Final Project for the **Complex Systems: Models and Simulations** and **Artificial Intelligence** courses
at MSc of CS at **University of Milano-Bicocca**

AUTONOMOUS EXPLORATION AGENT

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Task

Definition of a **single-agent obstacle-ridden**, **procedurally generated** environment

Training of the agent with Proximal Policy Optimization for a **target localization objective**

Evaluation and comparison of the agent’s **model variations**

Tools

Environment and agent architecture

unity

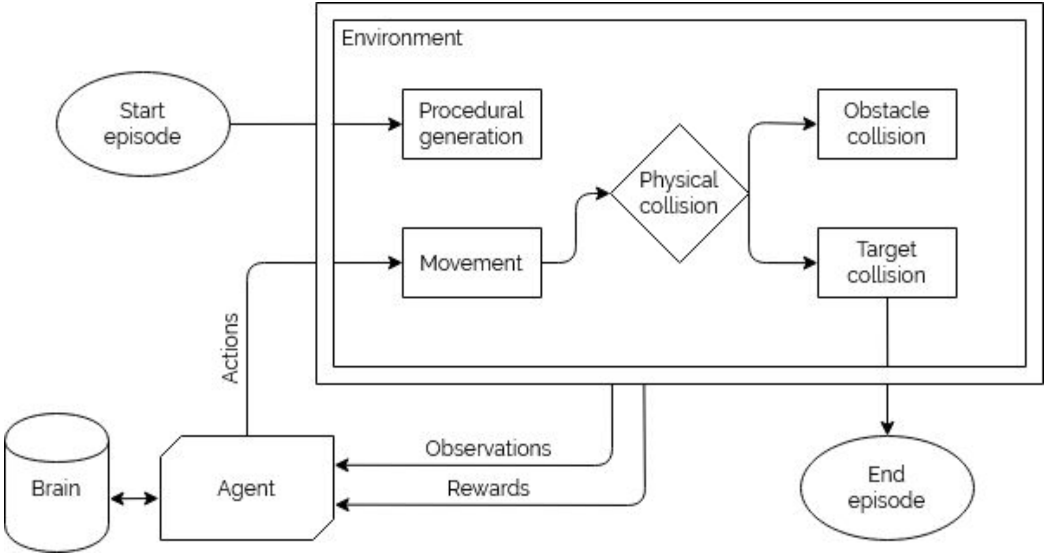
Reinforcement Learning

Unity's ML-Agents

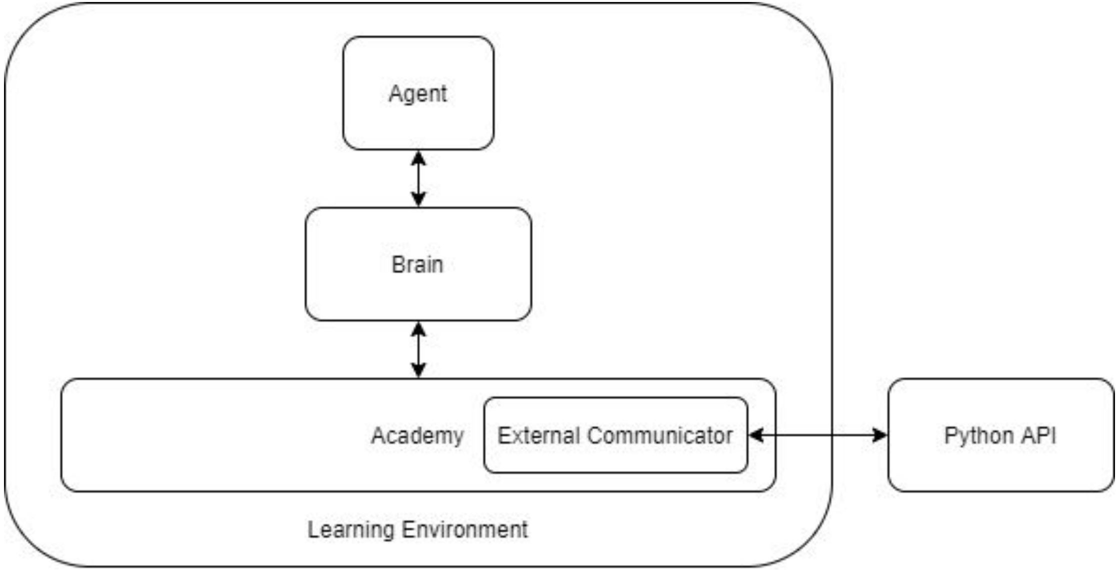
TensorFlow

System Architecture

Schema illustrating the **interactions** between the main **actors** of the system



System Architecture



ML-Agent Learning pipeline

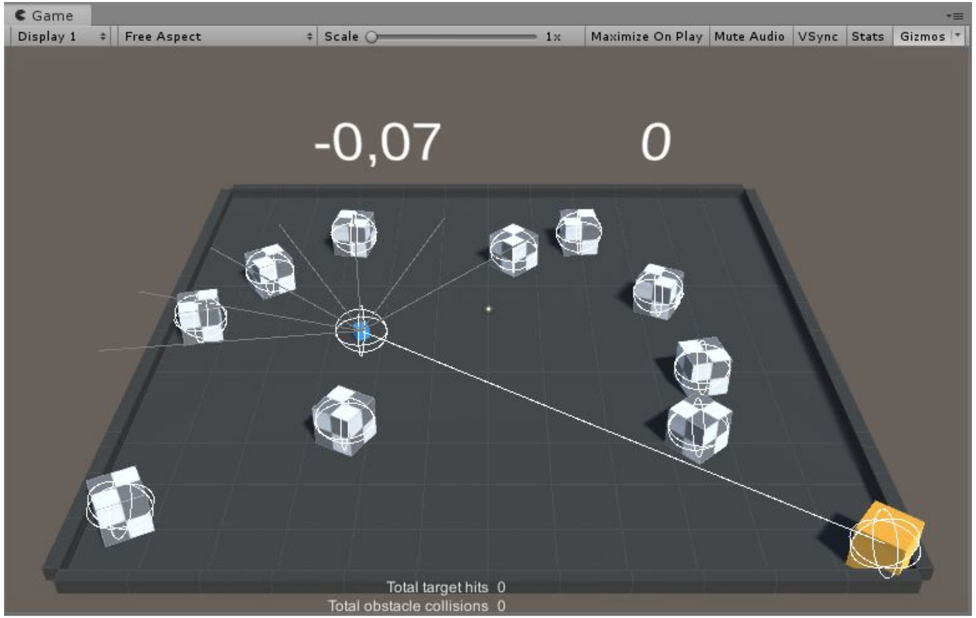
Simulation Main Phases

- **Environment procedural generation**
  - Parametrized spawning and positioning of the **Agent**, **Obstacles** and **Target**
- **Agent’s Actions and Movement**
  - Agent movement controller built with Unity’s **Physics System**
  - Actions inferred by ML-Agents **Brain** interface
  - Action space: **3D Discrete** (2D maneuvering case)
- **Collisions**
  - **Penalty** function for obstacle collision
  - **Reward** function and episode completion for target collision

Environment Procedural Generation

Constrained generation of the scene ensuring an approximately uniform distribution of the object in the environment according to different parameters, such as:

- Number of obstacles
- Minimum Target distance from the Agent
- Minimum distance between objects in the environment



Environment Procedural Generation

Agent parameters	
Dimensions	1x1x1
Max linear velocity	5
Max angular velocity	$5/3\pi$
Environment area parameters	
Level area	50x50
Obstacle dimensions	8x8x8
Target dimensions	8x8x8

Sensor parameters	
# LIDAR	14
Maximum range	20
Field of view	$[-\frac{2}{3}\pi, \frac{2}{3}\pi]$
3D Sensor parameters	
# LIDAR	42
Maximum Range	40
Horizontal field of view	$[-\frac{2}{3}\pi, \frac{2}{3}\pi]$
Vertical field of view	$[-\frac{1}{3}\pi, \frac{1}{3}\pi]$

Static environmental parameters

2D Maneuvering System

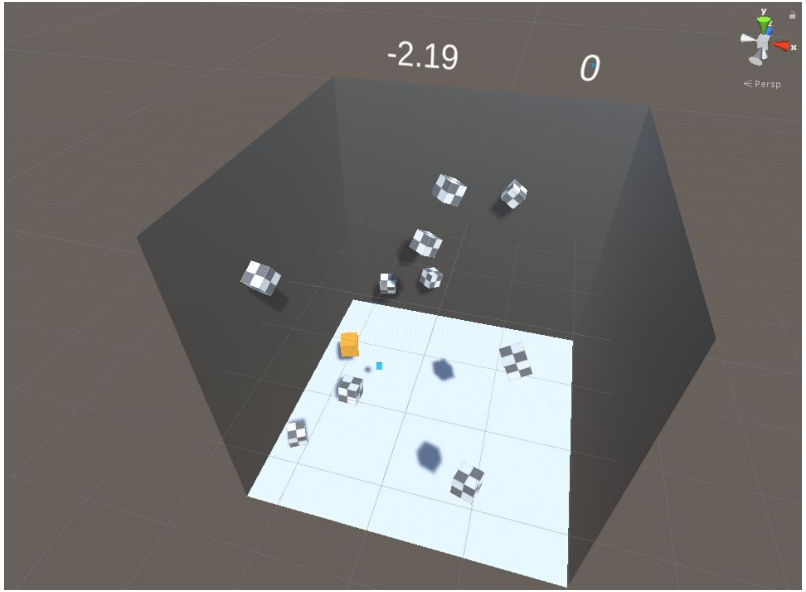
Movement

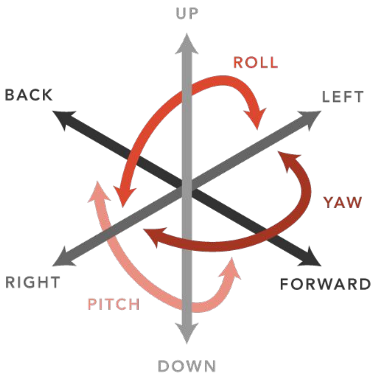
- Simple vehicle physics **approximation**
- Movement through physically grounded **force application**
- **Instant velocity** change to the agent's body (ForceMode.VelocityChange)
- Soft clamping to the max velocity

Actions

- **Decisions** coming from the Brain (model)
- **3D Action Space**:
  - x, z axis **translation** movement
  - yaw axis **rotation** movement

3D Maneuvering System





Movement - Physics system:

- **No gravity**

Actions - Augmented to a **5D** action space:

- x, y, z axis **translation**
- yaw and pitch **rotation**

Learning System

- Uses **Proximal Policy Optimization** as a RL algorithm
- The **reward signal** defines the goal of the task
- **Curriculum learning** scales the difficulty of the task according to the **cumulative reward** reached by the agent
- The same agent's **Brain** is trained on **parallel environments**

Reward Signal - Intrinsic Reward

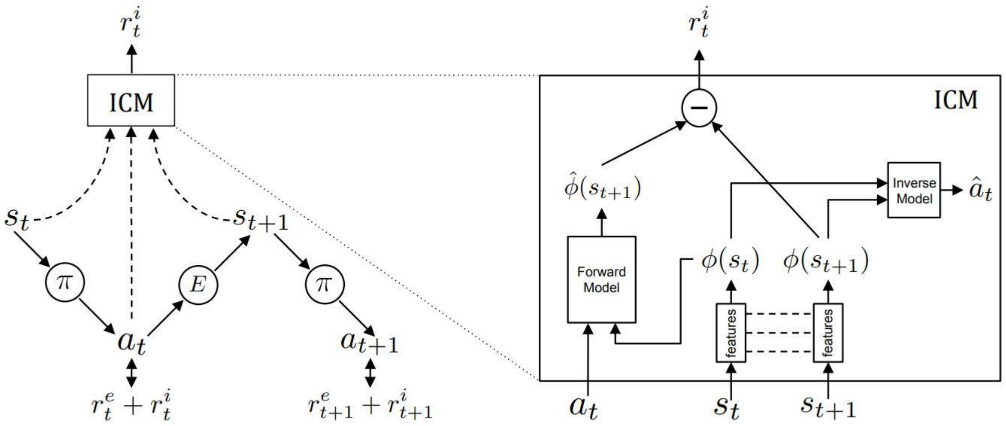
Given in response to the actions made by the agent in the environment, comprised of two components:

- Reward: *Positive reward - Penalty function*
    - Penalty function: α*obstacle_collisions+β*time*
    - Positive reward: γ*target_collisions*

Reward Signal - Extrinsic Reward

Representing the **curiosity** of the agent.

The more **unexpected** the action taken by the agent, the **higher** the curiosity signal.



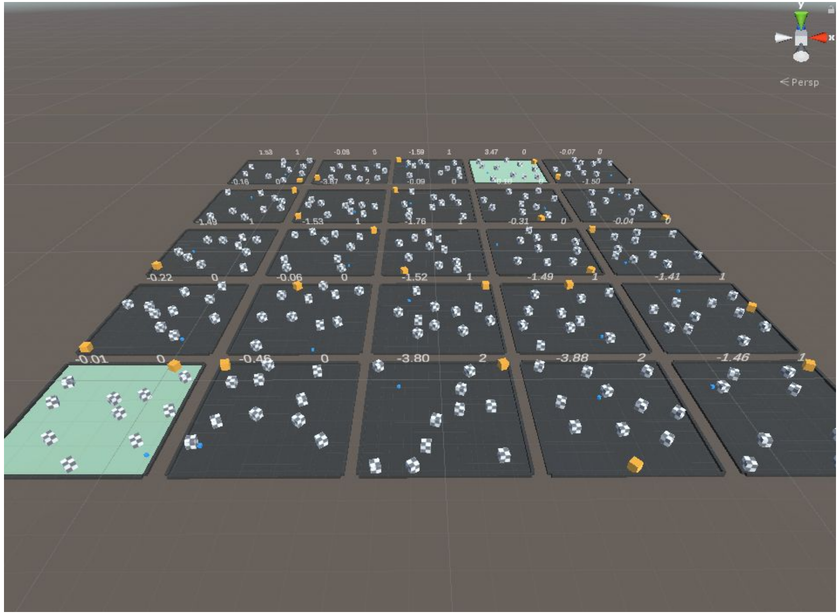
Curriculum Learning

Dynamically change the parameters **during training**, making the task **progressively** harder

In some cases, allows for **faster policy convergence**

Curriculum parameters
Reward threshold
Number of obstacles
Minimum spawn distance
Target-Agent distance
Penalty offset

Parallel Learning



Increases the experience **throughput** of the Agent through **parallel instances** sharing the Brain

Experiments

Performance analysis of different scenarios:

- Baseline
- Curriculum learning
- Harder Penalty function
- Camera sensors
- 3D maneuvering environment

Experiments - Evaluation

Evaluation made through two different types of measurements:

Traditional RL performance metrics

- Cumulative reward
- Policy loss
- etc

Environmental performance metrics

- Collisions per minute (CPM)
- Targets per minute (TPM)
- Collisions per target (CPT)

Experiments - Baseline

Fixed parameters:

Number of obstacles	10
Min spawn distance	2
Target distance	45

Penalty function:

$$p = collisions * 0.1 + time * 0.001$$

Observation sensors: LIDAR

2D maneuvering environment

Experiments - Curriculum

Curriculum parameters:

Reward thresholds	1	2	2.5	2.8	3	3.5	4
Number of obstacles	8	10	13	15	17	18	20
Min spawn distance	6	6	4	4	3	3	2
Target distance	25	28	30	33	35	37	40

Penalty function:

$$p = collisions * 0.1 + time * 0.001$$

Observation sensors: LIDAR

2D maneuvering environment

Experiments - Harder Penalty

Curriculum parameters:

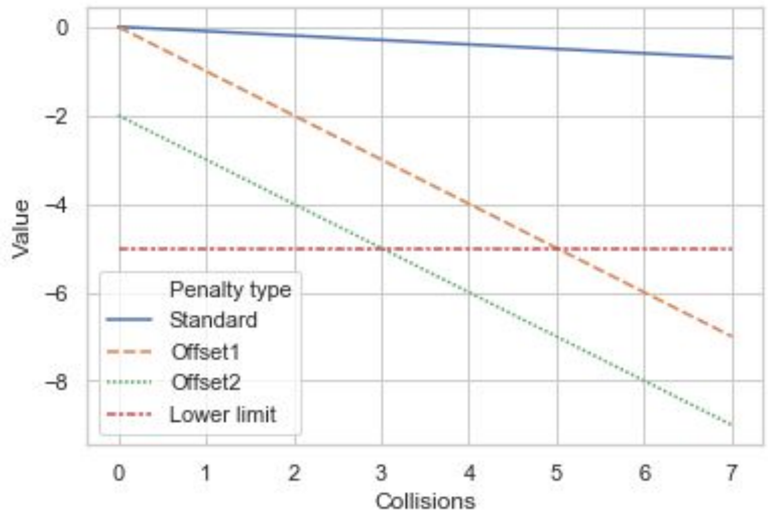
Reward thresholds	1	2	2.5	2.8	3	3.5	4
Number of obstacles	8	10	13	15	17	18	20
Min spawn distance	6	6	4	4	3	3	2
Target distance	25	28	30	33	35	37	40
Penalty offset	0.5	1.5	2	2.5	2.5	2.5	2.5

Penalty function:

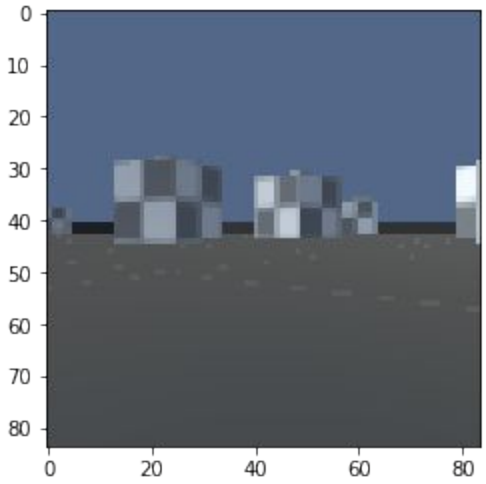
$$p = p_{offset} + collisions + time * 0.001$$

Observation sensors: LIDAR

2D maneuvering environment



Experiments - Camera Sensors



Curriculum parameters:

Reward thresholds	1	2	2.5	2.8	3	3.5	4
Number of obstacles	8	10	13	15	17	18	20
Min spawn distance	6	6	4	4	3	3	2
Target distance	25	28	30	33	35	37	40

Penalty function:

$$p = collisions * 0.1 + time * 0.001$$

Observation sensors: Camera, 84x84 RGB

2D maneuvering environment

Experiments - 3D maneuvering env.

Curriculum parameters:

Reward thresholds	1	2	2.5	2.8	3	3.5	4
Number of obstacles	8	10	13	15	17	18	20
Min spawn distance	6	6	4	4	3	3	2
Target distance	25	28	30	33	35	37	40

Penalty function:

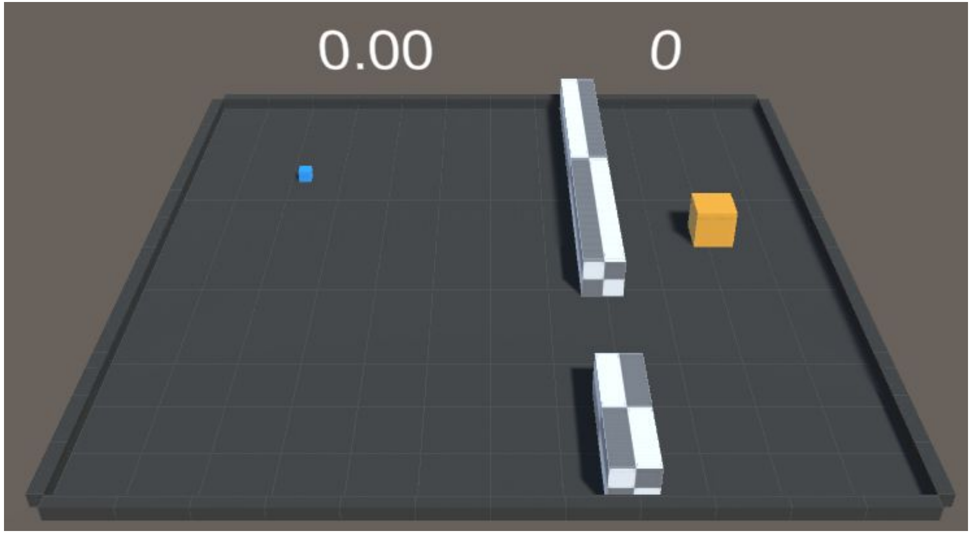
$$p = collisions * 0.1 + time * 0.001$$

Observation sensors: (Extended) LIDAR set

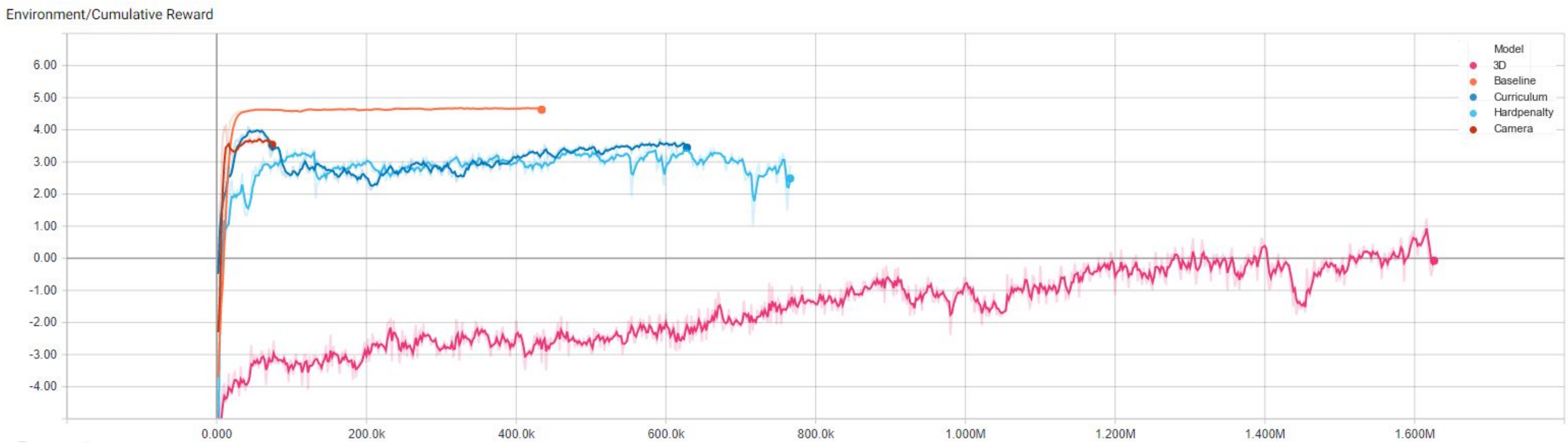
3D maneuvering environment

Experiments - Structured environment transferability

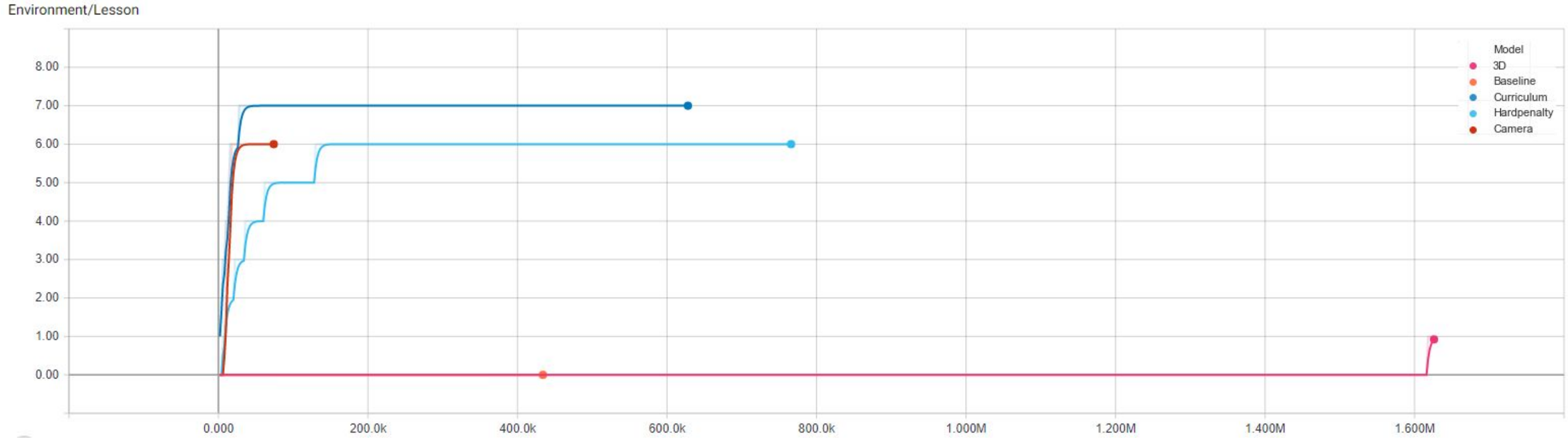
Performance evaluation of the **best** between the aforementioned models in a **structured** environment, performing the same task



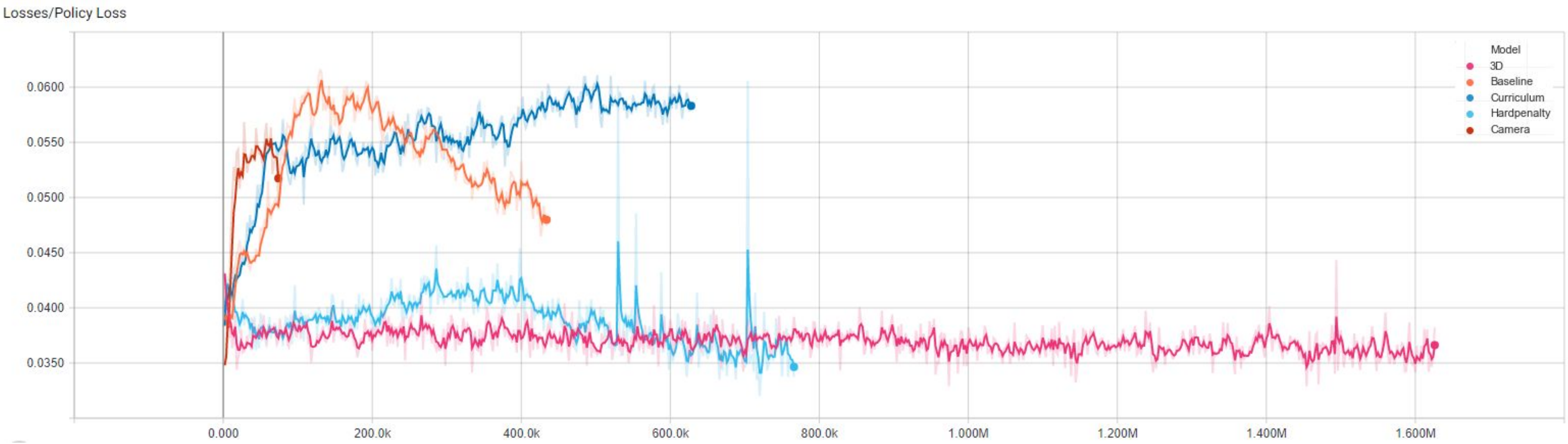
Results - Performance measures



Results - Performance measures

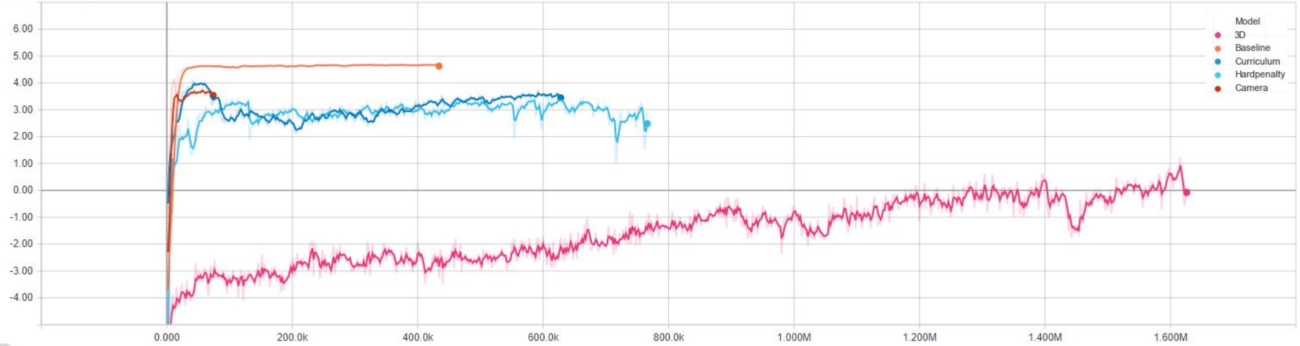


Results - Performance measures

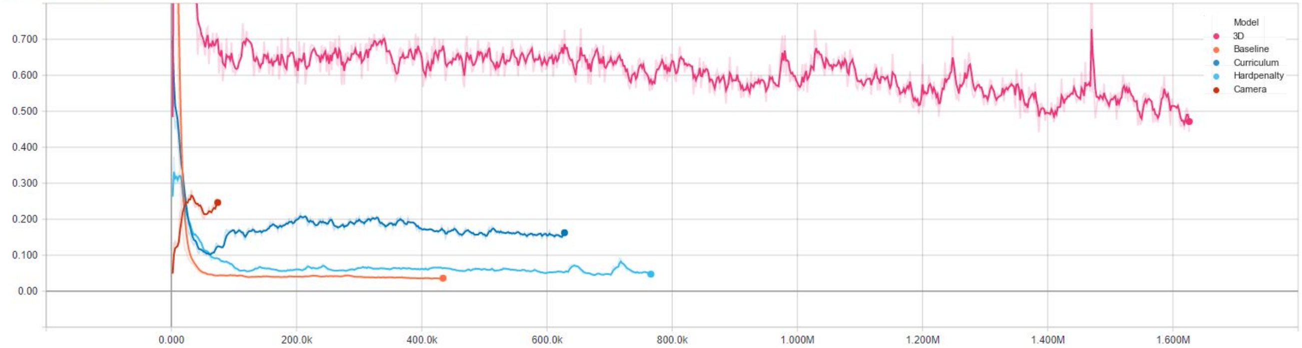


Results - Performance measures

Policy/Extrinsic Reward



Policy/Curiosity Reward



Results - Performance measures

Training time is not equal between experiments due to training time constraints.

The performance measures show **different levels of convergence** of the models and **different advancements in the lessons** of the curriculum that seem to not correlate directly with the training time.

Direct evaluation on these measures is **hard**:

- Which is the best model? The one with a better reward convergence? The one that advanced to the last lesson? The one with a better policy loss convergence? A mix of all them?
- Which measures are significative of the model performance in the experimental scenario?

Results - Environmental performance

Environmental performance measures allow us to measure the **empirical performance** of the models for the particular task they've been trained for.

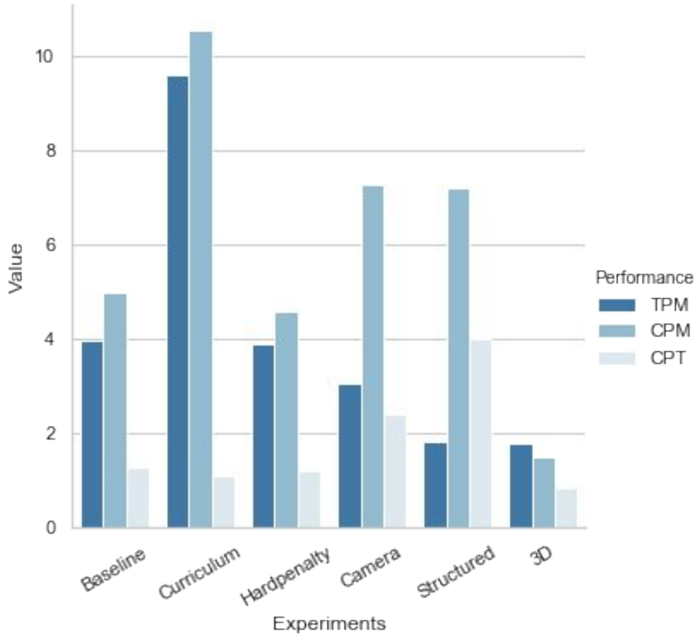
Environmental performance is hence a **domain-coupled measure**.

The measures used for this project are:

- **TPM**: Targets per minute
- **CPM**: (Obstacle) Collisions per minute
- **CPT**: Collision per target (CPM/TPM)

Each model has been evaluated on the **same environment**, having the **same parameters**, to make the comparison fair.

Results - Environmental performance



Best overall: *curriculum learning model.*

Almost every model managed to stay **below 2 CPT.**

The *harder penalty model* **did not improve** the performance.

The *camera model* **did not perform** as well as the LIDAR model, but also **did not train as much.**

The *3D maneuvering model* reached almost 2 TPM and CPM, but did not complete the whole curriculum

Conclusions

For robotic locomotion and target localization tasks **reinforcement learning** and **curriculum learning** perform effectively.

The results show a different outcome based on the **evaluation method** chosen, underlining the difficulty to evaluate correctly reinforcement learning scenarios.

The models proposed seems to converge on a policy of **random search**, a behaviour shared between every experiment model. Most probably due to the **lack of memory** of the NN and **procedural generation** of the environment.

The models are able to generalize **obstacle avoidance**.

Conclusions - Future works

- **Add memory to the system**: adding an RNN module (akin to the curiosity module) might allow the model to form an experience buffer of sorts and adopt smarter search policies.
- **Rework the reward and penalty functions**: implement more complex/effective functions, (eg soft-collisions)
- **Compare different RL algorithms**
- **Extend the types of scenarios**

Thanks for listening!

Project repository: https://github.com/nhabbash/autonomous-exploration-agent

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1.

TRANSITION HEADLINE

Let’s start with the first set of slides

“

Quotations are commonly printed as a means of inspiration and to invoke philosophical thoughts from the reader.

This is a slide title

- Here you have a list of items
- And some text
- But remember not to overload your slides with content

Your audience will listen to you or read the content, but won’t do both.

Big concept

Bring the attention of your audience over a key concept using icons or illustrations

In two or three columns

Yellow

Is the color of gold, butter and ripe lemons. In the spectrum of visible light, yellow is found between green and orange.

Blue

Is the colour of the clear sky and the deep sea. It is located between violet and green on the optical spectrum.

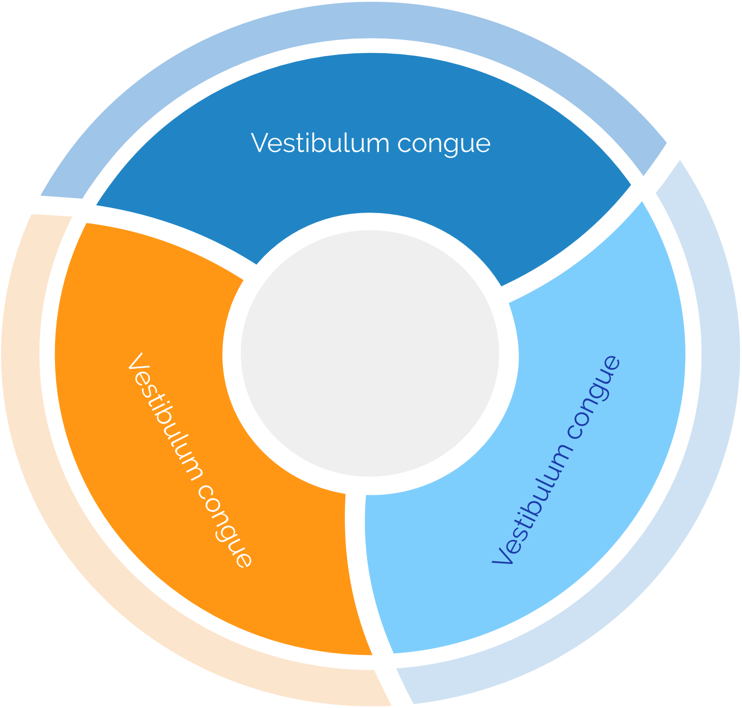
Red

Is the color of blood, and because of this it has historically been associated with sacrifice, danger and courage.

Want big impact?

Use big image.

Use diagrams to explain your ideas



And tables to compare data

	A	B	C
Yellow	10	20	7
Blue	30	15	10
Orange	5	24	16

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185,244 users

And a lot of users

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First	Second	Last
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Let’s review some concepts

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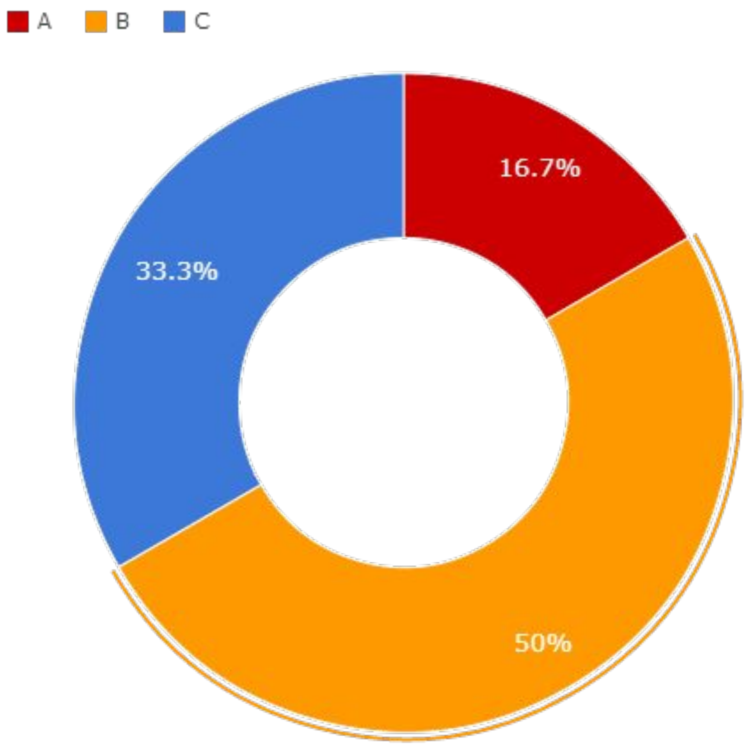

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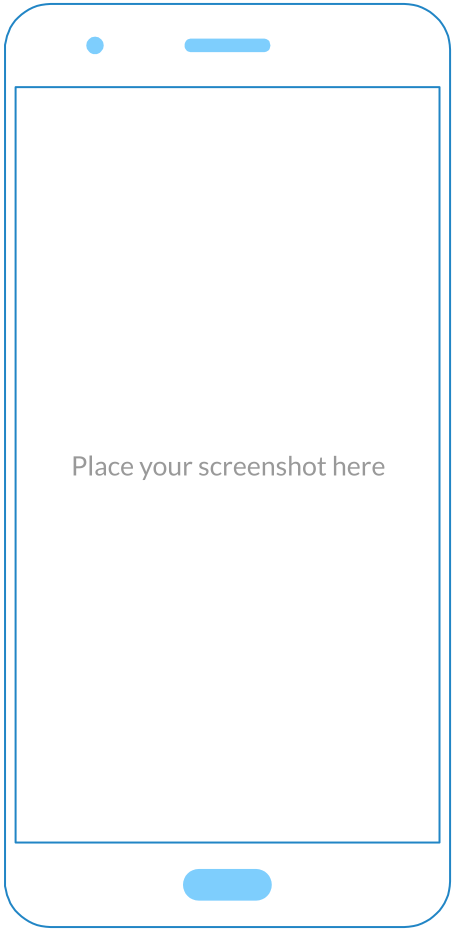

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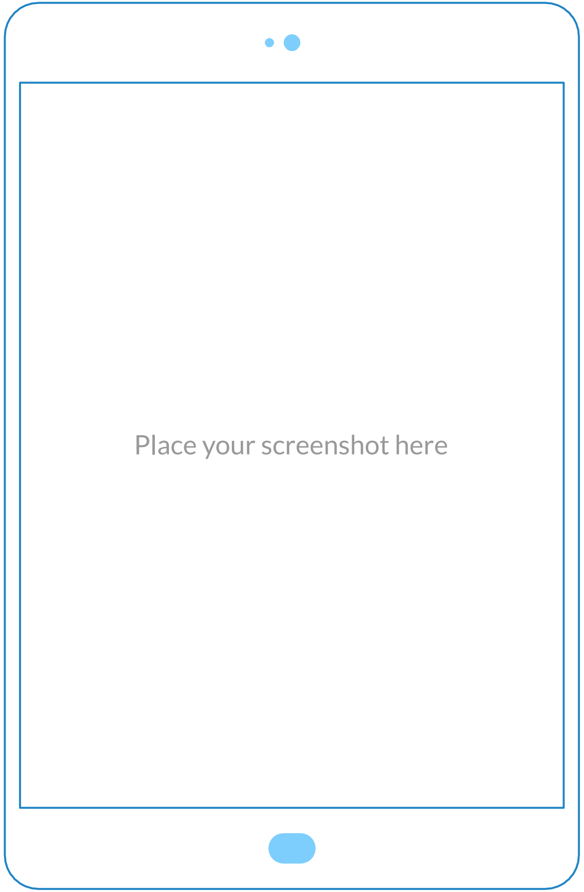

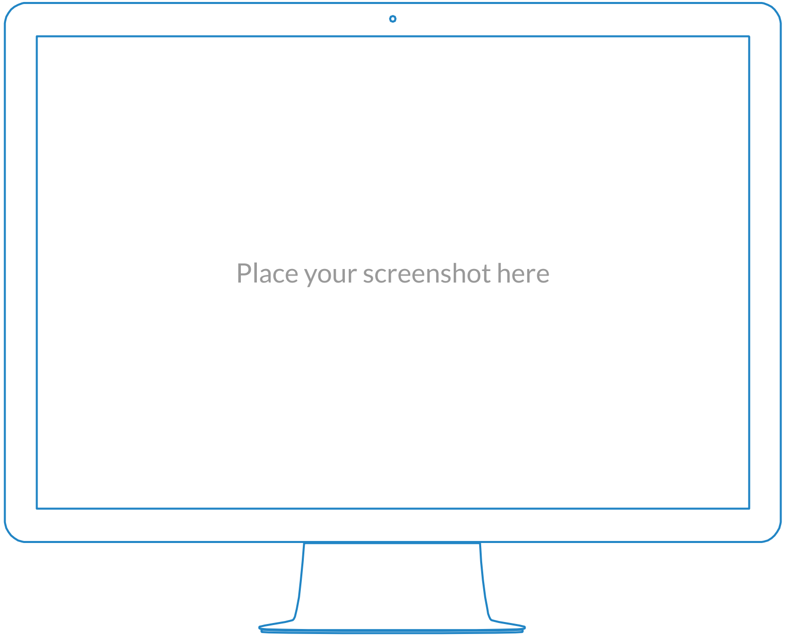

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- Dark blue **#2185c5**
- Light blue **#7ecefd**
- Yellow **#ff9715**
- Magenta **#f20253**
- Dark gray **#677480**
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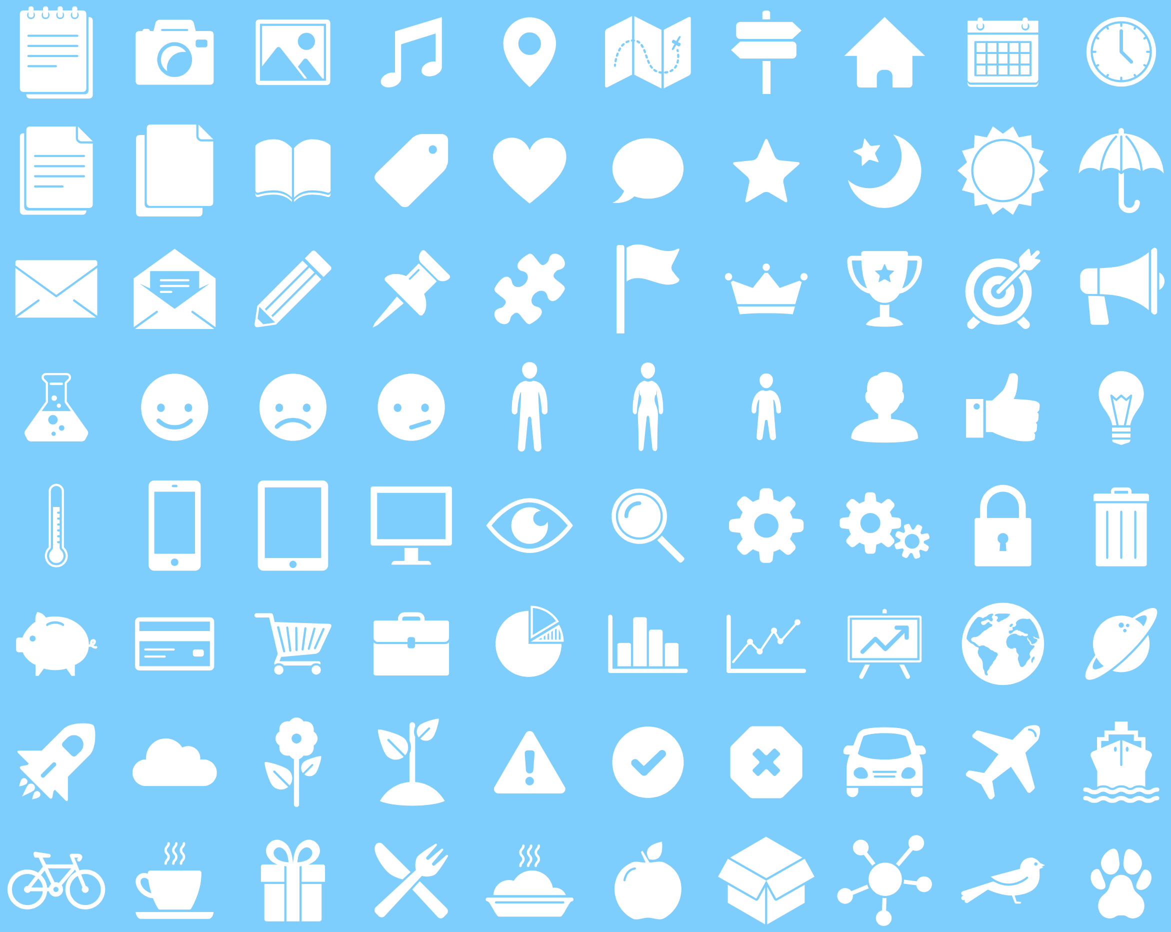

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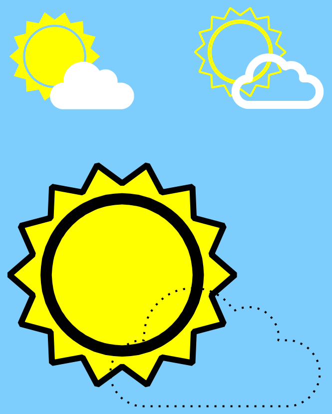

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