Top of Form

All right. The sessions are being recorded. Hi, everyone. I hope you're doing well. And welcome to Session 2 for YCBS 256 Data Science for Business Decisions. And today we are going to have an interesting session. Interesting because before we get started with learning data science and actually implementing these models, it's important to talk about ethics and AI that is associated with data science. And this is as the course is bridge between data science for business decisions and data science and machine learning. It's important to know why this topic carries a great weight and the way we are going to proceed in today's session is we'll have a short discussion. So we like to call it a small workshop. So what we do is first we'll go through some of the key concepts of ethics in AI. And then the agenda is for you to work in breakout rooms for approximately 45 minutes and each of the breakout room has different questions to address. What those questions are, we we'll get to know in a couple of minutes. And based on this, the questions that you'll see there is an article associated with it, except there is one research paper which I would like to advise the class to check out and I'll show you where you can access the research paper. It's already on my courses. If you scroll all the way down to additional files and resources and inside module 2 you will find that there is a research paper that is that is being attached. And then we'll have a short presentation from all of you because I feel like and the way we have selected these article is, is that it covers a broader range of different fields and different kinds of issues associated with ethics related to that specific field. We will also have Nabil Betianjane, who will be joining us at 6:30 just to interact a bit. He's the data science and program coordinator. So you'll get to see him virtually as well. And then we'll get started with with the work in breakout rooms, you'll be working in teams of either four or five. The teams are already divided. So I'll take you through the logistics once we reach there. So let's get started as the topic itself suggests that what we are trying to do is understand bias that is associated with the data. So, so far we haven't discussed that how do we deal with data And we'll deal with this partly at 8:00 when we have the hands on session part of this. So here are some of the article clippings and the articles. The link is also pasted at the bottom so you can take a look if you want. But let's take a look at the main message. So there was an interesting story which says where Google apologized for making racist auto tags in the photo app and the racist photo tag was that it labeled two people as guerrillas and also in Flickr had same issue associated with identifying race from pictures. So both of them were considered very offensive and they had to publicly apologize and admit that there was something wrong. Now what's the problem with this? That's one second why such a problem even exists. Is it because a human is doing something? Is it because the algorithm are bound to learning these, these process, that's the main aim of today's session. It's about understanding the bias, how they affect us and finally, how do we mitigate them. Now, depending upon what field or what domain you're talking about, the way or the sources of these biases will be very different from each other. Hence, it's important that you that we have this short presentation at the end of at the end of the workshop, which will allow you to share with your peers and also get introduced with other kinds of biases that exist in different fields. Another example is this compass algorithm. How many of you are familiar with this? You can just say yes or no in the chatter, just say thumbs up. I think that will be quicker. So how many of you are actually familiar with this algorithm, or have even heard of it? Just taking a look at the chat? No, no, no. Oh, that's interesting. A lot of people have worked in the field but are not familiar with it. OK, so there's one who's familiar or OK, that's good. That's why we have this class So Compass algorithm, it's a correctional Offender Management profiling for alternative sanctions. So what this is, it's an algorithm based system that is that is used in quotes through United States. And what this system is meant to do is basically it predicts the likeness of criminal reoffending. So given that that a person has done something what is what are the chances that the person will redo a specific time. So it's a it's an algorithm based system. Now the problem with this system and it became a huge issue if if you followed the news and there is one of the article that is not directly associated with it but closely associated with this and and the issue that that happened was that black defendants were almost twice as likely to be misclassified with a higher risk of re offending in comparison with the white counterparts where the percentage if you talk in numerical terms for the black defendants it was approximately 45% compared to the white counterparts who had 23% of criminal re offending. Now that is problematic because based on these these scenarios are based on how the decision making processes involved in these algorithms a lot of decisions are being made and such a bias is not a good thing in the in the system. Now the problem becomes how do you even identify this bias? You cannot identify unless you test it sufficiently. So basically given an input data, you build your model on it and the model does something. I'm loosely using the term models and algorithm because we haven't formally defined it, which we will define in the next session, next hands on session. So until then I'm just using these two words interchangeably. So either model or algorithm takes an input data and tries to learn something on the data and then they do the downstream task whatever they are meant to do. Now the problem in this approach is the model is largely dependent upon the data and that data is collected from the society either by a third party organization or directly from the people. So it a lot depends upon how and what quality of data is being collected. Because your model decision is based on that and why it is problematic for a model to be to show such bias. You can see that it directly effects life of people and the the decision process that is being made. But that's with respect to court proceedings. How about language biases that persist and these biases are mostly associated with with gender neutral languages. I'm not familiar in Turkish, but some of you might be. So if you Google this or if you were using Google Translate couple of years ago, so translate from Turkish to English and you have to translate the sentence where you have to say that he or she is a nurse. The only answer that Google gave was the first option that you see at the top that she is a nurse. But then comes the the gender bias that exists that why can't the person be he? Because the profession can take both the genders. Here we are considering only two genders, and in that case it's it's a language bias that system automatically runs. So Google was able to correct this, I guess three years ago. But if you had come across certain terms, or if you were using Google Translate to translate from one language to another, you'd encounter this problem that how do how do you correctly interpret? And this becomes problematic because gender neutrality has to be taken care of whenever you're translating from one language to another. Yes, all good, yes. But in fact from Turkish, is it he or she? I was like, I'm just wondering in their language, like how it is translated, What? What's the meaning, What's the meaning of the differentiation between he or she? No, no. What's the meaning in Turkish Like in different languages you say you mean like it she or he? I don't know. But in Turkish this phrase like what they mean when they say that do you know like as I said like I'm, I'm not familiar with the with the language but the the motive of showing this was the the bias that happens in the translation from a gender neutral language to a gender bias language. Yes Sir, yes. So I'm of course I don't know Turkish but in Arabic it's it's we have different wording for you or he or she but they are they are brown browsed it differently but they are written the same. So if you provide it to Google translation, most probably it will not be clear in the way it's written only it's unless there are some, you know, additional special characters to be written or some way to like a different way to pronounce it. But other than that it may be not not possible to differentiate. Yeah, that's. Thanks for bringing that up. So there there exists multiple languages in which such a lot of semantics is just lost in the translation. And it's important because they convey different meanings, not in this smaller sentences, but in terms of when you're reading a bigger document or when you're trying to use it for research. There seems to be a loss of information. Another example which we can see over here. So this is a pseudo code, I'll pause for 30 seconds because you'll just take some time to read through it. For people who are not familiar with pseudo code, what it means is it's basically a set of variables that define a heuristic or a rule. So over here it is not saying that on which language this is coded or in which in which system it has to be implemented. All you need to know is that there is a basic logic that is being implemented over here and that logic is how to decide the salary of an employee and this is a pseudo code for that. Now take a take a look at it for maybe 30 seconds to a minute and don't speak but mention in the chat what do you think is the problem with this setup code. All right, I guess everyone is able to get to the point where, which is the second last paragraph. So there is a gender bias that is being automatically induced in the system and this is not based on any learning. This is like a human has coded it and the system is encoded this specific way, which is that male gets twice of male bonus and female only gets one. Now that is problematic because there is no quantitative parameters to justify that why one is receiving twice the multiple of bonus compared to the other one. There is another problem which no one actually pointed out, so I'll wait for 30 seconds more to see if anyone can figure it out. OK, there is, yeah, someone did mention in the chat. So there is no specification that which bonus is higher. Is it the male bonus or is it the female bonus. So the value of these numbers will also start mattering and that is an implicit bias that is being introduced in the system. So it is, it is being masked from the transparency and even if you have this multiple of two or not have multiple of 2, that's one factor. But you need actual numbers to actually compare these values and this this indeed turns out to be problematic. So there is a very good example that when ChatGPT came out and I tried to use it for discovering bias. What ChatGPT would return is that if gender equals to male and if ethnicity equal to such, and if few more parameters equal to this, that's the salary. So without even without even looking at the other parameters and if you try to regenerate the same thing. In today's ChatGPT it says that introducing bias is one of the non ethical thing to do in our system and we should be careful about it. So the bottom message being sucked with, When such problems are being introduced in a system, it's important to recognize that what can be the outcome or what can be the problems associated with systems like this. Over here there is another example that if person dot zip code, again it's a pseudo code. So if the zip code associated with a person is the zip code, deny the credit or grant the credit, what can be the bias associated in this? Of course there is a bias associated with the PIN code, but why? What is a deeper implication of that? How can this affect people? There's one interesting answer. There can be demarcation of rich or poor neighborhood, location, address or region, yes, but. But what's the what's the why the bias associated with yes? There's another very interesting answer that it may not be a diversified data set or a particular ethnicity must be targeted. So associated with this, have you noticed and I'm pretty sure, and this is an interesting question of debate, have you noticed that if most of you are living in in Canada and you you shift your apartment from one region to another and when you try to change your address for the for let's say for the car insurance, the insurance rates change even though you are in the same city? Have have you noticed this? What's what's the reason that you have received? Did did anyone try to inquire or have anyone thought, can you repeat the question? So you must have noticed that when you when you change your region or when you change your apartment within Canada, let's take the example and when you change the address, the insurance rates change and we are just talking about car insurance and what's the what's the most common reason you received that? Why did your insurance rate change? Because the person did not change. The person has the same driving history, same record and same status. Yes, Sam, Yes, it's like it happened with me and I asked the insurance and they said that it's because of the maybe the area even within the same city there is higher accident rates or maybe more claims reported for cars car theft or car stolen. So because of that they they consider the area as a factor to do assessment for the rates. Yeah, thanks. So and most of you are rightly pointed out and some of you have pointed out very interesting reasons which I also think is true and which is crime rate in the area, number of car thefts. Someone has also pointed out proximity to a fire station, that's a really interesting one and in fact that's also taken into account. Now the question is that let's say that you know five or six, six of these parameters. How do you put them together in order to come up with a number? For example, if it is, if you just change one factor. For example, if you change the factor that proximity to a fire station, how much of contribution just that one factor has to a specific target, which in this case is what should be the insurance premium if the distance to the file station changes or any of the other parameters. That is something that is learned through model and we try to learn that through data. Someone was saying something. Was that a mistake? OK, so the reason behind discussing all this is 1. All this is coming from data. So whenever we start with data analysis and we'll be starting with them today, sometimes it's very difficult to even detect that there is a bias in the in the system. Also, how do we differentiate between an existing bias in the system with the nature of the data itself? Is it the data that is telling us a true story? Or is it just a bias that exists in the data And these two problems are very much entangled together and there exists some formal ways but there's no clear separation that how do you exactly perform this task? So when we'll be taking real life examples and you'll be working with the data set, always remember back of your head that there may be bias in the data set that's why your results are like this. And 2nd, we would ideally want to differentiate that how does this bias affect the target function that whatever we are trying to analyze. In this case it was car insurance. And lastly, even though we are aware that there exists bias in the data set, how do we ignore that bias and look for something that is relevant? This is a research topic that's been going on even today and is very difficult to address. So let's take a few more examples. How do we address the bias? And there is this popular discussion which is about before addressing it, you need to identify the bias. So there are statistical methods and techniques that allow you. To identify the bias and there are some separate techniques that allow you to mitigate the bias and we'll be talking about some of these. We won't be implementing any of the algorithms today because this is also an introductory post, but definitely we'll be doing some hands on data right from today itself. So now depending upon different topics that we have identified for multiple areas, you will be working in a set of different groups and these topics are mentioned over here. So before we get started with the topics, there is this slide which is to just point out the fact that you will be put in different groups and these groups are already created. This is based, so three of the discussions is based on the reading that was allotted today and remaining four of the discussions are based on small articles because the reading that was pre allotted for the class that those are long articles. So it will take some time to go through that and the ones that are assigned right now, I'll share the link. Those are shorter articles and the reason why we are doing this is so that once you discuss among your group and you make this short 5 minute presentation in the class today, we'll have a better idea that how in different field it affects and how it can be mitigated. So as I mentioned that before mitigating the bias, it's important to at least address or know what sort of bias exist in the data. So let's quickly go through seven of these different topics and then Nabil will join us for some time and then you can get started in the breakout rooms. So the first discussion that we have and these are three allotted readings for the class which was we are in diversity crisis which was said by Co founder of black in AI and what's poisoning algorithms in our life. And this is this is a very interesting article that shows why diversity is important in terms of the problems that we are dealing with today. The second one is the foundation of algorithmic bias. And this is more of a technical article that shows what are different sources of bias, how bias comes into the data set and how it can be addressed. Does not talk about any specific feed. The third one is malicious use of artificial intelligence, how you can forecast, prevent and mitigate. You might have seen AI has been used for a lot of destructive things, specifically the use of deep fake videos using generative AI to generate or synthesize image, creating fake news. And once it's out there on social media, it's very difficult to distinguish between what is the actual news and what is a fake news. And people get swayed or people get affected or build opinion based on these fake news. In fact, if you're a bit more familiar and just to get you intrigued, Meta has a separate division that only works on deciding whether an article is fake or real. And it's a very tough task to do because of the as AI is progressing, it can be used in a way, in ways that it makes it really difficult for the users or the consumers to decide that which is a good path or is it a real or a fitness. The next one is algorithmic bias and detection, which talks about best practices and policies to reduce consumer harms. And this course is on data science for business decision. So there is always a consumer side associated with it. So not only from the side of creators, but from the side of consumers, how are they affected in terms of these biases that exist in some of these datasets. The next one is artificial intelligence and algorithmic bias implication for health system and this is specifically associated and talks with bias in healthcare system and it's an article that's taken from Harvard Review and it's an interesting way that shows why in fact all these AI models that are performing great out there still they are not implemented in healthcare and the reason behind not implementing them and what is the decision making process that affects implementing AI in healthcare systems. So in the context of bias And the second last one is also AI in healthcare and this specifically is interesting and whoever is in Group 6, it's interesting because it talks in the context Of Montreal. So this clip and this is for everyone in the class who are not even in allotted in Group 6. So this article is taken from Montreal Ethics and AI Institute. As you know Montreal is becoming a hub for AI, So it's important that that you get associated with some of the cutting edge things that are happening out there. So do check out this website. It's an institution that is based in Montreal Montreal AI Ethics Institute and this is an article that was published there. So this specifically refers in the context of Montreal's healthcare how practitioners can engage and are affected by biases and what are some of the anti bias measures that has been taken to address some of the grievances that can happen because these these methods are difficult to distinguish. And once you also go through some of these articles in your group and once you have a discussion, you'll realize that it's really difficult to address some of these points. And the last one, I haven't attached the clipping, but I'll share my screen where you can find it because it's a research paper. So let me share my screen one second. So that should be visible to everyone. And if you look at the bottom of the screen to additional files and resources over here Additional files and resources Module 2 reading article and that's an article from a journal paper. It shows algorithmic bias in data-driven innovation in the age of AI. And as I said, all of you should read this because you're working in data science and the most interesting part of this is this map. So give me a second. I'm just trying to enlarge this and re share. Can you see it enlarged? So in this case if you scroll all the way to the bottom, there is a flow chart or an algorithmic chart that you can see which is which shows algorithmic bias in DDI's. So data-driven informations and you'll see different phases in which bias can happen, in the training phase, in the method bias, or in the societal bias. So give it a read and it's an it's an important read because it it enlightens you to this world of problems that happen and the problems that you should be familiar with. And in fact, later on, if someone decides to pursue the job of data scientist, there is a niche division in data science which literally and only focuses on handling bias, mitigating bias and debiasing the data. And after you have debiased, you go for any of the statistical analysis of the data. So with that, we'll drop the discussion and it will be you who will be following the discussion. So what you can do is if anyone can share their screen, I can show you how to access the questions. And so let me enable the screen sharing. If one of you would be kind enough to please share your screen, I can do it. Please go ahead. Let's talk a bit. Hi, Nabil. Yeah, Hello. So hi, my name is Nabil. I'm what they call academic program coordinator for the data programs. Normally, under normal circumstances I would be teaching this course with Omar, but Omar is doing it on his own. I'm teaching another course, so I had to put all my attention over there so I don't have the opportunity to meet you. Besides, you know, through this invitation by Omar, welcome aboard. You are embarking on either the Data Science and Machine Learning PDC or the Data analytics one. In either case, you should be quite challenged throughout the road You take, I believe by now you, you know, you have looked at the course outline. You kind of understand what's in there. I am what they would call an escalation point. So after Amar, the next point of escalation would be me. After that, it'll be the manager I have. Her name is Elisa, Elisa Schaefer. If there's any issues you'd like to discuss about the course, you know, obviously Amar is your first point of contact. However, you're more than welcome to talk to me or Elisa at any time. If you want to discuss where you're going. Obviously Amar is a good person to talk to. He knows a lot about the industry he's worked in, the industry. He's finishing his PhD right now. He's met a lot of people along the way. He knows he has a very big network of people that he can refer you to. But you're more than welcome also to reach out to me or to Elisa to discuss, you know, where you're going. Some questions you may have Should I do this program? Should I do that program talk to you really. We're we're around. I have office hours usually Fridays. Just send me a note saying hey I'd like to talk. That's it really. So if you have any questions ask. You know like we're we're really here to help you along the way. You you do have a good network. You know you're starting already with close to 30 people if not more I think 32 and I forget the exact number right now. So you already have a good starting point with people to get to know and build your network in the data world. Obviously add Omar obviously add me on to your LinkedIn that that will increase your your network. There will be activities outside of here that we will let you know about. You might just see an e-mail coming from me or from Omar telling you, hey, there's going to be some conference going on. There's going to be some lunch and learn going on. There's going to be something happening. Please join us. We'll be very happy to to have you know, to to see you in other places besides in the classroom. Any questions for me like I'm, I'll stick around for a little bit just until you jump into the rooms etcetera. Then I don't think I'll need it anymore. But if you have any questions, please feel free to ask about the program, about the duration, about what class do you teach? What course do you teach? I normally teach this is my this was used to be my primary course. I teach also in the capstone sometimes and the leading data science teams and projects on the Data Analytics for Business 1. Right now I'm teaching a course called Applied Data Science. It's graduate certificate we're teaching. I'm teaching it for the first time. So we're I'm designing the course and then after that I will be, you know, handing it over to other people. Maybe Amar might pick it up or somebody else might pick it up depending on time etcetera. So I'm doing this course next semester. I'm teaching a course called Information Visualization. That's the other course I'll be designing and building. And then after that, we'll see if anybody else wants to pick these courses up or, you know, depending on workload, I might do them. Thank you so much, Nabil, for your introduction. Nice to see you. Hi, Kevin. Yeah. So don't hesitate like you you're you have, you're in good hands. You know with Amar, definitely you have someone who knows the material, who knows data science, who knows you know a lot of things like it's it's kind of interesting. You know, I'm not trying to pump them up, pump them up too much. But you know, whenever we talk about any new technology that's coming out, it's like, yeah, I've been working on it for the last couple of years. He doesn't even say that but he has been working on some leading edge technologies and it's it's it's great to pick his hat his head on different topics. Keep in mind that the basics of data science do not change much. This is something that people have to understand is that what we're teaching the course, we're teaching a lot of fundamental elements that you, you know, building blocks that you will take forward with you. Those are very, I want to his word, immutable, but they're very, you know, the basics don't change. You know we need to, you need to understand them, you need to understand how things fit together, you need to understand the process, you need to understand and you need to do a lot of hands on. So the purpose of this course, and I think Mark told you about this, is really to talk about concepts but also work with your hands, with Tableau and with Altrix. It's very important to get the hands on experience with data because talking about it only takes you so far. Thanks Nabil for joining the session. I think from my perspective would would love to meet you and Amar in person and you know get your, you know kind of how to say you know your your thought process or your or you're understanding on how a person should look at data signs And if someone wants to you know get into a data scientist kind of a role where to start with of course I mean and how Megal can help with that. Like you know, I know I went online I searched for these courses I'm working so I had to find something which is not full time. Again it comes with you know additional responsibility to finish off the courses assignments. So how do you think we as in you know especially people who are doing PDCS, how we can leverage our time short amount of time to to maximize our understanding around data science and where to start with You know I if you Google you will find a hell lot of courses about you know a hell lot of technologies but it's it's it's bombardment of information but not something concrete something that someone can start with. So would be good to have a session with you Sure maybe something Yeah. Sorry, we can do something on that if you want to, but I'll I'll give you the quick answer. Just you know like what I what I tell normally people on this we designed this course approximately 6 years ago. The courses are being or the PDC is constant. There's always some evolution inside the PDCS. However it's very important to to understand this is what I'm saying. The basics are not immutable but the basics are basics. So what I mean by that is the what we're trying to do in the in the program as a whole within the minimal amount of time possible, you know, which is five courses, you know probably can do it a little bit less than that. You know, like there's maybe one course that you can skip or a course and a half maybe. But within this five course structure we're giving you enough that you have a good understanding of what data science is about and how to solve a problem with machine learning. So I just jumped, you know, before coming here, I was in another class and the other class is the capstone and we were listening to the Chief Information security Officer of the City Of Montreal explained to us the problem they were trying to solve, a problem they were trying to solve, which we are giving to the students to solve at this semester. So it's incredibly important to realize or to under to see that throughout the courses we're going to be giving you, we're adding knowledge on, you know, layering knowledge. So we're starting off by the Broadview, then we're you know, work with data, then learn about machine learning, then learning more about machine learning, then learn about data engineering, then you come back and solve the start to end problem. So by doing that, you are what I would call in a good position to understand what data science is. And then and the different roles are there and then you can make decisions. Do I want to go deeper here? Do I want to go deeper there? What, you know, in my job, What are they looking for? Who else can I work with? Do I want to go deeper into data engineering? Do I want to go deeper into this or that? There's so many different areas you can go deeper into and then. Yeah, and then you can decide where you want to go. So what we decided to do, and this is the the purpose of the program, is to give people a path where if you do all these things, you can solve a problem from start to end. Now you can solve the problem from start to end. Then you can start saying, OK, now I want to focus on a technique or a series of techniques. I want to learn about images. I want to learn about text. I want to learn about this time series. I want to learn about different areas. So now you take what you've learned and then you start going deeper into the area you want to focus on. I want to learn about how do I move data from one place to another, etcetera. So this gives you a base and then by with that base and working with a different instructors along the way you get that map of OK, this is the map of the land and now I now I can take that map and go to other places with it and I can build on top of it. This is why we have another certificate after called applied AI. Usually there we're looking more into for example how to deploy models. That's something we do not and we don't have the time to teach in the first course. So it's very important to understand these little details if I can use that term. You know the big picture that you know working with the data, solve for problems and then you can go and focus on different areas or go deeper into different areas also in terms of opportunities. Just to add, like last year we had a dataton that was organized by Altrix and it was for the students of YCBS 256 and. Some of the other courses that focus on. So we we do partner with these companies in order to organize some of the competitions and they get to see from their side like how how do you solve the problem and a a real life problem And then you it's it's more like having fun with the data and then it bolster your skill and you also get to hear from the company people that what you actually study in the course is, is relevant from the industrial perspective. So it's definitely hands on and quite directly implementable into the real world. And I guess just following on that path will eventually lead you to a better position in terms of acquiring and policing your skills both at the same time. Thanks Nabil. Thanks so much. Welcome. Yeah. No. And we're here for that. This is one of the reasons why we do these kind of lunch and learns and different seminars. We don't do them very frequently, but it's a question of meeting different people, meeting different expertise, you know, seeing people from the industry doing different things. Yeah, I have just opened up the breakout rooms. In case you don't have any questions, please join your breakout room and we'll come there and we'll give you the questions. By me, I mean me and Michael Ange. So just enter your breakout room and just give us 2 minutes to manage all this and you should be good. Please take out your breakout room numbers and join your respective breakouts. Thank you. Thanks everyone. Great seeing you everyone. Good luck. Have fun and there's do spend a lot of time learning. Like you have access to data camp and other sites you'll be given along the way. Data camp is a fantastic way to pick up knowledge both conceptual and hands on and and the access for Data Camp will be provided like it's already provided. Yeah, I I did already provide the people who filled out the survey before the weekend. I'll check again for the remaining people and they should also get the link. Yeah. I I filled it. Yeah. OK. OK. Thank you. Thanks. Sorry. OK, sorry. How we see the numbers, which number is like My Room for example, it's under more and Groups. So on top of the screen you'll see more and just click on groups you'll see a number at the end of Data Science for business decisions. OK. Hi. Sorry I I have a question for the bell. Yeah. Yeah hi. I just wanted I was wonder I just want to follow up on the data camp because I'm currently doing like prepping for their data analysts and data science. I just wonder how valuable they are for pursuing a data science ditched career. Actually that's a good quick. I'm trying to figure that out myself too. From what I can tell, there is some value there, like I'm not going to, I'm not going to. We do see value in the courses. We do see value in the knowledge, the certifications that they have, where I'm trying to actually, I sent out a message to them. I may become an ambassador for them just to understand what you know extra values that it does provide. But from what I can tell they even have a job, you know where not a job like they have a job board and people do look at you know people that are finishing etcetera. So it may have some value because people in the US and can't you know I would say probably more in the US because data camp is more US centric than Canada centric. They probably would have a lot more positions available that you make you can look at from by doing these certifications. The way I look at it is the more knowledge you have the more valuable you are because you can. You know we we see people that when they went through it at one point at the beginning it takes more time. It takes you 4 hours to do each course whatever what the for the four hour courses then you can start doing them a lot faster. The more you know how to program and how you the more you know how things work, you can start doing them a lot faster and move through the through the material a lot quicker. And then you can start doing the code alongs or the projects and those that's where the real value is I would say. Because then things you can show people you know that you've done not just a course, you know, I've done this, I've done that. The projects are for me very, very value added. So the portfolio is more valuable than the. Yeah, basically. Yeah. Thank you. All right. Please join your respective breakout rooms, please. Sorry and unmuted, everyone can see. Yeah. OK. So we we tackled the article about why a the black researcher was concerned that there was a lack of other black people in AI. So our first question was to discuss in what ways lack of black researchers and engineers effects all of us, not just black people or other individual groups that we may be talking about. And if the most obvious one was that, you know, if you're trying to make an, A model that is going to be useful for an entire population, having a representative sample of that population is important. You know, I think it's fairly obvious that if you're not accounting for biases properly, properly, it just makes its way into your model and that's going to mislead future predictions. And yeah, more practically you know not finding ways for in this case black people to get into AI means we lot lose a lot of potential talent and perspective that we would gain from them and the field kind of suffers from suffers as a whole. But you know I I think ultimately it reflects inequality and unfairness that the whole point of this of a data science approach is to remove. So that kind of shows that, you know, if we're not, if we're not controlling for that, what else aren't we controlling for? And how is that going to affect our models? Chances are it's going to make them worse. As for diversity in general, what other types of diversity might we want to see in AI? Gender diversity is a big one. Thinking about, you know, different medical outcomes between men and women, diversity and abilities. You know, disabled people versus otherwise abled people. You know, what are their requirements? We don't know. Geographic diversity is a big one. You know, the experiences of someone in the Western world is going to vary quite differently from someone elsewhere in the world. You know, we do have, whether we like it or not, a bias towards the West in our in our daily activity. And of course, you know, that comes with cultural diversity. And another big one is age diversity. Thinking about how older or younger people might fare relative to the population when fed into an algorithm or an algorithm is used upon them. And so yeah, so just incorporating more diversity really just it feels like it gets you better models because you are more aware on average of the flaws at an individual level and so you can account for that in your in your model. And of course one of the big these we learned about is variety. And you know, I think just having a diverse team working on your data gets you not just variety in your data, but variety in your team, you know, other perspectives. And of course, if you're taking this, if you're taking account of the diversity in a population and developing an AI to deal with them, you can maybe take a more personalized approach and not apply a broad brush to a what might be a very nuanced problem. Lastly, you know the effects of AI on businesses in in general and and employee society, you know we want to go for efficiency, lowering costs, giving us tools to make decisions that we couldn't make otherwise. You know it's going to be disruptive to the job market. It's going to eliminate some jobs while essentially creating other jobs or at least jobs that are meant to support AI. It can lead to increased productivity and economic growth, but it obviously still has many privacy and ethical concerns that need to be dealt with and in some cases must be dealt with before rolled out to a large population. And yeah, it just seems whether we like it or not, it's here to stay and it'll be important to have in our tool sets. All right, great. There are a couple of questions and comments, but I'll provide the the detailed feedback in the in the submission that that you have submitted. The only point that I would like to mention from my side on this is so it's about bringing more diversity and that's directly related to an AI problem that once you are diverse, your generalization performance is higher. So this is in terms of modeling. You're able to generalize better if for example you can think in the context of health researchers data that is trained only on ethnic ethnic diversity of a specific region. It fails to generalize on any other ethnic diversity although you may be looking at the same disease. But that's one of the biggest challenges that medical medicine or healthcare system is having that they do not have more confederated data from all across the world that you can build a single unified AI based system. That happened for a language based system, hence tactically started existing but it's currently it's only good for English. So that's the lack of a single Federated system that that has to come into play. But in the with respect to time, we are a bit short so we'll jump to team two. Team two, can you please show me your screen? Team two, are you speaking if you're muted is there a problem? I think we were doing the slides and that's they were cut off. So I don't know if what stage are. Yeah, I can, I can start if you want. So basically sorry about that. I actually thought that we were Group 4 and I didn't say anything, sorry about that. So Yep, so our our article that we were that we were discussing on was the Foundation of Algorithmic Bias by Zachary Lipton. So basically the the, the, the article was measuring about the potential risks of AI and potential risks that it could have on bias specifically. So from that perspective, we've got those questions saying in what ways can math statistic or AI predictions become unhelpful in solving a problem? How do we ensure that these tools continue to guide our decisions without impairing our ability to consider other sources of information? So in terms of the first part of the question, whether it's unhelpful, we said that it could be whether on its decision making capability, whether it says that it's wrong or right, it's actually right. So answering ethical and moral questions, when the data source is has a bias data, this also can lead to bias results and this is something that that the the developers of the tool always needs to keep that in mind and when. Also when the data is out of context may result in bias results at the same time as well. And lastly, the human interventions may lead to a bias result and the the main goal is to find the right balance between them. Sorry they're not really well written but basically what we're trying to say is we could blame the tool, we could blame the data, we could blame also the human interventions and this could all lead to you know the tools capability. So basically the tool needs to guide the users and to remind those users of its capability of its limitation as well as the tools guidelines. So that will be the mostly the company sell policy for example we've we've used Open AI with with you know your your example Mr. with deep fake for example and those and those are the company policies and also social norms that you know that doesn't allow the users to to use those abilities right. So and also on top of that we will it will be better if the end to enlarge the amount of data for the for to to to to teach the algorithm as that would also reduce bias. However, we are aware of the issue where it's an economic factor. So it's not only a financial matter but also the resources matter to be able to enlarge the amount of data that we would like to gather for, for for an AI. But that's also something that we have discussed. So decision makings, so also for the decision makers that's what we call them, but it's people actually validating the tools should be knowledgeable of the tools potential to be biased as well as the limitations and to force as the company to keep working on the retrofit loop, so the feedback loop itself. So both from the testers internally as well as from the users as well to keep receiving feedbacks here and there and to improve to keep improving the the tool. And the second question we had is think about an application of an AI and your field of work. So one of the example that we got it was news Siz. So it's for the news, not only the news but also for social media to have a click baiting articles, click baiting sources you know videos on YouTube for example. That's also what what it is also for my example that's one of an example that I gave for for an aircraft data and in this case I kind of took the word fairness as something that's truthful that's that's how I took it and and and that way. So what I've done is I've gave an example of an aircraft data where we are generating algorithm to trans engine health and to identify symptoms and we always go back to those algorithm and what they've pushed you know given given us as results as whether they're successful, false positive or missed events. So whether it's successful runs or whether it's false positive because it's have given us an alert without without you know a real symptom in the real field or a missed event because the algorithm has missed and that's all to that's all within the feedback loop that we've mentioned in the previous question to actually to help out to the improvement of the algorithm. And lastly the reflect on the impact on the AI and the business employee society and the data science community is actually in first we started with the general answers such as cost reduction because of optimizations jobs getting removed such as examples in customer services. However, we've also mentioned that the impact especially on the bias side that all those targeting algorithms they're resulting in a political divisions. It's it seems like it's a common theme in all over the world as well as the risk of bias as technology technological limitations and and also the human implement human involvement such as company policies and society norm. Those are what we had to present what we had discussed. Yeah. Thank you for sharing the the insights team three. If you can please go. Sure. I'm going to share my screen and let me know see it. Thank you so much. Great. Yeah. OK, perfect. So it was an article regarding the malicious use of AI. So we had three questions. The first question was played in two. So Freddie, Rick, I was with Freddie, Rick, Stefan and Jan Young. So we're all going to speak to it. So Freddie, Rick will quickly answer question 1. Stefan 2, Johnny had three and me 4 very high level. So Stefan not Stefan. Sorry. Federica, go ahead. You can go ahead. Yeah. Thanks. Well, I did a slide on on my own while while I was waiting to speech. I don't know if you want me to share my my slide or or I can tell what I have found. Well, so far no what we have seen about. Norms that should frame AI research and publishing. We found like 4 norms that we believe are important. The ethical norms to avoid biases, discrimination and increase fairness. But but the the four norms that we have found is the first one to integrate AI ethics into every phase of technology research. So means that do not engage into AI research that goes against laws or ethics or morality. The 2nd norms was about improving data quality, so no improving the consistency and accuracy of data. The third norm was about the safety and security of the algorithm that are designed. So it means having a traceable and and predictable AI code and algorithm. And the 4th and last one was avoiding bias and discrimination and data. So while trying to achieve inclusivity, fairness and non discrimination. So that was the first answer to the first question. And yeah, so when we, we asked ourselves how would these norms affect an industry like the retail banking industry and we, we found that these norms could could, could affect both in a positive and negative way. On the plus side, AI could enable more efficient personalized banking services. We're talking fraud detection, credit scoring, financial advices and everything that has to do with security and trustworthy making sure that the customer have control over their data. But it it can also pose pose some threats. Threats to topics like privacy, security, autonomy of customers. Their you always have to make sure you're not well. The banking industry, like any other industry that plays with IT, are always subject to data breaches, identity theft and algorithm algorithm biases we spoke about. To make it more concrete, we spoke about an example of personal loan where the when when when a person goes for a a personal loan, the decision of allowing that loan could be based well is usually now based off an algorithm and that algorithm could have been trained on a bias data set. You the the outcome of that is your you you potentially filter out people that shouldn't be excluded. Here we're really talking about in the banking industry and here now we're going to learn how to apply those recommendations in the banking industry. So four recommendations here. The first one is collaboration with the technical researchers or technical team, and so a bank needs to collaborate with a technical team to strengthen its security measures. You know you have to constantly engage with the technical researchers to make sure they stay ahead of the potential malicious use of AI. For example, the fraud detectation algorithm may unintentionally target certain customers. The second one. The second is taking dual use national nature seriously. So they should always access potential impacts and engage with the AI ethics that comes to ensure the fairness and transparency and the decision making process. We just talk about the the loan and the banking system and how to get the credit score with the AI Agri system. The third one is an importing best practice. So this is how to apply best practice for addressing dual use concerns and how to keep the sensitive customer data in the safe place and to prevent unintended leaks. The last one is expanding stakeholder involvement. So basically have like different people on the team and the bank needs to ensure that potential biases and risks that I I identified and this diverse participation will make sure we have a comprehensive understanding of potential risks and benefits associated with the the AI, AI and banking. So another good example is in our class. You know, we imagine we all look the same, we come from the same university, we have the same background. It won't be interesting so that overall the banks can have a more secure interrogation of our AI in their operations to promote the the collaboration and also ethical consideration in general. All right. Thank you, James. And the last, the last part was a high level question. What is our reflection on the impact of AI on businesses, employees and society in general. So first obviously increased performance, so task that would take hours to complete. People can use AI to to reduce the the the time it would take to to complete those talks. But at the same time there is a greater risk so more data is being generated. So which comes to more risk because other people could use it as it was mentioned in the article in a negative negative way. So people will need to be aware of the other ways to use AI not for good. The last part, more high level at the society level is more to develop critical thinking. With those risk there is a faking more fake information that is out there. So the society in general would need to to develop that critical thinking and to to make sure the right decision or or taken or questioned that the data the right way to make sure it is not based on on biases. So that's over what we came up with. Thank you for sharing the insights. One of the most important thing in these cases are actually establishing the norms. I have my comments in the chat, but again because of the time and we also have to move on to the hands on session, we'll switch to team four. Yes, I'll share my screen. So we are Team 4 and our article was algorithmic bias detection and mitigation best practices and policies to reduce consumer harm and we will be talking collectively throughout the presentation. Yeah. So we start with the first couple of slides. It was for the question to discuss some of the biases that exist in areas such as criminal justice algorithms, facial recognition technology. And we have identified, based on the document we have gone through, that there are five of these biases we can identify. One of them was gender bias and it was identified in the online recruitment tools in Amazon in particular. And it was found that the algorithm was taught to recognize word patterns in the resumes rather than relevant skill sets, which was again based on the history of the resume There was for white male. And they found that there is an issue with this algorithm with this bias. And the 2nd is for the word association. Again this was reported from Princeton University researchers. It's found that European names were perceived as more pleasant than those of African Americans. Racial and just gender bias. This is again one type of gender and racial bias. The third one reported or CNN online search queries, again for the names for the African American names were more likely to return ads so as to that person from a service that renders arrest records. And again, this is a type of bias. And for the online ads, it was a similar kind of bias for again, African American names were more likely to return as that person from service that renders arrest records as compared to the ad results for white names. The last one was for the facial recognition technology and it was failing to recognize darker skinned complexity complexions. And this is again just to add that the person in the photo was white man. The software was accurate 99% of the time identifying the person as male. This again the causes to this. Before we go to the details, we can go to the second slide to share the main reasons or causes for this behind these types of bias. So first of all we can say that most of this were related to the data, but a couple of them I think more related to the algorithms used to analyse the this data. So the first one is for the data, for the historical human bias. Again the the bias by like even the human bias is reflected in those algorithms, maybe due to the teams working on this, maybe due to diversity, there's no diversity in the team working which is coming again and in another point. So it's important actually as as other teams highlighted that it's important for the teams working on on a specific task or project for data analysis to have to represent the different cultures, different backgrounds. This is not only important for the sake of diversity for the team, but also even for the success of the project based on what what was found. So the other point is for the incomplete or unrepresentative training data. This is again related to the data side of this issue. It's causing the algorithm to be biased because think of it as if the data the algorithm trained the two is always coming from a specific source or representing a specific group of people or group of data sites. So again, the result will always reflect this bias, will always reflect this one side representation of data and ignoring the other side or having less accuracy. The Third Point is for the lack of diversity among the programmers designing the training sample, which we highlighted before. This is very important. As I said it's it's it's important not only for the diversity within the team or to have different ideas, but also to have a kind of balanced algorithm, balanced data representative or how the algorithm will resolve or will correctly report the prediction or the result. These two points are more related to the algorithm. The following two points it's for the algorithm, it's not for the data. So if the algorithm has too much data or over representation, so it's kind of counter intuitive, It's something that we may be surprised to have that if we have too much data then we have more accuracy or a better result. But this is not the case and I think this is related to what we call maybe overfitting or sometimes it's it's representing a specific group over representation for a specific group with ignoring or less data for the main group. And then again one more point related to algorithms, which is careful handling of the sensitive information. This is again a big question mark on on how to, on how. This may because like it's very important to also consider whatever sensitive information, how to handle, how to deal with to avoid any bias and then again back to the points related to the data. It's incorrect data points that lead to discrimination. This is misleading and if the data fit into the algorithm is incorrect, then expectation is the result again will not be good representation or correct as expected. Now moving to the third slide. Yeah, after. So one of the question that we need to answer is like how we can identify, detect and expose these biases. So throughout the article what we have seen is there are four. I won't say that the final answers, but something to begin with is basically to compare the outcomes of four different groups. So let's say you have two different data sets. You can compare the outcomes of those two different data groups, the training sets and understand how the outcomes are different. One of the key feature is to implement simulation before deploying this model into production and or maybe to real life, it's better to simulate that model with different type of training data set. The Third Point is to capture secondary data collection or build a process to capture to collect secondary data which is basically different from what data set that we have been using for training the model. And last one is talking about the error rates where we want to capture the error rates for different set of data or in in in general terms for different groups and and understand how much errors are we capturing for one group as compared to the other group. And that's how we can understand how our model is biased or you know moving towards by state outcomes. Moving on to the next point, I'll touch on this one. Thank you. So for this one here, and actually even if we have let's say an algorithm that's you know, seems to be very accurate, we really need to factor in the fact, you know, fairness so made to ensure that the social costs of having this extra accuracy are justified. So sometimes, let's say we're building a model, even if you want to add a variable that increases the accuracy, it can actually introduce unfair bias. For example, it might discriminate against the classic of people. So we really need to find a way first and foremost focus on how can we go about, you know, reduce this disparity between the groups without, you know, you know, compromising the performance of the model. So this is where the trade off lies. Now there are actually frameworks to help, you know, drive this discussion. The EU actually recently released one. But despite even though we have these frameworks in place, there is no really simple clear cut answer or you know simple metric you can use to say what's fair. That's fairly subjective thing and like we saw in the case with the the compass that was mentioned earlier on the class, there is no really replacement for human judgement. So human should always be kept in the loop and have a key role in this yes. So thanks Vavok. So just continuing, I know that we're at 5 minutes already, but I'll wrap this up quickly discussing on the how we can mitigate those biases. So first of all, we can update our public policies making sure that they're up to date and reflecting today's like society. For example, the laws that were input that were incorporated a few years back there might be not applicable now and we have to keep those up to date. And the there's also self regulatory assessments that that operators can do and almost having a very continuous feedback from the consumers on the performance of the those bias mitigation effort and always having an air open to to your consumers. And also the cross functional team that works on monitoring those algorithms is is very important and not a set a set group of people and it should be diverse and from different backgrounds. Thank you, Thank you team four for sharing your insights. I have a really detailed comment because this article was also very interesting to me and it's a recent article that that I've picked. So I have some of the detailed comments in the chat, but we'll proceed to Team 5. And if you can please maintain the time, that would be great. Field five. Yeah. Hi. I can share my screen. Yeah. Please go ahead. Yeah. Can you see my screen? Yes, we do. Yeah. Yeah, we can see it. OK. So, Rich, maybe I can go first. Yeah, sure. OK. So our article is artificial intelligence and algorithmic bias implementations in the health system. So next slide. So there are mainly 3 challenges for the algorithmic bias in the health system. The first one is the lack of a clear standard of fairness. So the previous group also discussed about fairness. But I think in health system this problem is even bigger. So this lack of standard is mostly due to a lack of broadly recognized quantitative summary matrix photo fairness. And the second one is a lack of contextual specificity. So because nowadays the AI models are usually like generally applicable for all groups, all socio economic group for example, so it's not specifically developed for one certain group. So if the health system we need to apply this in say like female than mail then this AI model is probably not specific enough. So the third one is that the dignowning nature is basically a black box. So if so we cannot know how algorithm produced a particular outcome or prediction. I'll pass it to Rich. OK phone. OK, so my part is to define the like how it affect the how it implicate implications and affect the society with the bias in the society in the healthcare. So what I noticed in the article that it affect the diversity of of representation and diversity of discipline patient representation. So it impact on the decision making. So which in healthcare bias algorithm can influence critical decisions related to diagnose, treatment plans and resources, resources allocation. These decisions are secured. It can have real and potential life alteration consequences for individual. And second also I noticed that it impact the imbalance in certain socio economics, class groups and the sample as much as others or ET all and it impact on the public. If you if healthcare it's a really important place for the human and emotionally it impact the person because it connected the emotionally connected the person at the healthcare. So it impact the public prescription and backlash in in sense of biased AI can lead to public backlash and negative prescription. High profile cases of bias algorithm in healthcare and if data centers clinical then patients cannot know how exactly an algorithm produce a particular outcome or predict it may not be able to apply it in the health system. In the last we define algorithm bias in the health system. Risk inheritance in AI and the presence of algorithm by should however not be the end of discussion on the application in the AI in healthcare system by the beginning of a new one. How algorithm can be developed in a way to minimize bias and also how health system eliminates the deeply enhanced entrenched inequities algorithm buys me further ago. So there are a few actions the counter the risk of algorithm, algorithm, algorithmic biases in the healthcare system. So the first is to establish processes to counter the risk of bias in the development. The key to it is not to hide any problematic variables, because the more you hide it, the deeper it's going to get and eventually it will be found out by the algorithm and it's going to cause more problems. So the it's very important to address different differential needs for different groups. By doing that you need to build a multi disciplinary team of team members from different origins. The next one is to establish processes to counter the risks of bias in algorithm that wait it's the same thing. Sorry, in the OH, the first one is to establish the contest. The second one is establish the process to counter the risks. So it's important to build a human in a loop system to pass important decisions to humans so that they can pick out the necessary caveats that the machine learning model cannot pick up. It's important to train the team member to have the eye to catch all the caveats and the third one is the balanced development of the discipline of health, health data science and the key to it is diversity with awareness and sensitivity. Basically you need a lot of insight from clinicians for relevant because building the machine learning model, sometimes we don't have the practical variables that are important in real life. I suppose the clinicians can provide a lot of insights on that. And the next one is to have transparency and explainability in the algorithm development. It's again it's about communication with clinicians for the counterfactual they can provide bidding sites on. When you have the transparency with the clinicians, they can provide insights on how to build a model and explain why the model is behaving in a certain way. And the last one very importantly is the role of public sector in AI and countering the risk of the biasing health system. So the role of public sector is very important that they can establish, they can help stabilize establishing standards of fairness. So they can help regulating algorithms, they can help addressing emerging issues unknown to the algorithm. They can also work with the private sector to ensure that the AI is built to benefit all. And that's all the actions mentioned by the article. Thank you to five. In fact, the area that deals with explainability models for deep learning and exposing bias, that's also my area of research. So quite close to my heart. But there there is a lot of problems with the healthcare segment. Specifically dealing with the issues of issues of biases and lack of trust and faith by the clinician and doctors actually creates problem and that's why they're not there in the clinic yet. Maybe five years down the line, some models are incorporated, but we are quite far from there. Team 6. Sure. I will share my screen. Can you see my screen, the slide deck loading up. Yes. All right. Perfect. So OK, So hello. Yes. So my group discussed AI biases in healthcare and qualification of society from a case study that's developed in expert identified patients with complex healthcare needs and would benefit from better attention. So I would pass it to the group to summarize to provide summary power discussion. OK, so our first question was what are some of the sources of biases in healthcare system. So we came up with a few. So the first one is outdated behavior, stereotyping and the way data is collected. Also, there's using incorrect proxy measures for complex matters such as health needs and through outdated decision making practices. So for our specific example in our article, it was the the goal of the algorithm was to better serve patients and cut costs, which led to the algorithm using healthcare costs. And we'll see the impact of this further in the the next questions. But this was a bias, a specific bias for the article. If not, there's emphasis on group level information instead of individual level data. So regrouping the the patients in groups implicit and explicit pro white devices in Western countries. So in this article this case the algorithm was based in the Western countries, American and when you use this algorithm after in Canada with more diversity with well it doesn't work like we thought and implicit and explicit biases regarding obesity, gender and age and not taking into account socio economic factors. So the second the second question, what are the implications associated with these biases and how do they affect society? The first one is that certain people didn't have access to the healthcare system. Another thing that came up was a labeling bias. So this data set in particular discriminated against minorities. It determined that black patients were less sick than white patients, but that was based on the amount of money that the black patients spent over the white patients. And another one is the algorithm became biased against recommendations to different patients. The last question what steps are proposed to counter the risk of algorithm bias? So the first step would be to approach the decision more critically. We ask the question whether the data set or the way we proceed is right and so on. And the second up second step would be to use quantifiable criterion of health, which means we need deeper understanding as the group 5 I mentioned earlier, we need some clinician perspective like someone who really understand the data can like reduce the biases obviously and diversifying data set to include underrepresented population. This has been mentioned in other groups as well. So if we do not have diversified data set there will be some omission problem or any like data can produce bias and we also need to apply individual lighting and the perspective taking and evaluation algorithms apply social intelligence. Earlier we already mentioned that the in our specific article they did not consider socio economic factors. So that's why the bias was forecasting wrong, wrong result basically. And also we need to keep investigating and keep monitoring the algorithm if any suspicions arise. And lastly like we need to educate decision makers on possible biases to avoid any substantial biases. This is pretty short presentation. That's it for our group. Thank you. Team six, we're we're in close association with team Five in terms of the the findings. I have my comments in the chat. And last but not the least, we'll quickly move to team Seven. Yes, coming up. I think you need to stop sharing. Sharing. How do I stop sharing? Sorry. Oh, OK. Thank you. All right. I will share my screen. Screen. Hey, guys. Seeing the screen. Yes. All right. So this text was talking about the importance of the outdoor 10 minute digital economy. It was in fact the article was emphasizing on the ethical challenge and the algorithm bias, specifically addressing concern related to fairness, accountability and transparency in the system. The author in the article he identified the resources of algorithm biases with data biases, method biases and societal biases. They can arise from data sets or bias method, societal factors respectively, going a little bit more into the the details of those 3 bias that I mentioned. So the characteristics of the training data sets can influence the algorithm behavior leading to biases. Example in sample of inadequacy and selection bias and out of group homogeneity bias it can so so probably the popularity biases, assimilation biases and bias related to polarization could impact the recommendation of the engines going to method. The methodological and procedural approaches in designing and developing and deploying the machine learning implication was contributing to the bias and also correlation fallacy. There was over generalization and confirmation bias could arise from these methodological, methodological choices and in going to societal biases. So obviously there's a sociocultural the demographic. Our historical factors can introduce bias in the algorithm and it can lead to discrimination in areas just as credit approval, employment and housing. Like we discussed a bit earlier during the class. The main not the main, but one paragraph of this article was interesting. It was a case study which was called the Australia's Robo Depth Scheme. So they implemented Australia implemented some algorithm that was after some time deemed a failure. It was strongly impacting some population they it was about sending the for the welfare money. So they initially thought that it was pretty successful but over time realized that it was targeting specifically some population and it lead to big consequences, financial reproduction, increased societal burden and even incessive suicide which is major outcome if you if you after realizing this these are major outcomes that we're very negative with this algorithm that the Australian government had set up. So I'll pass the the baton to my colleague to continue the. Yeah, the PowerPoint, yeah, let me know if you want me to switch. Are you able to switch? No, it's just me. I don't know if you can pass to the next one. Perfect. So as Kevin said, in the case of the article, there were several type of biases that affected the system and currency. First of all, able to data bias the use of old data and considering changes in people's work situation like illness or lack of work. Also the method of bias it was the system design gets people's work hours and earnings instead of using real data and the society bias like it was referred to people with unpredictable work hours reflecting an unfair not equal society and also unfair, not equal AI system. That's it for. Yep, sorry. Yep. Thank you Kevin for the last question that was I told us what solution would you like to prefer to mitigate some of the issues mentioned mentioned in the text. So has or my other colleagues explained. The article mentions all the possible sources of bias such as the data set. The method was applied in order to build the model. And also the Seattle, the Seattle factors and have a solution in order to mitigate these these possible bias sources. And the article try to create something like like a framework in order to take into consideration all this knowledge of all the possible bias that can occur during the the creation of the model and try to create in the beginning of the project a comprehensive data shift of all the information considering the data set. The data set utilize their limitations. The possible solutions that were discussed in order to reduce the possibility of bias because of the data set and also because of the method choices that were chosen. And create something like a product card that will show all the information in order to possibility for the users later on to have access to that. And this will also create something more of a trust for for the use of the the the the algorithms. So basically the the solution proposed is having a a considered amount of knowledge about all these possible sources of bias and taking into consideration during the the production, during the development and deployment of those algorithms and if if necessary proposed in calibration in order to solve these problems and less applying fairness by design principle to mitigate the the method bias possibilities. For example, working the data science team working for example with social social scientists in order to try to mitigate some of the problems that could could show up because of the the the method bias and also being sure that the data set is expressing the population that is trying to modulate in a fairness way. That was the the solution that they proposed. Thank you. Great. I guess that's the end of all the presentation took slightly more time than expected. But thanks Team Seven for for sharing your thoughts. As a general message I I just also mentioned in the chat that do take a look at Article 7 as it is important from the perspective of giving you a complete overview of methods that are generalizable and it's available under additional files and resources. So if some people who are following the chat you should be able to access it. So what we'll do now is switch to the hands on session. Now usually this this hands on session, sometimes it will begin early sometimes late. Today it's it's already pretty late, but given the time that we have we'll at least get started with with the hands on session and we can continue in the in the next session. So just give me two minutes. I need to switch my computer system to a different 1:00 so that I can share outreach. So take a short pause for basically 2 minutes and we'll get back until I set up my another system. Am I audible from the other system? Yep. Can you recheck please? Am I audible? Yeah, yeah, yeah, yeah, perfect. So let me just share my screen again. It's the same issue on the Mac user. So I'm also using a Mac. That means I need to switch the system Amar Indy. If you follow the the Module 2 in the on the learning, it says that we're going to do an exercise on in Tableau. Yeah, are we using Tableau or altrix. So as I explained in the first class, this was the the hands on session are different from the practice sessions that happens there. So that is for you to learn on your own. I'm not going to repeat the the same thing for which the recording is already there. This is more like some extra information and more practical in terms of how data can be handled. So there you learn, you just learn the tools, but you don't learn how to up into the models. And here we'll be discussing something more. So in combination of both the things, it gives you a lot of information that you need to have. OK, so let me show my screen should be coming up right now. OK, so at the bottom of this page as the classes are going further you can see under Additional files and resources still coming up. Now wait a second. Yes Balti you have a question here. So at the bottom. So if you close this and you have two different screen which is OneDrive link that OneDrive contains all the data files that you need either to solve your or videos in high resolution. So in case you can't find something just refer to this OneDrive it will be available there. And the tutorial files are available over here. So just go to this link. The first files will be you will already be available. But as we progress this will keep on increasing. So those are the only two folders that you need to be concerned about. You can you can type your question value but you cannot unmute yourself. So those are the just the two logistics of the tutorial. With that let's get started. So let me share a different screen and all these presentations are also shared with you in the OneDrive link that I just showed. It's available under tutorials now, so I guess this should be visible. Yeah? So the way I was this works is we have this one hour although not today but last one hour dedicated to hands on session which is extra information in addition to whatever we discuss in the class and extra in terms of any information that you'll find on the hands on exercises that is available through videos for you. So you have self-directed exercise for Altrix and Tableau that's definitely there. But this is this, this hands on session is different and it contains different information and every year like people have found this to be useful, there is question in the chart. So we'll jump from one software to another or it is split it. So for the hands on session, first four sessions we'll be spending with Altrix, we'll get trained in Altrix, we'll go to the modelling section and then we'll go to the tableau. So first we'll start with Altrix that will learn a bit of tableau and towards session 6-7 both of them are together and you'll realize later on why it is important to know both the software and what are the capabilities. When do you use one over the other? So all that will come with a bit of experience for getting started in the hands on session. We'll be starting with Altrix and the installation instruction was given to you already. Here is an example from Altrix Designer 2018. The two files that you need to install with the admin version if you have admin access to the computer and the predictive tool. So that's just a quick introduction to this. Before we get started with any software, and especially with data handling, there are some basic operations that you need to know. And this is true for both Tableau and not completely restricted to options. These basic operations are reading and writing to a file, output to a specific file, summarizing the data, performing basic sort operations and then mapping which is trying to locate positions of different places on the map and also able to compute the location between different places their geographical location. So if I give you the latitudes and longitudes of a place, you should be able to map them on the on whatever location on earth they exist and perform data analysis on that. What kind of data analysis you can perform on that? That's a bit more advanced question, but at least for the for the big nurse you should be able to perform these these basic operations. Some of you have this question that why it is important to know simply reading and writing this to a file. So reading of course, because you are able to perform data analysis. Why it is important to know how to write to a file. So learning any software why would be? Why would it be important that you know how to write to a given given file? Any answers? I guess Paul, it's good to know. Especially when you're working with data, you know, it's good to have the ability to inspect your kind of work as you go. Next check it afterward, you know if one. If that's the correct answer, it's a checkpoint to see your work Sam a different one. I think it's mainly to output the results, like if you have whatever calculation, analysis of the data and the results, maybe a chart, maybe another set of data, a different representation. So it's again simply to have a representation of the output and to keep it, not to go through the whole process again and again and again to reach at the same point. Yeah, so that's a very important point and I guess everyone should remember this point when you are doing your final business case because the case is longer and you'll realize that if you keep rotating, same thing again and again, you won't be able to do it. So it's basically not only a method to check your work, but also to to save a part of your work that is repetitive in a data science process. And we talk about this in session six and seven that what a data science process is. So in summary, it's to avoid redundancy. There is another reason why you should know to write to a file to communicate between different softwares. For example, you might be skilled in one of the software and your your organization or your company deals in something else. So it's not only about the software. How do you establish communication between different tools. So forget about talking in terms of softwares, let's just call them tools. The difference being you can use a programming language such as Python or Java to analyze data and that's also fine. So those are just tools, they're not softwares, they're programming languages. Hence I use the word tools. So it's more generalized usage in our case as well. We'll use this information to communicate between Altrix and Tableau, and the main difference being Tableau is really good in terms of visual analysis trying to map or plot the data. And Altrix is really good in performing numerical or quantitative analysis. So I must pay attention to the file being written and just a few moments I'll show you how to write to different files and one of the things that you want to know over here is what's the difference between a CSV and an Excel file? People have experience with that. So can someone comment? Does anyone have an ID? So you save as a file, as a CSV versus you save a file with a domain Excel SX. What's the difference? Stefan, you are muted yourself. Do you have a comment? Well, Excel uses. Excel uses a CSV to it's like the visual part of it's how Excel decides to present the data in the form of a grid. CSV is really the data itself, formatted in a particular way. Yep, so that's that's definitely one difference. CSV is a raw format file, and Excel in itself is a tool that allows you to visualize CLV. But what other difference exist in terms of data science, Sam? Yeah, sorry I got disconnected for some point so I didn't hear the question. But I understand what you're saying. You're asking about the difference between CSV and the Excel file, right? So CSV is just is a text file with like comma separated values. So that's why the name CSV. So it's CSV can be opened by a simple text editor and also can be opened by Excel file. However, the excel file can be opened only by Excel mainly and maybe by other tools that are designed specifically to open spreadsheets including excel. But it cannot be opened as a text file. It will be kind of and distorted or something. And CSV is I think. I think it is my experience it can be easier to have Python program to extract data from CSV. There are some libraries to extract from Excel, but it's easier to work with a text file line by line or separated to deal with the multiple values in line. That's that's again programming wise or code wise, Yeah, that's that's also the difference. It's easier to handle a CSV file because it's just raw and an Excel file comes with all the bells and whistles given by Microsoft Excel. There is 2 very important points where I wanted you guys to think which is made in the comment that Excel is limited in data size and CSV can have unlimited amount of data. So that's one of the biggest difference. There is no limitation to how many number of rows you can have in a CSV file. A single CSV file could literally be like one terabyte. That's it. Which is huge. That's more than a lot of standard computers hard disk versus an excel file. It's limited to number of rows and number of columns it can have. So an excel is not a great tool to visualize a CSV file. Main reason being if the CSV file has more number of rows or is large enough, the excel only visualizes a part of the data. Hence we use other tools such as Altrix or any of the data analysis based tools that is that is able to perform this task or perform a quick data analysis. Now some of you will have this question why use Altrix and why not Python. That's there is there is a debate at various level. One quick reason is in Altrix and this tool is used industry wide. So it's not an unknown tool that that we are including in the course. It's popularly used in a lot of industries and and the main reason being the ease of analysis. Not everyone wants to program. Although you know how to program, not everyone wants to. For a quick analysis that a quick check that you want to do, you don't need to write 10 or 15 lines of code. If you have these tools and if you have them required skills you can just do it very quickly. So let's me share my Alteryx screen and let's get started with doing some of the basic tasks. I I think that you're already closing to the client. There's just 4 minutes. So we'll just get introduced to the panels of Altrix and we'll continue from there. So I guess this should be visible, yeah. So an Altrix screen looks like this. Most of your tools are in this area. So that's the tool area and the tools that are associated. I guess you can see me scribbling on the screen. Yep. Yeah, so that's tool area from where you grab multiple tools and these tools depends upon what logic you are deploying and what actions you want to perform. The next is the configuration area, which is over here. So this mainly checks for the configuration of the tools that you grab from area 1. So let's call this one, let's call this two. So you grab any of the tools from area one and two tells you the configuration or settings for any of the tools from area 1. Area 3 which is over here is the most important area because that's your workflow. Anything that you that you do inside a workflow is only executed. Rest it doesn't matter. So all the workflow that you want to build happens in this area and after building every workflow you have to hit this button Run. So run is more like a compile. You want to execute whatever logic you have built in in area 3 and if there are any errors, that is shown over here. If there are any warnings, that is also shown over here and if there are none, what happens is an output is generated depending upon the tool that you're using. So this area which is area 4 is your results and results in terms of errors, in terms of warnings and also in terms of any output. And I'm saying any output because that literally depends upon the tool that we are using in order to analyze data. So and over here let me clear this your outlines. So over here you'll see that there are a bunch of tools that is available on the top and as we progress in the course, we'll learn to use couple of them. And this is the part where modeling happens. So where we deal with creating machine learning models and also testing machine learning models. So this is the part which will come in at an advanced stage which is towards the end of the course, but in the next session, in the next hands on session, we'll get introduced to practicing some of these basic tools and the tutorial files is already shared with you. So do take a look, but we'll spend some time in order to go through this, this information. Unfortunately we have run out of time and I do not want to keep you long. It's already a three hour last today. So we'll we'll pause here and we'll continue in the next session. Yes, Ma. OK, we have a question. OK. And on the question for the the, I can't talk anymore the the question that we have to give you.