FTC PrivacyCon
January 14, 2016
Segment 3
Transcript

>> WE'RE PLEASED TO HAVE DMIRGS

JULIE BRILL FORA FI REMARKS.

HE'S ON PRIVE SEA ASK DATA AND

WE'RE THRILLED TO HAVE HER HERE

TODAY.

COMMISSIONER BRILL.

>> THANK YOU CHRISTIAN AND THANK

YOU EVERYBODY WHO IS HERE AS

WELL AS ALL OF YOU OUT IN TV

LAND.

LUNCH MAY BE OVER BUT THE FEAST

OF SCHOLARSHIP WILL CONTINUE.

IT'S REALLY MY PLEASURE TO OPEN

THE AFTERNOON WITH A FEW REMARKS

ABOUT THE RESEARCH THAT'S ON

DISPLAY HERE AT PRIVACY CON BUT

BEFORE I DO THAT I HAVE TO TAKE

A MOMENT TO DO EXACTLY WHAT

CHAIRMAN RAMIREZ AND THAT IS TO

THANK THE STAFF WHO WORKED

INCREDIBLY HARDe1WELL TO PULL THIS TOGETHER.

CHRISTIAN, DAN,I KNOW I'VE LEAVINBUT THEY'VE BEEN A WONDERFUL

JOB.

COULD WE HAVE A ROUND OF

APPLAUSE FOR THESE FABULOUS

PEOPLE.

GREAT JOB.

ASIDE FROM THE QUALITY OF

PROJECTS AND PRESENTATIONS, ONE

THING HAS STRUCK ME ABOUT

TODAY'S AGENDA.

INSTEAD OF BEING ORGANIZED BY

DISCIPLINE, YOU KNOW, COMPUTER

SCIENCE HERE, ECONOMISTS OVER

THERE, THE DAYS ARE ORGANIZED+óISSUES IN CONSUMER PRIVACY.

THIS THOUGHTFUL ORGANIZATION IS

LEADING US TOWARDS SOMETHING

THAT WE NEED FOR SOUND PRIVACY

POLICY DEVELOPMENT.

ACROSS DISCIPLINARY RICHLY

DETAILED PICTURE OF CONSUMERS

AND HOW THEY MAKE DECISIONS

ABOUT TECHNOLOGY USE.

LURKING BEHIND THE MAIN

REGULATORY APPROACHES TO
PRIVACY, WHETHER IT'S NOTICE AND
CHOICE, INFORMATIONAL SELF
DETERMINATION OR A USE BASE
MODEL, OUR QUESTIONS ABOUT
INDIVIDUAL CONSUMERS, THEIR
GOALS IN EXERCISING THEIR
PRIVACY RIGHTS AND THEIR ABILITY
TO DO SO IN THE ENVIRONMENT
AROUND THEM.
AT A HIGH LEVEL, I THINK TWO
PRINCIPLES SHOULD GUIDE POLICY
AND PRACTICE.FIRST, INDIVIDUALS HAVE TO BE IN
THE LOOP, REGARDING DECISIONS
ABOUT WHAT DATA IS COLLECTED
ABOUT THEM AND HOW IT IS USED.
OUTSIDE THE PRIVACY SPHERE,
COMPANIES HAVE EXCELLED IN
HELPING CONSUMERS MANAGE AND USE
HIGHLY COMPLEX SYSTEMS.
NOW WE HEARD A LITTLE BIT ABOUT
CHIPOTLE AND THE BURRITOS.
I THINK ON A "BETTER ANALOGY IN

THIS SPACE WOULD BE CARS.
CARS ARE NOW COMPUTERS ON WHEELS.
BUT WE CAN ALL DRIVE THEM BECAUSE COMPANIES HAVE KEPT THE COMPLEXITY BEHIND USER INTERFACES THAT ARE SIMPLE TO USE.
I THINK COMPANIES CAN DO THE SAME FOR PRIVACY BUT%O BUILDING THE RIGHT TOOLS DEPENDS ON UNDERSTANDING WHICH DECISIONS ARE IMPORTANT TO INDIVIDUALS.
SECOND, I'M WEARY ON SOLUTIONS THAT DEPEND TOO HEAVILY ON ANY ONE TECHNICAL MEASURE.
NOW JUST AS AN EXAMPLE IT'S A POSITIVE DEVELOPMENT THAT COMPANIES ARE OFFERING MORE SERVICES THAT ALLOW INDIVIDUALS TO ENCRYPT THEIR COMMUNICATIONS AND THESE ARE GETTING MORE USER FRIENDLY.

BUT THEIR EASE OF USE IS LIMITED

TO COMMUNICATIONS THAT STAY

WITHIN ONE PARTICULAR SERVICE.

IF YOU WANT TO COMMUNICATE,EFORCED TO USE TOOLS THAT ONLY A

FEW SELECT EXPERTS CAN REALLY

IMPLEMENT PROPERLY AT THIS TIME.

BUT THESE PRINCIPLES LEAVE MANY

QUESTIONS OPEN AND DETAILS

UNSPECIFIED.

WHAT DATA DO CONSUMERS EXPECT

COMPANIES TO COLLECT FROM THEM.

HOW DO THEY EXPECT COMPANIES TO

USE THIS DATA.

WHAT DO CONSUMERS UNDERSTAND

ABOUT WHAT ACTUALLY HAPPENS TO

THEIR DATA.

WHICH ASPECTS OF DATA PROCESSING

SHOULD BE UNDER CONSUMER'S

CONTROL.

AND HOW EFFECTIVE ARE THE TOOL

THAT COMPANIES OFFER TO

CONSUMERS TO EXERCISE THIS

CONTROL.

ANSWERING THESE QUESTIONS REQUIRES A THREE DIMENSIONAL APPROACH. SO I WAS EXCITED TO HEAR THIS MORNING FROM RESEARCHERS WHO ARE USING STRUCTURED SURVEYS, QUALITATIVE INTERVIEWS AND LOOKING AT HUMAN COMPUTER INTERACTIONS TO MAP OUT WHAT CONSUMERS UNDERSTAND ABOUT THE DATA PRACTICES OF THE SERVICES AND DEVICES THEYZ USE. OF COURSE, IT IS JUST AS IMPORTANT TO UNDERSTAND MORE ABOUT WHAT HAPPENS BEHIND THE SCENES, OUT SIDE THE VIEW OF CONSUMERS. DATA AND DEVICE SECURITY ARE INCREDIBLY IMPORTANT TO CONSUMERS, YET ASSESSING SECURITY REMAINS WELL BEYOND THE CAPABILITIES OF MOST CONSUMERS. INCLUDING MOST OF US BUT NOT ALL

OF US IN THIS ROOM.
SO I'M THRILLED TO SEE
RESEARCHERS DOING A DEEP DIVE ON
SECURITY VULNERABILITIES ON
SPECIFIC INTERNET OF THINGS
DEVICES.
WHILE OTHERS ARE ANALYZING DATA
FROM THOUSANDS OF VULNERABILITY
REPORTS, TO BETTER UNDERSTAND
THE KINDS OF INCENTIVES THAT
WILL SPUR A VIRTUOUS CYCLE OF
DISCOVERY, REPORTING AND
PATCHING.
ALSO BEYOND CONSUMERS LIVES THE
DATA ANALYTICS THAT HAVE
DEVELOPED MORE QUICKLY THAN HAVE
FRAME WORKS FOR SPECIFIC
CONCRETE GUIDANCE ON LEGAL AND
ETHICAL ISSUES.
OUR BIG DATA REPORTWEEK IS INTENDED AS OUR FIRST
STEP TOWARDS PROVIDING SUCH
GUIDANCE.
THE REPORT RECOMMENDS THAT

COMPANIES REVIEW THEIR DATA SETS

AND ALGORITHMS TO DETERMINE

WHETHER THEY MAY BE HAVING

UNINTENDED EFFECTS.

SUCH AS TREATING CERTAIN

POPULATIONS DISOPERATELY AND INiDESPERATELY.

THEY BRING THEIR USE INTO BIG

DATA ANALYTICS.

THE PRESENTATIONS IN THE NEXT

SEGMENT OF PRIVACY CON ADDRESS

EXACTLY THOSE ISSUES.

FINALLY, I WANTED TO GIVE A

SHOUT OUT TO THE INSTITUTIONS

THAT HAVE HELPED PRODUCE THE

SPECIFIC PIECES OF RESEARCH THAT

WE'RE HEARING ABOUT TODAY.

THEY ARE JUST AS IMPORTANT AS

THE RESEARCH ITSELF.

MUCH OF THE RESEARCH PRESENTED

TODAY COMES FROM UNIVERSITIES

THAT HAVE MADE SUBSTANTIAL LONG

TERM COMMITMENTS TO EXAMING THE

RELATIONSHIPS BETWEEN LAW AND

PUBLIC POLICY.

IN ADDITION TO GENERATING NEW RESEARCH THAT ALSO CONTAINS POLICY INSIGHTS, THESE UNIVERSITIES HELPSTUDENTS TO BECOME LEADERS IN THEIR FIELDS.

TECHNOLOGY FOCUS SUMMERS AND CLINICS HAVE SPROUTED UP AT LAW SCHOOLS ALL OVER THE COUNTRY IN THE LAST DECADE.

THEY EXPOSE LAW STUDENTS TO TECHNOLOGY AND PROBABLYH JUST AS IMPORTANTLY TO THE WAY TECHNOLOGISTS THINK.

DEPARTMENTS, SCHOOLS AND EVEN ENTIRE CAMPUSES THAT MAKE INTERDISCIPLINARY WORK A CORE MISSION, ARE DOING MUCH THE SAME FOR STUDENTS OF COMPUTER SCIENCE, ENGINEERING, ECONOMICS, PUBLIC POLICY AND SOCIAL SCIENCES.

BUILDING THESE PROGRAMS HAS NOT

BEEN EASY.

IT'S OFTEN EASIER TO STICK

CLOSER TO TRADITIONAL

DISCIPLINARY LINES.

SO LET ME OFFER A WORD OF

ENCOURAGEMENT.

PRIVACY CON IS JUST ONE EXAMPLE

OF THE IMPACT THAT SCIENTISTS,

LAWYERS AND OTHERS CAN HAVE WHEN

THEY ARE TRAINED TO DO GROUND

BREAKING RESEARCH AS WELL AS TO

IDENTIFY AND ANALYZE PUBLIC

POLICY QUESTIONS AND ISSUES.

THIS COMBINATION OF RESEARCH

CAPABILITY AND CAPACITY FOR

ACTION ALSO DESCRIBES JUST

COINCIDENTLY THE DESIGN OF THE

FTC ITSELF.

SO NATURALLY WE ARE A READY

AUDIENCE3" FOR RESEARCH THAT SHEDS

LIGHT ON THE CHALLENGES WE

CONFRONT IN ENFORCEMENT AND

POLICY DEVELOPMENT.

AND I HOPE THAT THE INSTITUTIONS

THAT MANY OF OUR PRESENTERSY,B<÷ CALL

HOME WILL BEFOR ROBUST EXCHANGE OF IDEAS

WITH THE PUBLIC AND PRIVATE

SECTORS FOR MANY YEARS TO COME.

SO WITH THAT, LET'S HERE WHAT

YOU HAVE.

THANK YOU VERY MUCH.

DAN WILL INTRODUCE THE NEXT

PANELISTS, THANK YOU.

>> THANK YOU COMMISSIONER BRILL.

COULD THE NEXT PANEL COME ON UP.1?P$i

OUR FIRST SESSION TODAY REALLY

LOOKS AT WHAT KIND OF DATA IS

BEING COLLECTED ABOUT CONSUMERS.

OUR SECOND PANEL, WHAT DO

CONSUMERS EXPECT IS HAPPENING

ABOUT DATA.

AND NOW THIS SESSION WE'RE GOING

TO LOOK AT WHAT ACTUALLY IS

HAPPENING WITH THE DATA.6p

SO I'M REALLY PLEASED TO HAVE

WITH ME RESEARCHERS WHO ARE

GOING TO PRESENT THREE STANDING
RESEARCH PRESENTATIONS, AND
WE'RE GOING TO THEN DISCUSS
THEM.
SO WHY DON'T WE GET THINGS
STARTED WITH A PRESENTATION FROM
MICHAEL TSCHANTZ AND ANUPAM
DATTA.
THEY'RE GOING TO LEAD THINGS UP
WITH A PRESENTATION TITLED
AUTOMATED EXPERIMENT ON AD
PRIVACY SETTINGS.
>> THANK YOU.
I AM MICHAEL TSCHANTZ AND THIS
IS A JOINT PRESENTATION WITH
ANUPAM DATTA.
WE'RE LOOKING AT ON-LINE
TRACKERS AND WHAT INFORMATION
THEY ARE LEARNING ABOUT PEOPLE
THAT SHOWEDb(
ADS TO PEOPLE.FIRST IT IS POSSIBLE TO DO THIS
WITH SCIENTIFIC RIGOR DESPITE
NOT HAVING ACCESS TO THE SYSTEM.

AND SECOND, WE CAN FIND

INTERESTING INFORMATION BUT WE

CAN'T FIGURE OUT WHY THEY

HAPPENED.

SO LET'S GET STARTED BY

MOTIVATING THE PROBLEM.

HERE'S A WEB PAGE, IT'S THE

TIMES OF INDIA.

I FIND IT AS AN INTERESTING

EXAMPLE BECAUSE IT HAS A LOT OF

ADS FROM GOOGLE HERE.séQá"h:==ACROSS THE INTERNET.

IN FACT THIS WEB PAGE HAS TWO

PIECES OF CODE AND THESE PIECES

OF CODE REPORTS BACK TO GOOGLE

ABOUT WHAT OTHER WEB PAGES YOU

VISITED.

GOOGLE CAN THEN SELECT THE ADS

IT SHOWED ON THE TIMES OF INDIA

BASED UPON THIS INFORMATION.

THIS IS GENERALLY TRUE OF

ON-LINE BEHAVIOR TRACKERS AS

MANY TRACKERS WITH LITTLE PIECES

OF CODE ALL OVER THE PLACE.

THERE'S A SEEMINGLY END LESS

NUMBER OF COMPANIES DOING THIS

KIND OF THING.

BUT IT CAN BE DISCONCERTING.

SUPPOSE FOR EXAMPLE YOU WANT TO

SHOW A FRIEND A NEWSPAPER

ARTICLE AND YOU SEE NOTHING BUT

ADS FOR ANTIDEPRESSANTS WHICH

WILL SHOW UNDER CERTAIN

CIRCUMSTANCES.

NOW, GOOGLE UNDERSTANDS THAT

PEOPLE HAVE CONCERNS LIKE THIS,

SO THEY AND OTHER COMPANIES HAVE

PROVIDED THINGS LIKE THEI4 AD

PRIVACY SETTINGS.

HERE IS A SCREEN SHOT OF MY AD

PRIVACY SETTINGS.

IT SHOWS VARIOUS INFORMATION

INFERRED ABOUT ME.

GOOGLE GOT MY AGE CORRECT BUT

GOT MY GENDER WRONG.

GOOGLE ALSO ALLOWS YOU TO GO IN

AND EDIT THIS INFORMATION.

SO IF I CARED, I COULD GO IN

THERE AND PROVIDE MY CORRECT

GENDER.

GOOGLE DOESN'T GIVE US A WHOLE

LOT OF INFORMATION ABOUT EXACTLY

HOW THIS THING IS WORKING,

HOWEVER.

SO, WHAT WE HAVE IS A SITUATION

WHERE WE HAVE OUR WEB BROWSING

BEHAVIOR GOING INTO AN AD

ECOSYSTEM.

YOU HAVE VARIOUS THINGS LIKE AD

SETTINGS SITTING IN THE MIDDLE

SORT OF A WINDOW HOW THAT AD

ECOSYSTEM WORKS.

PROVIDING INFERENCES THEY CREATE

AND ALLOWING YOU TO PUT EDITS IN

AND THEN WE SEE AAVERTISEMENTS

COMING OUT THE OTHER END.

BUT WE WOULD.THE FLOWS OF INFORMATION IN THIS

SYSTEM BETTER THAN THEY

CURRENTLY MAKE CLEAR FROM THEIR

PRIVACY POLICIES AND

DESCRIPTIONS OF HOW THESE

SYSTEMS WORK.

THIS IS A DIFFICULT TASK BECAUSE

THE SYSTEM IS OPAQUE.

WE DON'T KNOW WHAT'S GOING ON IN

THATeGOOGLE AND OTHER ON-LINE

BEHAVIORIAL TRACKERS WON'T SHARE

ITS SOURCE CODE WITH US, WE

CAN'T DO THE TRADITIONAL FORMS

OF PROGRAM ANALYSIS.

SO WE DESIGNED AD FISHER A

SYSTEM THAT ALLOWS US TO RUN

EXPERIMENTS ON THESE AD OPAQUE

ECOSYSTEMS.

LET ME RUN THROUGH WHAT AD

FISHER WORKS.

IT CREATES FIREFOX INSTANCES

WHICH STIMULATE USERS.

SO THESE COULD BE SIMULATING

PEOPLE WHO BROWSE VARIOUS

WEBSITES.

IT RANDOMLY ASSIGNS THEM TO

EITHER A CONTROL OR AN

EXPERIMENTAL GROUP.

THESE TWO GROUPS OF SIMULATED

USERS WILL DISPLAY DIFFERENT

THEY THEN INTERACT WITH THE

INTERNET IN VARIOUS WAYS AND WE

COLLECT MEASUREMENTS ABOUT HOW

ADVERTISERS CHANGE THEIR

BEHAVIOR TOWARDS THESE SIMULATED

USERS.

THESE MEASUREMENTS GO INTO A

TEST OF STATISTICAL

SIGNIFICANCE, WHICH REPORTS

WHETHER THERE'S A STATISTICALLY

SIGNIFICANT SYSTEMATIC

DIFFERENCE BETWEEN THEdAÑli

EXPERIMENTAL AND THE CONTROL

GROUP.

IF SO, WE KNOW THAT WHATEVER

INFORMATION DESCRIBES THE

DIFFERENCE BETWEEN THESE TWO

GROUPS AND HOW THEY BEHAVE

TOWARDS THE AD ECOSYSTEM IS

INFORMATION BEING USED BY THE AD

ECOSYSTEM TO SELECT ADS.

SO THIS IS OUR MAIN CONTRIBUTION

IS THAT WE BROUGHT DERIGOR OF

EXPERIMENTAL SCIENCE TO THESE

SORT OFqé ON-LINE BLACKú0"

BOXEXPERIMENTS IN SUCH A WAY THAT

ALLOWS US TO DEFECT EFFECTS

WHICH ARE=INFORMATION WITH THE THEOREM.

IT DOES IT WITHISTIC

SIGNIFICANCE WITHOUT MAKING

QUESTIONABLE ASSUMPTIONS ABOUT

HOW GOOGLE OPERATES.

THIS IS IMPORTANT BECAUSE

GOOGLE'S AN EXTREMELY COMPLEX

SYSTEM PRETTY MUCH ANY

ASSUMPTION YOU MAKE ABOUT HOW IT(6y÷ç

OPERATES, MIGHT NOT HOLD OR

PERHAPS IT HOLDS IT FOR ONE

MOMENT IN TIME BUT NOT LATER

WHEN YOU'RE RUNNING YOUR

EXPERIMENT.

AND WE PROVIDE A HIGH DEGREE OF

AUTOMATION.

SO NOW I'M GOING TO GIVE YOU AN

EXAMPLE OF ONE OF THE FINDINGS

WE DISCOVERED WITH OUR SYSTEM.

THIS EXPERIMENT, WHAT WE DO WAS

WE FIRED UP OUR SIMULATED USERS

AND WE HAD HALF OF THEM SIT THE

GENDER BIT TO BE MALE ANDLv:9á¦

OTHER HALF TO FEMALE ON THE

GOOGLE AD SETTINGS PAGE.

WE HAC¦ THEM ALL BROWSE WEBSITES

RELATED TO FINDING JOBS.

WE THEN COLLECTED THE ADS SHOWN

TO AT THE TIMES OF INDIA AND WE

FOUND SIGNIFICANT DIFFERENCE

FROM THE ADS OF THE MALE AND

FEMALE GROUPS.

THIS ISN'T TERRIBLY SURPRISING.

WE KNOW ADVERTISERS SHOWS

DIFFERENT ADS TOWARDS MEN AND

WOMEN.

WHAT'S CONCERNING IS THE NATURE

OF THISTHAT AD FISHER CAN ALSO SHARE

WITH US.

WHAT WE FOUND IS THERE WERE A

SERIES OF ADS FROM A CAREER

COACHING SERVICE THAT WAS SHOWN

ALMOST ONLY TO THE MALE

SIMULATED USERS.

IN FACT, THE RATIO WAS SO LARGE

THAT IT'S IN VIOLATION OF THE80% RULE OFTEN USED IN

EMPLOYMENT LAW TO DETECT

DISPARATE IMPACT.

WE'RE NOT CLAIMING THIS IS AN

INSTANCE OF ILLEGAL DISPARATE

IMPACT.

THIS IS A COACHING SERVICE, IT'S

NOT ACTUALLY FOR A JOB.

NEVERTHELESS WE FIND THISBEING SHOWN PREDOMINANTLY TO MEN

TO BE CONCERNING.

NOW THIS IS JUST ONE OF THE

FINDINGS.

WE HAVE ANOTHER INTERESTING ONE

INVOLVING SUBSTANCE ABUSE.

WE FOUND THAT IF YOU VISITED A

WEBSITE FOR A REHAB CENTER,

GOOGLE WILL START SHOWINGhLADS FOR THAT REHAB CENTER ACROSS

THE WEB OR AT LEAST AT THE TIMES

OF INDIA.

THIS IS CONCERNING SINCE IT'S

SORT OF LIKE MEDICAL INFORMATION

BEING USED FOR DETERMINING THE

ADS YOU SEE ON A NEWSPAPER'S

WEBSITE.

SO I USE MY TIME TO EXPLAIN SOME

OF THE THINGS WE KNOW.

ANUPAM IS GOING TO EXPLAIN SOME

INTERESTING QUESTIONS LEFT OPEN.

>> I'M VERY EXCITED TO WHERE

THIS RESEARCH AREA'S GOING IN

TERMS OF DEVELOPING RIGOROUS

SIGNS AND USEFUL TOOLS THAT ARE

BEGINNING TO FIND EFFECTS IN THE

AN ON-LINE PERSONALIZATION

SYSTEMS.

AT THE SAME TIME I'M DEEPLY

CONCERNED ALSO ABOUT THE

FINDINGS?QZS THEMSELVES THAT WE AND

OTHERS IN THIS RESEARCH AREA ARE

BEGINNING TO DEVELOP AND WE'LL

HEAR MORE FROM THE TWO OTHER
SPEAKERS SHORTLY ABOUT OTHER
FINDINGS.
THESE STUDIES ARE BEGINNING TO
GET A LOT OF ATTENTION IN THE
POPULAR PRESS INDICATING THAT
THESE CONCERNS ARE SHAREDh% MUCH
MORE BROADLY IN THE COMMUNITY.
BUT THERE'S MUCH MORE TO DO IN
THIS CASE.
THERE ARE QUESTIONS LIKE HOW
WIDE SPREAD ARE INSTANCES OF
DISCRIMINATORY TARGETING OR
TARGETING THAT VIOLATES PRIVACY
EXPECTATIONS, OF PERHAPS
CONTEXTUAL INTEGRITY OR OTHER
NOTIONS.
AND THEN THERE'S ALSO THE
QUESTION OF WHO IS RESPONSIBLE.
SO I WANT TO TAKE A FEW MINUTES
TO HIGHLIGHT THAT THESE
QUESTIONS ARE INCREDIBLY NUANCED
TO ANSWER IN THE PRESENCE OF THE

COMPLEXITIES OF DATA ANALYTICS
AND OTHER PIECES OF AN AD EQUAL
SYSTEM.
SO I'M GOING TO FOCUS ON THIS
QUESTION OF RESPONSIBILITY
PARTLY BECAUSE FOLLOWING UP ON
THE CONVERSATIONS FROM THE
MORNING, I THINK THAT DETECTION
IScCAN'T JUST STOP THERE.
WE HAVE TO GO TOWARDS
ACCOUNTABILITY, MEETING
ASSIGNMENT OF RESPONSIBILITY AND
INSTITUTION OF CORRECTIVE
MEASURES.
AND THIS IS GOING TO INVOLVE
COLLABORATION BETWEEN COMPUTER
SCIENTISTS AND LEGAL SCHOLARS
AND PROBABLY POLICY CHANGES.
I WANTED TO FOCUS ONLY ON THE
COMPUTER SCIENCE PIECE OF IT FOR
NOW, BUT WE ARE WORKING ON THE
INTERACTION BETWEEN COMPUTER
SCIENCE AND LAW INEç=CCOLLABORATION WITH DAVID MILL

BEGUN -- THIS IS WHERE JOB RELATED ADS WERE BEING SERVED IN NUMBERS IN SIMULATED MALE USERS. WE'RE TALKING ABOUT WHAT PARTY SHOULD BE RESPONSIBLE. ONE POSSIBILITY IS THAT GOOGLE'Síc PROGRAMMERS INTENTIONALLY TARGET IT THIS WAY. WE CONSIDER THAT TO BE HIGHLY UNLIKELY BUT NEVERTHELESS IT'S NOT SOMETHING WE CAN RULE OUT BECAUSE WE DON'T HAVE ENOUGH VISIBILITY OR ACCESS INTO THE SYSTEM THAT THEY USE INTERNALLY. ANOTHER POSSIBILITY IS THAT THE ADVERTISERS, THE SPECIFIC ADVERTISER, IN THIS CASE THE BARRETT GROUP THAT WAS ADVERTISING FOR THIS CAREER COACHING SERVICE, MIGHT HAVE INDICATED WHEN THEY SUBMITTED THEIR BID FOR THE AD THAT GOOGLE SHOULD SHOW THIS AD MORE TO MALE

USERS THAN TO FEMALE USERS, AND

GOING MAY HAVE HONORED THAT

REQUEST.

A THIRD POSSIBILITY IS THAT

PERHAPS THE BARRETT GROUP

INDICATED THAT THE AD SHOULD BE

SHOWN TO HIGH EARNERS.

IN FACT, IN RESPONSE FROM

QUESTIONS FROM THE JOURNALISTS

AT PITTSBURGH GADGET THE BARRETT

GROUP ACTUALLY SAID THEY WERE

TARGETING USERS OVER THE ABLE OF

45 AND WHO EARN MORE THAN

$100,000 PAUSE THEY THOUGHT THAT

WOULD BE AN APPROPRIATE GROUP TO

TARGET FOR PEOPLE WHO WOULD WANT

TO GO ONE LEVEL UP AND GO FOR

THE 200K PLUS JOBS.

IT COULD BE THESE HIGH EARNERS

ARE MUCH MORE STRONGLY

CORRELATED WITH THE:THAN THE FEMALE GENDER AND

GOOGLE MAY HAVE INFERRED THAT

AND THEN DECIDED THAT THEY

SHOULD SEND MORE IMPRESSIONS OF THIS AD TO MALE USERS THAN TO FEMALE USERS.

YET ANOTHER POSSIBILITY IS THAT OTHER ADVERTISERS MIGHT BE TARGETING THE FEMALE DEMOGRAPHIC MORE, AND THERE'S SOME EVIDENCE THAT FEMALE DEMOGRAPHIC IS TARGETED MORE BY ADVERTISERS.

BECAUSE THEY MADE MORE PURCHASING DECISIONS, AND THOSE OTHER ADS MAY HAVE COME WITH HIGHER BID AMOUNTS WHICH TOOK UP THE SLOTS FOR THE FEMALE USERS AND THE MALES JUST GOT THE AD FROM THIS PARTICULAR SERVICE BECAUSE THEY WERE THE LEFT OVER UNTARGETTED, THERE WAS JUST MORE SLOTS AVAILABLE FOR THE MALE USERS.

YET ANOTHER POSSIBILITY, AND THIS WOULD BE THE CASE OF MACHINE LEARNING INTRODUCING

DISCRIMINATION IS THAT GOOGLE'S

INTERNAL SYSTEMS MAY HAVE

OBSERVED THAT MORE MALE USERS

ARE CLICKING ON THIS?v PARTICULAR

AD THAN FEMALE USERS.

AND SINCE MACHINE LEARNING

SYSTEMS LEARNED FROM THESE KINDSw[y

OF OBSERVATIONS AND THEY ARE

TRYING TO OPTIMIZE FOR THE CLICK

THROUGH RATE, THEY MAY HAVE

SERVED MORE IMPRESSIONS TO THESE

ADS TO THE MALE USERS.

ALL OF THESE ARE HYPOTHETICAL

SCENARIOS BECAUSE WE DON'T HAVE

AVAILABILITY INTO THE SYSTEM TO

DETERMINE WHICH OR ANY OF THESE

SITUATIONS POSSIBLE EXPLANATIONSÑR[uñ

IS THE REAL EXPLANATION.

I WANTED TO HIGHLIGHT THIS TO

EXPLAIN THE NUANCE OF THIS

PROBLEM THAT THIS IS A VERY

COMPLICATED PROBLEM.

IF YOU WANT TO GO TOWARDS MAKING<4

SYSTEMS MORE ACCOUNTABLE IN THIS

SPACE, THEN THE RESEARCHERS WILL

NEED ADDITIONAL ACCESS TO THE

INTERNS OF THE SYSTEM.

SO BEING ABLE TO WORK NOT JUST

FROM THE OUTSIDE LIKE WE HAVEéKTHIS WORK AND ROXANA WILL TALKER

ABOUT THIS IN HER WORK.

THE PEOPLE WHO HAS ACCESS AND

PROACTIVELY TESTING THEIR÷XSYSTEMS.

THAT ADDITIONAL STEPS WILL BE

VERY CRUCIAL TOWARDS PROACTIVE

DETECTION OF VIOLATIONS AS WELL

AS IDENTIFYING RESPONSIBILITY.

THAT'S SOMETHING THAT I URGE

THIS COMMUNITY TO GO1p TOWARDS AND

IT'S OPEN CALL TO WORK WITH

RESEARCHERS LIKE US TO WORK ON

PROBLEMS LIKE THIS FORM THAT ARE

SOCIALLY IMPORTANT.

LET ME STOP HERE WITH THE

SUMMARY THAT WHAT THIS BODY OF

WORK AD FISHER AND PREVIOUS

RESULTS THAT INTRODUCES THE

METHODOLOGY BRINGS RIGOROUS

EXPERIMENTAL DESIGN IDEAS TO

THIS RESEARCHóÑe# AREA WHICH LETS US

DISCOVER CAUSAL EFFECTS WHICH

IT'S REALLY THE DIFFERENCE IN

GENDER WHICH CAUSE THE

DIFFERENCE OF JOB-RELATED ADDS

BEING TARGETED WITH

STATISTICALLY SIGNIFICANCE.

WITH CONFIDENCE IT'S NOT JUST A

FLUKE OBSERVATION BUT IT'S

REALLY HOW THE SYSTEM IS

BEHAVING.

AND A THIRD KIND OF CONTRIBUTION

HERE IS TO BRING AUTOMATION THAT

ALLOWS US TO DISCOVER THESE

KINDS OF EFFECTS AT SCALE.

AND THIS

COMBINATION WAS THEFIRST IN OUR WORK AND THEN THE

COMMUNITY HAS WITHDRAWN AND

DEVELOPED IT IN MANY DIFFERENTtGDIMENSIONS.

SO WE FOUND EVIDENCE OF

GENDER-BASE DISCRIMINATIONED.

THAT WAS ONE SPECIFIC HIGHLIGHT
AND THE OTHER HIGHLIGHT HOW
BROWSING RELATED WEBSITES HAVE
AN EFFECT IN PARTICULAR
SUBSTANCE ABUSE, BROWSING
SUBSTANCE ABUSE WEBSITES RESULT
IN REHAB ADS BEING TARGETED.
THE TWO OPEN QUESTIONS THAT I
WANT US TO OPEN UP FOR
DISCUSSION AND THESE ARE ACTIVE
AREAS OF RESEARCH IN THIS AREA
IS HOW WIDE SPREAD IS THIS
DISCRIMINATION AND HOW DO WE GO
FROM HERE TO ASSIGNING
RESPONSIBILITY.
AS A COROLLARY, I WOULD LIKE TO
EMPHASIZE THAT ADDITIONAL ACCESS
TO THE INTERNS OF THE SYSTEMS,
PEOPLE WITH ACCESS WORKING WITH
SUCH PEOPLE IS GOING TO BE
HIGHLY CRUCIAL TOWARDS THAT.
THANK YOU VERY MUCH.
>> THANK YOU ANUPAM AND MICHAEL.

NOW WE'RE GOING TO HEAR FROM
ROXANA GEAMBASU SUNLIGHT FINE
GRAINED TARGETING DETECTION AT
SCALE WITH STATISTICAL
CONFIDENCE.
>> HELLO EVERYONE.
I'M VERY HAPPY TO BE HERE.
I WILL NOW TELL YOU ABOUT SOME
TOOLS THAT WE ARE BUILDING AT
COLUMBIA TO INCREASE THE WEB'S
TRANSPARENCY AT LARGE SCALE.
TO MOTIVATE OUR WORK, I'LL START
WITH AN EXAMPLE THAT SHOWS JUST
HOW OPAQUE TODAY'S WEB IS.
AND YOU P@DBABLY ALREADY KNOW
THAT G MAIL USES E-MAILS IN
ORDER TO TARGET ADS.
BUT YOU KNOW THE KEY WORDS ARE
INFERENCES DRAWN FROM THESE
E-MAILS ARE BEING USED TO TARGET
YOU SPECIFICALLY.
I'LL TEST TO SEE HOW AWARE YOU
ARE OF HOW YOU'RE BEING TARGETED

BY SHOWING YOU SOME EXAMPLES

THAT WE GOT FROM AN EXPERIMENT.

WE CREATED THIS G MAIL ACCOUNT

AND POPULATED IT WITH A BUNCH OF

VERY SIMPLE TOPIC E-MAILS.

HERE ON THE LEFT-HAND SIDE FIVE

OF THOSE E-MAIL ARE ABOUT 300

THAT WE CREATED.

ON THE, AFTER THAT WE RETRIEVED

ADS THAT G MAIL SHOWED IN THIS

ACCOUNT.

I'M SHOWING HERE ON;. THE

RIGHT-HAND SIDE ADS OUT OF

20,000 WE GOT.

THIS IS A PRETTY LARGE SCALE

EXPERIMENT.

WHAT I WANT TO DO IS TO

CHALLENGE YOU GUYS TO TELL ME

WHAT EACH AD IS TARGETING.

SO FOR EXAMPLE WHAT ISTARGET.

WHICH OF THE E-MAILS?

WHAT DO YOU THINK?

JUST QUICKLY.

WHATEVER COMES TO MIND.

VACATION.

WELL, IT ACTUALLY TURNS OUT THAT

AD ONE TARGETS THE

PREGNANCY-RELATED E-MAIL.

IT'S PRETTY HARD TO TELL, RIGHT.

NOTHING IN THE AD TELLS YOU

ANYTHING ABOUT HOW IT'S ACTUALLYTARGETED.

WHAT ABOUT AD TWO.

IT'S ABOUT A HOTEL.

WHAT ISÑñ THIS ONE TARGETED?

I'M SORRY.

YOU GOT IT RIGHT.

THAT'S EXACTLY RIGHT, THE

HOMOSEXUALITY-RELATED E-MAIL.

AGAIN IT'S STILL PRETTY HARD TO

TELL.

IT'S NOT JUST ABOUT TARGETING OF

ADS ON GMAIL THAT'S HARD TO

DISCERN, EVERYTHING IS OBSCURE

ON THE WEB.

FOR EXAMPLE THEY'VE GOT BROKERS

APPARENTLY ARE USING, YOU KNOW,

CAN TELL WHEN YOU'RE SICK OR DEPRESSED AND APPARENTLY SELL THIS INFORMATION.

OR SOME CREDIT COMPANIES FOR EXAMPLE ARE TRYING APPARENTLY NOW TO USE FACEBOOK INFORMATION IN ORDER TO DECIDE WHETHER OR NOT TO GIVE OUT A LOAN.

YOU KNOW, YOU MAY HAVE HEARD OF THESE THINGS FROM THE MEDIA JUST LIKE I DID, BUT DO YOU KNOW THAT WHEN, WHETHER THESE THINGS ARE ACTUALLY HAPPENING, TO WHAT DEGREE AND HOW THOSE THINGS AFFECT YOU.

I BET NOT, PEOPLE DON'T KNOW TOO MUCH ABOUT THESE THINGS.

WELCOME TO THE DATA-DRIVEN WEB.

MEDIA OF WEB SERVICES AND THIRD PARTIES COLLECT HUGE AMOUNTS OF INFORMATION ABOUT US, YOUR LOCATION, EVERY SITE, EVERY VISIT, EVERY CLICK YOU HOCKEY

AND -- CLICK AND SO ON.

THEY LEVERAGE THIS FOR

INFORMATION.

SOME IN LINE WITH OUR INTERESTS.

FOR EXAMPLE WE LIKE PANDORA

RECOMMENDATIONS BUT OTHER USES

MAY NOT BE SO BENEFICIAL FOR US.

THE BIG PROBLEM IS WE HAVE

ABSOLUTELY NO VISIBILITY INTO

WHAT HAPPENSTHIS HUGE COMPLEX WEB DATA

ECOSYSTEM.

WE HAVE ACCESS TO RAW DATA.

FOR WHAT PURPOSES ARE THEY USING

IT.

IS THIS GOOD OR BAD FOR US.0.p#¦

HOW DO THEY USES AFFECT US

REALLY.

IT'S NOT JUST THE END USERS THAT

DON'T KNOW HOW TO ANSWER THESE

QUESTIONS, BUT SOCIETY AS A

WHOLE HAS A HARD TIME ANSWERING

THESE QUESTIONS AND

YOU HAVE TO SEE AS WELL FROM MY

COMMUNICATIONS WITH THEM.

AND THAT'S VERY DANGEROUS

BECAUSE OBSCURITY AND LACK OF

OVERSIGHT CAN LEAD TO ABUSES

EITHER INTENTIONAL OR NOT T SO

IN -- NOT.

SO IN MY GROUP AT COLUMBIA WE'REçPWHICH WE CALL TRANSPARENTY

INFRASTRUCTURE THAT SHOULD LIGHT

INTO THIS DARK DATA DRIVEN WEB.

OUR GOAL IS TO BUILD REALLY

LARGE SCALE INFRASTRUCTURES THAT

CAN GO OUT THERE ON THE WEB AND

TRACK THEAND REVEAL IT, OWE THAT ON ONE

HAND WE CAN INCREASE USERS'

AWARENESS WHAT HAPPENS TO THEIR

DATA ON-LINE AND ON THE OTHER

HAND INCREASE, EMPOWER PRIVACY

WATCHDOG SUCH AS THE FEDERAL

TRADE COMMISSION TO AUDIT WHAT

WEB SERVICES ARE DOING WITH THE

DATA AND KEEP THEM ACCOUNTABLE

FOR THEIR ACTIONS.

AND OVER THE PAST SEVERAL YEARS

WE'VE BEEN BUILDING A NUMBER OF

THESE TRANSPARENCY

INFRASTRUCTURES AND WE'RE

CONTINUING TO DO SO NOW.

AND I'LL TELL YOU ABOUT JUST ONE

OF THESE 249ONE OF -- IN THE REMAINING TIME

JUST ONE OF THESE STRUCTURES.

THE DOMAIN INFRASTRUCTURE THAT

WE'VE BUILT.

BEFORE I DO THAT, I WANT TO

ACKNOWLEDGE MY STUDENTS AND

COLLABORATORS WITHOUT WHOM

OBVIOUSLY I WOULDN'T BE STANDING

HERE TELLING YOU ABOUT THESE

SYSTEMS.

SO WHAT'S SUNLIGHT.

IT'S A GENERIC SYSTEM USED FOR

THE SPECIFIC PURPOSE OF

TARGETING AND PERSONALIZATION.

IT DETECTS WHICH SPECIFIC DATAAL

ABOUT THE USER SUCH AS E-MAIL

SEARCHES OR VISITED WEBSITES.

ARE BEING USED TO TARGET WHICH

SERVICE OUTPUTS SUCH AS ADS,

RECOMMENDATIONS OR PRICES.

THE ADS THAT I SHOWED YOU AT THE

BEGINNING OF THE TALK THEY'RE

TARGETING WAS DISCOVERED BY

SUNLIGHT HAS THREE UNIQUE

PROPERTIES IN THEIR COMBINATION

COMPARED TO EVERYTHING ELSE THAT

EXISTS.

IT IS PRECISE, SCALABLE AND VERY

APPLICABLE.

WE'VE ALREADY TRIED IT WITH

GREAT SUCCESS TO REVEAL

TARGETING OF GMAIL ADS, ADS ON

ARBITRARY WEBSITES.

RECOMMENDATIONS ON AMAZON AND

YOUTUBE AND PRICES ON VARIOUS

TRAVEL WEBSITES.

NOT ALL OF THESE HE CAN

--EXPERIMENTS ARE IN OPEN DOMAIN.

SOME OF THESE WORK WITH HIGH

PRECISE AROUND 95%.

IT IS INTUITIVE.

SUNLIGHT IS FIRST TARGETING BY

CORRELATINGpq USERS' INPUTS WITH

E-MAILS SUCH AS SERVICE OUTPUTS

LIKE ADS BY PERFORMING E-MAILS

ON ACCOUNTS WITH DIFFERENTIATED

USERS INPUTS.

WE CAN ACTUALLY MAKE THE LINK

FROM CORRELATION TO CAUSATION IF

WE CONTROL HOW THOSE INPUTS ARE>[:L¦

PLACED IN THE ACCOUNTS.

LET ME SHOW YOU AN EXAMPLE

QUICKLY JUST TO ILLUSTRATE THIS

PROCESS.

SO REMEMBER THE ADS THAT I

SHOWED YOU AT THE BEGINNING OF

THE TALK.

I'LL SHOW YOU HOW SUNLIGHT MIGHT

HAVE DETECTED

LET ME FIRST SIMPLIFY THE

EXAMPLE.

LET'S KEEP JUST THREE E-MAILS

AND ONE AD.

LET'S DITCH THE CONTENTS OF THE

E-MAILS AND ADS.

SO WHAT WE HAVE IS A MAIN

ACCOUNT THAT CONSISTS OF

E-MAILS, E1, E2 AND E3.

THESE ACCOUNTS IS AD ONE.

WHAT WE WANT TO DO IS TO EXPLAIN

THE TARGET IN AD 1 ON THESE, ONE

OR A COMBINATION OF THESE THREE

E-MAILS.

WHAT WHOLE DO IS THREE THINGS.

FIRST, WE CREATE A SET OF EXTRA

ACCOUNTS.

WE CALL THESE SHADOW ACCOUNTS,

SAY THREE, THREE ACCOUNTS.

AND POPULATE THEM WITH DIFFERENT

SUBSETS OF THE/c E-MAILS.

WE DO THIS IN A RANDOMLY SO THE

PLACEMENT OF THE E-MAILS INTO

THE:jh6P(áeEÑ IS RANDOM, IS DONE

RANDOMLY, INDEPENDENT OF ANY

OTHER VARIABLE.

SECOND, WE COLLECT ADS FROM THE

SHADOW ACCOUNTS AND YOU KNOW SAY

FOR EXAMPLE IN THIS EXAMPLE,

THAT SHADOW ACCOUNTS TWO AND

THREE OBSERVE AD ONE BUT ONE

ACCOUNT DOESN'T.

THIRD WE ANALYZE THESE

OBSERVATIONS AND YIELD THE

TARGETING PREDICTION.

AND IN THIS CASE THE MOST

NATURAL PREDICTION THAT WE WOULD

REACH IS THAT AD 1 TARGETS

E-MAIL 3 BECAUSE THE E-MAIL

APPEARS IN E-MAIL 3 BUT NEVER IN

ACCOUNTS WITH E-MAIL 3.

THAT'S KIND OF HOW SUNLIGHT

WORKS.

NOW THERE'S AN IMPORTANT

DISTINCTION THAT I'D LIKE TO

MAKE WHICH IS THAT THE FIRST TWO

PAGES OF THIS PROCESS POPULATING

SHADOW ACCOUNTS WITH SUBSTANCE

OF THE E-MAILS AND COLLECTING

ADS FROM THEM ARE SERVICE

SPECIFIC.

IN PARTICULAR IN SUNLIGHT KIND

OF MINDLESS PRETTY SYMBOL,

SIMPLISTIC, WE JUST DO SOME ODD

MAKES.

THE -- ODD MAKES.

TO YIELD THE TARRING PREDICTION

IS INTELLECTUAL CHALLENGING AND

THAT'S WHAT SUNLIGHT ACTUALLY

PROVIDES.

SPECIFICALLY THE EXAMPLE I

SHOWED YOU HERE IS TRIVIAL.

IN REALITY, THE SCALE IS MUCH

LARGER, THERE ARE A LOTdR MORE

E-MAILS TO CONSIDER, A LOT MORE

ADS TO EXPLAIN, THERE'S A LOT

MORE.

SO ALL OF THESE THINGS MAKE

TARGETING PREDICTION

CHALLENGING.

AND SUN LIGHT ADDRESSES THESE

CHALLENGES BY DESIGNING A

RIGOROUS METHODOLOGY THAT

LEDGERS STATISTICS FOR TARGETING

PREDICTIONS.

IT DOES SO VERY IMPORTANTLY AND

QUITE UNIQUELY SO WE CAN USE IT

IN DIFFERENT SERVICES LIKE I

SAID BEFORE.

LET ME NOW SHOW YOU SOME OF

THESE CHALLENGES JUST TO EXCEL

PLY THE KIND OF MECHANISMS WE

ADDRESS THEM.

LET'S LOOK AT THE SIMPLE EXAMPLE

WE HAD WITH THE THREE E-MAILS.

LOOK AT WHAT WE DO.

WE USED THREE SHADOW ACCOUNTS IN

ORDERTHREE E-MAILS.

THAT'S A LOT OF ACCOUNTS, SHADOW

ACCOUNT THAT WE6[q-¦ NEEDED TO

CREATE.

WHAT IF WE WERE TRYING TO

EXPLAIN TARGETING ON A MORE

REALISTIC USER ACCOUNT WITH

THOUSANDS OF E-MAILS.

AND POTENTIALLY OTHER ON-LINE

ACTIVITY TOO THAT COMPOUNDS

TOGETHER WITH E-MAILS TO PRODUCE
THE ADS.
WE WOULD HAVE NEEDED TO CREATE,
WHAT WOULD WE HAVE NEEDED TO
CREATE COMBINATIONS, A NUMBER OF
ACCOUNTS FOR OUR COMBINATIONS OF
THESE INPUTS.
THAT'S A SCALING CHALLENGE, A
HUGE SCALING CHALLENGE I CAN USE
IS TREMENDOUSLY IMPORTANT.
AND YOU KNOW, IT TURNS OUT IN
FACT THAT WE DON'T NEED AS MANY
EXTRA ACCOUNTS.
WE CAN GET AWAY WITH A LOT FEWER
AND A NUMBER OF INPUTS WE'RE
TRYING TO EXPLAIN TARGETING ON.
MY COLLABORATOR PROVED THIS
ASPECHNÑEXPERIMENTALLY.
IF WE CAN ASSUME THAT AN AD
TARGETS ONLY A SMALL SUBSET OF
THE MANY INPUTS THAT WE HAVE IN
A MAIN ACCOUNT, THEN WE CAN
LEVERAGE PROPERTIES THE SAME

CONCEPT UNDERLINE COMPLEX SYSTEM
WHICH SAYS YOU DON'T NEED A
WHOLE LOT OF OBSERVATIONS IN
ORDER TO RECONSTRUCT ACCURATELY,
YOU KNOW, AS FAR AS SIGNAL.
FOR THOSE OF YOU WHO ARE
FAMILIAR WITH MACHINE LEARNING,
I GUESS, WE USE [INDISCERNIBLE]
AND THAT'S WHAT WE USE IN
SUNLIGHT.
HOWEVER, THESE PARTICULAR
METHODS DON'T, YOU KNOW,
GUARANTEE, ONLY GUARANTEE
CORRECTNESS, DO NOT GUARANTEE
THE CORRECTNESS OF ANY
INDIVIDUAL PREDICTION.
7'ASSESSMENT OF INDIVIDUALS
TARGETING SO INFORMATION SO WE
CAN TRUST THE RESULTS THAT WE
GET FROM SUNLIGHT.
AND FOR THAT, WHAT WE DO IS USE
JUST LIKE IN ADD FISHER.
ONE MORE METHOD THAT PRICE

GSIGNIFICANCE OF EACH PREDICTION.

OKAY.

SO YOU KNOW, SUNLIGHT PUTS ALL

OF THESE THINGS AND OTHER

MECHANISMS TOGETHER IN A

PARTICULAR ARCHITECTURE THAT

PROVIDES THE UNIQUE PROPERTIES

THAT I MENTIONED BEFORE,

SCALABILITY AND PRECISION.

I WON'T GO INTO THE DETAILS OF

THIS.

AND INSTEAD, WHAT AIL DO IN THE

REMAINING TWO MINUTES IS I'LL

TELL YOU, YOU KNOW, HOW SUNLIGHT

CAN BE USED.

SPECIFICALLY SUNLIGHT IS A

TRANSPARENCY4ñ INFRASTRUCTURE

WHICH PROVIDES SOME VALUABLE FOR

TARGETING PREDICTION.

ON TOP OF IT WE AND OTHERS BUILD

TRANSPARENCY TOOLS FOR STUDYING

SPECIFIC SERVICES.

WE DID A BUNCH OF THESE TOOLS

AND IT'S ACTUALLY EXTREMELY

CONVENIENT TO BUILD ON TO THE

SUNLIGHT.

I'LL TELL YOU ABOUT JUST ONE OF

THESE TOOLS THAT WE BUILT.

WHICH WE CALL THE GMAIL AD

OBSERVATORY.

IT'S ON GMAIL ADS IN BOXES.

THEY APPLY SORT OF E-MAILS ON

WHICH WE WANTED TO DETECT

TARGETING.

THIS USES SORT OF GMAIL ACCOUNTS

IN ORDER TO SEND E-MAILS TO A

SEPARATE SET OF GMAIL ACCOUNT

THAT BECOME THEN THE SHADOW

ACCOUNTS FROM WHICH WE HAVE THE

OBSERVATIONS OR COLLECT THE ADS

FOR THE TARGETING.(R1bw

THE GMAIL AD OBSERVITY COLLECTS

THE ADS PERIODICALLY AND

SUPPLIES THEM TO-u SUNLIGHT TO GET

THEIR FURTHER TARGETING.

AND WHAT WE DID, SO THIS IS KIND

OF THE TUNE WE BUILT AND WHAT WE

DO IS USED THIS TOOL TO RUN A 33

DAY STUDY OF TARGETING IN GMAIL.

A PRETTY LARGE SCALE STUDY.

WE GOT OVERALL ABOUT 20 MILLION

IMPRESSIONS, ABOUT 20,000 UNIQUE

ADS.

AND WHAT WE FOUND, WE FOUND A

BUNCH OF THINGS.

I'LL SHOW YOU JUST ONE RESULT

WHICH IS A CONTRADICTION OF ONE

PARTICULAR POLICY OR STATEMENT

THAT GMAIL MAKES IN ONE OF THEIR

FAQs.

SPECIFICALLY THEY SAY THEY DO

NOT TARGET ADS BASED ON

INFORMATION SUCH AS RELIGION,

SEXUAL ORIENTATION, HEALTH OR

FINANCIAL CATEGORIES.

WELL GUESS WHAT.

WE ACTUALLY FOUND EXAMPLES IN A

LOT OF EXAMPLES OF ADS THAT

TARGET EACH AND EVERY OF THESE

SPECIFIC TOPICS.

AND I'VE ALREADY SHOWN YOU FOR

EXAMPLE THE ADS THAT TARGET

HOMOSEXUALS.

LET ME SHOW YOU ANOTHER EXAMPLE

FROM THE HEALTH TOPIC

SPECIFICALLY.

THERE ARE SOME RELATED, A LOT

ACTUALLY OF SENIOR ASSISTED

LIVING ADS THAT TARGET

ALZHEIMER'S.

OTHER ADS MANY OTHERS THAT

TARGET ALZHEIMER'S IN GENERAL.

THERE'S AN IYOU CAN SEE THERE THAT TARGETS

DEPRESSION-RELATED KEY WORDS.

THE AD FOR CHEATING SPOUSE SITE,

APPARENTLY.

AND THERE ARE A NUMBER OF ADS AS

WELL IN OUR EXAMPLE THAT TARGET

THE KEY WORD CANCER.

I'M SHOWING HERE JUST ONE OF

THEM.

WE FOUND A NUMBER OF OTHER ONES.

SO THAT'S RIGHT.
TO WRAP IT UP, I'VE TOLD YOU
ABOUT OUR AGENDA OF BUILDING J
J -- GENERIC AND APPLICABLE
TOOLS THAT ENABLE OVERSIGHT AT
SCALE.
THEYBB
ñATHI NOTICE DO RESCOTCH IN MACHINE
LEARNING BY GOOGLE BAIA WHO BY
MICROSOFT FOR DOING DATA
ANALYSIS FOR MAYBE DOING THE
TARGETING.
AND SO THIS IS KIND OF A, HAS A
DIFFERENT PERSPECTIVE.
I'M GOING TO GIVE A DIFFERENT
PERSPECTIVE ON THIS PROBLEM.
BUT YOU KNOW, YOU'RE ALL WELL
AWARE OF THE KIND OF ISSUES THAT
COME UP WITH A LOT OF THESE DATA
DRIVEN APPLICATIONS.
SO MAYBE YOU PROBABLY HEARD OF
THE STUDY THAT WAS DONE ABOUT
DIFFERENCES AND PRICES FROM

STAPLES TO ON-LINE STORE SORT OF
BASED ON WHERE YOU LIVE.
THIS WAS AN UNINTENDED
CONSEQUENCE OF THE PRICING
MECHANISM THAT STAPLES WAS
USING.
AND0HTHIS KIND OF DATA-DRIVEN
APPLICATION THAT MAY HAVE SOME
KIND OF UNINTENDED CONSEQUENCES
WHICH WAS IN THE CASE OF
GOOGLE'S IMAGE TAG IN AN
APPLICATION WHERE IF YOU WERE TO
UP LOAD PHOTOS ON TO GOOGLE'S
SOCIAL NETWORK SERVICES, GOOGLE
WILL TRY TO AUTOMATICALLY TAG
YOUR IMAGES.
LIKE SAY THERE'S A CAR HERE,
HERE ARE FRIENDS.
THIS WAS VERY UNFORTUNATE
INCIDENT WHERE PEOPLE FOUND THAT
AFRICAN AMERICAN USERS, THE
PICTURES ARE BEING TAGGED AND IT
TAGGED BY GORILLAS AND THIS IS

NOT SOMETHING THEY WANTED TO HAPPEN.

THESE ARE SORT OF PROBLEMS THAT ARISE WHEN YOU ARE CREATING THESE KIND OF DATA-DRIVEN APPLICATIONS.

AND WE WANT TO ARGUE IN THIS WORK THAT THESE ARE BUGS AND SORT OF DEVELOPERS SHOULD BE TESTING THEM, TESTING FOR THESE KINDS OF BUGS AND TRYING TO DEBUG THEM, TO CORRECT THESE ISSUES.

SORT OF AT THE SAME TIME THAT THEY WOULD TRY TO CORRECT OR DO DEBUGGING TO FIND THESE KIND OF FUNCTIONALITY BUGS, PERFORMANCE BUGS AND SO ON.

SO THIS IS WHERE OUR WORK COMES IN.

WE KNOW THAT THIS IS NOT AN EASY, THIS IS NOT SORT OF AN EASY PROBLEM TO SOLVE BECAUSE

THEY ARE PRETTY NEFARIOUS,

PRETTY HARD TO DETECT.

SO WHAT PEOPLE MIGHT SUGGEST IS

SHOULD TAKE SOME PREVENTIVE

MEASURES.

BUT WE KNOW THEY ALSO HAVE A LOT

OF LIMITATIONS.

SO ONE THING YOU MIGHT SUGGEST

TO DO IS TO OKAY MAYBE WE SHOULD

JUST COMPLETELY IGNORE CERTAIN

ATTRIBUTES ABOUT THE DATA WHEN

WE WERE DESIGNING THESE

DATA-DRIVEN APPLICATIONS SO THAT

WE DO NOT SORT OF CREATE THESE

KINDS OF UNWARRANTED

ASSOCIATIONS IN THE SERVICE

OUTPUTS.

BUT WE KNOW THIS DOESN'T WORK

BECAUSE THERE ARE OTHER

ATTRIBUTES THAT MAY BE

ASSOCIATED OR CORRELATED WITH

THE SORT OF SENSITIVE ATTRIBUTES

LIKE INCOME LEVEL OR RACE.

THIS IS INDEED WHAT HAPPENED
WITH THE STAPLES PRICING
APPLICATION WHERE LOCATION JUST
HAPPENED TO BE SORT OF
CORRELATION WITH INCOME LEVEL.
SO THAT MIGHT NOT WORK.
ANOTHER THING THAT YOU MIGHT TRY
TO DO IS TO APPLY SOME KINDS OF
CHECKS TO SEE IF THERE'S FISCAL
PARITY IN YOUR OUTPUTS TO MAKE
SURE IF YOU LOOK AT RACE YOU'RE
SORT OF PARITY ACROSS DIFFERENT
RACE ATTRIBUTES.
WE KNOW AGAIN, THIS IS, THIS CAN
BE INSUFFICIENT AS WELL JUST
BECAUSE THERE COULD BE SOME SORT
OF SMALLER SUBPOPULATIONS WITH A
PARTICULAR ATTRIBUTE THAT END UP
HAVING A STRONG ASSOCIATION WITH
THIS SERVICE OUTPUT.
THESE ARE REALLY HARD PROBLEMS
FOR DEVELOPERS TO SOLVE.
SO WHAT WE THINK OR ARE TRYING

TO ARGUE HERE IS DEVELOPERS
REALLY DO NEED NEW TOOLS TO HELP
THEM FIND THESE KINDS OF BUGS.
WE'RE DETECTING THESE
ASSOCIATIONS ALREADY WHICH IS A
HARD TASK TO DO.
THESE WHERE OUR RESEARCH COMES
IN.
WE'VE BEEN DEVELOPING THIS
TOOLKIT, WHAT WE CALL FAIR TEST
AND WE CALL IT TESTING SWEEP FOR
A DEVELOPER TO INTEGRATE TO
THEIR TOOL CHAIN TO TRY TO CHECK
THE APPLICATION TO DO DEBUGGING,
TO RUN EVERY TIME THEY COMPILE
TO MAKE SURE THAT THEIR
APPLICATION'S WORKING AS THEY
WANT IT TO BEHAVE.
SO THE WAY WE KIND OF
CHARACTERIZE OR CHAIR YOUR
CARICATURE, WE PUT DATA INPUTS
AND THERE'S SOME KIND OF OUTPUTS
THAT THE APPLICATION PROVIDES.

THE SERVICE PRICES, IMAGE TAGS,
RECOMMENDATIONS AND SO ON.
OR SOME KIND OF FUNCTIONS OF
THESE OUTPUTS.
SO MAYBE THINGS LIKE THE USER
INPUTS MIGHT BE LOCATIONS OF THE
USERS AND THEIR PROFILES,
WHETHER THEY CLICK ON VARIOUS
THINGS ON THE WEBSITE.
LIKE YOU SAID APPLICATIONS AND
PRICES.
SO THE FAIR TEST COMES IN BY
SOMETHING YOU COULD STRAP ON TO
YOUR DEVELOPMENT TOOL CHAIN.
AND THEY WOULD LOOK AT THESE
KIND OF USER INPUTS AND THE
APPLICATION INPUTS AND TRY TO
CHECK FOR VARIOUS KINDS OF
UNWARRANTED ASSOCIATIONS BETWEEN
THE OUTPUT AND SORT OF PROTECTED
ATTRIBUTES THAT YOU WOULDN'T
WANT TO HAVE SOMETIMES DRAWING
ASSOCIATION THERE.

AND SO FAIR CHOICE IS A TOOL FOR
AUTOMATICALLY DOING THIS.
THIS IS WITH SOME KIND OF DATA
AND THE HOPE IS IT WILL AT THE
END PRODUCE SOME KIND OF BUG
REPORT THAT THE DEVELOPER WILL
BE ABLE TO LOOK AT.
SO WHAT THE DEVELOPER WOULD HAVE
TO DO IS TO SORT OF SPECIFY
WHICH OF THE SORT OF USER INPUT
ARE THE ONES THAT ARE, THAT WE
WANT TO CHECK FOR A STRONG
ASSOCIATION WITH.
THESE ARE WHAT WE CALL THE
PROTECTED VARIABLES, THE
PROTECTED ATTRIBUTES.
THESE MIGHT BE THINGS LIKE THE
GENDER OR RACE OF THE USER.
THERE ARE MANY OTHER VERY
LIKELY, MANY OTHER ATTRIBUTES
THAT ARE USED BY THE
APPLICATION.
AND THESE ARE THINGS WE'RE GOING

TO USE TO SORT OF TRY TO DEFINE

OR TO SEARCH, TO DEFINE VARIOUS

KINDS OF CONTEXT IN WHICH THERE

MIGHT BE SOME KIND OF

UNWARRANTED ASSOCIATION.

AND THEN THE LAST ONE I'LL TALK

ABOUT IN A BIT.

SO THE GOAL OF FAIR TEST AGAIN

IS TO DEFINE THESE KINDS OF

CONTEXT SPECIFIC ASSOCIATIONS

BETWEEN SOME KIND OF PROTECTED

ATTRIBUTES AND THE APPLICATION

OUTPUT.

AND THEN THE BUG REPORTS IS

SOMETHING THAT WILL APPLY SOME

STATISTICS OR MACHINE LEARNING

IN ORDER TO PRODUCE SOMETHING

THAT THE DEVELOPER CAN

UNDERSTAND INAKIND OF CONTEXT, WHICH KINDS OF

ASSOCIATIONS WERE FOUND BY THE

FAIR TEST AND TO SORT OF RANK

THEM BY+rUSO THAT IS SOMETHING THE

DEVELOPER CAN ACTUALLY LOOK AT

AND UNDERSTAND.

OKAY.

SO LET ME SAY A LITTLE BIT ABOUT

HOW FAIR TEST WORKS.

IT'S SORT OF AT ITS CORE.

IT'S A MACHINE LEARNING

ALGORITHM OR MACHINE LEARNING

APPLICATION.

SO FAIR TEST ITSELF IS SOME KIND

OF DATA-DRIVEN APPLICATION.

AND THE WAY THAT IT WORK IS THAT

IT STARTS BY COLLECTING OR YOU

START BY PROVIDING SOME KIND OF

SOURCE OF DATA, AND HERE IS

WHERE IT'S REALLY IMPORTANT FOR

THE DEVELOPER TO REALLY BE, TO

HAVE SOME KIND OF SOURCE OF DATA

THAT IS REPRESENTATIVE OF A

POPULATION OF A USER BASE.

THIS IS WHERE IT'S SORT OF

DIFFICULT FOR MAYBE OTHER

PARTIES TO HAVE ACCESS TO THIS

BUT THE DEVELOPER PRESUMABLY

THEY'RE AT MICROSOFT SO THEY
HAVE THIS KIND OF DATA ALREADY.
WHEN THEY HAVE THIS DATA THEY
CAN SORT OF CHECK THE
APPLICATION ON THE REAL USER
POPULATION AND TO REALLY
DISCOVER EFFECTS THAT HAVE SOME
MEANING IN TERMS OF THE ACTUAL
USERS.
OKAY.
SO FAIR TEST RELIES ON THESE
KINDS OF DATA.
WHAT WE'LL DO IS SOMETHING VERY
SIMILAR TO HOW AD FISHER AND
SUNLIGHT OPERATE.
WE'LL PUT THIS DATA INTO TWO
PARTS.
ONE WE CALL THE TRAINING DATA
AND THE OTHER PART WE CALL THE
TEST DATA.
AND WE USE THE TRAINING DATA,
PART OF THE DATA SET TO SORT OF
FIND THESE KINDS OF ASSOCIATIONS

THROUGH SOME KIND OF CLEVER

MACHINE LEARNING ALGORITHM.

AND THEN ONCE WE FIND THESE

KINDS OF SORT OF ASSOCIATIONS

BETWEEN PROTECTED ATTRIBUTES AND

APPLICATION OUTPUTS, WE'LL USE

SORT OF REMAINING DATA OR

SEPARATE DATA TO ACTUALLY VALID

THESE THINGS AND -- VALUATE -- VALIDATE

THESE THINGS AND ARE THESE

HARMING A LARGE SEGMENT OF A

POPULATION AS VERY SIGNIFICANT

AND SO ON.

THIS IS WHERE THERE'S A LOT OF

TECHNICAL MACHINERY COMING FROM

MACHINE LEARNING.

AT THE END, ACTUALLY A LOT OF

WORK HERE IS TO MAKE THESE KINDS

OF FINDINGS, SORT OF CONSUMABLE

BY THE APPLICATION DEVELOPER.

SO SOMETHING THAT'S

INTERPRETABLE THAT THEY CAN

ACTUALLY USE TO HELP THEM MAYBE

DEBUG THE APPLICATION.

LET ME GIVE YOU AN EXAMPLE.

WE ACTUALLY APPLIED THIS TOOL TO

A COUPLE SORT OF APPLICATIONS.

SOME REAL APPLICATIONS THAT ARE

SORT OF DATA-DRIVEN

APPLICATIONS.

SO ONE OF÷T&á¦ THEM, THE FIRST ONE I

WANTED TO TELL YOU ABOUT IS THIS

SORT OF HEALTHCARE APPLICATION.

THIS IS ACTUALLY SORT OF

SUBSTANCE THAT WAS PRODUCED BY

ONE OF THESE MACHINE LEARNING

CONTESTS OR DATA SCIENCE

CONTESTS WHERE SOME COMPANY THAT

IN THIS CASE IS HERITAGE HOUSE

COMPANY.

THEY RAN THIS KIND OF

COMPETITION WHERE THEY TRIED TO

GET, THEY PROVIDED SOME KIND OF

DATA ABOUT PATIENTS GOING TO

HOSPITALS, SORT OF DESCRIPTION

OF THE PATIENT RECORDS, YOU

KNOW, HOW MANY TIMES THEY'VE

BEEN TO THE HOSPITAL BEFORE AND

WHAT WERE THEIRDKTHINGS LIKE THIS.

AND THE TASK WAS TO USE THIS

INFORMATION TO PREDICT WHETHER

OR NOT OR HOW MANY TIMES THE

PATIENT WOULD VISIT THE HOSPITAL

IN THE NEXT, THE FOLLOWING YEAR.

SO THIS IS KIND OF READMISSION

RATE PREDICTION.

SO WE DID, WE LOOKED AT THE

WINNING ENTRY TO THIS

COMPETITION.

A PRETTY GOOD ENTRY AND CERTAIN

APPLICATIONS THAT WAS ABLE TO

CORRECTLY PREDICT WITH SOME

PRETTY HIGH ACCURACY, AROUND 85%

ACCURACY.

WHETHER OR NOT THE PATIENT WOULD

BE READMITTED INTO HOSPITAL IN

THE FOLLOWING YEAR.

OKAY.

SO THIS IS THE DATA DRIVEN

APPLICATION, INPUTS ARE AGE,

GENDER, NUMBER OF TIMES THEY'VE

BEEN TO THE HOSPITAL AND SO ON.

AND THEN IT TRIES TO PREDICT

WHETHER THEY WILL BE READMITTED

INTO THE HOSPITAL.

SO WHAT DID WE FIND BY APPLYING

FAIR TESTS HERE.

WHAT WEÑCREALLY ARE SOME SPECIFIC CONTEXT

WHERE THERE'S AN ASSOCIATION

BETWEEN THE AGE OF THE PATIENT

AND HOW BADLY THE PREDICTIONS,

HOW BAD THE PREDICTIONS WERE,

THE RATE, ERROR RATE ORO×2¦ THE SIZE

OF THE ERROR IN THE PREDICTION.

SO THIS WAS, THIS IS SORT OF A

CONTEXTUAL ASSOCIATION THAT WE

DISCOVERED.

IT WAS NOT FOR THE ENTIRE

POPULATION BUT FOR THE SOME WELL

DEFINED SEGMENT OF THE

POPULATION.

I THINK IT WAS SOMETHING LIKE

MALE PATIENTS WHO HAVE BEEN TO

THE HOSPITAL AT LEAST, WHO HAVE

BEEN TO THE ER AT LEAST TWICE IN

THE PAST, WHO HAVE BEEN TO THE

ER AT LEAST LIKE TWICE IN THE

PAST YEAR AND SO ON.

BUT WITHIN THISWHO HAVE BEEN TO THE ER LIKE

TWICE IN THE PAST YEARPó+

ON.

BUT WHEN WE, WITHIN THIS

SUBPOPULATION, THERE WAS A

REALLY STRONG EFFECT, REALLY

STRONG ASSOCIATION BETWEEN AGE

AND ERROR IN THEM32xx PREDICTION.

SO THIS IS AN INTERESTING

FINDING.

WE THINK THAT THIS IS ACTUALLY

SORT OF IMPORTANT IN A SOCIAL

SENSE BECAUSE THIS IS SOMETHING

THAT COULD REALLY LEAD TO ACTUAL

HARMS FOR INSTANCE THIS

APPLICATION WAS ACTUALLY GOING

TO BE USED FOR INSURANCE

PURPOSES AND KIND OF ADJUST YOUR
INSURANCE PREMIUMS AND SO ON.
THESE ARE ASSOCIATIONS THAT CAN
REALLY BE, HAVE SOME IMPACT ON
THE PATIENTS THAT THEY ARE, OR
USERS OF THE SYSTEM.
I WANT TO TELL YOU ABOUT SORT OF
ANOTHER APPLICATION.
THIS IS NOT A REAL PLAINATION,
SORT OF A HISTORICAL APPLICATION
THAT WILL ILLUSTRATE SORT OF A
DIFFERENT CAPABILITY OF FAIR
TESTS.
SO THIS IS A VERY WELL-KNOWN
DATA SET SO THE APPLICATION, YOU
CAN THINK OF IT AS THE GRADUATE
SCHOOL ADMISSIONS APPLICATION.
WHAT IT DOES IS TAKE PEOPLE WHO
APPLY TO BERKLEY GRADUATE SCHOOL
AND WHETHER OR NOT TO ADMIT THEM
OR NOT.
OKAY.
SO THIS IS A WELL-KNOWN DATA SET

FROM LIKE THE 70'S.

IF YOU DON'T KNOW ABOUT THIS

DATA SET, WHAT HAPPENED WAS THAT

THEY DISCOVERED THAT THERE WAS

THIS KIND OF GENDER BIAS AND

ADMISSION RATE AT BERKLEY.

SO MEN WERE BEING ADMITTED IN

HIGHER RATES THAN WOMEN.

SO INDEED FAIR TEST CAN BE USED

TO DISCOVER THIS KIND OF

ASSOCIATION.

BUT WHAT WE CAN ALSO DO IS TRY

TO EXPLAIN WHERE THIS

ASSOCIATION COMES FROM.

INDEED THIS IS WHAT THIS PAPER

IN 1975 DISCOVERED THAT ONCE YOU

CONDITION ON WHICH DEPARTMENT

THE APPLICANT WANTED TO GET

INTO, THEN THE EFFECT EITHER

GOES AWAY OR IN FACT MAYBE

REVERSES AND SPECIFIC

DEPARTMENTS WOULD BE ADMITTED

HIGHER RATES OF WOMEN THAN MEN.

THIS IS TO SILL GREAT HOW FAIR TEST CAN BE USED TO SORT OF HELP WITH THE DEVELOPER OR DEBUG THE SYSTEM TO TRY TO EXPLAIN WHAT WAS GOING ON, GOING WRONG IN THEIR SYSTEM.

MAYBE THERE'S THIS OTHER CAPABILITY AND FAIR TEST FOR DOING THIS.

WE CALL IT PROVIDING SOME KIND OF EXPLORATORY VARIABLES.

THIS WILL MAKE THIS A REAL SYSTEM OR REAL TOOL FOR DEVELOPERS TO USE TO DEBUG THEIR APPLICATIONS.

SO LET ME JUST MAKE A FEW CLOSING REMARKS.

SO WE ALSO APPLY FAIR TEST IN A COUPLE OTHER APPLICATIONS.

YOU COULD READ ABOUT IT IN OUR PREPRINT WHICH ISTHE WEB.

SO YES, I ALREADY MENTIONED THERE'S ANOTHER FEATURE OF THE

VARIABLES.

THERE'S ANOTHER SORT OF BIG

ISSUE OUT THERE IN DATA ANALYSIS

WHICH IS THAT OF ADAPTIVE DATA

ANALYSIS WHERE YOU WANT TO BE

ABLETIMES.

THIS IS SOMETHING WE'RE STARTING

TO LOOK AT INTEGRATING INTO FAIR

TESTS AND THIS IS SORT OF AN

OPEN SOFTWARE THAT CAN BE USED

BY DEVELOPERS RIGHT NOW.

SO JUST TO SOME UP, REALLY WHAT

WE'RE TRYING TO ADVOCATE HERE IS

WE REALLY NEED TO EMPOWER

DEVELOPERS WITH SORT OF BETTER

FISCAL TRAININGS THAT ARE

PHYSICAL TOOLS TO MAKE THESE

DATA-DRIVEN APPLICATIONS MORE

FAIR AND MORE SOCIALLY CONSCIOUS

AND SO ON.

WE THINK THAT'S A GOOD WAY TO

START HERE.

THANK YOU.

THE.

>> JOINING ME ON THE STAGE NOW

ARE DISCUSSANTS JAMES COOPER OF

GEORGE MASON UNIVERSITY LAW

SCHOOL AND DEIDRE MULLIGAN AT

UNIVERSITY OF BERKLEY.

WE HEARD ABOUT PRESENTATIONS

ABOUT TOOLS DESIGNED TO SHED

SOME LIGHT ON HOW DATA IS

COLLECTED FROM CONSUMERS.

HOW CAN RESULTS RECEIVING

TARGETED ADS, WEB CONTENT, WORK

RESULT DISCRIMINATION.

LET ME TURN FIRST TO JAMES AND

DEIDRE.

WHAT ARE THEmOÑi COMMON THEMES YOU

SEE RUNNING THROUGH THESE

PRESENTATIONS.PT"I

>> SO I TEACH AT THE SCHOOL OF

INFORMATION AT BERKLEY, AND I

SPEND ONE OF THE DEPARTMENTS,

ONE OF THE PROGRAMS IN WHICH I

TEACH IS A MASTERS IN DATA

SCIENCE.

AND WE TEACH ABOUT PRIVACY, WE

TEACH ABOUT SECURITY.

THESE ARE PEOPLE WHO ARE GOING

TO BE DOING DATA ANALYTICS AND

ONE OF THE AREAS WHERE WE'VE

BEEN LACKING BOTH METHODOLOGIES

AND TOOLS IS TO DEAL WITH ISSUES

OF FAIRNESS, RIGHT.

HOW DO WE THINK ABOUT THE BIASES

IN OUR DATA.

HOW DO WE THINK ABOUT THE BIASES

IN OUR ALGORITHMS.

AND MOST IMPORTANTLY I THINK

WHAT IN PARTICULAR, AND I'M KIND

OF MOST DEEPLY ENGAGED WITH

ANUPAM AND MICHAEL'S WORK

BECAUSE WE HAVE SOME

COLLABORATIVE WORK WE'RE DOING.

HOW DO WE THINK ABOUT BIAS IN

SYSTEMS WHERE THERE ARE MULTIPLE

INPUTS.

AND SO IT'S VERY;spV DIFFICULT TO

TRACK2

¦ñ AN OUTPUT BACK TO A SINGLEACTOR'S DECISIONS.

AND SO SOMEBODY WHO IS WORKING

IN THAT SORT OF PROGRAM, ONE OF

THE THINGS I THINK IS MOST

IMPORTANT ABOUT THESE TOOLS IS

ON THE ONE HAND, WE HAVE OUR

HADN'T PRESENTATION FAIR TEST

WHICH IS ACTUALLY TRYING TO

EMPOWER PEOPLE WHO WANT TO AVOID

ALL ALGORITHMS HAVE BIASES.

IF YOU DESIGN AN ALGORITHMS

WITHOUT A BIAS IT HAS NO PURPOSE

IN THE WORLD.

LET'S BE CLEAR.

IT HAS A BIAS WE JUST WANT TO

AVOID CERTAIN BAD OUTCOMES.

THE QUESTION ABOUT HOW WE

EMPOWER PEOPLE WHO ARE DESIGNING

SYSTEMS TO PROACTIVELY AVOID

THOSE OUTCOME IS SOMETHING WE

NEED RESEARCH ON TECHNICAL

SYSTEMS.

PEOPLE HAVE CALLED, OH WE NEED ACCESS TO THE ALGORITHM, WE NEED ACCESS TO THE DATA AS THOUGH THEY CAN LOOK AT IT, THEY'RE GOING TO UNDERSTAND$mf:ñ IT.
AND THAT JUST ISN'T THE CASE IN MANY INSTANCES.
SO WE ACTUALLY NEED TECHNICAL SYSTEMS.
WE NEED THE USE OF STATISTICAL MACHINE LEARNING TECHNIQUES TO POLICE MACHINE LEARNING SYSTEMS.
AND THIS IS PARTICULARLY IMPORTANT BECAUSE I THINK WHAT ALL OF THEM ARE HIGHLIGHTING AND REALLY FOCUSING ON IS NOT, I MEAN WE'RE CONCERNED ABOUT INTENTIONAL DISCRIMINATION BUT WHAT I THINK MANY OF US ARE WORRIED ABOUT EXPLODING IS DISPARATE IMPACT.YG
NOBODY IS INTENDING FOR BAD THINGS TO HAPPEN BUT WHAT

MACHINE LEARNING ENABLES, WHAT
MAKES IT DIFFERENT FROM WHAT'S
GONE DOWN BEFORE THE MEANING OF
INFORMATION EMERGES, RIGHT.
SO IT TURNS OUT THESE THREE
PIECES OF DATA ADD UP TO SOME
PARTICULAR PROTECTED TRAIT.
AND AS MACHINE LEARNING
TECHNIQUES CONTINUE TO UNCOVER
THE WAY IN WHICH WE HAVE
CORRELATIONS THAT EQUATE TO
THESE DIFFERENT THINGS, WE'RE IN
THIS, WE HAVE THIS ONGOING NEED
TO TRY TO FIGURE OUT PROACTIVELY
HOW TO AVOID THOSE SORT OF
PROBLEMATIC CORRELATIONS.
SO I THINK THEY'RE ALL WORKING
ON THIS SHARED PROBLEM FROM TWO
DIFFERENT SIDES, RIGHT.
THERE'S A LONG HISTORY OF
TESTING WHEN WE THINK ABOUT
DISCRIMINATION, HOUSING
DISCRIMINATION, SENDING PEOPLE

OUT IN THE WORLD.
SO I THINK THE AD FISHER AND
SUNLIGHT ARE WORKING FROM THAT
SIDE.
CAN WE TEST FROM THE OUTSIDE.
DANIEL IS SAYING FOR THE PEOPLE
TRYING TO DO GOOD TRYING TO
AVOID THE OUTCOME CAN EMPOWER
WITH TOOLS THAT ARE BASED ON THE
SAME SORTS OF STATISTICAL
TECHNIQUESIN MACHINE LEARNING.
SO I THINK THEY'RE REALLY
POWERFUL IN THAT WAY.
>> JAMES, WHAT DO YOU SEE AS THE
COMMON THEMES.
>> I WOULD AGREE WITH WHAT
DEIDRE SAID.
COMMON THEMES ARE PRETTY SELF
EVIDENT.
BACK AND FORTH ON TWO PAPERS AND
PAPERS KIND OF DESCRIBE
ALGORITHMS THAT DO VERY SIMILAR
WORK AND I THINK VALUABLE WORK

AS DEIDRE POINTED OUT.

I DON'T HAVE MUCH TO ADD BEYOND

THAT.

>> DEIDRE POINTED OUT IN THE

REAL WORLD THERE ARE LOTS OFEN

PUTS.

CONSUMER PROFILE CONSISTS OF A

MILLION DATA POINTS OR MORE.

HOW CAN YOUR TOOLS ACCOUNT FOR

THAT?

WHEN YOU'RE CREATING USER

PROFILE IS THERE ANY WAY TO

REALLY MANIPULATE WHAT WOULD

REALLY BE HAPPENING TO A

CONSUMER?

>> THIS IS A REAL PROBLEM, VERY

VERY BIG PROBLEM.

I WOULD QUOTE IT AS THE BIGGEST

PROBLEM IN WEB RANSPARENCY WORK

TODAY IN MY OPINION WHICH IS TO

ACTUALLY EMULATE REAL USERS WITH

CONTROLLED EXPERIMENTS.

BOTH OF THE AD FISHER AND

SUNLIGHT HAVE CONTROLLED HE CAN

PERIMENTS WITH FAKE ACCOUNT THAT

ARE ASSIGN, FAKE INPUT SETS OR

INPUTS.

AND THAT RESULTS IN SOMEí÷1í¦

TARGETING.

WE ARE SEEING ALL OF US, SOME

TARGETING BUT IT'S NOT

NECESSARILY TRUE THAT IT'S

REALISTIC KIND OF TARGETING OF

THE KIND THAT REAL USERS WOULD

ACTUALLY SEE WE MAY ACTUALLY

HAVE TARGETING THAT REAL USERS

NEVER SEE AND SO ON.

I THINK THAT'S A BIG BIG

PROBLEM.

I THINK WE NEED RESEARCH IN

DESIGNING TOOLS THAT LEVERAGE

DIRECT USER DATA FROM REAL USERS

TO ACHIEVE SOME OF GOALS WEd8é7ñ HAVE

IN OUR SYSTEM.

TRANSPARENCY GOALS WE HAVE IN

OUR SYSTEM.

THAT SAID I THINK FOR EXAMPLE I
BECAUSE I'VE BEEN WORKING SO
MUCH ON FOCUS AND INVESTED ON
SCALABILITY, BUILDING SCALABLE
SYSTEM THAT CAN TAKE MANY
INPUTS, MILLIONS, BUT NOT THE
SIZE THAT REAL USERS PRODUCE
CERTAINLY.
WE'VE BEEN FOCUSING ON THAT AND
SUNLIGHT DOES SCALE PRETTY WELL
WITH RESPECT TO MANY, TRYING
MANY INPUTS AND DISCOVERING
EFFECTS ON MANY OF THESE INPUTS.
BUT THERE ARE BIG LIMITATIONS
STILL EVEN THERE.
I ALSO WANTED TO POINT OUT
BECAUSE MAYBE THE AUDIENCE
DIDN'T REALIZE.
SO [INDISCERNIBLE] SUNLIGHT WERE
BOTH COLLABORATORS ON BOTH.
WE JUST SPLIT THE TALKS SO WE
WOULDN'T HAVE TO CREATE, TO TALK
BOTH ABOUT FOR EACH ONE OF THEM.

>> MAYBE ONE QUICK THING I WOULD
ADD HERE IS THEIR TWO WAYS TO
GETTING ACCESS TO REAL DATA.
ONE IS TO ACTUALLY WORK WITH THE
TECHNOLOGY COMPANIES TO HAVE
THAT DATA.
WE HAVE AN ONGOING COLLABORATION
WITH MICROSOFT RESEARCH WHERE
WE'RE ACTUALLY BEGINNING TO GET
STARTED WITH WORKING WITH THE
INTERNAL DATA THAT THEY HAVE
ABOUT THEIR USERS.
THE OTHER WAY TO DO IT OR AT
LEAST ONE OTHER WAY TO DO IT IS
TO TRY TO DO, GET DATA FROM REAL
USERS THROUGH CROWD SOURCING.
SO THERE IS A RECENT INTERESTING
PAPER FROM RESEARCH AND
COLLABORATORS ELSEWHERE WHICH
TRY TO DO THAT.
SO THE WAY THEY DO THEIR
EXPERIMENTS IS TO JUST CROWD
SOURCE ITpUSERS ABOUT THEIR BROWSING

PROFILES.

AND THEN COMPARE IT AGAINST THE

SAME USER WITHOUT THE HISTORY.

SOME AMOUNT OF THE HISTORY.

AND THEN SEE IF THERE'S

DIFFERENTIAL TREATMENTS.

THAT'S BEGINNING TO GET TOWARDS

EXPERIMENTAL FINDINGS THAT HAVE

SOME AMOUNT OFh>> SEEMS TO HAVE A QUESTION.

>> WELL SURE.

IT'S SORT OF A QUESTION AND A

COMMENT.

I'M AN ACADEMIC SO OF COURSE

I'LL SAY WHAT I WANT TO SAY AND

THEN I'LL ASK YOU.

SO ONE OF THE ISSUES, I GUESS I

THINK APPLIES PROBABLY MORE TO

MICHAEL AND ANUPAM'S PAPER BUT I

THINK ALL THE PAPERS IS, YOU

KNOW, IF WE THINK ABOUT THE

TRANSMISSION OF YOUR FINDINGS

INTO POLICY, I THINK ONE OF THE

TOUCH STONES OF POLICY, AT LEAST

IN MY VIEW SHOULD BE HARM.

SO I GUESS I THINK ABOUT YOUR,

THE FINDING OF THE JOB SEARCH

DIFFERENT FROM MEN AND DIFFERENT

FROM WOMEN.

AND IF YOU LOOK AT LET'S ASSUME

THAT THE DATA'S THERE AND

THERE'S A STATISTICAL

DIFFERENCE, WE CAN EVEN SAY IT'S

CAUSAL, DIGGING DOWN DEEPER,

WHAT'S THE REAL WORLD IMPACTING

THAT IN A SENSE.

SO CLICK THROUGH RATES ARE WHAT,

MAYBE ONE OUT OF A THOUSAND IF

YOU'RE LUCKY.bf

THAT'S THE AVERAGE.

ONE OUT OF A THOUSAND.

SO LET'S SAY ONE OUT OF A

THOUSAND PEOPLE WHO VISIT THIS

WEBSITE, THEY WOULD CLICK ON

THAT AND THESE ARE PEOPLE WHOSE

PROFILES HAVE VISITED OTHER JOB

SEARCHING WEBSITES.

SO MY POINT, THERE WOULD BE TO
WHAT EXTENT, THEY'RE NOT GOING
TO BE LIMITED.
THIS ISN'T REALLY NECESSARILY
HEY I'VE GONE TO A THOUSAND
WEBSITES BUT NOW I'VE GONE TO
THE TIMES OF INDIA.
I'M JUST GOING TO TAKE A JOB.
I'M GOING TO FOLLOW MY CAREER
BASED ON THIS AD THAT SERVED TO
ME I THINK THAT'S PROBABLY NOT
LIKELY.
BY YOU KNOW AND THEN I VISITED
BOTH THOSE WEBSITES.
I DON'T KNOW, I'M SURE YOU HAVE
AND I DON'T KNOW HOW MANY HAVE
BUT THE ONES THAT HAD A HUNDRED
WEBSITES, IT'S GOT THE NICE
BANNER, 200K PLUS.
BUT IT'S A HEADHUNTER.
I'M NOT SAYING IT'S, I'M SURE
IT'S LEGIT BUT NOT SUGGESTING
THE FTC LOOK INTO IT OR

ANYTHING, BUT COMPARED TO THE
OTHER ONE, THE WOMEN WERE SERVED
MORE OFTEN.
THIS WAS I THINK JOBS NEAR YOU.
YOU GO ON THAT AND THE FIRST
PAGE CLICKED ON METROPOLITAN YEW
THEY'RE NOT LIKE BLUE COLLAR
JOBS, THEY'RE ACCOUNTANT,
LAWYER, BIO.
IF YOU LOOK AT THE TWO RANDOM
PEOPLE MAN AND WOMAN, THE WOMAN
SAYS WELL I DIDN'T SEE THE
HEADHUNTER AD SO I'M JUST GOING
TO GO WITH JOBS FOR ME.
SO I LOOK, I THINK ABOUT LIKE
THE REAL WORLD IMPACT.
YOU DID DETECTOR.
YOU DID FIND, YOU KNOW,
STATISTICALLY SIGNIFICANT
DIFFERENCE BETWEEN MEN AND WOMEN
BUT AT THE END OF THE DAY, YOU
KNOW, BEFORE WE GET INTO ISSUES
OF HARM WHICH I THINK SHOULD BE

A TOUCH STONE OF ANY POLICY
ESPECIALLY HERE AT THE FTC, DO
YOU NEED TO FIND MORE.
IS THERE ACTUALLY SOME SORT OF
EVIDENCE OF HARM HERE?
>> WELL, THERE'S A SAYING
AMONGST ADVERTISERS WHICH IS I
WASTE HALF OF MY BUDGET.
I JUST WISH I KNEW WHICH HALF.
SO I REALLY DON'T THINK ANYONE
CAN LOOK AT ANY ONE AD AND
NECESSARILY KNOW WHAT ITS ENTIREIMPACT IS.
BUT WE DO KNOW THAT ADVERTISERS,
YOU DON'T SEE COKE ADS ON THE TV
BECAUSE THEY EXPECT YOU TO
STOPWATCHING THE AD AND RUN OUT
AND BUY A COKE.
THESE ADS CAN BE FUNCTIONED IN A
SIMILAR WAY.
IT'S ABOUT CREATING AN IMPACT
UPON PEOPLE THAT LASTS WHEN THEY
SEE SOMETHING OVER AND OVER
AGAIN OR DON'T SEE SOMETHING

OVER AND OVER AGAIN.
WE'RE CONCERNED ABOUT THE WOMEN
NOT BEING EXPOSED TO THE
ENCOURAGEMENT TO SEEK HIGH
PAYING ADS JUST AS MUCH AS WE'RE
CONCERNED ABOUT ANY ONE PERSON
CLICKS ON THAT AD OR NOT.
YOU'RE RAISING A POINT THAT THIS
FIRM PUTTING UP THIS AD, YES I
LOOKED UP SOME CUSTOMER REVIEWS
ON IT AND IT DIDN'T REALLY HAVE
THE HIGHEST CUSTOMER REVIEWS.
IF WE LOOK AT JUST THE LACK OF
PERHAPS WOMEN DEVELOPING A
BUSINESS RELATIONSHIP WITH THEM,
THEN IT MIGHT BE ACTUALLY IN
THEIR FAVOR THAT THEY'RE NOT
SEEING THIS AD.
SO, I DON'T KNOW.
YOU ARE CORRECT.
WE CAN'T PINPOINT AND MEASURE
THE EXACT AMOUNT BUT WE DO KNOW
THAT MEN AND WOMEN --

>> OR ANY HARM.

I WOULD KIND OF GO THAT FAR.

>> SO I THINK THERE ARE A FEW

THINGS TO HIGHLIGHT.

ONE THERE WAS ANOTHER EXAMPLE

BROUGHT OUT ABOUT PROXIMITY TO

WORK.

I DON'T REMEMBER WHO SAID IT.

>> TO THE LOCATION OF THE STORE.

>> NO, NO, THE PROXIMITY REPORT.

IT MAY BE IN THE BIG DATA REPORT

THAT JUST CAME OUT.

IF YOU WERE LOOKING FOR

POTENTIAL EMPLOYEE THAT YOU

WANTED TO ADVERTISE TO AND YOU

SAID OH WELL PEOPLE WHO LIVE

CLOSE TEND TO BE BETTER

EMPLOYEES.

THEN YOU MIGHT LOOK AND FIND OUT

THAT HAS A LOT TO DO WITH

INCOME.

IT COULD BE A PROXY FOR

SOMETHING ELSE.

AND WE DO WHEN WE'RE THINKING

ABOUT EMPLOYMENT, EQUAL ACCESS

TO NOT JUST EMPLOYMENT

OPPORTUNITIESg¦ BUT ALSO WE THINK

ABOUT THE ADVERTISING OF THOSE

EMPLOYMENT OPPORTUNITIES AS

SOMETHING WHERE WE'REtweúABOUT RACIAL DISPARITIES AND

GENDER DISPARITIES AND HOW WE'RE

MAKING INFORMATION ABOUT

OPPORTUNITIES AVAILABLE AS A

LEGAL MATTER.

WE'RE CONCERNED ABOUT THAT SO

LET ME FINISH, HOLD ON.

SO KIND OF SETTING ASIDE THIS

PARTICULAR EXAMPLE, RIGHT, WHICH

WE AGREE IS PROBLEMATIC FOR MANY

REASONS.

AND I THINK ONE OF THE MOST

INTERESTING THINGS AT THIS

PARTICULAR EXAMPLE OF THE

HEADHUNTER AD BROUGHT OUT WHICH

ANUPAM NOTED, THE MOST LIKELY WE

THINK, RIGHT, WE THINK OR AT

LEAST THE HIGHLY LIKELY REASON

THAT MEN WERE SEEING THIS MORE

THAN WOMEN IS THAT PEOPLE WERE

WILLING TO PAY MORE TO SELL, TO

SHOW WOMEN ADVERTISEMENTS FOR

HAIR CARE PRODUCTS AND OTHER

THINGS, RIGHT.

AND THE POINT BEING THAT IF Yt

WERE A COMPANY AND YOU WERE

TRYING TO USE THIS TO MAKE

INFORMATION AVAILABLE ABOUT

EMPLOYMENT OPPORTUNITIES, YOU

DON'T HAVE COMPLETE CONTROL OVER

WHO SEES THEM FULL STOP, RIGHT.

WHEN WE'RE THINKING ABOUT

ANYTHING THAT REQUIRES WHAT YOU

AS AN ADVERTISER WANT TO BE

ATTENTIVE TO WHO IS GETTING

ACCESS TO YOUR ADS BECAUSE

YOU'RE INTERESTED IN MAKING SURE

THEY ARE EQUALLY AVAILABLE TO

THE POPULATION TO FIND THEM

WHATEVER WAY YOU WANT.

YOU REALIZE THERE ARE OTHER
PEOPLE WHOSE BIDDING AND
DECISIONS ARE INTERFERING WITH
YOUR ABILITY TO KNOW WHETHER OR
NOT THEY ARE GOING EQUALLY TO
MEN AND WOMEN OR THEY'RE GOING
EQUALLY TO PEOPLE OF DIFFER
RACES, WHATEVER.
YOU BEGIN TO SAY WOW HOW DO WE
THINK ABOUT CAUSALITY, RIGHT.
AND HOW DO WE THINK ABOUT THE
RELATIONSHIP BETWEEN OUTCOMES
AND INFRASTRUCTURE BECAUSE IT
BECOMES AN INFRASTRUCTURE ISSUE.
EVEN IF YOU ARE IN THE STAPLES
EXAMPLES, STAPLES HAD ACCESS TO
THEIR DATA.
THEY WERETHEY HAD ACCESS TO LOTS OF STUFF
AND THEY WEREN'T SEEKING TO HAVE
A PARTICULAR BAD OUTCOME FROM
YOUR DESCRIPTION, DANIEL.
YET THEY DIDN'T DO ENOUGH WORK
OR THEY DIDN'T THINK THROUGH

WHAT WAS GOING TO HAPPEN.
SO AGAIN IT'S ABOUT HOW DO WE
CREATE AN INFRASTRUCTURE AND
TOOL.
>> MY ONLY MOMENT WAS USING
FINDINGS LIKE THIS TO INJECT
INTO POLICY AND POTENTIAL
ENFORCEMENT ACTIONS.
BECAUSE THAT SEEMS TO BE SORT OF
AN UNDER CURRENT IN THE PAPERS
AT LEAST TWO OF THEM WHERE
HERE'S A GOOGLE PRIVACY POLICY
AND WAIT MY AD SUGGESTS THERE'S
TRACKING WHICH COULD LAY THE
PREDICATE.
SO MY POINT IS THERE SEEMS TO BE
LACK OF HARM.
NOW THE STAPLES EXAMPLE TO SAY
NON-INTENDED OUTCOME I THINK
IT'S COMPLETELY INTENDED.
THAT'S JUST CHANNEL CONFLICT
LITIGATION.
I HAVE A BRICK AND MORTAR STORE.

>> THEIR INTENT WASN'T TO
DISEMPOWER PEOPLE.
>> NO, ABSOLUTELY.
I GUESS WHEN YOU SAID THEY
DIDN'T INTEND TO BAN THE
OUTCOME, TO THEM IT'S THE
CORRECT OUTCOME BECAUSE IT'S THE
CORRECT OUTCOME BASED ON THAT'S
THE LOCAL PRICING.
I'M NOT GOING TO UNDER CUT.
IT HAS EVERYTHING TO DO WITH
COMPETITION AND I MEAN THAT HAS
NOTHING TO DO WITH WOW BECAUSE
THERE'S NO, THERE'S ABSOLUTELY,
YOU THINK ABOUT THERE'S REALLY
NO MODEL OF PRICE INFORMATION
AND SAY LET'S CHARGE THE POOR
PEOPLE MORE AND THE RICH PEOPLE.
WHEN I GO TO THE MOVIES AND HOLD
UP MY GEORGE MASON ID, I TRY TO
COVER UP THE FACULTY PART OF IT.
THAT'S WHY BECAUSE THEY CHARGE
THE STUDENTS LESS.

OH, YOU'RE FACULTY.

>> CAN I MAKE A BRIEF COMMENT ON

THAT QUESTION.

SO FOR THE JOB-RELATED

ADVERTISING EXAMPLE.

I THINK THIS IS WHERE I WAS

POSITIONING THIS, THAT OPEN

PROBLEM OF COPYING HOW WIDE -- EXAMING HOW WIDE

SPREAD THIS PHENOMENA IS.

THIS AD ISN'T ENOUGH FOR US TO

CHANGE HOW THE POLICY WORKS.

BUT IF PART OF WHAT ROXANA IS

DOING IS BUILDING

INFRASTRUCTURES THAT ALLOW

EXAMINATIONS OVER MANY MONTHS.

IF THEN SHE@iï

¦ THAT THERE AREMANY INSTANCES OF THESE KINDS,

MAYBE NOT THIS PARTICULAR

QUESTIONABLE AD BUT FROM

LEGITIMATE SERVICES THAT ARE

SHOWING UP REPEATEDLY IN A

DIFFERENTIAL TREATMENT FORM,

DIFFERENTIAL DISPARATE IMPACT

AND THE ESTABLISHMENT OF HARM
COMMENT THAT YOU'RE SAYING IS
ABSOLUTELY VALID.
ADDITIONAL LAYER ANALYSIS WILL
NOT COME FROM THE TOOLS WE'RE
BUILDING, THAT HAS TO COME FROM
PEOPLE LIKE YOU AND THE
REGULATOR AGENCIES WILL LOOK
DEEPER, DIG DEEPER INTO, DIG
DEEPER INTO IS THIS REALLY A
LEGITIMATE DISPARATE IMPACT.
THE ADDITIONAL HARM
CONSIDERATION.
SO I'M ABSOLUTELY ON BOARD WITH
YOU ON THAT IN ADDITION TO THE
OTHER COMMENTS.
>> I JUST WANTED TO SAY
SOMETHING VERY VERY BRIEF.
I COMPLETELY AGREE.
WHAT I WANTED TO NOTE IS THIS
RESEARCH IS AT THE BEGINNING.
THIS KIND OF RESEARCH INTO
BUILDING INFRASTRUCTURE THAT CAN

TELL US WHAT'S HAPPENING IS AT

THE BEGINNING.

AS A RESULT WE KNOW VERY LITTLE.

WE HAVE A BUNCH OF EXAMPLES.

THAT'S PRETTY MUCH WHAT WE HAVE.

I HAVE GREAT HOPE FOR THIS FIELD

ESPECIALLY BECAUSE MORE AND MORE

PEOPLE ARE COMING INTO IT.

THAT WILL DEVELOP, THE KINDS OF

INFRASTRUCTURES WE'LL NEED IN

ORDER TO ACTUALLY MAKE IMPACT ON

THE LEGAL DOMAIN.

BUT RIGHT NOW, YOU KNOW, I THINK

WE KNOW TOO LEGAL IN ORDER TO DO

THAT.

>> HAVING PROOF OF EXISTENCE IS

USEFUL AS A STARTING POINT.

WE DON'T HAVE EVIDENCE THAT IT'S

WIDE SPREAD.

>> I óZWANTS TO ENSURE IT'S NOT

DISCRIMINATING CAN USE DANIEL'S

TOOL.

AND THE OTHERS CAN GET CAUGHT BY

OTHER TOOLS.
>> THAT'S EXACTLY THE WAY WE'RE
THINKING AND WHY WE'VE BEEN
DEVELOPING FROM THE EXTERIOR TO
THE EXTERIOR,÷AND FOR THE DEVELOPERS TO
ACTUALLY HELP THEM FIGURE OUT
WHAT TO DO WHEN THE PRESSURE'S
ON FROM THE EXTERIOR.
>> SO WE HAVE 50 SECONDS THAT
GIVES EACH OF YOU ABOUT TEN
SECONDS TO GIVE A FINAL THOUGHT.
>> JUST TO COMPLETE MY THOUGHT,
WE'VE DECIDED IN EMPLOYMENT MEN
AND WOMEN SHOULD BE TREATED THE
SAME.
SO TO ME THE FACT THEY'RE NOT
BEING TREATED THE SAME IS IN AND
OF ITSELF A HARM.
MAYBE IT'S NOT TO YOU BUT THAT'S
MY OPINION.
>> SO I WOULD SAY THAT WE NEED A
COMPLETE ACCOUNTABILITY TOOL
CHAIN THAT GOES FROM DETECTION

TO RESPONSIBILITY ASSIGNMENT TO
CORRECTION MECHANISMS.
AND THERE IS AN EMERGING BODY OF
WORK ON EACH OF THESE PIECES OF
THE PUZZLE.
OUR FOCUS HERE HAS PRIMARILY
BEEN ON DETECTION.
THERE'S A SMALL AMOUNT OF
EXPLANATIONS ON THE LAST TALK
BUT THERE'S A HUGE SET OF OPEN
QUESTIONS RELATED TO
RESPONSIBILITY ENVIRONMENT AND
CORRECTIVE MEASURES.
>> THAT'Syñç,x OKAY.
>> WITH THAT, WE WILL WRAP UP
THIS SESSION.
SO THANK YOU ALL SO MUCH.
THE CAFETERIA WILL BE OPEN
DURING THIS BREAK.
YOU CAN GET COFFEE WITHOUT
STANDING IN A LONG LONG LINE.
WE'LL BE BACK IN 15 MINUTES.