

Dr Nina Dethlefs (module leader)

n.dethlefs@hull.ac.uk

9 September 2022

Assignment - Artificial Intelligence

551458/500086 - 2022/2023

Description:

The assessment for this module will consist of a single piece of coursework that accounts for 100% of your final mark. As part of this coursework, you will use Python to compare a set of approaches for analysing social media data relating to deforestation. Any results you obtain should be summarised in a single written report of no more than 3,000 words submitted as a single PDF file. You are required to submit your code alongside the report, but it will not be separately graded.

Dataset

You will be working with a dataset collected from Twitter. The data were gathered between 15 December 2020 and April 2021 and contain 1,188 individual posts from the hashtags #deforestation. Retweets and duplications were excluded from the dataset, though some may remain (e.g. when different users post the same text individually). The dataset is available to you for the purpose of this assignment. It may not be further shared, copied and disseminated, in accordance with Twitter's T&Cs and the University of Hull's ethical clearance on the use of this data.

The data is partitioned into training (80%) and test data (20%), please retain the splits as they are and make sure you report *validation accuracy* for your experiments below.

You will see that this is a small dataset in comparison to other we have worked with and in comparison to what is normally expected for deep learning. You may take any steps you deem appropriate to **enhance the dataset** e.g. via pre-processing it as we have done.

You can download the data from Canvas [here](#).

Your assignment specifically includes the following steps:

1. **Train a neural network for sentiment analysis.** Given the dataset in csv format, read it into your programme and carry out any preprocessing steps you see fit - make sure you document and motivate them in your report. Then design a neural network (any type you wish / deem most suitable) that takes as input a string of text (a tweet) and outputs a single binary sentiment label (positive/negative or 0/1). Justify your choice of network. In this initial “baseline” implementation you should use a simple embedding layer that is trained directly from the dataset provided. Make sure to provide all hyperparameters in your report and provide the results obtained in a table and/or learning plot. You should make an informed decision on what evaluation metric/s will be most suitable.

2. **Vary the knowledge representation.** Using the same learning model as above, include a pre-trained language model (e.g. Word2Vec, GloVe, BERT, GPT-2, or any other you can find) as your embedding layer. Explain which model you chose, why and the observations that you made. Which model works “best” - e.g. considering performance or computation time. Include a brief reflection on the ethical implications of pre-trained language models and weigh these up against potential benefits.

3. **Create a probabilistic baseline.** Finally, design an alternative (non-machine learning) approach to the task of sentiment classification using the same dataset. You can opt for a Bayesian approach or for a finite state / agent-based approach as discussed earlier in the trimester. Explain your design decisions and the assumptions you made when handcrafting your knowledge representation.

In your assignment you are expected to consult **academic references** and include these as citations in your report. Referencing should be done using the Harvard style of referencing, see [here](#) for a guide. References should be *academic*, i.e. from peer-reviewed editorials, such as journal papers, book chapters, conference proceedings, etc. Web-based resources, such as blogs, youtube, private websites, etc. are less suitable.

You should be able to draw on the **code we worked with** during our lab sessions, and it's ok to reuse code as much as possible. You are not permitted to collaborate with others (collusion) or to copy-paste materials (code, text, etc.) from external sources without reference (plagiarism).

Report details:

Your report should have **3,000 words** (10% more or less is ok) excluding references, tables, images, captions, etc. You can structure your report any way you like, e.g. around the individual coursework components, but for a good result make sure to address the questions asked clearly and in detail.

Please note: we will not go into your Python code to find answers to the questions asked - anything that is not provided in the report will be considered absent and will not incur points. However, anything included in the report that is not backed up in the attached code (i.e. is missing) will also be considered absent.

Code submission:

You will need to submit your code alongside your report. As stated, it will not be marked separately but will be checked to ensure that it supports the functionality described in the report and is not plagiarised. As before, *please note that anything you want me to see is in the report as I'm not awarding marks for the code separately.*

Hand-in deadline:

The report is due: Thursday, **8 December 2022, 2pm**

Hand-in will be via Canvas.

Marking criteria:

Report marking criteria and weighting:

Neural network: 30%

Knowledge representation: 30%

Probabilistic approach: 30%

Referencing: 5%

Quality of presentation: 5%

Specific marking criteria are as follows (continues on next page):

Criteria	First	2:1	2:2	Third	Poor
Neural network	<p>Learning model is explained in fully replicable detail and any design decisions are fully motivated against alternatives, including preprocessing. Evaluation is conducted against the validation set using appropriate metrics.</p> <p><i>30 points max</i></p>	<p>Learning model is explained in replicable detail and design decisions are motivated, including preprocessing - though some open questions remain. Evaluation is conducted against the validation set using appropriate metrics.</p> <p><i>20 points max</i></p>	<p>Learning model is explained though lacking in detail and/or motivation of the design decisions made. An evaluation is presented but contains some shortcomings.</p> <p><i>15 points max</i></p>	<p>A learning is presented but the model and/or presentation is flawed. An evaluation is present but not sufficiently motivated and/or detailed, or is not fully suitable.</p> <p><i>8 points max</i></p>	<p>Some elements are presented but with significant flaws in the setup and/or evaluation of the model.</p> <p><i>5 points max</i></p>
Knowledge representation	<p>An alternative knowledge representation is successfully integrated into the earlier learning model. The choice of representation is fully motivated against potential alternatives. A thorough account of ethical consideration is given and evaluated.</p> <p><i>30 points max</i></p>	<p>An alternative knowledge representation is integrated and motivated against alternatives, but with some shortcomings. Ethical considerations are discussed and evaluated.</p> <p><i>20 points max</i></p>	<p>An alternative knowledge representation is used but is not motivated sufficiently (e.g. it doesn't consider alternatives). Ethical considerations are discussed but lacking depth.</p> <p><i>15 points max</i></p>	<p>An alternative knowledge representation is addressed but not fully / successfully integrated with the earlier learning model.</p> <p>Ethical discussion lacks depth.</p> <p><i>8 points max</i></p>	<p>An alternative knowledge representation is not used and/or the ethical considerations relating are not addressed satisfactorily.</p> <p><i>5 points max</i></p>
Probabilistic approach	<p>A probabilistic approach is fully implemented and evaluated. Any design decisions and implications are discussed in detail. Insightful conclusions are drawn on the comparison with the neural net.</p> <p><i>30 points max</i></p>	<p>A probabilistic approach is implemented and evaluated, with some shortcomings. Design decisions and implications are discussed with some open questions. Conclusions are drawn on the comparison with the neural net.</p> <p><i>20 points max</i></p>	<p>A probabilistic approach is implemented and evaluated, but the design is not fully explained and/or the evaluation is not fully successful.</p> <p>Conclusions are drawn.</p> <p><i>15 points max</i></p>	<p>A probabilistic approach is attempted but it not fully implemented and / or not fully evaluated.</p> <p>Conclusions are offered but are lacking in depth.</p> <p><i>8 points max</i></p>	<p>A probabilistic approach is not implemented and / or not evaluated.</p> <p>Conclusions are insufficient.</p> <p><i>5 points max</i></p>

Criteria	First	2:1	2:2	Third	Poor
Referencing	A substantial number of references are provided and embedded into context; Harvard referencing is used throughout. <i>5 points max</i>	A number of relevant references are provided and are mostly cited correctly. <i>4 points max</i>	Few references are provided and / or given in the incorrect format. <i>3 points max</i>	References are cited incorrectly, i.e. in terms of format or content. <i>2 points max</i>	No references, or relevant are irrelevant. <i>1 point max</i>
Presentation	The organisation of the report is clear and supported with appropriate tables and graphs. Writing is clear and of high standard (i.e. proofread). <i>5 points max</i>	The organisation of the report is clear with some shortcomings. Limited tables and visualisations are provided. Writing is good. <i>4 points max</i>	The organisation is reasonable with shortcomings. Limited visualisations are given. Writing is satisfactory. <i>3 points max</i>	The organisation of the report is confusing in places, no visualisations are provided, or they are inappropriate. Writing is messy in places. <i>2 points max</i>	Confusing organisation and presentation, no visualisation or tables. Writing is messy in places. <i>1 point max</i>

Learning objectives:

This coursework will assess the following learning objectives as per module description. Students will be able to:

- Understand the basic concepts of Artificial Intelligence including the ethics issues associated with this topic (evidenced through the motivation of different design and algorithm choices in Parts 1 and 3, e.g. of learning models, embeddings, and the discussion of ethics in Part 2).
- Gain a practical understanding of developing and using artificial intelligence techniques to solve problems (evidenced through the Python-based implementation, presentation of hyperparameters and results observed).
- Gain an understanding of knowledge representation issues and their use in designing AI programs for problem solving (evidenced through the motivate choice and comparison of knowledge representations in Parts 2 and 3).

It is not essential but it may help you to bear these in mind so that you can optimise the presentation of your report to demonstrate these **learning objectives**.