

# Machine (or Reinforcement): Learning to assist vessel docking in extreme environments

## Bachelor defense

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# Agenda



- ▶ Quick introduction to the problem
- ▶ Reinforcement Learning
- ▶ Simplified model
- ▶ Results & Discussion
- ▶ Conclusion & Future work

# Introduction

## The Vessel and the problem



The issue is keeping the vessel stable enough to attach to the windmill during a storm.



# Introduction

The problem and the solution





## Overview of the problem

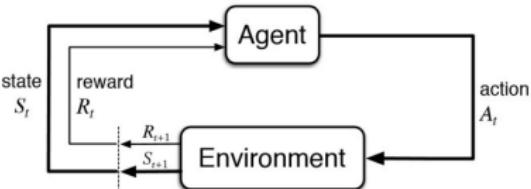
- ▶ Vessel stabilizer
- ▶ Why is a vessel stabilizer needed?
- ▶ What is Dacoma's current solution?
- ▶ The objective
- ▶ The approach

# Reinforcement Learning

## Classic Reinforcement Learning & Terminology



- ▶ Agent
- ▶ Environment
- ▶ States, Statespace,  
Actions & Actionspace
- ▶ Reward and Reward  
function
- ▶ Policy



# Reinforcement Learning

## Classic Reinforcement Learning & Terminology



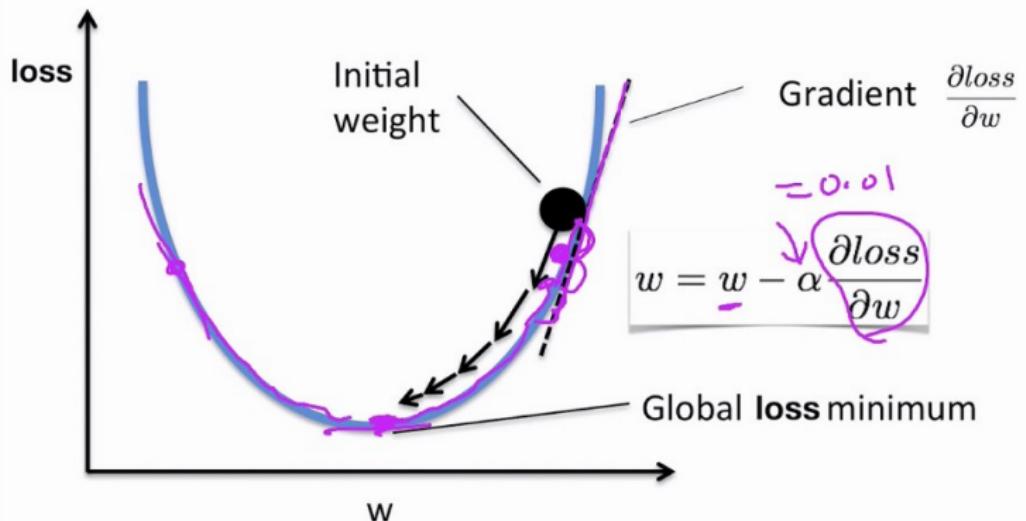
Why does classic Reinforcement learning not work for this problem?

# Reinforcement Learning

## The Policy gradient methods



### Gradient descent algorithm



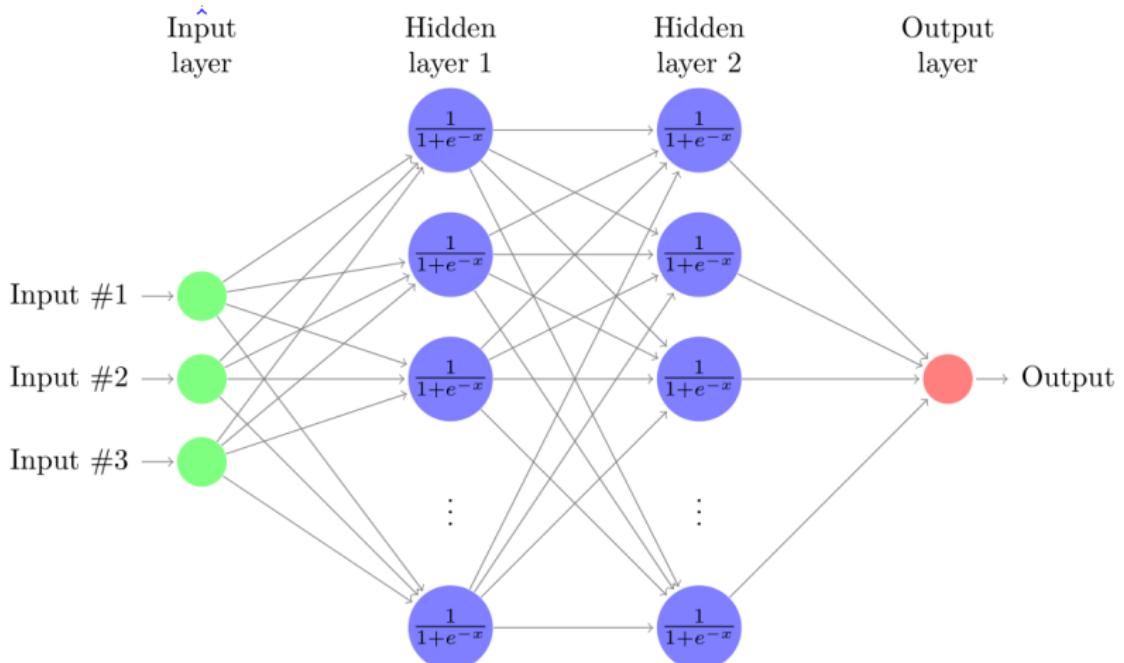
What makes Policy gradient well-suited for this task?

# Reinforcement Learning

## The Neural Networks



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# Reinforcement Learning

## The Optimizer



$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

Moving averages of gradient and squared gradient.

$$\hat{m}_t = \frac{m_t}{1 - \beta_1}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2}$$

Bias corrected estimators for the first and second moments.

# Reinforcement Learning

## The Optimizer



$$w_t = w_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$$

# Reinforcement Learning

The approach - finite differences method



Central difference ?

$$\Delta_h[f](x) = f(x + \frac{1}{2}h) - f(x - \frac{1}{2}h)$$

# Reinforcement Learning

## The approach - Implementation specifics



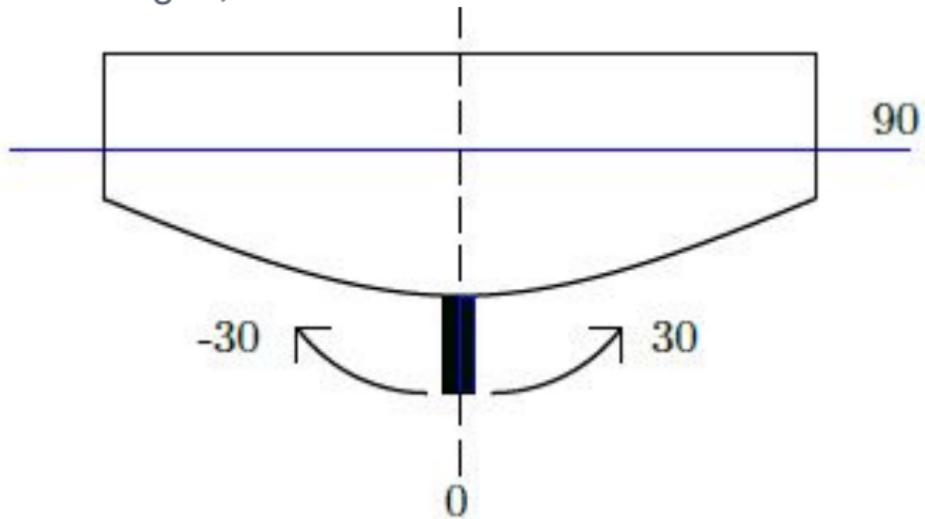
- ▶ Reward & Reward Function

# Simplified Model

## Intro

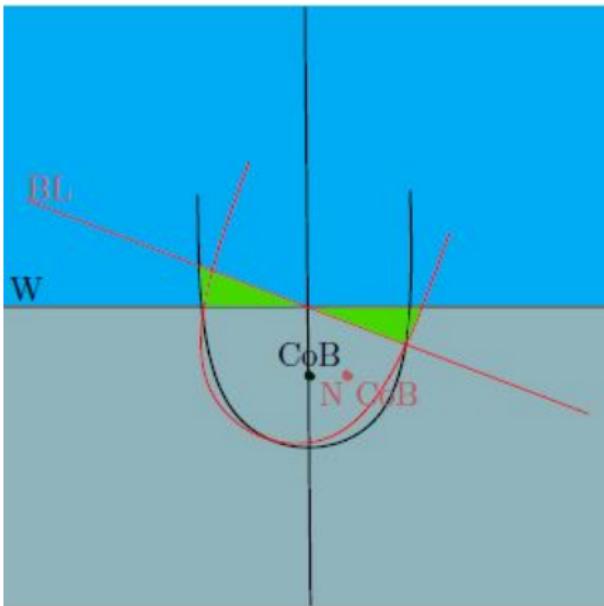


Using Archimedes principle and a adjustable air keel works to our advantages, the boat can stabilize itself.



# Simplified Model

## Bouyancy

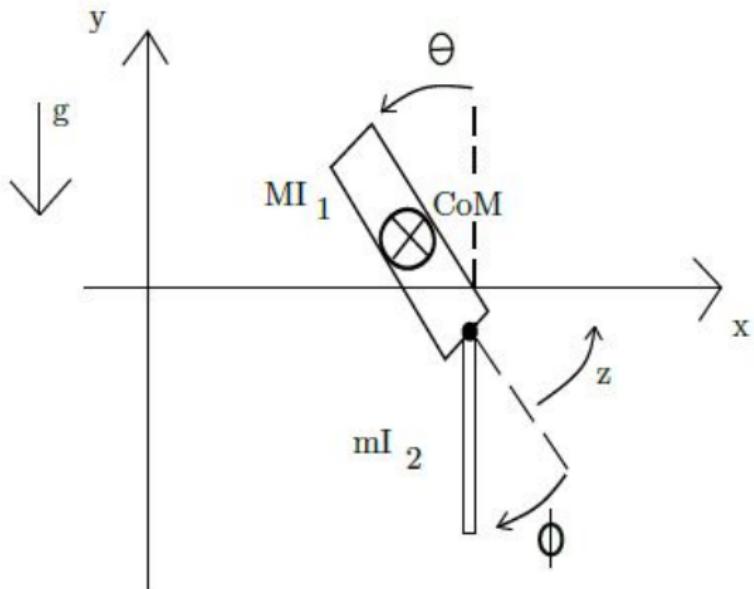


# Simplified Model

## Boat modelling



### ► Boat modelling



# Simplified Model

The model



$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(g)k_\epsilon q + B_F\dot{q} = \Gamma$$

where  $M(q)$  is the inertia matrix,  $C(q, \dot{q})$  are the Coriolis terms,  $G(q)$  is the gravity vector,  $k_{eqsilon}$  is a matrix with the elastic constants,  $B_F$  is the friction terms and  $\Gamma$  is the vector of generalized external forces applied, i.e  $\Gamma^\tau = [0, 0, 0, z]$ .

Limitations?

# Results & Discussion

## Training



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### Training and testing settings and limitations

- ▶ 500 rollouts, 200 iterations and two simulations
- ▶ Random generated bias values
- ▶ Angle limitations for the keel ( $\pm 40$ ) and boat ( $\pm 30$ )
- ▶ Angles randomly generated to be between  $\pm 25$ .
- ▶ Activation function = Leaky ReLU
- ▶ Central finite difference,  $\epsilon = 0.1262$
- ▶ Adam as optimizer
- ▶ Stopping criteria is  $\pm 1$

# Results & Discussion

## Tuning



### Tuning hyperparameters

- ▶ NN architecture
- ▶ Learning rate

|    | HL = 1 & NoN = 8 (HL1) | HL = 2 & NoN = 8,4 (HL2) | HL = 2 & NoN = 8,8 (HL2) |
|----|------------------------|--------------------------|--------------------------|
| LR | 0.1                    | 0.01                     | 0.001                    |
| LR | 0.2                    | 0.02                     | 0.002                    |
| LR | 0.5                    | 0.05                     | 0.005                    |

Table: Displays the different learning rates tested with the three different architectural choices.

# Results & Discussion

## Tuning - NN architecture

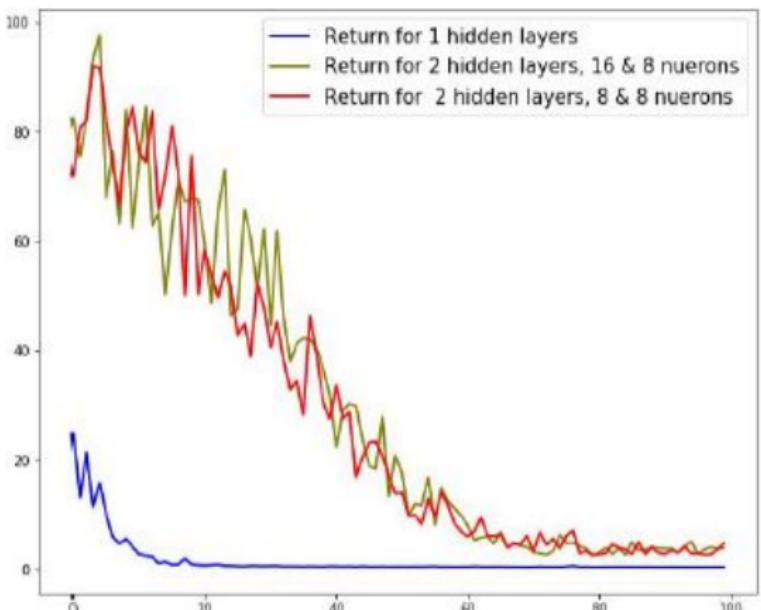


Figure: Learning rate: 0.001

# Results & Discussion

## Tuning - NN architecture

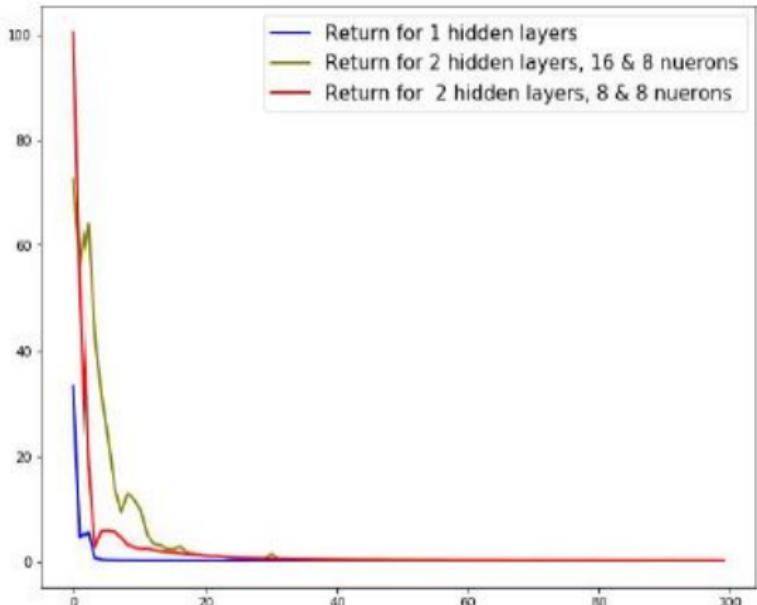


Figure: Learning rate: 0.01

# Results & Discussion

## Tuning - NN architecture

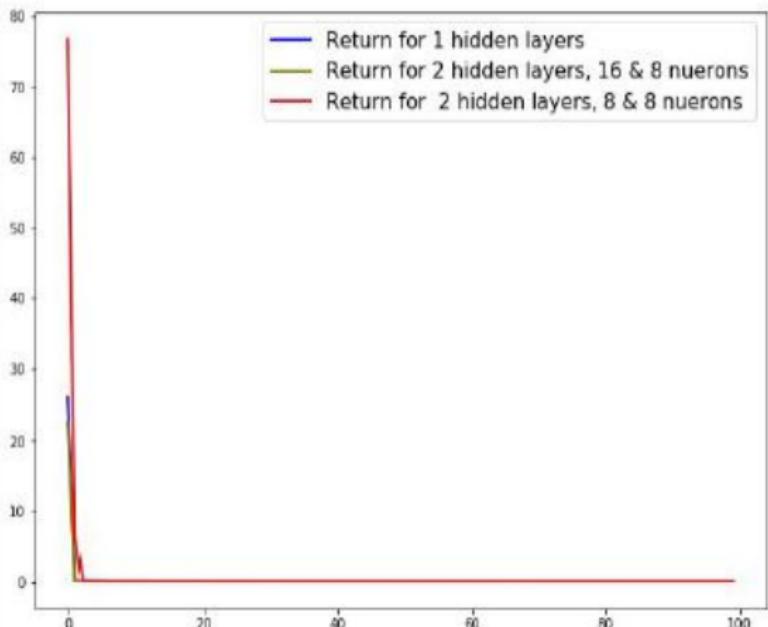


Figure: Learning rate: 0.1

# Results & Discussion

## Tuning - Learning rates

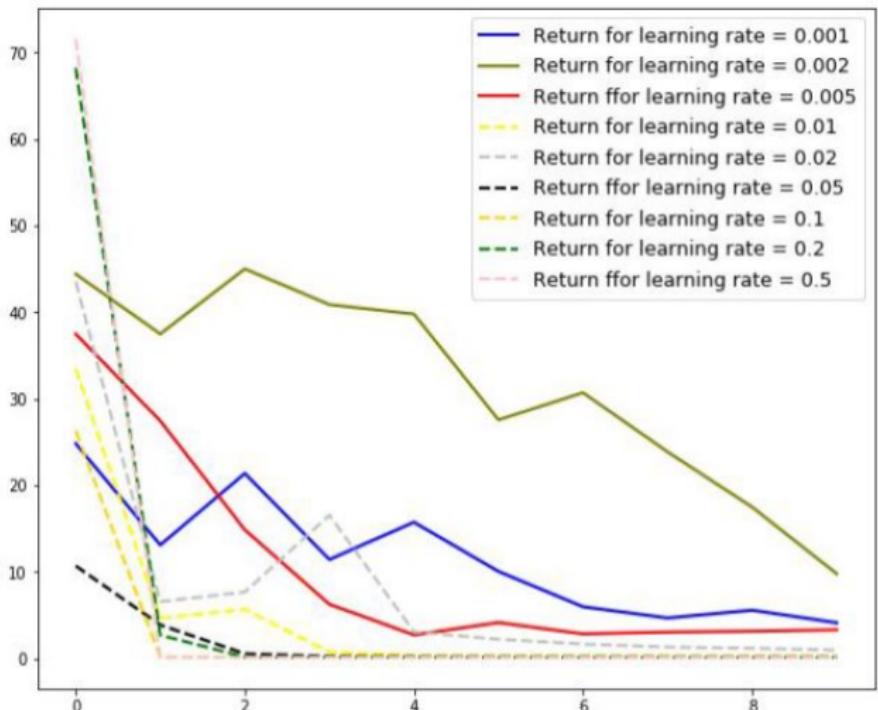


Figure: All learning rates cropped from 0 to 10 iterations

# Results & Discussion

## Tuning - Learning rates



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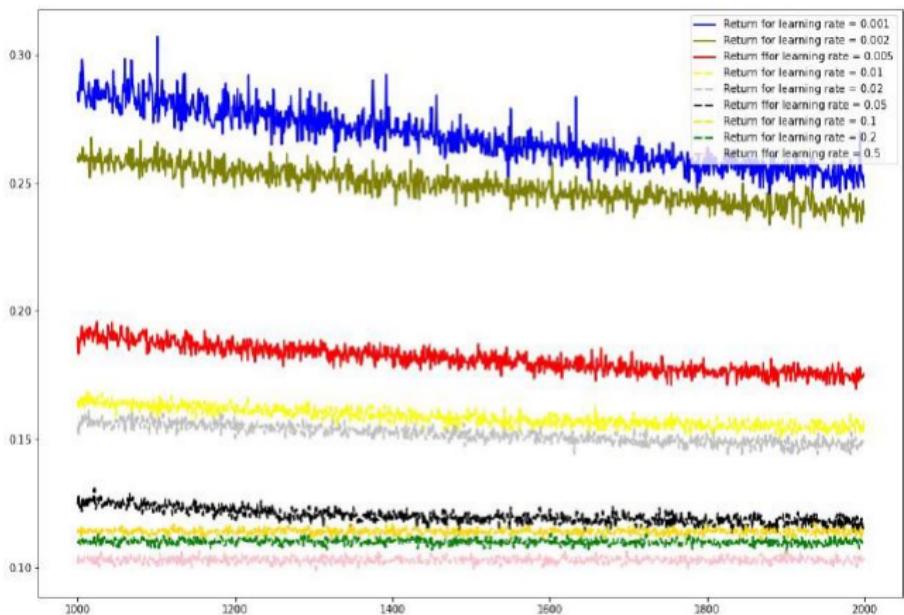


Figure: All learning rates cropped from 1000 to 2000 iterations

# Results & Discussion

## Tuning - Learning rates



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Figure: Shows the weights from chosen learning rates

# Results & Discussion

## Tests and results



| $\phi$ | $\theta$ |
|--------|----------|
| 0°     | ±20°     |
| 0°     | ±15°     |
| 0°     | ±10°     |
| ±5°    | ±20°     |
| ±5°    | ±15°     |
| ±5°    | ±10°     |
| ±10°   | ±20°     |
| ±10°   | ±15°     |
| ±10°   | ±10°     |
| ±15°   | ±20°     |
| ±15°   | ±15°     |
| ±15°   | ±10°     |
| ±20°   | ±20°     |
| ±20°   | ±15°     |
| ±20°   | ±10°     |

# Results & Discussion

## Tests and results



| Test # | $\phi$ | $\theta$ | CC without torque limit | CC with torque limit |
|--------|--------|----------|-------------------------|----------------------|
| 1      | 0°     | -20°     | 0.1345                  | 0.9                  |
| 2      | 0°     | -15°     | 0.1341                  | 0.73                 |
| 3      | 0°     | -10°     | 0.1320                  | 0.48                 |
| 4      | 5°     | -20°     | 0.1423                  | 0.9                  |
| 5      | 5°     | -15°     | 0.1395                  | 0.74                 |
| 6      | 5°     | -10°     | 0.1350                  | 0.48                 |
| 7      | 10°    | -20°     | 0.1384                  | 0.9                  |
| 8      | 10°    | -15°     | 0.1365                  | 0.73                 |
| 9      | 10°    | -10°     | 0.1324                  | 0.48                 |
| 10     | 15°    | -20°     | 0.1348                  | 0.74                 |
| 11     | 15°    | -15°     | 0.1384                  | 0.73                 |
| 12     | 15°    | -10°     | 0.1354                  | 0.73                 |
| 13     | 20°    | -20°     | 0.320                   | 0.91                 |
| 14     | 20°    | -15°     | 0.1315                  | 0.91                 |
| 15     | 20°    | -10°     | 0.1321                  | 0.9                  |

# Conclusion & Future Works

## Conclusion



- ▶ Use reinforcement to apply a torque to the air keel in order to keep the vessel stable.
- ▶ Derived a simplified model for simulation use.
- ▶ Trained an agent and found the best policy using the simplified model.
- ▶ Added a mock limitation on the amount of torque which the agent could apply.
- ▶ Works well, maybe even a bit too well?

# Conclusion & Future Works

## Future works



- ▶ Torque limitations
- ▶ A model that includes the proper effect of Dacoma's air keel
- ▶ Adding waves to the model/training the model out in the sea