Continual Learning Techniques for Image Classification: Project Plan

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1 Introduction

Typically, training a neural network requires the entire dataset that you want to train on to be complete and present at training time. The dataset is split into batches and used repeatedly to train the model prior to it being used for inference. This is known as offline training and it is the current standard approach to training models but it is does not allow the model to adapt to a chaning data distribution or be updated in response to real-time data.

Fundamentally, the inspiration for neural networks is derived from biological observations as networks are modelled on the interaction of neurons in the brain [1]. However, the capability of humans, and many other animals, to learn continuously and adapt to changes in non-stationary datasets is often ignored [2]. Continual learning techniques, where the dataset is incomplete and the model is continuously updated on new data as it becomes available, attempts to introduce this concept into the training of machine learning models. The motivation for pursuing continual learning are the potential applications of training a model in real-time to respond to changes in the data and realise the benefits this could bring.

The primary purpose of this project is to establish a robust and complete evaluation of historical, state-of-the-art and cutting edge continual learning techniques applied to the domain of image classification. It is clear from the literature that it is difficult to compare proposed techniques due to multiple inconsistencies such as: the setup of the continual learning problem across papers [3], the use of different metrics to evaluate techniques [4], and the use of datasets of significantly different difficulty [5]. To achieve this aim, the plan is to implement a variety of different continual learning techniques from different solution paradigms described in the literature and compare their efficacy and real-world applicability.

Further to this, the secondary purpose of this project will be to explore avenues highlighted in the literature to enhance techniques with the aim of creating a novel continual learning technique that can achieve competitive performance. This will follow on from the evaluation of existing techniques because the lack of standardised comparisons in the literature at present makes it difficult to truly evaluate the effectiveness which obscures the direction that would be most promising to pursue.

2 Deliverables

Initially, the focus of the project will be on implementing and comparing existing solutions. As highlighted in the literature survey, it can be difficult to compare across different techniques as discussed previously. In terms of deliverable objectives, these are:

- Implementation of baselines (Basic) - The baselines, finetuning (a single pass over the stream of data) and offline training, are key for comparison
- Implementation of historic techniques (Basic) - Significant techniques, such as Elastic Weight Consolidation [6] are important for measuring the progress of techniques
- Implementation of state-of-the-art techniques (Intermediate) - State-of-the-art techniques represent the current achievements of the continual learning domain
- Implementation of cutting edge techniques (Advanced) - Cutting edge techniques explore interesting future avenues for continual learning
- Evaluation and comparison of techniques (Intermediate) - Comparing and evaluating techniques is a core part of the project

After this, the project will focus on exploring novel solutions to the continual learning problem. The deliverable objectives for this section will be:

- Theoretical underpinning (Advanced) - It is important to establish a theory-based background prior to implementation to ensure that the proposed solution has potential
- Implementation and revision of solution (Advanced) - Implementing the proposed solution will enable comparison to existing methods and validate the theoretical ideas
- Comparison with novel solution (Intermediate) - Finally, it will be important to compare the solution against those from the first section to evaluate its effectiveness

The end goal of the project will be to have completed a comprehensive comparison of existing and new techniques to aid in the progress of the continual learning domain.

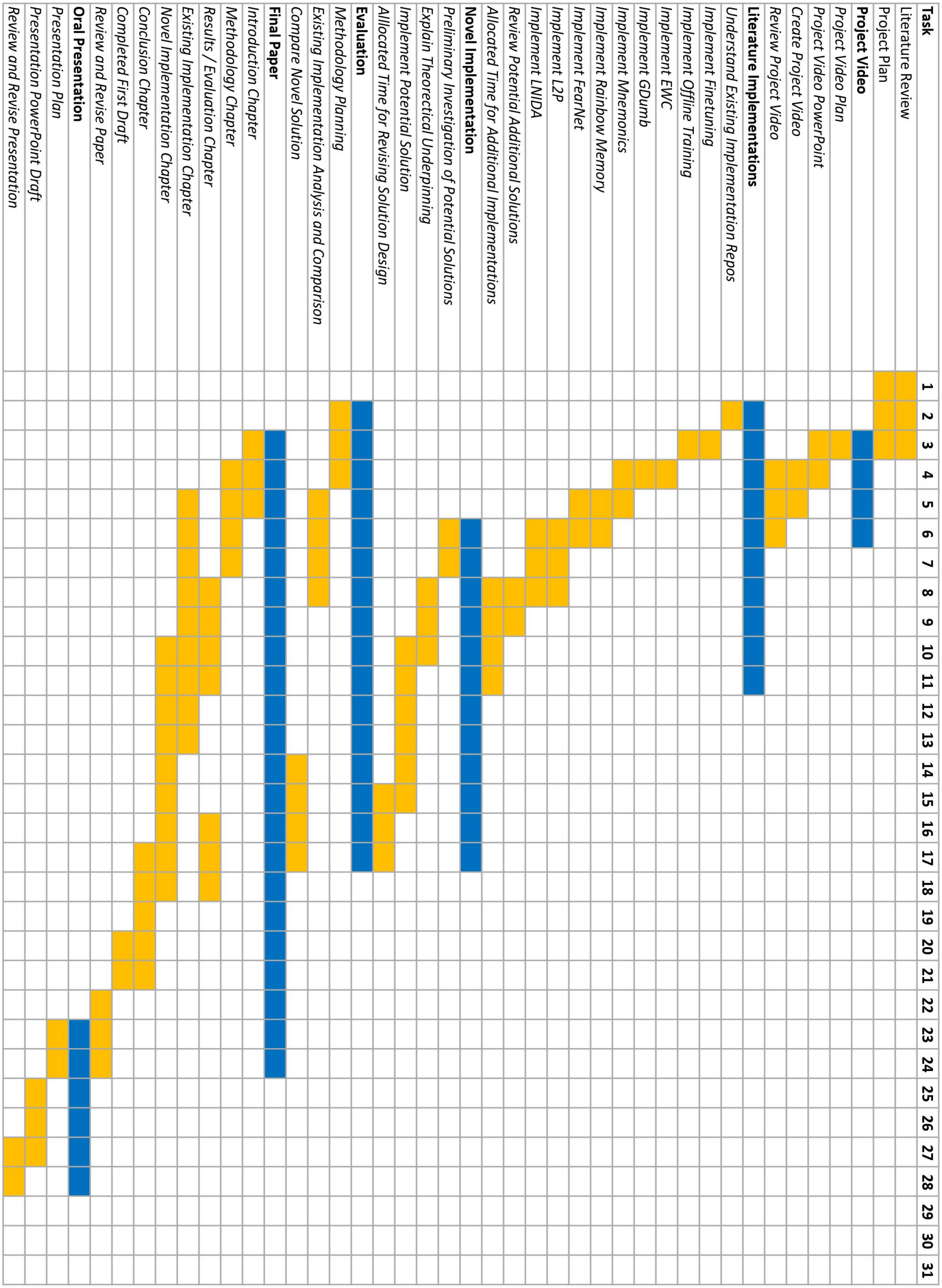

Fig. 1. Project Gantt Chart

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