IN3062: Introduction to Artificial Intelligence
Coursework

Submission deadline: Sunday 22nd December 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).

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 8 pages)
- an individual written reflection and discussion evaluating your work (max 1 page)
- your practical implementation (code)

Module mark

This coursework is worth 100% of the mark for IN3062: Introduction to Artificial Intelligence.

Teamwork

This coursework should be completed in **groups of four (or possibly five)**.

- Groups will be assigned and will be available on Moodle.
- The code and the main report will be developed and written as a group.
- All team members are expected to contribute to all parts of the work (pre-processing, models fitting and selection, discussion)
- You will also write a max one-page individual reflection and discussion worth 20% of the module mark.

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 Final Work

Submission will be through Moodle, and you will need to submit your report, individual reflection and discussion, 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 Daniel Chicharro (github: ChicharroCity), Atif Riaz (github: atifR), and Youssef Arafat (github: youssefarafat).

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.

Feedback

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/PyCharm 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 problem 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 8 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 the aspects above as appropriate (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 problem 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.

We 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 8 pages, including all figures. A word template is available on Moodle.

Individual Reflection and Discussion

This is a chance to expand conclusions and critical discussion of your work from your individual perspective, reflecting and illustrating what you have learning in the module. This might include reflections on your dataset and its preprocessing, your choice of models, your methodology, the results you achieved, and on future work.

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 rewarding.

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

Appendix A: University Grade-related criteria (Undergraduate)

>85 First class: 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.

70-84 First class: 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. It will be clearly written and adhere to the principles of good academic practice.

60-69 2:1: 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 and will demonstrate good academic practice.

50-59 2:2: Fair. Work that demonstrates knowledge of the subject area and attempts to address 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, but use of data might be problematic. The report will provide some evidence of analysis but may be largely descriptive. It will have structure but this may not always be clear. Attempts to demonstrate academic practice will be evident.

40-49 Third class: Satisfactory. Work that demonstrates basic knowledge of the subject area and provides some level of response to the assessment criteria, but only meets these criteria to some extent. 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. Expression and structure of the report will lack clarity and evidence of academic practice will be limited.

34-39 Fail: Poor. Unsatisfactory work that demonstrates very limited knowledge of the subject area and does not succeed in grasping the key issues. Assessment criteria are not realised. There will be no real development of ideas and few sources will be used or used correctly. Presentation is confused or lacking in clarity. This will be seriously incomplete work or an incoherent report.

<34 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

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

Knowledge and understanding:

- ✓ Use and explain the core concepts and theories of computer science and computer applications
- ✓ Discuss scientific and engineering practice and theory in computing and extend your knowledge through self-led study
- ✓ Discuss management issues concerning the planning, design and delivery of computer-based systems
- ✓ Identify and model requirements for specialised computing systems and propose and evaluate solutions to fulfil them
- ✓ Use appropriate theories, practices and tools for the specification, design,
- ✓ Implementation and evaluation of computer-based systems
- ✓ Explain the concepts of computer programming and critically evaluate and predict their utility in models, tools and applications
- ✓ Demonstrate advanced, specialist theoretical and practical knowledge in a range of computer science sub-fields

Skills:

- ✓ Analyse, develop and select algorithms for computational tasks
- ✓ Analyse and solve problems based on theoretical considerations
- ✓ Analyse and abstract problems and propose and apply effective solutions
- ✓ Synthesise information from disparate sources to compose systems and documents
- ✓ Apply controlled compromise in meeting requirements
- ✓ Apply techniques and tools for modelling and managing information
- ✓ Design and execute methodologically sound scientific and engineering studies
- ✓ Plan work
- ✓ Manage personal time
- ✓ Present and communicate complex ideas
- ✓ Apply sound research methods
- ✓ Understand, evaluate, synthesise and apply complex ideas

Values and attitudes:

- ✓ Assess the nature of intellectual property and its ownership, and respect it accordingly