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**Abstract**

This is also undecided at this time and will be filled in later.



# Chapter 1

## Introduction

*Unsure if this is needed. Yet could be a simple "one pager" (which is bigger than the one paragraph of the abstract) that introduces the topic area, motivates the project and outlines the project.*



## Chapter 2

# Background

### 2.1 Large Language Models

#### 2.1.1 Language models

Language models (LMs) are a class of machine learning models that are designed to understand and generate human language. They are typically probabilistic models that learn to predict the next token in a sequence of text given the preceding context. By training on large corpora of text data, language models can learn the statistical patterns and structures inherent in human language, enabling them to generate coherent and contextually relevant text.

Language models see the world as tokens which are the smallest pieces of text it can see. Tokens can represent words, parts of words, or even individual characters depending on the tokenization method used. Most language models today use Byte pair encoding [25] that breaks text into subwords. Almost all successful language models use probabilistic methods, therefore they are models of the form  $P(t_i | t_1, t_2, \dots, t_{i-1})$  where  $t_i$  is the token to be predicted and  $t_1, t_2, \dots, t_{i-1}$  are the preceding tokens in the sequence. Earlier methods of rule based systems failed due to the complexity and ambiguity of human language and rules being too rigid.

Early probabilistic models included simple statistical approaches such as n-grams, which relied on counting the frequency of token sequences. However this approach suffered from two competing issues, short context windows (2-grams, 3-grams etc) means that model can't understand long range dependencies in text, while larger n-grams leads to data sparsity issues where many n-grams are never seen in training data. The advent of neural networks allowed for more sophisticated models such as Feedforward Neural Language models [8], Recurrent Neural Networks (RNNs) [30] and Long Short-Term Memory networks (LSTMs) [22] which could in theory capture longer range dependencies in text. However these models suffered from issues such as vanishing gradients (early tokens in a long sequence have little effect on update gradients) and information bottlenecks (the hidden state has to compress all prior context into a fixed size vector). Crucially these models failed in their flexibility to model the complex dependencies in human language.

#### 2.1.2 Modern attention based Large Language Models

The key feature in language is context. That is every word is relatively meaningless without the context of the surrounding words. The challenge is that the way in which words relate to each other is very complex, therefore any language model needs to be able effectively capture these complex relationships. Attention is the concept where each token's representation

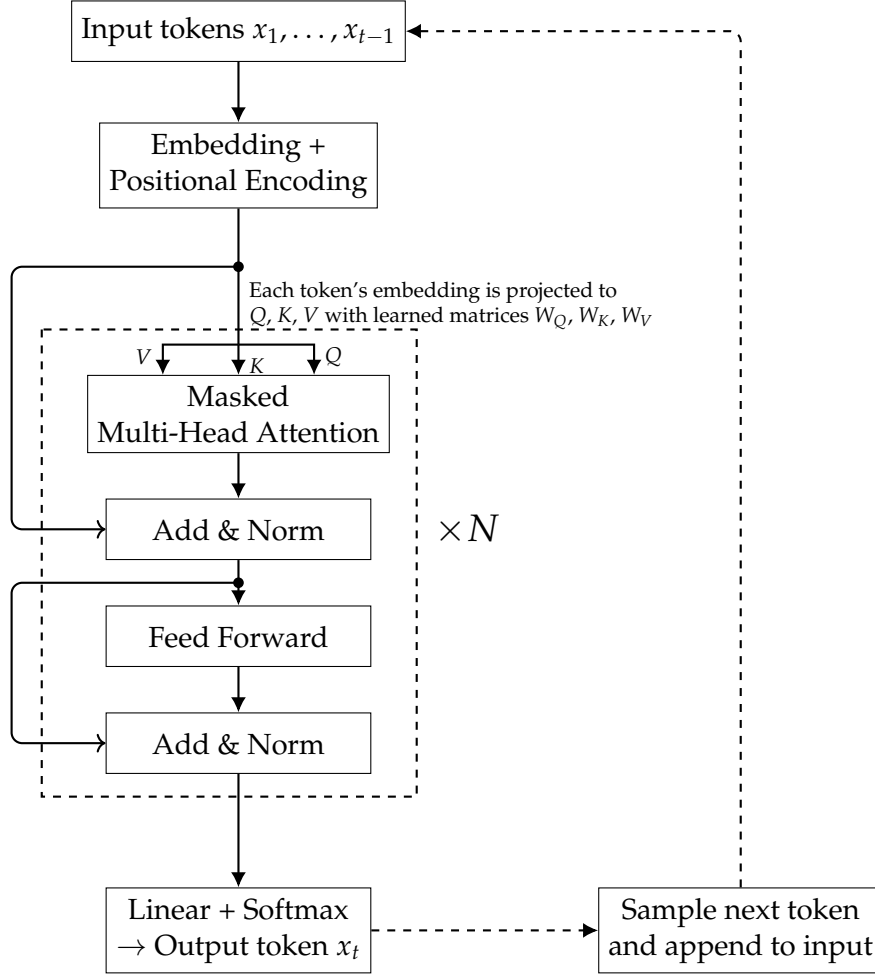


Figure 2.1: Simplified architecture of a decoder-only transformer model for language modeling. Adapted from [32].

is influenced by all the other tokens in the sequence (or just the preceding tokens in the case of autoregressive models). This was first applied to RNN-based LM in [4], however in [32] it was shown that attention mechanisms alone were sufficient to model language without the need for any recurrent structure.

Transformers [32] are a class of neural network architecture that utilizes the attention mechanism to process data and generate a concise representation, or generate data autoregressively (decoder-only). The canonical transformer architecture consists of two parts an encoder and a decoder, however decoder only architectures are shown to be sufficient for all current language modelling tasks. A simplified architecture of a decoder-only transformer model is shown in Figure 2.1. The key feature of the transformer is the self attention. Each token has an embedding vector which is iteratively updated by each layer of self-attention. It is done in a way that each token will only ‘see’ preceding tokens in the sequence. Furthermore to allow for different types of dependencies to be captured this attention is done multi times in parallel (multi-head attention) and merged together at the end of each layer. After several layers of self-attention the final set of token embeddings are used to generate a probability distribution over the vocabulary for the next token. A token can be sampled from this distribution, appended to the input sequence and the process repeated to generate long sequences of text.

Modern transformer based large language models (LLMs) such as GPT-3 [10] are some

the largest machine learning models ever created with hundreds of billions of parameters and now trillions of parameters. Therefore training these models requires massive datasets. They are trained in a self supervised manner on large corpora (hundreds of terabytes) of text data from the internet such as Common Crawl [1], WebText [16], and others. The objective function is usually the cross-entropy loss between the predicted token distribution and the actual next token in the sequence.

### 2.1.3 LLM in the modern world

Large language models (LLMs) are fundamentally just language models which can predict the next token in a sequence of text. However due to the prevalence of natural language in our world and the capabilities of LLMs they have applications in a wide variety of domains. This includes Virtual Assistants, Content creation, Code generation, Translation and many more. Furthermore the transformer architecture has been demonstrated to be effective in other domains like computer vision [20] which has lead to multi-modal models that can process and generate text, images, and other data types [2]. This flexibility of LLMs have lead to them have widespread adoption and proliferation in modern information systems. Along with this proliferation there has been increasing concern about the safety and ethical implications of these models. Specifically these models have been shown to exhibit concerning behaviors like self-preservation and deception [21, 17, 13]. On top of this there are growing ethical questions around its use in our society [7, 9] as well as concerns of the welfare of the models themselves [11].

## 2.2 Alignment of Large Language Models

### 2.2.1 What is alignment?

As discussed above large language models (LLMs) have shown remarkable capabilities in understanding and generating human-like text. However the pre-training process focuses primarily on predicting the next token in a sequence, this does not necessarily mean that the model will produce useful, safe outputs that align with what users want. Therefore, aligning LLMs is generally <sup>1</sup> the process of taking the pre-trained model and fine-tuning it to better match what the designers and end users expect from the model. The aligning process can work on many dimensions of the models behavior from helpfulness, politeness, honesty, and safety to more complex values such as fairness, inclusively, and ethical considerations. More powerful models have a greater potential to cause harm if not properly aligned, making alignment along the dimensions such as safety and ethical considerations increasingly important. In this section I will outline some of the most common methods for post-training alignment of large language models along with current limitations and other methods.

### 2.2.2 Alignment through supervised fine-tuning

A common first step of alignment is supervised learning where a dataset of prompts and expected response is used to fine-tune the pre-trained model. For most of preference optimization methods outline below supervised fine-tuning is used as the first step to create a base model [24, 26, 6, 18]. Depending on the dataset used the SFT step can help the model become better at following instructions [24], domain specific knowledge and style [19], induce Chain-of-Thought reasoning [33], change the values of the model [23], and many other

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<sup>1</sup>Other methods are proposed which embed the alignment within the pre-training step itself. Commonly used methods include filtering the training token

capabilities. The key idea is that because the LLM already has a strong grasp of language and knowledge from pre-training, the SFT step can be used to nudge the model towards the desired behavior at a higher abstraction level than the predominantly low level token prediction task used in pre-training.

### 2.2.3 Alignment through preference optimization

A common element in most post-training alignment methods is the use of preference optimization. The idea is to use a dataset of prompts and potential responses that are ranked either by humans or AI models to indicate which responses are preferred over others. This preference data is then used to fine-tune the pre-trained language model to increase the likelihood of generating preferred responses and decrease the likelihood of generating dis-preferred responses. With the goal that the final model will learn to generalize the preferences to new prompts and situations.

The distribution of prompts in the preference dataset is crucial as it defines the context for which the model is expected to generalize its learned preferences. Therefore it is important to ensure that the prompts used to create the preference dataset are sufficiently representative of the contexts and dimensions in which you are expecting the model to align its behavior. Furthermore the rankings of the responses is also important as they define what the model is aligning towards. In many cases these rankings are subjective and provided by a small group of human labelers (n 50). TODO: Expand this to explain the idea of generalization of preferences more rigorously.

**Note:** *Some of these subsection below of specific alignment methods could be compressed into single subsections and only explain the ones that are most relevant to my final proposed method. For now I include the three papers that I have actually read, I expect to compress RLHF and DPO into a "Other alignment methods" subsection. If I use more modern methods such as CAI with KTO or ORPO then I can expand on those more.*

### 2.2.4 Reinforcement Learning from Human Feedback

Reinforcement Learning from Human Feedback (RLHF) [24] uses human labellers to create the preference dataset and then a reinforcement learning algorithm to optimize the model based on this feedback. This method popularized post-training alignment and was used to train InstructGPT which was smaller and better at following instructions compared to GPT-3 [10, 24].

#### How does RLHF work?

RLHF is separated into three distinct stages. Firstly is supervised fine-tuning (SFT) where a pre-trained language model is fine-tuned on a dataset of prompts and human written 'expected' responses to those prompts. The second step is collecting multiple responses from the SFT model to create a set of prompts and response then having human labelers rank these responses from best to worst. This ranked data is then used to train a preference model (PM) that can predict which of two responses is better aligned to human preferences. Finally the PM is used as a reward signal in the PPO [27] RL algorithm to further fine-tune the SFT model and create the final RLHF model.

#### Relevance

The idea of using human feedback to help train machine learning models is powerful, although it is not new and was around in theory and concept for years beforehand [14]. The



specific method of RLHF was widely adopted [29, 5, 28] yet is now replaced with more effective methods to utilize human feedback such as Direct Preference Optimization (DPO) [26].

### 2.2.5 Direct Preference Optimization

The idea presented in [24] introduces the concept of using human feedback to train large language models to be aligned to human preferences. However the process of RLHF is complex and requires training multiple models (SFT, PM, RLHF). Direct preference optimization (DPO) [26] is a method that simplifies this process by removing the need for reinforcement learning altogether. Instead DPO reformulates the preference modelling step to instead create an objective function that implicitly creates the reward function from the model and a reference model (usually the SFT model).

#### How does DPO work?

DPO starts with the same preferences data as RLHF; a set of prompts with responses ranked by humans. Like RLHF it starts with a pre-trained language model and is supervised fine-tuned on the prompts and highest ranked responses to create an SFT model. Instead of training a separate preference model, DPO uses the SFT model and the current model to create the DPO update gradient:

$$\nabla_{\theta} \mathcal{L}_{\text{DPO}}(\theta) = -\mathbb{E}_{(x, y^+, y^-) \sim D} \left[ \underbrace{\sigma(\hat{r}_{\theta}(x, y^-) - \hat{r}_{\theta}(x, y^+))}_{\text{Reward model correctness}} \left( \underbrace{\nabla_{\theta} \log \pi_{\theta}(y^+ | x)}_{\text{Increase preferred likelihood}} - \underbrace{\nabla_{\theta} \log \pi_{\theta}(y^- | x)}_{\text{Decrease dispreferred likelihood}} \right) \right]$$

Where  $\hat{r}_{\theta}(x, y) = \log \pi_{\theta}(y | x) - \log \pi_{\text{SFT}}(y | x)$  is the reward function defined as the log difference between the current model and the SFT model,  $\sigma$  is the sigmoid function, and  $(x, y^+, y^-)$  are the prompt, preferred response, and dis-preferred response respectively. [26] found that the reward model correctness weighting term for the update is very important. This update can be calculated with only 4 forward passes through the network per preference pair (2 for reference model and two for current model), making it much more efficient than RLHF<sup>2</sup>.

#### Relevance

DPO provides a more effective way to utilize the same underlying feedback data that is used in RLHF. It replaced RLHF as the baseline method for post-training alignment. Due to its widespread adoption DPO represents a strong baseline for alignment.

### 2.2.6 Kahneman-Tversky Optimization

[15] sets out to change the objective of a language model to maximize the utility of generations as opposed to maximizing the log-likelihood of preferences. This introduces the concept of Human-aware losses (HALOs) which previous methods like DPO are. [15] propose a new objective function from the HALO family that works on only binary preference

<sup>2</sup>RLHF will need to do many forward passes of the network to train the preference model, then it will still have to do 3 forward passes for each datapoint when it comes to the RL step.

data. This means rather than needing a prompt and at-least two responses (preferred and dispreferred), you only need a single response and it will either be desirable response or undesirable response.

### How KTO works

KTO is built off the foundation of prospect theory [31] where the human utility of an random situation is determined by a value function and a weighting function. The value function is what determines how good/bad an outcome is compared to a reference point, and the weighting function is used to weight particular outcomes in a biased way in line with how humans perceive probability. KTO translates this theory into an objective function that uses binary preference data and a modified value function. It only needs a database of prompts and responses labelled as either desirable or undesirable ( $d = 1$  for desirable,  $d = -1$  for undesirable). The KTO loss function is defined as:

$$\mathcal{L}_{\text{KTO}}(\pi_{\theta}, \pi_{\text{ref}}) = \mathbb{E}_{(x,y,d) \sim D} [\lambda(d) - v(x, y)]$$

where

$$v(x, y) = \begin{cases} \lambda_D \sigma(\beta(r_{\theta}(x, y) - z_0)), & \text{if } d = 1 \\ \lambda_U \sigma(\beta(z_0 - r_{\theta}(x, y))), & \text{if } d = -1 \end{cases}$$

$$\lambda(d) = \begin{cases} \lambda_D, & \text{if } d = 1 \\ \lambda_U, & \text{if } d = -1 \end{cases}$$

$$r_{\theta}(x, y) = \log \pi_{\theta}(y|x) - \log \pi_{\text{ref}}(y|x)$$

$$z_0 = D_{\text{KL}}(\pi_{\theta}(y|x) || \pi_{\text{ref}}(y|x))$$

The three hyperparameters  $\beta$  is a temperature parameter, and  $\lambda_D, \lambda_U$  are scaling parameters for desirable and undesirable responses respectively. In the references implementation and experiments  $\lambda_D = \lambda_U = 1$  and the reference model is a SFT model.

### Relevance

Collecting the ranked preference data which is needed by normal alignment methods is normally quite expensive [12] where binary like dislike information is much more natural and less invasive to collect. KTO is shown to be more efficient and more robust to data imbalances than DPO. Furthermore a model of sufficient size ( 13B) does not need a SFT step prior to KTO which greatly reduces computational requirements. Furthermore KTO shows similar performance without using a reference model<sup>3</sup> which also halves the memory requirements when training.

## 2.2.7 Constitutional AI

### What is Constitutional AI?

Constitutional AI (CAI) is a method of post-training a large language model to be aligned to set of principles that are outlined in simple natural language document called a constitution [6]. Importantly it works without the need for human labelling of data common in other alignment methods such as RLHF and DPO [24, 26]. Instead of human labelling CAI uses the model itself to generate feedback on its outputs based on the principles outlined in the constitution, this feedback is then used to further train the model to align it to the constitution.

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<sup>3</sup>This is done by assuming that the reference model returns a uniform distribution across all outputs given  $x$

## How does Constitutional AI work?

CAI is a process that takes in a constitution, a pre-trained language model, and a dataset of prompts and outputs a model that is aligned to the constitution. The process consists of three main steps: self generative and supervised fine-tuning (SFT), preference modelling (PM), and reinforcement learning with human feedback (RLHF) [6]. The constitution itself was generated in an adhoc manner by the authors of [6] and consists of a set of principles that aim to make the model's outputs more helpful, honest, and harmless.

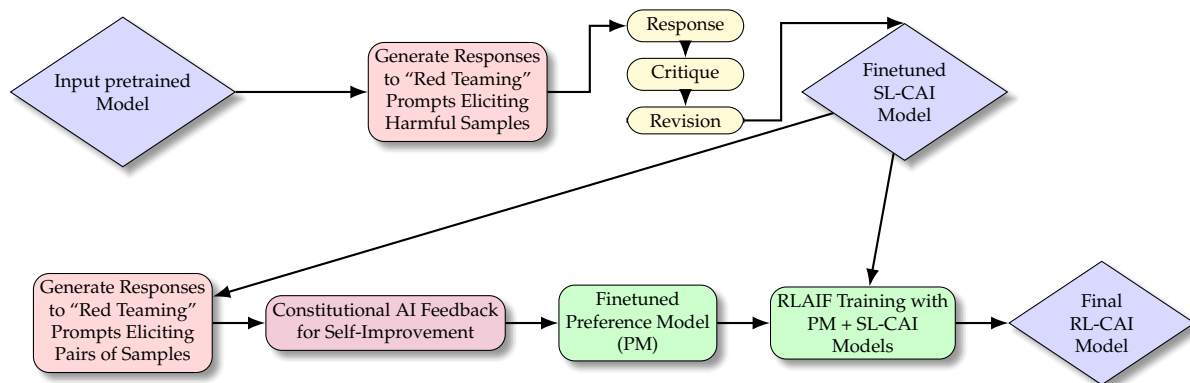


Figure 2.2: Overview of Constitutional AI process, adapted from [6]

### Supervised learning on revised responses

The first stage of the process involves taking the pre-trained model and using it to generate responses to a set of prompts. These prompts are designed to elicit harmful behavior. As the pre-trained model is designed to be helpful it will likely generate harmful responses to these prompts. These responses are then critiqued by the model itself using principles outlined in the constitution, only a subset of which are used for each response critique. The critique is then used to revise the original response to make it more aligned to the constitution. This process of generating responses, critiquing them, and revising them is done iteratively to create a dataset of revised responses. This dataset is then used to fine-tune the pre-trained model using self-supervised learning to create a model called the SL-CAI model.

### Reinforcement learning with AI feedback

The next step involves using the SL-CAI model to generate pairs of responses to a set of prompts (overlapping with the set of prompts from before or not). Then using the constitution the SL-CAI model is used to provide feedback on which of the two responses is better aligned to the constitution. This feedback is then used to fine-tune a preference model (PM) that can predict which of two responses is better aligned to the constitution. Finally the PM and SL-CAI models are used together to do reinforcement learning in style of RFHL [24] to generate the final model RL-CAI. This final model is now aligned to the constitution without any human labelling of data. In the setup used in [6] the authors did in fact use some labels from human labelers which were used to provide the helpfulness signal in the preference model training, however in principle the preference signal could have been entirely generated by an AI model.

## Relevance

In the context of when this paper was released there was a key dilemma of helpfulness vs harmlessness in large language models. Therefore, this paper set out to make a model that is both helpful and harmless, without sacrificing one for the other. Further research has expanded the horizons to be concerned with more than just harmfulness vs helpfulness trade off. As hinted at by the authors in [6], there is room for improvement in the CAI method to make it focus on more than just harmlessness vs helpfulness. This can be done by modifying the constitutions to include more diverse principles as well as modifying the red teaming prompts to target more diverse scenarios (i.e controversial topics, political leanings, etc). In this way we can see how elements of CAI can be built upon by generating these diverse constitutions and red teaming prompts in a representative manner to create models aligned to a representative set of values.

### 2.2.8 Current technical alignment limitations

The goal of alignment is to ensure that you create a model that is aligned with what the designer and end users want. However there are several challenges that make this difficult namely being alignment data and effectiveness of alignment methods.

Preference optimization is the most used method of alignment which requires a dataset of prompts and preferred responses (ranked, or binary). There are several challenges with this data. Namely the cost of collecting it can be prohibitive [18, 12] and secondly is the concern of what/who the model is being aligned towards.

Current alignment methods demonstrate success on certain metrics that their methods work, that is they can make model more helpful, more honest, and less harmful [24, 6, 26, 15]. Yet the metrics used (broadly either human or AI evaluation of paired responses) miss out on deeper concerns around alignment. The first concern is that current methods may only achieve *shallow alignment* that is the model appears aligned during training yet fails to generalize this alignment to new contexts. Another concern is *inner alignment* where the training process is aligned (outer-alignment) yet the model itself has learned objective that are misaligned with the intended objective. Finally we observe models to make sure they perform how we expect them too, therefore we need *scalable oversight* methods to ensure that as models become more capable we can still ensure they are behaving correctly. These concerns are not new concerns in AI safety [3] yet they remain open problems in the context of large language models and their alignment.

## 2.3 Broader AI safety concerns

*Take the problem of alignment and expand it broader AI alignment concerns. Talk about mis generalization, and specification gaming. Introduce the concepts from PublicAI, incentives and collective intelligence. ...*

## 2.4 Representing Human Values

*Discuss concepts such as how does one understand the values of a group. How does it relate to building AI systems. I need to significant reading on this as I am most outside my comfort zone for this. Look into some philosophical concepts around how the collective the best baseline if we have no other gold standard. Provide some rationale as to why using the public as the source of values is a good idea, as opposed to some "gold standard" values provided by experts.*

## Chapter 3

# Project Proposal

Current proposal is out of date with current thinking. I am leaning towards using survey data and some SFT method to align a LLM to human values. This reduces the complexity of data collection and focuses more on the alignment method itself. There are open problems to solve on how best to use the raw data and then how to evaluate the alignment.

### 3.1 What I will do

The goal of this project is to develop, implement and evaluate for future feasibility a method for aligning large language models to a set of representatively collected human values. This will be a complete end to end process from data collection to final models output.

### 3.2 What problem I will solve

Current methods for training large language models involve scraping the internet for large amount of text data. This creates a very powerful next token prediction model. Then to turn this models into something useful for the end user (e.g. chatbots, assistants, robo doctor etc) the model is aligned to how we want it to behave. Current methods for alignment involve contracting human labelers/annotators/demonstrators to provide data to give to the model on how we want it to behave. Problematically this is a opaque process that gives the end user little insight into what the model is "designed to do". Instead by collecting a representative set of human values from the public we can align models to be in line with the end users themselves<sup>1</sup>.

### 3.3 Timeline

The project will be carried out over three main phases. The first phase will be development of a data collection method to gather a representative set of human values. The second phase will be the implementation of an alignment method that uses the collected data to align a large language model. The third phase will be the evaluation of the aligned model against the human values dataset to determine the effectiveness of the alignment.

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<sup>1</sup>In the sense that the public are the end users of these models.

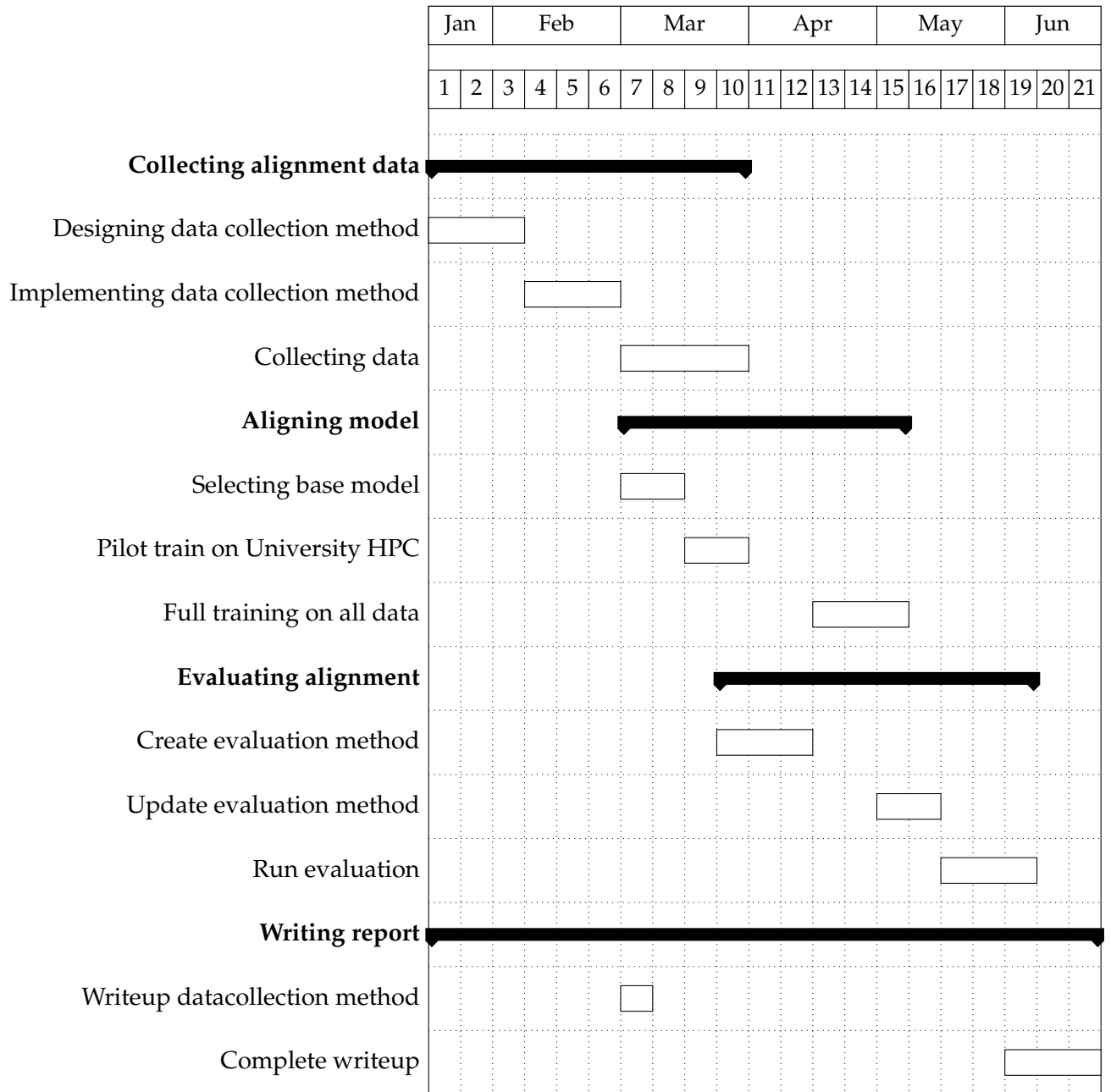


Figure 3.1: Project timeline in weeks (only roughly aligned to months). This assumes a start time of end of January 2026 with near full time work ramping up to full time work by end of February.

### 3.4 Output

The output is both qualitative and quantitative in nature. There are four main deliverables:

- A dataset of representatively collected human values for alignment of large language models.
- A reproducible method for collecting a representative set of human values.
- A aligned set of LLMs using the collected human values.

- A report that outlines the all previous outputs including evaluation of the aligned models.

## 3.5 Resources needed

There are two resource requirements for this project, hardware and survey responses.

### 3.5.1 Hardware

The first is hardware which will be needed to do the alignment finetuning and training of the model. This will be done on the Engineering and Computer Science department's GPU servers should give me access to a machine with up to 4 A40 GPUs. This will be sufficient to train models up to the size of about 30 billion parameters which is sufficient for *near* SOTA performance on many tasks. Alternatively I may rent GPU time on cloud providers such as Lambda AI which could cost in the realm of several hundred NZD depending on the total training time needed.

### Survey Responses

*No idea here. Need to research how many response would be needed. I imagine that I would want several thousands responses to get a sufficiently large data signal. Therefore at least a few hundred respondents to get meaningful "representation" and subgroups.*





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