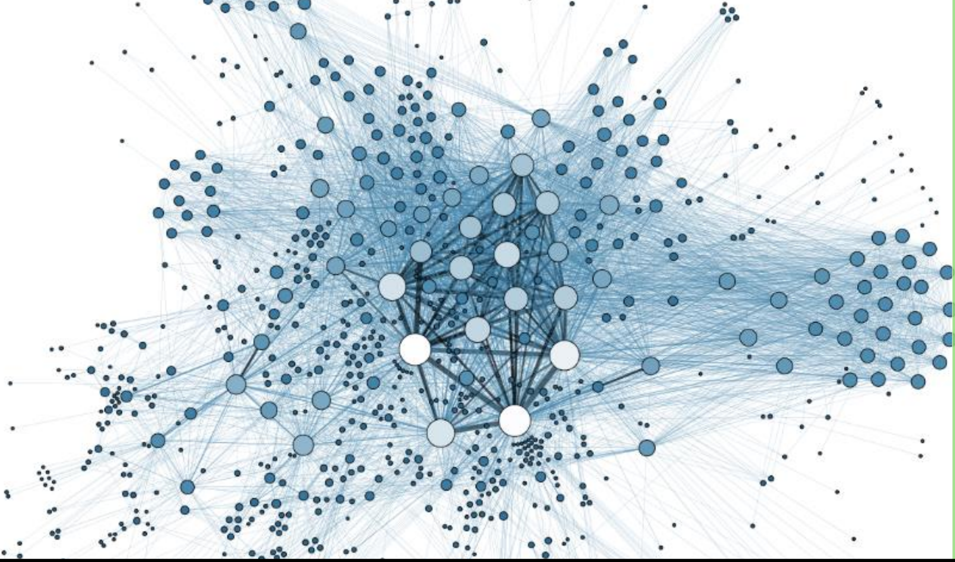
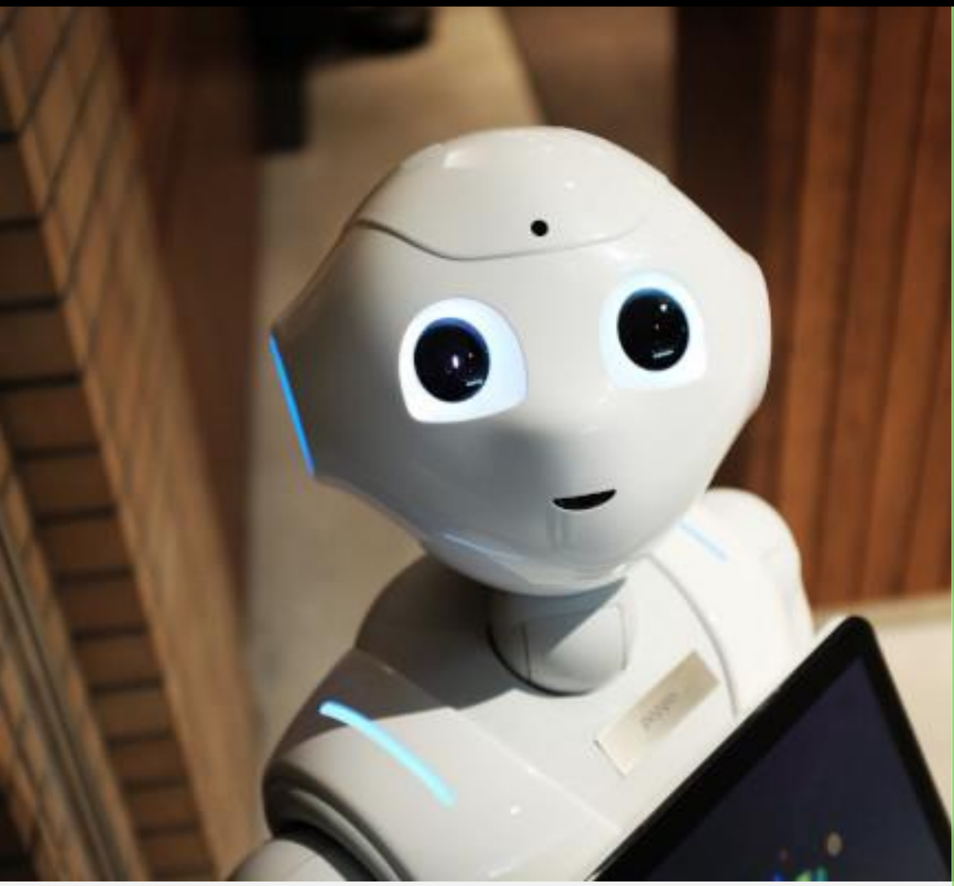
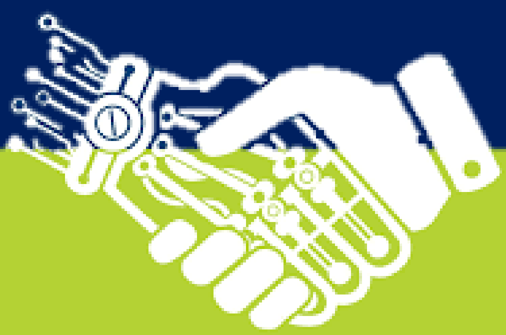


2025

Reinforcement Learning for Bioengineers (BIOE70077) Coursework (V 1.2)





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Department of Bioengineering
Imperial College London, UK

IMPERIAL

Important Information

Method of Submission

Submission via Blackboard; check Acadiary for any changes

Naming convention for the PDF to upload on Blackboard: *FirstName_LastName.pdf*

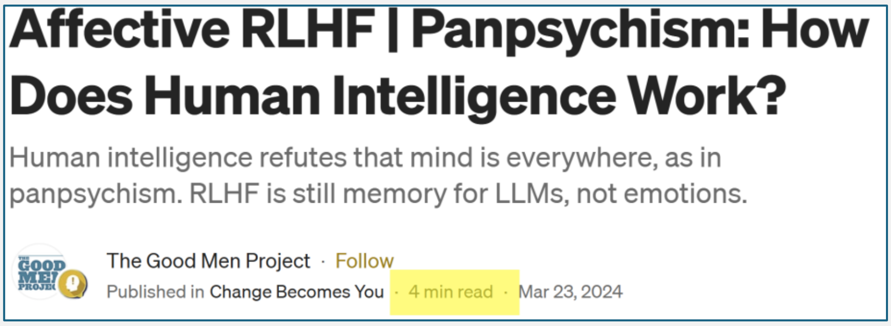
Link to your online article **should the first thing at the top of your PDF.**

Instructions

This is an '*open world'* coursework that requires that you complete 1 task, that will make up for 75% of the module mark. The other 25% will be assessed by an in-class test/quiz. This coursework offers considerable flexibility, emphasising independent learning, core RL concepts, self-directed research, creativity, and programming skills. It places significant importance on employability and acquiring new competencies, including technical reading and writing about RL principles, familiarising oneself with seminal works in the field, and engaging with insightful blog posts.

Word Limit

There is no word limit, however, your article should not be longer than ***10 minutes read***. This will show up under the title of your article, for example:



This coursework is an out-of-the-box learning approach that has tangible benefits for your career if done right. It offers you a unique opportunity to not only learn advanced RL methods, coding, and applications but also to build a professional online portfolio. By publishing your tutorial on platforms like Medium.com, you will showcase your expertise in RL to a global audience, demonstrate your ability to understand complex concepts, run and interpret experiments, and establish a credible and visible presence in the academic and professional community.

Additional Information for Completion of Assessment

This is an individual piece of work. Please make sure you have a clear understanding of the grading principles for this component as detailed in the Marking Scheme. If you are unsure about any aspect of this assessment, please seek the advice of a member of the delivery team.

Important Information on Dishonesty & Plagiarism

Plagiarism will be dealt seriously. Students are directed to the college regulations for details of the procedures and penalties involved. For further information, see www.plagiarism.org

Use of Generative AI

For this coursework, you are ***strongly encouraged*** to use generative AI tools (e.g., Copilot, ChatGPT) to support your work, such as for generating ideas, drafting, or summarising information. However, it is mandatory to acknowledge the use of these tools within your submission.

When acknowledging the use of generative AI tools, please include the following details:

1. The name and version of the AI tool used (e.g., ChatGPT-5).
2. The publisher (e.g., OpenAI).
3. The URL of the AI tool.
4. A brief description of how the tool was utilised in your work.
5. Concerning that the final submission is your own work.

You can find further information on the use of GenAI at this link:

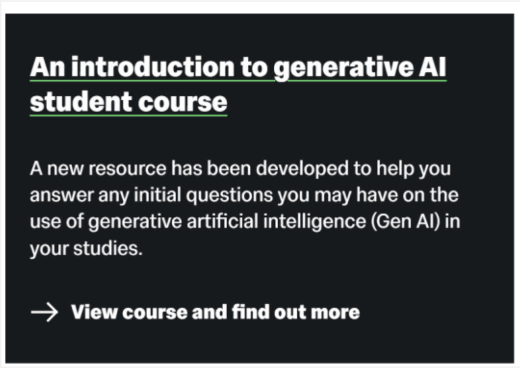
https://www.imperial.ac.uk/staff/educational-development/teaching-toolkit/use-of-generative-ai-for-teaching-learning-and-assessment/

Example Acknowledgment Statement: "*I acknowledge the use of ChatGPT 5 (OpenAI, https://chat.openai.com/) to generate an outline for background study. I confirm that no content generated by AI has been presented as my own work*."

Additionally, ensure you adhere to the following guidelines when using AI tools:

- Avoid entering sensitive or confidential data into these systems, as queries may be stored and could contribute to training datasets.
- Do not input personal or private information into AI platforms.

If you are new to Generative AI, the college offers a free course to get you up to speed with it. You can enrol in the course by clicking on the following image:



Click here to enrol in the course.

Please note that, as of today, none of the most renowned top-tier tutorials, books, papers, lessons, or articles are generated by generative AI (GenAI). They remain the result of human creativity, expertise, and dedicated effort. This coursework, therefore, is not only an opportunity to engage with cutting-edge technology responsibly but also to develop a valuable skill that may not present itself again soon. Embrace this as a chance to enhance both your understanding of RL and your ability to critically evaluate the use of these tools in a professional and academic context.

Task Overview

This coursework is designed to help you achieve the core learning objectives of the module, while simultaneously preparing you to apply advanced RL methods in the context of bioengineering. By focusing on advanced RL techniques, this coursework reflects the module's emphasis on theory, implementation, and evaluation, with a strong alignment to real-world bioengineering applications. Your task is to write a high-quality tutorial on one of the selected reinforcement learning methods. The tutorial should explain the chosen method in a clear and engaging way, focusing on its practical implementation and how it could be applied to real-world scientific problems. While you are **NOT** required to write new code, apart from minor changes necessary to produce visuals; you must demonstrate that you understand and can run the method by generating your own plots, graphs, or visualisations. Contextualising the method within a bioeng can earn you up to **5 bonus marks**.

You may choose from any **ONE** of the following topics to write a tutorial, that is easy to follow and help understand the method in simple words. You can choose a more advanced topic, but please discuss this beforehand with me. Please note that these topics build upon what we have learned in this module, but vary in complexity, ensuring there is something to learn for students of all abilities and backgrounds. The quality of your tutorial, the challenge it addresses, and how effectively it simplifies the topic will be the key factors in determining a higher mark. There is no limit on how many students can choose to write on the same topic – hence you are in a competition. Here is a list of topics you can choose from, but is not an exhaustive list:

Human-Level Control with DQN

This method applies DQN to Atari games, demonstrating how deep RL can achieve human-level performance in complex, high-dimensional environments like video games. It leverages DQN and Double DQN concepts for scaling to more complex tasks. https://arxiv.org/abs/1509.06461

Double Deep Q-Networks (Double DQN)

Double DQN addresses the overestimation bias in DQN by decoupling action selection and action evaluation, improving stability and performance in environments with noisy rewards. It builds on DQN's foundations, refining its accuracy and robustness. https://arxiv.org/pdf/1509.06461

Deep Deterministic Policy Gradient (DDPG)

DDPG is an actor-critic method designed for continuous action spaces, combining deterministic policies with deep function approximation for efficient learning in robotic and control tasks. It transitions from discrete action spaces (DQN) to continuous ones, introducing policy gradient methods. https://arxiv.org/abs/1509.02971

Asynchronous Advantage Actor-Critic (A3C)

A3C introduces parallel training for actor-critic methods, improving sample efficiency and stability while learning value functions and policies simultaneously. It builds on actor-critic architectures like DDPG and extends them with asynchronous updates for faster convergence.
https://arxiv.org/pdf/1602.01783

Addressing Function Approximation Error in Actor-Critic Methods (TD3)

TD3 improves upon DDPG by addressing overestimation bias using twin Q-networks, delayed policy updates, and target smoothing, leading to more stable and robust training. It builds on DDPG, directly addressing its limitations in stability and overestimation. https://arxiv.org/abs/1802.09477

Proximal Policy Optimisation (PPO)

PPO is an on-policy reinforcement learning algorithm that simplifies trust region policy optimisation, making it more efficient and scalable. It uses clipping and surrogate objectives to stabilise updates, achieving state-of-the-art performance in both discrete and continuous control tasks, such as robotics and high-dimensional simulations. https://arxiv.org/abs/1707.06347

Soft Actor-Critic (SAC)

SAC is an off-policy actor-critic algorithm that incorporates entropy regularisation to encourage exploration. It refines actor-critic methods like DDPG and A3C by improving exploration and robustness in high-dimensional continuous tasks. https://arxiv.org/abs/1801.0129

Model-Agnostic Meta-Learning (MAML)

MAML is a meta-learning framework that trains models to adapt quickly to new tasks with minimal data, making it highly versatile for RL and multi-task learning scenarios. It builds upon actor-critic and policy gradient methods, focusing on generalisation across multiple tasks.
https://arxiv.org/abs/1703.03400

You can find implementation details, commentary and discussion of these papers on **https://huggingface.co/** . It also connects you to the global research community and ensures your work aligns with industry standards, making it an invaluable tool for mastering reinforcement learning.

You are welcome to watch YouTube videos, tutorials, take inspiration from other people's work and use ANY implementation to get started on your topic.

Example Medium Articles to get started:

Here are some articles worth checking:

Deep Q-Networks (DQN): Step-by-Step

Structured Control Nets for RL

Our NIPS 2017 Learning to Run Approach

Convolutional Neural Networks: A Comprehensive Guide

Machine Learning is Fun, Part 8: How to Intentionally Trick Neural Networks

RL — Actor-Critic Methods: A3C, GAE, DDPG, Q-prop

Simple Reinforcement Learning with TensorFlow (Part 8): Asynchronous Actor-Critic (A3C)

Guide to Transformers — Step-by-Step Explanation

Marking scheme

A Simple Introduction (5 Marks)

Begin with a clear and concise overview of the reinforcement learning method. Highlight its significance in solving practical problems, and explain the challenges it addresses.

Theoretical Explanation (10 Marks)

Provide a conceptual explanation of the method, outlining its key mechanisms. Include sufficient mathematical detail to explain its functionality (e.g., loss functions or core algorithm steps) but avoid complex derivations. The focus should remain on accessibility and clarity.

Code Demonstration (5 Marks)

Showcase the method's implementation by focusing on its core logic—what makes it work. Avoid a line-by-line explanation but ensure key parts of the code are thoroughly explained. Include links to the original code (e.g., GitHub or Papers with Code) to provide transparency and reproducibility.

Results and Visualisation (25 Marks)

Be creative! Use the provided or referenced code to generate original learning curves, heatmaps, or policy visualisations, tables, figures etc. Explain these results clearly, focusing on what they reveal about the method's performance and behaviour. If you are unable to run or understand the entire code, instead of leaving this part blank, do as much as you can and state any limitations. If takes too long – then try to run a more manageable version of the code or look for alternative implementations.

Professional Presentation: 5 Marks

Figures, style, clarity, structure, innovation etc.

Bioengineering Contextualisation (Optional, up to 5 *Bonus* Marks)

Suggest how the RL method could be applied to a bioengineering problem. Examples include optimising robotic prosthetics, designing personalised drug delivery systems, or modelling biomechanics for rehabilitation.

Note: If for ANY reason you ***do not want to publish online***, you can upload just the PDF of your article to the blackboard. The grading criteria will remain the same. However, you may benefit from your online visibility showcasing your work.

Submission Requirements

Create a PDF version of your tutorial and upload it to Blackboard by the deadline (check Acadiary for any changes). Please do not leave submissions to the last minute to avoid mishaps, as the student office will penalise late submissions.

Publish your tutorial on Medium.com and submit the link in your PDF. All visualisations (e.g., learning curves, Q-value heatmaps) must be original and generated by you. Submit on BB or cite (link) any scripts or notebooks used to generate your results.

Tips for a Good Read

Here are some tips that will be helpful:

Make Your Article Insightful, In-Depth, and Easy to Understand:

Explain the RL method clearly, breaking down complex concepts into manageable parts. Use examples, figures, and simple language to make the content accessible to readers, especially those with a bioengineering background.

Ensure Your Content is Original:

Write in your own words, and add unique insights or examples that connect the RL method to bioengineering applications. Original figures and visualisations will help demonstrate your understanding.

Focus on Clear Messaging:

Ensure your tutorial has a clear narrative. State the significance of the method early on and maintain focus throughout. Avoid unnecessary technical jargon unless it is explained.

Use a Short, Catchy Title and Meaningful Subtitles:

Choose a title that reflects the method and its relevance. Use subtitles to guide the reader logically through the tutorial, such as theoretical explanation, code demonstration, results, and bioengineering context.

Deliver Value to Your Audience:

Think about what other students, professionals, or researchers could gain from your tutorial. Highlight the practical applications of the RL method and provide actionable insights.

Display Code Clearly (if included):

Include only the most important sections of code in your tutorial, focusing on the core functionality of the method. Format the code neatly and provide links to the full implementation for reproducibility.

Fact-Check Thoroughly:

Verify your explanations and results. Ensure your tutorial aligns with the theoretical understanding of the method and that all claims are backed by evidence or references.

Keep Your Conclusion Concise and Focused:

Summarise key findings and discuss the significance of the method. Highlight strengths, limitations, and potential future applications, especially in bioengineering.

Use Precise Tags:

Choose tags that reflect the content of your tutorial, such as "Reinforcement Learning," "Deep Q-Networks," or "Bioengineering Applications," to help your article reach the right audience.

Include Engaging and High-Quality Images:

Create original figures, such as learning curves or heatmaps, using the results of your experiments. Ensure visuals are clear, relevant, and enhance the tutorial's readability.

Cite Data and Sources Properly:

Reference any external code, papers, or resources used in your work.

Seek Feedback Before Submitting:

Share your draft with peers, friends, or mentors for constructive feedback.

Guaranteed First Route (optional):

If you go beyond learning and adapting an RL method by applying it to a real problem to produce new results, or by innovating the method itself to reach a standard suitable for publication, I will gladly support you in writing and submitting a paper to a relevant journal or conference. Any work (*but not limited to*) that reaches publication-ready quality is guaranteed to receive a higher first-class mark – given other requirements for the assessment are met. As your module leader, I will be the judge of that. You can show it to me in when your results are ready and we can discuss that further. If there are enough papers, this could then be submitted as a collection to a conference or a journal.

Rationale

Typically, most coursework courseworks are designed primarily for learning and feedback. However, under academic pressure and tight deadlines, such tasks can often become a burden, something students wish to complete quickly and move on from. As a result, once the coursework is submitted, students tend to forget about it. Their work is rarely revisited or read again, sometimes not even by themselves.

This means that the significant effort invested in the coursework, while valuable, often stops bearing fruit in terms of advancing the student's professional, academic, or entrepreneurial career.
To change that, this coursework offers the following tangible benefits:

1. **An online article** (e.g., on *Medium*) showcasing your expertise and establishing your professional portfolio and online presence. You can include this in your CV, and potential employers will be able to find and read your article when they research your online portfolio.
2. **Engagement with the wider AI, ML, and Data Science community.** For those who enjoy writing, this can help you build a following and potentially become a recognised voice in the field. In addition, platforms such as *Medium.com*, *SuperDataScience.com*, and *SAGE Publications* pay authors per read once you monetise your content.
3. **Potential for formal scientific publication.** If your work (optionally) evolves into a *scientific article* or *conference paper*, it can be listed on your CV and will remain a permanent part of your professional profile. When you move between employers or academic positions, it moves and stay with you. You don't need to have a ready to submit paper by the end of this module (we can work on it later), but your innovation, results and contribution would be explained in your medium article.
4. Moreover, though very ambitious, but applying RL to a domain of your personal interest could even inspire an **entrepreneurial venture or startup idea** (just saying!). This could feed to other modules or projects too. A chance of that happening is way more than winning a lottery.

Here are some papers for inspiration:

The Health Gym: Synthetic Datasets for Health RL
Model-Based RL for Glycaemic Control
Offline RL for Blood Glucose Control
RL for Multimorbidity Management from EHRs
Deep Offline RL for Treatment Optimisation
pH-RL: Personalised Healthcare Reinforcement Learning
Multi-Agent RL for 3D Medical Segmentation
Multi-Step RL for Imbalanced Medical Segmentation
Representation Learning for RL in Healthcare
RL for Brain Lesion Detection on MRI

Here are some datasets to get you started:

https://www.kaggle.com/datasets?search=reinforcement+learning&sort=published

https://huggingface.co/datasets

https://physionet.org/about/tutorial/

https://www.cancerimagingarchive.net/access-data/

https://archive.ics.uci.edu/

https://medmnist.com/

https://github.com/tensorflow/agents

Happy Learning!