# Contents

# Introduction to AI safety: course syllabus

*Syllabus for Dean's Teaching Fellowship course proposal, Milton Lin*

As artificial intelligence models like chatGPT become increasingly capable and ubiquitous, the need to understand their inner workings intensifies. Imagine an autonomous vehicle taking an unexpected turn or a medical AI diagnosing a life-altering condition; the importance cannot be overstated. Despite their widespread applications, our grasp of these models remains alarmingly limited. This course is designed to survey this gap.

The course is roughly divided into two parts: the empirical study of AI through *mechanistic interpretability* and the theoretical aspect of AI supervision through reinforcement learning, *RLHF* and *Constiutional AI*. Papers from AnthropicAI, OpenAI, and MIT's Tegmark Group will serve as key resources. The latter part of the course can be technically heavy - necessary readings will be provided. The technical requirement of this course is to the very minimum as long as the students are willing to learn mathematics and *how* to use the provided codes.

## Pedagogy

*Notes for myself*

- Establishing a culture. It is fine that you don't know! We are all learning. We don't judge each other. We are all learning.

## Course requisites

- Necessary: at least a one term precalculus course 110.105.
- Strongly recommended. Calculus II and III, (110.107 or 109 ).
- Recommended but not necessary: Basic understanding of python/pytorch coding. Linear Algebra 110.201, Probability and statistics courses as 553.310 or 311. A short note will be posted before course commencement for review.

## Assessment

Student assessment will be based on both weekly reading assignments and a course-long project. The homework would be broadly split into two parts:

- Written / literature review. Every week, articles would be selected for students to summarize and analyze.

- Empirical tests: once the code is set up during coding session, students will be asked to modify parameters of the models and record their observations.

There will be two take home exams, both written. The distribution of grade is Homework 60% and exam 40%.

# 1 Course Content

*I have attached some sample content after the syllabus.* There will be 2-3 weeks of course content followed by 1 buffer week of review and problem discussion. This is to foster collaboration and interaction between students. In terms of contents, they can be classified into three blocks. Week 1-4, Week 5-8, and Week 9+. Each block focuses on different aspects of AI safety.

- Weeks 1-3: The first week will go through what will and will not be covered in the course. This will be followed by an introduction section for students who are not familiar with matrix manipulation. The students will have at least 2 weeks of practice before concretely working on examples. Week 2 sets the stage of the type of AI we are discussing (supervised learning). Our goal is to have in mind 4-5 examples the students can use throughout the course. Week 3 explains how robustness is important in these examples.

- Week 5-8 discusses the problem of goal misgeneralization. Our goal is not to relearn reinforcement learning, but use it as the basic example.

- Week 9+ discusses a modern technique of "reverse engineering" machine learning models. Students do not need to have experience in coding. There are freely available codes online for students to tinker with and observe how these models behave under changes of their components. We will review approximately 2 papers and discuss their findings.

### Week 1: introduction to Alignment

Introduction to the topics and scope of the course. The goal is to give a sense of the topics involved in the AI Safety community where the topics of the course fit in this picture. As examples, we discuss the problems of alignment and robustness in a nontechnical way. Some of these concerns are near-term: how do we prevent driverless cars from misidentifying a stop sign in a blizzard? Others are more long-term: if general AI systems are built, how do we make sure these systems pursue safe goals and benefit humanity?

Textbook and references: The field is extremely young, with no complete surveys about this. However, there are a number of useful survey article on this subject.

- The main article we will be looking at is the survey *Unsolved Problems in ML safety*, [12]. This is by Dan Hendrycks at the center of AI safety.
- For broader perspective, there are articles by Rohin Shah [1] and Nanda [21].

Homework: this week's homework will require student to read over certain articles that examinines the socio-technical complexities of ensuring that AI and humans share compatible goals.

### Week 2: The mathematical prerequisites

The language of matrices will form the basis of our discussion, we will go through a few basic matrix manipulation. The background is minimal, we do not require full Linear Algebra course background equivalent to that of 110.201, but similar content to the first 2 weeks.

Textbook and references:

- Linear Algebra with Applications, 5th Edition, [4], Otto Bretscher, Prentice Hall, December 2012, ISBN-13: 978-0321796974. This is the course text book for 110.201.
- A concise and sufficient introduction is in Stanford CS229, see [18, Sec. 1-3].
- Section 1-3 of Strictland's notes lectures [26, p1-3]

### Week 3: Learning Methods and Robustness

The goal of this week is to give an overview of what is meant by *AI*, in the context of this course. This involves introducing the first of the three most common machine learning techniques;

1. Supervised learning.
2. Reinforcement learning.
3. Unsupervised learning.

We will discuss the second technique the following week, and not really go into detail about the third example until we discuss language models.

The examples are used to understand the *capabilities* of ML method and highlight examples of failure modes, particularly in the context of adversarial examples, [15], see **??** for a more detailed collection of references.

One important aspect of this week is that we will phrase the machine learning paradigm in terms of *function learning*. This is particularly simplistic but is sufficient for our purpose.
References and texts:

- This lecture will be a summary of the field of ML, similar to Ngo's post.
- The requisite is minimal and we will be going through the most basic supervised learning example.

### Week 4: Homework discussion and buffer

### Week 5 - 6: Reinforcement Learning and Goal Misgeneralization

We will discuss one to two basic examples of each and finish with how this leads to the problem of outer and inner alignment. The main reference for this week is by Rohin Shah et al. on *Goal Misgenralizations*, [24]. As in previous topics, we will go through the main example in the paper and discuss current methods of approaching it.
References:

- We will cover section 1 of the reinforcement learning textbook. We will use the classic reference by Sutton and Barto [27].

### Weeks 7: Oversight of AI Systems

Exploration of the challenges in AI system oversight. Topics include reinforcement learning from human feedback [6]. Introductory talk [16].

### Week 8: Homework discussion and buffer

### Week 9: Transformers and tinkering with language models

One lecture is *optional* would be devoted to the theoretical underpinning for those who are interested, and the other lecture would be compulsory for all students everyone so they can set up a small GPT with which they can play. *It is important to note that, to do the homework problem or future weeks in the course, we do not require a deep grasp of the inner details of the transformer models.* The optional theoretical lecture only needs minimal understanding of matrix multiplication, which by now students should be familiar with.

The theoretical lecture is *different* to the standard course in transformers that is often taught. The main reference paper is the *mathematical framework for transformer circuits*, [9]. This will be left as an optional homework.

What we require is for the student to be able to tinker with the code. This involves changing various parameters in the model. All the code would be based ARENA's freely available colab notebook. The student would *not need* any coding experience.

References and texts:

- *Mathematical framework for transformers circuits*[9] is the main reference text for the optional theoretical lecture course. I will also write accompanying lecture notes.
- We will *not* follow the classical paper as in Vaswani et al. [29]. However, students are welcome to discuss with me.
- Additional resource: Goodfellow et al. [10].
- For the compulsory coding lab session, we will use available codes from ARENA . This is a well known AI repository.

### Weeks 10-11: Introduction to Mechanistic Interpretability

Now that in previous week we have set up the coding, it is time for students observe the behaviors of this language model. Students will get a feel of using their own small versions of GPT. Here we will do practical empircal exercises based on the concept of mechanistic interpretability. The key papers we will consider will be the *Zoom series*, Olah et al. [23].
In the two weeks:

- Using the TransformerLens library developed by Neel Nanda to locate *induction heads* in a 2-layer model.
- Intepreting model trained on toy tasks, e.g. classification of bracket strings or modular arithmetic.

Textbook and references:

- Mechanistic intepretability is a growing field with many resources, a large collections is provided in Neel Nanda's site, [20]. For the purpose of this course, [23] is sufficient.

### Week 11: More case study in mechanistic intepretability

This week would be both be emprical and discussion based. In this week, I will survey two papers, *toy models of superposition*, [8], and We will discuss *Progress measures for grokking via mechanistic interpretability*, [22]. Both papers are built upon the previous lectures.
The last lecture would serve as a summary of what have been learnt so far. We have the same reference as previous week.

### Week 12: Homework discussions and buffer

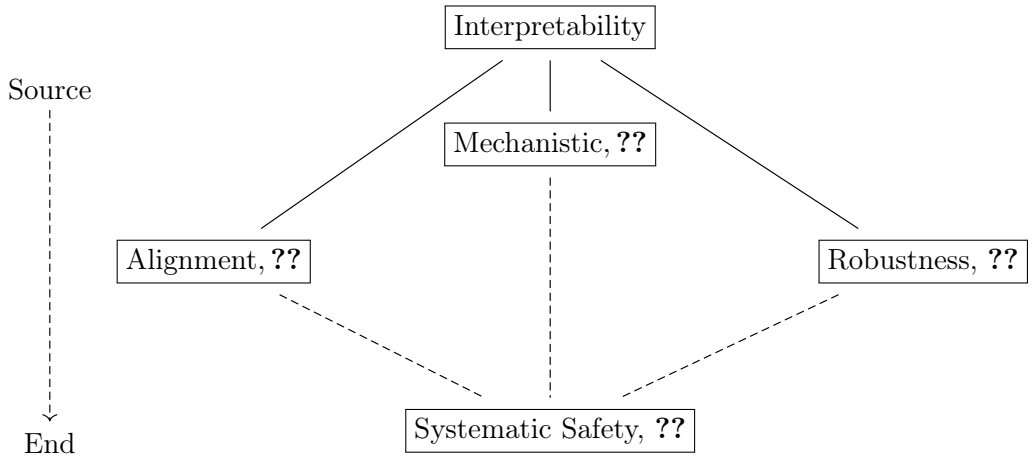
# 2 Safety in AI

References:
At a high level overview definition

**Definition 2.1.** *Machine learning* methods are automatic methods for extracting information from data for various *AI tasks*.

## 2.1 A bird eye view of the subject

To organize the article, I categorize the various research areas.




The vertical hierarchy can be thought of as getting from the source (foundational design of the AI systems) to end (their use and place within society). The arrows only mean "contribute". A brief summary of each box is given in, 2.2. Importantly, the whole lifecycle of AI has various stakeholders involved:

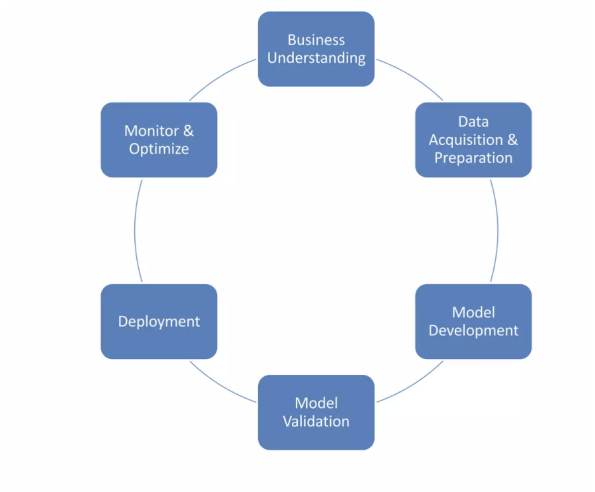



Figure 1: The AI Life Cycle

We refer to [7] for further details. Example, [28]. The various stake holders.

| Field | Examples |
|---|---|
| Buisness | Making loans. |
| Regulation | Laws against discrimination such as age, disability status, race , etc. See GPDR |
| Model developers | Which training examples are most influential?<br>Debug and improve |
| Legal professionals | |

## 2.2 Overview of each field

We will focus on three of four types of problems, as explained in [12].

- *Robustness*. There are broadly two types of events:
  - *Black swan*: rare extreme, unsual events. Examples of such include the 2010 Flash Crash, [17], or those apperaing in autonomous vehicle. In the context of statistics, these are also referred to as *long tail events*. Long tail distributions make the usual arsenal of statistical tools can become less useful. Examples include power law distributions.
  - *Adversaries*: carefully crafted threats, or as Goodfellow et al. describes, " *adversarial examples* are inputs to machine that an attacher has intentionally designed to casue the model to make a mistake." Much literature has focused on "perturbation defense", which was mostly focused from Szegedy et al's, [28]. We discuss more details of this in Sec. **??**.

- *Alignment*, we list a number of main difficulties in alignment.
  - specification. Encoding goals such as judgment, experiences, and happiness is hard. Research is done to assess the language model's ability to evaluate scenarios that could be morally contentions. [11].
  - even when one is able to describe a value to be learned:
    * it can be difficult to optimize, as models can have unintended undesirable secondary objectives. To understand and steer agent's moral values, researchers could dconstruct relevant environments, for instance, Jiminy Cricket, which has 25 text-based games with diverse scenarios, [13].
    * *brittle*, due to reasons as proxy gaming. Further, even with "human approved" proxies, there is the risk of deception from computers. Future systems should strive to address the problem of verification, past attempts include an adversarial process, where during training two agent takes turn making short statements with human judges on the final result, [14].
- *systematic safety*, is the deployment of ML systems in the larger context, including software systems, organizational structure or human society. Two main examples of systematic research are in cybersecurity, such as the defense of potential hackers, and informed decision making.

### 2.3 Homework

*Homework for week 1 is a reading exercise.*
In this week, you will read the following two papers, [12], [2]. For the first paper,

1. Describe a nontrivial strength or weakness of the paper that isn't explicitly mentioned in the readings themselves. (300-400)

2. Summarize the reading. Be sure to read and summarize the contents of each section; do not just describe the overall idea of the paper/article. (400-500)

For the second paper (which is more technical),

3. Write one concept in the article that confuses you/you hope to understand more. Explain why.

# 3 Linear Algebra Review

**Learning Objectives**

- Learn the basic language of linear algebra.

Notations:

- $\mathbb{R}$ denotes the real numbers.
- $\mathbb{Z}$ denotes the set of integers. We let $[n] = \{1, 2, \ldots, n\}$ denote the set of the first $n$ positive integers.
- For an arbitrary set $X$, $X^n$ will dentoe the set of ordered sequences of $n$ elements in $X$. The set is also denoted as $\{(x_1, \ldots, x_n) : x_i \in X\}$.
- We assume the reader is familiar with the basic terminology of functions and sets.

**Definition 3.1.** A $m \times n$ matrix in $\mathbb{R}$ is a function

$$[n] \times [m] \to \mathbb{R}$$

This is often denoted in two ways:

- as a square with $m$-row and $n$-columns.
- or from the compact notation $(a_{ij})_{i \in [m], j \in [n]}$.

For example, below are $2 \times 3$

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix}$$

a $3 \times 2$ matrix

$$\begin{pmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{pmatrix}$$

**Definition 3.2.** Let $M_{m \times n}(\mathbb{R})$ be the set of $m \times n$ matrices.

## 3.1 Pytorch

There are number of libraries which allows one to work with *tensors*. The common libraries are PyTorch, TensorFlow, Jax... Here are some common operations: Modifying shape of tensors:

| |
|---|
| `torch.cat(tensors, dim=0, out None)` |
| `torch.sum, .prod, .max, .mean` |

Elementwise operations:

### 3.1.1 Broadcasting

### 3.1.2 Slicing

Here's a dictionary

| | |
|---|---|
| `:` | all indices |
| `3:7` | indices |

# 4 Neural Networks

References: [25, 1-2].

**Learning Objectives**

- Understand what a neural network is. Understand its difference to classical statistics.
- Phrasing AI tasks in terms of functions.
- Play with the TensorFlow playground. [a]

[a] We will *not* need to know how to code.

The three most common techniques

1. Supervised learning.
2. Reinforcement learning.
3. Unsupervised learning.

**Question**

How can an AI system fail? A taxonomy via observability, [5]. Now that we know the pipeline of machine learning: there are two areas

1. *Observable failures*
2. *Unobservable failures*

We will begin by showing how many AI tasks such as classification be rephrased as learning a function.

$$\{\text{Machine learning problem}\} \longrightarrow \{\text{Represented as a function}\}$$

This language, especially in sec [transformers], reduces the verbosity of the presentation.

### 4.1 Overview of supervised learning

Consider classifying whether an image is a cat. Solving this problem is to find a function

$$f : \{0, 1, \ldots, 255\}^{28\times 28} \to [0, 1]$$

$$f(\text{image}) = \begin{cases} 0 & \text{image is cat} \\ 1 & \text{image is not cat} \end{cases}$$

The domain of the function is the set of all possible images when expressed in vector form: an image has $28 \times 28$ pixels and a value of 0-255 in grayscale. This is often referred to as the PAC or SLT model.

**Example**

- Classification on whether an object is a chair or not.
- Detecting whether an email is spam or not. We can have a number of emails labeled (by human) according to a number of features.

| "money" | "pills" | bad spelling | Known sender | spam? |
|---|---|---|---|---|
| Y | N | Y | N | Y |
| Y | Y | Y | Y | N |
| ... | ... | ... | ... | ... |

  - There are four features in this table. This will often be depicted as a vector, to encode the "Y=Yes" or "N=No".

  Our goal is to approximate a function:

$$f : \mathbb{R}^4 \to \mathbb{R}$$

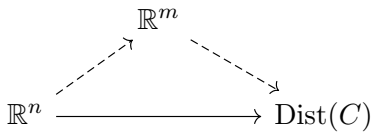
$$f(\text{features of email}) = \begin{cases} 1 & \text{if spam} \\ 0 & \text{if not spam} \end{cases}$$

  where the data can be represented in terms of a vectors in $\mathbb{R}^4$. We may also use the first two features as training, to approximate a function:

$$f : \mathbb{R}^2 \to \mathbb{R}$$

**Example**

In practice, we would want to learn a function is in fact a *distribution* on the outcome. Suppose we are at a classification task of given $n$ features (encoded as a vector $\mathbb{R}^n$), our goal is to give a distribution on the classes, $C$, where $|C| = m$.




Given $f(x) \in \text{Dist}(C)$, we can ask

$$\text{argmax}_{c \in C} f(x)(c)$$

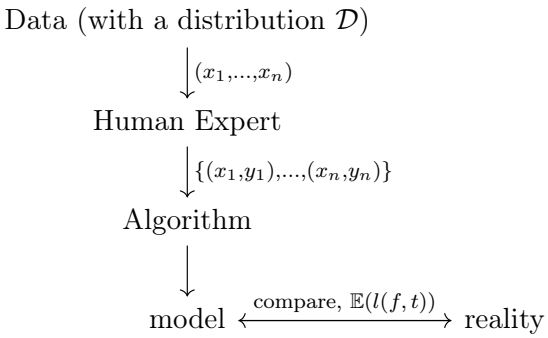
**Example**

Model voter distribution.

Such process is the same as what happens in a *log-linear model*.

**Definition 4.1.** A *supervised learning method* is a method that creates a function (*predictor*) that *generalizes* well from *input data*.

The typical set up can be visualized in the following diagram:




Input:
- An *assumed* true function $t : \mathbb{R}^n \to \mathbb{R}$.
- Finite set of data sampled from real world :

$$(x_i, y_i)_{i=1}^N := \{(x_1, y_1), \ldots, (x_N, y_N)\}$$

  This is the *ground truth*.

Output: Some function $f : \mathbb{R}^n \to \mathbb{R}$ it *generalizes*, 4.2, well to the true function

The three theoretical aspects, each of intensive study are thus:

1. Optimization. How does it behave? Why does optimization work so well?
2. Approximation error. This is the choice of the architecture, or the its *expressitivity*.
3. Generalization. There is where we see the phenomena of double descent, [3].

## 4.2 What it means to generalize

In an ideal world, where we have access to a true function, we can measure the discrepancy between our predictor and true function using

**Definition 4.2.** The *true risk* of a predictor, $f$, is

$$t\text{-err}(f) := \mathbb{E}[l(f,t)]$$

where

$$l(f,t) : X \to \mathbb{R}$$

is a choice of loss function and $t : X \to \mathbb{R}$ is the *true* function.

**Definition 4.3.** The *bext predictor* is an element,

$$f^* \in \arg\min_f t\text{-err}(f)$$

**Definition 4.4.** The 0-1 loss function.

$$l(f,t)(x) = 1_{f \neq t}(x) = \begin{cases} 0 & \text{if } f(x) \neq t(x) \\ 1 & \text{if } f(x) = t(x) \end{cases}$$

**Example**

If $\mathcal{D}$ is the uniform distribution on[a] $X \subseteq \mathbb{R}^n$,

$$\mathbb{E}(l_{0,1}(f,t)) = |\{x \,:\, f(x) \neq t(x)\}|$$

where $|\quad|$ is the area[b] of the set.

[a] To be precise, a Borel measurable set.
[b] more precisely, Borel measure

**Definition 4.5.** The *training error* or the *empirical risk* of a function on a sample data

$$S := \{(x_i, t(x_i) =: y_i\}$$

$$\text{er}_S(f) := \mathbb{E}_S(l_{0,1}(f,t)) = \frac{|\{x_i \,:\, f(x_i) \neq y_i\}|}{N}$$

The *minimal emprical risk* is the set

$$\mathrm{ERM}_S(f) := \arg\min_f \mathrm{er}_S(f)$$

Does minimizing empirical risk imply minimizing true risk?

**Example**

Let us suppose $\mathcal{D}$ is the uniform distribution. We are to approximate the function

$$t : [0,1]^2 := \{(a,b) \,:\, a,b \in [0,1]\} \to [0,1]$$

using only a finite set, $S = \{(x_i, y_i)\}$, of ground truths. Suppose on $S$, we define

$$f_S(x) = \begin{cases} y & \text{if } x \in S \\ 0 & \text{otherwise} \end{cases}$$

Then

$$\mathrm{er}_S(f_S) = 0$$

In other words,

$$f_S \in \arg\min_f \mathrm{er}_S(f)$$

However

$$t\text{-err}(f_S) = 1/2$$

This is the problem of *overfitting*.

**Question**

What kind of functions $\mathbb{R}^n \to \mathbb{R}$ do we get from feed forward networks with one hidden layer? (Depends on $\sigma$ and width).

One can understand the typical pipeline in the following Colab note book.

### 4.3 Linear learning

**Example**

Can't learn XOR or the circle function.

## 4.4 Kernel methods

$$\mathbb{R}^n \xrightarrow{\text{non-linear}} \mathbb{R}^N \longrightarrow \mathbb{R}$$

The non-linear map is often called the *feature map*. Many tasks in traditional (pre-Neural network) is addressed using this.
Another example is : SVM.

$$\{\text{Blair, Bush}\} \xrightarrow{\text{PCA}} \mathbb{R}^{150} \longrightarrow \mathbb{R}$$

## 4.5 Neural networks

*What we learn is complex, how we learn it might be simple. - paraphrasing Geoffrey Hinton.* The brain has approximately 80 billion neurons.

**Definition 4.6.** A *perceptron layer* is the datum of:

$$p(W, b, \sigma) : \mathbb{R}^n \xrightarrow{A_{W,b}} \mathbb{R}^m \xrightarrow{\sigma} \mathbb{R}^m$$

where

$$A_{W,b}(x) := Wx + b, W \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^{m \times 1}$$

is called an *affine transormation*. $\sigma$ is a *any* function.

Choices of $\sigma$ include

- ReLU $:= \max(0, -) : \mathbb{R} \to \mathbb{R}$ function. This induces component wise of the function ReLU $: \mathbb{R}^n \to \mathbb{R}$.
- You would *not* want $\sigma$ to be linear. The nonlinearity depends on a choice of basis. This destroys the symmetry[1], increasing in expressivity.
- Historically, the functions $\sigma(x \cdot w + b)$ are referred as *ridge functions*.

**Definition 4.7.** A *(vanilla) multilayer perception* or *nerual net* consists of a composition of multilayer percetpron

$$\mathbb{R}^{n_1} \xrightarrow{p_1} \mathbb{R}^{n_2} \xrightarrow{p_2} \cdots \longrightarrow \mathbb{R}^{n_k}$$

**Example**

Semantics. We can use this in the context of *semantic* parsing.[a]

[a] Syntactic on the other hand is giving the tree.

[1] If one is allowed to change the basis, then we can simply find a new basis so that all the functions are well behaved.

## 5 Homework 2

*Homework for week 2 is reading exercise, Due Wednesday.*
In this week: choose *one* of the following options (1 or 2): [2]

1. For those still want to familiarize themselves with supervised learning:
    - Read Vishal Maini. Answer (c).
    - Read a visualization on the progress and a survey by Ngo. Answer (a),(b) and (c) for the second paper.
2. For those who are already familiar with deep learning,
    - Read Zoom In. Answer (a), (b) and (c).
    - Read the case study of analyzing CNN. Answer (a) and (b).

General questions:

(a) Describe a nontrivial strength or weakness of the paper that isn't explicitly mentioned in the readings themselves. (300-400)

(b) Summarize the reading. Be sure to read and summarize the contents of each section; do not just describe the overall idea of the paper/article. (400-500)

(c) Write one concept or technicality in the article that confuses you/you hope to understand more. Explain why.

[2] the alphabet letters refer to the "general questions"

## 6 Homework 3

*Homework for Monday November 27th. This week read the following two resources*:

1. Watch the 2021 lecture lecture by DeepMind x UCL for an introduction to Reinforcement learning. Discuss three concepts that you would like to see further explained. (200-300 words)

2. Read a general introduction to reward misspecification by Krakovna et al., [19]. Discuss two examples of reward misspecification not given in the article. (200-300 words).

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