

SUSTAINMENT MANAGEMENT SYSTEM (SMS) SUMMIT 2024

Power Line Inspections: Moving
Forwards, and Improvement within the
Department of Defense



U.S. ARMY



US Army Corps
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WHY POWER LINE INSPECTIONS?



[https://engineering.purdue.edu/fsae/wordpress/purdue-college-of-engineering/;](https://engineering.purdue.edu/fsae/wordpress/purdue-college-of-engineering/)



WHY ARE POWER LINE INSPECTIONS IMPORTANT?



- Increasing demand
- Aging grid
- Disasters are devastating
- Lots of money involved

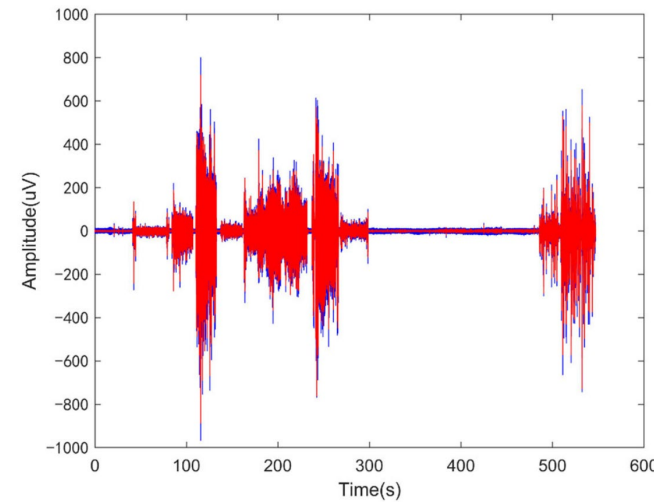


<https://abcnews.go.com/US/people-missing-devastating-colorado-wildfire/story?id=82034519>; <https://www.cummins.com/news/2019/08/28/10-us-states-longest-power-outages>



WHAT INFO DO POWER INSPECTIONS GATHER?

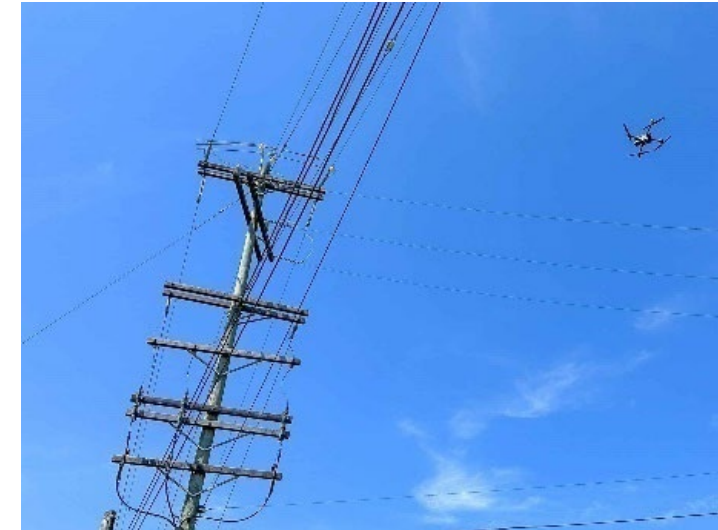
- Trees or foreign objects
- Temperature
- Excess slack
- Damaged components
- Frayed cables
- Internal cracks
- Corrosion
- Radio interference



<https://hort.ifas.ufl.edu/treesandpowerlines/goodandpoor.shtml>; <https://www.uavfordrone.com/powerline-inspection-by-drone-uav-thermal-imaging-camera/>; <https://www.oklahoman.com/story/weather/2014/09/18/update-winds-tipped-power-poles-in-north-oklahoma-city-as-storms-roll-through-thursday-morning/60798459007/>; <https://www.mdpi.com/1424-8220/23/11/5182>; <https://nj.pseg.com/safetyandreliability/safetytips/balloonkitesafety>;



WHAT CURRENT POWER INSPECTIONS LOOK LIKE



<https://www.tdworld.com/electric-utility-operations/article/20966170/take-a-look-inside-a-linemans-bucket-truck>; <https://www.linkedin.com/pulse/power-lines-inspection-methods-aispeco/>;
<https://www.meridianhelicopters.com.au/portfolio-item/powerline-inspections/>; <https://thedronelifenj.com/power-line-inspections-guide/>;



WHERE CURRENT POWER INSPECTIONS FAIL



1

Slow

4

Can miss defects

2

Tedious

5

Can be disruptive

3

Expensive

6

Can't go everywhere

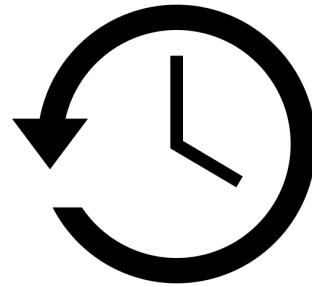


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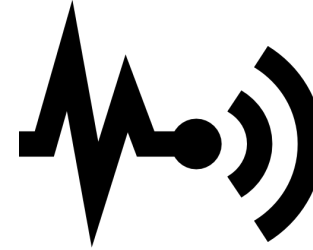
ROBOTS



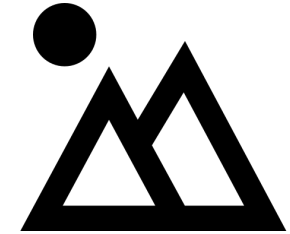
Less expensive



Continuous
Inspection



Can Use
Multiple Sensors



Can access hard-
to-reach areas



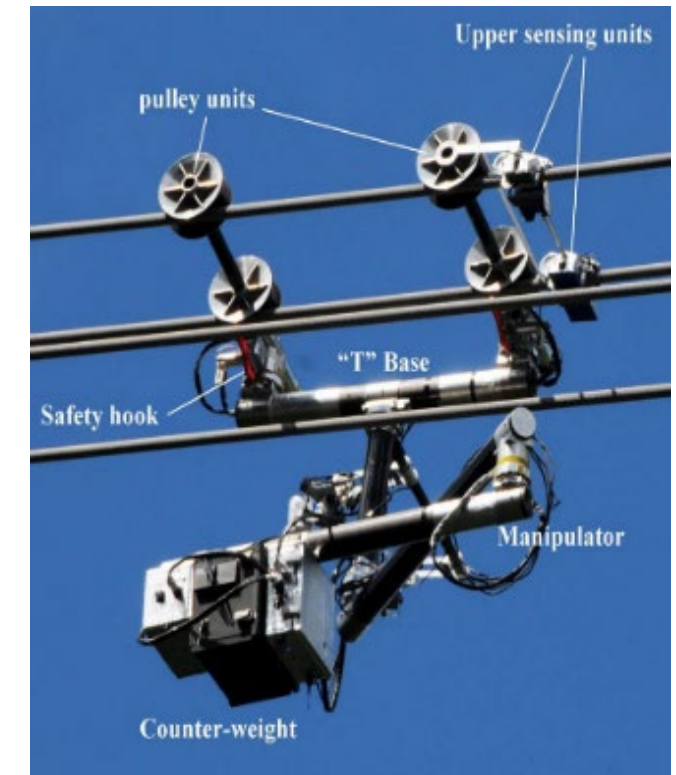
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CRAWLING ROBOTS



- Longer battery life
- Higher quality data

- Slower
- Not as mobile
- High voltages



<https://ieeexplore.ieee.org/document/5624434>; <https://ieeexplore.ieee.org/document/7030054>; <https://ieeexplore.ieee.org/document/8794397>;

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FLYING ROBOTS

- Fast
- Mobile

- Poor operating time
- Difficult to automatize
- Limited data acquisition



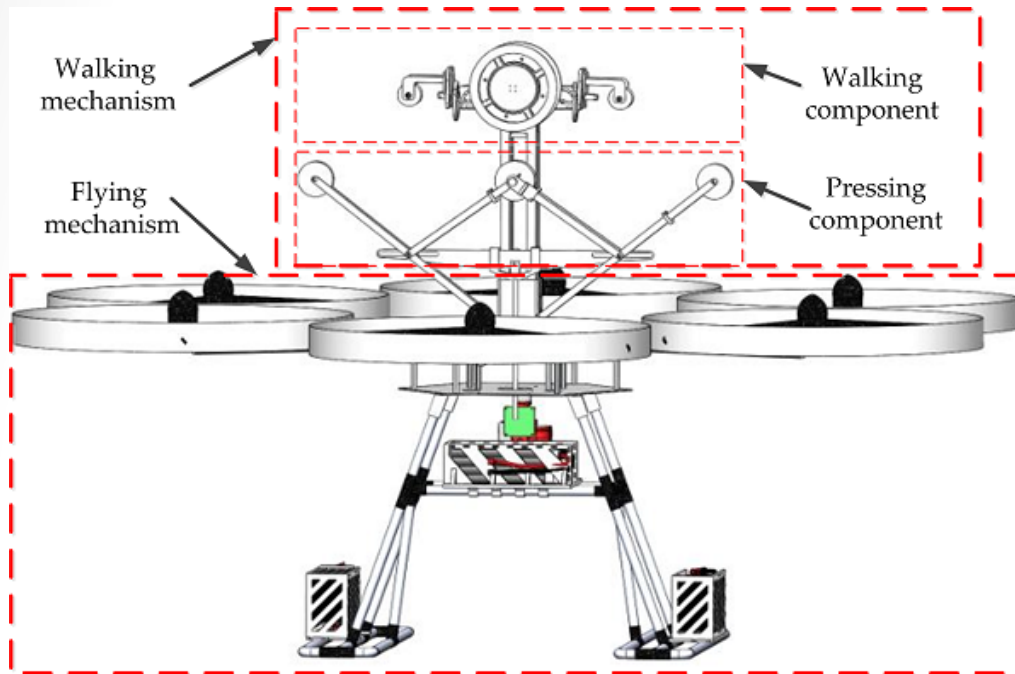
<https://www.flir.com/products/skyranger-r70/?vertical=uas&segment=uis>; <https://ieeexplore.ieee.org/document/5624430>;



HYBRID ROBOTS

- Best of both worlds

- More complex
- Balance of battery life vs. data acquisition



<https://ms.copernicus.org/articles/13/257/2022/>; <https://dl.acm.org/doi/abs/10.1145/3483845.3483850>;





OUR ATTEMPT

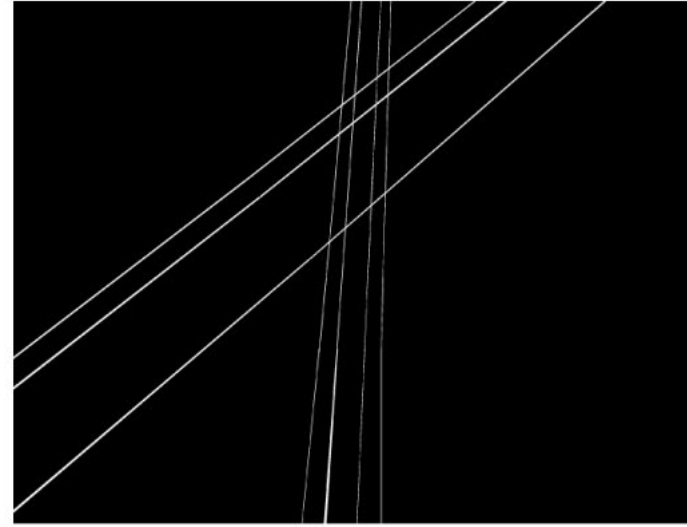
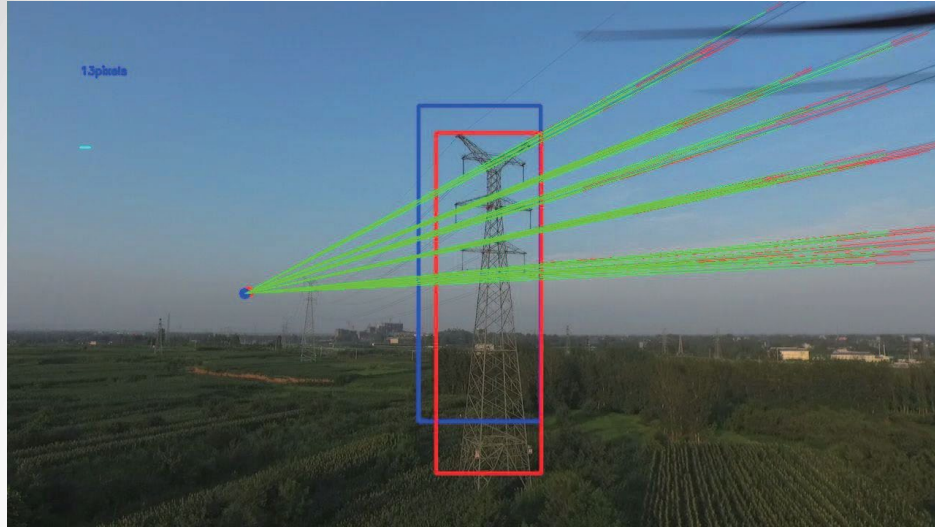
- ~4-month time frame
- \$1000 budget
- Not autonomous
- No sensing capabilities
- Possible with more resources and time





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OBJECT RECOGNITION

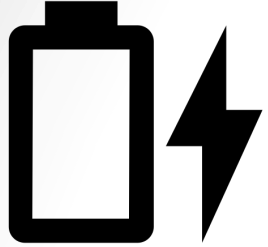


<https://ieeexplore.ieee.org/document/8377502>; <https://www.mdpi.com/1996-1073/12/3/543>; <https://ieeexplore.ieee.org/document/8822756>;

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OTHER CHALLENGES



Battery Life



Obstacle Detection and Navigation



Environmental Effects



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SUMMARY



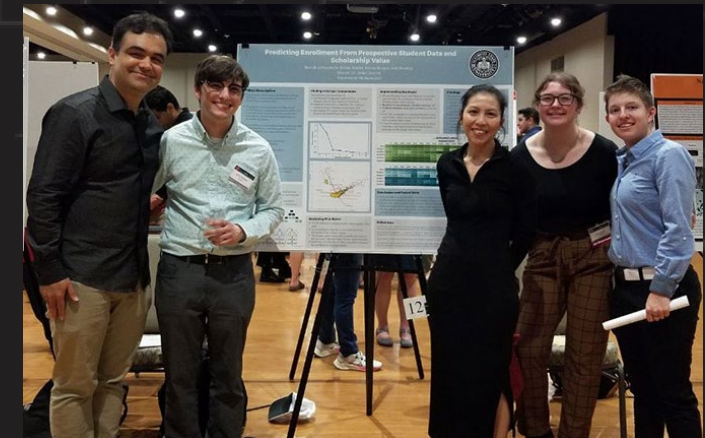
Power Lines
are Valuable

Deserve Better
Inspections

Can Improve
Drastically with
Resources

INTRODUCTION

- Robert Skudnig
- ISU Graduate '24
- Pure and Applied Mathematics
- Psychology
- Master's projected '25



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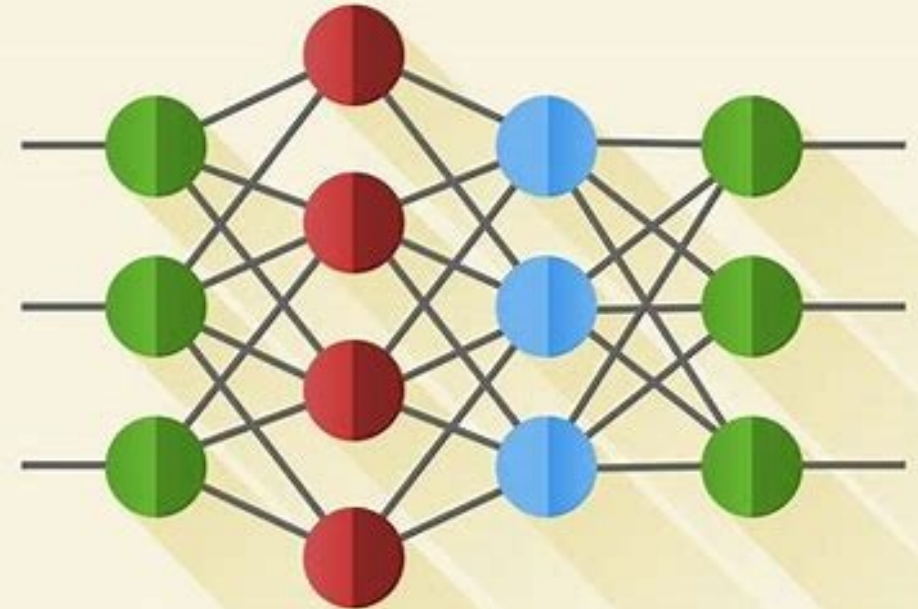
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NEURAL NETWORKS

Overview of a common Machine Learning concept



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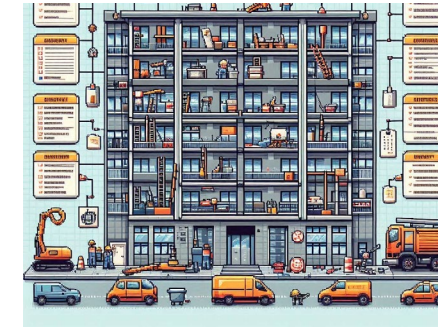
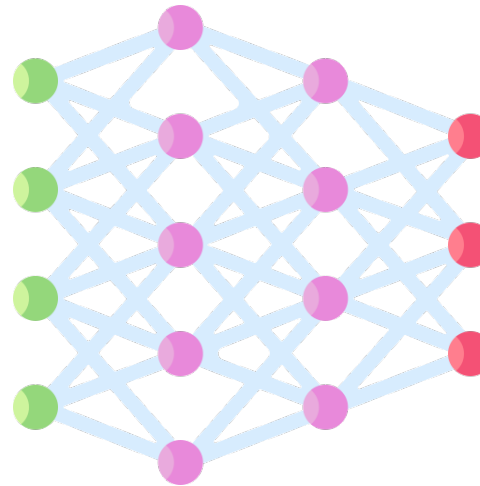
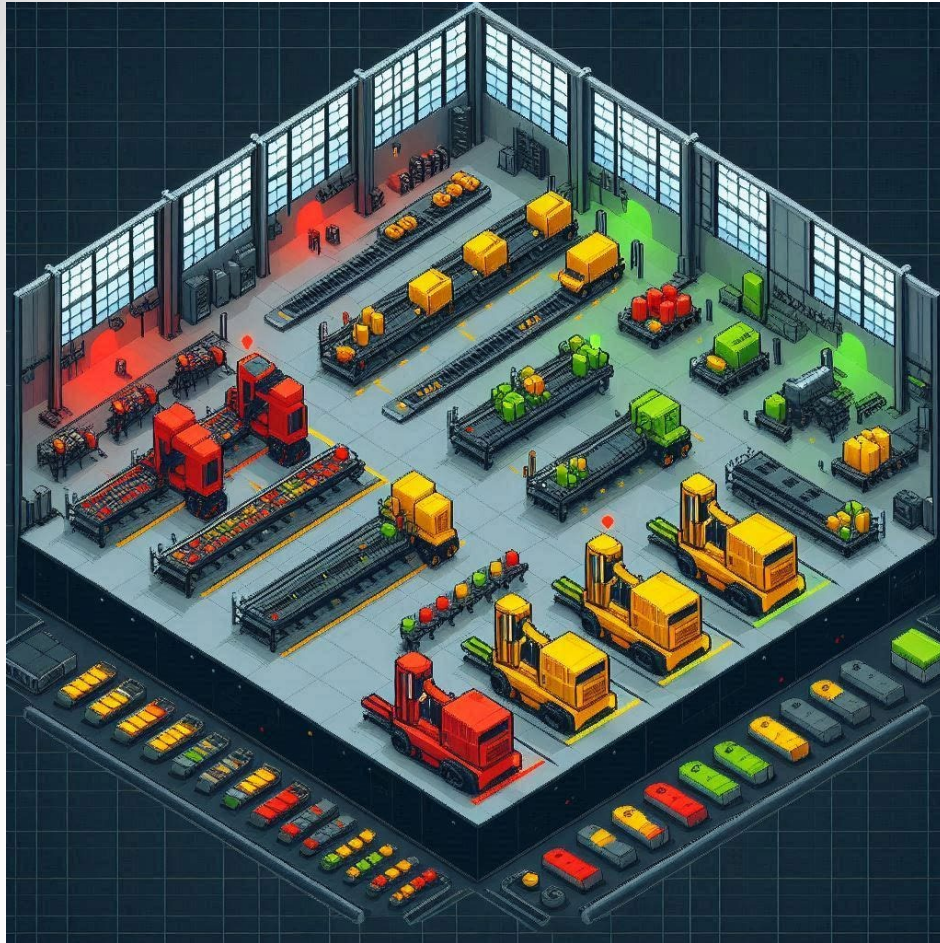


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WHY SHOULD WE CARE?



Maintenance Schedule

Start Date: Mon, 8/1/22 Start Time: 8:00 AM Interval: 60

Time	Monday, 1	Tuesday, 2	Wednesday, 3	Thursday, 4	Friday, 5	Saturday, 6	Sunday, 7
8:00 AM	Electrical Check - Contractor		Weekly Clean - Contractor				
9:00 AM	Monday Morning Clean	Start Trenching - Contractor		Top and Trench - Contractor			
10:00 AM	Front Lawn Mowing - Contractor		Leaf Blowing		General Garden Work	Soil Conditioning - Contractor	
11:00 AM							
12:00 PM	Lunch Break	Lunch Break	Lunch Break	Lunch Break	Lunch Break	Lunch Break	Lunch Break
1:00 PM	After Lunch Clean	After Lunch Clean	After Lunch Clean	After Lunch Clean	After Lunch Clean	After Lunch Clean	After Lunch Clean
2:00 PM				Water Trenching - Contractor			
3:00 PM	Flora Care	Flora Care	Flora Care	Flora Care	Flora Care	Flora Care	Flora Care
4:00 PM							
5:00 PM					Friday Clean up		

MATHIOU
MAINTENANCE SCHEDULE
8:00 AM

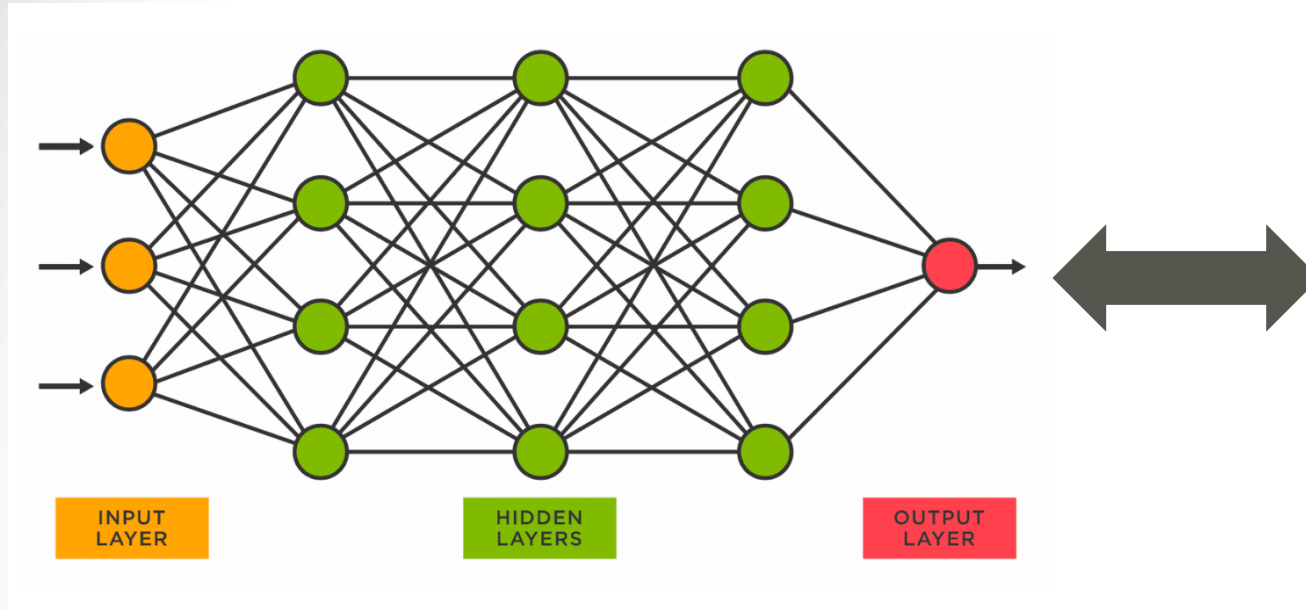
LEGEND
★ Mathieu M
🧹 Cleaner
🌿 Gardener
🚚 Contractor
🔧 Electrician
✅ Out of the Office
🚫 Out of the Office



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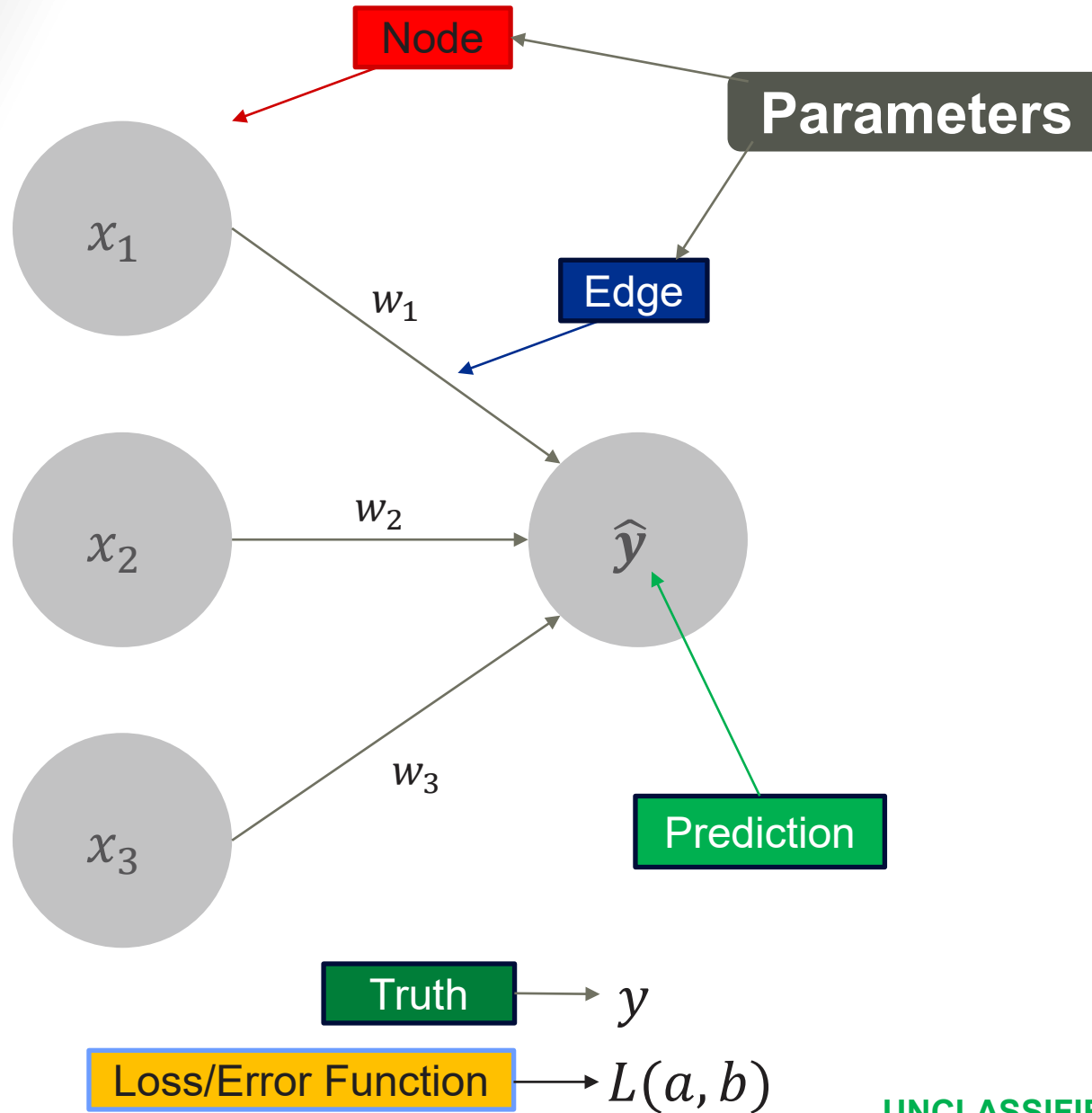


WHAT ARE NEURAL NETWORKS?



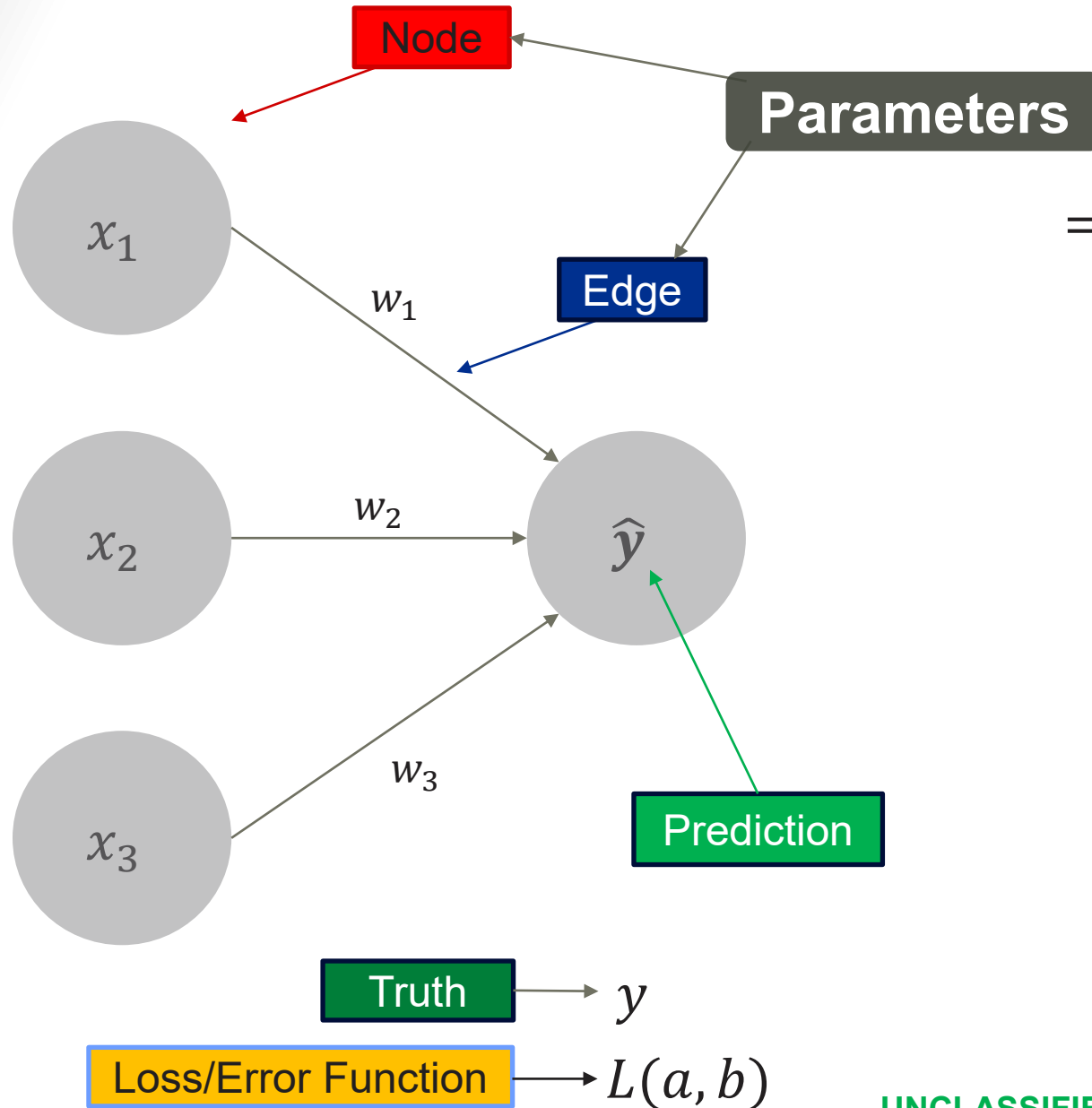


HOW DO THEY LEARN?





HOW DO THEY LEARN?



$$\hat{y} = x_1 w_1 + x_2 w_2 + x_3 w_3$$

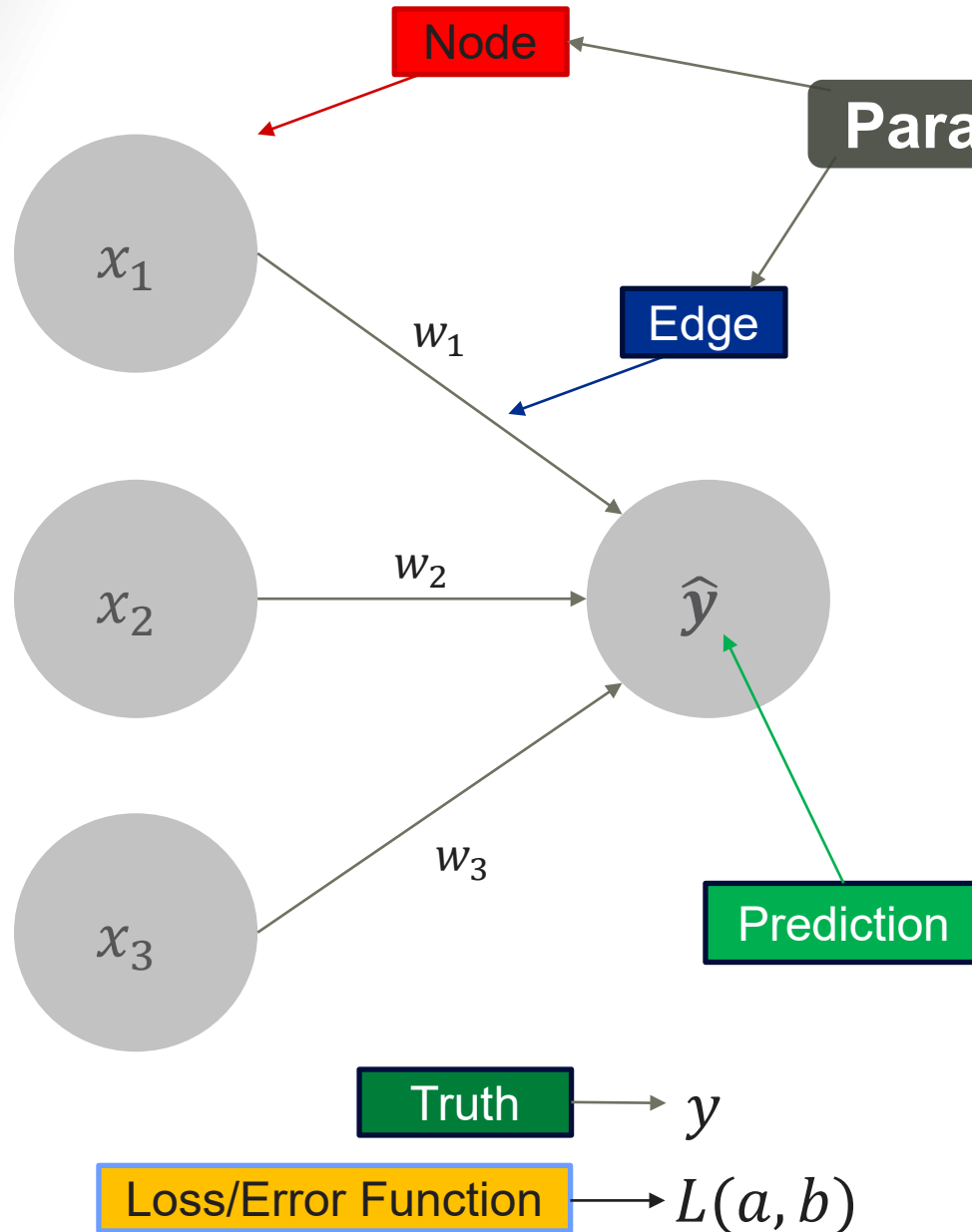
$$\Rightarrow L(y, \hat{y}) = L(y, x_1 w_1 + x_2 w_2 + x_3 w_3)$$

$$\Rightarrow L = f(x_1, w_1, x_2, w_2, x_3, w_3)$$

*



HOW DO THEY LEARN?



Parameters

$$\hat{y} = x_1 w_1 + x_2 w_2 + x_3 w_3$$

$$\Rightarrow L(y, \hat{y}) = L(y, x_1 w_1 + x_2 w_2 + x_3 w_3)$$

$$\Rightarrow L = f(x_1, w_1, x_2, w_2, x_3, w_3)$$

In order to make the model “learn,” we need to figure out two things:

1. How do the parameters generally impact the loss?
2. How do we change the parameters to decrease the loss?

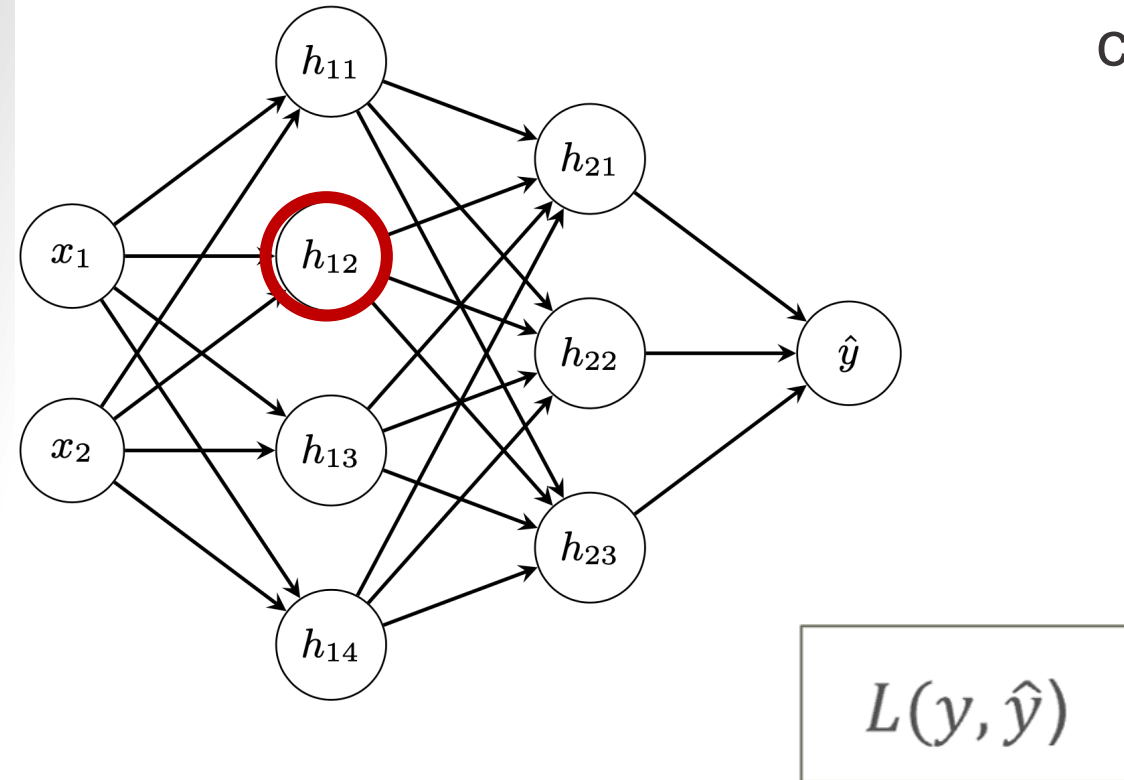


HOW DO THE PARAMETERS IMPACT THE LOSS?



- Example: How does the loss (L) change as we change node h_{12} ?

$$\frac{\partial L}{\partial h_{12}} = ?$$





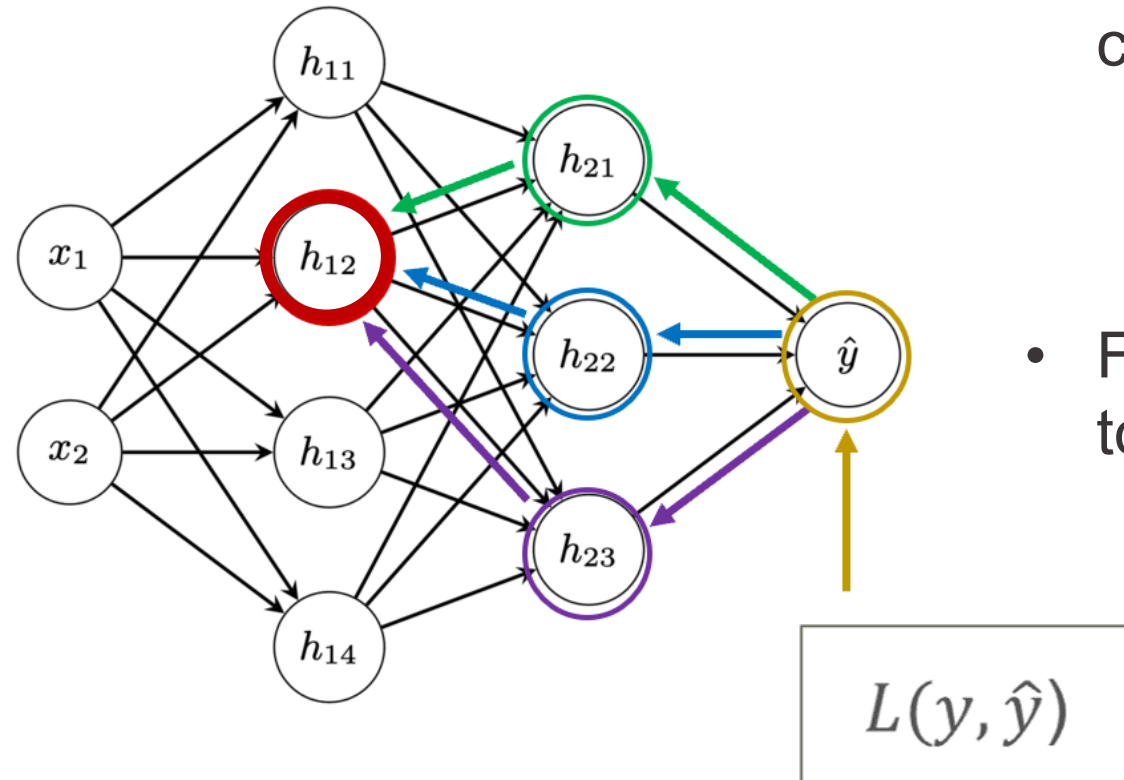
HOW DO THE PARAMETERS IMPACT THE LOSS?



- Example: How does the loss (L) change as we change node h_{12} ?

$$\frac{\partial L}{\partial h_{12}} = ?$$

- First we must determine every possible path back to the parameter in question





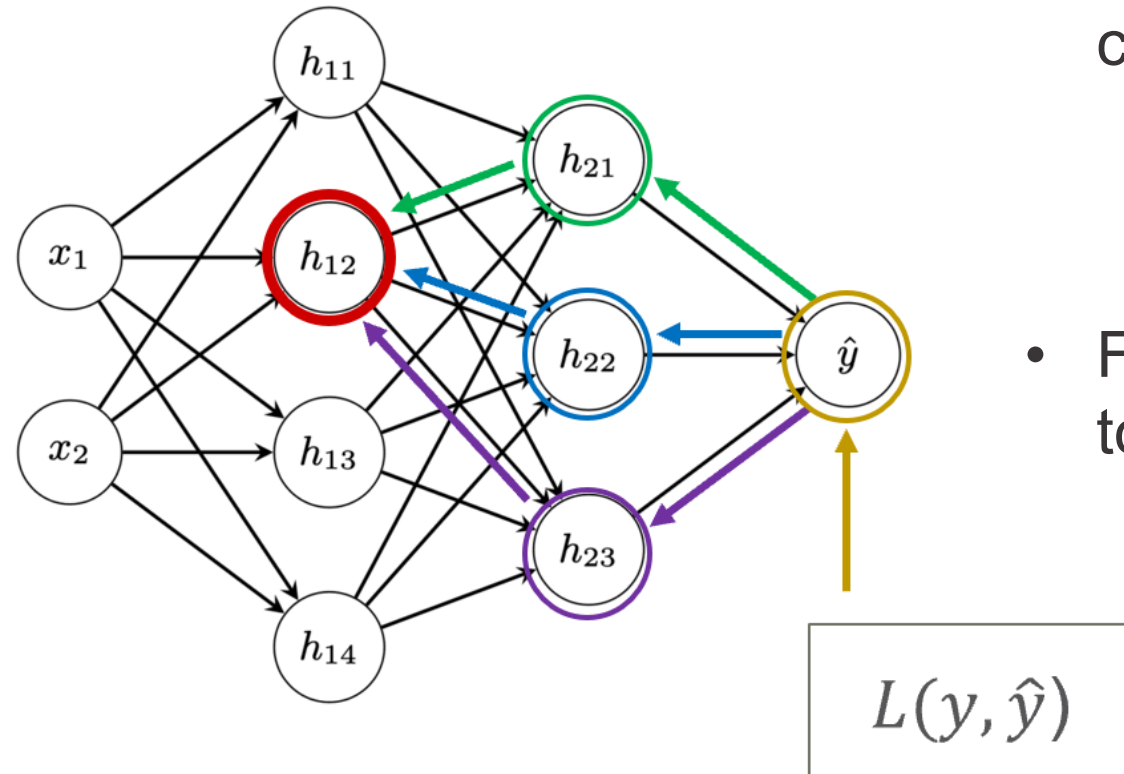
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- Example: How does the loss (L) change as we change node h_{12} ?

$$\frac{\partial L}{\partial h_{12}} = ?$$

- First we must determine every possible path back to the parameter in question



$$= \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial h_{21}} \frac{\partial h_{21}}{\partial h_{12}} + \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial h_{22}} \frac{\partial h_{22}}{\partial h_{12}} + \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial h_{23}} \frac{\partial h_{23}}{\partial h_{12}}$$



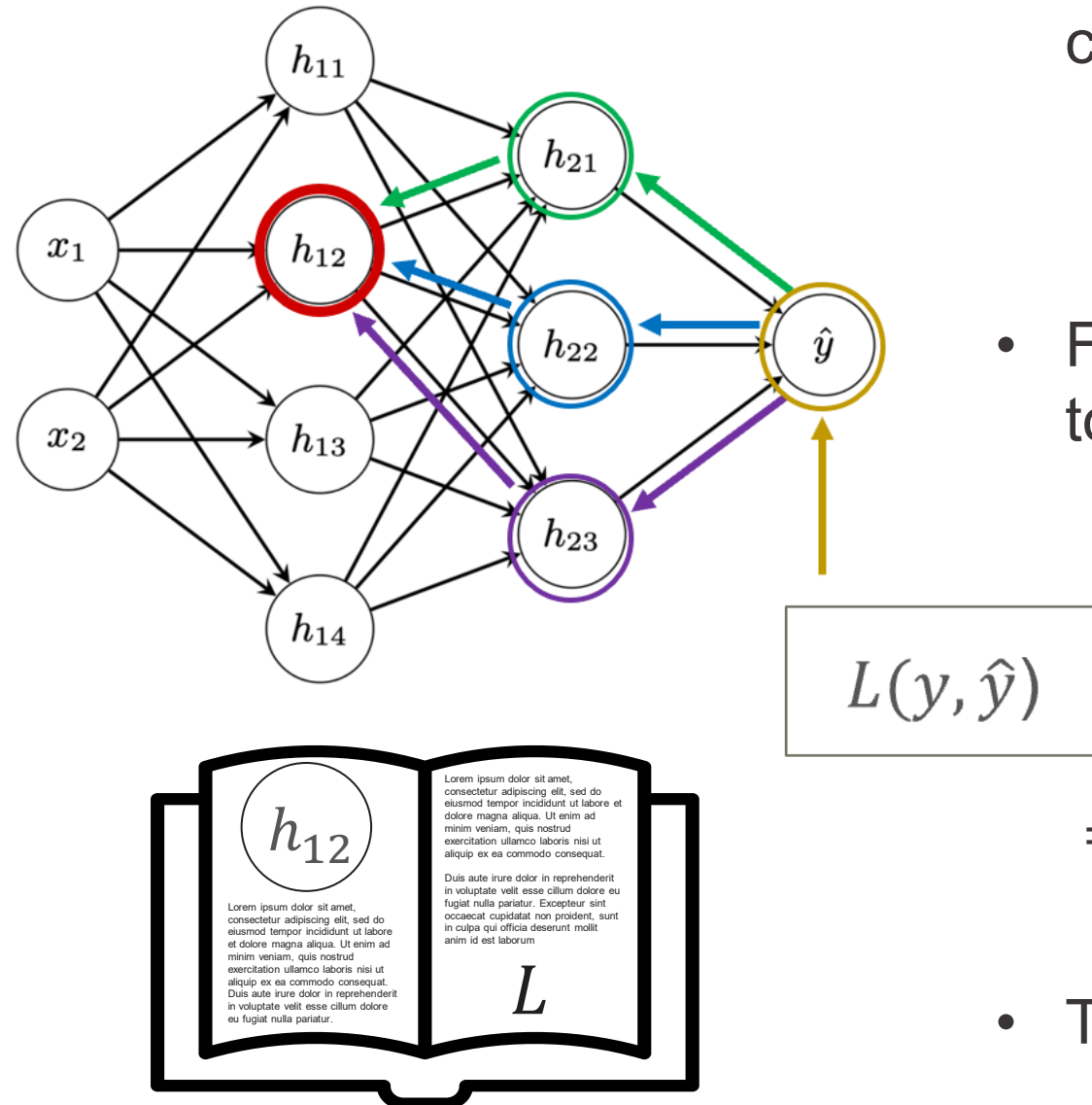
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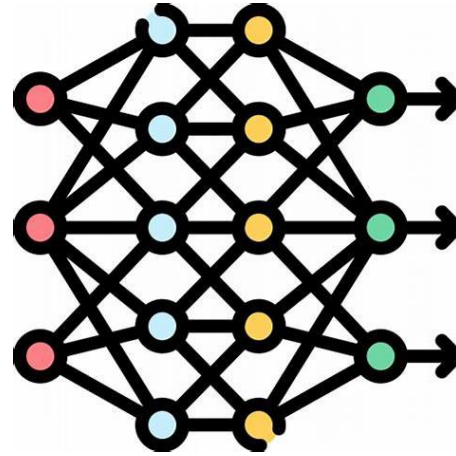
- This is called **backward propagation**



HOW DO WE DECREASE THE LOSS?



- Impossible to find the **absolute best** parameter set

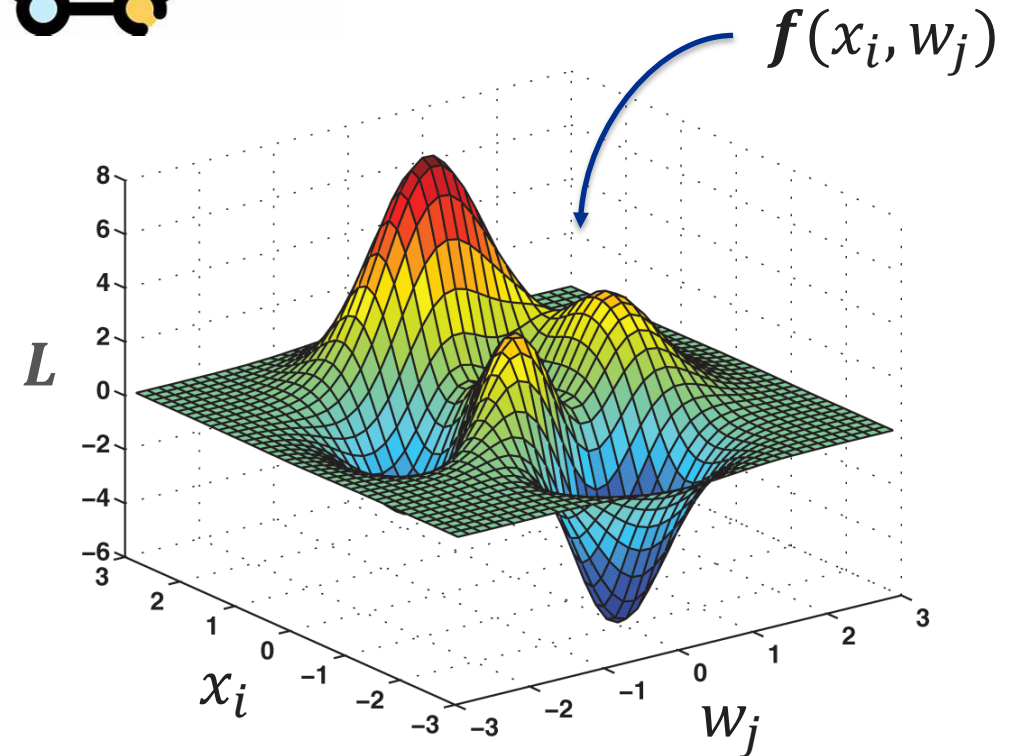
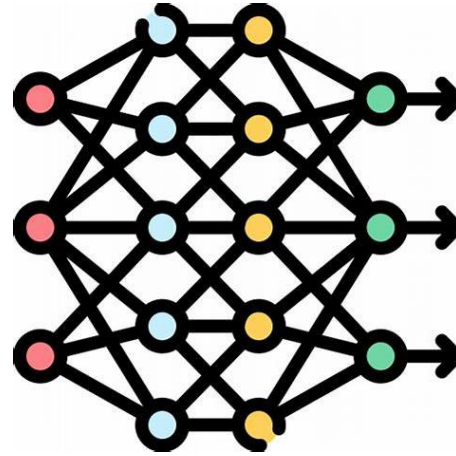




HOW DO WE DECREASE THE LOSS?

- Impossible to find the **absolute best** parameter set
- Let $L = f(\theta)$ where θ is the set of ALL parameters:

$$\theta = \{x_1, \dots, x_n, w_1, \dots, w_m\} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \\ w_1 \\ \vdots \\ w_m \end{bmatrix}$$



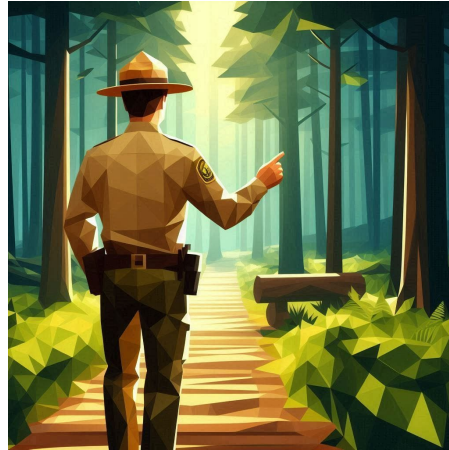


HOW DO WE DECREASE THE LOSS?

Let θ_0 denote the INITIAL set of model parameters. This is usually randomized.

In order to find a *better* set, we can perform the following operation on our loss function:

$$\overrightarrow{grad}_0 = \nabla L = \nabla f(\theta_0)$$



To obtain our next set of *improved* parameters θ_1 :

$$\theta_1 = \theta_0 - \overrightarrow{grad}_0$$



HOW DO WE DECREASE THE LOSS?

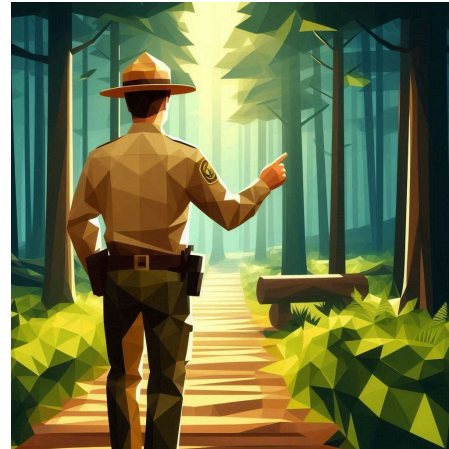


Let θ_0 denote the INITIAL set of model parameters. This is usually randomized.

This process repeats until the user is satisfied with the results:

In order to find a *better* set, we can perform the following operation on our loss function:

$$\overrightarrow{grad_0} = \nabla L = \nabla f(\theta_0)$$



$$\overrightarrow{grad_i} = \nabla L = \nabla f(\theta_i)$$

$$\theta_{i+1} = \theta_i - \overrightarrow{grad_i}$$

To obtain our next set of *improved* parameters θ_1 :

$$\theta_1 = \theta_0 - \overrightarrow{grad_0}$$



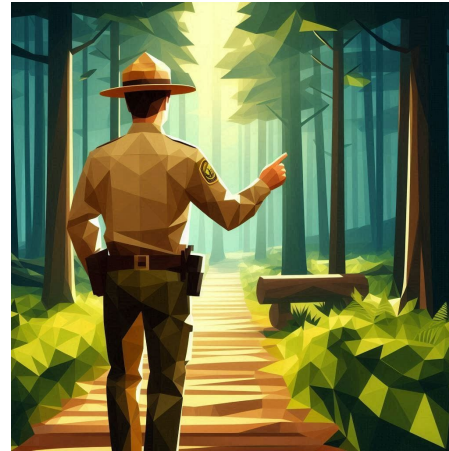
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$$\theta_1 = \theta_0 - \overrightarrow{grad_0}$$

$$\overrightarrow{grad_i} = \nabla L = \nabla f(\theta_i)$$

$$\theta_{i+1} = \theta_i - \overrightarrow{grad_i}$$

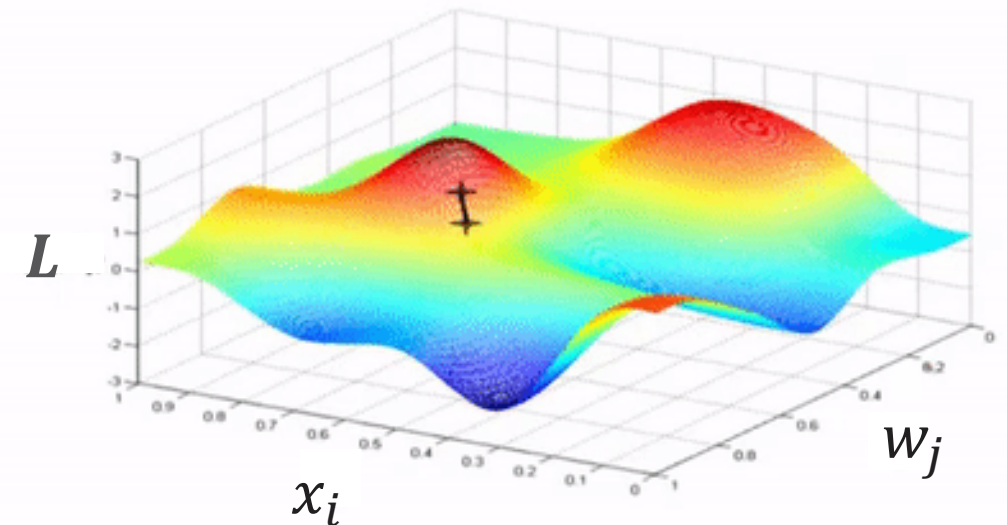
$$\begin{bmatrix} x_1^{i+1} \\ \vdots \\ x_n^{i+1} \\ w_1^{i+1} \\ \vdots \\ w_m^{i+1} \end{bmatrix} = \begin{bmatrix} x_1^i \\ \vdots \\ x_n^i \\ w_1^i \\ \vdots \\ w_m^i \end{bmatrix} - \begin{bmatrix} \partial x_1^i \\ \vdots \\ \partial x_n^i \\ \partial w_1^i \\ \vdots \\ \partial w_m^i \end{bmatrix}$$

This is known as **gradient descent**

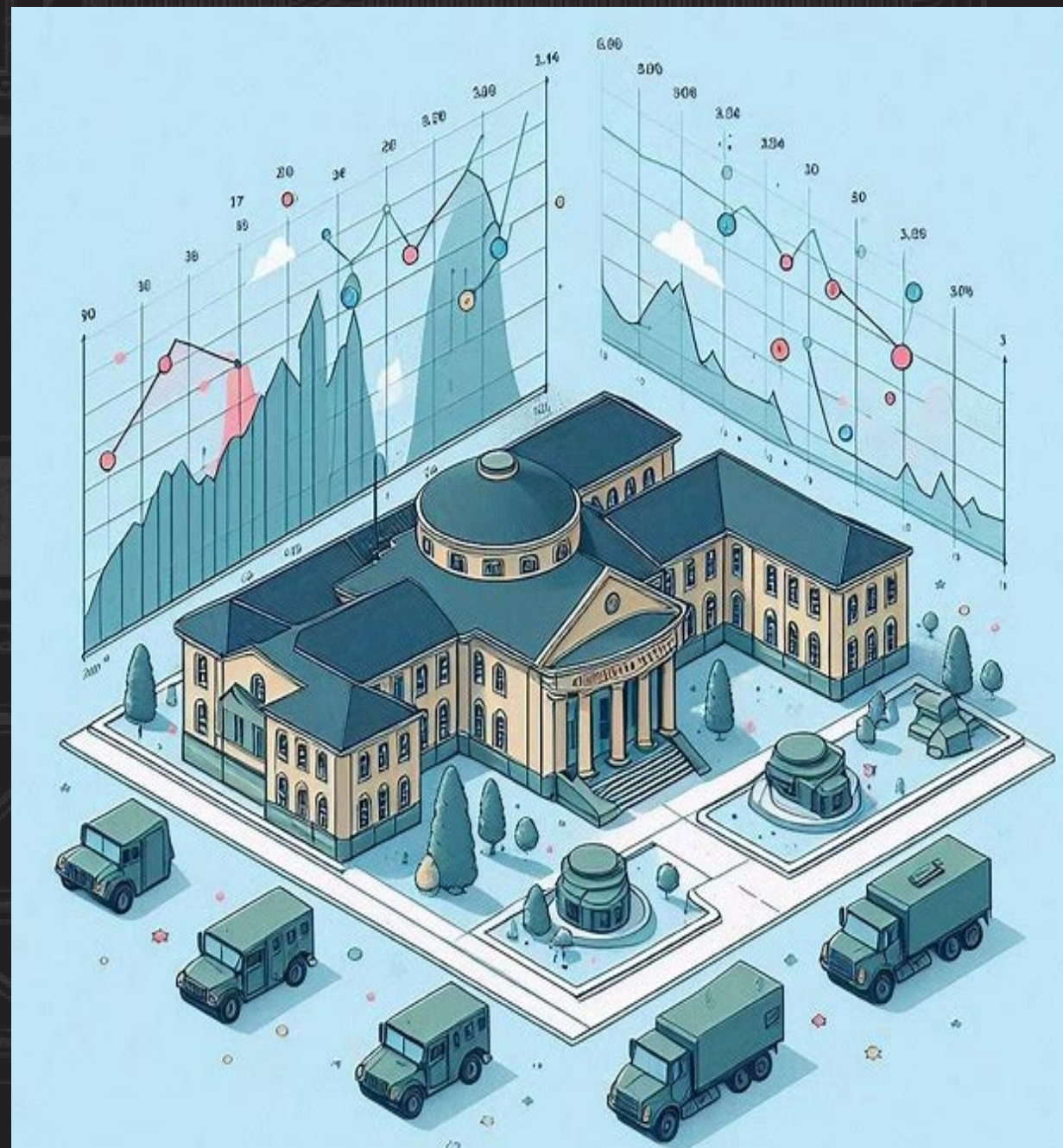


FOGGY MOUNTAIN ANALOGY

- Imagine a squad of soldiers on a foggy mountain returning to their outpost at the mountain's base.
- They don't know the exact route to the bottom, but they can tell which direction declines where they are standing.
- They continue down for as long as they can to try and reach the outpost.
- **Connection:**
 - Latitude-Longitude are the model **parameters**
 - Altitude is the **error/loss** at that coordinate
 - Slope is the **gradient** that is guiding them
 - There are other important concepts in the training process.**



Application of Neural Networks



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MISSION DEPENDENCY INDEX (MDI)

MDI Overview



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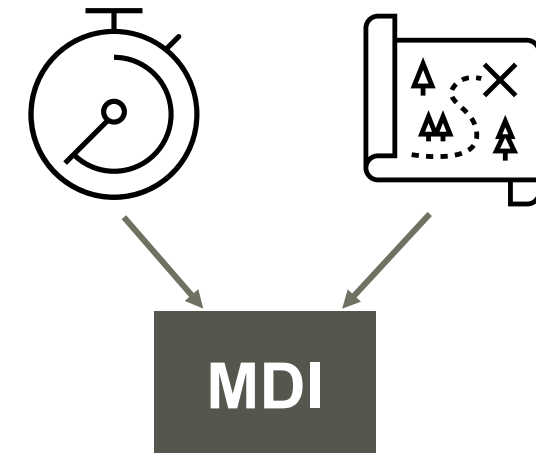
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WHAT IS MISSION DEPENDENCY INDEX?

- **Mission Dependency Index (MDI)**
- Usefulness to SMS
- Summarizes:
 - **Interruptability**
 - **Replicability**
- Matrix:

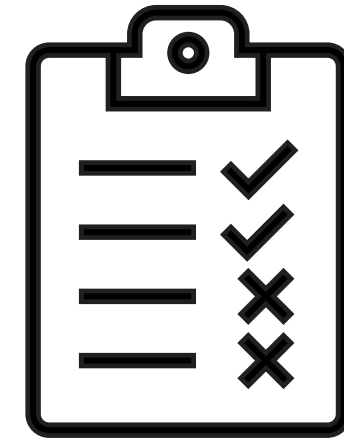
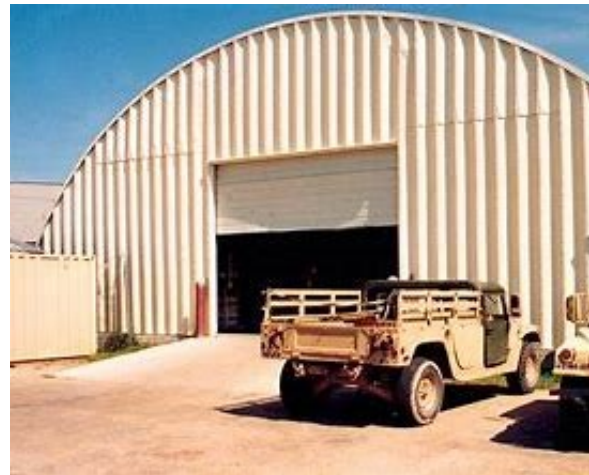
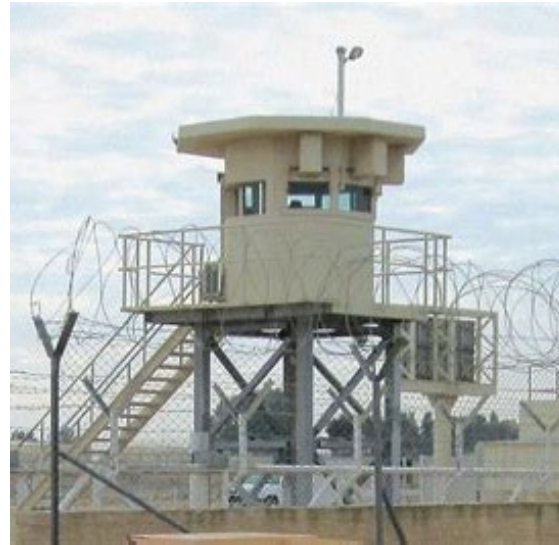
MISSION DEPENDENCY INDEX					
MDI		Question 1 INTERRUPTABILITY			
		How fast would the mission be impacted if the asset's operations were interrupted?			
		IMMEDIATE < 15 minutes	BRIEF < 24 hours	SHORT < 7days	PROLONGED > 7 days
Question 2 REPLICABILITY How difficult would it be to relocate the asset's mission capabilities?	IMPOSSIBLE	100	88	76	64
	EXTREMELY DIFFICULT	92	80	68	56
	DIFFICULT	84	72	60	48
	POSSIBLE	76	64	52	40





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THE MDI SURVEY



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THE SETUP

The Neural Network Setup for MDI Prediction



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TRAINING SETUP

Input Data

- Real Property Asset information
- PRV
- Size
- Facility Built Date
- Unit present (if any)
 - Type, Name, Hierarchy
- CATCODE
 - Name
- Misc.

Task:

Predict Interruptability and Replicability responses

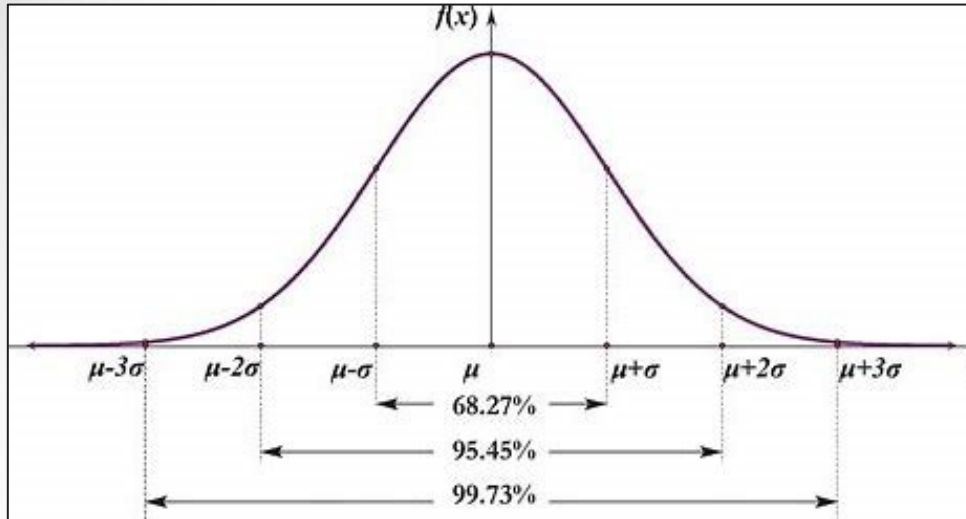
** MDI was inferred from these

MISSION DEPENDENCY INDEX					
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DATA TREATMENT

- Most data was either **standardized** or **one-hot-encoded**



A diagram illustrating the transformation of categorical data into a one-hot encoded matrix. On the left, a list of colors is shown: Red, Red, Yellow, Green, and Yellow. A blue arrow points to the right, where a matrix is displayed. The matrix has columns for 'Red', 'Yellow', and 'Green', and rows corresponding to each color in the list. The values are 1 for the matching color and 0 otherwise.

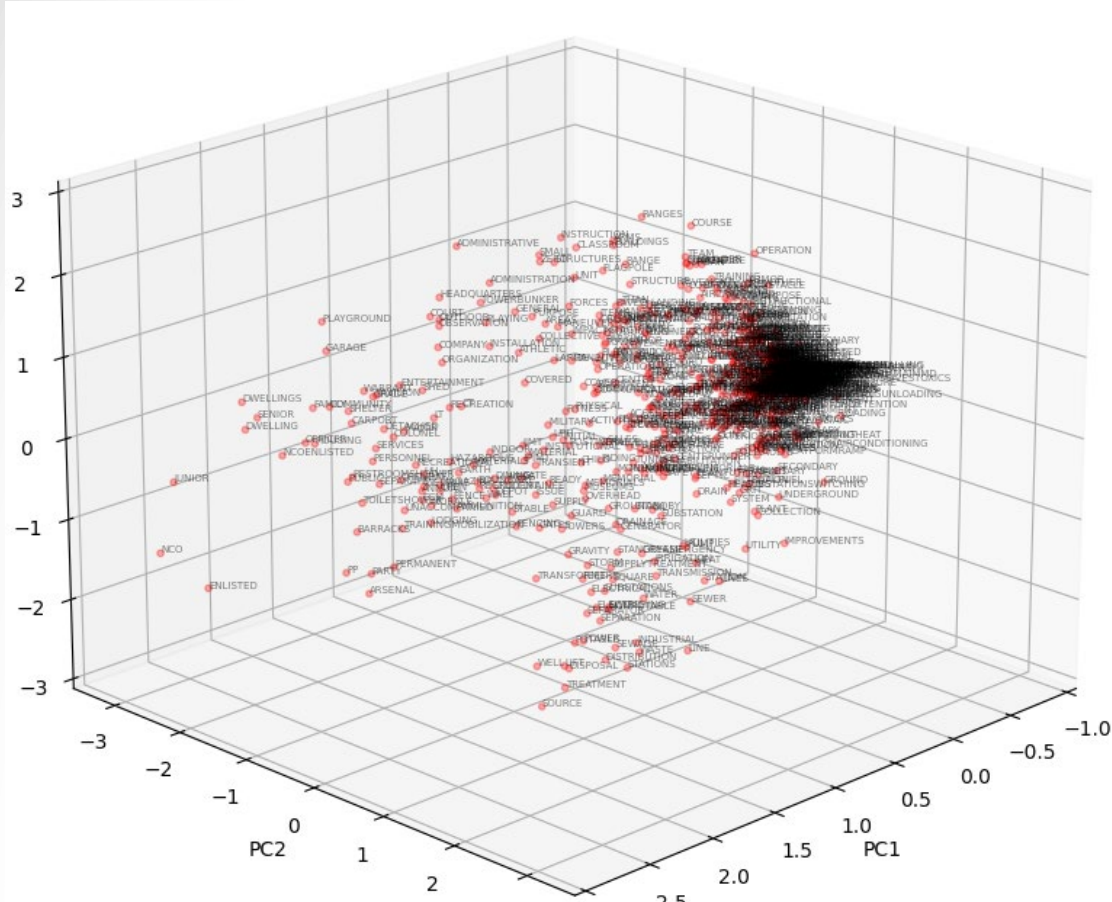
	Red	Yellow	Green
Red	1	0	0
Red	1	0	0
Yellow	0	1	0
Green	0	0	1
Yellow	0	1	0

- Outputs were also numerically represented
- Text data about units can't be fed directly into these models
- There are too many CATCODES to one hot encode
- Need to apply another method



DATA TREATMENT

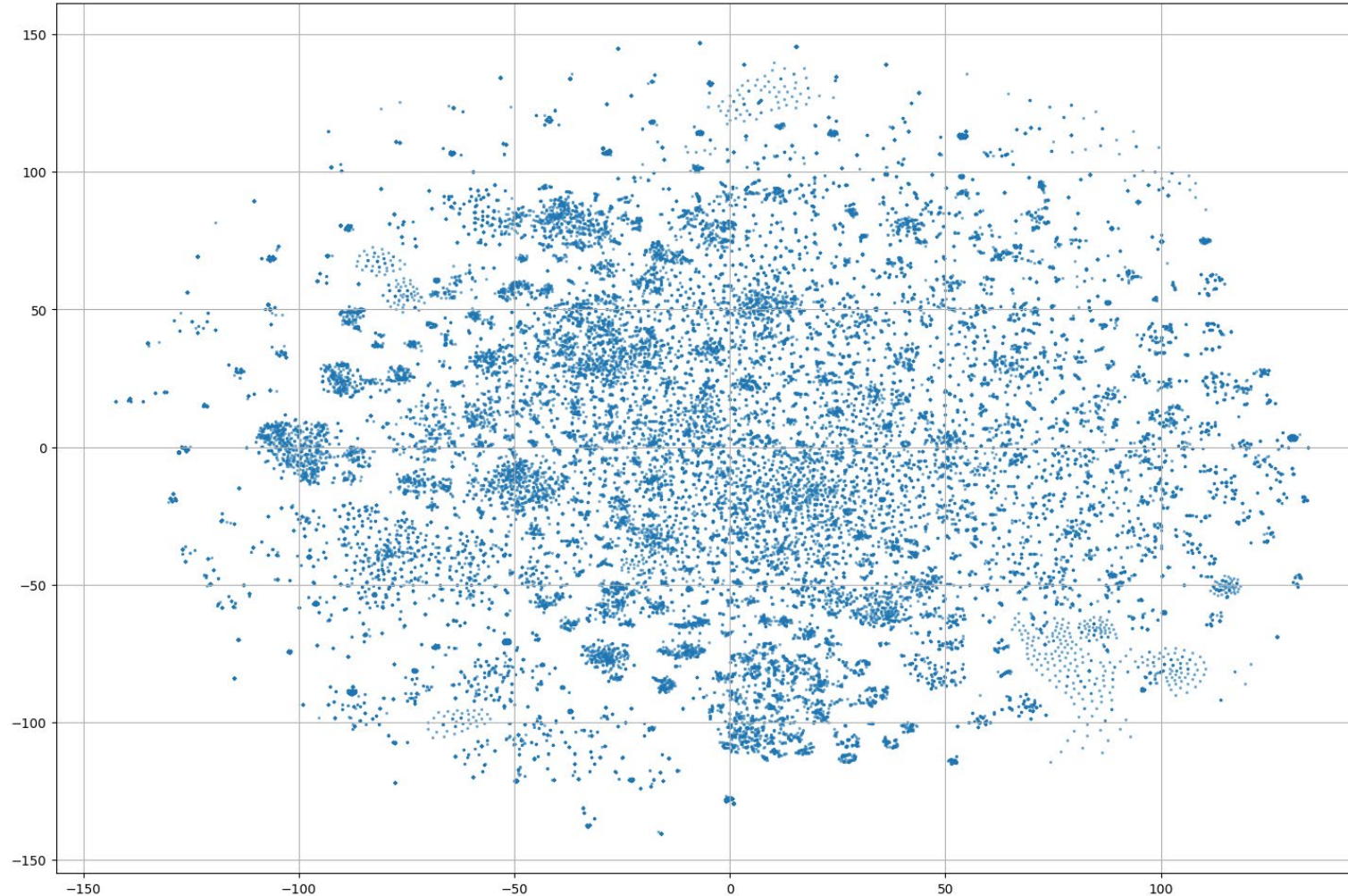
- Word embedding models:





DATA TREATMENT

- Bidirectional Encoder Representations from Transformers (BERT)
- Application to Unit Name data:



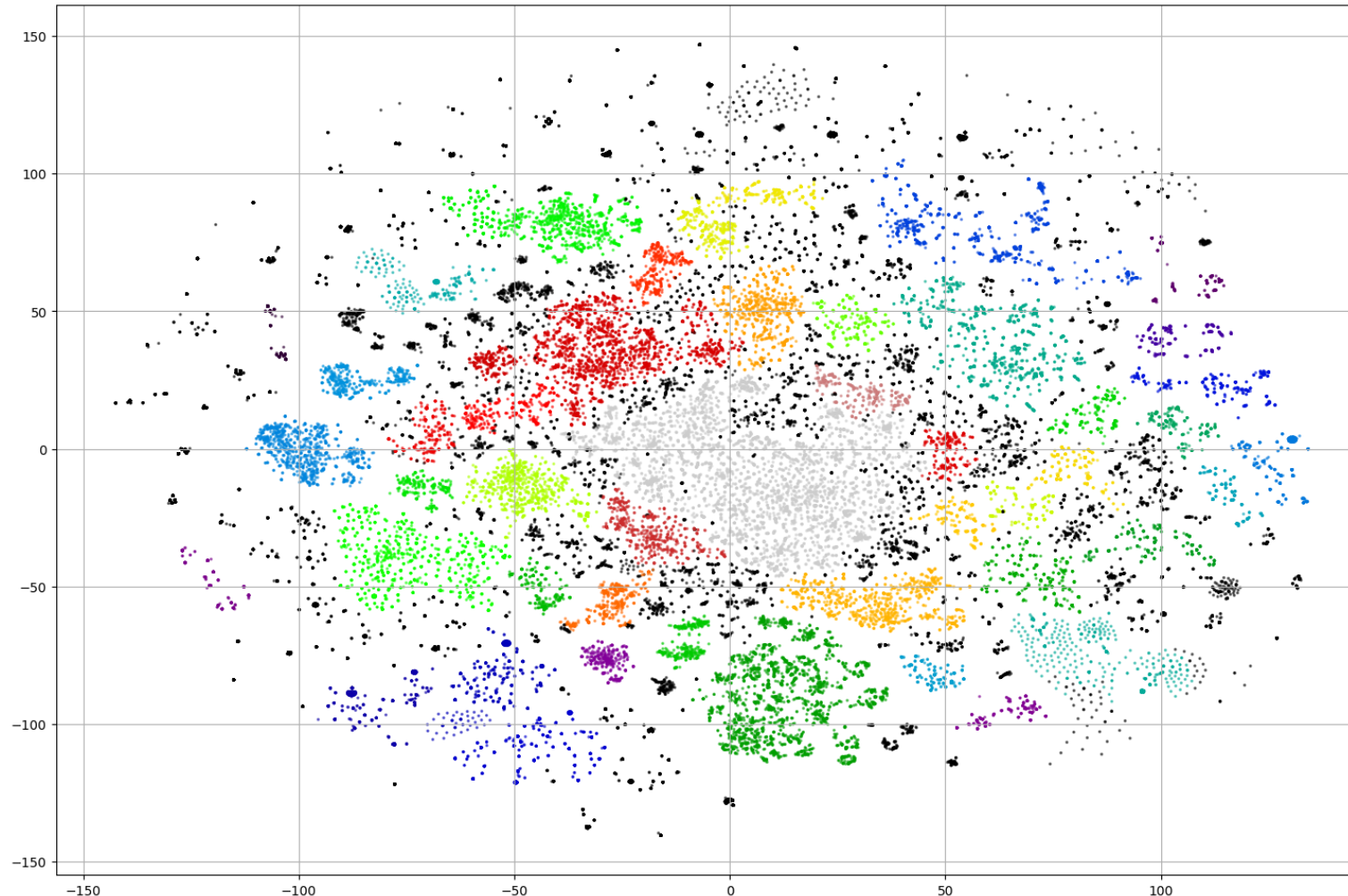


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DATA TREATMENT



- Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN)
- Application to Unit Name data:



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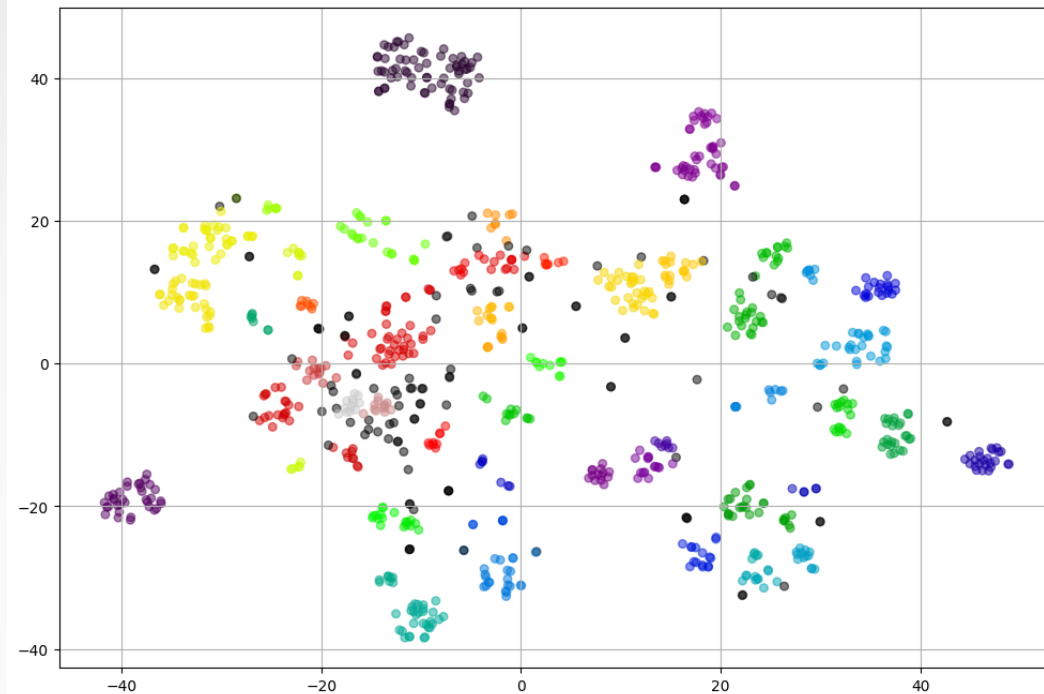
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DATA TREATMENT

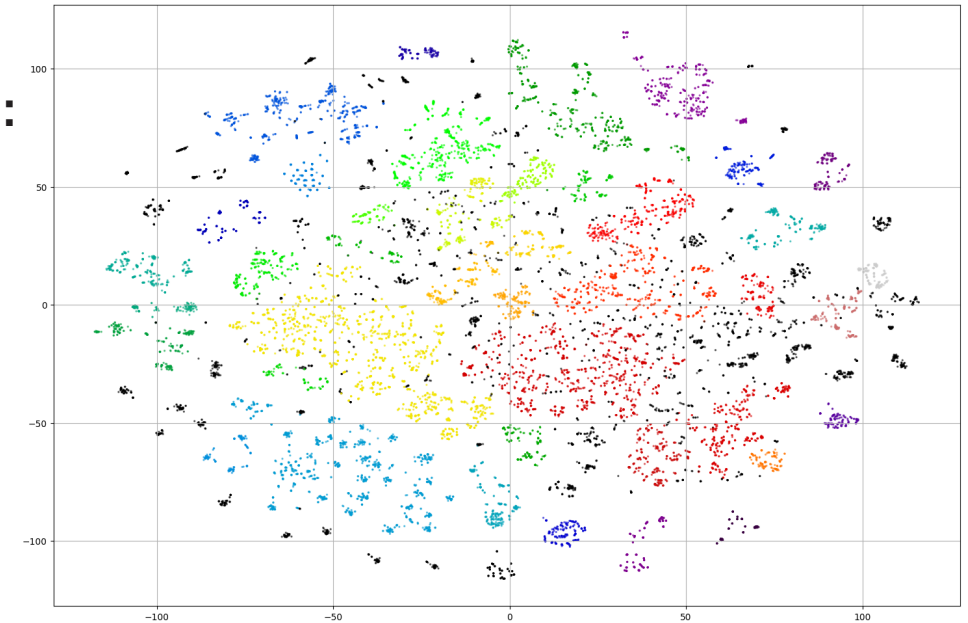


- All embedded-clustered results:

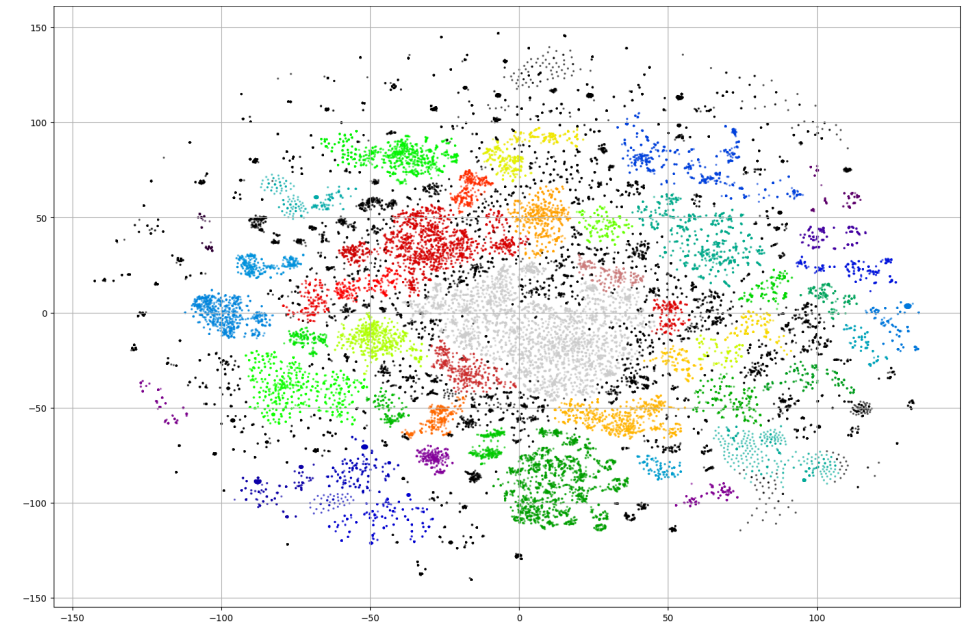
CATCODEs:



UIC (Hierarchy):



UIC (Name):

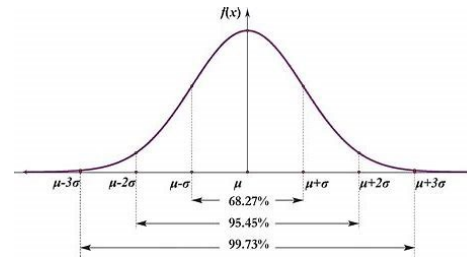
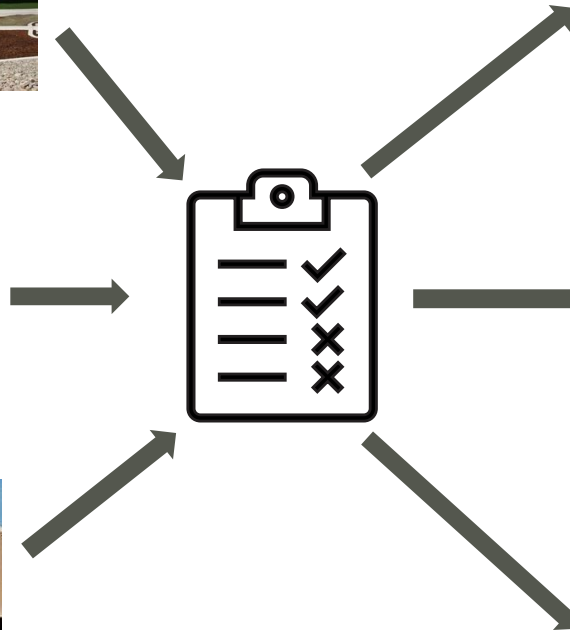
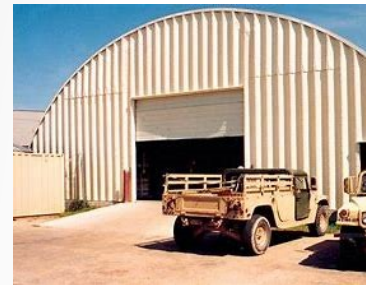


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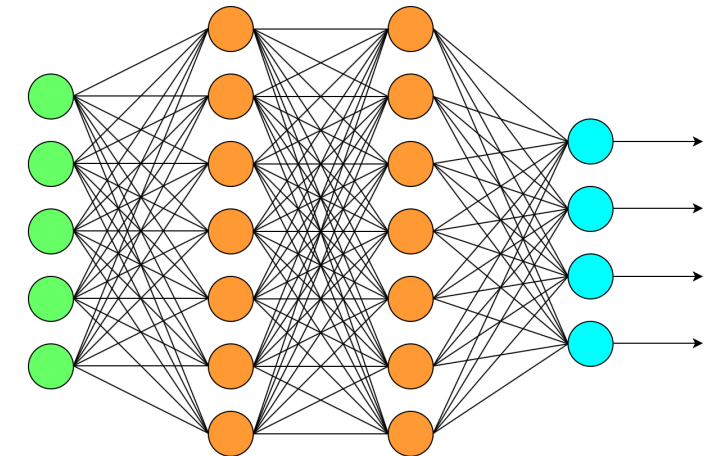
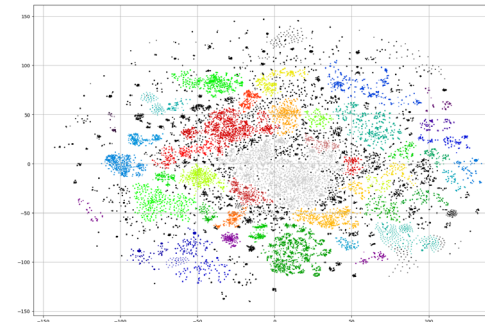


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MODEL STRUCTURE



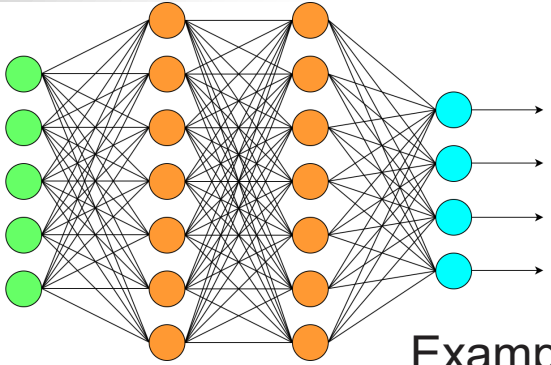
Red	Yellow	Green
1	0	0
1	0	0
0	1	0
0	0	1
0	1	0



UNCLASSIFIED



MODEL STRUCTURE



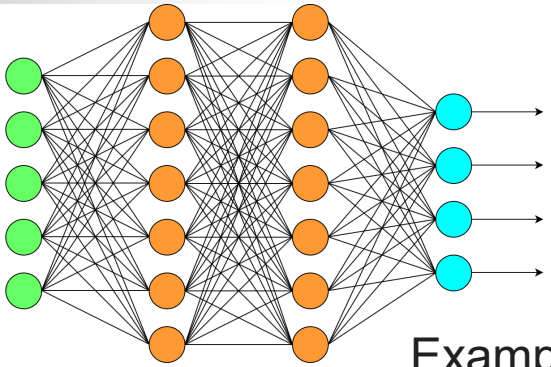
Example:

Interruptability			
Prolonged	Short	Brief	Immediate
p_0	p_1	p_2	p_3
0.03	0.12	0.56	0.29

Replicability			
Possible	Difficult	Extremely Difficult	Impossible
q_0	q_1	q_2	q_3
0.22	0.42	0.23	0.13



MODEL STRUCTURE



Example:

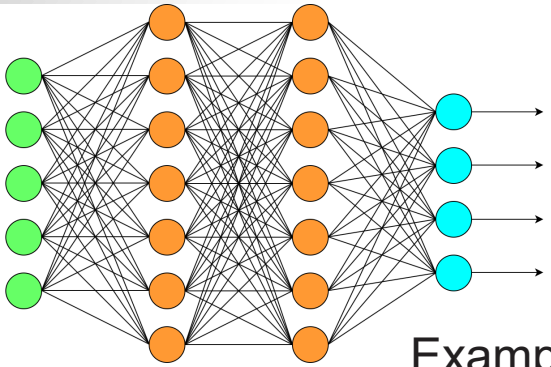
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Replicability			
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q_0	q_1	q_2	q_3
0.22	0.42	0.23	0.13

(Brief, Difficult)



MODEL STRUCTURE



Example:

Interruptability			
Prolonged	Short	Brief	Immediate
p_0	p_1	p_2	p_3
0.03	0.12	0.56	0.29

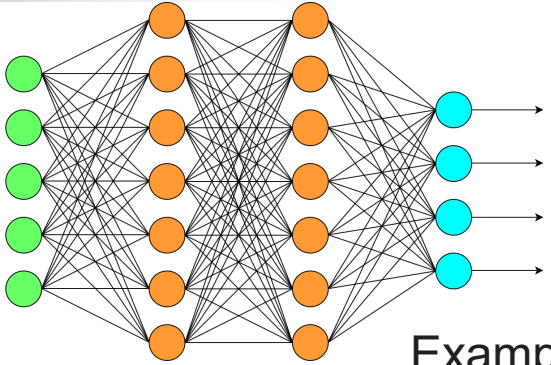
Replicability			
Possible	Difficult	Extremely Difficult	Impossible
q_0	q_1	q_2	q_3
0.22	0.42	0.23	0.13

(Brief, Difficult) ⇒

MISSION DEPENDENCY INDEX					
MDI		Question 1 INTERRUPTABILITY			
		How fast would the mission be impacted if the asset's operations were interrupted?			
		IMMEDIATE < 15 minutes	BRIEF < 24 hours	SHORT < 7 days	PROLONGED > 7 days
Question 2 REPLICABILITY	IMPOSSIBLE	100	88	76	64
	EXTREMELY DIFFICULT	92	80	68	56
	DIFFICULT	84	72	60	48
	POSSIBLE	76	64	52	40



MODEL STRUCTURE



Example:

Interruptability			
Prolonged	Short	Brief	Immediate
p_0	p_1	p_2	p_3
0.03	0.12	0.56	0.29

Replicability			
Possible	Difficult	Extremely Difficult	Impossible
q_0	q_1	q_2	q_3
0.22	0.42	0.23	0.13

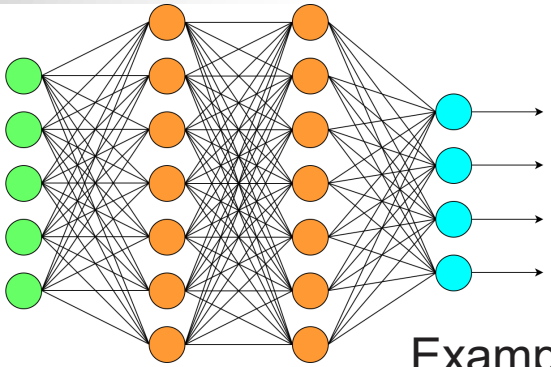
(Brief, Difficult) $\Rightarrow$

MISSION DEPENDENCY INDEX					
MDI		Question 1 INTERRUPTABILITY			
		How fast would the asset's operations be interrupted?			
		IMMEDIATE < 15 minutes	BRIEF < 24 hours	SHORT < 7 days	PROLONGED > 7 days
Question 2 REPLICABILITY	IMPOSSIBLE	100	88	76	64
	EXTREMELY DIFFICULT	92	80	68	56
	DIFFICULT	84	72	60	48
	POSSIBLE	76	64	52	40

 $\Rightarrow$ 72



MODEL STRUCTURE



Example:

Interruptability			
Prolonged	Short	Brief	Immediate
p_0	p_1	p_2	p_3
0.03	0.12	0.56	0.29

Replicability			
Possible	Difficult	Extremely Difficult	Impossible
q_0	q_1	q_2	q_3
0.22	0.42	0.23	0.13

(Brief, Difficult) $\Rightarrow$

MISSION DEPENDENCY INDEX					
MDI		Question 1 INTERRUPTABILITY			
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	DIFFICULT	84	72	60	48
	POSSIBLE	76	64	52	40

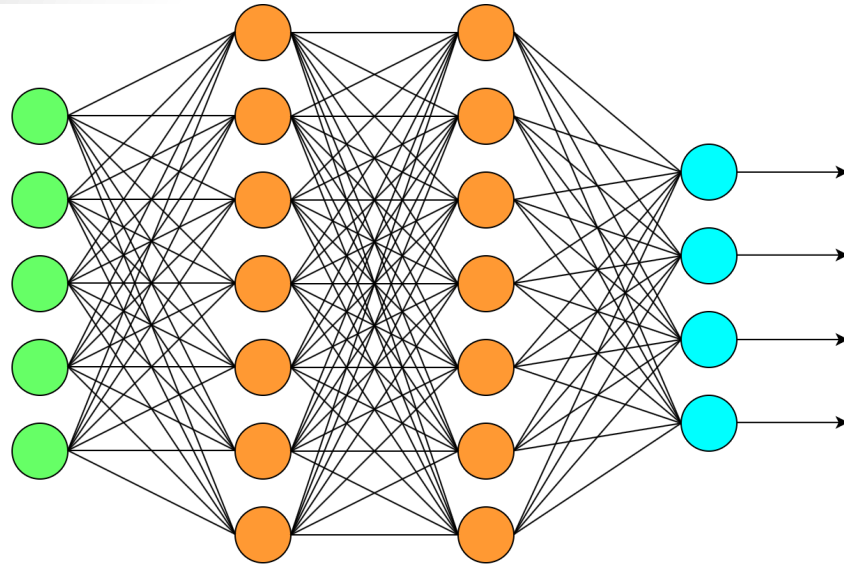
 $\Rightarrow$ 72

Unless (Prolonged, Possible)...

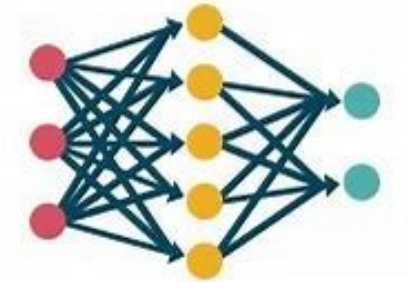


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MODEL STRUCTURE



IF
(Prolonged,
Possible)...



MDI $\in [0,40]$

ELSE...



MISSION DEPENDENCY INDEX					
MDI		Question 1 INTERRUPTABILITY How fast would the mission be impacted if the asset's operations were interrupted?			
		IMMEDIATE < 15 minutes	BRIEF < 24 hours	SHORT < 7days	PROLONGED > 7 days
Question 2 REPLICABILITY How difficult would it be to relocate the asset's mission capabilities?	IMPOSSIBLE	100	88	76	64
	EXTREMELY DIFFICULT	92	80	68	56
	DIFFICULT	84	72	60	48
	POSSIBLE	76	64	52	40

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THE RESULTS

The Neural Network Performance



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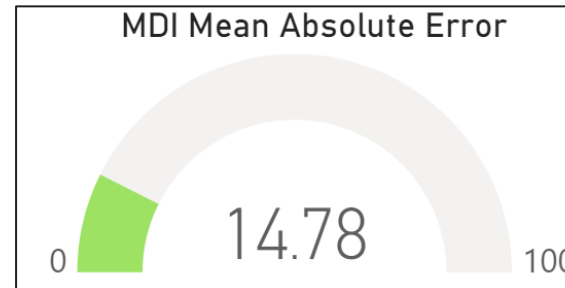


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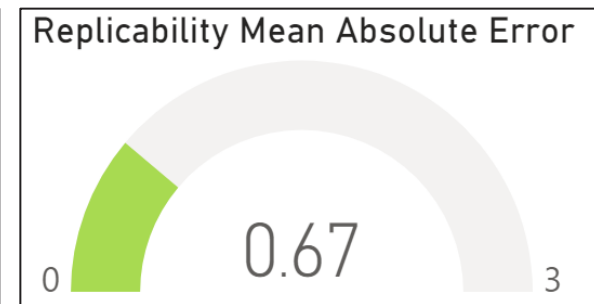
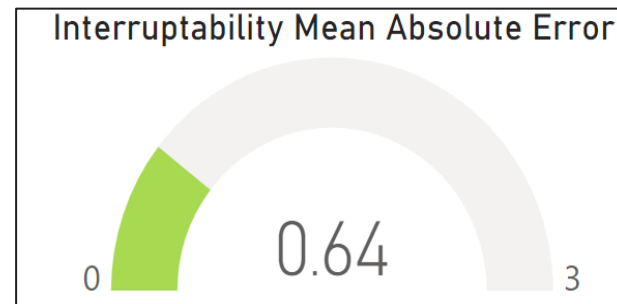


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PERFORMANCE AT A GLANCE



(Median: 8)



Class	Response
0	Prolonged
1	Short
2	Brief
3	Immediate

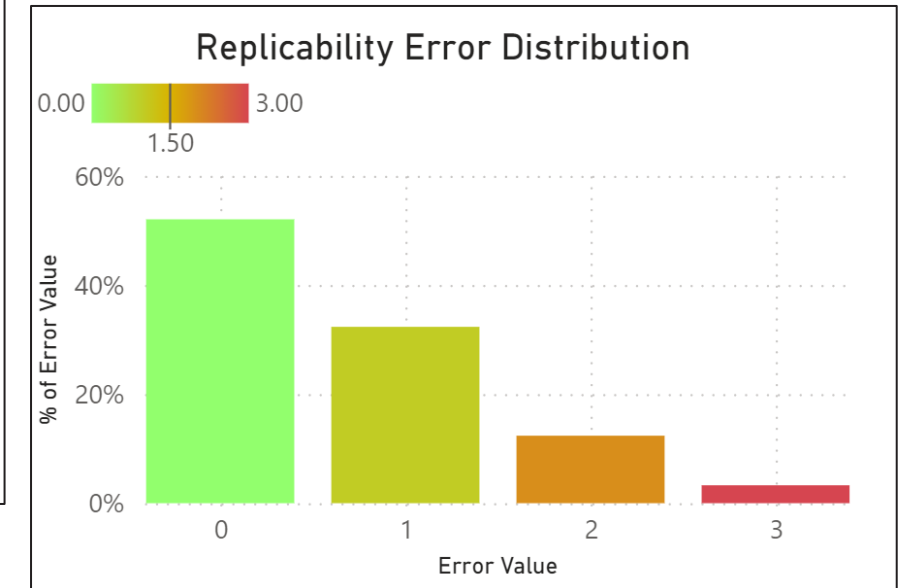
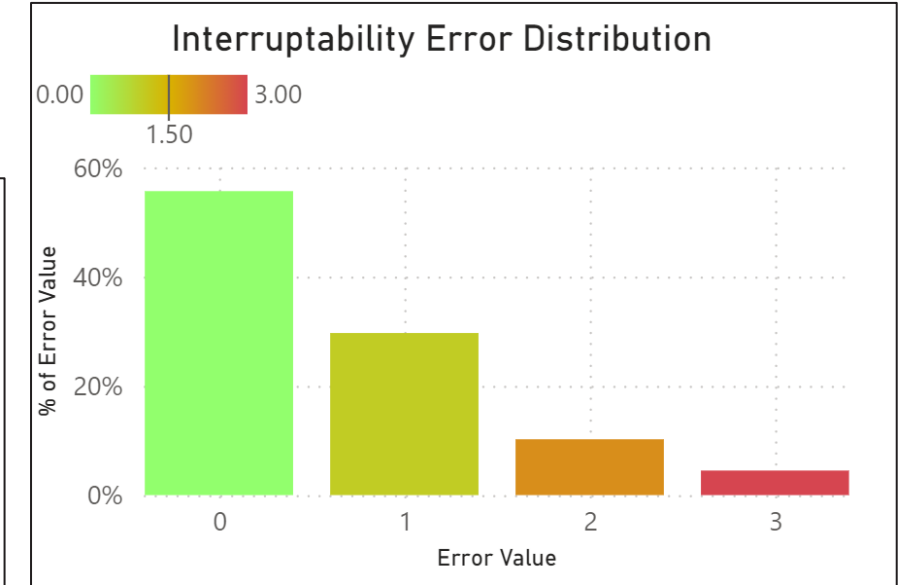
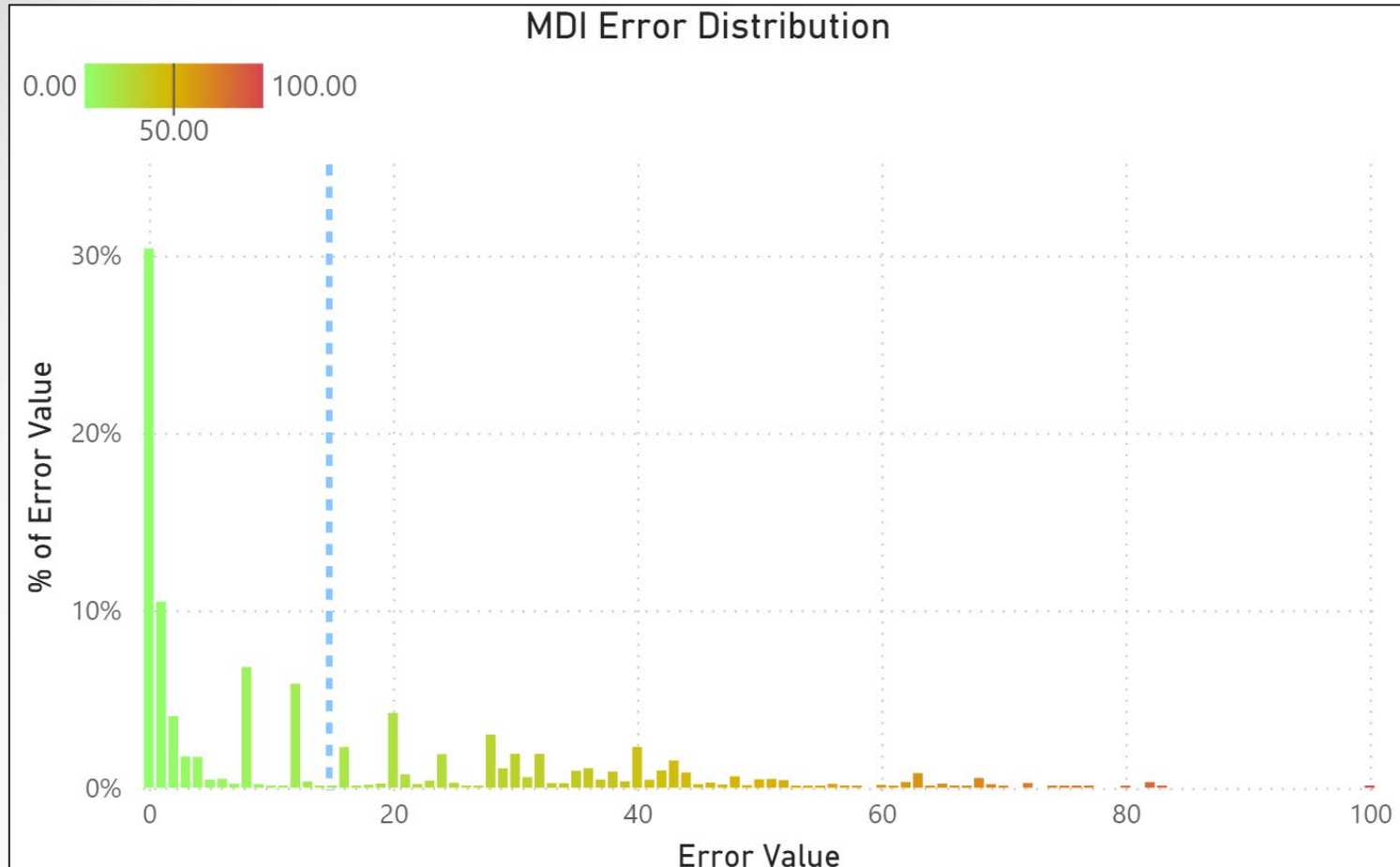
Truth	Predicted									
	Interruptability					Replicability				
	0	1	2	3	Total	0	1	2	3	Total
0	3414	1010	454	453	5331	3267	1419	711	310	5707
1	400	1374	692	282	2748	400	1209	706	367	2682
2	222	603	905	320	2050	115	507	850	302	1774
3	25	129	131	226	511	39	123	105	210	477
Total	4061	3116	2182	1281	10640	3821	3258	2372	1189	10640

Class	Response
0	Possible
1	Difficult
2	Extreme Difficult
3	Impossible

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PERFORMANCE AT A GLANCE





CALCULATING CONFIDENCE

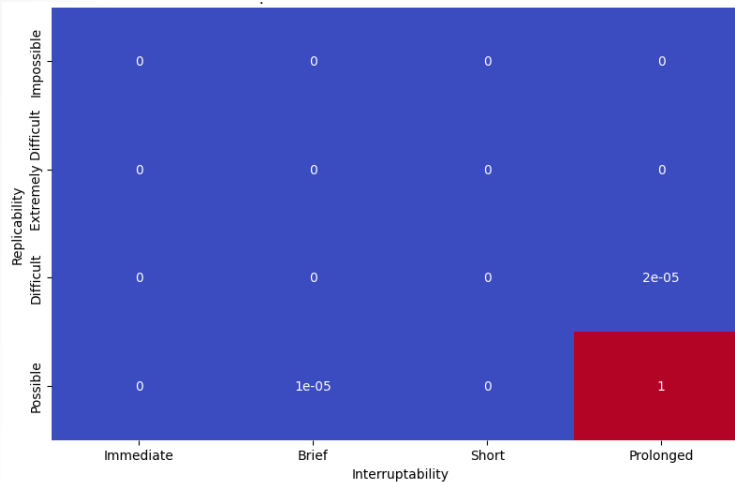


- The model outputs likelihoods
- Use these to get MDI likelihood
- Likelihood translates to confidence
- Confidence heatmap examples:

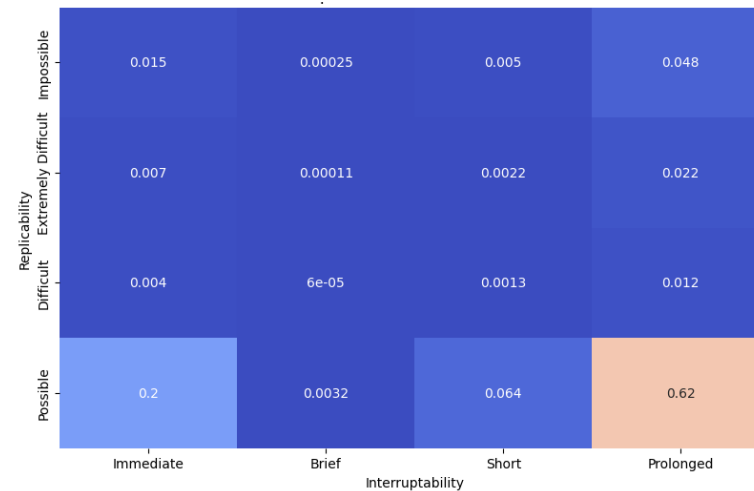
$$M = \begin{bmatrix} p_{3q3} & p_{2q3} & p_{1q3} & p_{0q3} \\ p_{3q2} & p_{2q2} & p_{1q2} & p_{0q2} \\ p_{3q1} & p_{2q1} & p_{1q1} & p_{0q1} \\ p_{3q0} & p_{2q0} & p_{1q0} & p_{0q0} \end{bmatrix}$$

MISSION DEPENDENCY INDEX					
MDI		Question 1 INTERRUPTABILITY			
		How fast would the mission be impacted if the asset's operations were interrupted?			
Question 2 REPLICABILITY How difficult would it be to replicate the asset's mission capabilities?		IMMEDIATE < 15 minutes	BRIEF < 24 hours	SHORT < 7 days	PROLONGED > 7 days
	IMPOSSIBLE	100	88	76	64
	EXTREMELY DIFFICULT	92	80	68	56
	DIFFICULT	84	72	60	48
	POSSIBLE	76	64	52	40

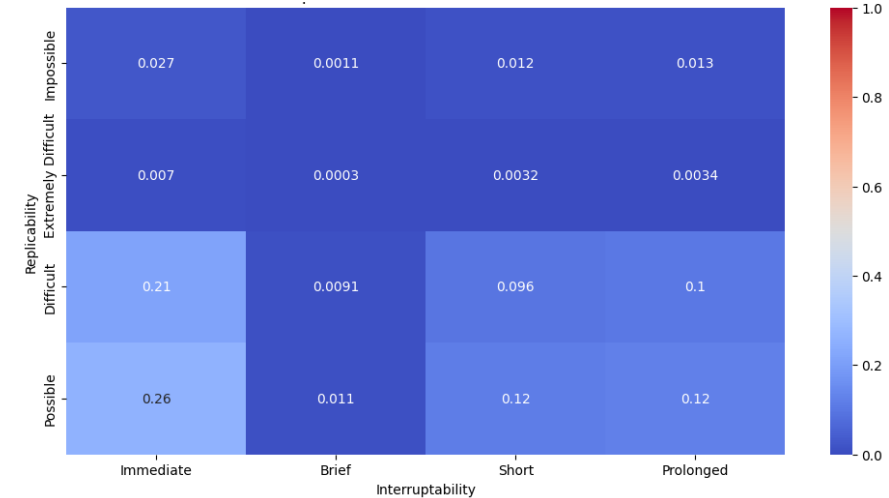
High



Moderate

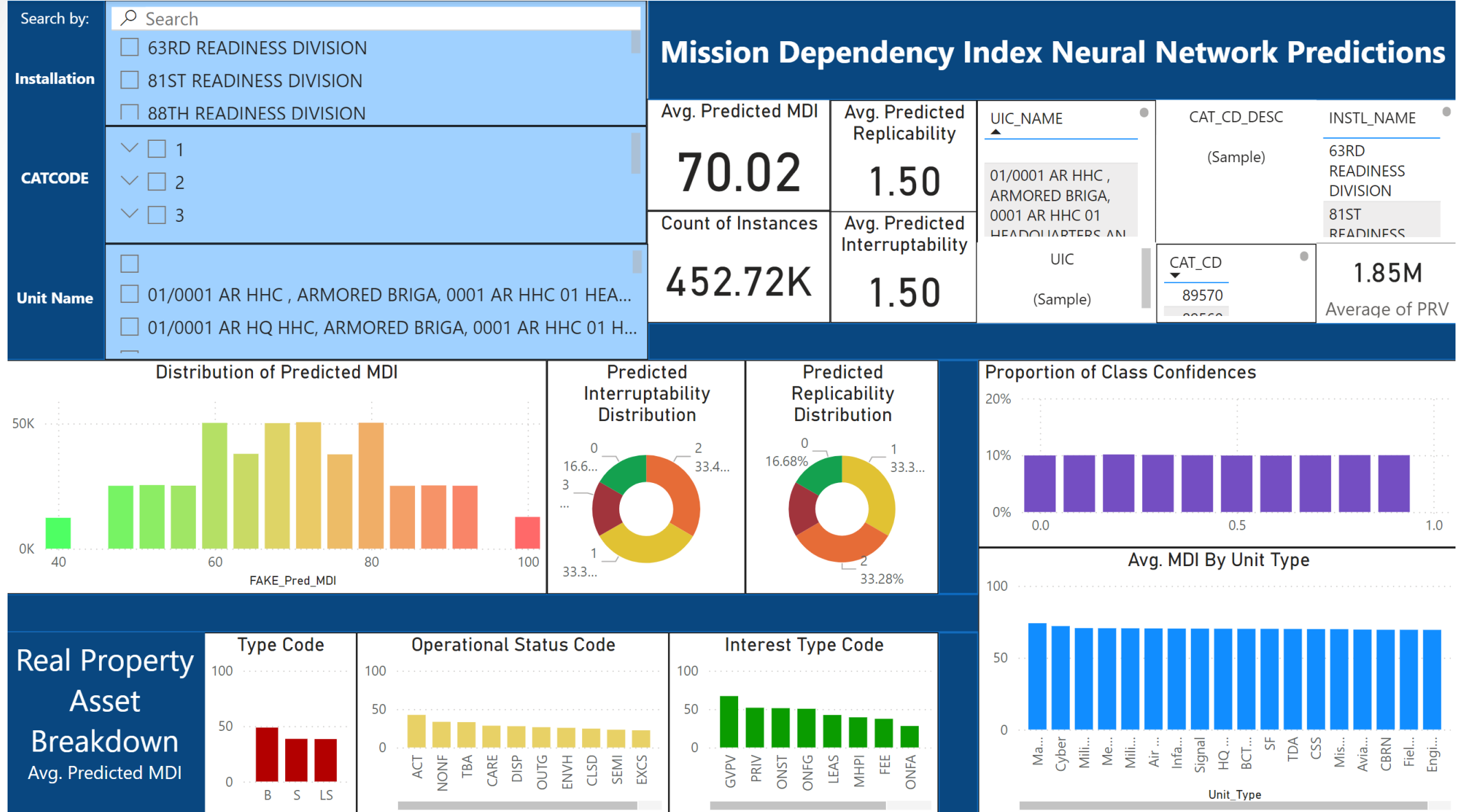


Low





POWER BI DASHBOARD





POWER BI DASHBOARD



WASHINGTON DC NATIONAL GUARD

Choose Unit Name:
☐
☐ HQ ARNG ELMT, JFHQ-DC,

Choose CATCODE:

☐ 1

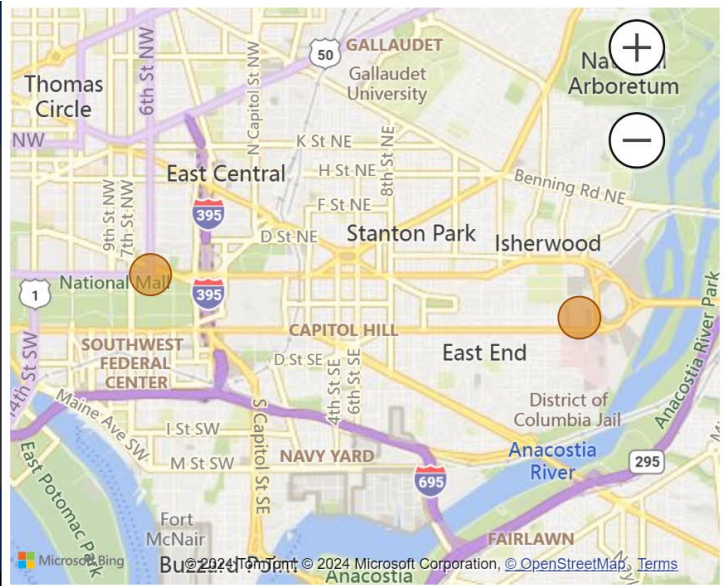
☐ 4

☐ 6

☐ 7

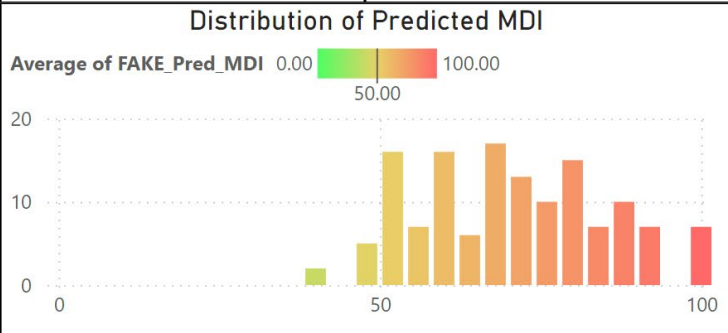
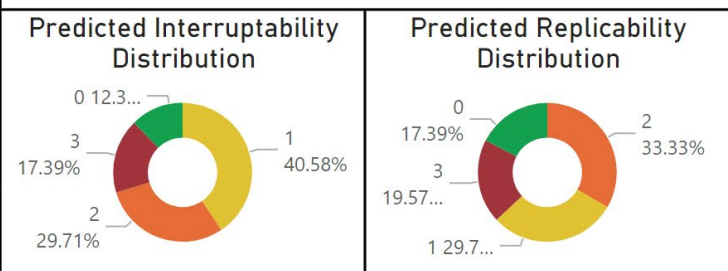
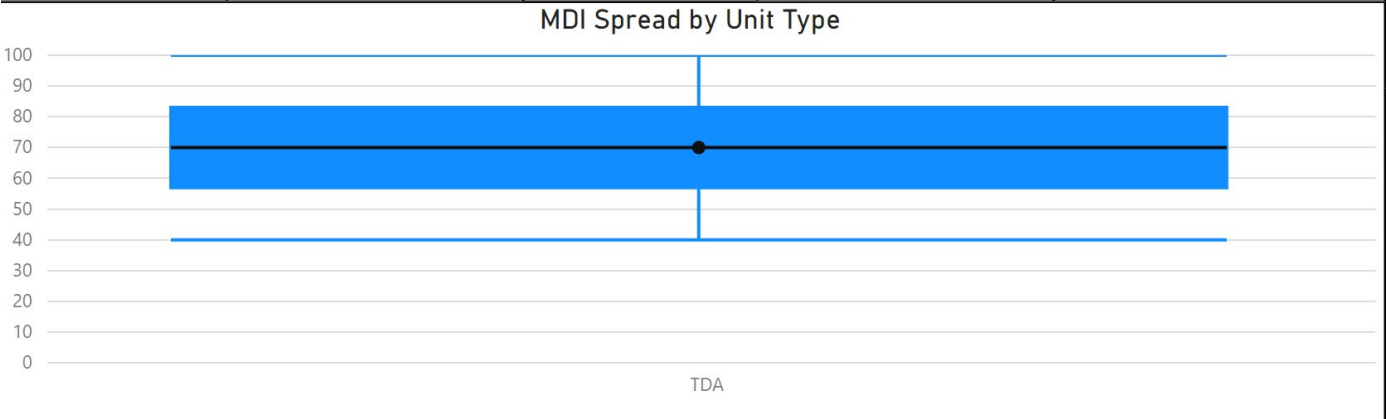
☐ 8

Choose Site Name:
☐ D.C.Armory
☐ Washington DC SFRO



Summary Statistics

Min.	Mean	Max.	Count	Average Confidence
40	70.67	100	138	0.48



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THANK YOU!



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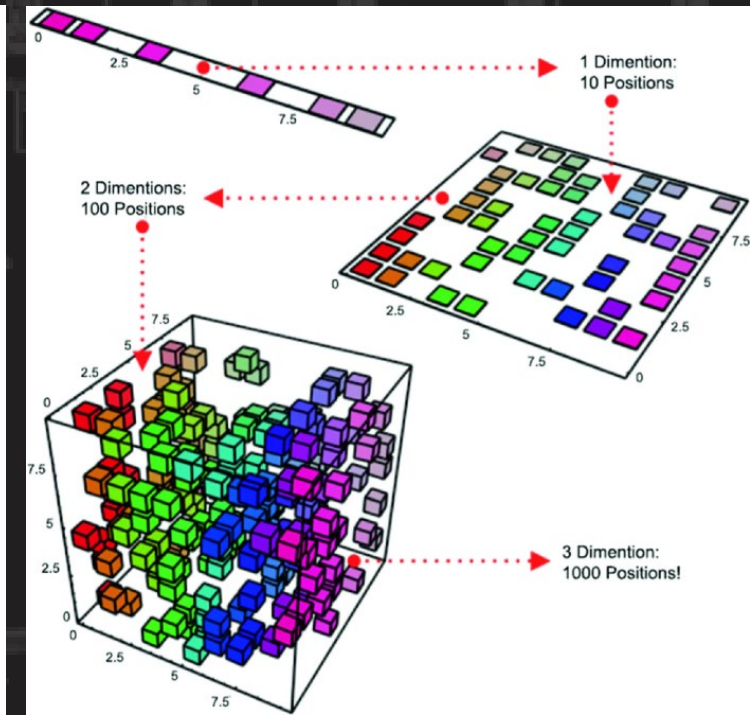
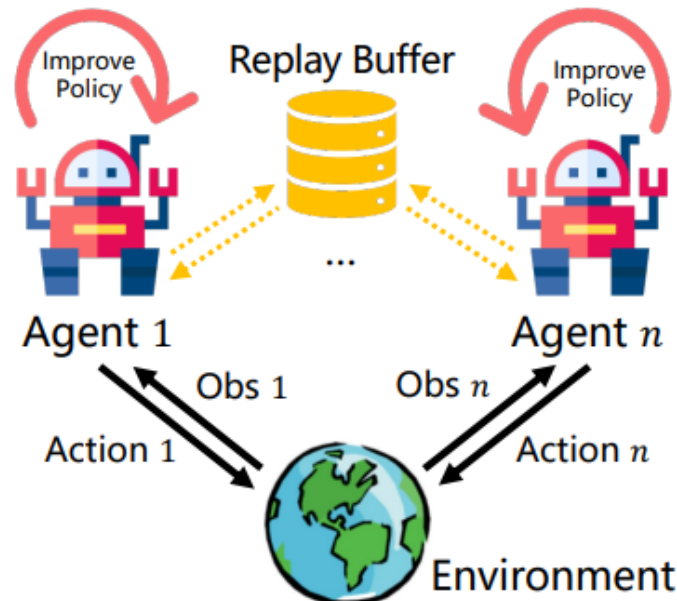


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OPTIMIZING MAINTENANCE THROUGH REINFORCEMENT LEARNING

Joseph Wittrock
Illinois State University
M.S. Mathematics 2025



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CONTENTS

1. Optimization Overview
2. Model Generation
3. Simulations
4. Multi Agent Systems

OVERVIEW



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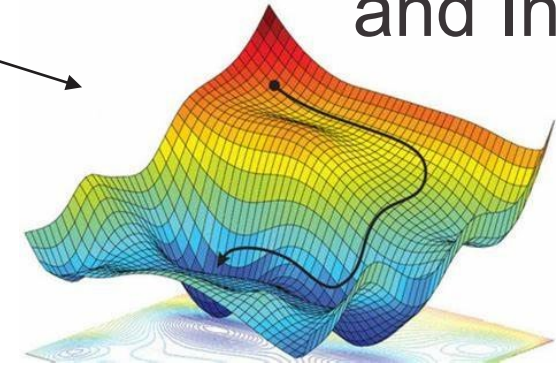


THE CYCLE OF OPTIMIZATION

Models and
Simulations



Optimization
and Insights



Real World Application



Accumulated
Data

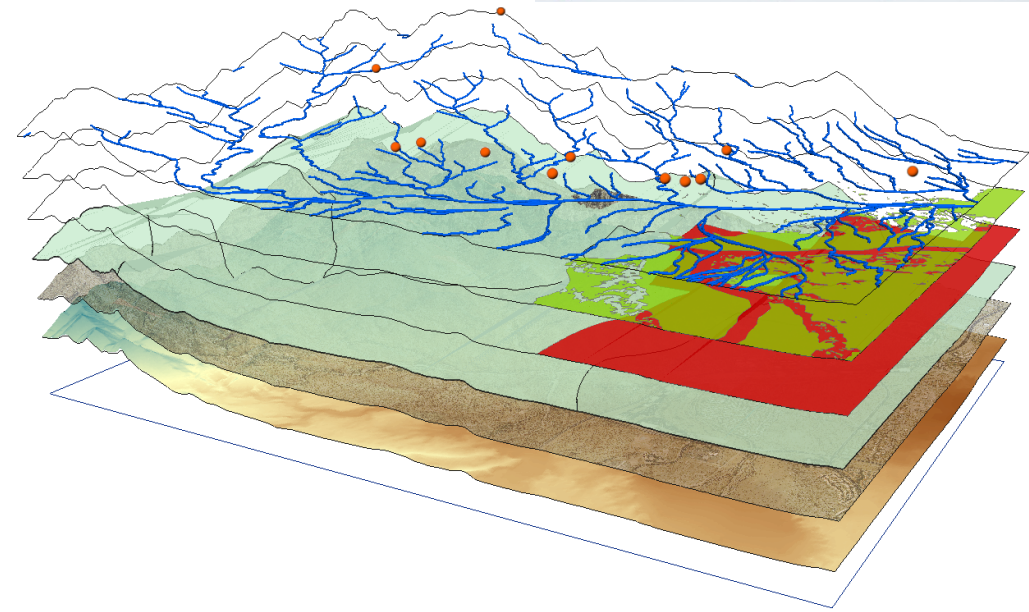
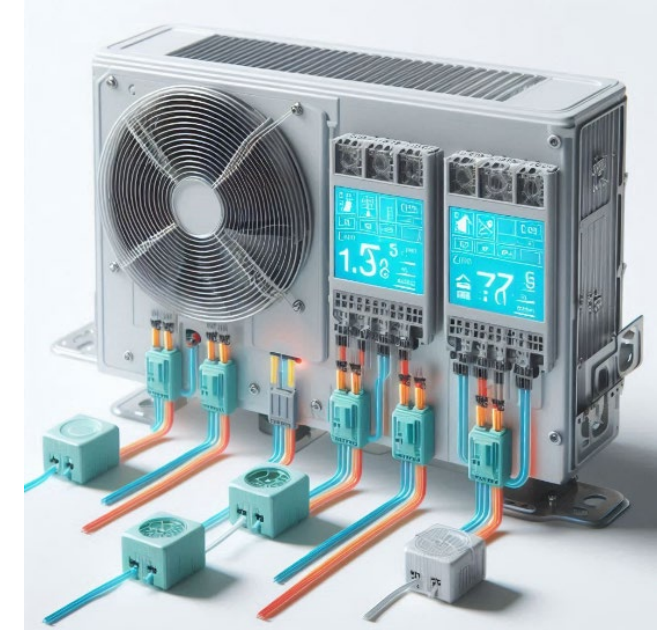




TYPES OF MAINTENANCE DATA



- **Inspection Data**
- **Sensor Data**
 - Thermal Sensors
 - Vibration Sensors
 - Occupancy Sensors
- **Geospatial**
- **Form Text**
- **Maintenance History**





WAYS DATA IS USED TO IMPROVE SUSTAINMENT

- Inspections of components help us **determine RUL**
- Sensors on components help detect and **predict Failures**
- Geographic data paired with component data help understanding of how different **climates effect** component degradation



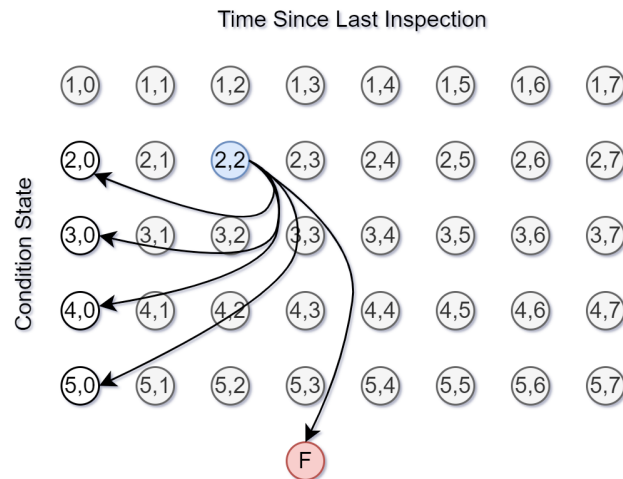


TYPES OF CONDITION MODELS



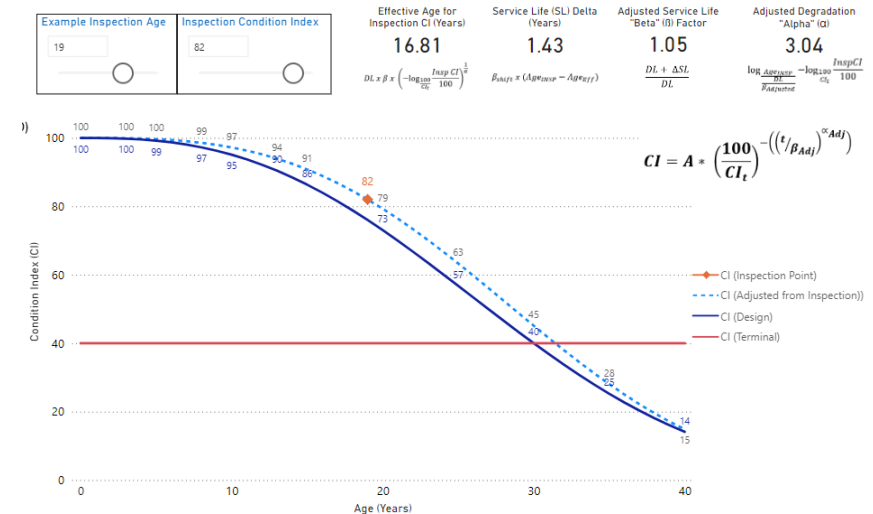
Discrete Models *

- Discrete Timesteps
- Discrete Condition Steps
- Generally Fast Computations
- Probabilistic by nature



Continuous Models

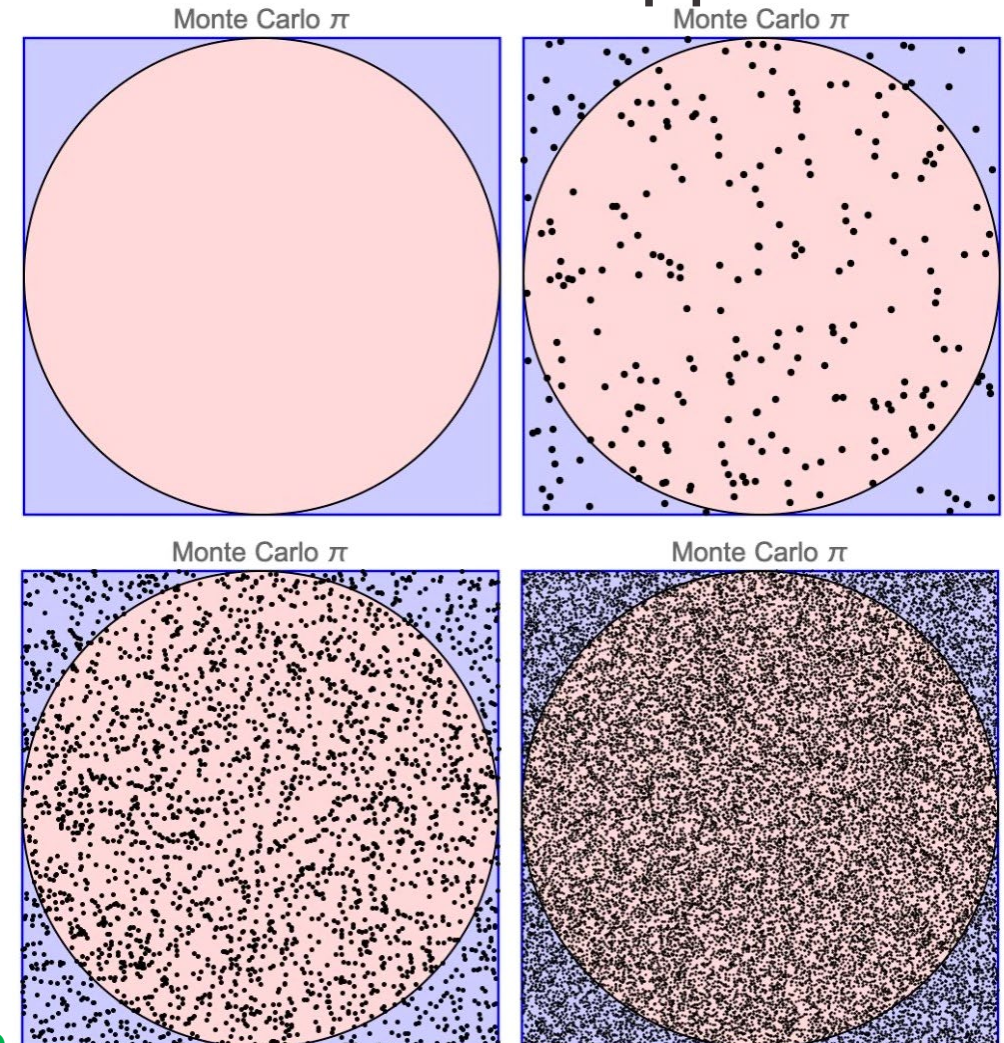
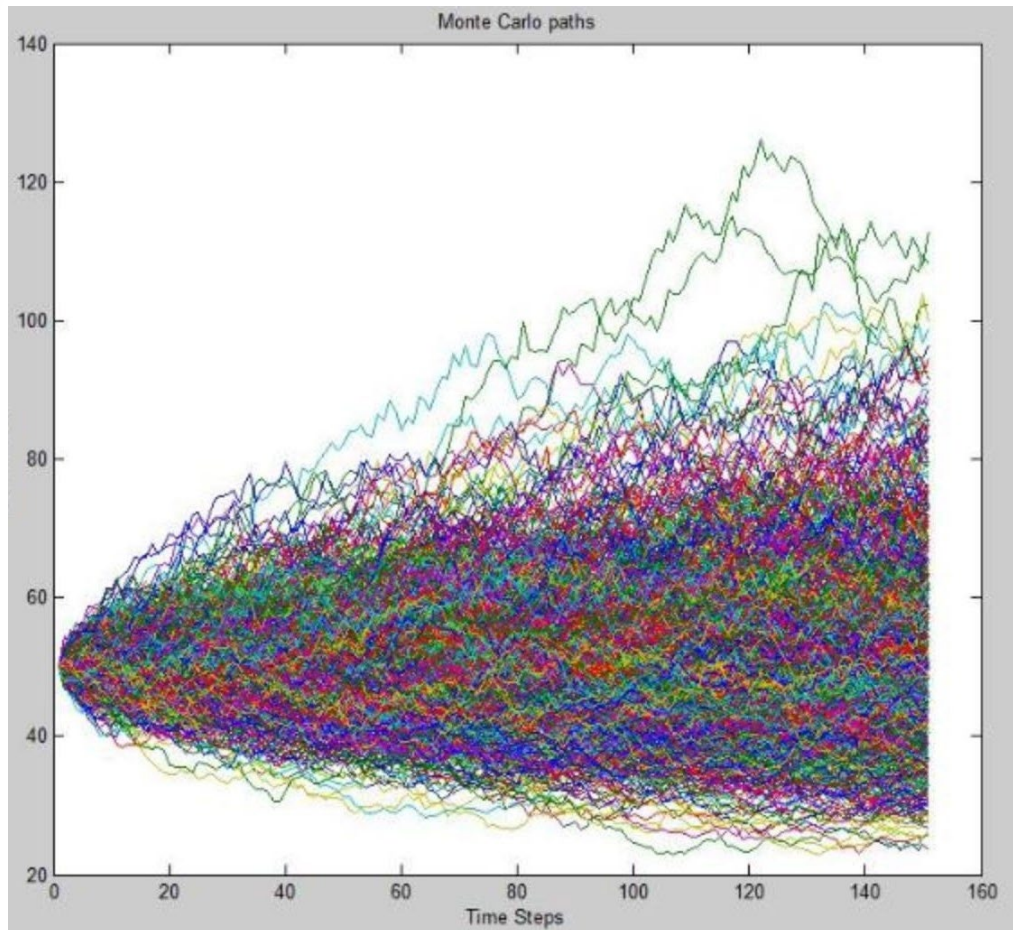
- Continuous Time
- Continuous Condition
- Slopes! Calculus!





Monte Carlo Simulations

- **Monte Carlo:** Simulate it a bunch and see what happens



DISCRETE CONDITION MODEL GENERATION



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DISCRETE MODELS



Condition
State

Class	Upper	Lower
1	100	99
2	99	92
3	92	86
4	86	76
5	76	65
6	65	55
7	55	40
8	40	10
9	10	0

1

2

3

4

5

F



DISCRETE MODELS FROM INSPECTION DATA



Inspection Data Format:

- **Last Inspected Condition**
- **New Inspected Condition**
- **Time Between Inspections**

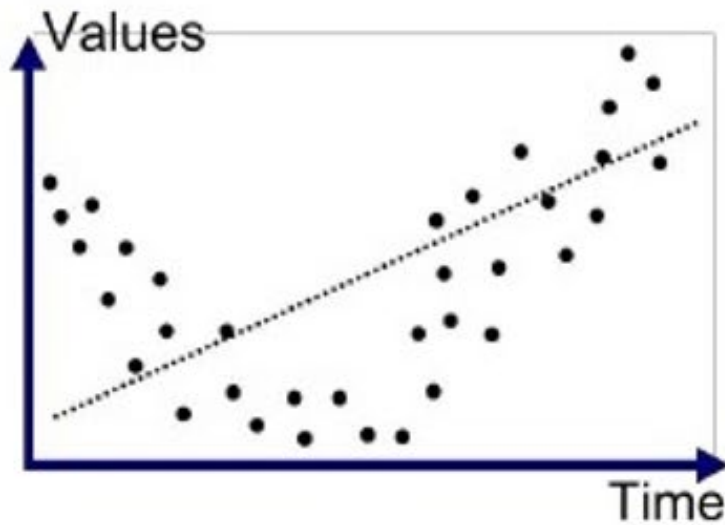
Discrete Markov Approach for Building Component Condition, Reliability, and Service-Life Prediction Modeling

Michael N. Grussing, P.E., M.ASCE¹; Liang Y. Liu, Ph.D., M.ASCE²; Donald R. Uzarski, Ph.D., P.E., M.ASCE³; Khaled El-Rayes, Ph.D., M.ASCE⁴; and Nora El-Gohary, Ph.D., M.ASCE⁵

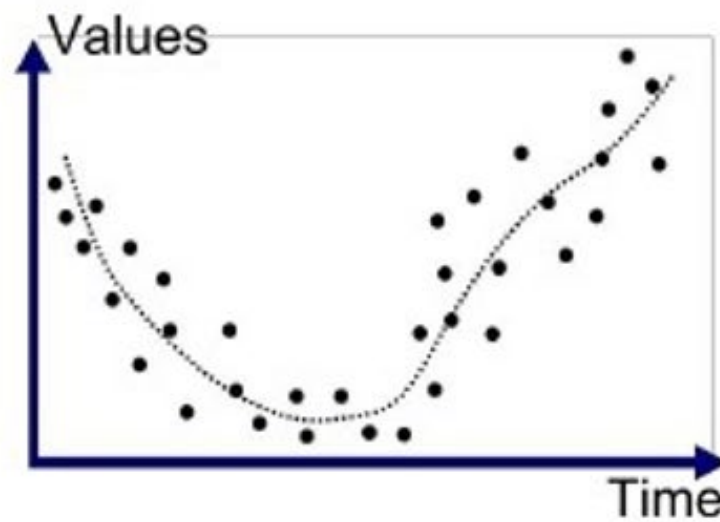
Abstract: Condition indexes have been developed to measure building component condition degradation due to age, use, and deterioration in support of asset management tasks related to work identification, planning, and prioritization. With the development of these indexes, a vast amount of condition index data have been collected for a wide range of components in buildings of varying type, use, and geographic



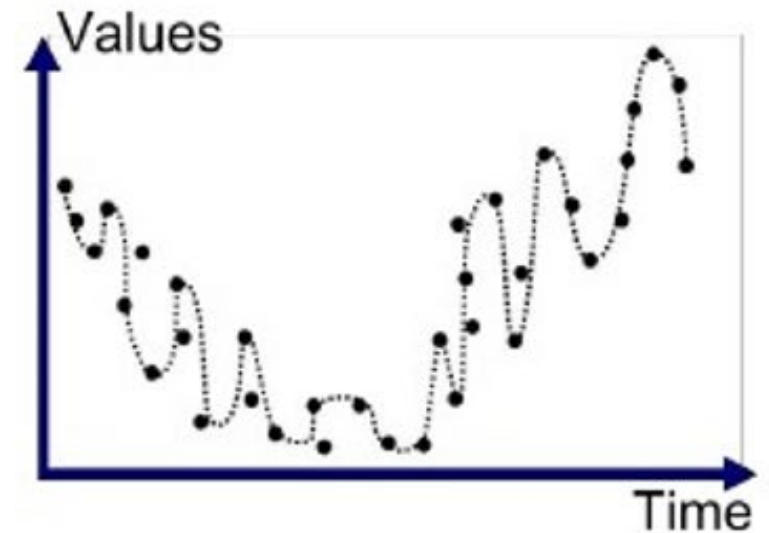
HOW DO WE KNOW IF A MODEL WORKS?



Underfitted



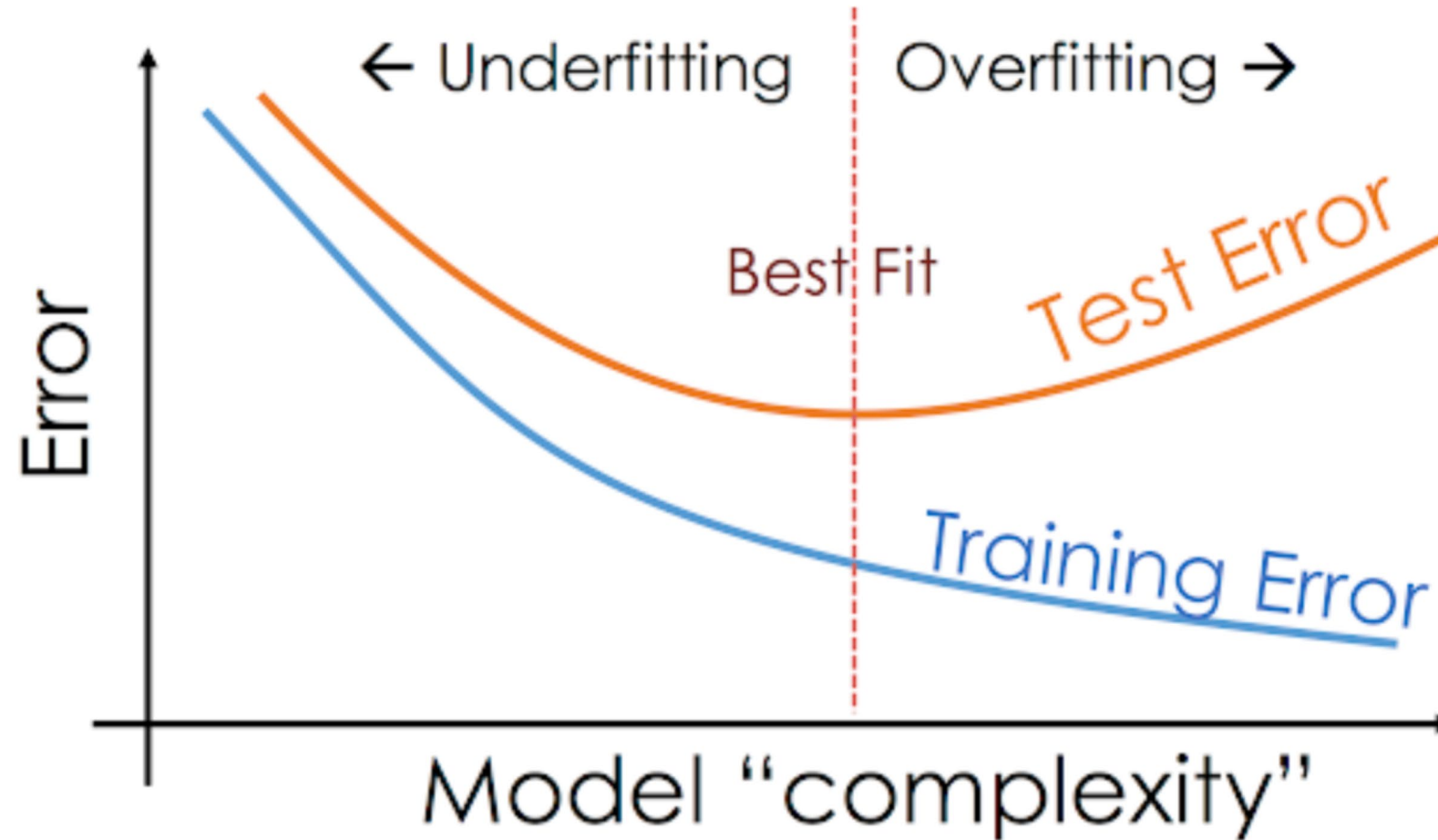
Good Fit/Robust



Overfitted



HOW DO WE KNOW IF A MODEL WORKS?



SIMULATIONS



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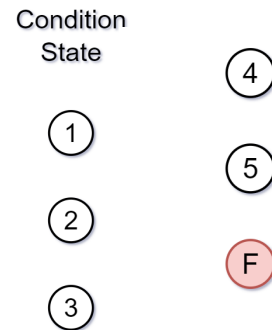
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MARKOV DECISION PROCESS



- A standardized framework for sequential decision modeling
- States: A 'Snapshot' of the environment

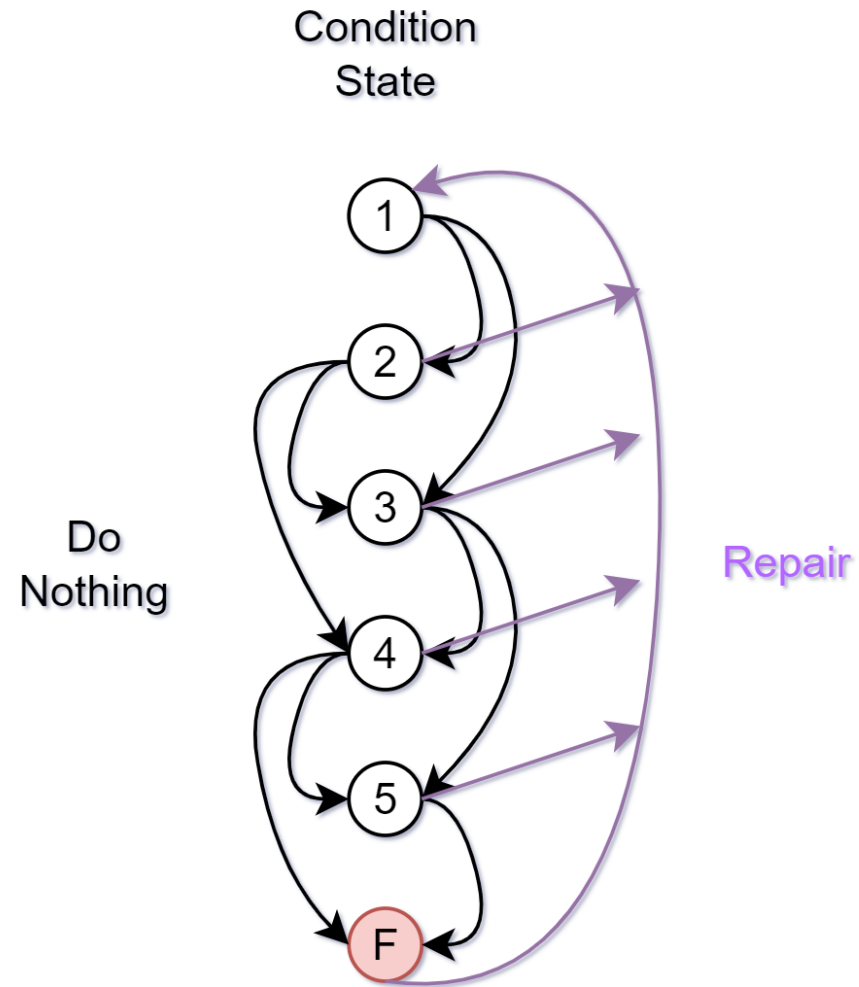


- Actions: Ways to interact with the environment given a state

Repair, Do Nothing, Replace,
Maintain, Inspect, ...



MAINTENANCE MDP EXAMPLE





POLICIES AND REWARD

Policies: Behavior – What actions are taken in each state.

$$\pi(s) \in A$$

Reward: A Measure of Goal

$$+ : \text{ (thumbs up icon) } R_t - : \text{ (thumbs down icon) }$$

Return: Sum of future reward

$$G_t = \sum_{i=t}^T R_i$$



VALUES

- Values describe the **Expected Return**, given a policy.
- **State Value** is the Expected Return if in a State

$$V_{\pi}(s) = E_{\pi}[G_t | S_t = s]$$

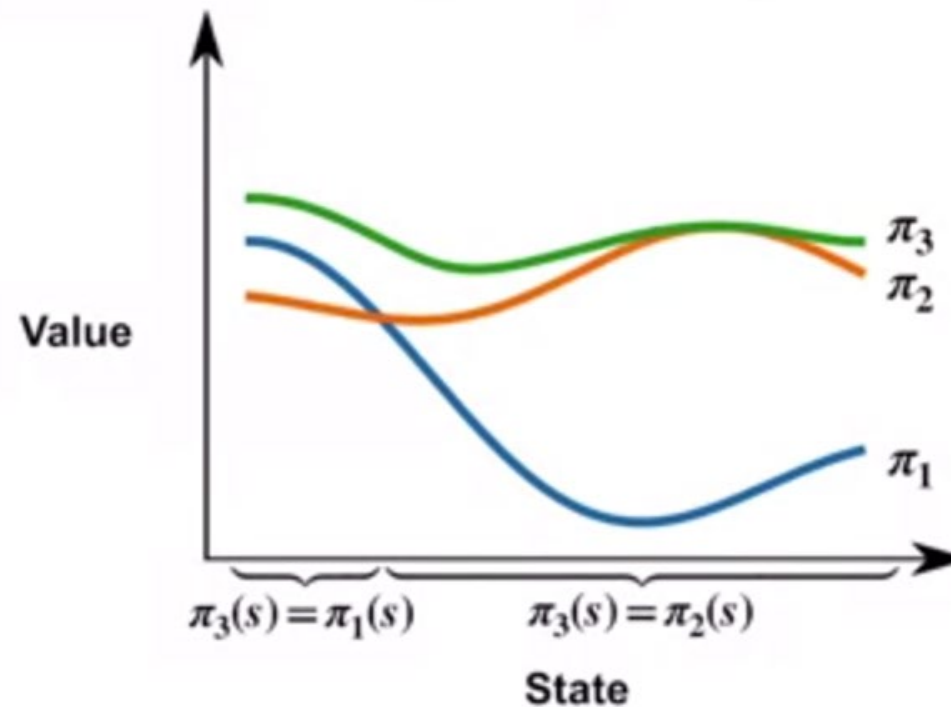
- **Action Value** is the Expected Return if an Action is taken in a State

$$Q_{\pi}(s, a) = E_{\pi}[G_t | S_t = s, A_t = a]$$



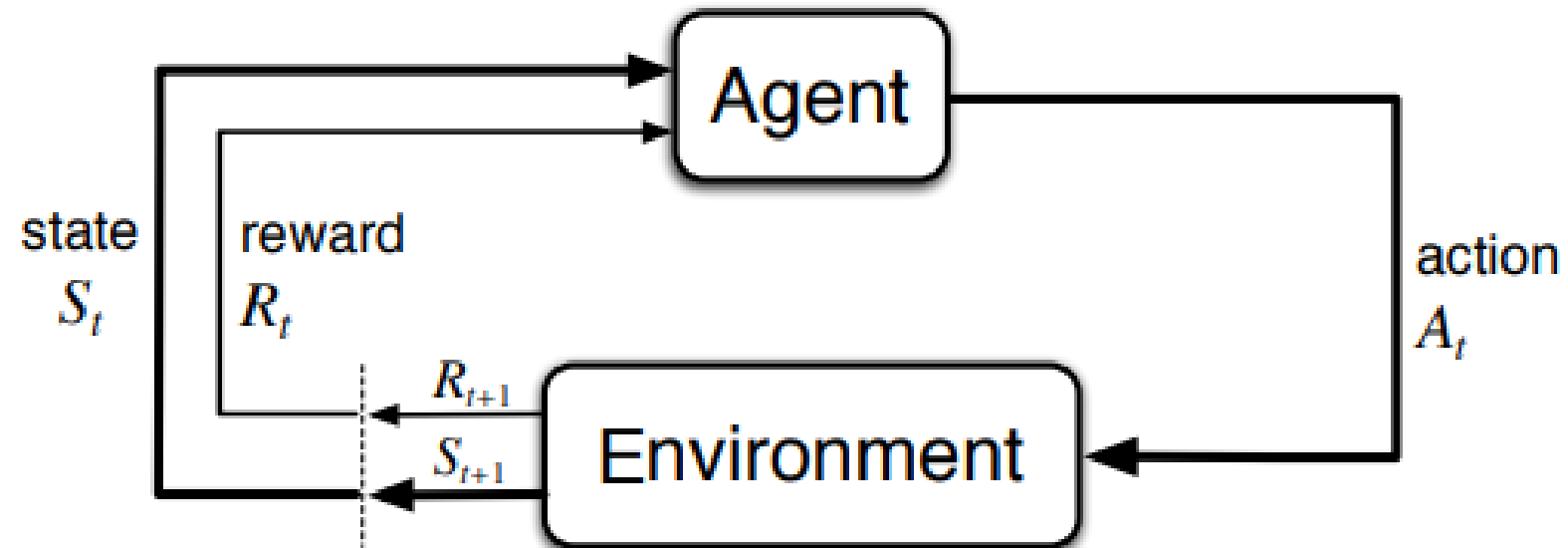
OPTIMAL POLICY

- The Optimal Policy is a behavior which takes actions that maximize the expected return.
- The Optimal Policy gives the largest Value of a State or Behavior





REINFORCEMENT LEARNING



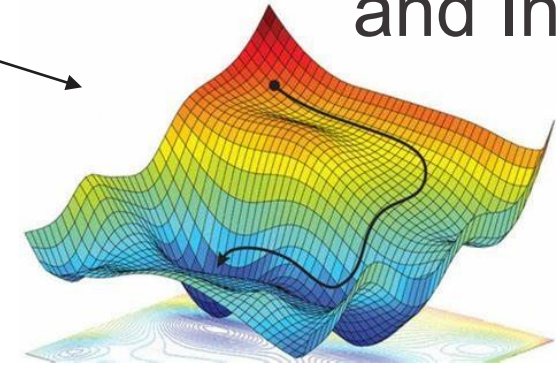


THE CYCLE OF OPTIMIZATION

Models and
Simulations



Optimization
and Insights



Real World Application



Accumulated
Data



OPTIMIZATION



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POLICY IMPROVEMENT

We want to find the actions that have a better value:

$$Q_{\pi}(s, a) > V_{\pi}(s)$$

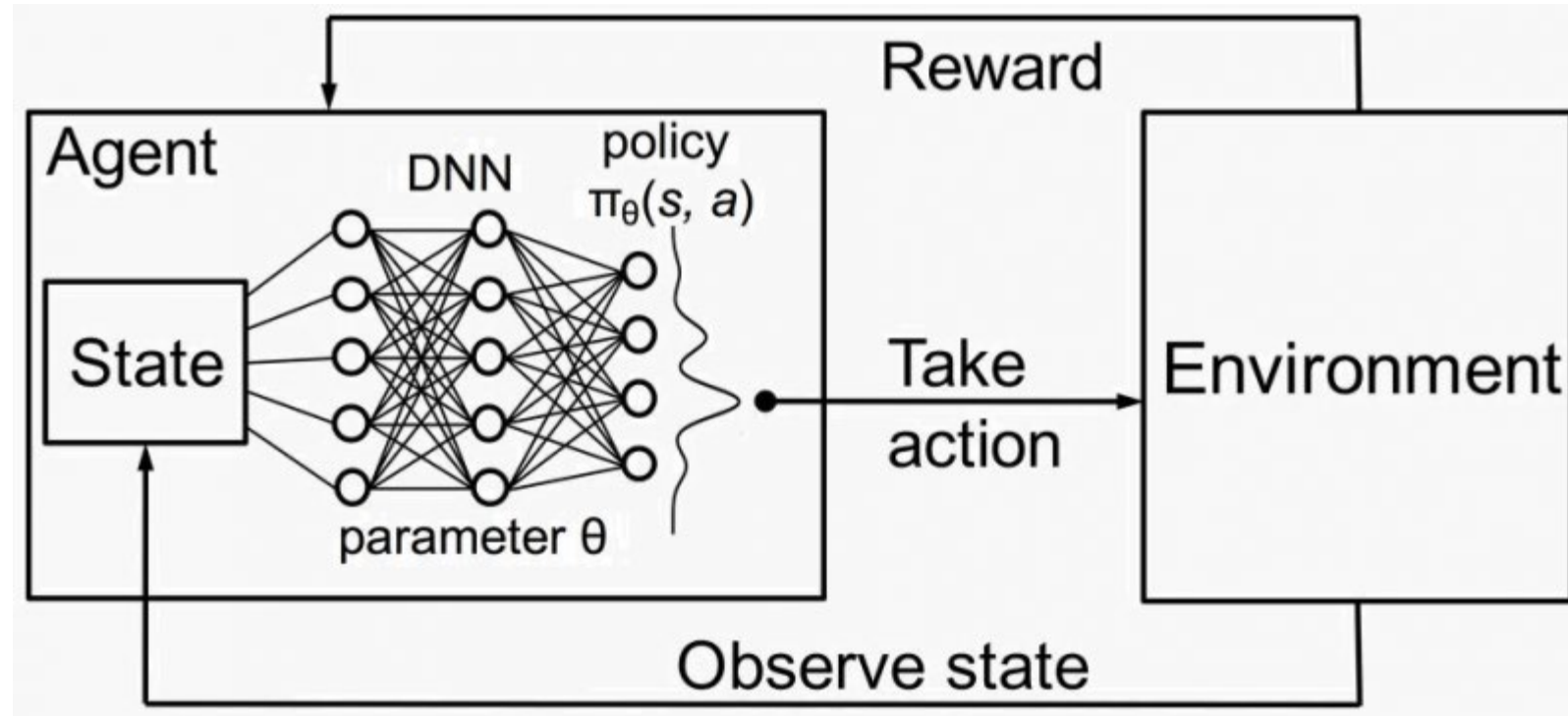
We improve our policy by taking actions with largest value

$$\pi'(s) := \operatorname{argmax}[Q_{\pi}(s, a)]$$



DEEP Q REINFORCEMENT LEARNING

- Neural Network used to approximate Q values.





SINGLE COMPONENT EXAMPLE



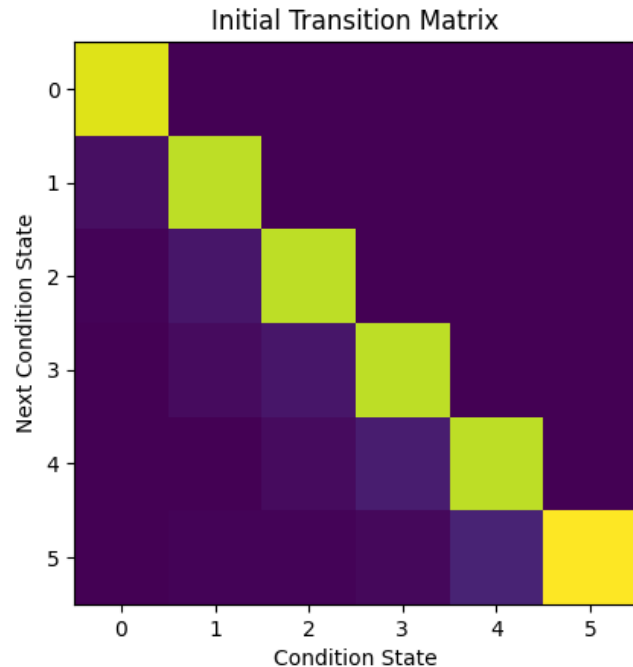
Costs:

40 – Failure

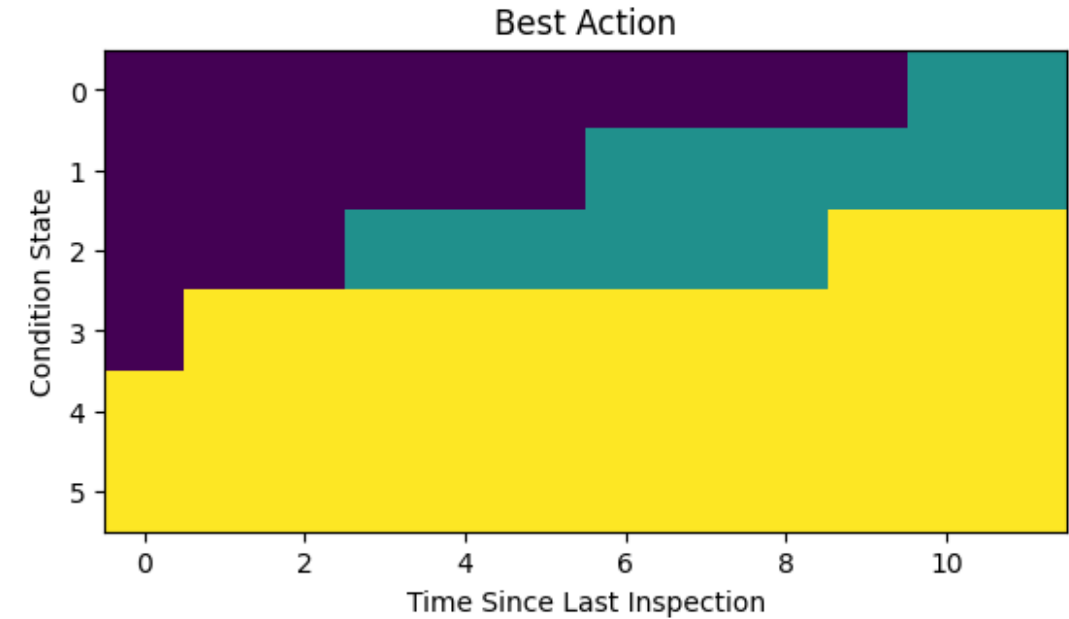
10 – Replacement

0.5 – Inspection

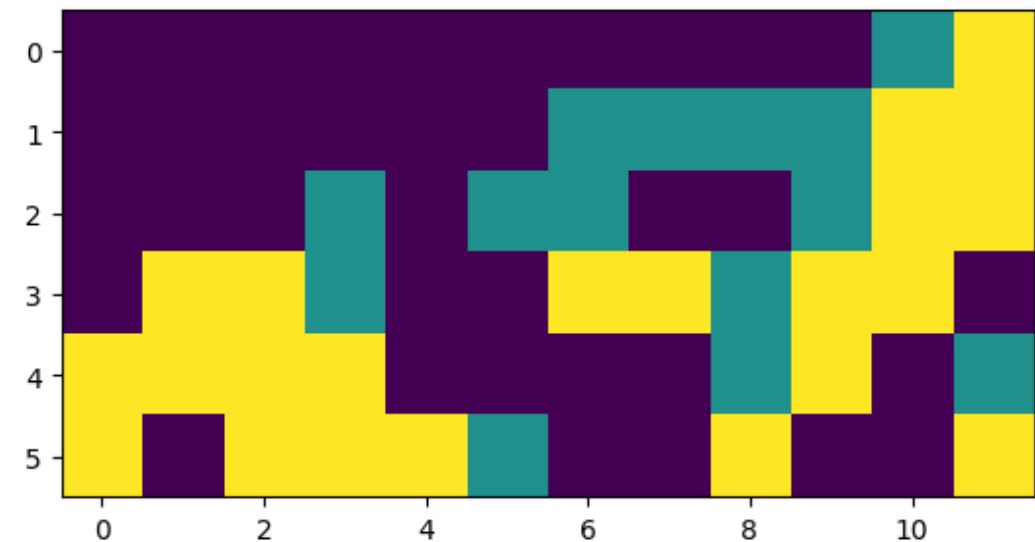
Transition Matrix:



Dynamic Programming:



Deep Q Learning:



MULTITALENT

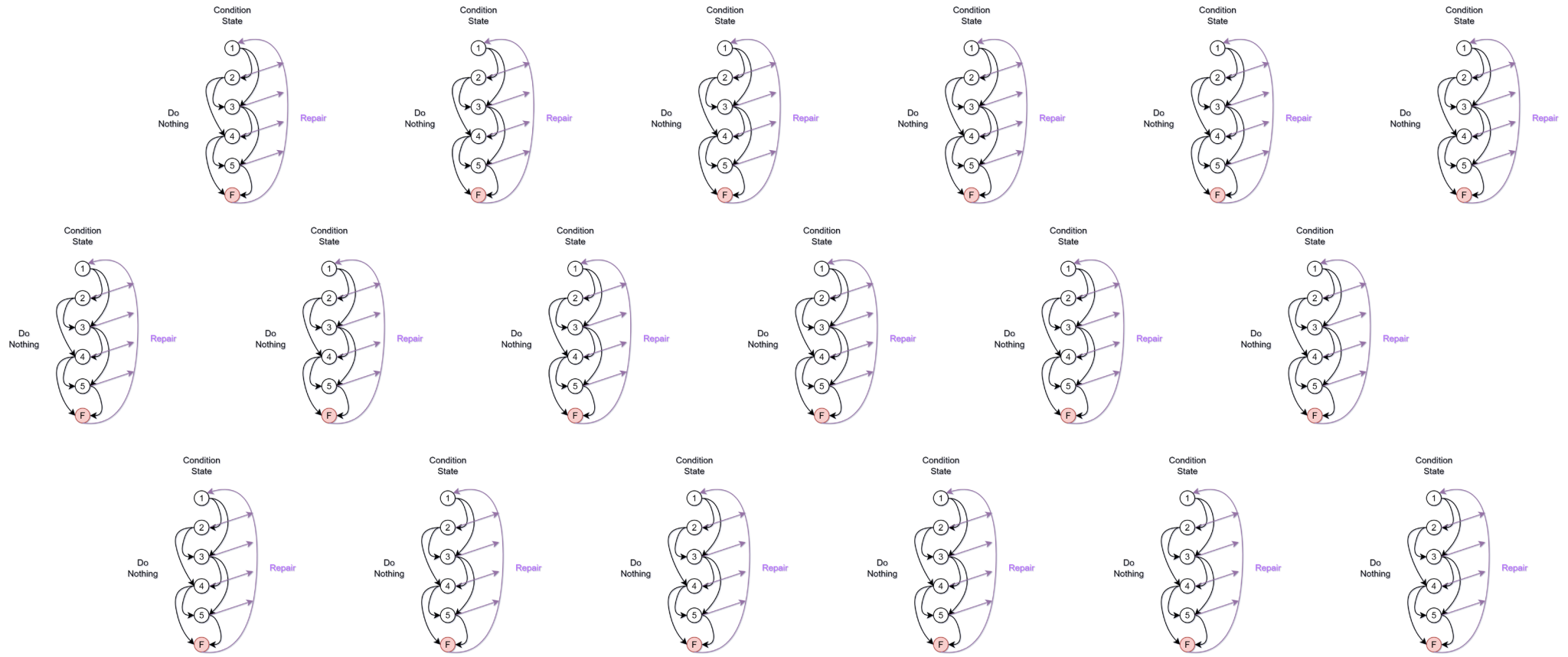


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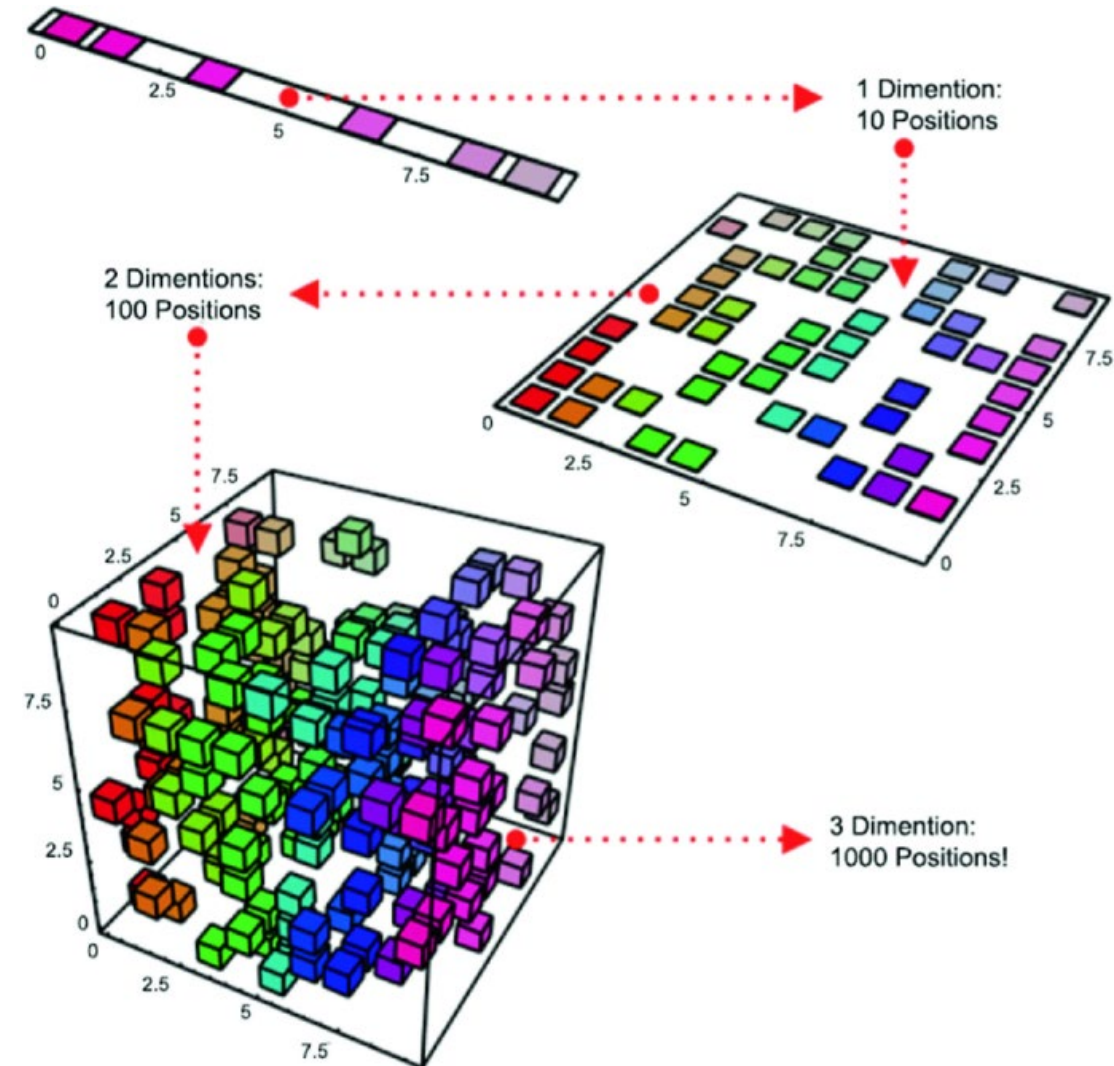
MULTI AGENTS





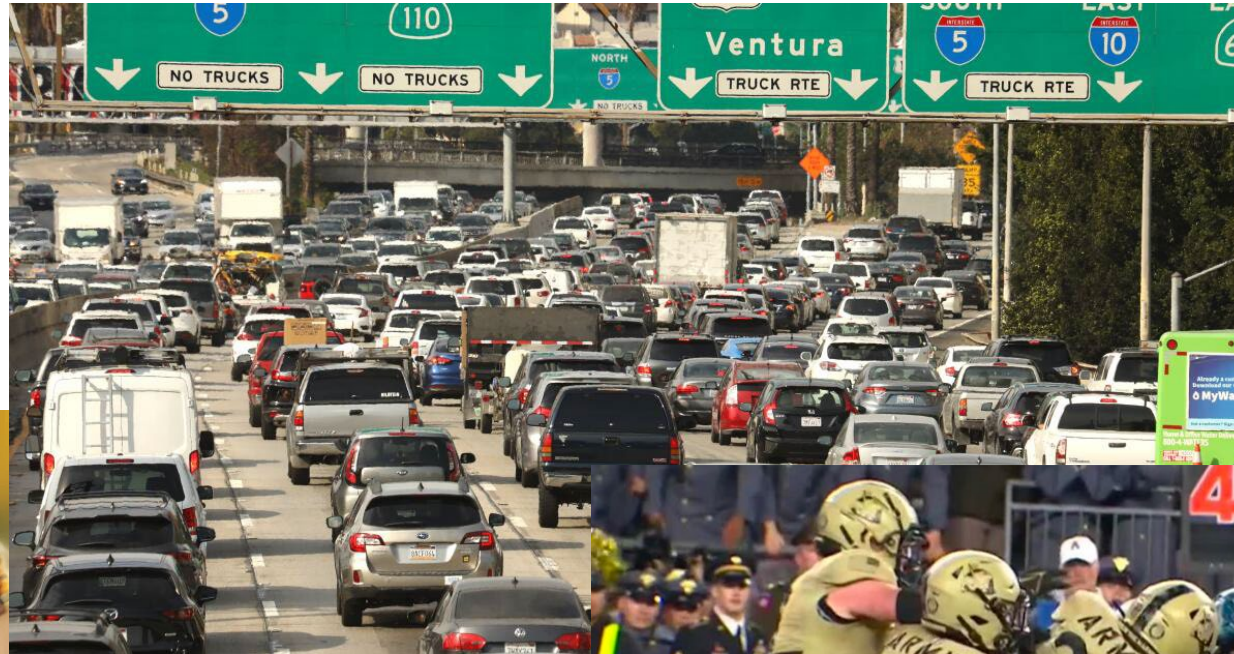
THE CURSE OF DIMENSIONALITY

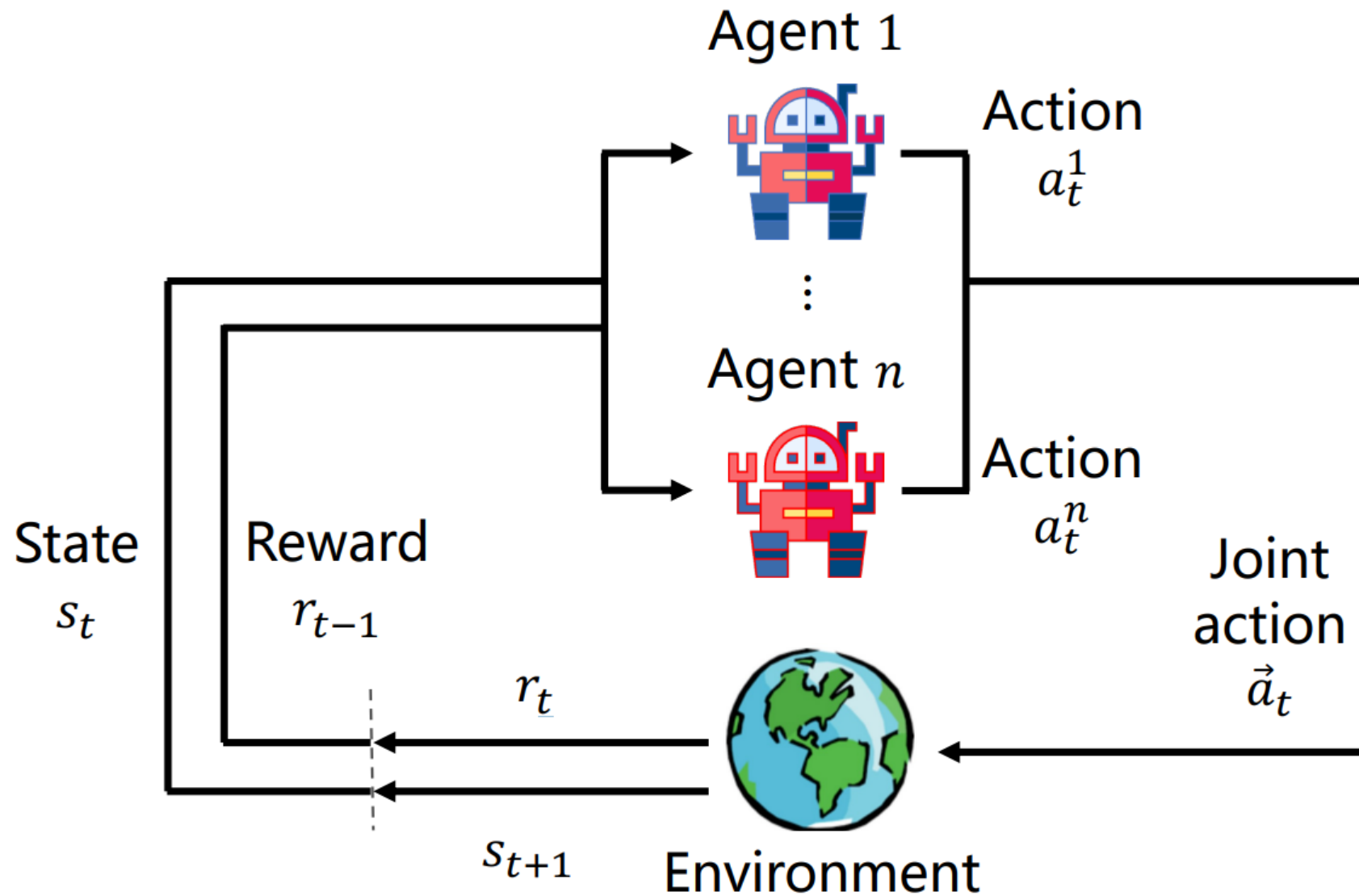
- If each of n agents can take one of K actions, then there are K^n possibilities for each state.
- If each value is a byte of data, with **15 components** we would need more than a **terabyte** of data to store all **action values** for a single state.





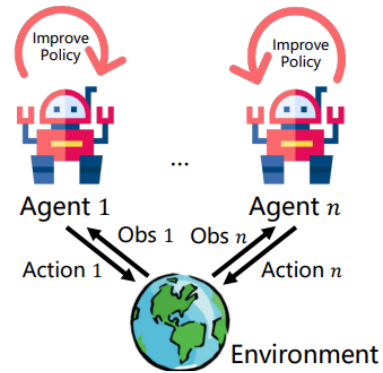
MULTI AGENT SYSTEM EXAMPLES



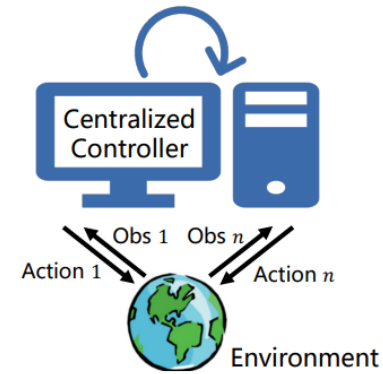




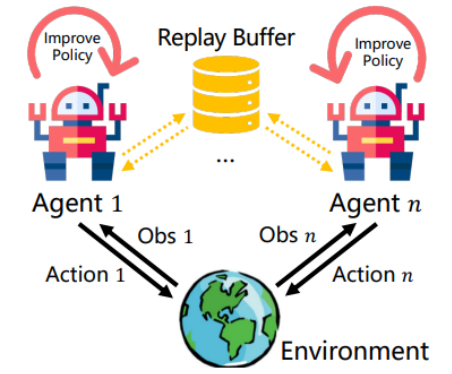
HIVE MINDS | (DE)CENTRALIZED



(a) Decentralized Training
Decentralized Execution



(b) Centralized Training
Centralized Execution



(c) Centralized Training
Decentralized Execution





CREDIT ASSIGNMENT

When a better action is explored by one agent, other agents may think that the better value was their doing.





NON-STATIONARY PROBLEM

As one agent learns, the environment dynamics change for the rest.





OBSERVATION AND PRIVACY

In real world problems, not every agent may be able to know everything about the other agents.





COOPERATED EXPLORATION

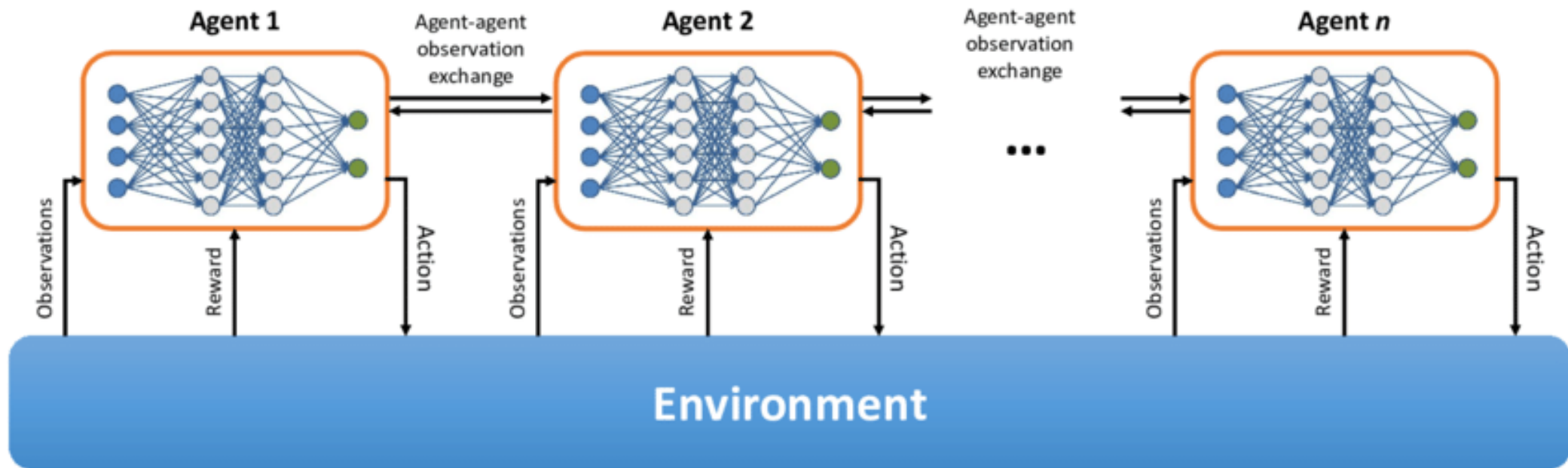
Exploring a massive state space can lead to slow and inefficient learning





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MADQRL

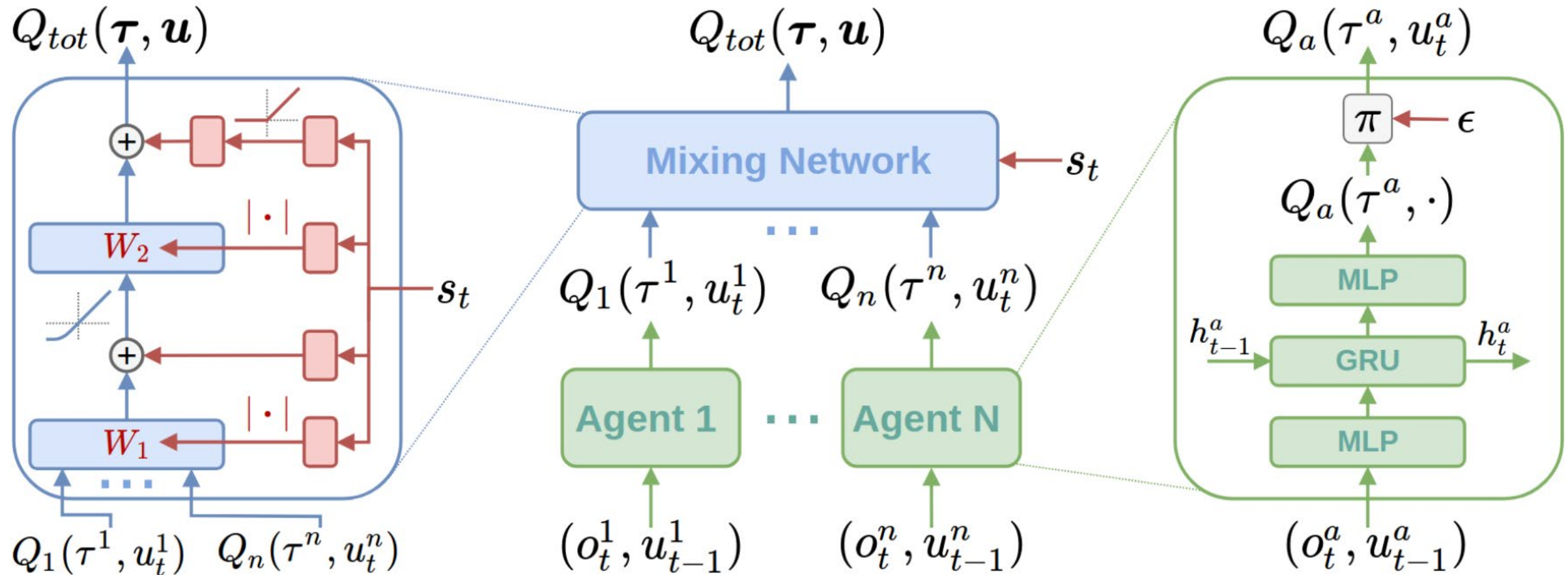


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QMIX



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MADQRL EXAMPLE

4 Agents learning when to best Inspect/Repair to minimize total maintenance cost.

Only 1 repair is allowed per timestep.

