



INM701: Introduction to Artificial Intelligence Coursework

Submission deadline: Sunday 14th January 2024, 5pm

Introduction

On completing this coursework, you should be able to:

1. Describe a machine learning problem and apply artificial intelligence techniques to that problem.
2. Use AI techniques covered in the module to apply, compare, contrast and critically evaluate **at least two** ways of analysing your problem data.
3. Describe the systematic application of your chosen artificial intelligence methodology to the chosen problem (for example, data preparation, parameter tuning).
4. Give an individual presentation of your work and your findings.

This coursework builds on the material covered in the tutorials and lecture. Python should be used for all implementations. Deliverables are:

- a written report of your work (max 9 pages)
- an individual written reflection evaluating your work, and your contribution to the project (max 1 page)
- your practical implementation (code)
- an individual presentation (12 minutes slot including questions, aim: 9-10 minutes talk and 2-3 minutes for questions); to be scheduled

Module mark

This coursework (including the presentation) is worth 100% of the mark for INM701: Introduction to Artificial Intelligence.

Teamwork

This coursework should be completed either in **groups of two** or **individually**.

- If you wish to work in a pair you must email Jacob Howe (j.m.howe@city.ac.uk) by 5pm Monday 30th October.
- If working in a pair the code and the main report will be developed and written as a pair.
- Both team members will receive the same mark for the nine-page main report, and the one page reflection will moderate this mark. For groupwork, all team members are expected to contribute to all parts of the work: both the coding and the report.

Time Allocation

This 15 credit module represents 150 study hours. 30 of these hours are on your timetable. The remaining time is for your self-direct study and for completing this assignment. Whilst different people might have different views on the balance between what is study for learning the material and what is time spent on the assignment, this coursework is designed to take *40-50 hours of study per team member*.

Submission

1. Ungraded Checkpoint Submission

You are able to submit a brief form (available on moodle) describing your initial choice of dataset, and the problem you intend to solve. You will receive feedback on the suitability of this choice as soon after the submission as possible.

Submission deadline for checkpoint: Sunday 12th November 2023, 5pm.

2. Final Work

Submission will be through Moodle, and you will need to submit your report, individual reflective evaluation and code. Full submission details will follow.

In addition:

- your code must be developed and available on github, with a full revision history indicating who has pushed what code. A single push at the end of the work is liable to score 0. This repository should be available to Jacob Howe (github: jacobhowe), Daniel Chicharro (github: ChicharroCity) and Atif Riaz (github: atifR).

Late submissions will score 0. You can upload work to Moodle more than once, so there is no need for last minute submission. Don't leave final submission to the last minute.

Presentation

You will be giving an individual presentation, of a maximum of 12 minutes, including time for questions. This is scheduled to be on January 19th.

Feedback

As well as the checkpoint described above, we can check your progress and give formative feedback in the labs and surgeries. Evaluative feedback and marks on your coursework will be given out once all assessment for IN3062/INM701 is complete and the work marked.

Coding

- You should use Spyder or Jupyter Notebook for your IDE.
- You should work with the libraries studied in the module. For neural networks: *Tensorflow/Keras*, for other techniques *scikit-learn*. You might possibly use other libraries to stretch your work, but those studied should form the core of your work.
- Your code should be well commented, including details of any reused code.

- As noted above, your work should be maintained on github, with a full revision history indicating who has pushed what code.
- It is possible that some of your experiments may take significant computation time, so it is in your interest to start running experiments for this coursework as early as possible.

The Task

In this coursework, you are expected to *demonstrate what you have learned in the module* by applying artificial intelligence techniques as covered in the module to a dataset and domain of your choice. This will include some or all of:

- Define the problem domain and dataset(s) (you are free to choose the domain and the dataset that you want to investigate).
- Define questions and analysis tasks (a brief overview of the domain, the questions that are being asked, a list of your objectives and the expected output(s) of your analysis).
- Perform an initial investigation of the dataset and the characteristics of the data. Develop a plan as to how you might transform the data to make it useable.
- Develop a plan as to which artificial intelligence techniques you might use and what sorts of potential observations these can lead to, and how you will evaluate these.
- Use models taught in the module. You must use models taught in the module, these are: perceptron, decision trees, linear regression, support vector machines, random forest, k-nearest neighbour, naïve Bayes, neural networks as well as unsupervised techniques k-means and GMM, and principal component analysis. Most supervised models have both classification and regression variants. You are encouraged to work with neural networks. An additional technique from outside the taught module content might be applied for comparison purposes, if this is done it should be clearly indicated and well justified.
- Split your dataset (train/validate/test, some datasets come pre-split). If you have a holdout test set then you most likely don't want to use this until the near the end of your work.
- Perform the analysis. Get the data ready for analysis, carry out your analysis/modelling as needed, validate your results and communicate observations, iterating through this process. Analytical operations can include data processing to an extent that is needed (not all datasets are messy) to prepare a useful and robust dataset to work within, and data derivation (such as feature engineering).
- You might establish a baseline result first, computing metrics on training and validation sets, analyse errors, work on succeeding iterations, and alternative models. (If initial baseline results are amazing and there are no errors is the problem too easy?)
- Generally, be close to your data (visualise the dataset, collect summary statistics, look at errors, analyse how different parameters affect performance, try out different model variants).

Report

Your final report should be a maximum of 9 pages from the start of the Introduction to the end of the Conclusion. You should in addition have a title page, and you may use as much additional space as needed for a references section.

Your final report should cover each of the aspects above (and any other element of your work that you believe should be reported). Graphical illustration of your results is expected (perhaps training/testing error curves, confusion matrices, algorithm outputs, etc), as well as results. Figures and Tables should be numbered and described. Following the above analytical process, make sure that in your report you answer the following questions where appropriate (this is ****not**** a report structure):

- What is your dataset, problem domain?
- Is your model classification or regression?
- Did you have any missing, corrupt or misleading data? If so, how did you cope it?
- Have you omitted some data? If so, why?
- Did you apply techniques to understand your dataset?
- How did you encode the input variables?
- What models did you use?
- What are the criteria for selecting model performance evaluation tools?
- What were your outputs?
- Did you have any problems or difficulties working with the dataset?

You should present the results clearly and concisely and provide a discussion of the results, with conclusions related to problem being addressed. The conclusions section might propose some further work based on the results of this coursework.

I hope that you will have a lot of work to report, maybe more than you can fit into the page limit. In this case you will need to display good editorial judgement as to what to report: what was most important, what was most interesting.

Your written work should be submitted in pdf format, single column, standard margins, font Arial 11, maximum 9 pages, including all figures. A word template is available on Moodle.

Individual Reflective Evaluation

This is a chance to expand conclusions and critical discussion of your work from your individual perspective, reflecting what has been learned about your problem. If working in a pair, you might also outline the balance of the work between the two team members.

Datasets

You are free to choose the domain and the dataset that you want to investigate. Here are some suggestions and sources for datasets.

You **cannot** use the datasets that come with scikit-learn, or others used in the exercises. Other heavily used datasets make bad choices.

Some of these sources will come with code. Whilst you may use this code if referenced, you get little credit for this.

General:

- Kaggle is Google's online data community, and contains thousands of datasets.
- UCI Machine Learning Repository. The University of California, Irvine has a collection of several hundred datasets (some of them a little small).

Some other possible sources of data:

Images: Labelme, ImageNet, LSUN, Google's Open Images, COCO

Text: Project Gutenberg

Clinical: MIMIC, The World Health Organisation (<https://www.who.int>)

General: FiveThirtyEight (<https://data.fivethirtyeight.com>)

There are many, many other sources of data available. At the cost of some effort, you might also collect or create your own dataset.

Note: You are not necessarily being marked on how good the results are. What matters is that you try something sensible and clearly describe the problem, method, what you did, and what the results were. Don't pick a dataset that is way too hard for your experiments. Don't pick a dataset that is too straightforward (too small) to produce interesting results. Be careful not to do foolish things like data snooping, testing on your training data, including plots with unlabelled axes, using undefined symbols in equations. Do sensible cross-checks like running your models several times, varying your random seed, leaving out small parts of your data, adding a few noisy points, etc. to make sure everything still works reasonably well. If you pick something you think is interesting it will make the process of getting it to work more enjoyable.

Don't be afraid to switch datasets if after some work you conclude that your initial choice was unsuitable. The earlier work will mean that you get to grips with a new dataset much more quickly.

Coding & Referencing

This is, in large part, a coding assignment. If you use code (or other materials) written by someone else, you should *cite* that code (or other material) in Harvard format. Your code itself should reflect sources in your comments. If you do not cite work appropriately you will have committed academic misconduct. Making superficial changes to the code does not make it yours. You are also expected to make a coding contribution, so if you use a large amount of code written by someone else, and cite it appropriately, your contribution will be low and your work marked accordingly.

Academic Misconduct/Plagiarism

If you copy the work of others (either that of another team or of a third party), with or without their permission, you will score no marks and further disciplinary action will be taken against you. The same applies if you allow others to copy your work. This is a group responsibility.

Extenuating Circumstances

If you are not able to submit your coursework on time for unforeseen medical reasons or personal reasons beyond your control you should contact the Programmes Office asap and fill an Extenuating Circumstances form. Strong evidence in the form of, for instance, medical certificates or legal statements will have to be produced.

Grading

Your work will be graded in line with the University's assessment criteria (see Appendix A), and you will receive an overall mark. An indication of the relative importance of aspects of your work are given below (these are not section marks):

- *Report, introduction*: description and motivation of the problem, description of the dataset including data types (e.g. discrete, continuous) (10%)
- *Report, methodology*: summary of the models used, with their pros and cons, a hypothesis statement, description of choice of training and evaluation methodology (15%)
- *Report, results*: description and presentation of the output. The code acts as an appendix to this section, and code quality (e.g. commenting) contributes. (20%)
- *Report, evaluation*: analysis and critical evaluation of results. (10%)
- *Report, conclusions and referencing*: lessons learned, references (using Harvard format) and future work. (5%)
- *Reflection* (10%)
- *Presentation* (30%)

Appendix A: University Grade-related criteria (Postgraduate)

>80 Distinction: Excellent or Outstanding. Work that demonstrates a comprehensive knowledge of the subject area and addresses the assessment criteria in full. Work will show evidence of independent reading, thinking and analysis, or creative problem solving. The report will be well-constructed and demonstrate a professional approach to academic practice. It will be of a professional standard.

70-79 Distinction: Very good. Work that demonstrates strong knowledge of the subject area and addresses the assessment criteria well. Two appropriate AI models will be developed and the data will have been clearly considered and appropriately used to meet a substantial challenge. The report will consider problems overcome and show evidence of comprehensive reading and critical ability. It will be clearly written and adhere to the principles of good academic practice.

60-69 Merit: Good. Work that demonstrates a sound level of knowledge of the subject area and makes a good attempt to address the assessment criteria, realising all to some extent and most well. Two appropriate AI models will be developed, and consideration will be given to the use of data. The approach to the problem will be clear and well contextualised. The report will be well-structured and logically written, will demonstrate good academic practice and critical ability will be evident.

50-59 Pass: Satisfactory. Work that demonstrates knowledge of the subject area and provides some level of response to the assessment criteria realising all to some extent and some well but

perhaps also including irrelevant or underdeveloped material. The work will develop two AI models, and attempts will be made to analyse work critically, but use of data might be problematic. Expression and structure may lack clarity. Attempts to demonstrate academic practice will be evident.

40-49 Fail: Poor. Unsatisfactory work that demonstrates very limited knowledge of the subject area and which does not succeed in grasping the key issues. Assessment criteria will not be fully realised. For example, only a single AI model is implemented. Work will not include important elements or will contain information that is not completely accurate, with limited development of ideas and critical analysis. Presentation is confused or lacks coherence.

<40 Fail: Very Poor. Work that demonstrates no real knowledge of the subject area and which demonstrates a totally inadequate attempt to address the assessment criteria. This might include code that does not run, failure to implement appropriate AI models, or failure to write a report.

Appendix B: Mapping of Assessment to Programme Learning Outcomes (MSc)

This assignment assesses the following programme (degree) learning outcomes.

Knowledge and understanding:

- ✓ Synthesise the acquired knowledge to demonstrate the ability to use artificial intelligence methods and techniques (e.g. in machine learning, mathematical modelling and simulation, computational cognition)
- ✓ Review and critically evaluate the literature and current developments and challenges in artificial intelligence, such as deep learning algorithms;
- ✓ Analyse and solve problems and develop innovative solutions, processing real data in classification, prediction and optimization tasks, designing, implementing and testing artificial intelligence methods and tools;

Skills:

- ✓ Analyse, develop and select algorithms and tools that can simulate intelligence;
- ✓ Specify, design, build and evaluate Artificial Intelligence programs and systems;
- ✓ Use new technologies to communicate topics in Artificial Intelligence effectively to technical and non-technical audiences.

Values and attitudes:

- ✓ Embrace technical challenges as an opportunity for personal development;
- ✓ Rationally exploit both traditional and novel technological approaches;
- ✓ Rigorously assess alternative approaches and novel designs;

Appendix C: Mapping of Assessment to Programme Learning Outcomes (MSci)

This assignment assesses the following programme (degree) learning outcomes.

Knowledge and understanding:

- ✓ demonstrate advanced, specialist theoretical and practical knowledge in a range of computer science sub-fields
- ✓ select and apply leading-edge computing techniques to practical tasks in an independent manner
- ✓ identify and manage scientific and technical risks and uncertainty associated with computer science and its application

Skills:

- ✓ analyse, develop and select algorithms for computational tasks
- ✓ analyse and solve problems based on theoretical considerations, and develop innovative solutions, taking into account user needs and constraints.
- ✓ design, develop, maintain and evaluate complex computer programs and systems
- ✓ analyse, evaluate and act upon descriptive documents
- ✓ use new hardware and software technologies to create computer systems that exceed current capabilities
- ✓ synthesise information from disparate sources to compose systems and documents
- ✓ present and communicate topics in computer science effectively to technical and non-technical audiences

Values and attitudes:

- ✓ embrace technical challenges as an opportunity for personal development
- ✓ rationally exploit both traditional and novel technological approaches
- ✓ rigorously assess alternative approaches and novel designs and implementations
- ✓ assess the nature of intellectual property and its ownership, and respect it accordingly