one for each part
 - Each project will make up ~15% of the grade.
 - All projects: Python, Ubuntu 16.04, ROS, SVN. Must be comfortable with all of these.
 - There will be no skeleton code. You will write ROS nodes starting from blank files.
 - You will get a budget of 5 late days on projects, to use how you see fit.

Written exams

- Midterm and final: each will make up ~20% of the grade.
- Pencil-and-paper questions: conceptual, algorithmic, math-y

Additional details for course structure, grading, collaboration policy, late submissions, etc. can be found on the Courseworks2 course webpage.