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June 7 at 1:00 PM (CST), 8:00 PM (CET)

Upstream Sources of Bias in Adaptive Learning Systems

Shamya Karumbaiah
Carnegie Mellon University & joining University of Wisconsin-Madison 2023

Abstract

Adaptive systems in education need to ensure population validity to meet the needs of all students for an equitable outcome. Recent research highlights how these systems encode societal biases leading to discriminatory behaviors towards specific student subpopulations. However, the focus has mostly been on investigating bias in predictive modeling, particularly its downstream stages like model development and evaluation. In this talk, I hypothesize that the upstream sources (i.e., theory, design, training data collection method) in the development of adaptive systems also contribute to the bias in these systems, highlighting the need for a nuanced approach to conducting fairness research. By empirically analyzing student data previously collected from various virtual learning environments, I investigate demographic disparities in three cases representative of the aspects that shape technological advancements in education: 1) non-conformance of data to a widely-accepted theoretical model of emotion, 2) differing implications of technology design on student outcomes, and 3) varying effectiveness of methodological improvements in annotated data collection. In doing so, I challenge implicit assumptions of generalizability and provide an evidence-based commentary on future research and design practices in adaptive and artificially intelligent educational systems surrounding how we consider diversity in our investigations.

1
00:00:11.460 --> 00:00:13.320
Shamya Chodumada Karumbaiah: Let me quickly share my screen.

2
00:00:20.670 --> 00:00:21.780
Shamya Chodumada Karumbaiah: Can you see my screen okay.

3
00:00:23.010 --> 00:00:23.430
Shamya Chodumada Karumbaiah: Great.

4
00:00:31.830 --> 00:00:34.830
Shamya Chodumada Karumbaiah: Okay Thank you so much for attending and.

5
00:00:36.210 --> 00:00:38.130
Shamya Chodumada Karumbaiah: i'm very, very excited to be here.

6
00:00:39.180 --> 00:00:51.600
Shamya Chodumada Karumbaiah: I have published in q3 the intervening 2020 and 2021 I believe and i'm very excited all the time to be you know talking about.

7
00:00:52.410 --> 00:01:01.200
Shamya Chodumada Karumbaiah: ways in which we can make qualitative and quantitative research, you know data analysis talk together so super excited to the cure to talk to you more about.

8
00:01:02.160 --> 00:01:12.150
Shamya Chodumada Karumbaiah: The entire section of that, along with the issues of bias, the topic that i'd be talking about today i'm really looking forward to our q&a to talk more about it.

9
00:01:12.960 --> 00:01:27.930
Shamya Chodumada Karumbaiah: Specifically, in the context of QA but my talk right now is designed to be a little more broad hopefully also touches upon the different aspects of learning analytics and learning sciences as well that you all may be interested in it without much.

10
00:01:29.070 --> 00:01:31.920
Shamya Chodumada Karumbaiah: further ado i'm going to start my my Doc.

11
00:01:33.690 --> 00:01:42.990
Shamya Chodumada Karumbaiah: Well, today i'm going to be presenting one of my dissertation studies on bias in upstream sources that shape real time adaptation in learning systems.

12

00:01:43.920 --> 00:01:49.890
Shamya Chodumada Karumbaiah: investigating bias in automated decisions, especially has become increasingly important in education.

13
00:01:50.790 --> 00:02:07.860
Shamya Chodumada Karumbaiah: Because of the harms caused by by a systems to specific students or populations, so in the presentation today I will discuss why it is important to investigate upstream sources for potential biases and empirically also illustrate some demographic disparities in once at source.

14
00:02:11.490 --> 00:02:16.050
Shamya Chodumada Karumbaiah: So let me begin by sharing quickly sharing my path to this work.

15
00:02:17.130 --> 00:02:27.540
Shamya Chodumada Karumbaiah: I came to this work as a computer scientist with expertise in machine learning and fascinated about a building models to accurately predict student needs in real time.

16
00:02:29.130 --> 00:02:38.970
Shamya Chodumada Karumbaiah: I such I started building predictive models of complex educational constructs such as an effect persistence motivation and matt success.

17
00:02:40.260 --> 00:02:50.520
Shamya Chodumada Karumbaiah: That idea and let children is to learn about dance in large amounts of data on a construct so said, the new data sample can be automatically labeled by the model in real time.

18
00:02:50.970 --> 00:03:03.210
Shamya Chodumada Karumbaiah: Like in one of my past work with Dr knives are used machine learning models to detect students emotion, using the official expression data i'm sure this is not new to the audience of this webinar.

19
00:03:04.530 --> 00:03:09.000
Shamya Chodumada Karumbaiah: The idea, basically, in a nutshell, is to create predictive models using past data.

20
00:03:11.130 --> 00:03:25.500
Shamya Chodumada Karumbaiah: But at the same time as a doctoral student in learning sciences, around this time I was introduced to the inextricable link between learning and context which made me question the role of context in model development from student data.

21
00:03:27.810 --> 00:03:39.540

Shamya Chodumada Karumbaiah: Particularly, I was interested in investigating how ignoring learner context in the design and development of adaptive learning systems could introduce harmful biases in them.

22
00:03:41.310 --> 00:03:48.720
Shamya Chodumada Karumbaiah: Let me illustrate this with an example of detecting students emotion using facial expression data.

23
00:03:50.610 --> 00:03:58.680
Shamya Chodumada Karumbaiah: Ignoring gender and racial context of students in this example is likely to introduce biases against female students of color.

24
00:03:59.190 --> 00:04:06.750
Shamya Chodumada Karumbaiah: due to poor performance of facial recognition on females with darker skin tones This is also true for other forms of data.

25
00:04:07.230 --> 00:04:19.830
Shamya Chodumada Karumbaiah: There have been reports of encoding bias against certain linguistic and ethnic groups in automated basis scoring and also in marketing African American English as toxic by hate speech detectors.

26
00:04:22.080 --> 00:04:29.640
Shamya Chodumada Karumbaiah: Now I present arguments for biases CDs for why is this a serious problem for the learning systems that I have been studying.

27
00:04:31.500 --> 00:04:48.840
Shamya Chodumada Karumbaiah: I studied contextual factors to understand bias, specifically in adaptive and artificially intelligent learning systems, the general goal of the systems is to optimize student learning with one on one instruction and immediate feedback, which is often hard to achieve in traditional schooling.

28
00:04:50.880 --> 00:05:02.850
Shamya Chodumada Karumbaiah: These systems attempt to identify key moments in students learning to adapt based on perceived student needs so automated decision making, often involves little to no human intervention.

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00:05:05.040 --> 00:05:10.860
Shamya Chodumada Karumbaiah: adaptive learning systems are being increasingly adopted in education, including formal public education.

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00:05:12.240 --> 00:05:21.210

Shamya Chodumada Karumbaiah: Several forms of adaptive systems exist today from fully online to blended learning environment from learning games to open ended learning systems.

31
00:05:21.750 --> 00:05:31.620
Shamya Chodumada Karumbaiah: And from skating based to dialogue based tutors and they have been designed for diverse subject matters and built on several platforms, including virtual reality and wearable technology.

32
00:05:32.970 --> 00:05:48.480
Shamya Chodumada Karumbaiah: I, as I say that I recognize that this all this is probably not new to most of most of the audience of this webinar but just wanted to give you a quick overview of the kinds of systems that I have been particularly focusing on which are adaptive learning systems.

33
00:05:50.730 --> 00:06:01.200
Shamya Chodumada Karumbaiah: Studying bias is in these adaptive learning systems is important because they make real time decisions that impact students learning and experiences closely.

34
00:06:03.270 --> 00:06:13.110
Shamya Chodumada Karumbaiah: But it is peculiarly challenging task as the systems, often involve models of complex educational constructs so does behavior to affect and motivation.

35
00:06:13.500 --> 00:06:19.350
Shamya Chodumada Karumbaiah: And it also utilizes rich student data such as fine grained a student interaction data.

36
00:06:20.100 --> 00:06:34.260
Shamya Chodumada Karumbaiah: These complexities may likely introduce complex biases which need a more nuanced approach to identify and medicaid also despite the wide usage of the systems biases in these systems have not yet been studied parity.

37
00:06:36.750 --> 00:06:52.890
Shamya Chodumada Karumbaiah: Let me give a quick example learn to have it is an intelligent routing system or an adaptive learning system uses an algorithmic model of student knowledge to predict a student's current skill level and decide the difficulty level of the content, they will see you next.

38
00:06:55.740 --> 00:07:04.410
Shamya Chodumada Karumbaiah: If the knowledge estimation modeling here well to be biased against female students, it may systematically deliver content below the students can level.

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00:07:04.800 --> 00:07:14.190

Shamya Chodumada Karumbaiah: leading to miss learning opportunities or suboptimal experience potentially lowering achievement and engagement in female students in the long run.

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00:07:15.420 --> 00:07:31.380
Shamya Chodumada Karumbaiah: motivate This could also become a self fulfilling prophecy wherein the incorrect prediction for female students may lead to actual low performance further confirm confirming the students bias, the system device, and this perpetuating the systems behavior.

41
00:07:32.610 --> 00:07:42.750
Shamya Chodumada Karumbaiah: In this fashion adaptive systems have the potential to obscure the root cause of bias and automate it affect making it harder to objectively identify and fixing.

42
00:07:45.180 --> 00:07:56.490
Shamya Chodumada Karumbaiah: In addition, the systems, often serve a diverse student population with a single system catering to students from different grade levels countries and socio economic and cultural backgrounds.

43
00:07:57.390 --> 00:08:07.110
Shamya Chodumada Karumbaiah: This further complicates the issue of bias, as now, the system behavior needs to be non discriminatory across all the students populations that it's serving.

44
00:08:09.120 --> 00:08:21.390
Shamya Chodumada Karumbaiah: Therefore, as the systems continue to be used by diverse student populations across the United States and the globe, they need to ensure that their pedagogical decisions meet the needs of all students for an equitable outcome.

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00:08:23.640 --> 00:08:32.970
Shamya Chodumada Karumbaiah: next step doesn't arguments for why we need to look beyond just algorithms to identify and mitigate bias in upstream sources that shape adaptive learning systems.

46
00:08:35.280 --> 00:08:41.220
Shamya Chodumada Karumbaiah: let's take the example of Africa detection and let's unpack the detector development process.

47
00:08:42.390 --> 00:08:53.490
Shamya Chodumada Karumbaiah: In the standard machine learning workflow we start by collecting samples as from a probability distribution fee for instance bears of images and annotated African states.

48
00:08:55.020 --> 00:08:59.640
Shamya Chodumada Karumbaiah: Then we choose a model class ah that's a set of neural networks.

49
00:09:00.780 --> 00:09:06.480
Shamya Chodumada Karumbaiah: Within find the model in this model class which has the lowest prediction editor on sample as.

50
00:09:08.250 --> 00:09:18.930
Shamya Chodumada Karumbaiah: Last year, and this is particularly important for our discussion we estimate the true error of this model for any future data by testing it on new data that is also drawn from.

51
00:09:21.150 --> 00:09:26.430
Shamya Chodumada Karumbaiah: This methodology is justified by the fundamental serum of machine learning on generalization.

52
00:09:27.540 --> 00:09:43.290
Shamya Chodumada Karumbaiah: into meltdowns, no matter how complicated the distribution is for a reasonable model class if we have enough data, then for any model, the editor on current data is a close approximation of the errors in the real world.

53
00:09:45.360 --> 00:09:53.040
Shamya Chodumada Karumbaiah: Simply put, if a model does well on the data in hand, it is expected to do well on any unseen data in the future.

54
00:09:55.980 --> 00:10:09.180
Shamya Chodumada Karumbaiah: While this approach may work well for predicting say pittsburgh's feather dorado it fall short in serving diverse student populations, especially those who are under or underrepresented in the sample.

55
00:10:11.550 --> 00:10:24.720
Shamya Chodumada Karumbaiah: As reported by packet and colleagues in the recent review of papers from education data mining student population information is often not reported with generalization estimates, making it especially hard to contextualize Marbles

56
00:10:27.150 --> 00:10:41.760
Shamya Chodumada Karumbaiah: It reminds me of the code by George box all models are wrong, but some are useful, the question that is often ignored is useful for who are the models disproportionately useful for some student populations over others.

57
00:10:43.530 --> 00:10:56.220
Shamya Chodumada Karumbaiah: By design most machine learning models are optimized for the majority population, because of its focus on reducing the overall edit This leads to bias towards those who do not look like the majority population.

58
00:10:57.930 --> 00:11:00.330
Shamya Chodumada Karumbaiah: There are several reasons for why this may happen.

59
00:11:01.470 --> 00:11:11.250
Shamya Chodumada Karumbaiah: The data collected may be less accurate for some groups, for example, earlier cameras were designed to bring out high contrast and better resolution for white skin color.

60
00:11:12.840 --> 00:11:19.920
Shamya Chodumada Karumbaiah: Or the construct of interest may look different in different subgroups, for example, cultural differences in the expressions of emotion.

61
00:11:21.840 --> 00:11:25.980
Shamya Chodumada Karumbaiah: or some subgroups may just be hard to predict, for example, students, wearing makeup.

62
00:11:28.350 --> 00:11:35.640
Shamya Chodumada Karumbaiah: Identifying the CDS issue several recent research projects have examined bias in algorithm existence in education.

63
00:11:38.070 --> 00:11:47.850
Shamya Chodumada Karumbaiah: However, the focus has mostly been on investigating bias in predictive modeling, particularly its downstream stages like model development and evaluation.

64
00:11:49.170 --> 00:11:58.260
Shamya Chodumada Karumbaiah: While this is an important step in the right direction, I argue that the issue of bias advisors, well before the actual module development.

65
00:11:59.580 --> 00:12:08.850
Shamya Chodumada Karumbaiah: And that the current emphasis on downstream status will limit the progress towards equity in in adaptive learning systems if we don't broaden our search.

66
00:12:11.160 --> 00:12:25.320
Shamya Chodumada Karumbaiah: by considering three upstream components separately my dissertation aim to bring to attention those aspects that closely shape adaptive decision making, but are often obscured in the evaluation of bias in an algorithmic model.

67
00:12:26.760 --> 00:12:37.740

Shamya Chodumada Karumbaiah: Data collection methods and system design directly impact modeling efforts motivational theories impact system design data collection and the algorithmic design.

68
00:12:39.180 --> 00:12:53.100
Shamya Chodumada Karumbaiah: letting an algorithmic model perpetuate an upstream bias in its discriminated this decision making, before the harm the sensitive groups, leading to outcomes that falsely confirm the upstream bias.

69
00:12:54.060 --> 00:13:12.060
Shamya Chodumada Karumbaiah: Studying upstream bias is important not only because it could form a basis for bias in an algorithmic model, but also because it could lead to direct discriminatory behaviors in an adaptive system, for example, an effective intervention, based on a biased theory.

70
00:13:13.620 --> 00:13:26.130
Shamya Chodumada Karumbaiah: But empirically analyzing student data previously collected from various virtual learning systems, I investigated demographic disparities in three representative cases of upstream buys.

71
00:13:27.840 --> 00:13:32.310
Shamya Chodumada Karumbaiah: bidding effectiveness of methodological improvements in annotated data collection.

72
00:13:34.020 --> 00:13:41.730
Shamya Chodumada Karumbaiah: Differing implications of technology design on student outcomes and raising rates of data conformance to a theoretical model.

73
00:13:43.290 --> 00:13:46.380
Shamya Chodumada Karumbaiah: i'm now going to present study three for my dissertation.

74
00:13:48.960 --> 00:14:00.870
Shamya Chodumada Karumbaiah: In this study I empirically illustrated demographic disparity in the non conformance of data to are widely accepted theoretical model used to design adaptability in learning systems.

75
00:14:02.250 --> 00:14:07.200
Shamya Chodumada Karumbaiah: Before I begin I would like to express my heartfelt gratitude to all who made this study possible.

76
00:14:09.690 --> 00:14:19.470
Shamya Chodumada Karumbaiah: I chose to study theory as an upstream source, because it closely influences several aspects of adapter decisions, including the conceptualization of.

77
00:14:20.010 --> 00:14:33.690
Shamya Chodumada Karumbaiah: construct the interpretation of student behaviors the construction of variables in modeling and the design of interventions in adaptive systems in this study I specifically look at an average of 30.

78
00:14:35.970 --> 00:14:45.660
Shamya Chodumada Karumbaiah: effect has been theorized to play three primary roles in learning by drawing attention to learning challenges appraising learning and guiding cognitive focus.

79
00:14:47.130 --> 00:15:00.930
Shamya Chodumada Karumbaiah: According the empirical studies and adaptive and artificial intelligence systems show strong correlations between Africa and the range of important educational constructs such as self efficacy and logical reasoning learning and motivation.

80
00:15:02.670 --> 00:15:19.710
Shamya Chodumada Karumbaiah: Identifying the inextricable link between aspect and learning affective computing in education items to recognize measure analyze and respond to student athlete to narrow to communicate this gap between the highly emotional human and the emotionally challenged computer.

81
00:15:20.880 --> 00:15:31.830
Shamya Chodumada Karumbaiah: Accordingly, studies in the past decade have built automated Africa detectors for adaptive learning systems using physical and physiological sensors and interaction log data.

82
00:15:33.180 --> 00:15:38.940
Shamya Chodumada Karumbaiah: These detectors have been used to design Africa sensitive interventions in these adaptive systems.

83
00:15:41.820 --> 00:15:52.560
Shamya Chodumada Karumbaiah: This considers this example of an effort of a tutor considerable research has investigated the development of what it's called Africa sensitive or effort aware learning systems.

84
00:15:53.190 --> 00:16:02.070
Shamya Chodumada Karumbaiah: They didn't student experience is personalized based on these two systems ability to detect and respond to students African states.

85
00:16:03.150 --> 00:16:15.810

Shamya Chodumada Karumbaiah: The foundational hypothesis of this research is that detecting and responding to students effect improves the quality of students interaction with the system by making it more engaging and effective for learning.

86
00:16:18.180 --> 00:16:32.160
Shamya Chodumada Karumbaiah: Recognizing the limited utility in mirror effect recognition significant effort has been put into understanding how these states evolve and interact in effortful learning activities and area of research, called Africa dynamics.

87
00:16:35.250 --> 00:16:45.030
Shamya Chodumada Karumbaiah: The popular theoretical model of Africa dynamics was proposed by the mellow increase in 2012 using theories of cognitive this equilibrium.

88
00:16:45.630 --> 00:17:03.270
Shamya Chodumada Karumbaiah: They postulate that this specific set of Africa transitions will be particularly prominent the model predicts that students who experienced an impasse during the flow start state will transition to a state of equilibrium which manifests itself as the effect of state of confusion.

89
00:17:04.410 --> 00:17:13.800
Shamya Chodumada Karumbaiah: If the student results this impasse they are predicted to transition back to flow if, however, the impact is not resolved.

90
00:17:14.340 --> 00:17:26.550
Shamya Chodumada Karumbaiah: Students are hypothesized to become stuck which is experienced as frustration if the first frustration versus the model suggests the learner will disengage and transitioning to boredom.

91
00:17:29.640 --> 00:17:47.010
Shamya Chodumada Karumbaiah: I chose to investigate potential biases in this model because it's a highly cited and readily accepted model in the field, which has been used in diversity context to design adaptive effective interventions, including some of my own earlier works in this area.

92
00:17:49.440 --> 00:18:04.200
Shamya Chodumada Karumbaiah: You understand the applicability of the model I first conducted a systematic review to investigate the impact of methodological and contextual differences in past empirical studies, particularly with respect to their conformance to the theoretical model.

93
00:18:06.270 --> 00:18:15.120
Shamya Chodumada Karumbaiah: Medicine suggest that the studies that show some evidence for the model, but it all collected in the United States with undergraduate populations.

94

00:18:16.800 --> 00:18:25.500
Shamya Chodumada Karumbaiah: They would also done in lab settings using learning systems that were primarily built for research and followed a linear design.

95
00:18:27.060 --> 00:18:35.730
Shamya Chodumada Karumbaiah: They also involved shorter learning activity and collected students self reports of assets retrospectively at the completion of the activity.

96
00:18:37.590 --> 00:18:42.630
Shamya Chodumada Karumbaiah: And that didn't what methodological difference is the inconsistent treatment of self transitions.

97
00:18:43.710 --> 00:18:56.850
Shamya Chodumada Karumbaiah: It may take a couple of minutes to quickly explain the implications of this choice on the validity of the results, also a way in which statistical bias, which is different from the bias of this, the bias that i've been talking about witches.

98
00:18:57.960 --> 00:19:11.910
Shamya Chodumada Karumbaiah: Society bias, to an extent it's there's a difference here and, this being a statistical bias, I wanted to quickly explain how this led to a statistical bias in the results and does to the conformance of the marketing.

99
00:19:14.610 --> 00:19:32.250
Shamya Chodumada Karumbaiah: The data used in this research is temporarily sequenced codes representing student traffic so at each interval of time and effort observation is collected, either by human annotation or automated after detection or students at reports.

100
00:19:34.290 --> 00:19:43.560
Shamya Chodumada Karumbaiah: Studies that did conform to the theoretical model use the sequence as he's In contrast, the studies that did show some evidence towards self.

101
00:19:44.070 --> 00:19:56.370
Shamya Chodumada Karumbaiah: Remove the self transitions as part of their data pre processing step but excluding the instances when a student remained in the same effort of states or two or more conservative observations.

102
00:19:58.230 --> 00:20:12.510
Shamya Chodumada Karumbaiah: The seemingly small step of excluding self transitions leads to the violation of independence assumption in the statistic used since the next eight now can only take values other than the previous state, let me quickly industry, plus with an example.

103
00:20:14.100 --> 00:20:26.550

Shamya Chodumada Karumbaiah: given enough sequence the statistic calculates the likelihood that an aspect of state will transition to a subsequent state, given the base rate of the State occurring and the value of L here is zero.

104
00:20:28.170 --> 00:20:39.780
Shamya Chodumada Karumbaiah: considered now an effective sequence, with three states A, B and C, in which all transitions are equally likely to compute the likelihood of a transition a to be.

105
00:20:40.560 --> 00:20:45.540
Shamya Chodumada Karumbaiah: The first compute the base rate of B, which is point three three here, as there are three states.

106
00:20:46.470 --> 00:20:55.590
Shamya Chodumada Karumbaiah: Next we compute the current conditional probability of be as the next step, given a, as the previous day since a can transition to a B or C.

107
00:20:56.190 --> 00:21:08.490
Shamya Chodumada Karumbaiah: The conditional probabilities also point three three and now, when we plug this in into the equation of La we get X equals zero, which is what we would expect, since all transitions are equally likely.

108
00:21:10.320 --> 00:21:13.950
Shamya Chodumada Karumbaiah: This is true for all nine possible transitions with three states.

109
00:21:15.390 --> 00:21:30.630
Shamya Chodumada Karumbaiah: Now, when we remove the self transitions the basic of be remains unchanged, as we still have three states, however, since angel can only transition into B or C and not to itself, because the most transitions.

110
00:21:31.560 --> 00:21:46.980
Shamya Chodumada Karumbaiah: The conditional probability of be as the next step given as the previous state becomes point five, and now, when we plug this in into the plug this into the equation of L we see that the chance value of a shift from zero to a positive value.

111
00:21:48.390 --> 00:21:54.270
Shamya Chodumada Karumbaiah: This is true for all the six possible transitions with three states, when some transitions are excluded.

112
00:21:56.190 --> 00:22:11.190
Shamya Chodumada Karumbaiah: This issue is evident in 2018 study that similarly excluded self transitions and reported mathematically impossible results within all transitions into the African state of engaged concentration, but more likely than chance.

113
00:22:13.020 --> 00:22:20.520
Shamya Chodumada Karumbaiah: In one of my previous papers, I presented a mathematical proof for this issue, and provided provided a simple fix.

114
00:22:21.270 --> 00:22:27.510
Shamya Chodumada Karumbaiah: Which shifted the chance value of L from zero to a positive value, based on the number of active states.

115
00:22:28.500 --> 00:22:36.210
Shamya Chodumada Karumbaiah: Do this treatment fix the problem, it could still need to misinterpretation of the results, due to the counterintuitive nonzero chance value.

116
00:22:37.200 --> 00:22:53.730
Shamya Chodumada Karumbaiah: So, motivated by this issue my my mathematician Dr Jeff matter you she and I developed developed a modified version of the statistic which we refer to as elster which gives the sense value back zito when self transitions are remote.

117
00:22:55.500 --> 00:23:10.200
Shamya Chodumada Karumbaiah: More importantly, this finding implies that the past studies that showed some evidence to the theoretical model we have overstated that possible effects are reported positive results and relationships were even know or negative.

118
00:23:12.420 --> 00:23:26.700
Shamya Chodumada Karumbaiah: better understand the models validity and the scope and scope of applicability idea analyzed and synthesized and previously collected after data sets from diverse learning context and relatively more diverse student populations.

119
00:23:28.080 --> 00:23:43.290
Shamya Chodumada Karumbaiah: All but one data sets were collected using human annotation by culturally sensitive trained and certified coders who observed students, while using widely used protocol called prompt to reduce data bias and observer effect.

120
00:23:45.360 --> 00:23:52.440
Shamya Chodumada Karumbaiah: I chose to use the redefined and statistic and propose to analyze treatment of edge cases that lacked consensus into the teacher.

121
00:23:53.820 --> 00:24:03.240
Shamya Chodumada Karumbaiah: I chose to exclude some transitions, as this would likely reveal a larger number of Africa patents that might otherwise be suppressed by persistent adjective sticks.

122

00:24:04.260 --> 00:24:09.390
Shamya Chodumada Karumbaiah: Lastly, are used oversee to summarize significance levels from the efficacy.

123
00:24:11.400 --> 00:24:21.810
Shamya Chodumada Karumbaiah: Somebody thing to significant levels across all the data sets that reveals that, among the six transitions hypothesized by the theoretical model, only one transition holds true.

124
00:24:24.000 --> 00:24:37.380
Shamya Chodumada Karumbaiah: If we just checked the scope of applicability by nationality Africa transitions appear to be a little more stable in the United States, with no transitions being significantly more likely than chance in the Philippines.

125
00:24:40.380 --> 00:24:49.140
Shamya Chodumada Karumbaiah: There are three main implications of this study first it showed non conformance of data to the widely accepted theoretical model of student effect.

126
00:24:50.100 --> 00:25:03.720
Shamya Chodumada Karumbaiah: I believe that it is highly unlikely that there are there is a general multistep pattern and academics well there may still be some contextually relevant patents useful to understand a student experience in specific students are populations.

127
00:25:05.610 --> 00:25:15.060
Shamya Chodumada Karumbaiah: Second, the study also entry some methodological concerns in Africa dynamics analysis that were overlooked in the past studies, especially in using a statistic.

128
00:25:16.890 --> 00:25:25.080
Shamya Chodumada Karumbaiah: Conducting transition analysis with Africa data has some continued challenges, for example, southern Africa states like frustration than to have.

129
00:25:25.470 --> 00:25:34.860
Shamya Chodumada Karumbaiah: low base rate also due to practical constraints and data collection feel observations tend to be done to produce short African sequences.

130
00:25:35.190 --> 00:25:43.770
Shamya Chodumada Karumbaiah: And these particular peculiarities have lead to issues with spurious results in using standard methods for transition analysis.

131
00:25:44.310 --> 00:25:56.640

Shamya Chodumada Karumbaiah: So, my colleagues and I have been working on innovative ways to mitigating some of these issues, one of which also used epistemic netflix analysis as a methodology for Africa dynamics analysis.

132
00:25:59.100 --> 00:26:11.400
Shamya Chodumada Karumbaiah: There are some more open questions on the implication of sampling rates screen size session lens of African studies, for example, field observation Stan to sample it slows lives.

133
00:26:12.210 --> 00:26:24.300
Shamya Chodumada Karumbaiah: They are also course the green as compared to our automated detection and we are here to look at these methodological choices and the impact they have on the validity and applicability of theoretical model.

134
00:26:26.550 --> 00:26:32.730
Shamya Chodumada Karumbaiah: More importantly, the study highlighted the need to focus on cultural factors in Africa nomics research.

135
00:26:33.870 --> 00:26:45.720
Shamya Chodumada Karumbaiah: Even the differences in national culture school culture use of ethic and forms of disengagement in the two countries studied it is difficult at this point to understand why we are seeing these differences.

136
00:26:47.010 --> 00:26:56.880
Shamya Chodumada Karumbaiah: More broadly, however, we know that culture influences emotional expression and regulation and that it also influences frequency and emergence of Africa.

137
00:26:58.650 --> 00:27:13.350
Shamya Chodumada Karumbaiah: Either contextual factors like age also influences emotional exclusivity and a better understanding of the role that context place in is important for any future Adams to study academics as a generalizable phenomenon.

138
00:27:16.530 --> 00:27:28.200
Shamya Chodumada Karumbaiah: Finally, like its predecessors, the study conceptualized conceptualized as an effect as experienced by an individual state a student and after dynamics and collaborative settings area to be studied.

139
00:27:30.180 --> 00:27:30.540
Shamya Chodumada Karumbaiah: Alec.

140
00:27:31.620 --> 00:27:37.140

Shamya Chodumada Karumbaiah: So taking a step back and going back to what I was telling before about upstream sources of bias.

141
00:27:38.040 --> 00:27:53.610
Shamya Chodumada Karumbaiah: Through the study that I just presented and the other two studies in my dissertation I illustrate the existence of potential biases in upstream sources such as theory design and data collection method that closely shape adaptive learning systems.

142
00:27:55.980 --> 00:27:59.070
Shamya Chodumada Karumbaiah: Now quickly summarize my key findings from the other two studies.

143
00:28:00.840 --> 00:28:12.240
Shamya Chodumada Karumbaiah: In my second study I examined the conditions under which the relationships between students behavior motivation and outcomes vary across different demographic context.

144
00:28:13.290 --> 00:28:24.510
Shamya Chodumada Karumbaiah: By doing so, I challenge the implicit assumptions of generalize ability in design choices, especially to the student populations that is currently understudied in price evaluation.

145
00:28:25.530 --> 00:28:31.680
Shamya Chodumada Karumbaiah: This includes students with low socio economic status English as a second language and special education.

146
00:28:32.700 --> 00:28:51.030
Shamya Chodumada Karumbaiah: I also demonstrated the use of publicly available school level demographics for bias research, where there is often access to larger and more diverse diverse samples of student data but individual student demographics may be difficult or impossible to acquire.

147
00:28:54.120 --> 00:29:09.000
Shamya Chodumada Karumbaiah: That is also my last study reveals demographic disparity in the effective methods of methodological improvement in data collection and this work I experimented with active machine learning to improve annotated data collection of Africa.

148
00:29:10.080 --> 00:29:16.590
Shamya Chodumada Karumbaiah: This method suffers from the cold start problem where it does not have access to sufficient data yet to learn from.

149
00:29:17.520 --> 00:29:31.560

Shamya Chodumada Karumbaiah: with Dr Andrew land I devised an approach to use past Africa data to overcome this limitation on experiments showed that mismatches in the urban city so suburban urban versus rural.

150
00:29:32.490 --> 00:29:47.160
Shamya Chodumada Karumbaiah: Urban city of the past eight of the schools where the data came from the mismatch in there, which is mixing up urban and suburban schools, for instance, could lead to bias data collection of effect for target students or population.

151
00:29:49.650 --> 00:30:02.010
Shamya Chodumada Karumbaiah: my dissertation identified upstream sources of biases in adaptive learning systems i'm also looking at are locating the origins of these upstream sources upstream biases.

152
00:30:03.630 --> 00:30:17.760
Shamya Chodumada Karumbaiah: As highlighted in the study I presented representation bias can occur for several reasons, most research tends to be conducted in Western countries with adaptive systems developed by designers in the West.

153
00:30:19.230 --> 00:30:26.340
Shamya Chodumada Karumbaiah: small scale experiments also tend to recruit from a convenient sample to do practical constraints of research projects.

154
00:30:27.900 --> 00:30:36.630
Shamya Chodumada Karumbaiah: Even when there is access to larger, more diverse data sets it is often harder to collect student demographics data due to concerns over student privacy.

155
00:30:38.490 --> 00:30:47.610
Shamya Chodumada Karumbaiah: search representation bias can invalidated assumptions for students or populations not represented in the experiments in forming these stream competence.

156
00:30:49.680 --> 00:31:08.370
Shamya Chodumada Karumbaiah: Similarly measurement bias can occur due to issues in data collection methods such as lack of reliability of measurement across different students or populations, for example, quarter biased you do cross cultural aspect coding and demographic disparities in the reliability of self reports.

157
00:31:10.650 --> 00:31:27.150
Shamya Chodumada Karumbaiah: And lastly, historical bias to do forming theories and design choices by observing the world as it exists, including it spices, but example earlier cameras were designed to bring out high contrast and better resolution for white skin color.

158

00:31:30.000 --> 00:31:34.200
Shamya Chodumada Karumbaiah: Lastly, I would like to present some of my future lines of inquiry.

159
00:31:36.270 --> 00:31:52.620
Shamya Chodumada Karumbaiah: motivated by the inextricable link between learning and context I embarked on this journey interested in investigating how ignoring learner context in the design and development of adaptive learning systems could introduce introduce harmful biases in them.

160
00:31:53.910 --> 00:32:11.400
Shamya Chodumada Karumbaiah: I have explored a few first steps towards building equitable educational technologies, I have tried to bring attention of bias research to those aspects of the design and development of adaptive systems that are often obscured in the evaluation of bias in an algorithmic model.

161
00:32:12.720 --> 00:32:30.420
Shamya Chodumada Karumbaiah: Specifically, my research so far has identified some of the issues in sources such as series design and data collection methods for demographic categories such as obesity, race or ethnicity economic status English as a second language, especially education and charter school.

162
00:32:31.470 --> 00:32:39.750
Shamya Chodumada Karumbaiah: Achieving equity in education and technology has a long way to go with several open questions that I intend to answer in my future work.

163
00:32:42.720 --> 00:32:54.720
Shamya Chodumada Karumbaiah: I am focused on these three lines of inquiry in the future and i'm looking forward to you know your feedback and your questions in your fees as well.

164
00:32:55.890 --> 00:33:04.650
Shamya Chodumada Karumbaiah: I want to I plan to develop theory and methods for understanding identifying and mitigating bias in adaptive learning systems.

165
00:33:05.160 --> 00:33:21.210
Shamya Chodumada Karumbaiah: And then, also for trying to focus on conducting empirical work that is focused intentionally on contextualizing the experiences of diverse students of groups to serve the needs of all students, especially those who are likely to be underserved by a biased system.

166
00:33:22.620 --> 00:33:27.900
Shamya Chodumada Karumbaiah: towards this i'm thinking of three lines of inquiry, so three ways of approaching this problem.

167

00:33:29.790 --> 00:33:35.790
Shamya Chodumada Karumbaiah: So the first line of inquiry is focusing on theory building for research design and practice.

168
00:33:36.930 --> 00:33:51.390
Shamya Chodumada Karumbaiah: The often overlapping conceptualization of bias and the harms they have because have themselves been considered a potential limitation that leads to that needs to be addressed as the work to mitigate it emerges.

169
00:33:51.810 --> 00:34:02.310
Shamya Chodumada Karumbaiah: Hence there is a new urgency to define or to provide definitions and theoretical grounding for the known biases in technology, enabling adaptive systems.

170
00:34:03.690 --> 00:34:14.670
Shamya Chodumada Karumbaiah: To respond to this challenge, especially for educational affective computing I plan to extend my research to develop a theoretical framework for bias, representing its sources.

171
00:34:15.150 --> 00:34:18.180
Shamya Chodumada Karumbaiah: origins impacted populations and harms.

172
00:34:18.960 --> 00:34:35.310
Shamya Chodumada Karumbaiah: And by narrowing the scope of this research away from the generalities of data and algorithms I hope to focus on developing sharper distinctions on the categories of bias for Africa of technologies while also grounding the categories in authentic educational constructs and theory.

173
00:34:37.950 --> 00:34:47.700
Shamya Chodumada Karumbaiah: i'm also hoping that we, we could do some auditing of the real world of data sex and sex and educational technology systems.

174
00:34:48.930 --> 00:34:52.650
Shamya Chodumada Karumbaiah: to sort of empirically test and further refine the framework.

175
00:34:54.390 --> 00:35:05.460
Shamya Chodumada Karumbaiah: i'm hoping that that this work would lead to providing a nuanced understanding of known biases to find ways to mitigate them and identify gaps for further investigation.

176
00:35:06.000 --> 00:35:16.680
Shamya Chodumada Karumbaiah: I hope that it serves as a shared language for researchers designers and back practitioners and also all stakeholders that can be used to audit.

177
00:35:18.000 --> 00:35:20.910
Shamya Chodumada Karumbaiah: Educational technologies for known biases.

178
00:35:22.980 --> 00:35:30.210
Shamya Chodumada Karumbaiah: The second way in which we could approach this problem is by looking at technical approaches to mitigating bias.

179
00:35:31.440 --> 00:35:38.520
Shamya Chodumada Karumbaiah: Through this line of inquiry, I want to develop context aware learning analytics method that considers student diversity by design.

180
00:35:39.930 --> 00:35:41.970
Shamya Chodumada Karumbaiah: There are new approaches being developed.

181
00:35:43.320 --> 00:35:55.200
Shamya Chodumada Karumbaiah: For fair machine learning the general idea is to add fairness as a constraint, while optimizing the model, such that the model with the best fairness trade off is selected.

182
00:35:56.040 --> 00:36:06.810
Shamya Chodumada Karumbaiah: More often than not, the issue of bias or unfairness in this discussion is conceptualized predominantly as a technical problem with little consideration to real world context.

183
00:36:08.310 --> 00:36:16.590
Shamya Chodumada Karumbaiah: The problem, however, is that there is no consensus on what fair even means fair to whom to answer.

184
00:36:17.310 --> 00:36:23.790
Shamya Chodumada Karumbaiah: We need to take an explicit position on where we as a society stand on the social construct of fairness.

185
00:36:24.660 --> 00:36:37.320
Shamya Chodumada Karumbaiah: Is it the benefit of the majority group, avoiding harm to the marginalized people making systems fair to all groups or providing justice to historically disadvantaged groups.

186
00:36:38.220 --> 00:36:50.250

Shamya Chodumada Karumbaiah: We also need to define the groups explicitly, which is also not straightforward, for example, is it a specific race or gender or sexual orientation or a specific combination of those.

187
00:36:51.690 --> 00:37:03.450
Shamya Chodumada Karumbaiah: As I mentioned earlier, one of my findings so far highlights how the group differences that matter most for educational technology design might not be the groups that are the most immediately obvious.

188
00:37:05.130 --> 00:37:24.060
Shamya Chodumada Karumbaiah: By grounding these investigations in an authentic educational construct, we can test the limits of advancements in fair machine learning by juxtaposing it with the complexities in the real world and highlighting the complexities involved in posing educational problems algorithmically.

189
00:37:27.450 --> 00:37:35.310
Shamya Chodumada Karumbaiah: I am going to skip this in the interest of time and quickly jump on to this last line of inquiry.

190
00:37:35.730 --> 00:37:43.620
Shamya Chodumada Karumbaiah: Where i'm hoping to explore ways to bring the voices of teachers and learners in designing equitable human Ai technology.

191
00:37:44.220 --> 00:37:55.620
Shamya Chodumada Karumbaiah: I believe that it is both an imperative and an opportunity to engage and Emperor stakeholders to use learning analytics as a tool to drive positive social change.

192
00:37:56.220 --> 00:38:04.350
Shamya Chodumada Karumbaiah: And in one of my previous work I worked with in service teachers to construct approaches to integrate computation or technology.

193
00:38:04.890 --> 00:38:15.360
Shamya Chodumada Karumbaiah: into their subject matters when we chose an approach of distributed expertise were in the features brought expertise of the pedagogical context and content.

194
00:38:15.720 --> 00:38:29.220
Shamya Chodumada Karumbaiah: And I went as an expert of technological knowledge and i'm hoping to do something similar here to conduct human centered studies with teachers who use adaptive learning systems in their classroom to.

195
00:38:29.850 --> 00:38:41.340

Shamya Chodumada Karumbaiah: sort of like develop research studies that would both elicit fairness understanding from them and to conduct collective audits to identify and detect bias in adaptive learning systems.

196
00:38:44.220 --> 00:38:53.160
Shamya Chodumada Karumbaiah: um well, I guess, I am almost out of time, and I want to give 15 minutes for q&a i'm very curious to hear.

197
00:38:54.570 --> 00:38:58.800
Shamya Chodumada Karumbaiah: Your feedback so i'm going to pause here and just say that.

198
00:39:01.110 --> 00:39:08.820
Shamya Chodumada Karumbaiah: I believe that the issues of bias is a serious one right now that people who are working on education and technology need to focus on.

199
00:39:09.180 --> 00:39:25.170
Shamya Chodumada Karumbaiah: And I believe that the three aspects that I mentioned, as the future lives of inquiry, including theory technical approaches and human centeredness, I believe, is going to be important in addressing and even understanding and approaching issues of face Thank you.

200
00:39:29.100 --> 00:39:31.050
Brendan Eagan: Thank you show me that was wonderful.

201
00:39:32.400 --> 00:39:44.190
Brendan Eagan: So now's the time when we get to open things up to questions and discussion so feel free to you know raise your hand if you'd like to ask a question, use the microphone or use the chat if you'd like to but.

202
00:39:45.330 --> 00:39:46.590
Brendan Eagan: let's open things up.

203
00:40:04.500 --> 00:40:05.130
Shamya Chodumada Karumbaiah: Yes, David.

204
00:40:06.300 --> 00:40:14.040
David Williamson Shaffer: i'm always happy to jump in so show me a you know that I think this work is really interesting and important, in part because we hired you.

205
00:40:15.150 --> 00:40:24.600

David Williamson Shaffer: So that's a pretty good signal on that um so one of the things that i've been puzzling around and i'm just interested to hear your thoughts on it.

206
00:40:26.130 --> 00:40:38.940
David Williamson Shaffer: And this is kind of over simplified way of describing the problem, but you know let's say I have, I have two groups, right in the in the data and I have some thing that i'm measuring.

207
00:40:38.940 --> 00:40:52.920
David Williamson Shaffer: It could be the code code rates or it could be more sophisticated model right and the whatever the results are different between the two groups so similar to the way that you're you know and even happened in the Philippines.

208
00:40:54.990 --> 00:41:10.980
David Williamson Shaffer: So sometimes that's evidence of bias, sometimes that could actually be what we would otherwise call result and how do you think about disentangling those things sort of both mythologically and conceptually as you're thinking about.

209
00:41:12.510 --> 00:41:16.380
David Williamson Shaffer: ways of measuring mitigating understanding bias.

210
00:41:17.970 --> 00:41:18.420
David Williamson Shaffer: question.

211
00:41:18.960 --> 00:41:19.950
Shamya Chodumada Karumbaiah: yeah absolutely.

212
00:41:21.570 --> 00:41:22.320
Shamya Chodumada Karumbaiah: Okay okay.

213
00:41:23.910 --> 00:41:24.870
Shamya Chodumada Karumbaiah: so far.

214
00:41:27.360 --> 00:41:31.860
Shamya Chodumada Karumbaiah: I don't think I would consider measure likes a measure of.

215
00:41:33.030 --> 00:41:48.660
Shamya Chodumada Karumbaiah: say we are measuring self efficacy or certain African state or you know, like I wouldn't say the difference in the measure of the educational construct itself as bias, but rather and correct me if i've got your question wrong David.

216
00:41:49.770 --> 00:41:55.380
Shamya Chodumada Karumbaiah: What I would consider as bias, especially in predictive modeling and automated decision making is.

217
00:41:56.190 --> 00:42:04.530
Shamya Chodumada Karumbaiah: The models performance in predicting that construct so if there is a difference in false positives if there is a difference in.

218
00:42:04.980 --> 00:42:14.880
Shamya Chodumada Karumbaiah: prediction accuracy, or any other AUC or any other measure that you have for the performance of the model or for its era differences in error rates and such.

219
00:42:15.270 --> 00:42:24.090
Shamya Chodumada Karumbaiah: So that difference in there is what I would consider as bias, one of the challenges that recently I was looking at a model of.

220
00:42:25.080 --> 00:42:36.090
Shamya Chodumada Karumbaiah: mooc dropout rates and one of the things that's interesting and that's challenging right now is what we call as bias is a model difference of say point 001 AUC bias.

221
00:42:36.510 --> 00:42:50.160
Shamya Chodumada Karumbaiah: How do we set a threshold, even for calling something as bias in the difference in in say accuracy for performance, for instance, I think, that is, that is, the bias that i'm talking about, but please correct me if i'm if I got your question wrong.

222
00:42:50.190 --> 00:42:59.310
David Williamson Shaffer: No yes you're saying it's the biases in the difference in error rate is rather than differences in this in a statistic overall.

223
00:43:00.750 --> 00:43:11.790
Shamya Chodumada Karumbaiah: or it could be something more sophisticated like if there is difference in false positives for one group was false positive rates for one group than the other, for instance, I think that's where sort of like the.

224
00:43:13.080 --> 00:43:20.370
Shamya Chodumada Karumbaiah: The conversations, at least in machine learning was sort of heightened because of the pro publica case where there was the difference in.

225
00:43:21.900 --> 00:43:23.820
Shamya Chodumada Karumbaiah: The the.

226
00:43:25.320 --> 00:43:27.270
Shamya Chodumada Karumbaiah: But all but only separated by.

227
00:43:28.290 --> 00:43:38.310
Shamya Chodumada Karumbaiah: Dates like false positives in a higher false false positive rates in African American population as compared to Caucasian population.

228
00:43:39.750 --> 00:43:42.840
Shamya Chodumada Karumbaiah: In somebody has been tagged as it said.

229
00:43:44.460 --> 00:43:46.350
Shamya Chodumada Karumbaiah: You know, higher likelihood of recidivism.

230
00:43:54.720 --> 00:44:02.010
Brendan Eagan: What other questions do folks have other ones I have a follow up to that one as people are thinking or just something that that sparked for me.

231
00:44:02.520 --> 00:44:16.800
Brendan Eagan: So if i'm understanding correctly you're saying that like one way of kind of operationalize or considering biases looking at differentiation in these in error rates that we can kind of have like different metrics of.

232
00:44:18.180 --> 00:44:18.780
Brendan Eagan: And I think.

233
00:44:20.130 --> 00:44:26.850
Brendan Eagan: In a case where, if you see differences say in a model result or description or a score or something, and you don't.

234
00:44:27.840 --> 00:44:37.560
Brendan Eagan: You don't have you can quantify that in terms of like getting the error rates, but if you just are otherwise seeing the description or the model result absent that or maybe setting that aside.

235
00:44:38.040 --> 00:44:48.240
Brendan Eagan: If you have differences between these two groups teasing out like I liked your description of theory or some of these other upstream things that could lead to descriptions of this is to say.

236
00:44:48.780 --> 00:44:57.090

Brendan Eagan: Is what i'm seeing in the model, the result of a phenomenon, there were these groups these different groups of people actually have differences that we think are.

237
00:44:58.140 --> 00:45:08.520
Brendan Eagan: The model is useful to kind of using the language that you use the model is useful and i'm actually picking up what I want to versus Oh, this is just a, this is not high fidelity, this is a source of.

238
00:45:09.570 --> 00:45:17.130
Brendan Eagan: Something it could be downstream or upstream, but what i'm seeing here is an artifact of bias, rather than the real thing that I want to see.

239
00:45:19.680 --> 00:45:30.540
Shamya Chodumada Karumbaiah: ya yeah absolutely so quickly to respond to that Brendan that that is true, in fact I guess what you mentioned is a possible upstream source of.

240
00:45:31.590 --> 00:45:42.060
Shamya Chodumada Karumbaiah: You know, a bias in a predictive model so if if there is fundamental differences in those two groups, but if the model has been designed keeping the majority group in mind.

241
00:45:42.450 --> 00:45:48.060
Shamya Chodumada Karumbaiah: Because you know machine learning models are designed, you know, especially when you're training and optimizing them you're optimizing for.

242
00:45:48.810 --> 00:46:04.800
Shamya Chodumada Karumbaiah: Say performance some performance metrics like say accuracy or a uc or whatever, of course, a model is going to you're going to pick the model that's going to do well overall because that leads to overall high accuracy so fairness was never designed into.

243
00:46:04.830 --> 00:46:05.250
Brendan Eagan: into a.

244
00:46:05.760 --> 00:46:13.620
Shamya Chodumada Karumbaiah: Big big yes so fundamentally if two groups or different say the features there's there are features that are more predictive for one group than the other.

245
00:46:13.920 --> 00:46:24.810
Shamya Chodumada Karumbaiah: Like extracurricular activities as a feature for predicting college success is going to be more accurate for groups that can afford to have extracurricular activities as high schools versus those.

246
00:46:25.800 --> 00:46:35.370
Shamya Chodumada Karumbaiah: That group which probably had to work a job or take care of their family and so that is not fundamentally predictive those features are not predictive for that other group so to have that as a.

247
00:46:35.730 --> 00:46:42.660
Shamya Chodumada Karumbaiah: As a predicted is then going to lead to possible biases because you know fundamentally the features themselves are.

248
00:46:43.140 --> 00:46:44.340
Brendan Eagan: baked into it already.

249
00:46:44.700 --> 00:46:46.320
Shamya Chodumada Karumbaiah: Exactly exactly yeah.

250
00:46:46.530 --> 00:46:57.390
Brendan Eagan: And I am remiss as the host I didn't see if you use question came into the chat or carl's came first, so I think I saw I think it maybe was Carl first Carl would you.

251
00:46:57.390 --> 00:46:59.490
YEYU WANG: Like directors Okay, thanks to you.

252
00:46:59.820 --> 00:47:02.520
Brendan Eagan: And then, why don't we do a you and then David.

253
00:47:04.050 --> 00:47:04.290
ZHIQIANG CAI: Okay.

254
00:47:05.850 --> 00:47:06.390
ZHIQIANG CAI: very nice.

255
00:47:08.430 --> 00:47:12.600
ZHIQIANG CAI: As to listen to your wonderful research again.

256
00:47:14.430 --> 00:47:34.470
ZHIQIANG CAI: So I took on crackle the preface questions, I do have, once the data set is that when the data is collected, I think that this we can do is to measure happiness and accurately unfairly, we can never measure anything.

257

00:47:35.490 --> 00:47:48.150
ZHIQIANG CAI: Absolutely accurate, it must be ever, the only thing we can control is fairly accurate, not just the measure this group, more accurately, but keep a lot of error in another group that's.

258
00:47:48.660 --> 00:47:54.930
ZHIQIANG CAI: I guess that's the best we can do so, I have a matter of thinking about these kind of things, one thing is.

259
00:47:55.380 --> 00:48:04.710
ZHIQIANG CAI: If we, of course, that is, can come at different levels Nike in the experimental design data collection, the way forget about that.

260
00:48:05.160 --> 00:48:20.220
ZHIQIANG CAI: just talking about for collected data set when we measured one model So what are the sources of the havers The thing that I have been thinking about, for example, for text data.

261
00:48:21.360 --> 00:48:26.370
ZHIQIANG CAI: The source, one of the sources of tires is the culture.

262
00:48:27.780 --> 00:48:37.110
ZHIQIANG CAI: Because, for example, well all use English language, but when we talk or something people from different culture.

263
00:48:37.800 --> 00:48:51.570
ZHIQIANG CAI: may use different ways may use different expressions to talk our fans so that's called Carter difference this up, but women are known as dead as well, now that.

264
00:48:52.110 --> 00:49:07.800
ZHIQIANG CAI: We may just pick the Carter the majority and then for example Code, the data I noted data we may pay more attention to annotate the way the majority talks about plans and.

265
00:49:09.210 --> 00:49:13.500
ZHIQIANG CAI: Under represent the minority group.

266
00:49:15.600 --> 00:49:31.620
ZHIQIANG CAI: That is that I don't know if that is right, what are the other major sources of pass that causes nurture errors I don't want to play it for me that he.

267
00:49:32.130 --> 00:49:38.040
Shamya Chodumada Karumbaiah: So, so your question is, if we have already collected data right.

268
00:49:39.630 --> 00:49:41.610
Shamya Chodumada Karumbaiah: If you have already collected data, then.

269
00:49:42.660 --> 00:49:51.330
Shamya Chodumada Karumbaiah: If we are at the process in the sharing the stage of the pipeline, where we are building a model then at that stage What could we be mindful of.

270
00:49:51.750 --> 00:49:59.820
Shamya Chodumada Karumbaiah: In terms of looking for possible ways in which our pipeline may be introducing bias right So yes, for sure so annotation.

271
00:50:00.390 --> 00:50:11.250
Shamya Chodumada Karumbaiah: Yes, so if I think annotation i'm thinking of an addition, as the label or the outcome of predictive model but also features rates for when you're designing features.

272
00:50:11.880 --> 00:50:21.840
Shamya Chodumada Karumbaiah: We could look for some you know some group differences in the feature itself differences in correlation between these features and predicting predicted.

273
00:50:23.580 --> 00:50:27.240
Shamya Chodumada Karumbaiah: that the outcome variable you know, like if there is differences in in in there.

274
00:50:29.160 --> 00:50:42.060
Shamya Chodumada Karumbaiah: I think there are several other ways to but then I I don't think we should stop at thinking that Oh, we have collected the data and and then right now we have to work with the data, and you know, like.

275
00:50:42.690 --> 00:50:45.960
Shamya Chodumada Karumbaiah: I think that is still important it's important that we do audits.

276
00:50:46.470 --> 00:50:55.350
Shamya Chodumada Karumbaiah: So save we have built model it's important that we go back if at any point, even if a model is in production and it's making automated decisions in the systems we have built.

277
00:50:55.740 --> 00:51:02.190
Shamya Chodumada Karumbaiah: I think it is still important that we go back to these models and audit them for the different subgroups that we are interested in.

278

00:51:02.640 --> 00:51:17.820
Shamya Chodumada Karumbaiah: Again I think question, there would be that, how do we know all the different subgroups and all of that, but you know that's it that's a difficult difficult it's very difficult problem that we all need to address in even understanding how do we come up with this list of Sub groups but.

279
00:51:18.990 --> 00:51:25.380
Shamya Chodumada Karumbaiah: Having an automated decision making algorithm in a system that is not being audited.

280
00:51:27.030 --> 00:51:30.690
Shamya Chodumada Karumbaiah: Just fundamentally makes me uncomfortable So that is where I would say that.

281
00:51:31.920 --> 00:51:40.800
Shamya Chodumada Karumbaiah: yeah So even if you have collected the data, there are several things you could do, while you're building a model, but maybe even after model is built in out in the.

282
00:51:41.370 --> 00:51:48.300
Shamya Chodumada Karumbaiah: out in production, the ways in which we can at least audit and be aware of potential base in which the biases systems could be.

283
00:51:48.720 --> 00:52:03.000
Shamya Chodumada Karumbaiah: could be bias, or in the future more data collection can then focus on finding ways in which we get focused to focus data collection for groups that we that are possibly underrepresented or under represented in our previous diversity connectedness it.

284
00:52:04.200 --> 00:52:12.450
Brendan Eagan: So it's almost sounds like very targeted types of closing the interpretive loop and QA speak to say like we're going to check for specific impacts of certain biases not just.

285
00:52:12.840 --> 00:52:26.070
Brendan Eagan: General stuff which I think would be a new articulation or practice that we kind of do the outlines of that so yeah you, you had a number of questions here, so I don't know if we can get through all of them in the remaining remaining time but i'll turn things over to you.

286
00:52:26.910 --> 00:52:36.420
YEYU WANG: yeah Thank you brandon since a lot of questions already touched by folks i'm going to ask focus on one question specifically which is you know we.

287
00:52:36.870 --> 00:52:57.030

YEYU WANG: are trying to model, the reality we collect data from the reality and I will try to make a model to make it abstract of the reality so during this process, I wonder how you could possibly quantify fairness in the model because I found is already.

288
00:52:58.290 --> 00:53:18.720
YEYU WANG: On tangible thing it's not like the Center deviation of the cracked versus now cracked it's, how do you think about that, like, how do you and that that into your model in terms of out there, regardless of the machine learning model model, what is the mechanism for that.

289
00:53:19.620 --> 00:53:35.610
Shamya Chodumada Karumbaiah: You, I just want to understand your question better here, so are you saying that there is difference between the proxies are the measurements of construct versus the true that the to construct the you know, there is a difference you're saying that there that there and how do we.

290
00:53:36.300 --> 00:53:44.550
YEYU WANG: yeah, as I said, our machine learning studies and maybe this will work is that will not only have a label for.

291
00:53:45.120 --> 00:53:59.250
YEYU WANG: esoteric prediction for going to college was is now going to college, that the ground truth level, but we probably have another set of the liberal in terms of their nose whether that's a fair representation versus not so we're.

292
00:53:59.340 --> 00:54:01.620
YEYU WANG: If we're examples of that.

293
00:54:02.040 --> 00:54:19.260
YEYU WANG: We make we calculate the loss function on both of that that could be a way out to operationalize and the quantified fairness in model, but I wonder how you guys quantify fairness in the models.

294
00:54:21.660 --> 00:54:26.730
YEYU WANG: And so that could be more aligned with what's reality is.

295
00:54:28.260 --> 00:54:39.720
Shamya Chodumada Karumbaiah: um I see I see um yeah actually this sort of can I don't know if my answer is, I don't think I have one answer for you, you here, but.

296
00:54:40.080 --> 00:54:53.730

Shamya Chodumada Karumbaiah: One thing, in which I have been thinking, because this is also specifically important for the kinds of automated decision making, that an adaptive learning system does like it's difficult to specifically say that something is fair versus unfair like say.

297
00:54:53.760 --> 00:54:58.860
Shamya Chodumada Karumbaiah: If a modern is giving a student, a question of particular skill set.

298
00:55:00.360 --> 00:55:09.450
Shamya Chodumada Karumbaiah: If it is below their current skill set or how do we reach out like how different is an algorithmic decision making, from a human decision making that.

299
00:55:09.780 --> 00:55:18.960
Shamya Chodumada Karumbaiah: Hope we hope is unbiased so maybe there is a way in which we could bring in voices of like teachers, maybe here in to even understand whether or not.

300
00:55:19.230 --> 00:55:32.430
Shamya Chodumada Karumbaiah: What we are considering, as these measures and what we we are defining as fair or unfair in the educational practice if that makes sense that kind of conception makes sense that's not really a concrete answer for you, you bet that's where my thinking is right now.

301
00:55:33.480 --> 00:55:35.040
YEYU WANG: yeah thanks so much shame yeah.

302
00:55:35.400 --> 00:55:40.620
Brendan Eagan: Well, I think I think a lot of these issues are we are should be part of ongoing discussions, obviously.

303
00:55:40.710 --> 00:55:42.300
Brendan Eagan: Like which I think you laid out nicely in your.

304
00:55:42.300 --> 00:55:48.510
Brendan Eagan: future work we are technically at time so i'd like to thank everyone for coming and quickly mentioned.

305
00:55:49.110 --> 00:55:55.620
Brendan Eagan: we're still finalizing some of the dates and timings, but we do have at least two if not three more of these webinars coming up.

306
00:55:56.040 --> 00:56:04.560

Brendan Eagan: I know, one of them for sure is going to be about teaching qe which will be happening, I believe, in September, and then there's a few others to look out for as well.

307
00:56:05.040 --> 00:56:16.200
Brendan Eagan: But please follow up with xiaomi yes, she is has been kind enough to drop her email into the chat there and i'm going to stop the recording now, and I would like to just thank.