Dr Rootman and Dr Karlin introduce their project - Teams assigned to Dr. Rootman and Karlin watch this video prior to Friday

Yeah. Okay. You were saying yes, Danielle. I was saying that there's this study I was centered around that was done that looked at patients who underwent rhino plastic and no job, yeah. And it turned out that they use the publicly available age detection from Microsoft and they put in pictures before and after knows surgery. And it turned out the patients after surgery, we were on average a few years younger, younger, quote unquote, than before surgery. While I think that's an a and the result I want ours to be maybe a little bit more interesting than just that. I note the type of having different types of surgery may make the study a little bit more robust. Looking at which type of surgery and also validating different models and showing which one performs best in this circumstance. Actually, if you have nose and you have I, the type of surgery itself can become a variable. You know, absolutely. You have people. And then, I mean, the analysis won't be hard, but the interesting thing is becomes like a ethanol some kind of a model you can do for how much younger people look after doing the nose versus doing the eye or, or also, or how much younger. Different nationalities wait, Look, I know Iran has every single Iranians has had an old highest per capita Rhino class dealer world is in Iran. That's what I'm saying and it was very funny whenever back in the day in Iran, every office I went to, there was a girl or a guy and it's not that gender differentiated either sitting there with a little plastic on the nodes? Yes. I'm at why? Some of them sit with the plastic on the nose and they haven't had a nose job because it's almost a status symbol. Oh boy, I didn't know that. I'm here sometimes being the very poor parts of town. And I will tell him, I said Look at this, What's going on here? And sometimes the surgeries in the very, in the richer area would look a little bit better than the less affluent. So I think if we can have, if you can find axis, if you found access to the Asian, you can, if you could find access to the Persian, some kind of patient database that would be interesting to photos of before and after. You know what I mean, right? I don't think we quite have enough data and RZ right now, only a 100 or so patients to be able to separate by ethnicity quite yet, but I'd have to look into it. I'm sure I could find no. I mean, I've found the nose for patients. You know what I mean? And right. I could I could talk to, you know, there's another there's a third Plastic Surgery at also at UCLA who published a study on the nose. Sorry, So maybe we can ask him to borrow. All right. Are you talking I think he was my sense classmates. Let me see, lady minimum remembering names. Time. Yeah, exactly. Rust die young doctor who study and his allies, friends, you know, he and Allie, my sand. We're very close friends. Yeah. I I yeah. I I really like to study. I thought it was good. So I want to add a little bit more on top of what is already there. He is in David Geffen, you know, I know I know exactly where it is right. You know, they used to be in medical school. They worked together at UCLA, write a wonderful, It's a small world. I think, I think ten, we had called me earlier today. We spoke briefly. I think he's in the process of looking for the projects, but maybe the meantime, we can kind of narrow down what we were going to ask student yes, you I think that's a very good idea before that shows up. Yes, Go ahead, please. So I think one thing that's pretty low hanging fruits would be pretty straightforward for the students to do is to repeat the same analysis that the previous students did, but with using the new model that I trained. So I trained a new model with faith, not just front-facing, but, but I train the model on faces, all different angles of phases. I also incorporated photographs from different from different datasets. Also I'm, in my sense that I value so far is that this model is quite a bit more accurate and less I would like to test the reliability of this one compared to the previous one. So I think that that would be pretty straightforward for the students to do. And it would be a good, kind of a good educational experience for them to just, they could do the same thing that the last group did. But then what we could also do is we could, because last, last time the group didn't have

enough time to compare the different types of surgery. We can have them compare the different types, the upper, the lower, and the upper and lower together to see if there was a difference. How your how much longer they look exactly that have one other sort of caveat is, I think previously the students had only looked at sort of the relative difference in age between pre-operative and post-operative. They had mentioned something in their report about also wanting to analyze the absolute difference. If we can establish that the model is at least to some degree accurate. In addition to being reliable, then maybe would make sense to, to check what the what the how the model performs compared to the patient's actual age. You see what I'm saying? So I am from what I hear in so far is that you have trained a different model, pictures from photos from different angles. So how many handguns, if I may ask? It's a good question. I it's I think it's, you know, it's at least at least three different angles. So, you know, from the right, three borders last three-quarters front-facing. And of course, and sometimes even from below, we sometimes take pictures from below. But the real key on that one is that the model was trained with about 100 thousand photos. And that's compared to the previous model, that was only about 10 thousand photos. So the number of photons have increased. So we expect the reliability to be better. And so in other words, that's what I would have you believe. Okay. So you have the right key forth left 34 down below. And we'll we know the data. The data is labeled as to what angle we're having. No. In fact, it's not labeled as to what angle we add. And one other thing there there may be more than one front-facing photo for each patient because some of them act looking and 12, looking at left gaze, looking and write gaze, gaze and down gaze. So we have some group. Let's say you give a patient a, you may have eight photos for patient a, which includes the different angles as well as multiple front facing different directions of gaze. So the Isley pointed in different directions, so we have left gaze and then what gains upcase, downcase. So my question is, how are students supposed to be able to subdivide this data set to these different angles before they can Canadian reliability, is there? Well, the real, the real question is I, so they won't really be able to, I don't think in any meaningful way in a time period that they have because it's, the data is not labeled by direction of gaze nor is it legal to buy ankle. But it is labeled by patient name and Asian age. And that's really all the data that we have. So what you're, what you're asking is whether you can check reliability as a function of if your direction of gaze or angle a photograph, my understanding correctly, your restaurant because Year 1, you are wanting them to repeat reliability. Now, if you want them to be done liability for the 10000 photos regardless of the direction. That should be easy. Well, last backup for a second. Let me backup for saying, so the model that we trained was one dataset and then we use this a series of tests, photos, which is the patients that have had pre-operative and post-operative. Remember, so that was a totally separate dataset. So I wonder if they said that we had previously looked at the ones that were pre-operative and post-operative and check reliability on that. But using the, we can run those photos to predict. We can run the predictions using the new model, but on the same dataset that they'd used before. So previously they had a model that was trained on 10 thousand photos and then we checked reliability on a held-out set of 300 photos. This time we have a model that was trained on a 100 thousand photos, but we can still check reliability on that same 300 photos. Does that make sense? Even though they're all front-facing? Now, the other thing is, I could prepare a separate Set of random patients from different directions of photograph and directions of gaze. And we could check reliability on those also. But I don't know if that's as necessarily as useful question to ask. So if I get you right, you want to train a model based on the a 100 thousand observations, then use that equation to predict the age of those 300 patients in the data set and see how closely, how close your predictions are. You got it made based on, that was trained on 100000 compared to a model that was trained based on 10 thousand. Exactly. I

want to I want to compare the accuracy and reliability of the two models, the 10 thousand model and a 100 thousand Martin. Sam, you have any comments here? That seems like a good straightforward project. So that's different from the one that has the different phase angles because those ten thousand, one hundred thousand to just have the same phase angle. Well, they the 10 thousand followed, those are all front. The 100 thousand photos are many of the same patients. But for each patient you may have 67 or even eight photos from different angles and in different directions of gaze. Then on top of that, in a 100 thousand daily base, I've also added additional photos that I found from previously validated data sets online that have been used to train age and face recognition models. That makes sense. It's a grab bag, but I expect that will improve the reliability because we're using data from sort of different, a different dataset. Yeah, and then to the students because then Mao's army training, they don't actually have to deal with a backpack. Then they start at different angles. Correct? Their nose 100 thousand. Even if you kind of like think that the angles are equal, would still give you 25 thousand front-facing. I mean, if even if he was assuming that, correct, No, you're not. And I have even if you were assuming that, you know, you'll have the front, you told me the 3 fourth and the 3 fourth on the front and whatnot. So for directions, even if you wanted to randomly divide your 100 thousand photos, you're still catching myotonic. You make a good point. We have the possibility of training a third model. So we have let, let, just to summarize for a second, we have, we have 1. The initial dataset that we used for training to develop the algorithm initially was 10 thousand photos front-facing from UCLA. Second dataset would be a 100 thousand photos combined front-facing and multiple angles from UCLA. And from outside, I just put in quotes outside datasets. You could potentially have a third dataset that will be less than a 100 thousand photos, maybe on the order of more like 30 thousand photos or so. That would be front-facing UCLA plus quote, other data sets and we get back and be the third one. So we can see if adding the other angles, the other dataset would make any, makes a difference. So in one case you are tripling the dataset and the dataset number 3 is exactly like data set number one is only three times more exactly at the end or the other. The other thing is that the photographs are not all from UCLA there front-facing photographs that are from other datasets that are being combined in. Yeah, I saw you, I figure that. And then all you want to do, you want to train a model and test that model on the data set of 300 that was usually prior study? Correct? Okay. So far, it looks like a pretty straightforward and if you give us all the thirty thousand, a hundred thousand, then we can probably divide the group and have each one continue to work on one part. And okay, from the discussions you had with students yesterday, so all these datasets that you have, is there any additional variable that can identify lack as an identifier, like gender or age or something. Let me think. Well, in the big data sets that are used for training a neural network algorithm, The answer's no. At least not easily. I could, I could probably get some data on gender. The other thing that I could probably get data on is which, which actually wouldn't be terribly hard, would be photograph, exposure and quality and so forth. That would be somewhat possible. I can probably figure out a way to get information on the exposure and then probably the camera that was used to take the photograph for the UCLA photos. I think if you take that man is here, you get that data set for those 300 data sets, then that can be a data set of its own. When you looked at the explosion and stuff, right? Yes, absolutely. And that would be much easier for me to get so I could get additional data for those patients, I think for now, because we're going to assign the groups. Sometimes. I think this be correct. For now, if you could just get whatever information you get for those 200, that would be good enough, you know. And then we'll get we can look toward getting more information from other groups for next year. Or I teach an experimental design. As in the summer. Maybe we could get it for that. Dependent. And sine i than welcome. Hi, Sorry, I was on mute our

normal It's okay. Don't no worries. So Justin, I have my camera here. Sorry. All right. Nice to see you. Yeah. Hi. Hi. So Justin so far summarized for us that he has a data set of a 100 thousand trained that the photos are from different angles. And, you know, 3434 to the right, 34 to the left, front-facing and one other angle. And from down. And he says that what he likes to do is to train a model based on that 100 thousand dataset and then test it on the 200 patients that he has from UCLA to see whether the reliability and accuracy increases. And then he has another data set of td tags and some of whom are from UCLA and some of them are from outside and everything is front-facing and the same thing to be repeated with that data set. Am I right? Am I correct? Am I summarizing this correctly? Perfectly. Okay. And then we were talking that whether he had any identifiers for the data set of 300, he says he could get us some identifiers like maybe age or gender or something. And then the exposure. And yeah, I could get, I could get photograph exposure. I could get ethnicity, and I could get gender. And certainly I could get photographs exposure. That's not a problem. Okay, then we can look at a model. We're looking at the difference between the actual age and the predicted age, probably could be the outcome. And see how that varies. Those predictors or, or whatever else, just, just as an idea. So yeah. So this is what we have talked about so far. Doctors would run me again. Suggestions or no if because those are reasonable extension projects. I don't know how to talk to Justin about exactly where the photographs you're coming from. I'm not sure about the outside institution. Do you have somebody reminder or you just scraping them? There are you might be breaking up a little bit. Can you guys hear me? Yes. Yeah, I'm here. Yeah. Yeah. Yeah. I think that maybe he's Pablo. Yeah. Because I have a question. I Irenaeus, we validate you're going to get where you're going to get the secondary data sent from UCLA in from somewhere else? No, it's actually there. There are three different datasets that that I've found, that actually four different datasets that I found that had been used previously to train h recognition models that are front-facing photo is one of them is a bunch of like research assistants and lab students. One of them is, is as based on celebrities and their age. And that photograph that has been scraped from, let's say, YouTube and Wikipedia. There's four different data sets and I can show you each one to see that. But what I was thinking that we could combine, all of those are front-facing. And so what I was thinking is combining our front-facing data with those front-facing photographs and seeing if that improves the reliability of the model. And then also what I was thinking is just combining our front-facing with those front-facing plus our photos from all different angles, The zillions of photos we have for all different angles. I think that perhaps improve the reliability. Yeah. Okay. Too, just trying to improve the model. Exactly. I mean, I think that right now the name of the game is optimization. And then I was thinking also as sort of a fourth dataset, quote, quote unquote dataset, is we could compare the performance of these models to that of the commercially available microsoft API, which previously did not do a great job on the photographs that we had. But i'm I'm willing to try. And again, especially on the photographs where we have a full face, which not all of them are full face. But that fourth idea that I just talked about still needs to be fleshed out of it. I think these three, these three datasets are enough. Microsoft API data. Is this something that students could find on the Internet? Name? Well, they could. That's available actually the UCLA students. It's it's under the term Azure ACH, I'm sorry, AACU re Microsoft Azure ACU are E and they have it available as part of UCLA if you want. In any kind of any kind of AI model, you can use this platform and they have one that's particularly meant for faces. It's called Face API. And that's one that the students would most certainly get access to. I'd be happy to help them to figure it out. Or in fact, I could just run the 300 photos through it myself and it shouldn't be a problem. That would be I mean, I think that we want to make sure that the project is a stats project and not an AI project. You're absolutely right. That's why I was kinda leaving this one baby for your average

separately. So I think the stats portion of it would be more interesting. Compare the three, you just compare the accuracy with the different models. Exactly precise, reliability accuracy, precise. I'm actually I don't know how much training. Let me ask let me ask Sam how much how much training our students getting high? I don't think they have any like required in the stats curriculum, I think, but there are other classes that they could take, so it will depend upon what other facets students have taken. But I don't, there might be like a cursory sort of overview of, of neural networks and some of the classes that I take. But I don't think that it's any any very deep material on it. Okay, Well, we're going to think about I think the reliability is priority to better angle to take because we don't want them to be spending a lot of time trying to figure out AI when they're trying to like exactly. I think the most important thing is we provide them with the data and then they can actually gave it away. I don't want to adapt to run experiments or anything like that. Right? Okay, So I have to write that one. Okay? So I have a couple of projects that we could look at. Number 1 is related to 0. Tonight you have the screenshare, is that you just saw you on it? I can give you one. I think I think dr. It's February. Yeah. Okay. Okay. Okay. So this is a project where we were looking at certain type of orbital masses and it's an imaging project. And so this is, there are three kind of masses that are, that appear pretty similar. One is called an SFD or solitary fibrous tumor. This is a very unusual SFD. It's a bad example, but everyone is Sadia, sorry. What does SFDs, baneful, solitary fibrous tumor. And that's this thing here. Can you see my pointer? I don't know if you can WhatsApp, but it's the big thing behind the eye. And then there's this thing called the cavernous venous malformation, which is this thing here. And then there's another thing called a schwannoma, which is this thing here. And they all are, there's actually a fourth thing which is lymphoma, which is not in here, but we have the data on that as well, or at least part of it. And basically one of the things that defines these three lesions is that they're basically round. No well-defined lesions that occur behind the globe. This is the eye, that bright circle thing. And, and so what we did is we, we have to combine sites, our site here and another site in Adelaide, Australia. And because they're all pretty rare lesions, we pulled the data together to be able to put together a relatively modest sized sample. And so we have, let me see, I'll switch it to this one. And so we have all this data on. From UCLA, we have I think that this it starts at nine, so it's like 42 from UCLA of these three different types, schwannoma is the least common. And then from Adelaide we have another, you know, 12 or something like that or 13. And then we collected a whole bunch of data on it. So there's some demographics. Which side? There's clinical presentation. So we have all this stuff about the different types of signs and symptoms of the disease. And then we have these imaging features, location, MRI kind of things, you know, T1, T2, different different features that we went through and looked at and then CTP of which they've not not many of them have CTs because the MRIs are much better for East Asians. And then we have some stuff on clinical course, which is not really that important. So basically we've collected all this data. And what we want to do is to basically find what types of imaging features are specific for which legion. So like, how do you tell them apart? What is the key characteristic that makes you think one is going to be lesion 1, one is lesion to, and one of the lesion three. And then we could also look at some multivariate modelling to see, to look at the clinical features. If there are some clinical features that can separate it as well. Which might be useful to look at as well. Or maybe it's a multivariate model than it. It's a combination of features that separates these three lesions from each other. So that some fact that I could be yeah. Yeah, Could be. So that's basically the project is that there's a whole bunch of data of all of these different features that we looked at. And then we're trying to determine which feature differ which different features differentiate those three different lesions. Yeah. So like if they have feature a and B, then it's a schwannoma, if they have feature C and D, It's caverns, Venus if they have pitcher E and it's

this or maybe it's like feature a and NOT E or B and D. You know what I mean? Like what combination of features were Christian? He's okay. I have a question. You got some things that are coming from radiology, like measures like MRI and what are their stuff? Or should we start for looking for those features within MRI and then within clinical? First, yeah, I would separate the two. I prediction is that the clinical is not going to tell you anything. Bio you can put that in later. So we could that that's what I was asking. It becomes pretty I mean, even if you think about it. From the viewpoint of just logic, it doesn't make sense to try to mix cleaning column radiological, so right. So it'll be interesting to look at the reading. Maybe loop starts reading radiological, is that you want us to start? Yeah. I mean, it's mostly an imaging study. Okay. The clinical data is not that much, but, you know, it'll be important to have that clinical data just to say like when you're describing the sample. This these tumors tended to be the age was 52 and these ones the ages 48. That after probably we look Zidane radiological. Then we can start to connect those radiological from exploratory point of view into your description of the patient, right? For example, if you're older or are you more likely to have that kind of lymphoma compared to debit whole bunch of them. I don't remember. Yeah, that would be fine to look at that as a separate thing. And then it may be possible that you end up producing one model that explains everything. And if it involves demographic characteristics or something like that, then maybe that model will be useful as well. I could just one big model. But I think to start would be to look at the radiologic predictors, like the sensitivity and specificity of these different signs. And like to find the ones that are most sensitive and specific for one lesion and not the other mike, how to differentiate them? I am a silly question. Okay. Yes. To guide the students. So let say there are four types of lesions behind the eye, right? So are you going to get a 01 for each of them? Like if you have this one, you have a one. If you don't have it, you have yours wherever one. Okay? So then our outcome variable, if I get it right, would be, let's say legion 1, 2, 3, and 4. And for each of those you get is either a 0 or a one, either a 0 or one, or a 0 or a one or, and so on. So these become your outcome variables, right? Yeah, you could do it. I mean, I don't know how you plan on doing. I mean, the other way to do it is you have one variable that you get a 1, 2, 3, or 4. So the domino, I know, but that's what I'm asking. If you're interested in one at a time, you know whether you have this or you don't, you have this or you don't, then you can start looking at each, each by itself. But if all the regulatory or are they people who have more than one? No, never. Okay. Then I think Sam, please stop me and they come in with your viewpoints to because, you know. Sam is one of our ad introduce some to you, is one of our PhD students. And low serum is a Senior Consultant in the consulting centers and knowledgeable and nice to work with. So if you treated this as 0 ones, then you can go in and start looking at the radiological staff. And as you said, figure out sensitivity specificity for each condition by itself. You know what I mean? Yeah, I mean, the problem is that I wonder about I don't know exactly how you did get to this. But the problem I wonder about is like if you do that and you end up with one feature that's very sensitive for two different lesions. It's not really helpful because it doesn't differentiate between all three. I think we should start having a lot of explanation first before we talk about modelling. Sure. Yeah. What do you think, Sam? Yeah. Sounds like again, I'm going to give the students the explanation. Yeah. I think it's like a good project that's ironically well circumscribed. Well, I'm awful. Another thing I like about it is that you're not done all the time with students think the whole world about big data. And I remember that we had a seminar where the guy who created these statistics department actually was saying, one of these days, this whole fantasy with big data is going to just disappear, you know? And then there are situations you have big data, small data, average data and whatnot, you know. And so I think the fact that they see data sizes of 50 or 60 is really good for them. Because they don't, that their job as data scientists is just go clean up stuff and

come up with some time and I'm neither logs, you know. Right. Well, that's a perfect segue to the second project. The second project that I had an idea. Sorry, I'm having trouble opening the but it is a big data project. And that is there's a database called the seer database, which is the surveillance and or I can't remember what it is. But there's it's a database that looks at cancer to cancer database. I think I killed my Microsoft Excel. That's why I'm having trouble with it. Okay, but anyhow, this is a freely available database and we have a copy of it. It's freely available. And we're interested in looking at some. One of the things that databases are good for is looking at rare tumors. And so we're interested in looking at some very rare type of tumor called lipo sarcolemma. And so the idea would be to to clean up the database and then find the cases of lipo sarcoma and describe some of the features of it. Where is it located? What's the survival? How often does occur in the orbit? Those type of things. Okay. That this database is available on the internet, right? Yeah. We have a copy of it. So I could just give it to you. Okay. So I think Sam, what we can do, we can break up those people that we assigned to treat groups, right? Yeah. I think I think that's good because I was looking at the list and I think we have had three people assigned to Kelly because we broke up the PO2 international groups. So I think there's room for yeah, having a third group one-on-one out. What I'm saying is that the two groups we assigned it already pretty large. Yeah. You don't need international students in here because yeah, there with Kelly, the international students will carry. But what I'm saying is that originally the two, the two groups, he thought about 12 or 14 students in there, right. How many students? Oh, I see. You can just divide only. Whoops. Yeah. Yeah. I will get the, um, the groups, but I think that'll work. Yeah, that's what they do. Okay. God, these look like k, a very interesting project. So then I think we have the 300 people and their permission. We're going going, we're going to decode it. Let the students started by looking at the report from the prior quarter for the project, what the students did, and for doctors root months projects, I think that there's nothing relevant that they have to read from the studies that's been done before. So I think has, you know, if you can send us the I just already saw the combined data from Australia on your database. If he could have yeah, I can I can I can send that. And then the SIR data, we can do that too. I think in crashed, but the, all of the variables are explained at the top of the file. Okay? So if you could send that to us and we'll even call it what you want to call that project. Just call it orbital tumor. Or because I have a question about that. Well, circumscribed, probably. Great. And you tell me if you think that this might be interesting to tack on. I mean, I see that, that you have a bunch of variables, both categorical and then you also have some descriptive variables and some are to us as well. I wonder if it would be worthwhile. It's sort of the second analysis to say if there's like a clinic or radiologic correlation for some tumors but not others. Do you see what I'm saying? Like let's say you have do you have data on the patient's vision and their optic nerves? Yeah. I mean, I think that that's that's part of the plant. Yes. Yeah. Because I think that's our main goal. Try and do. It would be most interesting if you said, let's say you have, I'm just imagining it's a, you have a tumor that's near the optic nerve of one type tends to really affect the vision, but a tumor of a different type. That's the optic nerve doesn't affect al. Almost. Yeah. I mean, I think we're getting ill. Yeah. I mean, that'll be part of the modeling of the clinical side. My prediction is that you won't find anything there. Okay. Just, just knowing these lesions, they're all pretty similar and in clinical behavior. So that's my prediction, but that should come out in the clinical modeling. Can examine association. I would not I would suggest it because it came to my mind by tablet. Yeah. I mean, yeah. Professor, if you're talking about big data, you really, you're looking at big data, which is dance brain, seen so many of these. So that's where the big data really low, but I can honestly, that's why I always tell the students. I give examples of stupid cuts, for example, that I'm making the dataset. And then I tell them, look, this is really stupid. Did the frequencies look right? But from a clinical

point of view, this is meaningless. You know, then what I can say, You have to talk to the experts, for example, to say where to cut, you know what I mean? Where to decide? Because a lot of the times in statistics we take those numerical variables and chop them off into intervals. One of the big things is that, you know, where do I, where do I chop this off based on where my frequencies look right? And not necessarily because it just you have to depend on what the expert is telling you. I like to always talk to them about that. And I'm absolutely really thankful to you guys for providing this amazing opportunity for the students to be able to talk to people like you. I know that doesn't happen very often. I mean, believe me, doctoral students who have TA, for this class have told me that they haven't had this type of opportunity and Sam can speak to that. And in the air classes because it just, you know, not always doesn't always happen. And then we've been doing lots of work with just the UCLA community with extension, with likely the sphere. Right now we'll be working on what kind of commencement students want, because that is the projects we work on, because you're constantly, we get data. And for example, we did a lot of work and one of the interesting projects was last course that we did, toxic courses. What cause combination can you take to totally screw up your Aboriginal within stem? And so there is some aching. There are so many things. The other way around is a better question. No, but you avoid, then you have. And what about crime? What's the perfect combination of classes to maximize your GPA? The right font, you could look at those too. But the thing is that sometimes there are so many projects running around that I totally lose, totally lose track of what's happening where. But it makes it very exciting to work with you guys. Thank you so much. So DCL, this year, we are going to. Some of the groups a lot earlier. So I taught the material much faster. So we have one extra week, meaning that the students are ready to go next week. And so we will have them watch a video. Those teams that are going to work with you and try to figure out what this whole thing is about and have them look at the data set. But we want to absolutely ascertained that they understand the question. So when would be the best time and like like next week, Wednesday. Is that a good time for us to meet with the teams? And around this time or Wednesday is bad. We want people Thursday. Oh, sorry, that's this Wednesday. Sorry. Next Wednesday. Sorry. Next my next one. Just gives us a date and I make them come because I know you guys are busy with your time. I take Thursday will be better for me. Next Thursday is really good for me. Okay. Then okay. I have I have a meeting until about three o'clock. One do you go after 30? 330, 15 or whatnot? To 330. Good. Just just in case. And then yeah. Do you want to send an email? Put us in a material and I will send an email and a link to DEA. Because when I grade on CCLE and I'm the host in very easily get saved to the cloud and I can put it right on the Internet. And when I send it to us, then it's one more step for you guys to post it on to say with and they don't want to take your time. Yeah. That's fine. Okay. Perfect. So we look forward to getting the data. I can I guess we can get the data, the Australian and the other data right away, write them out in a few days to give you the file with the 300 with the exposure? Yeah, maybe carrot guy have until next week. I'll try to get it you buy beginning of next week if I can work this one's compiled or did have the 300 data, Dante. Right? They have that one. I don't want to give you an expanded data set that has the predictions based on those two new models we talked about and also Latin. But I can give them I can give them the whole folder of what happened last quarter so they can get familiar with what the absolute quickly. You hadn't sent to us by Monday or Tuesday the extra stuff, then I really, And another thing I can do, I can give you access to the course website. And there's a one we don't want. You can always do that then you can go and post in the folder whatever you love, but you don't have to do that. It takes one step further for you. So just When you walk in and students end up with any specific questions. Once we set the data next week, I'd be happy to answer. And if you need me to upload or sent to you anything, I'm happy to write. Okay.

I think I could have the students send an e-mail to me and I forward it to you guys because we don't want them to body. We know you're busy. But the students are also pretty careful with, you know, emailing and stuff. Some you have any questions. I think it's best for us to start looking at the data. I'm playing around with it. So in this, yeah, I think suddenly seem like really good, good projects for their students and I think you'll learn a lot from her. Yeah. All right. But because you had a question, you gave us on photos, on exposure to light. If the picture of the photos of the people are taken away. And can that be treated like a public dataset or no? What do you mean public country you to have other students look at it in the future. If I was, if I was writing a book, suppose, could I use the data as examples, as long as there's nobody's name or photo with it, just the whole set with a whole bunch of numbers? I imagine. So. I don't see why not okay. To just make sure that there but I don't see why not now we had an IRB for it. You're not putting anybody is four per day, right? I'm in the hole by now. I mean, it's just the data. One way we could get around that is we could just put you on the IRB. Yeah. Okay. Because I was thinking of writing. I've been thinking and publish as I've been talking to me and I need to maybe put my act to get that. Ideally like those datasets for repeated measures because they're so interesting. Yeah. Okay. Thank you so much for everything. And if you talk to us, we are here under root one. If any of your other fellows or people who are working on a project, or people you want to have to be under project or have contact with us, you know, or you can contact for data without bothering you. And the same doctor know, we'll we'll get there. I think I'll try to see if they can come to the meeting at 330. It's a bit variable on Thursdays, but maybe let us know who they are and we'd be very happy to collaborate. And if you write papers will be more than happy to write the statistical section. It's a lot easier for Azure. Them have students play around with it because it takes us shorter and we make sure we write the writing. Okay? Yeah. Okay. Thanks a million. Okay. We'll see you next week. Thank you. Thank you. Thank you. Take care. Bye. Bye.