



Plan de Recuperación,
Transformación y Resiliencia



Financiado por
la Unión Europea
NextGenerationEU



ACT. 4.24 OPTIMIZACIÓN DE RUTAS DE INSPECCIÓN DE
MANTENIMIENTO

IA4TES

www.baobabsoluciones.es

Programa Misiones de I+D en Inteligencia Artificial 2021, en el marco de la Agenda España Digital 2025 y de la Estrategia Nacional de Inteligencia Artificial, Proyecto IA4TES financiado por el Plan de Recuperación, Transformación y Resiliencia.

Número de expediente TSI-100408-2021-0



1. OUR PROBLEM

Overview of the Multi-Period Team Orienteering Problem with Time Windows (TOPTW), focused on optimizing routes by considering power generators, time constraints, and team availability.



2. RL

Application of reinforcement learning algorithms to address combinatorial optimization challenges, emphasizing their adaptability compared to heuristic methods.



3. HEURISTIC

Development of daily updated solutions incorporating merging processes to effectively manage multi-period complexities, balancing practicality with efficiency.



4. RESULTS

Analysis of average outcomes across 256 instances, demonstrating the advantages of RL over heuristics in computational efficiency and performance under specific conditions.

MAINTENANCE ROUTE
OPTIMIZATION

INDEX



LEARN TO DEVELOP RL ALGORITHMS TO SOLVE COMBINATORIAL OPTIMIZATION PROBLEMS.

- Understand the drawbacks of RL in comparison to heuristics.
- Explore the advantages of RL over heuristics.



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DEVELOP A RL METHOD



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DEVELOP A RL METHOD

DEVELOP A BR - HEURISTIC



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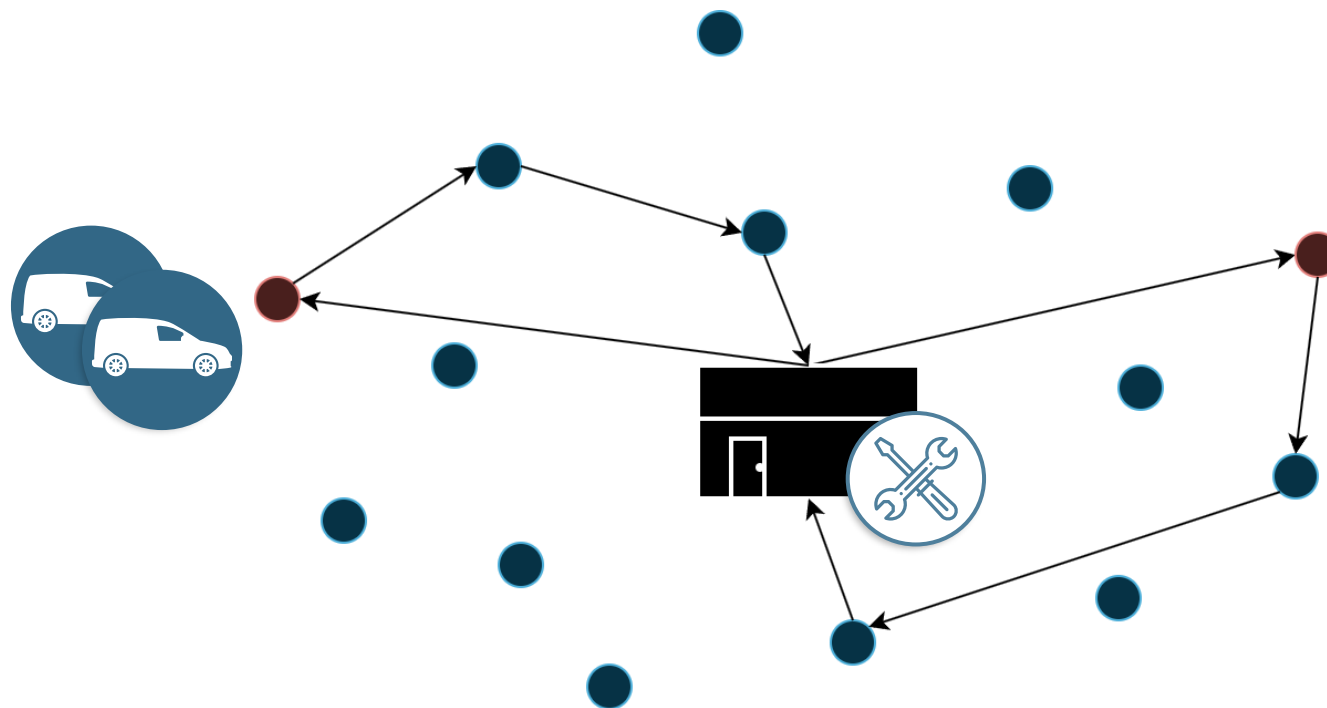


TOP

Team Orienteering
Problem

MAINTENANCE ROUTE
OPTIMIZATION

OUR PROBLEM



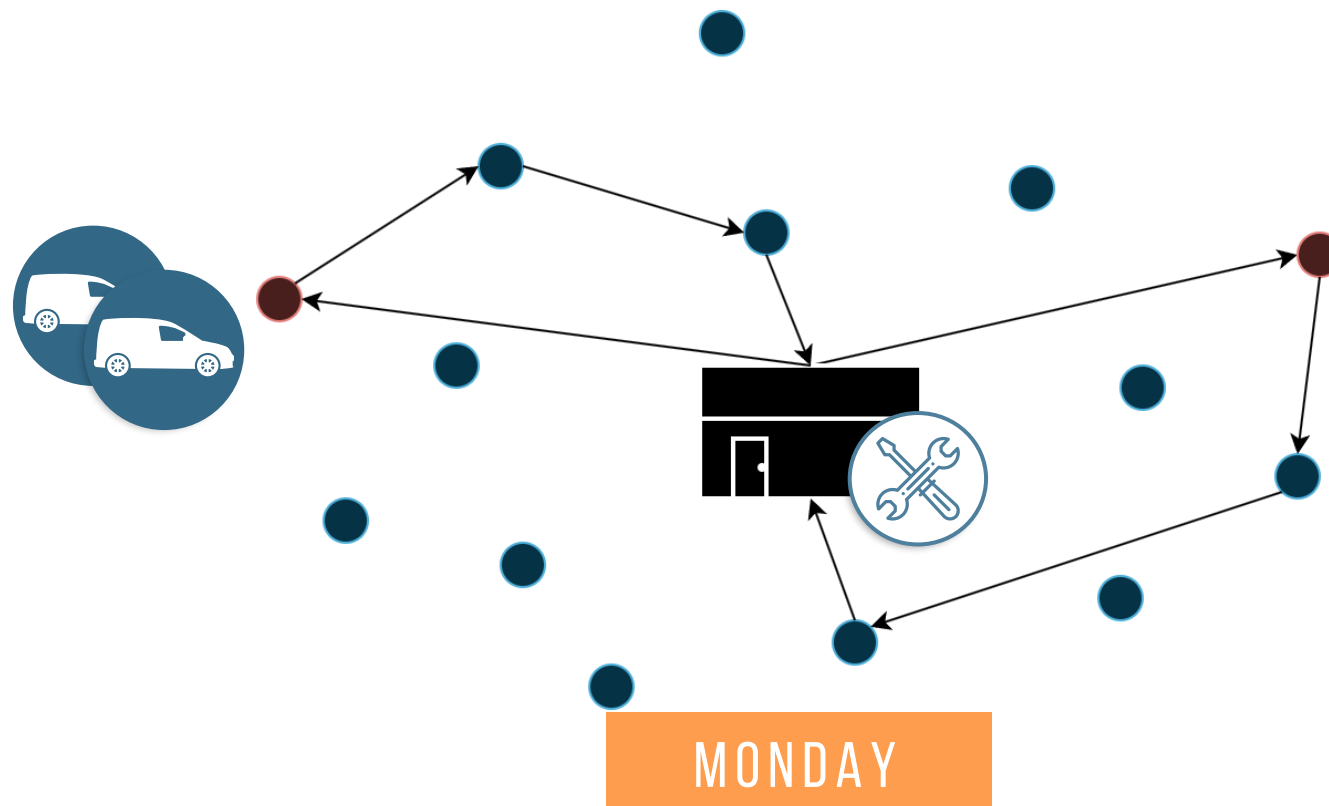


TOP

Team Orienteering
Problem



MULTI - PERIOD



MAINTENANCE ROUTE
OPTIMIZATION

OUR
PROBLEM



Team Orienteering Problem

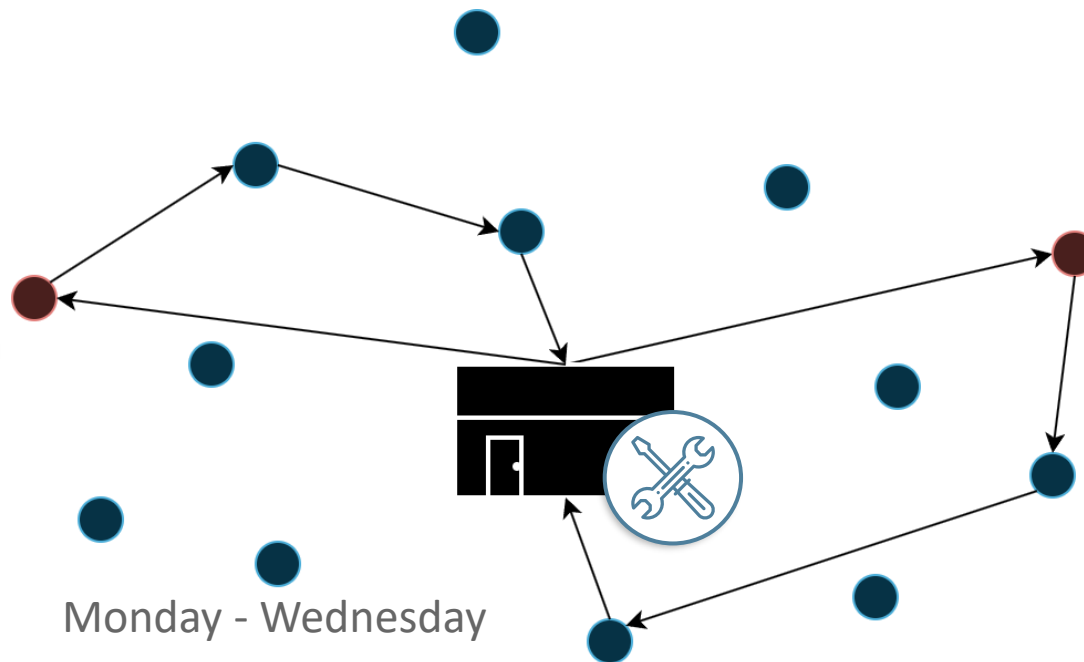


MULTI - PERIOD



TW

Time Windows



Monday - Wednesday

MONDAY

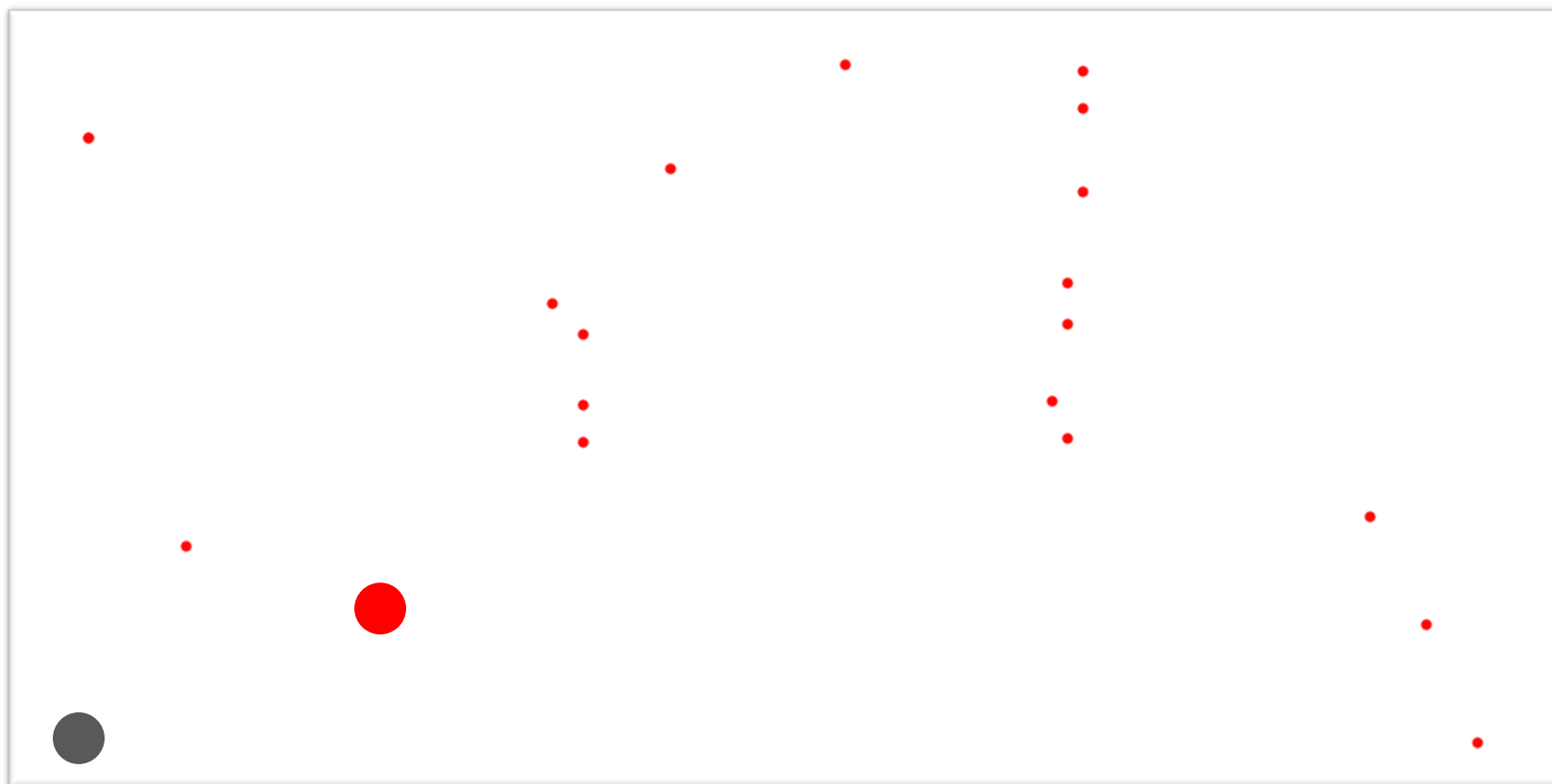
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NextGenerationEU

MAINTENANCE ROUTE OPTIMIZATION

OUR PROBLEM

OUR PROBLEM



● POWER GENERATORS / NODES

● STARTING / ENDING POINT

MAINTENANCES:



Corrective



Preventive



Predictive



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OUR PROBLEM

ASPECTS TO CONSIDER:

Monday to Friday

Work 8 hours/480 min

Multiple teams

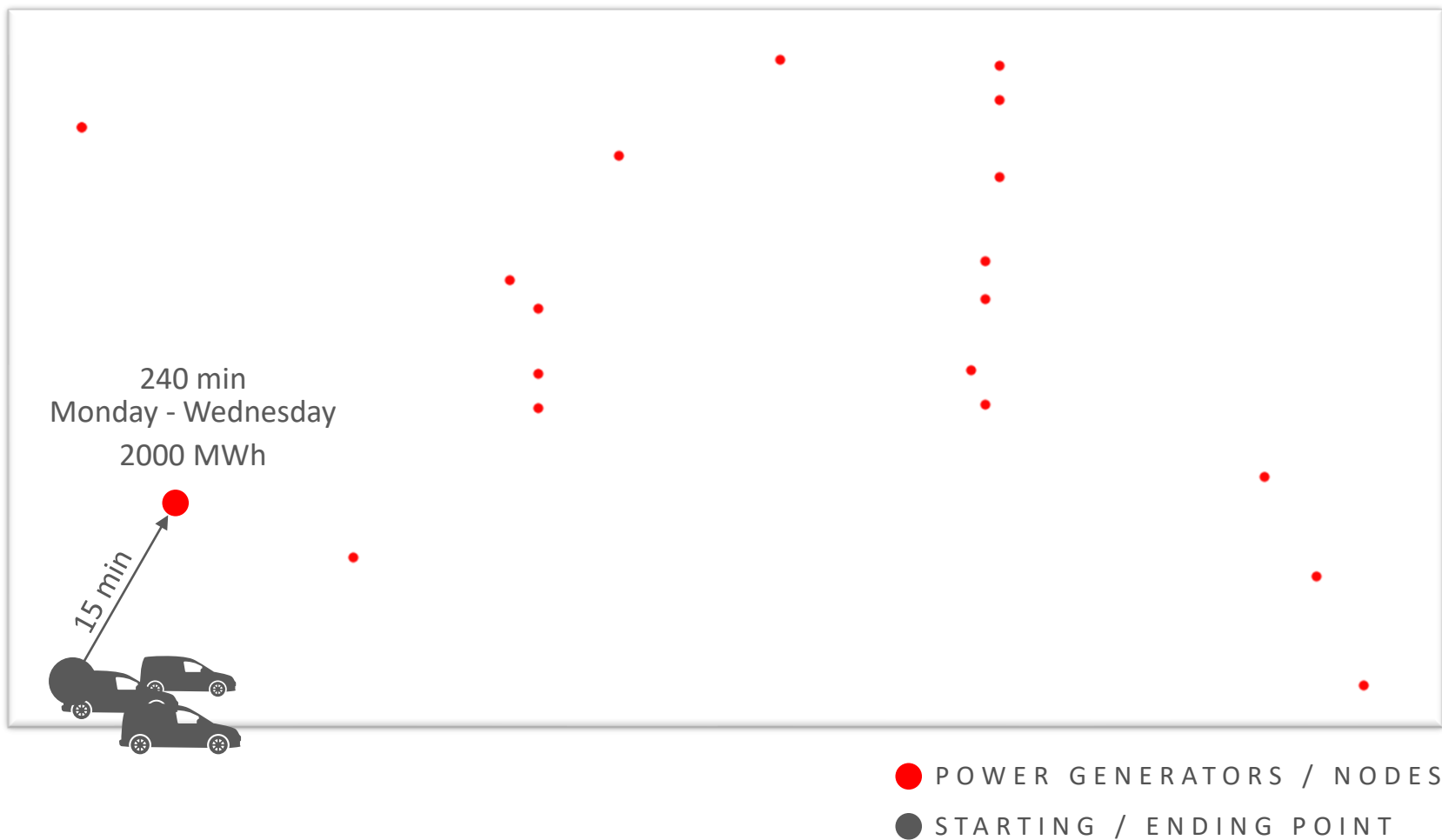
Travel times

Maintenance duration

Time Windows (TW)

Energy production

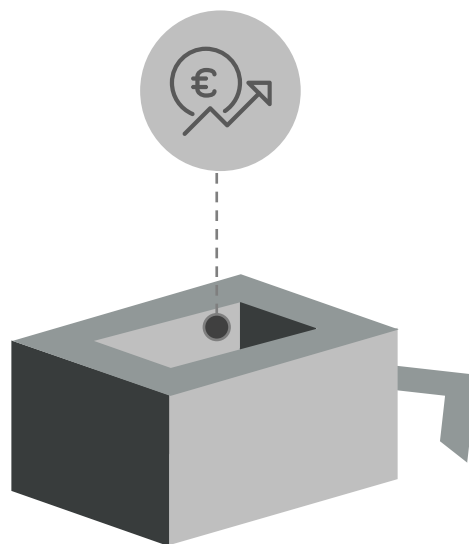
Energy price



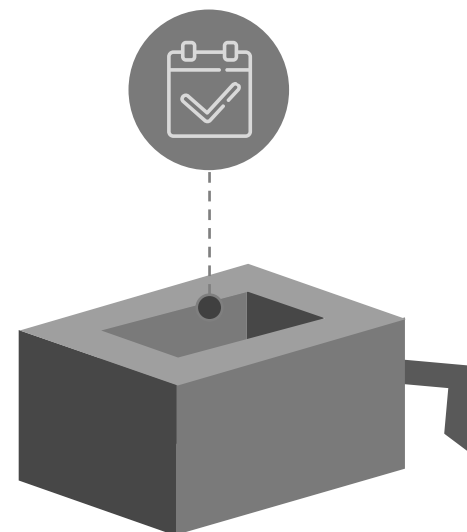
MAINTENANCE ROUTE
OPTIMIZATION

OUR PROBLEM GOAL

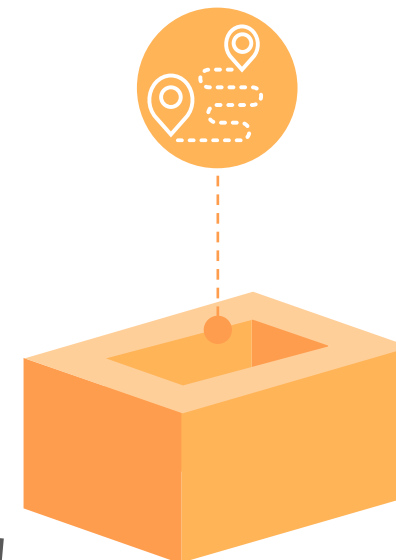
MAXIMIZE PROFITS



ORGANIZE WEEK
SCHEDULE



OPTIMIZE ROUTES





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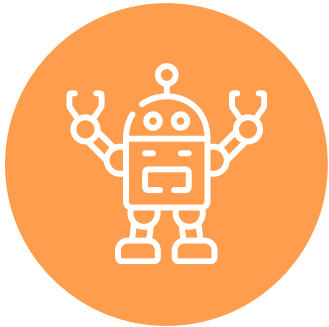
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MAINTENANCE ROUTE
OPTIMIZATION

INDEX

M E T H O D O L O G Y (R L)

REINFORCEMENT LEARNING



AGENT

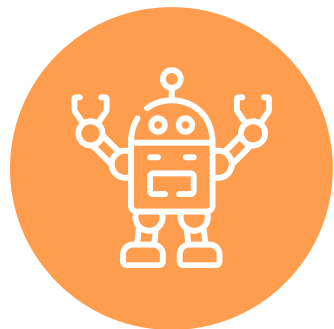


ENVIRONMENT



M E T H O D O L O G Y (R L)

REINFORCEMENT LEARNING



AGENT

OBSERVATIONS

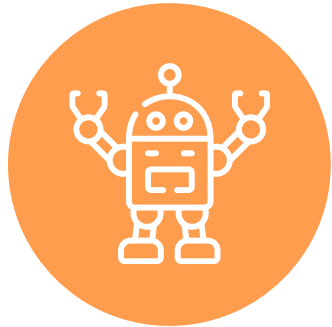


ENVIRONMENT



M E T H O D O L O G Y (R L)

REINFORCEMENT LEARNING



AGENT

ACTIONS

OBSERVATIONS

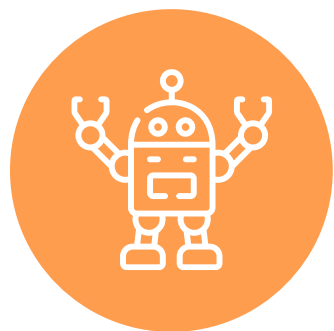


ENVIRONMENT

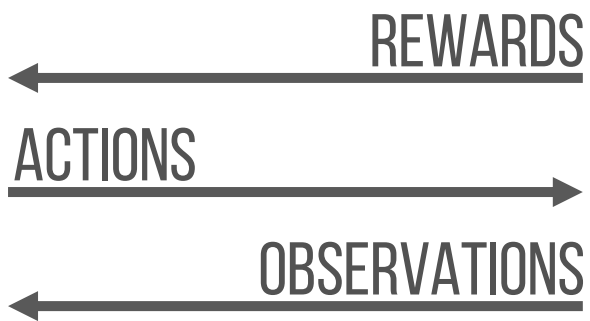


M E T H O D O L O G Y (R L)

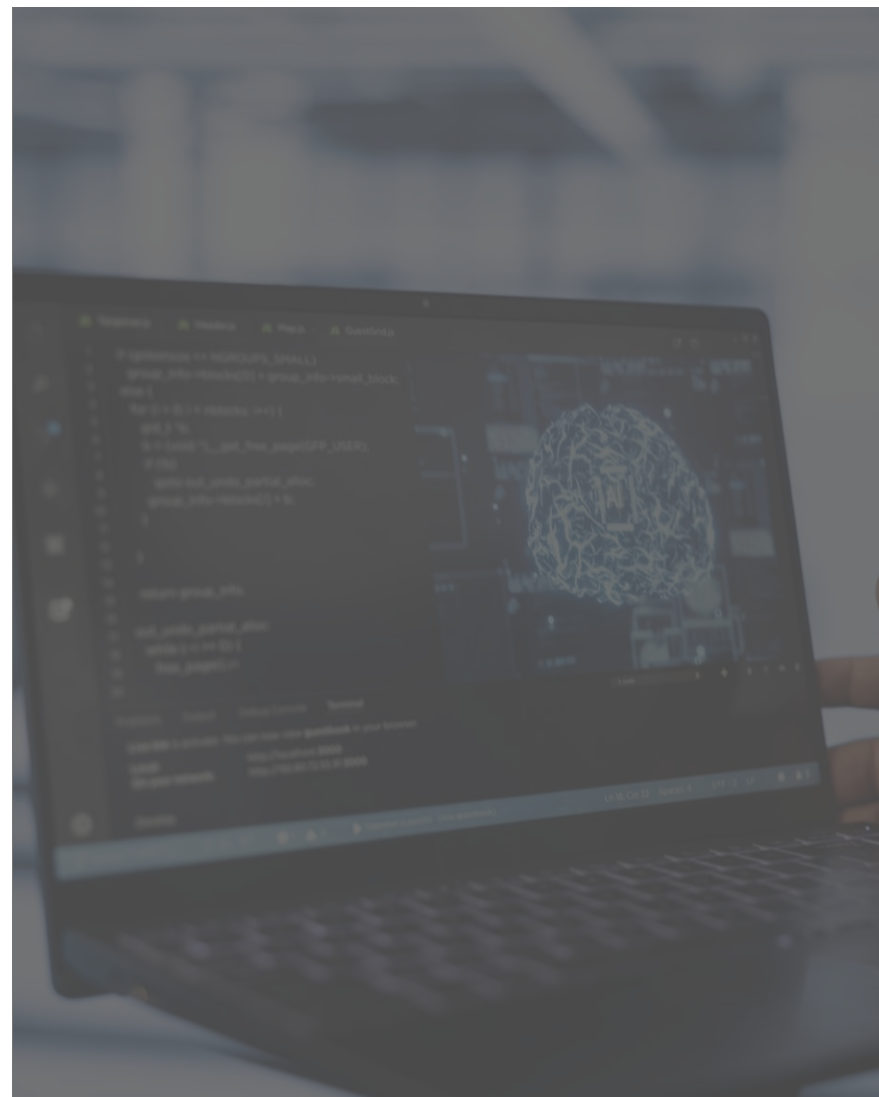
REINFORCEMENT LEARNING



AGENT

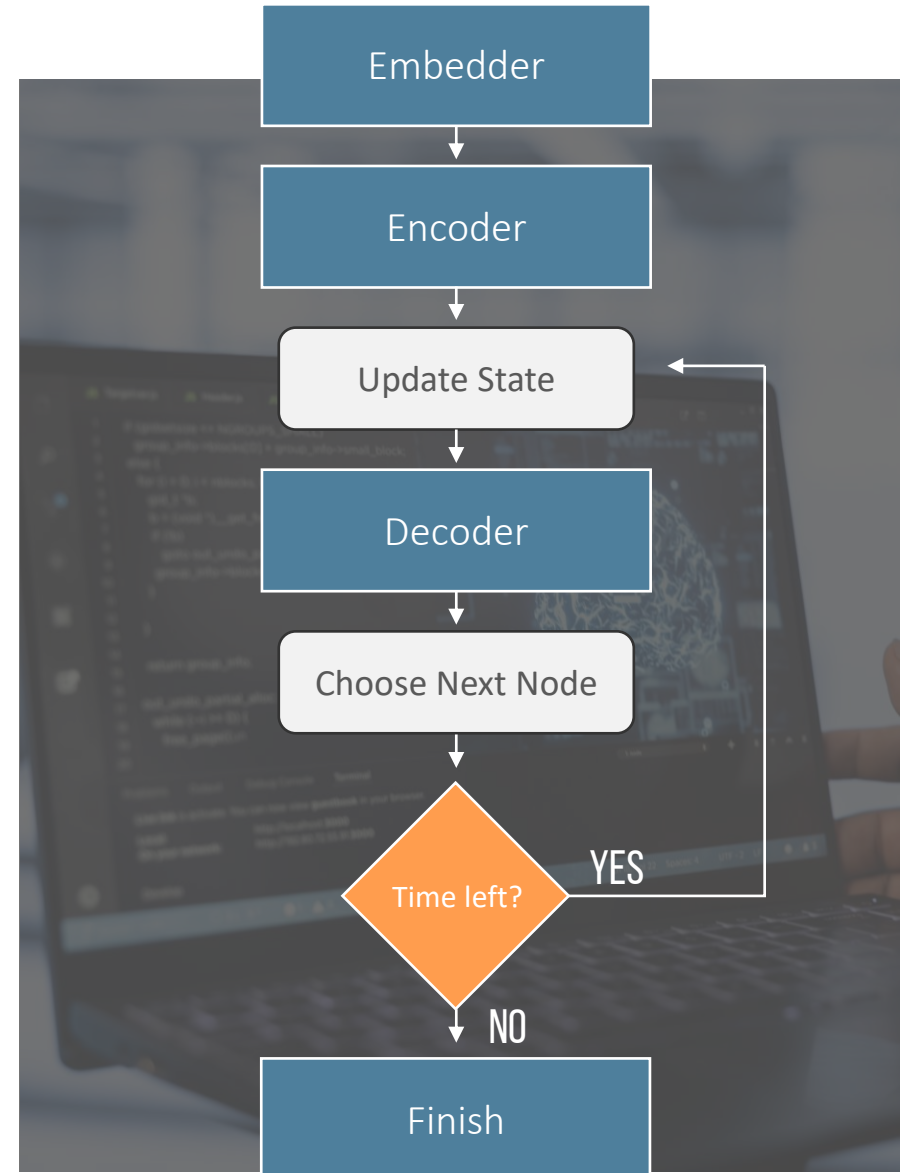
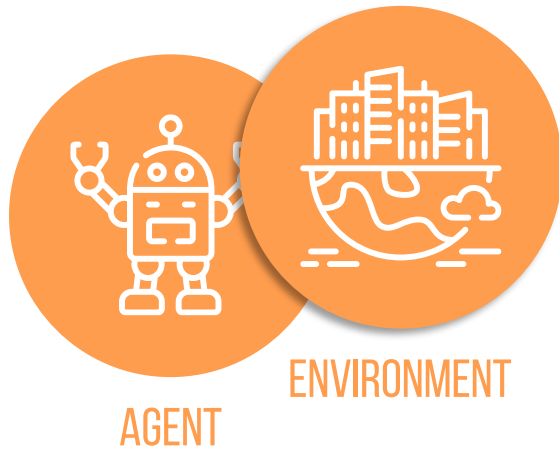


ENVIRONMENT



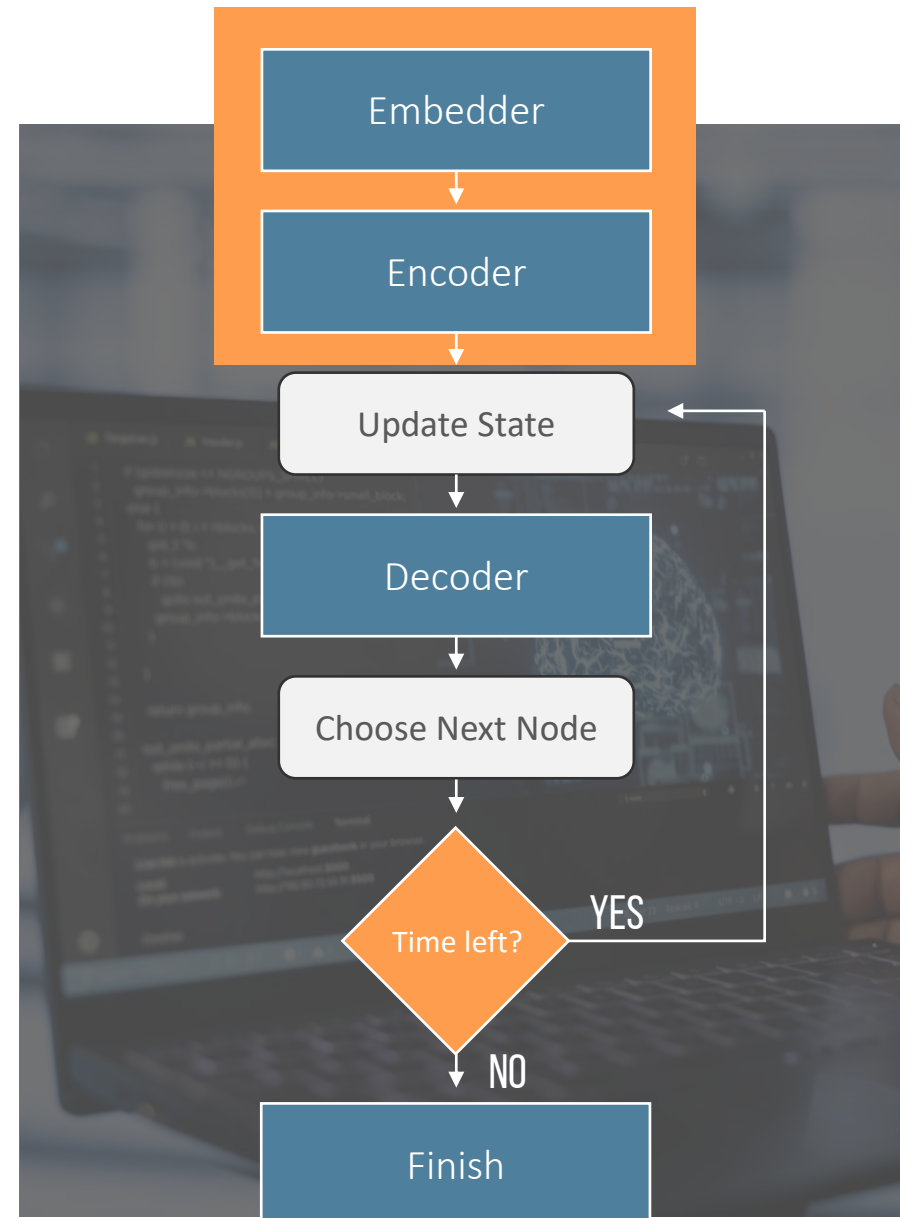
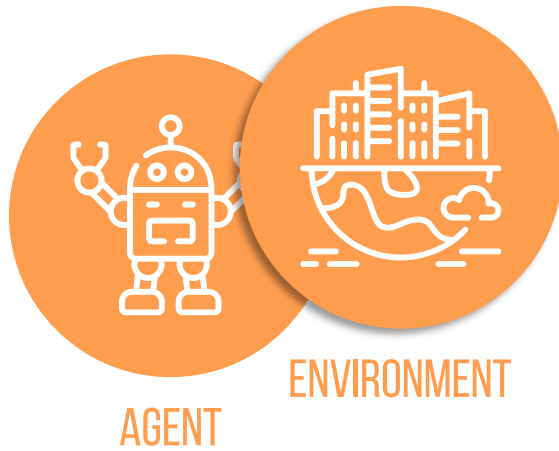
M E T H O D O L O G Y (R L)

REINFORCEMENT LEARNING



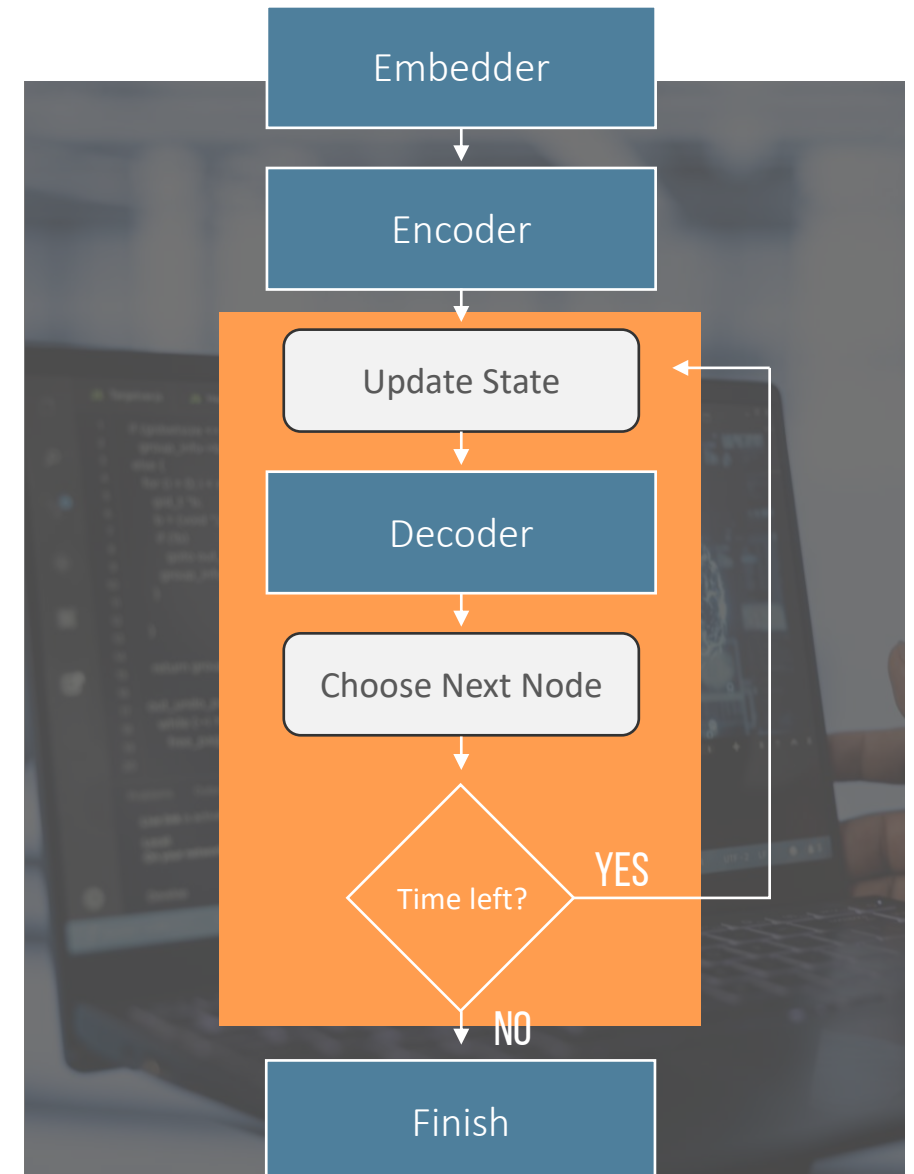
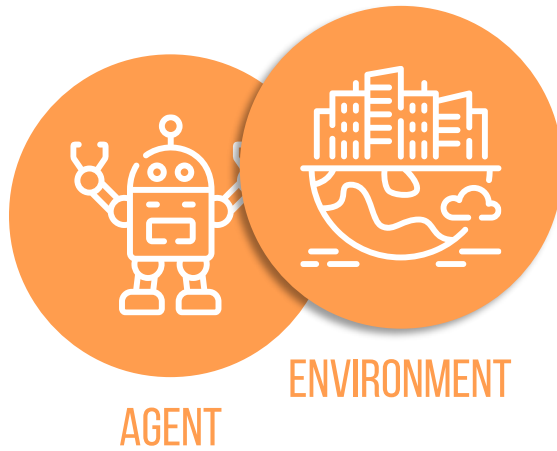
M E T H O D O L O G Y (R L)

REINFORCEMENT LEARNING

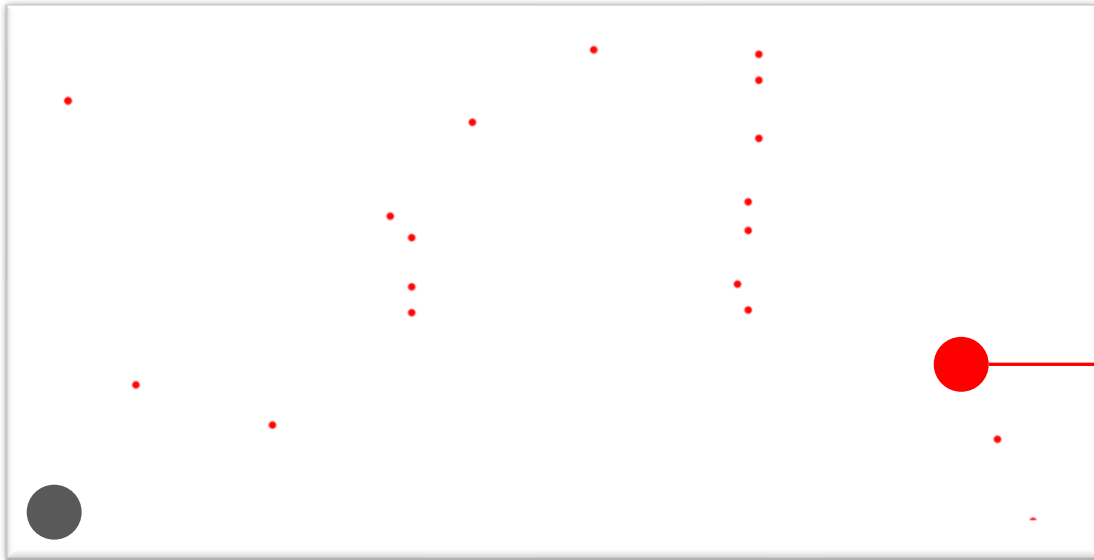


M E T H O D O L O G Y (R L)

REINFORCEMENT LEARNING



● POWER GENERATORS / NODES
● STARTING / ENDING POINT

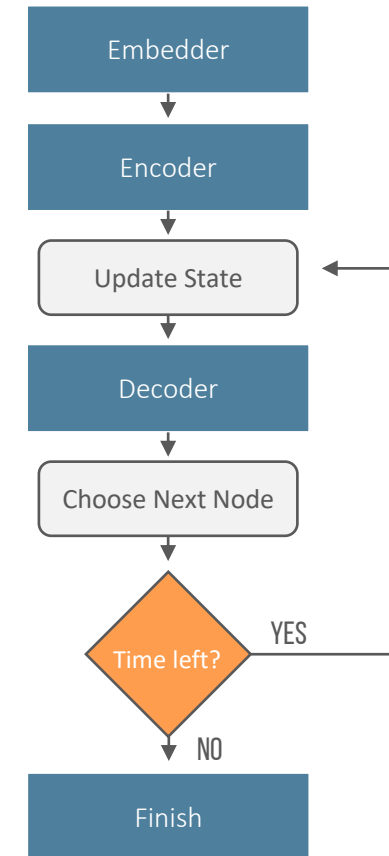


NODE

CHARACTERISTICS

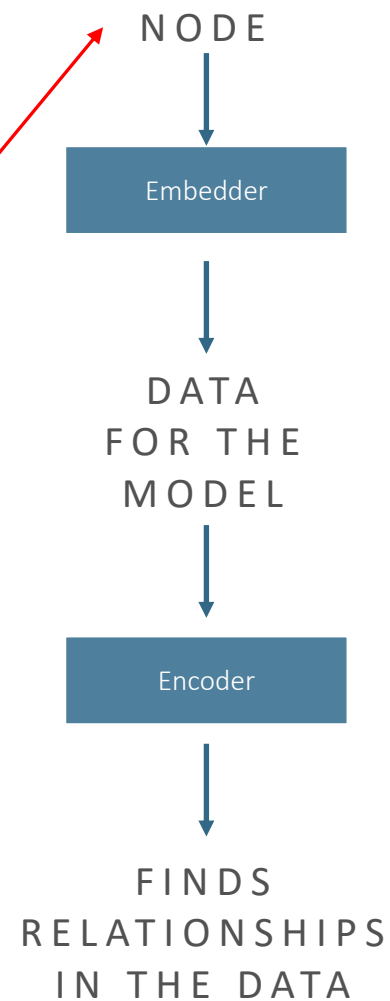
Position,
etc.

NODE REPRESENTATION

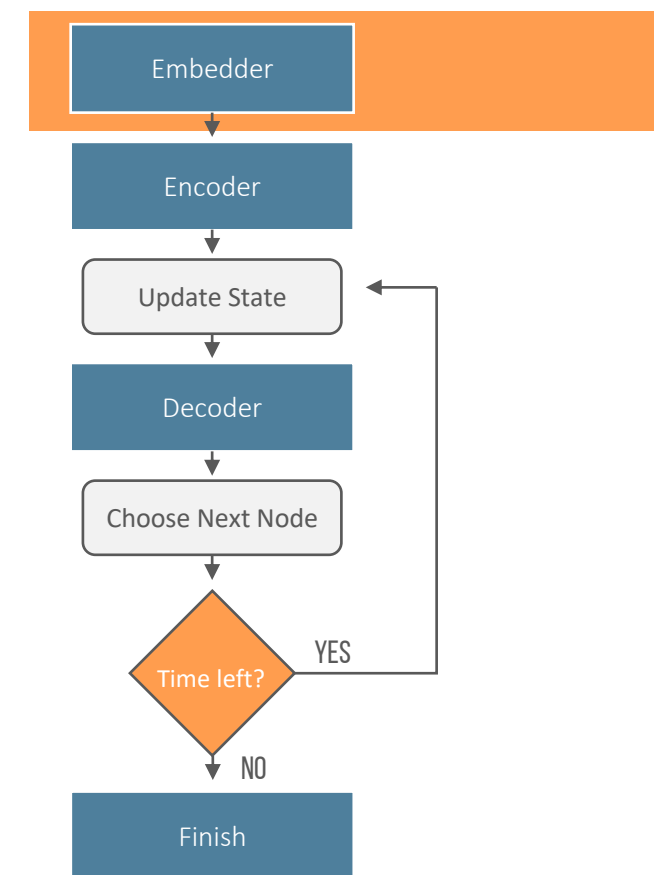


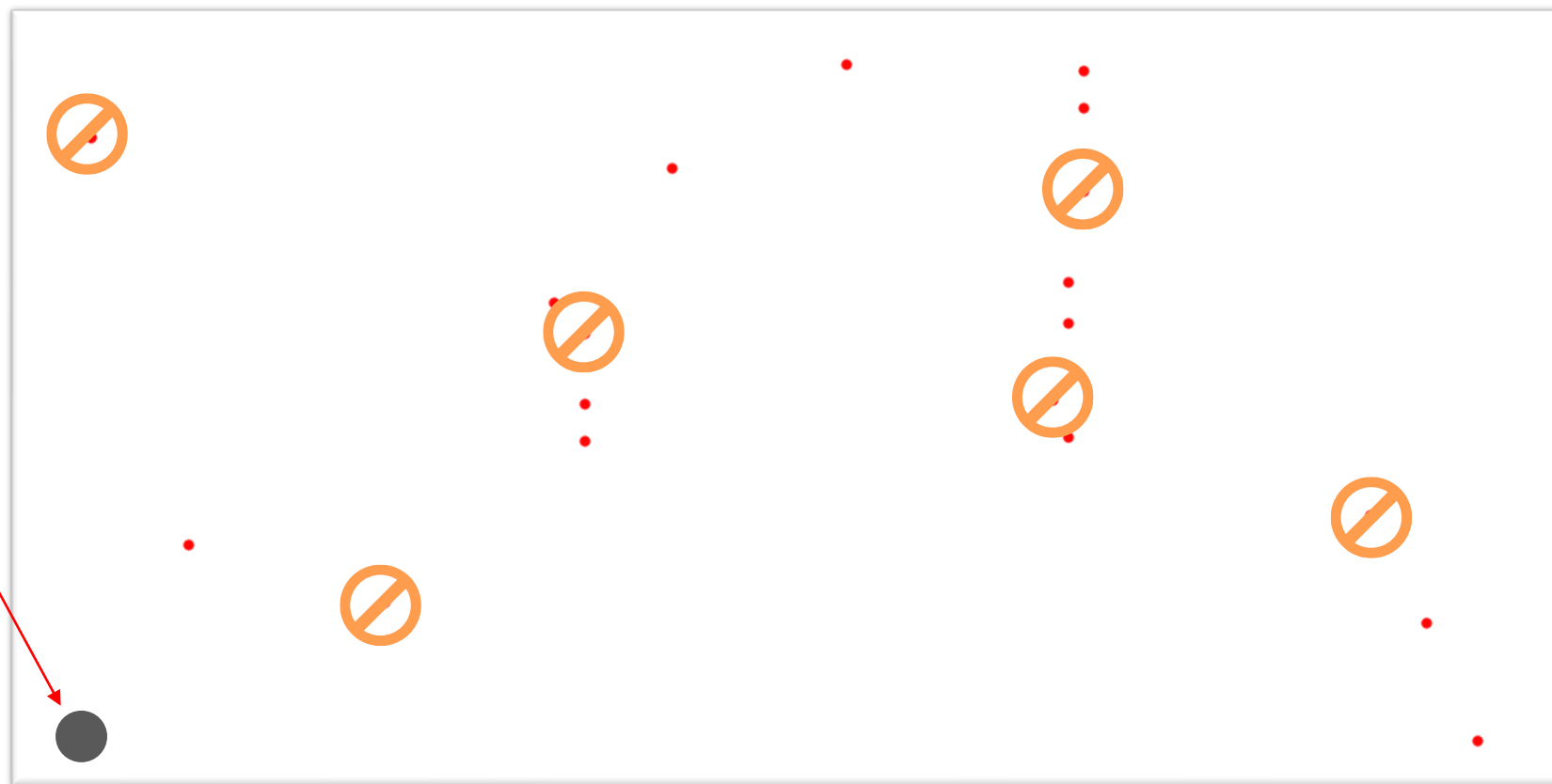
● POWER GENERATORS / NODES

● STARTING / ENDING POINT



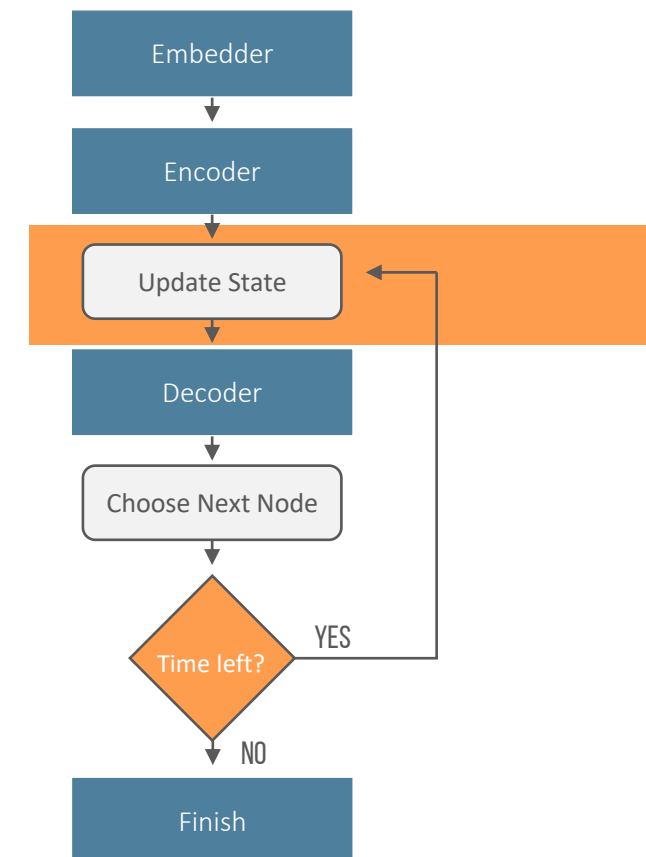
EMBEDDER



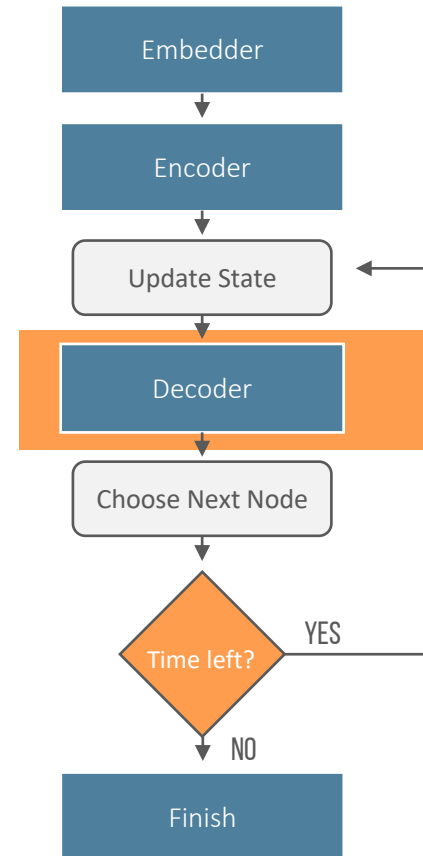
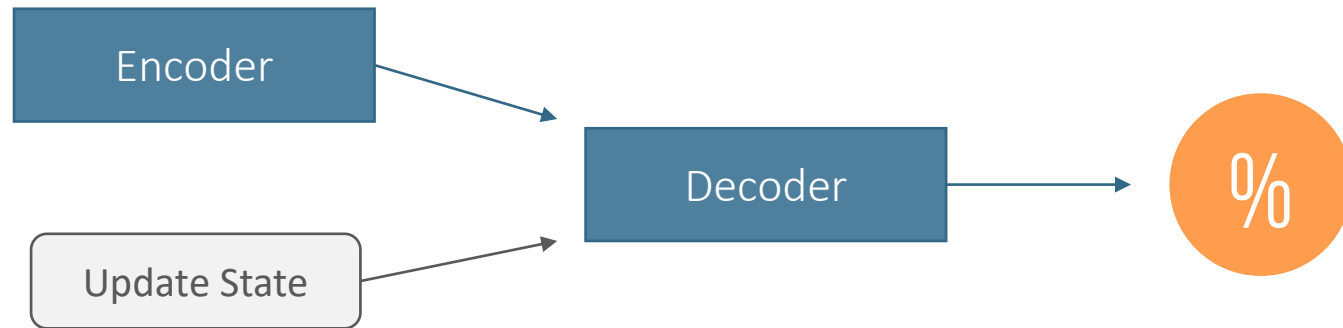


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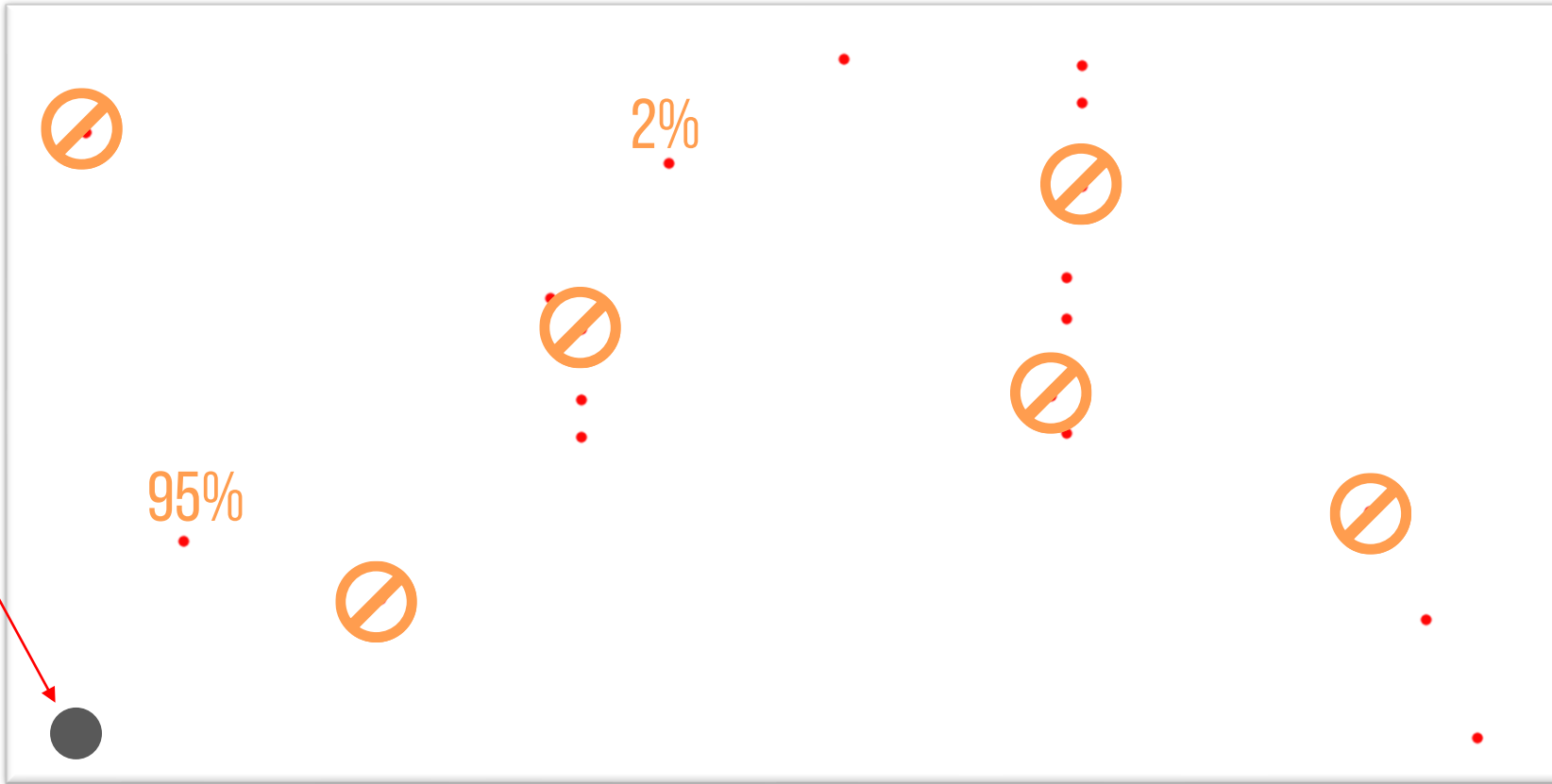
UPDATE STATE



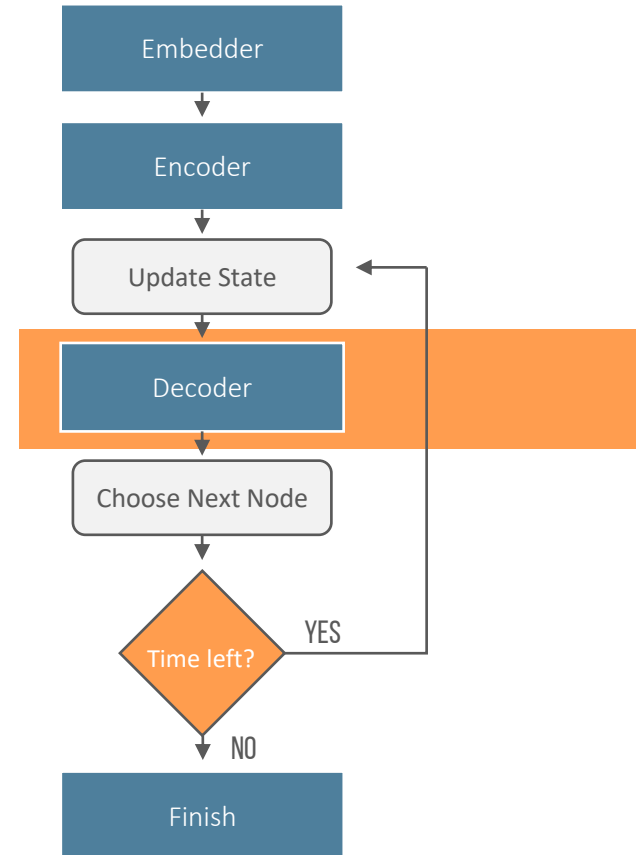
DECODER



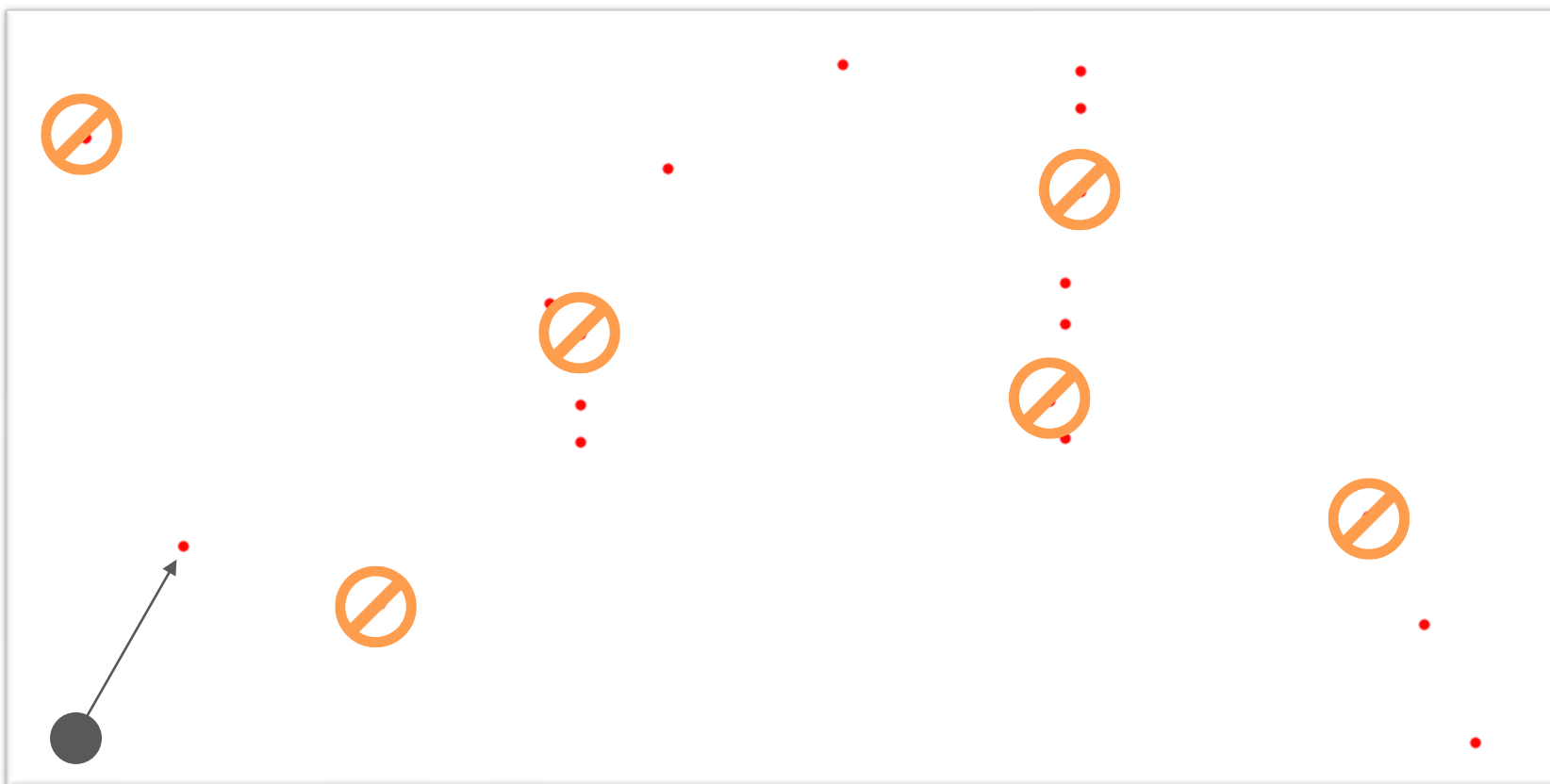
● POWER GENERATORS / NODES
● STARTING / ENDING POINT



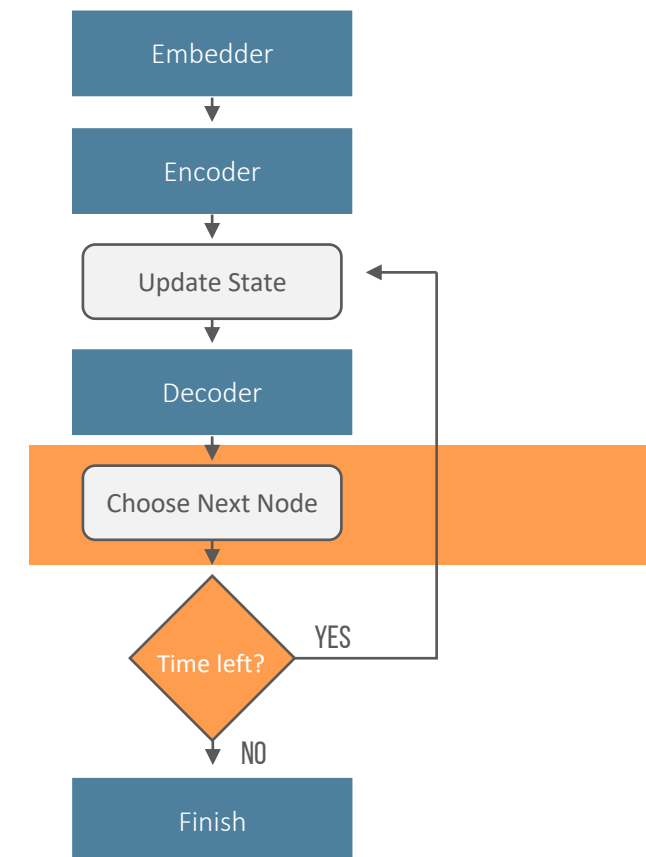
DECODER





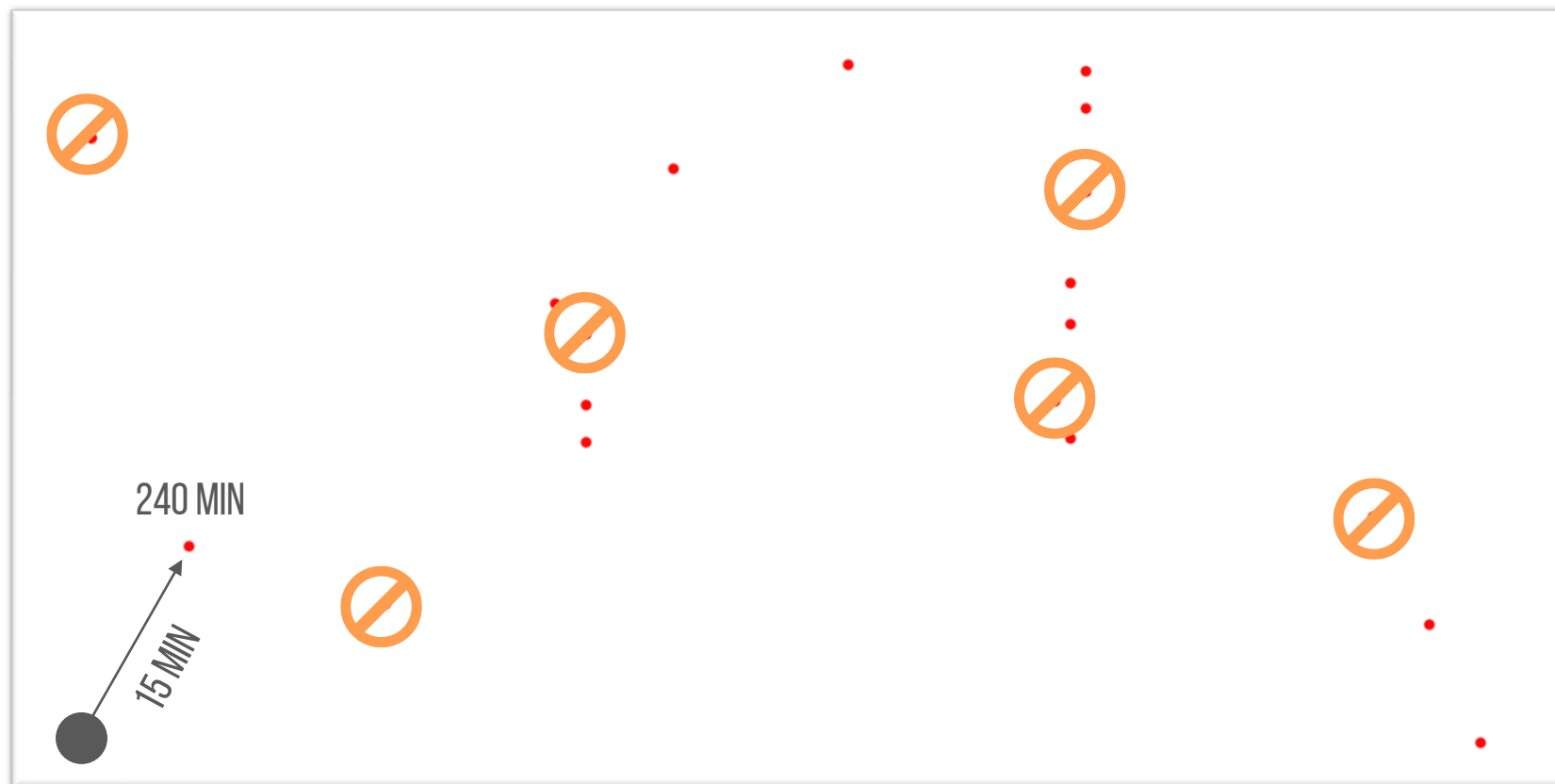


CHOOSE NEXT NODE



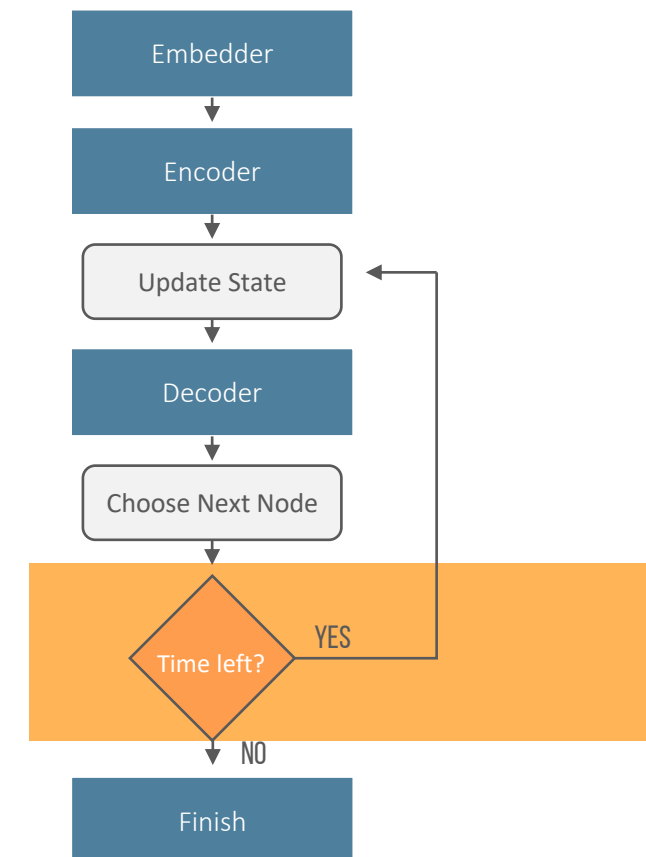
● POWER GENERATORS / NODES

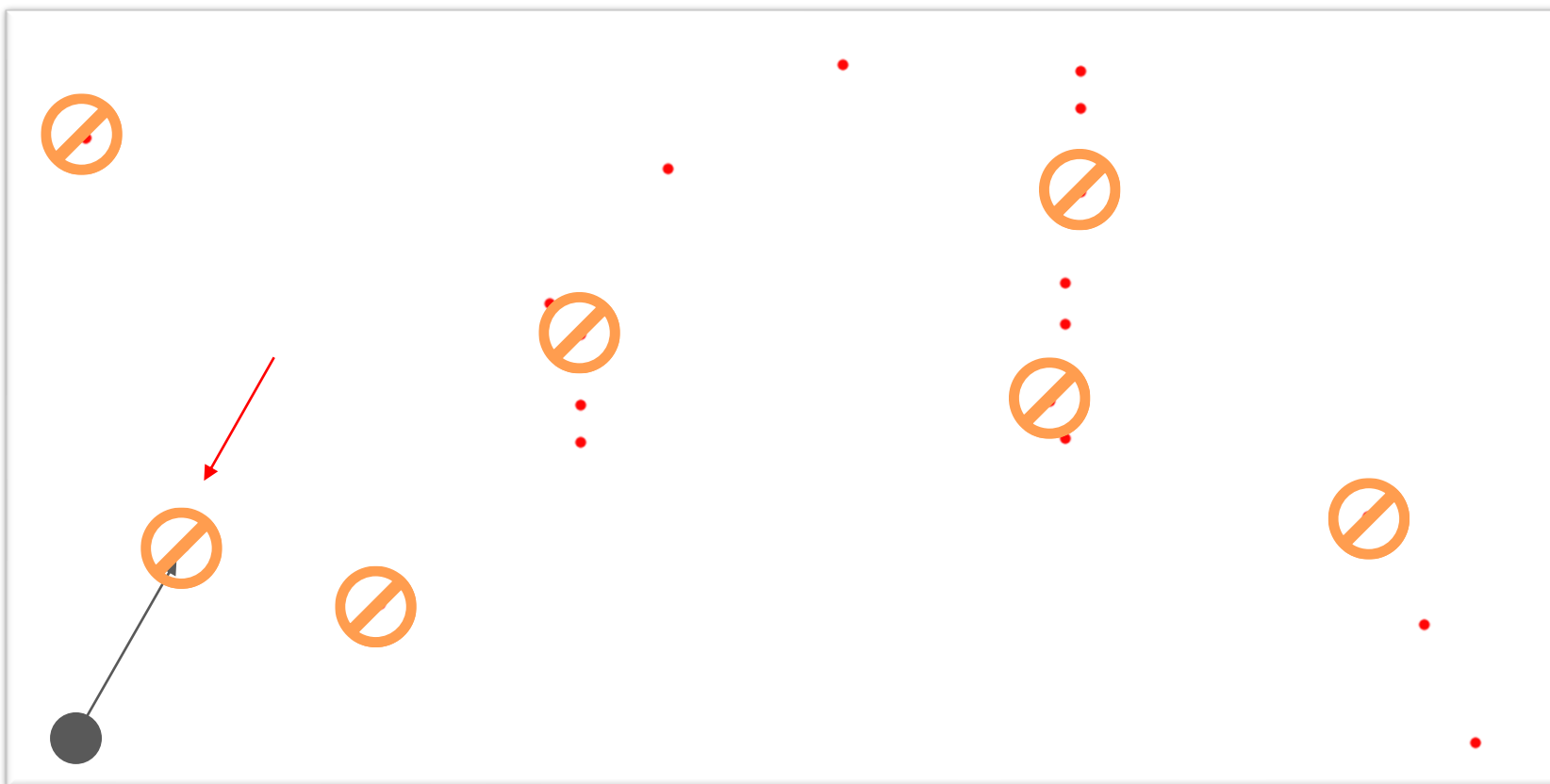
● STARTING / ENDING POINT



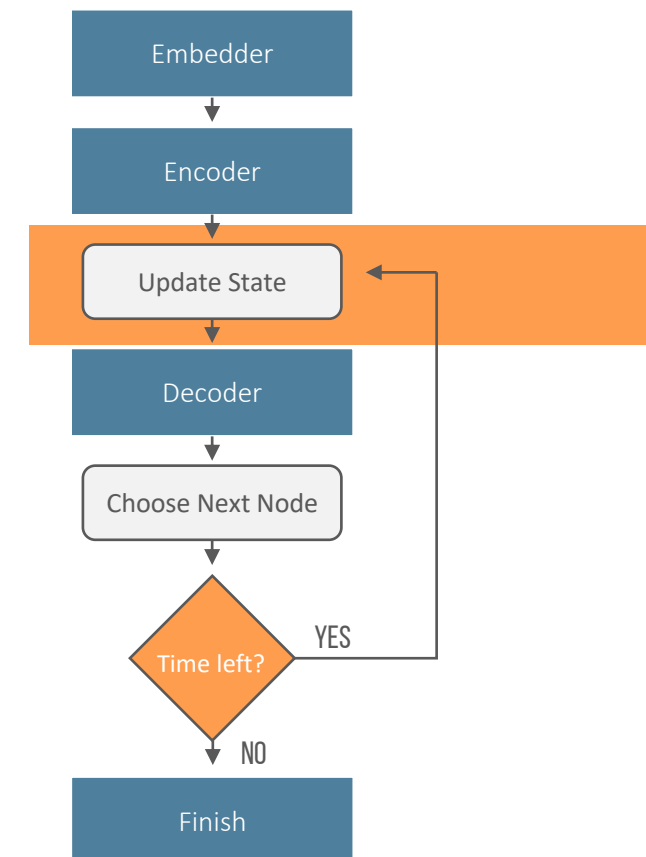
$$480 - 240 - 15 = 225 \text{ MIN LEFT}$$

TIME LEFT?



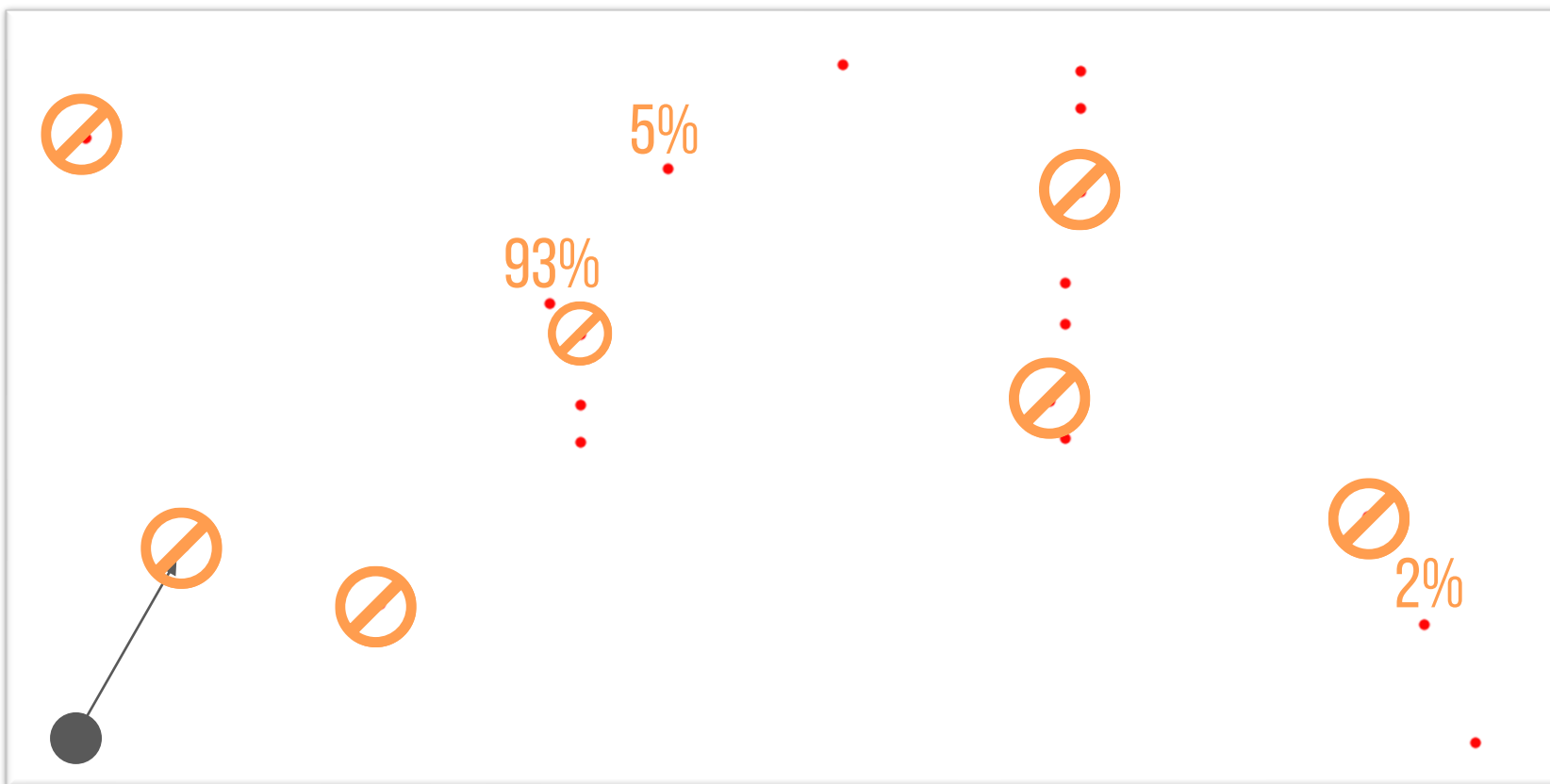


UPDATE STATE

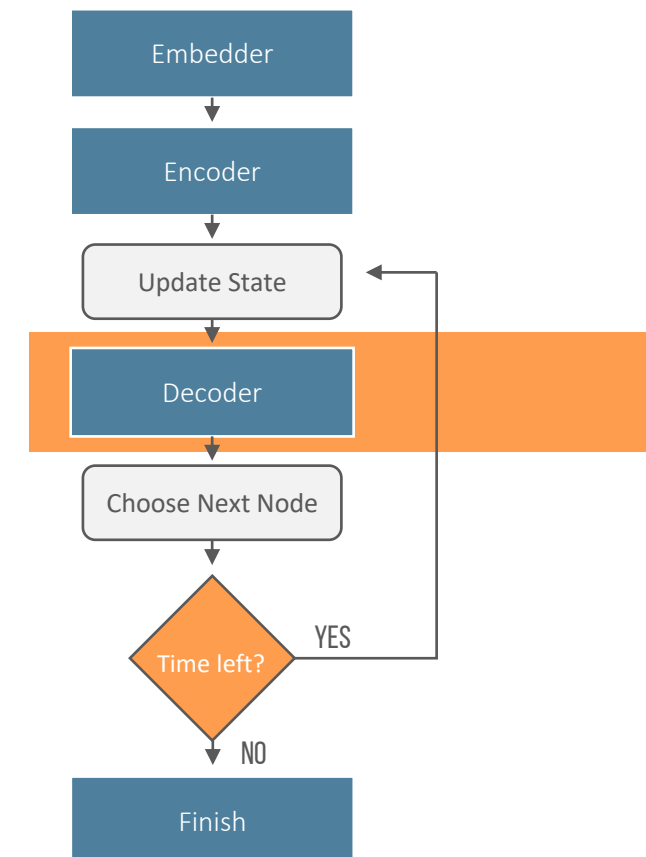


● POWER GENERATORS / NODES

● STARTING / ENDING POINT

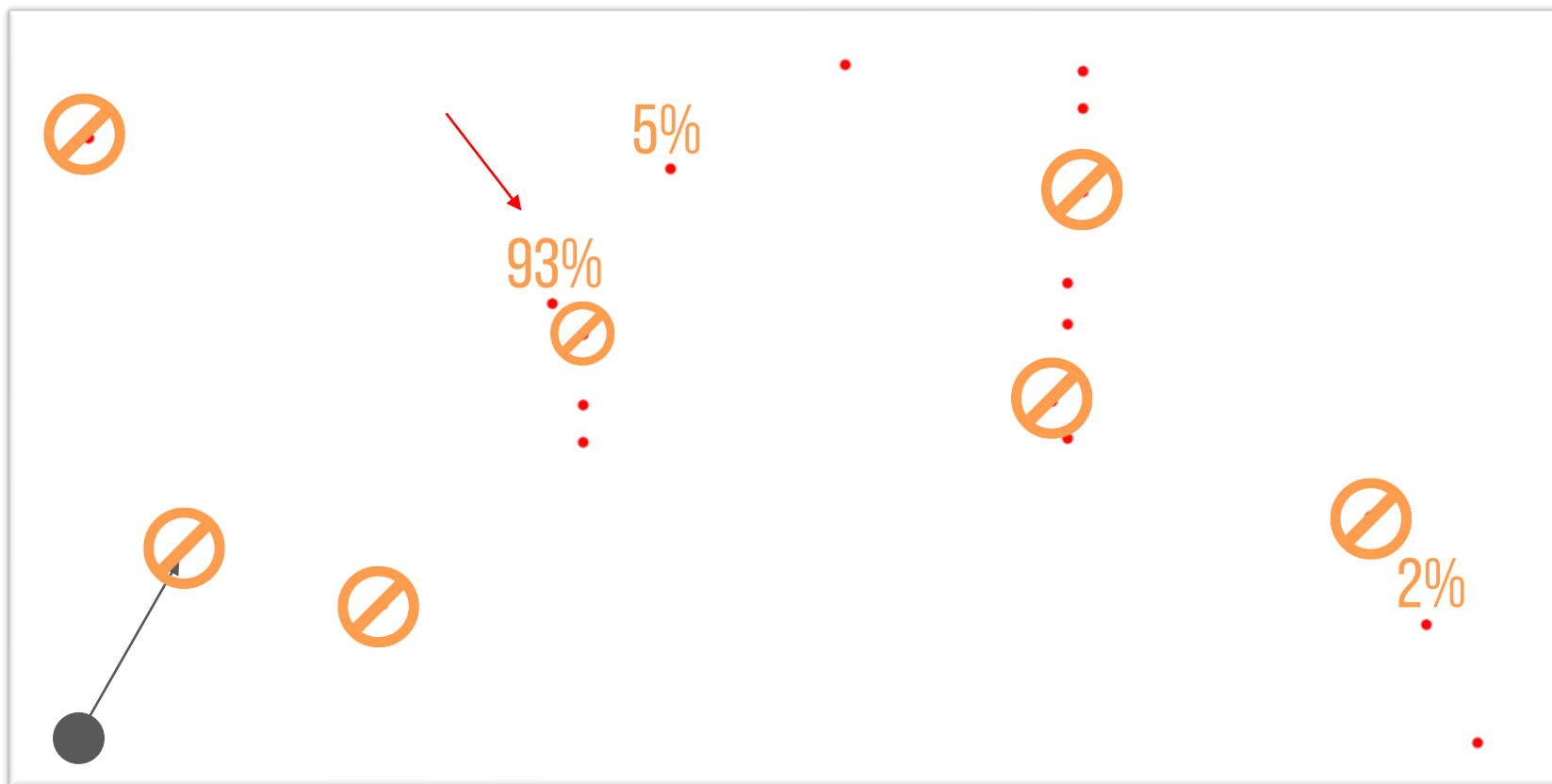


DECODER

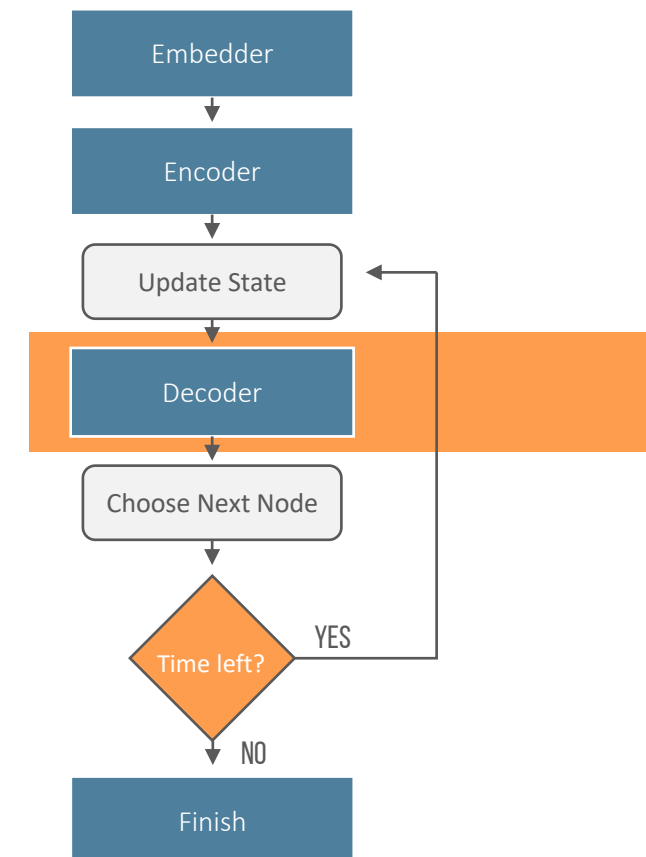


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● STARTING / ENDING POINT

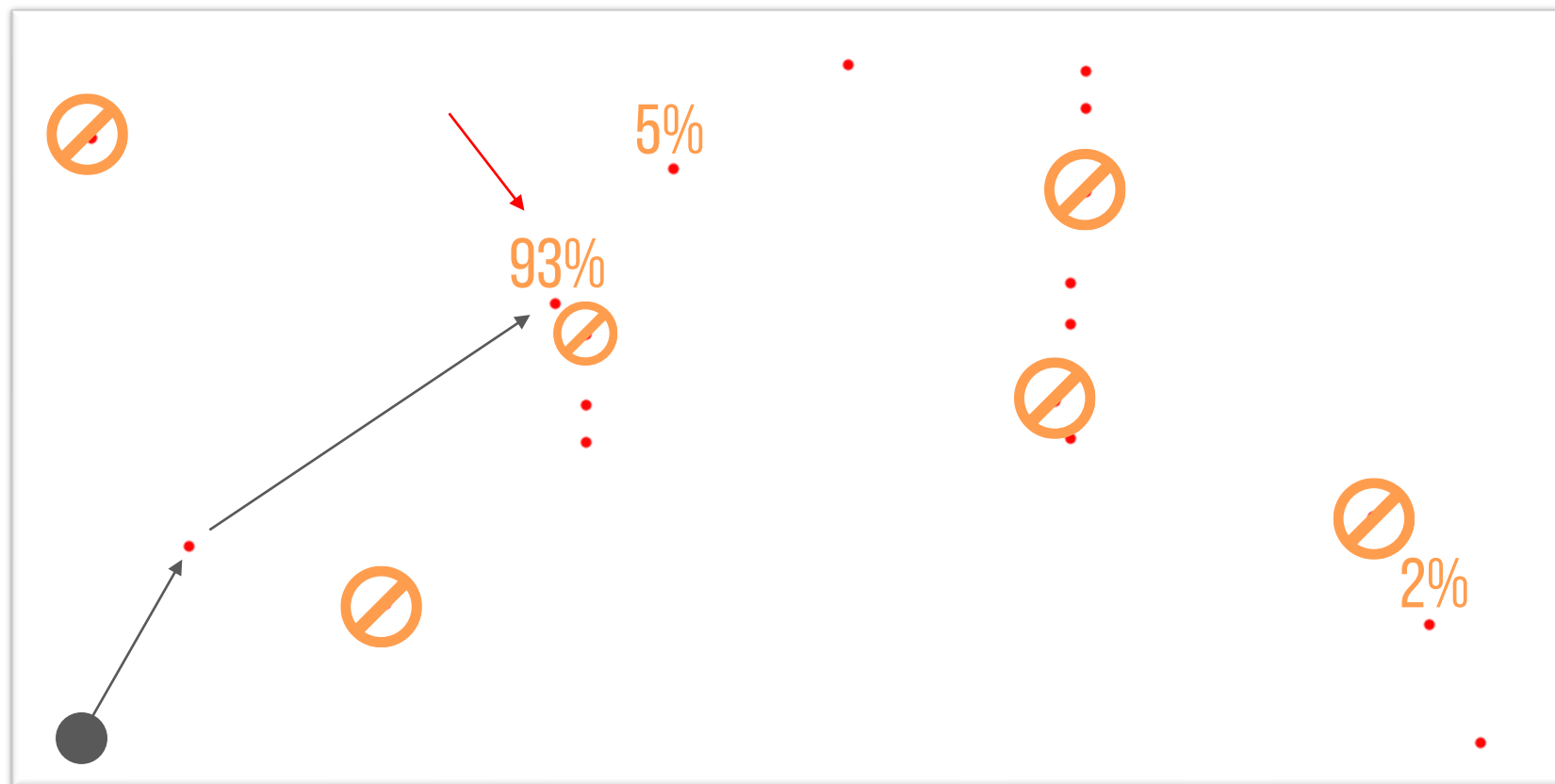


DECODER

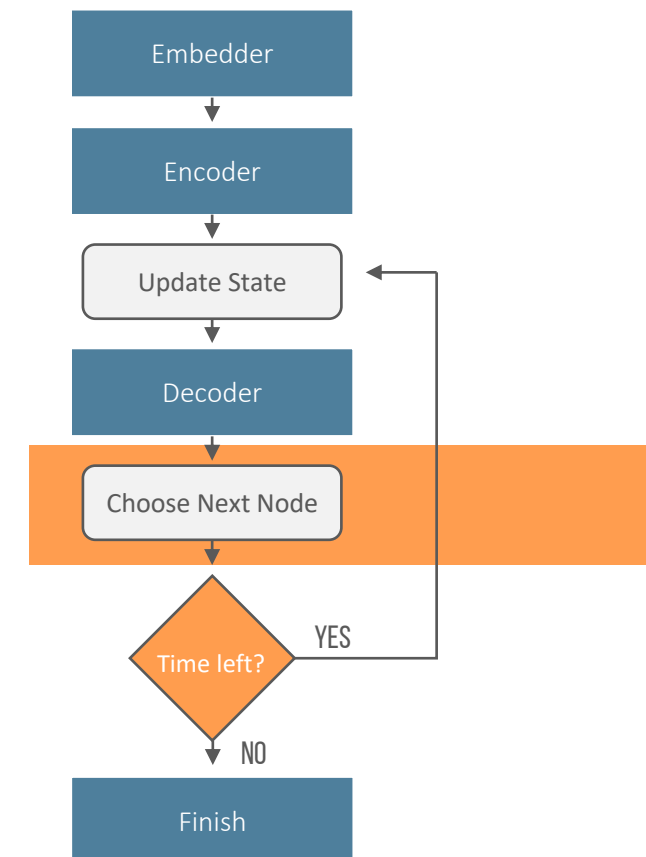


● POWER GENERATORS / NODES

● STARTING / ENDING POINT



CHOOSE NEXT NODE



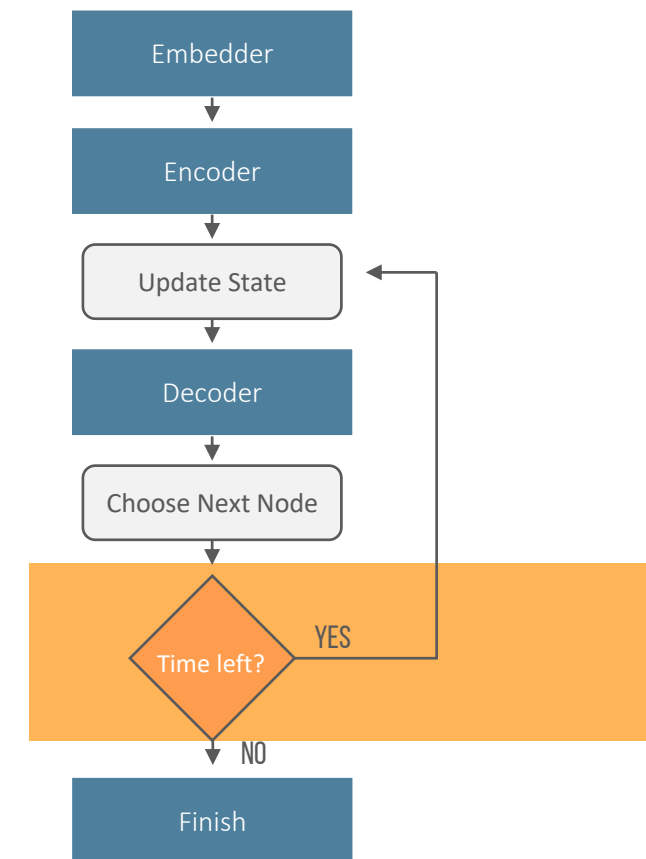
● POWER GENERATORS / NODES

● STARTING / ENDING POINT

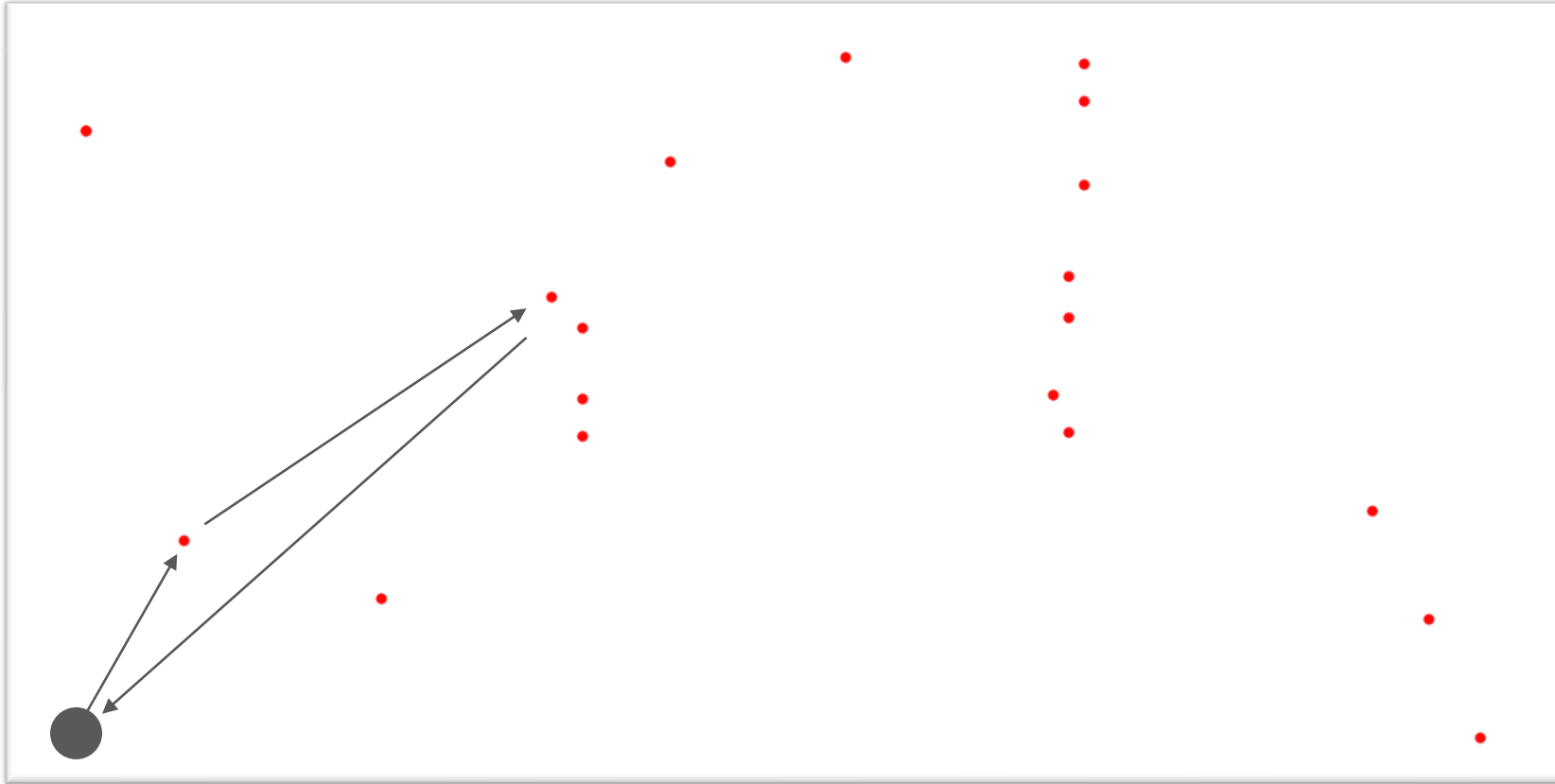


$$225 - 150 - 30 = 45 \text{ MIN LEFT}$$

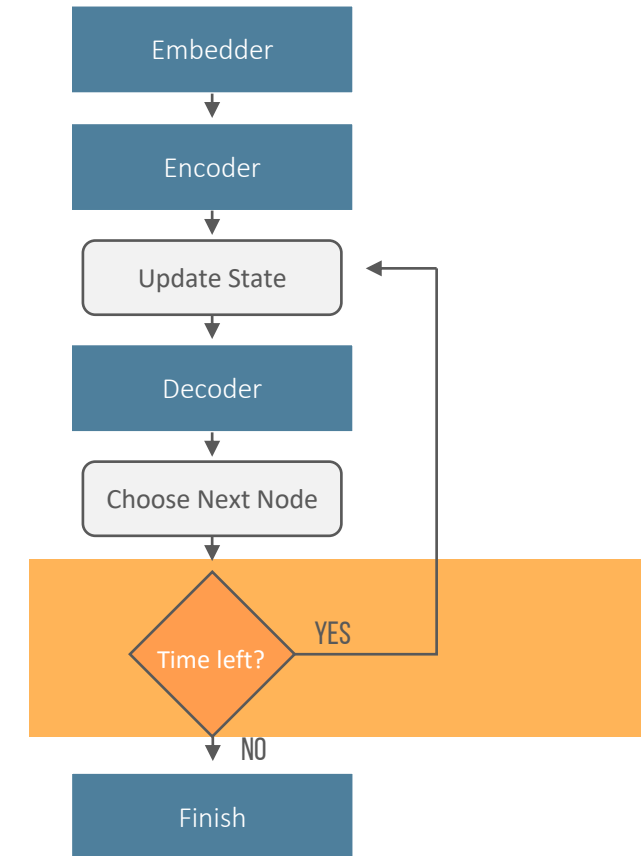
TIME LEFT?



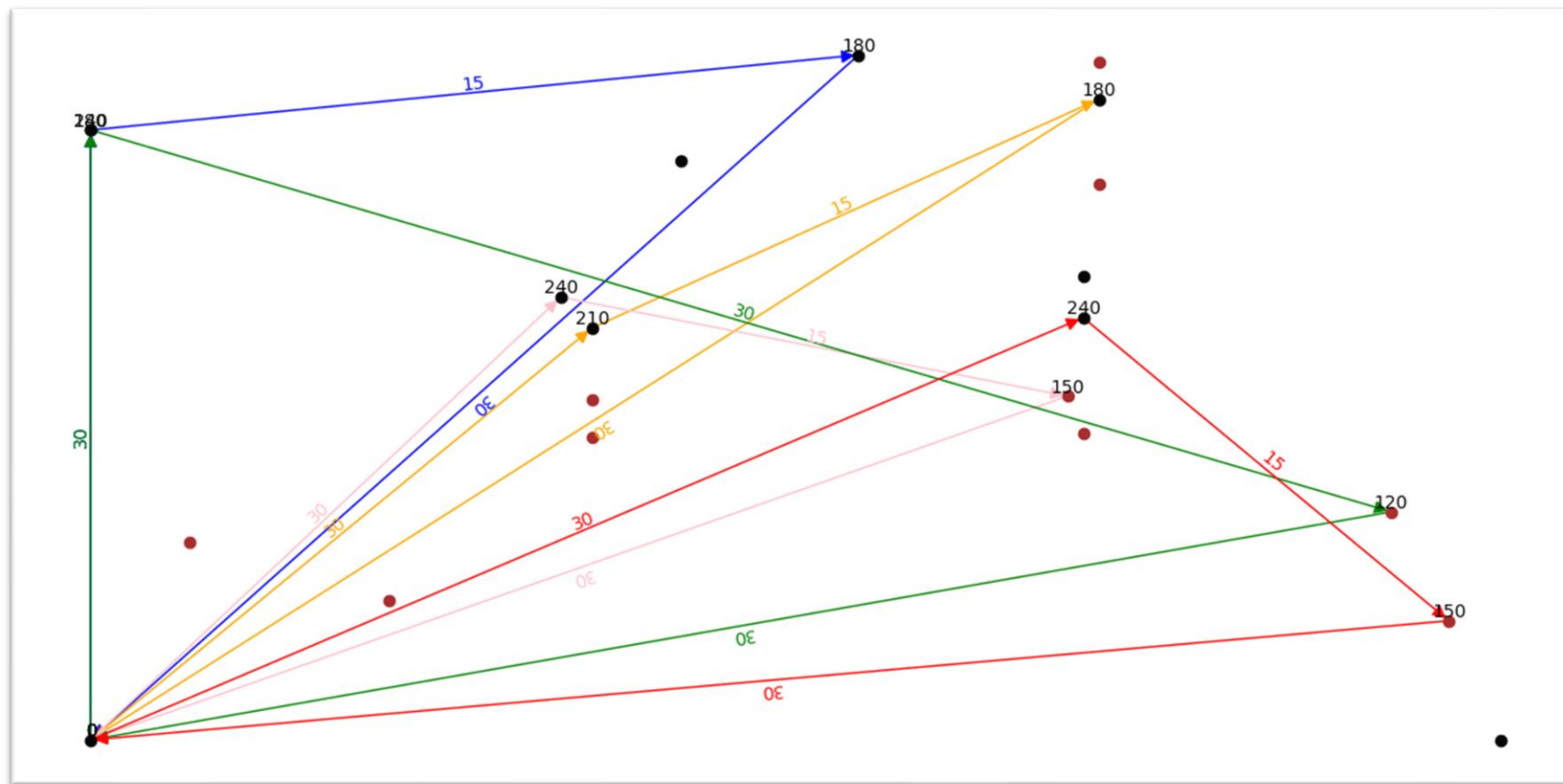
● POWER GENERATORS / NODES
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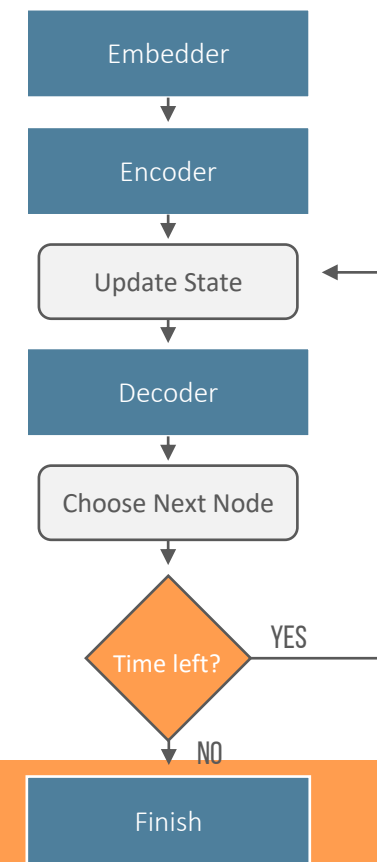
TIME LEFT?



FINISH



MONDAY, TUESDAY, WEDNESDAY...



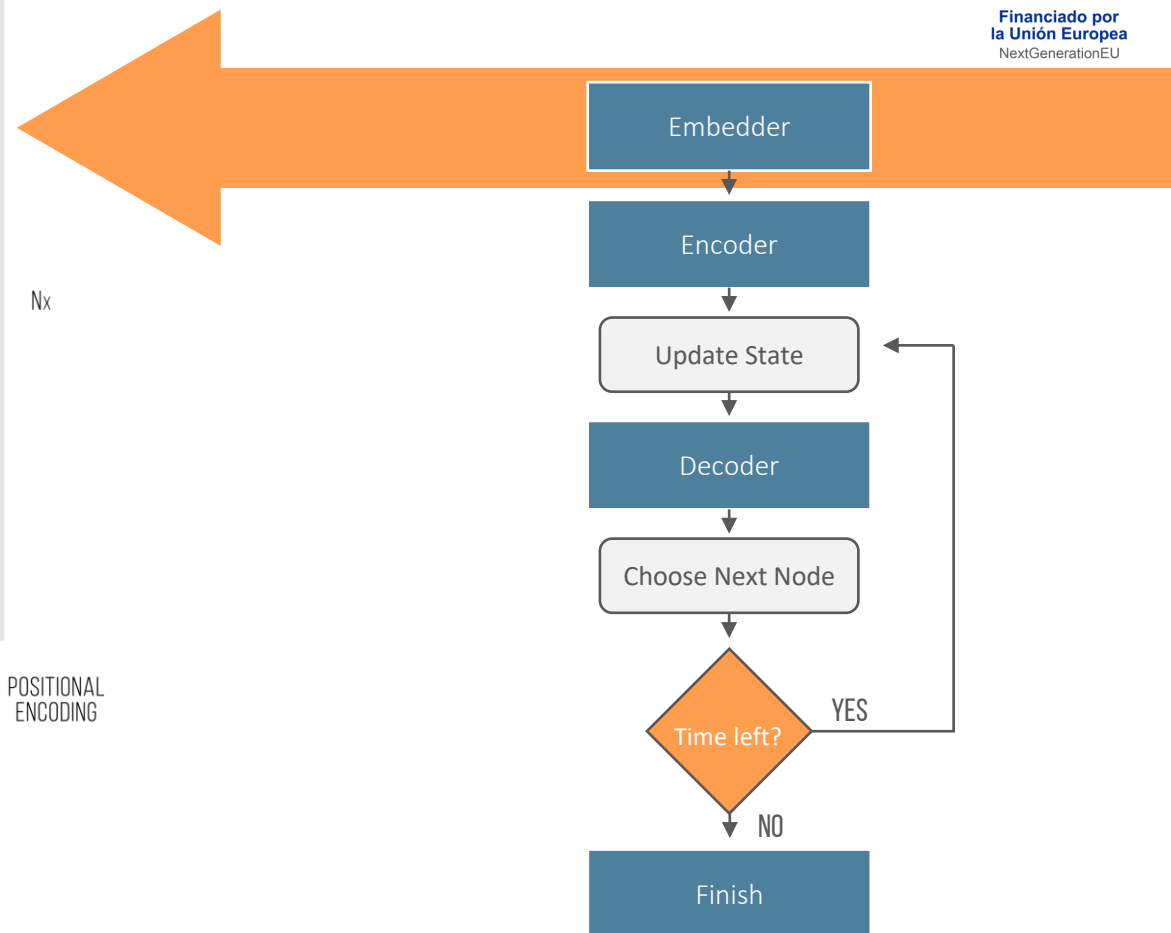
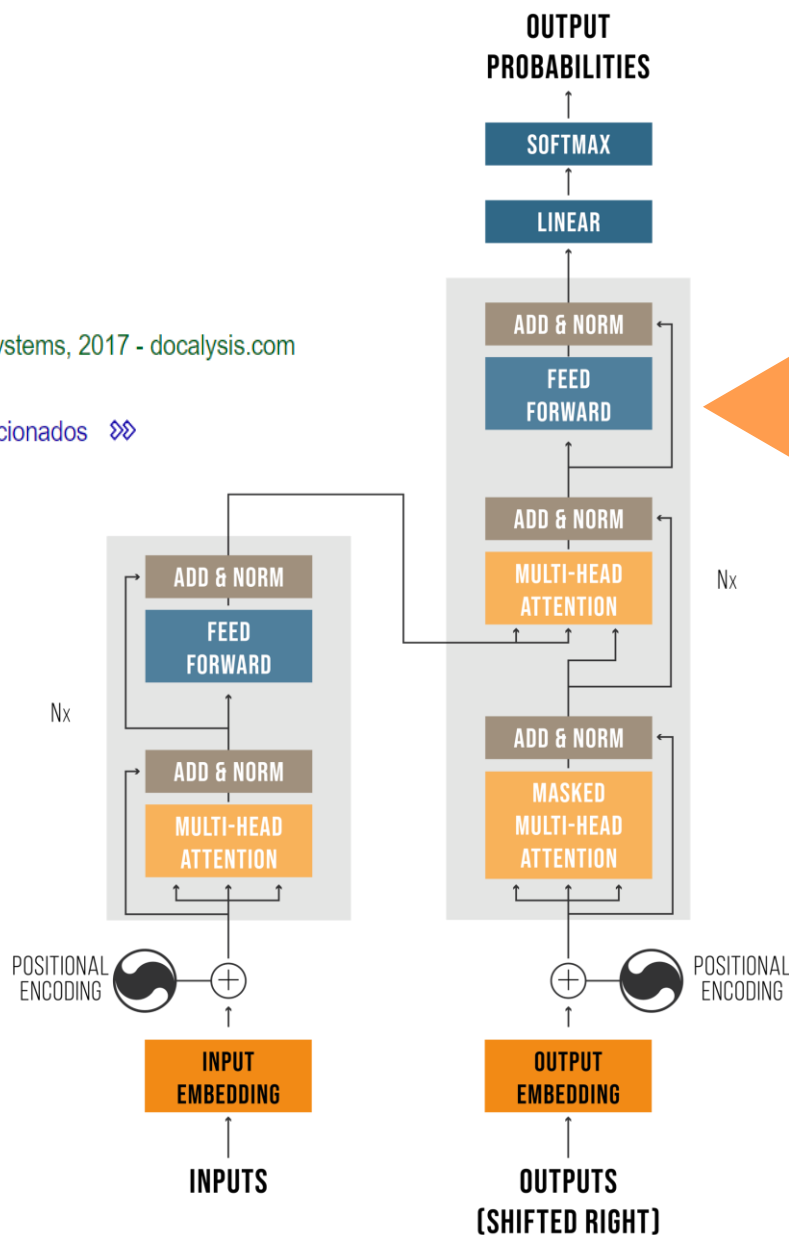
ARCHITECTURE

[PDF] **Attention is all you need**

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Attention is all you need Attention is all you need ...

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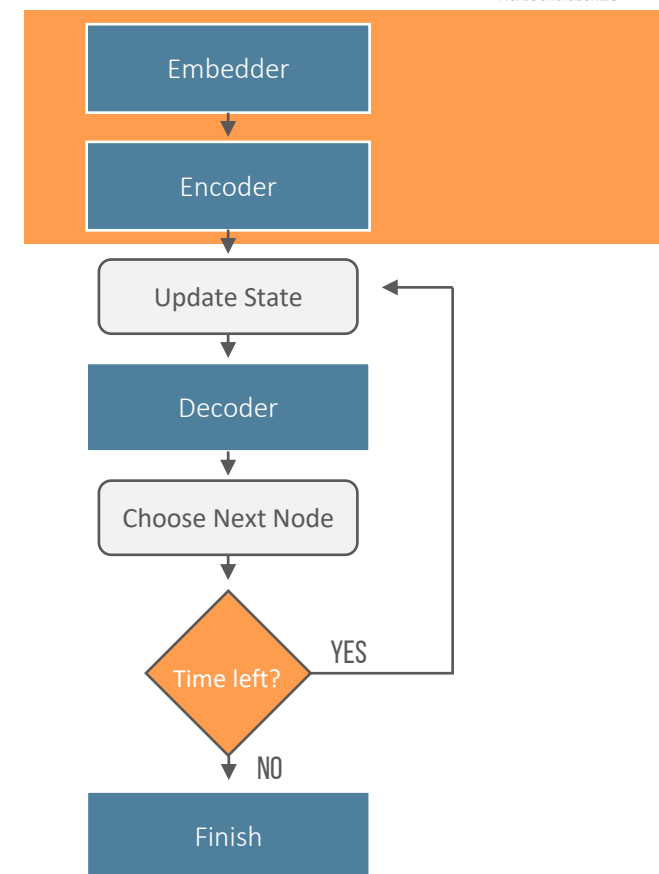
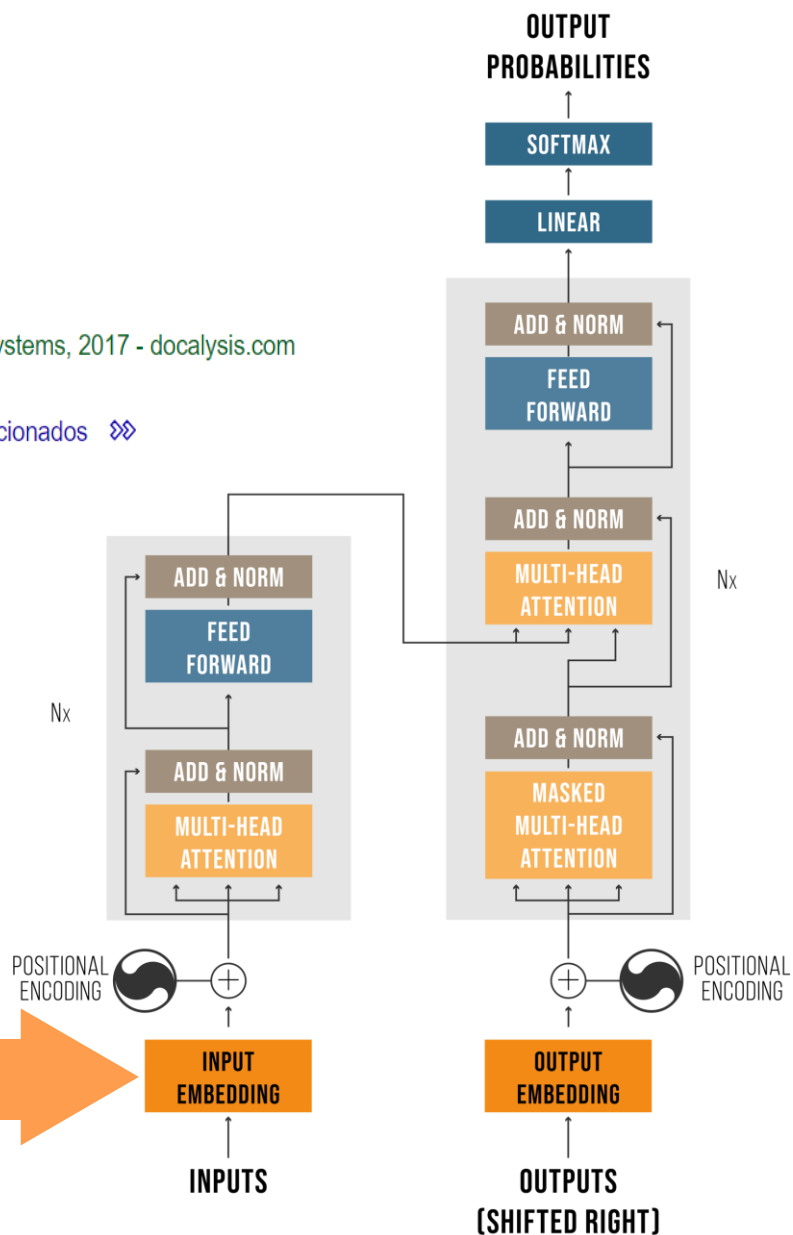
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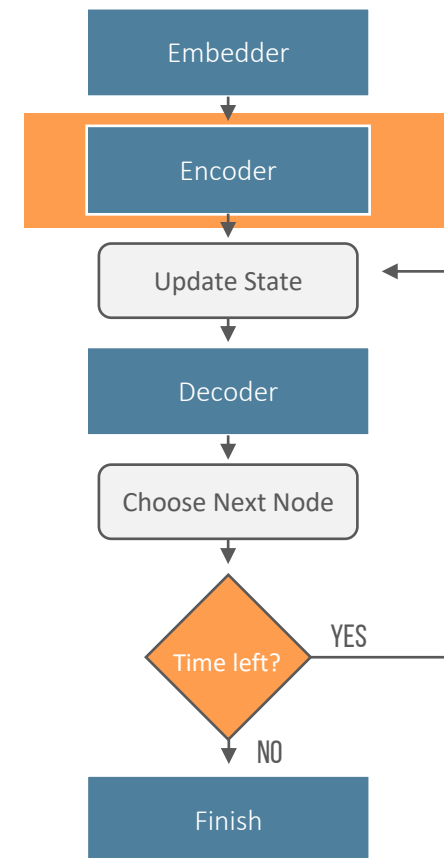
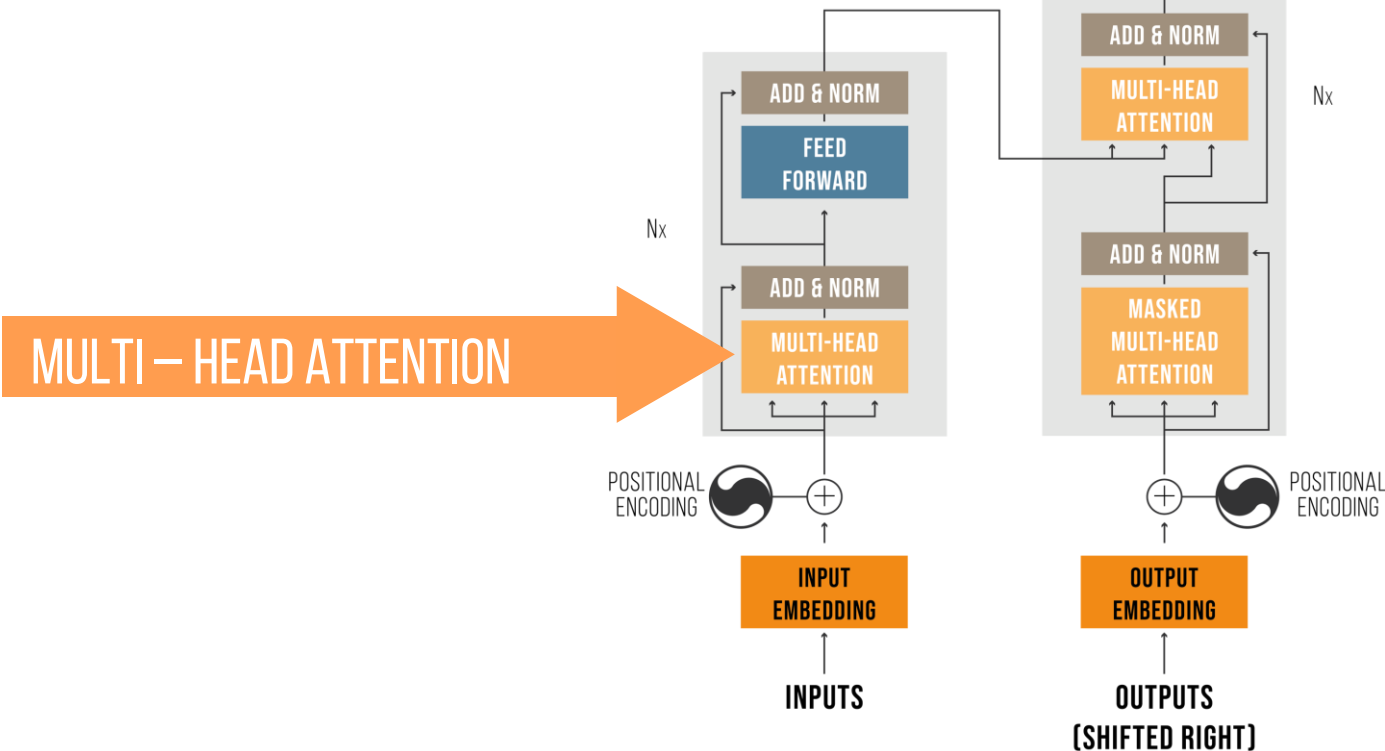
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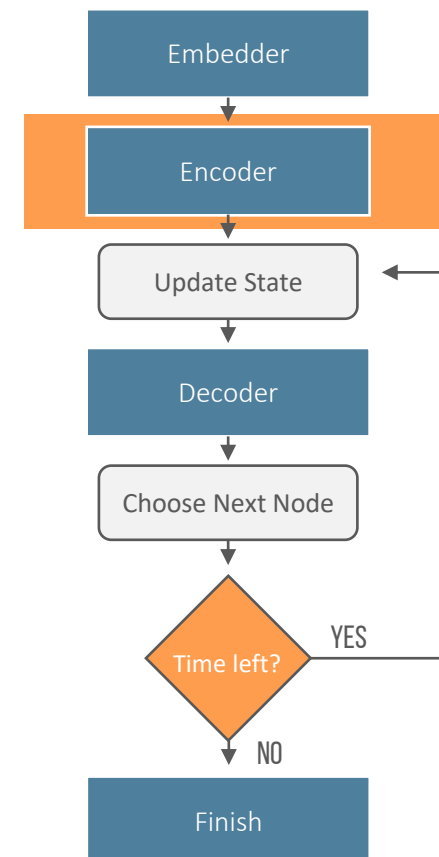
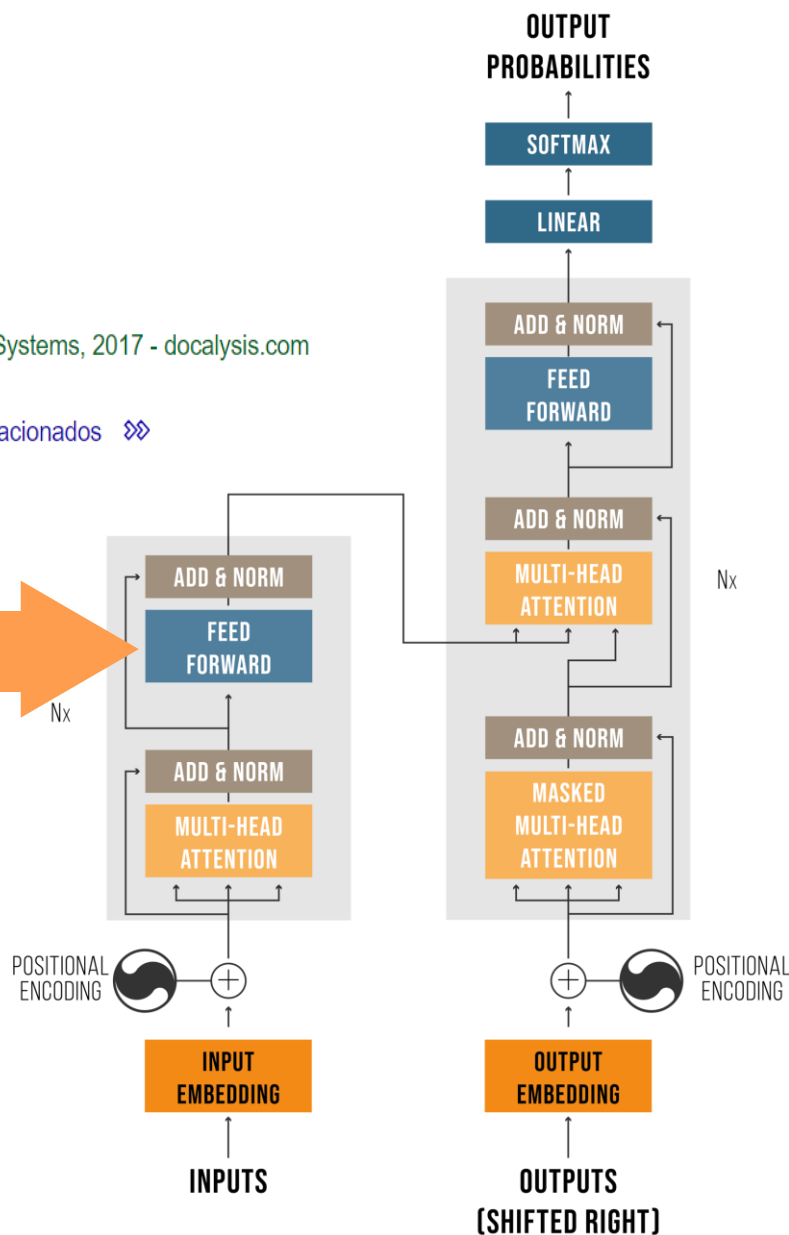
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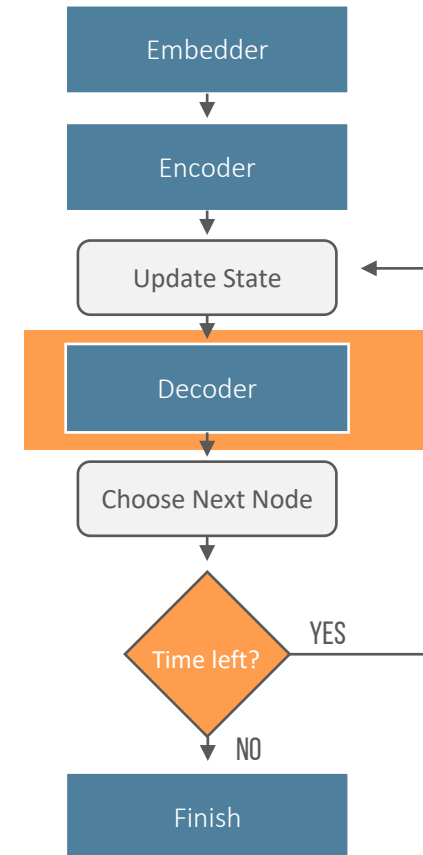
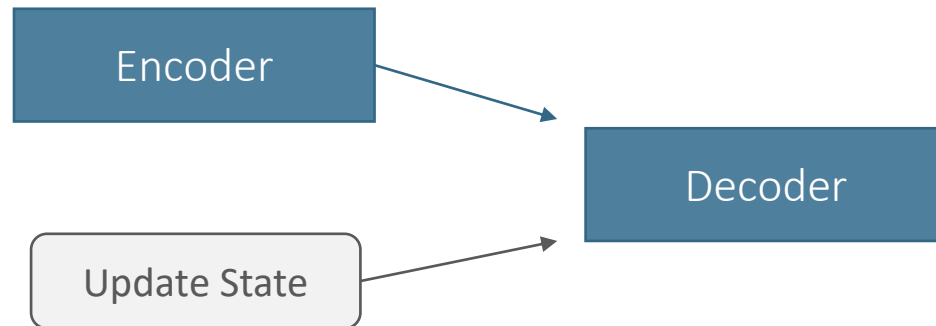
FEED FORWARD

1. Linear
2. Relu: $f(x) = \max(0, x)$
3. Linear



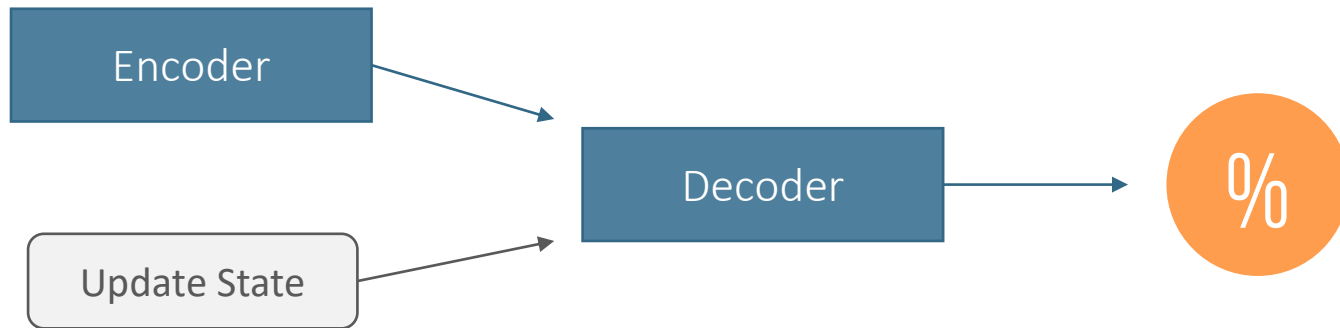
ARCHITECTURE

MULTI – HEAD ATTENTION LAYER: HANDLES THE STATE CONTEXT

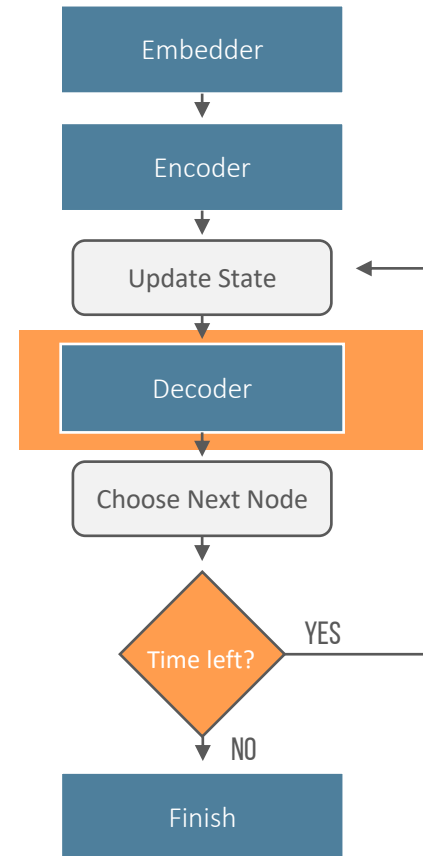


ARCHITECTURE

MULTI – HEAD ATTENTION LAYER: HANDLES THE STATE CONTEXT



SOFTMAX: RETURNS THE PROBABILITY





REINFORCE

TRAINING

$$\nabla_{\theta} J(\theta) \approx \hat{g} = \sum_{t=0} \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) R(\tau)$$

Estimation of the gradient (given we use only one trajectory to estimate the gradient)

Probability of the agent to select action a_t from state s_t given our policy

Cumulative return

Direction of the steepest increase of the (log) probability of selecting action a_t from state s_t

HUGGINFACE



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4. RESULTS

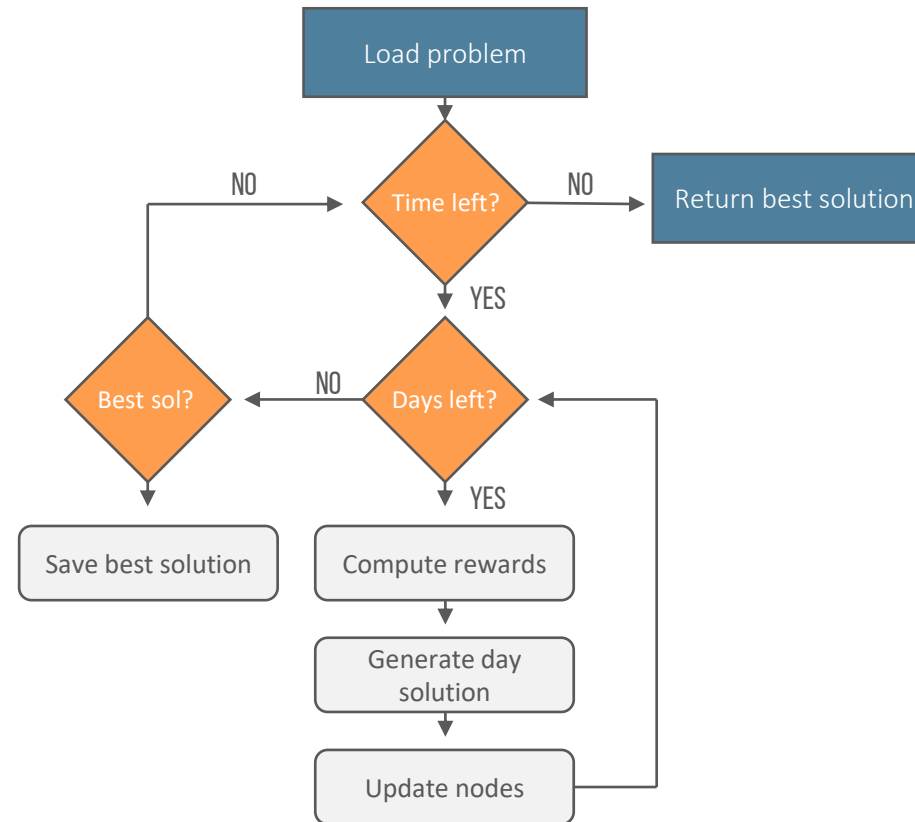
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MAINTENANCE ROUTE
OPTIMIZATION

INDEX

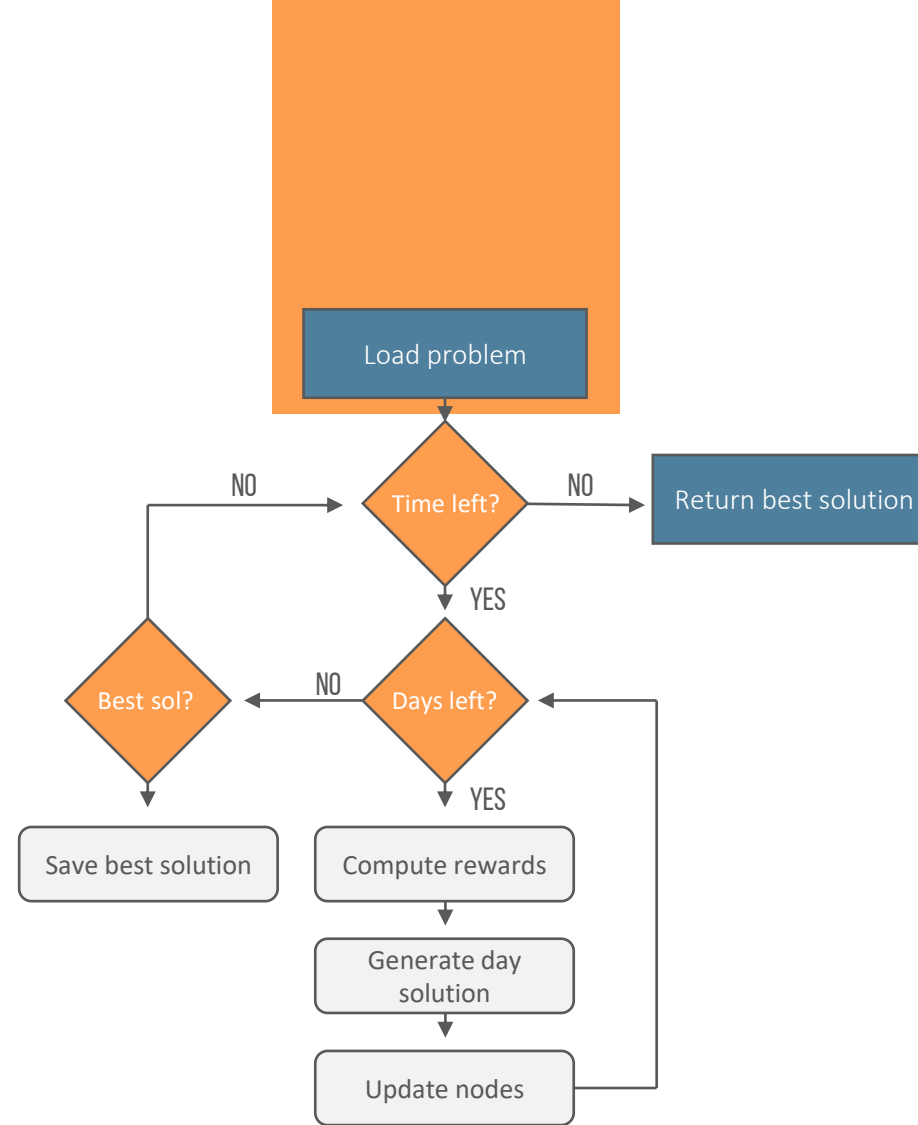
METHODOLOGY:

HEURISTIC



METHODOLOGY:

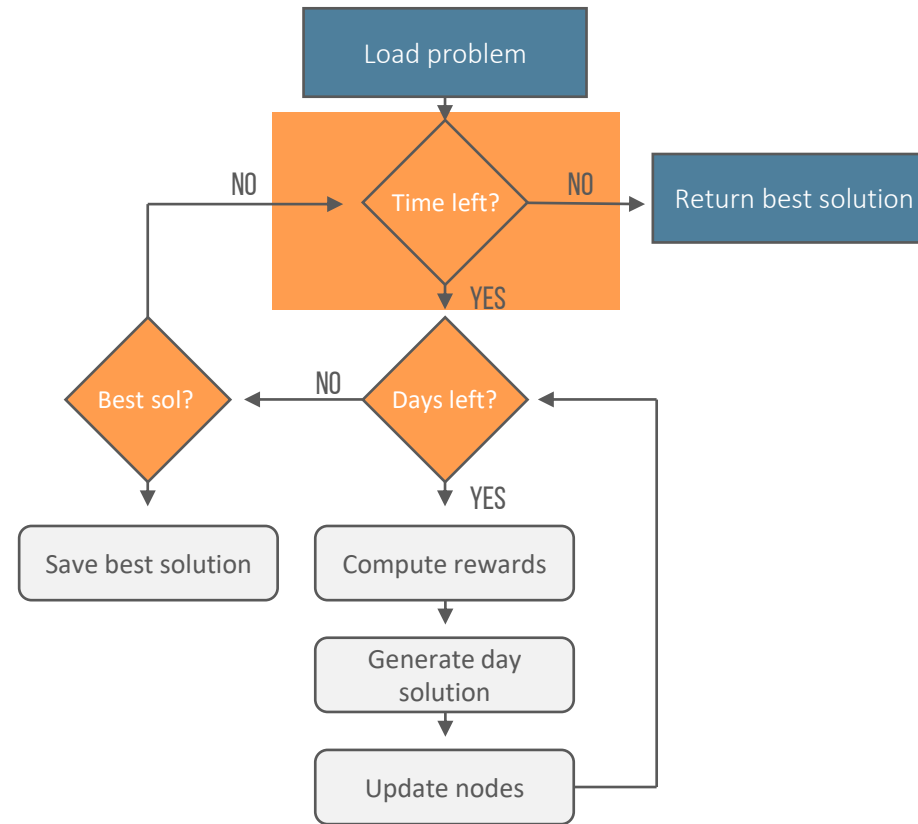
HEURISTIC



METHODOLOGY:

HEURISTIC

A maximum amount of time is given



METHODOLOGY:

HEURISTIC

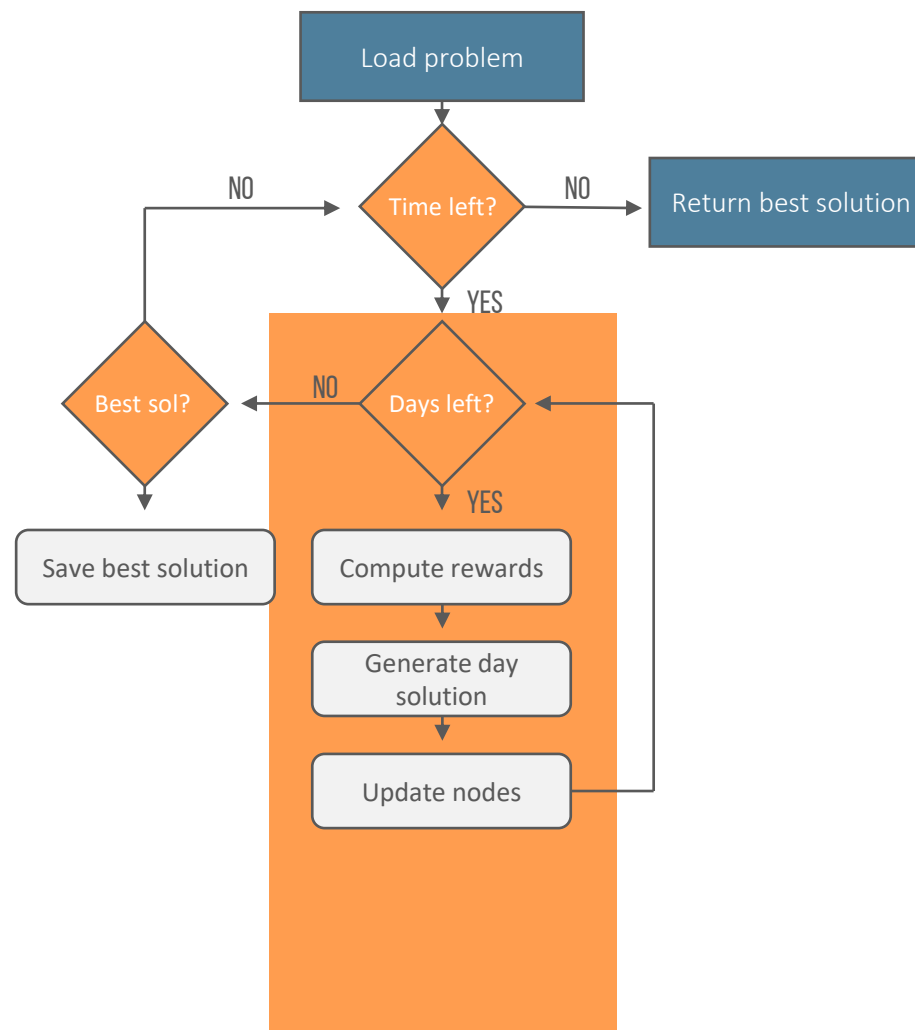
The reward varies daily.

A new solution is generated for each day.

- Dummy solution.
- BR-Merging process.

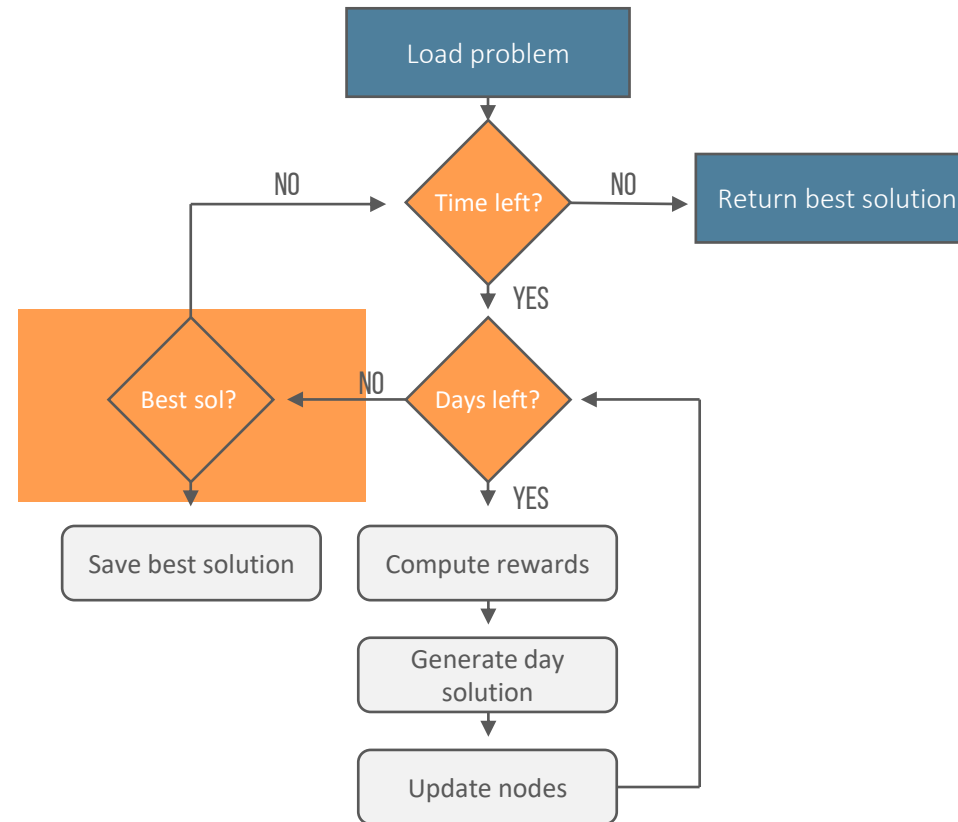
The available nodes are updated daily.

Some mechanisms are introduced to handle the multi-period aspect.



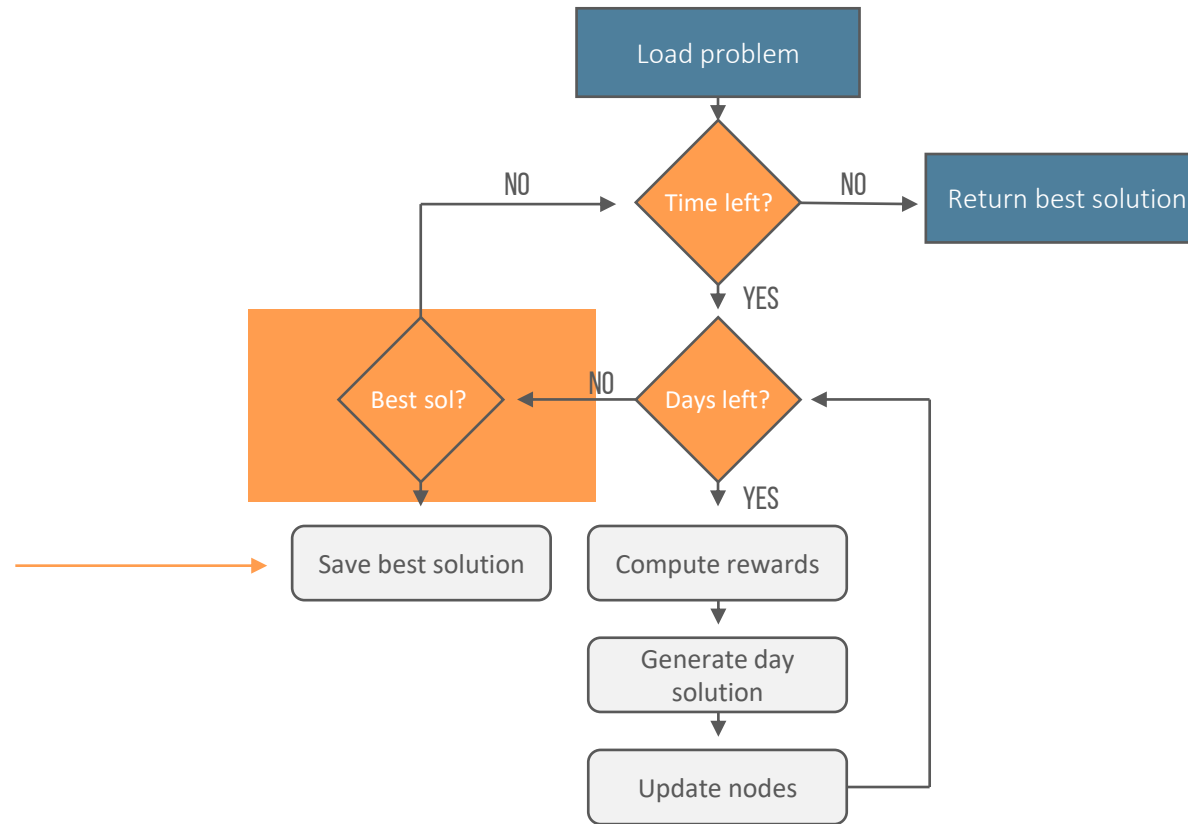
METHODOLOGY:

HEURISTIC



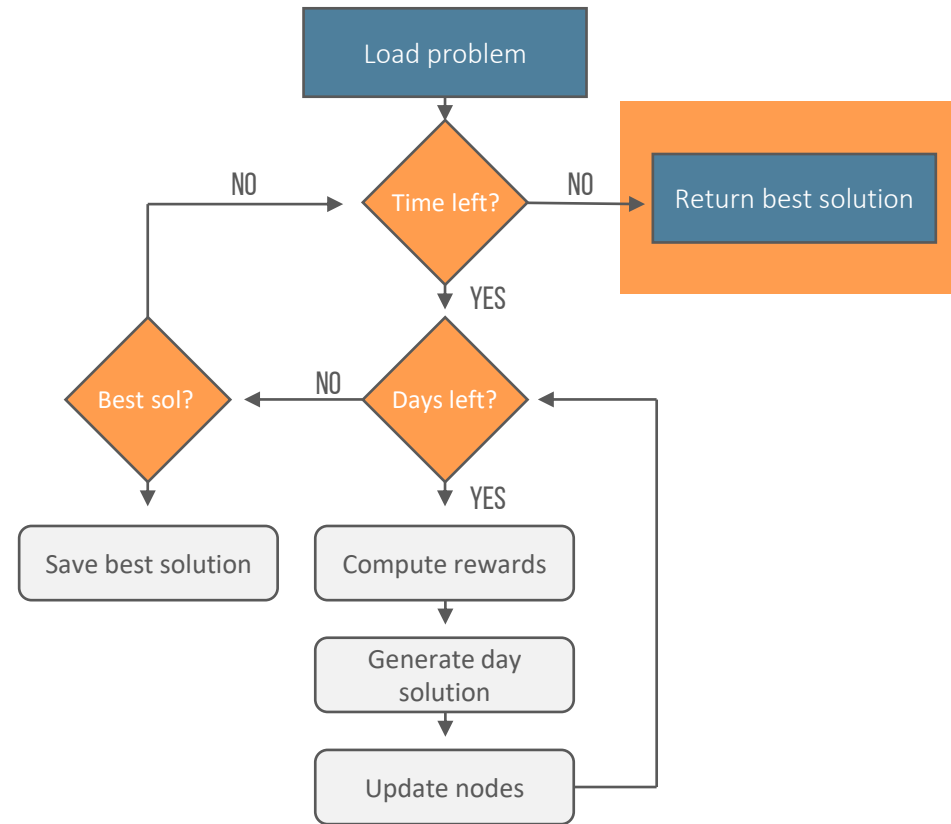
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1. OUR PROBLEM

Overview of the Multi-Period Team Orienteering Problem with Time Windows (TOPTW), focused on optimizing routes by considering power generators, time constraints, and team availability.



2. RL

Application of reinforcement learning algorithms to address combinatorial optimization challenges, emphasizing their adaptability compared to heuristic methods.



3. HEURISTIC

Development of daily updated solutions incorporating merging processes to effectively manage multi-period complexities, balancing practicality with efficiency.



4. RESULTS

Analysis of average outcomes across 256 instances, demonstrating the advantages of RL over heuristics in computational efficiency and performance under specific conditions.

MAINTENANCE ROUTE
OPTIMIZATION

INDEX

RESULTS

		Reward	Corr. Maint. (%)	Prev. Maint. (%)
Heuristic	0.5 seconds	19.42	100%	76.04%
	2 seconds	19.55	100%	76.69%
	120 seconds	19.65	100%	76.43%
Reinforcement Learning Model	Greedy	19.09	100%	76.17%
	Sampling	19.43	100%	77.08%
	Augment.	19.50	100%	76.69%
	Rot. + Augment.	19.56	100%	76.30%

MEAN RESULTS OF 256 INSTANCES

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MEAN RESULTS OF 256 INSTANCES

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		Heuristic	RL Model		
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30 Maintenances	$N = 2^*$ $M = 3$ $S = 25$	19.05	13.35	13.87	15.22
	$N = 1$ $M = 2$ $S = 27$	12.76	7.60	7.84	8.47
45 Maintenances	$N = 2^*$ $M = 3$ $S = 40$	19.55	19.09	19.43	19.56
	$N = 3$ $M = 3$ $S = 39$	21.68	19.62	20.61	21.06

RESULTS UNDER DIFFERENT CONDITIONS

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Plan de Recuperación,
Transformación y Resiliencia



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NextGenerationEU



ACT. 4.24 OPTIMIZACIÓN DE RUTAS DE INSPECCIÓN DE
MANTENIMIENTO

IA4TES

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