

# 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

## Overview



### Overview:

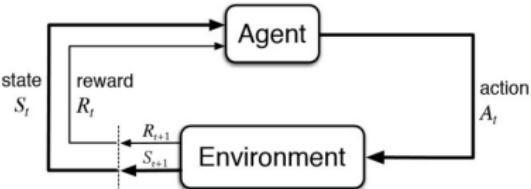
- ▶ Classic Reinforcement Learning & Terminology
- ▶ The Approach
- ▶ Issues and Shortcomings

# Reinforcement Learning

## Classic Reinforcement Learning & Terminology



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



# Reinforcement Learning

## Classic Reinforcement Learning & Terminology



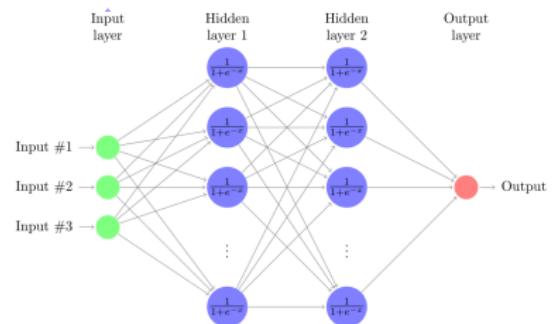
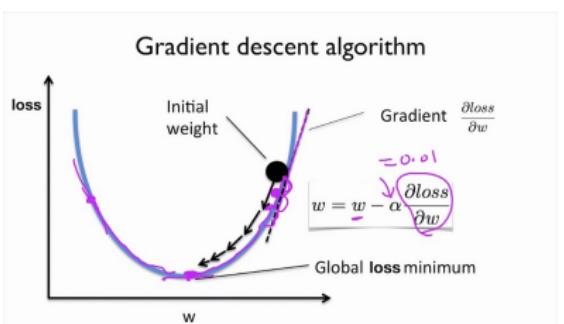
Why does classic Reinforcement learning not work for this problem?

# Reinforcement Learning

## The 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 - Implementation specifics



Implementation specifics:

- ▶ Finite differences
- ▶ Reward & Reward Function

# Reinforcement Learning

## The approach - Implementation specifics



Implementation specifics:

- ▶ Finite differences
- ▶ Reward & Reward Function

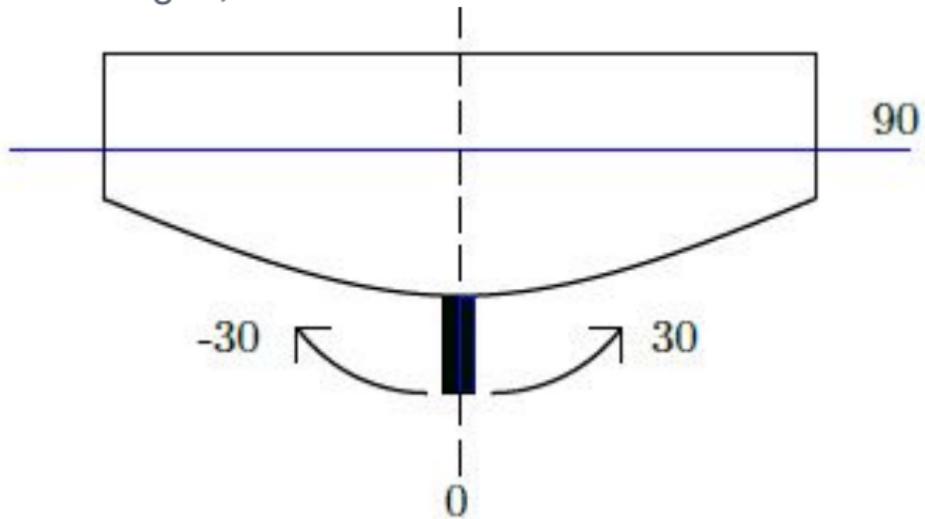
# Simplified Model

## Intro



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

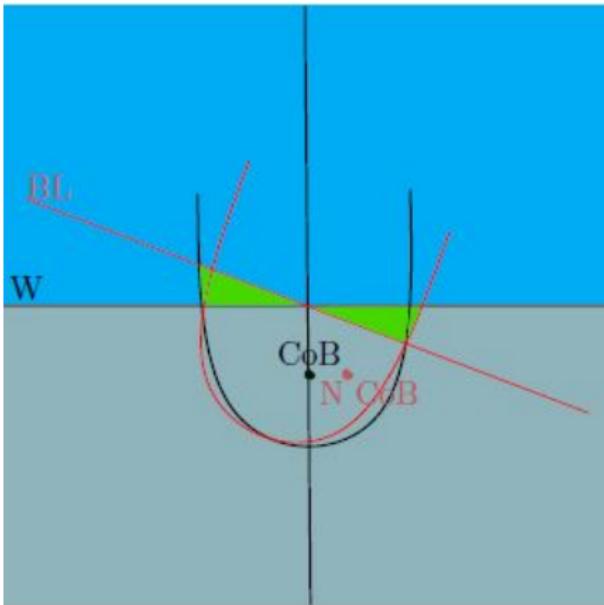


# Simplified Model

## Bouyancy



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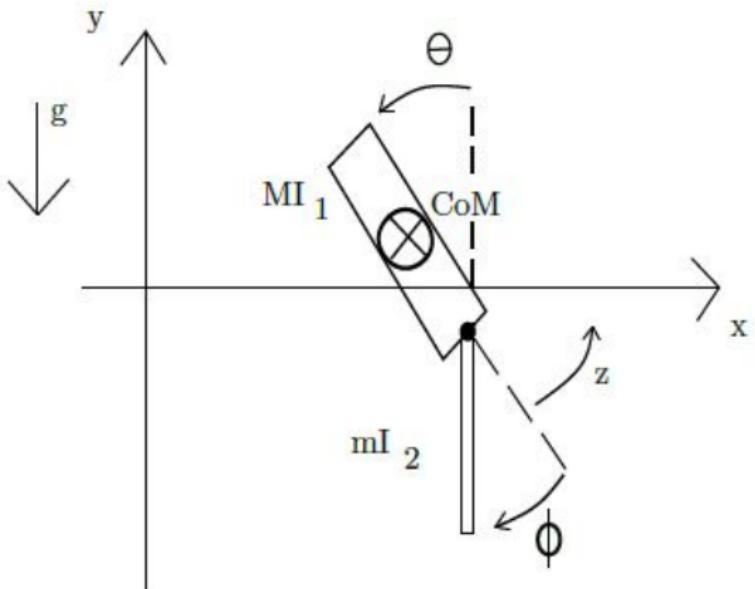


# Simplified Model

## 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  $\Gamma^\tau = [0, 0, 0, z]$ .

# Simplified Model

## Limitations



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- ▶ An approximation

# Results & Discussion

## Introduction



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- ▶ Training and testing settings and limitations
- ▶ Tuning hyperparameters
- ▶ Test and results

# Results & Discussion

## Training



- ▶ Training and testing settings and limitations
- ▶ Tuning hyperparameters
- ▶ Test and results
  
- ▶ 500 rollouts, 200 iterations and two simulations
- ▶ Random generated bias values
- ▶ Angle limitations for the keel and boat

# Results & Discussion

## Tuning



- ▶ Training and testing settings and limitations
- ▶ Tuning hyperparameters
- ▶ Test and results
- ▶ 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

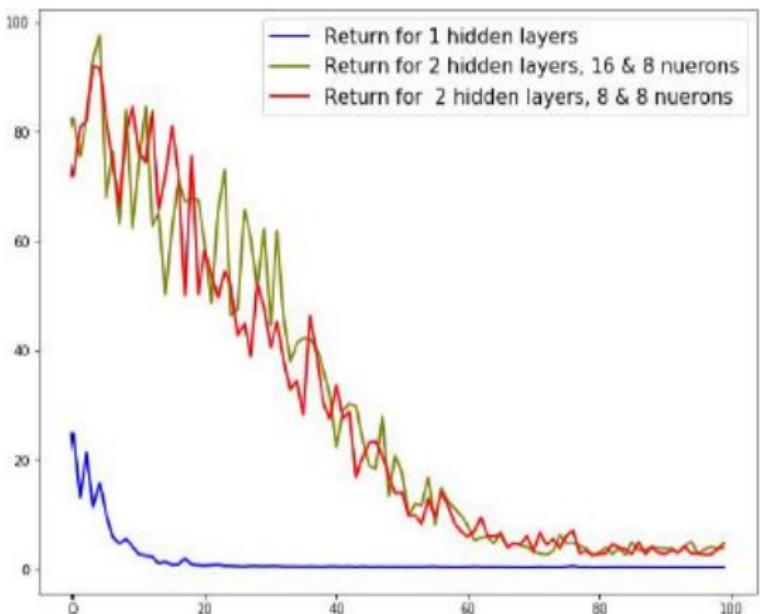


Figure: Learning rate: 0.001

# Results & Discussion

## Tuning - NN architecture

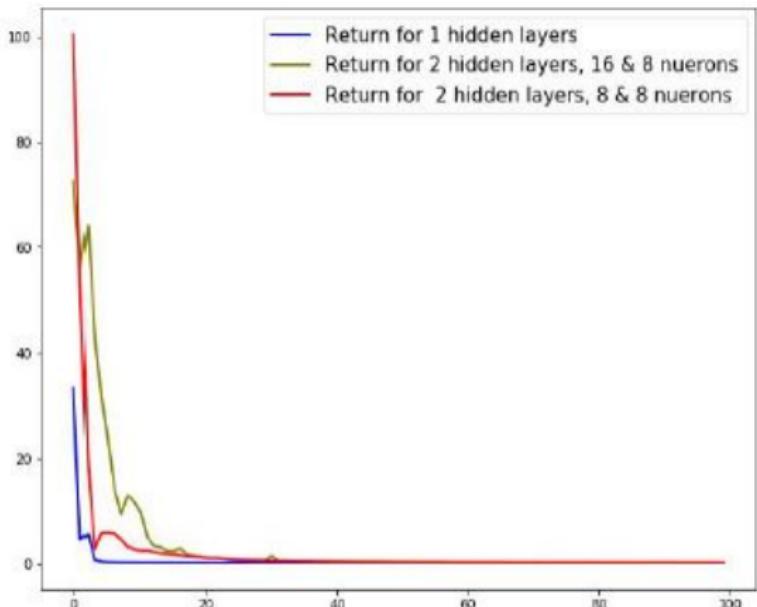


Figure: Learning rate: 0.01

# Results & Discussion

## Tuning - NN architecture

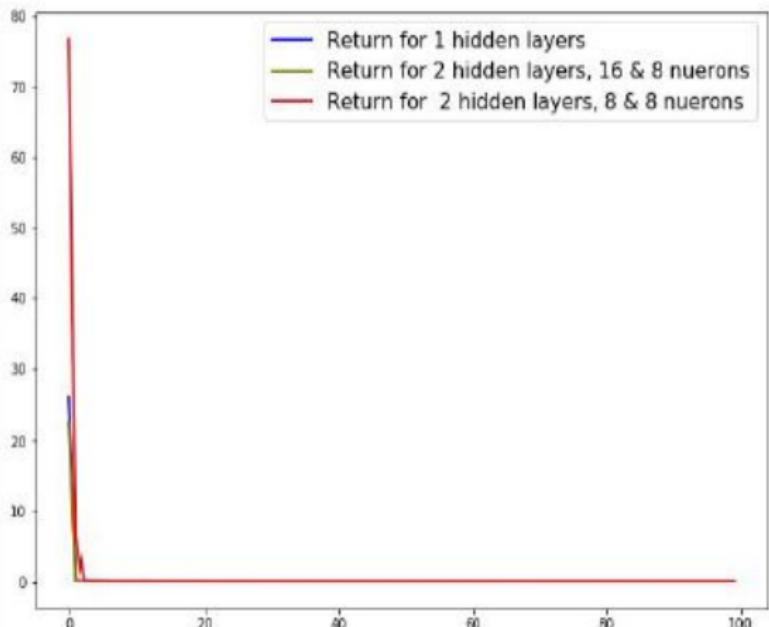


Figure: Learning rate: 0.1

# Results & Discussion

## Tuning - Learning rates

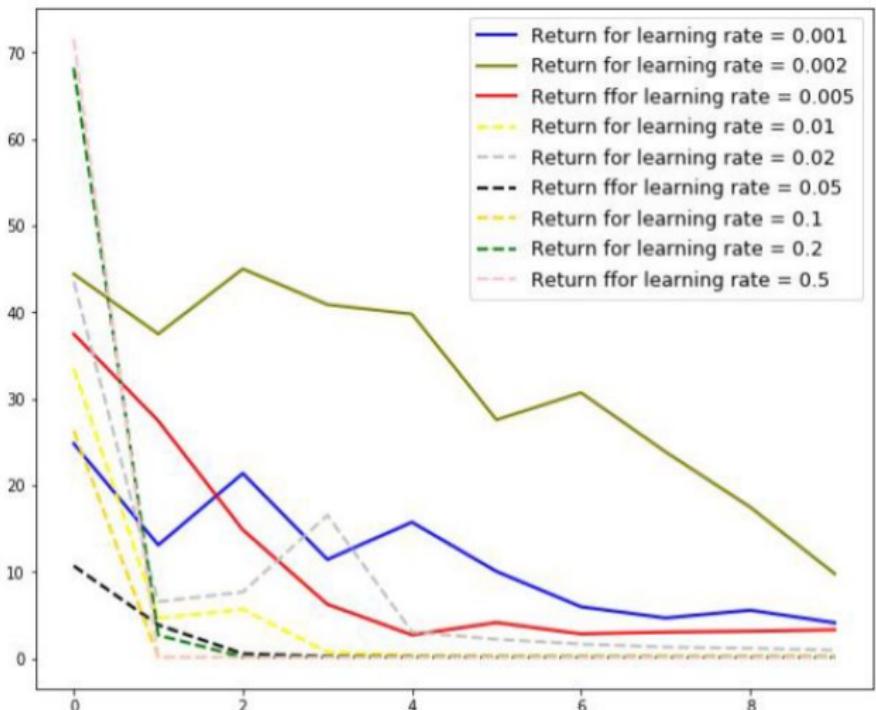


Figure: All learning rates cropped from 0 to 10 iterations

# Results & Discussion

## Tuning - Learning rates



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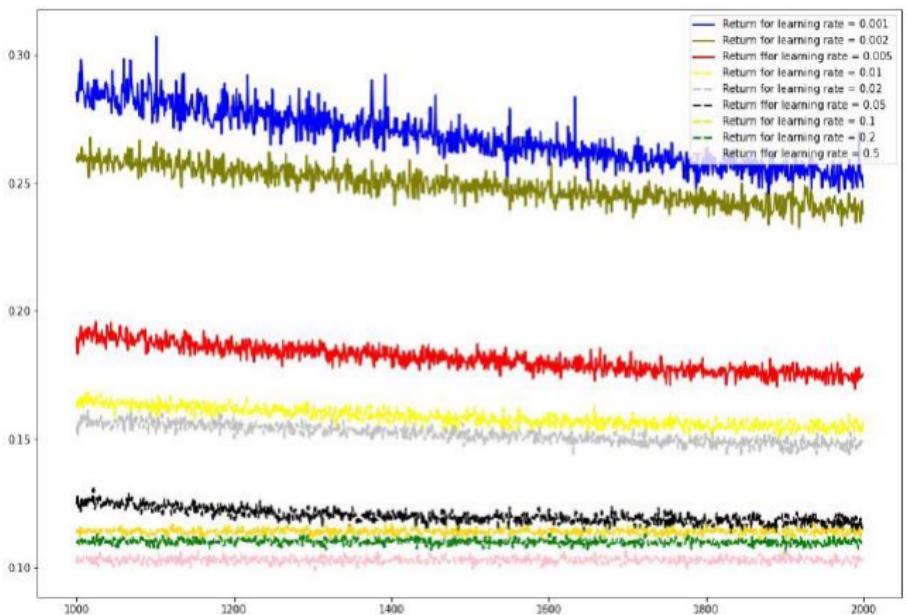


Figure: All learning rates cropped from 1000 to 2000 iterations

# Results & Discussion

## Tuning - Learning rates



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Figure: Shows the weights from chosen learning rates

# Results & Discussion

## Tests and results



- ▶ Training and testing settings and limitations
- ▶ Tuning hyperparameters
- ▶ **Test and results**

# 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

Conclusion



# 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