INTERACTIVE & EXPLAINABLE AI

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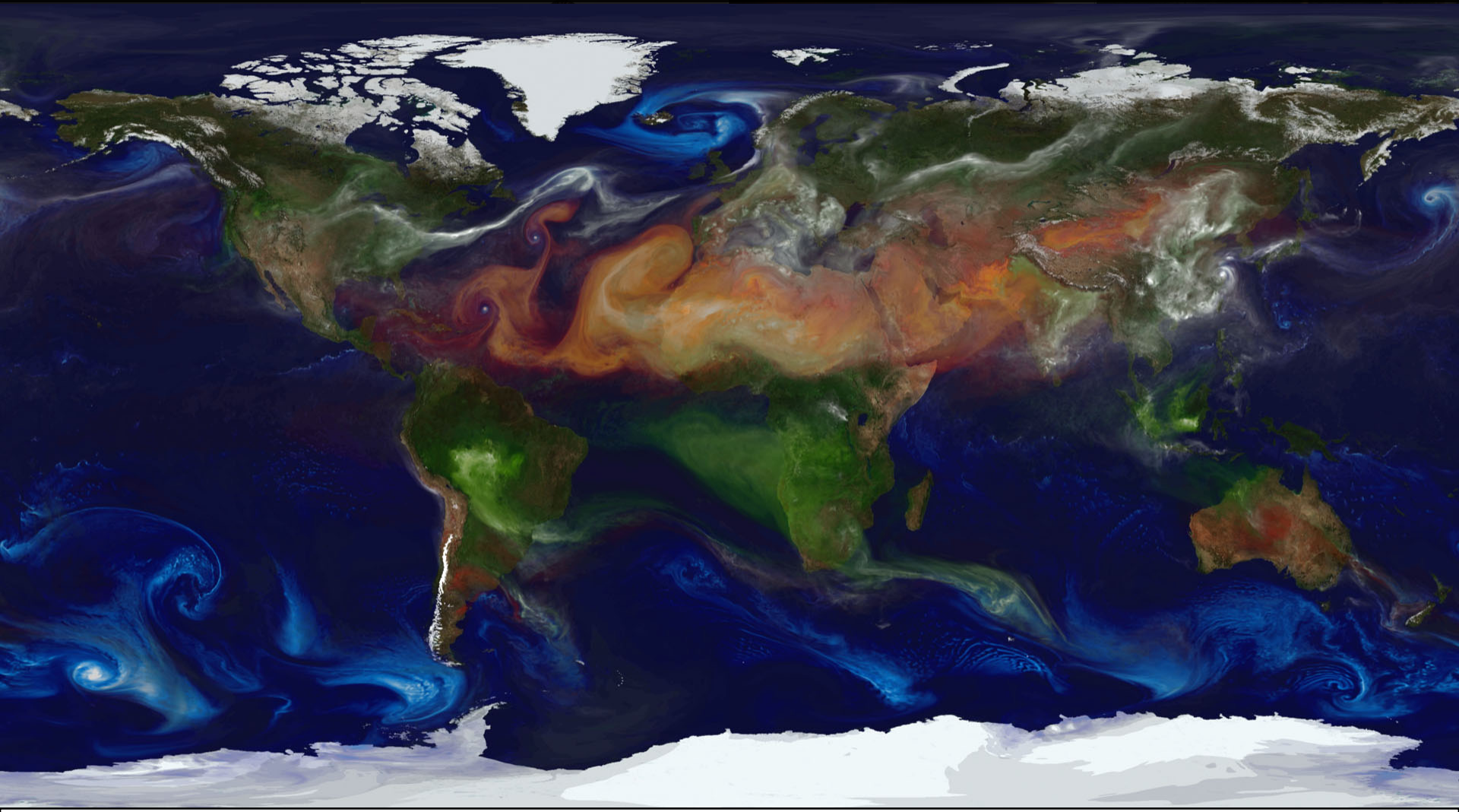
The 6th Summer School on Computational Interaction – Day 4

CompHCILab | EECS ELECTRICAL ENGINEERING AND COMPUTER SCIENCE UNIVERSITY OF MICHIGAN

ABOUT ME

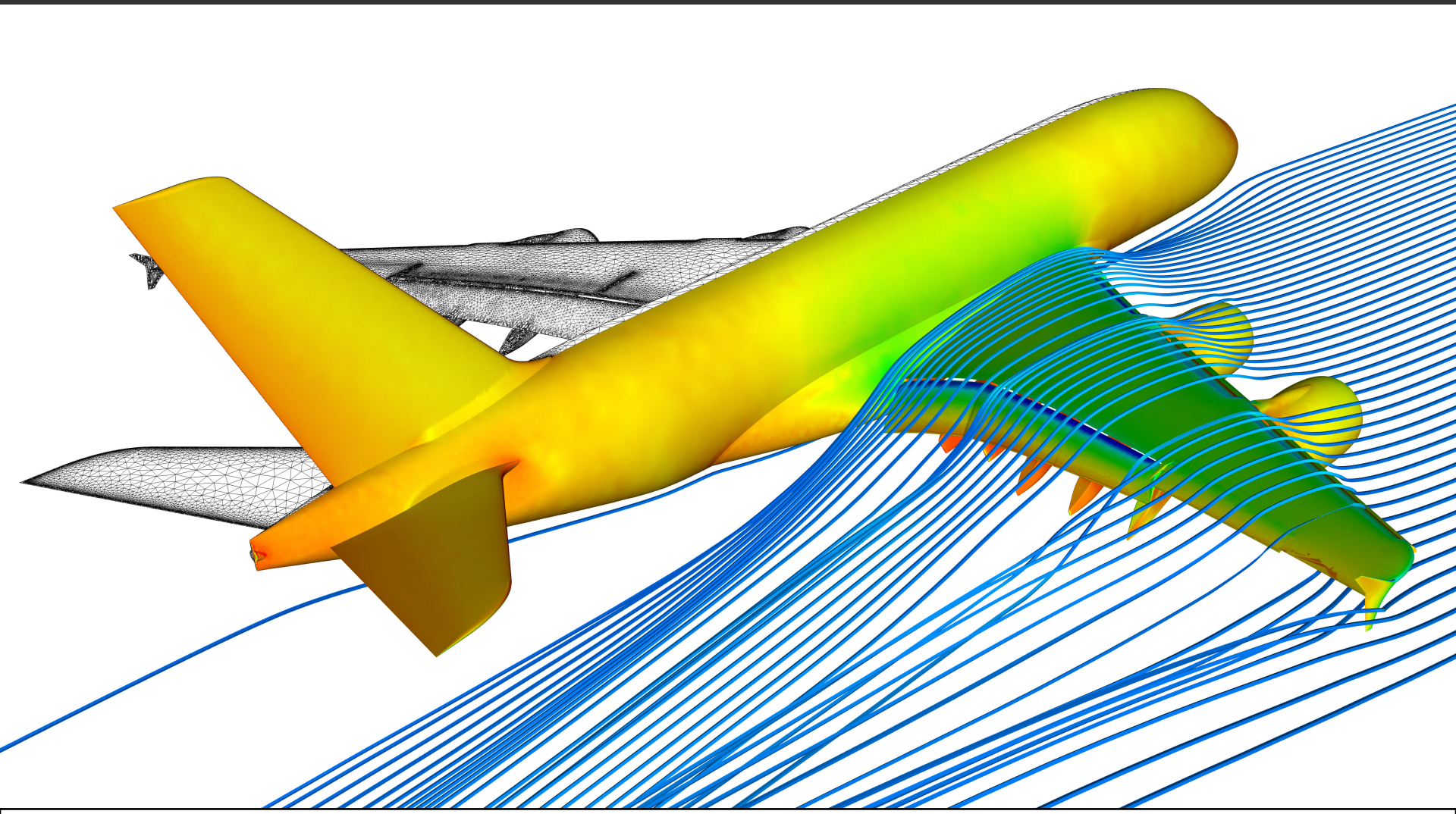
- Assistant Professor at the Computer Science and Engineering department at the University of Michigan
- PhD in Human-Computer Interaction from CMU
- Computer scientist doing HCI research; focus on Computational Interaction
- Research Interests:
  - Human Behavior Modeling
  - Explainable and Interpretable AI
  - Behavior-aware User Interfaces

COMPUTATIONAL MODELING: A TOOL TO STUDY AND EXPLORE COMPLEX SYSTEMS



View of aerosol movement created by NASA's models and supercomputers. NASA/Goddard Space Flight Center.

COMPUTATIONAL MODELING: A TOOL TO STUDY AND EXPLORE COMPLEX SYSTEMS



HUMAN-COMPUTER INTERACTION STUDIES PEOPLE'S INTERACTION WITH TECHNOLOGY

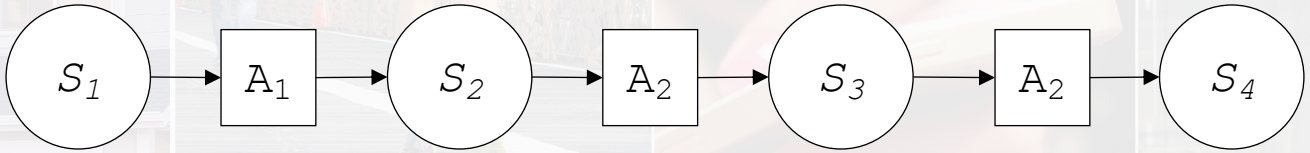
MODELING POINTING AND TYPING BEHAVIORS

Banovic, Sethapakdi, Hari, Dey, Mankoff. 2019. The Limites of Expert Text Entry Speed on Mobile Keyboards with Autocorrect. In *Proc.* MobileCHI '19. ACM.

Banovic, Rao, Saravanan, Dey, Mankoff. 2017. Quantifying Aversion to Costly Typing Errors in Expert Mobile Text Entry. In *Proc.* CHI '17. ACM. ***Honorable Mention Award***

Banovic, Grossman, & Fitzmaurice. 2013. The Effect of Time-based Cost of Error in Target-directed Pointing Tasks. In *Proc.* CHI '13. ACM.

MODELING COMPLEX ROUTINE BEHAVIORS

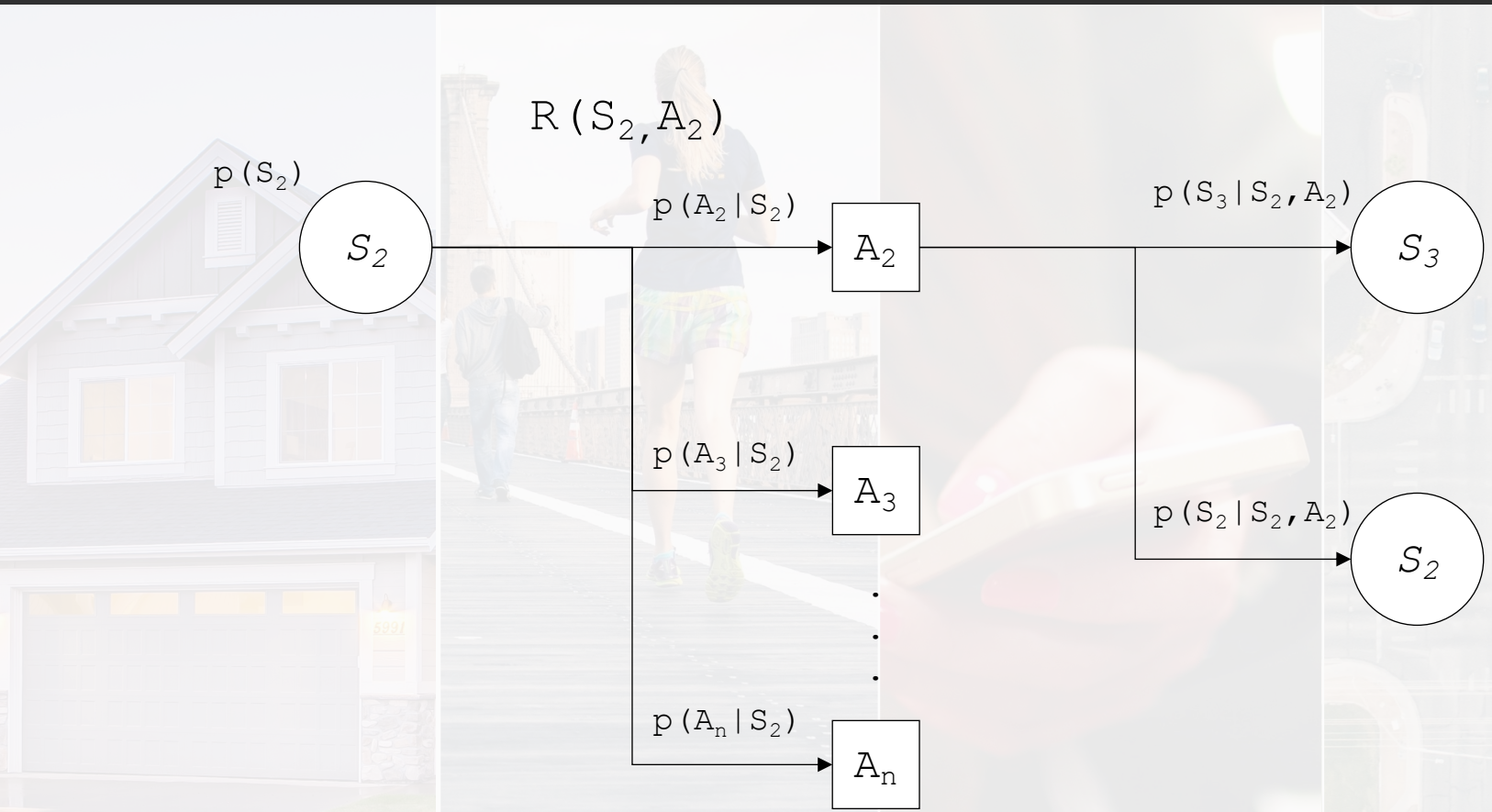


Banovic, Mankoff, and Dey. 2018. Computational Model of Human Routine Behavior. In *Computational Interaction.* Oxford University Press.

Banovic, Wang, Jin, Cheng, Ramos, Dey, & Mankoff. 2017. Leveraging Human Routine Models to Detect and Generate Human Behaviors. In *Proc.* CHI '17.

Banovic, Buzali, Chevalier, Mankoff, & Dey. 2016. Modeling and Understanding Human Routine Behavior. In *Proc.* CHI '16. ***Honorable Mention Award***

MODELING COMPLEX ROUTINE BEHAVIORS



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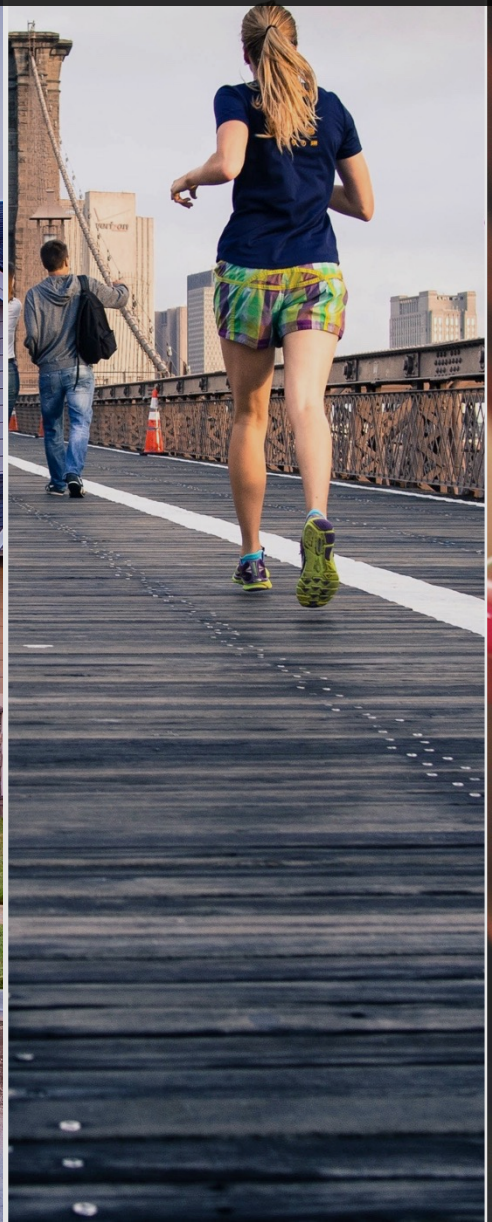
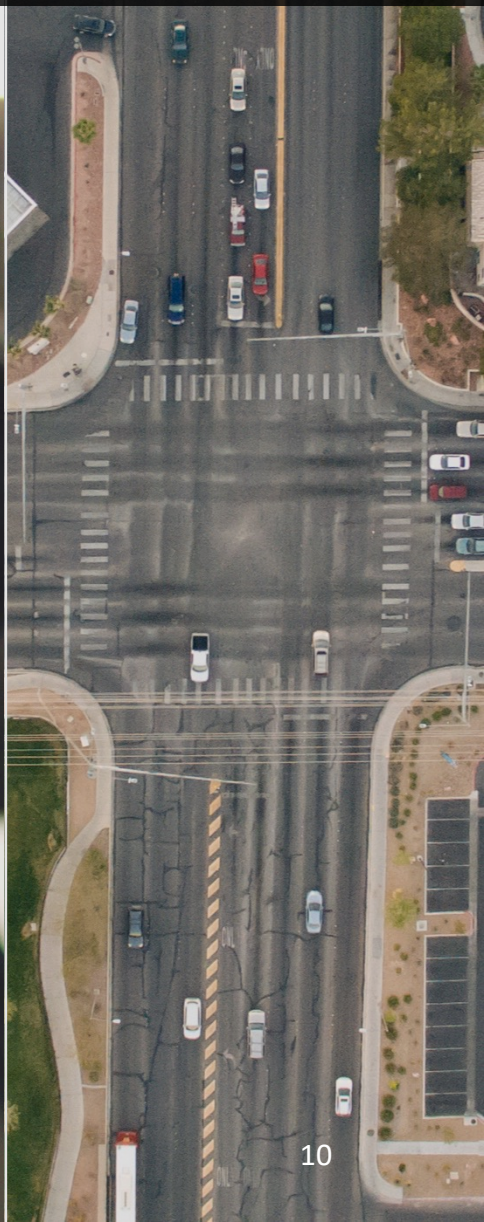
Banovic, Buzali, Chevalier, Mankoff, & Dey. 2016. Modeling and Understanding Human Routine Behavior. In *Proc.* CHI '16. ***Honorable Mention Award***

SENSE, COLLECT, AND STORE DATA ABOUT PEOPLE AT SCALE

NEW SOURCE OF DATA TO STUDY BEHAVIORS ABOUT MANY ASPECTS OF PEOPLE'S LIVES

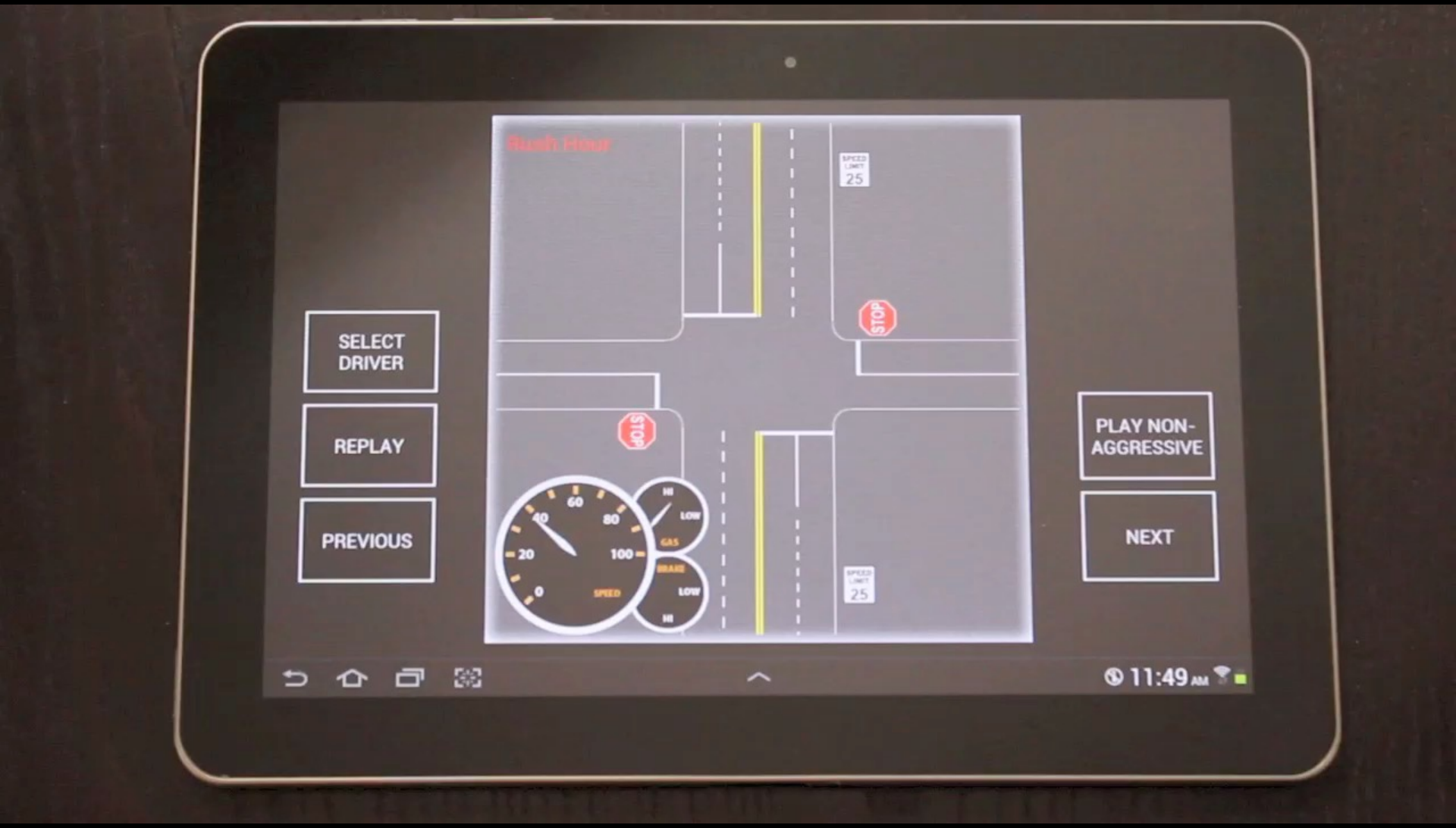




DRIVER COACH DETECTS AGGRASSIVE DRIVING & SIMULATES NON-AGGRESSIVE ALTERNATIVES

Banovic, Wang, Jin, Cheng, Ramos, Dey, & Mankoff. 2017. Leveraging Human Routine Models to Detect and Generate Human Behaviors. In *Proc.* CHI '17.

DRIVER COACH DETECTS AGGRESSIVE DRIVING



Banovic, Wang, Jin, Cheng, Ramos, Dey, & Mankoff. 2017. Leveraging Human Routine Models to Detect and Generate Human Behaviors. In *Proc.* CHI '17.

WHY EXPLAINABILITY MATTERS TO ME

- To use such computational models to understand people, the models we use need to be explainable
- To deploy behavior-aware user interfaces we need to ensure that we can assess the capabilities and limitations of such systems

LEARNING GOALS

- Define Explainability and Interpretability
- Learn what we mean by Explainable AI (XAI) including Human-Centered XAI (HCXAI)
- Lean about interactive model exploration (a particular HCXAI method)
- Take a deep dive into an example interactive model exploration implementation

DAY 4 SCHEDULE

9:30 – 11:00	Lecture and discussions (will have a coffee break)
11:00 – 11:30	Go over GAN Explorer code (see the github repository)
13:30 – 15:00	Mini hackathon
15:30– 16:30	Showcase

WHAT IS ARTIFICIAL INTELIGENCE (AI)?

Even code: #2426146
https://app.sli.do/event/ut4dDWikQr64YLzNqBDHVr

You have 120 seconds…

DONE!

WHAT IS ARTIFICIAL INTELIGENCE (AI)?

"Intelligence demonstrated by machines."

WHAT IS EXPLAINABLE AI?

Even code: #2426146
https://app.sli.do/event/ut4dDWikQr64YLzNqBDHVr

You have 120 seconds…

DONE!

WHAT IS EXPLAINABLE AI?

"AI that humans can learn how it works, and know its capabilities and limitations."

"AI that can provide reasons or justifications for its actions, decisions, or beliefs."

WHAT IS INTERPRETABLE AI?

Even code: #2426146
https://app.sli.do/event/ut4dDWikQr64YLzNqBDHVr

You have 120 seconds…

DONE!

WHAT IS INTERPRETABLE AI?

"AI with inputs and outputs that can be translated into something that humans can understand."

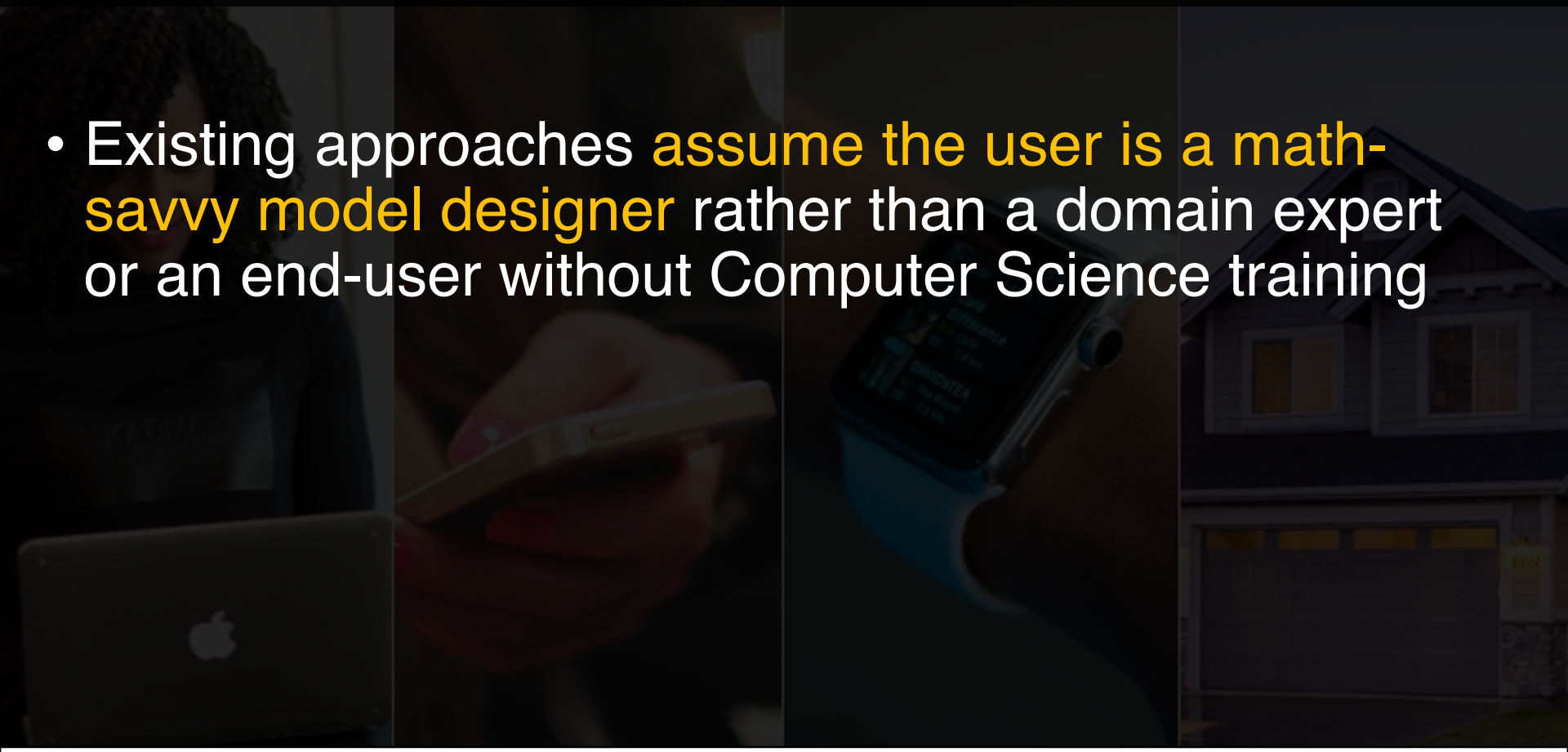
EXPLAINABLE ARTIFIAL INTELIGENCE (AI)

Explainability is of critical importance to technology-driven innovation and broader societal adoption of AI.

EXPLAINABLE ARTIFIAL INTELIGENCE (AI)

- The ability to explain capabilities and limitations of an AI and justify its decisions aids in its trustworthiness, accountability, fairness, inclusivity, and accessibility.

EXPLAINABLE AI (XAI)



- Existing approaches assume the user is a math-savvy model designer rather than a domain expert or an end-user without Computer Science training

Carvalho et al. 2019. Machine Learning Interpretability: A Survey on Methods and Metrics. Electronics 8, no. 8: 832. https://doi.org/10.3390/electronics8080832

Gilpin et al, 2018. Explaining Explanations: An Overview of Interpretability of Machine Learning," DSAA 2018, pp. 80-89. doi: 10.1109/DSAA.2018.00018.

Ras et al. 2018. Explanation Methods in Deep Learning: Users, Values, Concerns and Challenges. In Explainable and Interpretable Models in Computer Vision and Machine Learning. https://doi.org/10.1007/978-3-319-98131-4_2

EXPLAINABLE AI (XAI)

- Existing approaches assume the user is a math-savvy model designer rather than domain experts or end-users without Computer Science training

- Such explanations often do not match the end-users' mental models; thus, are ineffective and at times even harmful

Danding et al. 2019. Designing Theory-Driven User-Centric Explainable AI. In CHI '19, Paper 601, 1–15. https://doi.org/10.1145/3290605.3300831

Alqaraawi et al, 2020. Evaluating saliency map explanations for convolutional neural networks: a user study. In IUI '20, 275–285. https://doi.org/10.1145/3377325.3377519

Lakkaraju et al. 2020. "How do I fool you?": Manipulating User Trust via Misleading Black Box Explanations. In Proc. of the AAAI/ACM Conference on AI, Ethics, and Society, 79–85. https://doi.org/10.1145/3375627.3375833

EXPLAINABLE AI (XAI)

- Existing approaches assume the user is a math-savvy model designer rather than domain experts or end-users without Computer Science training
- Such explanations often do not match the end-users' mental models; thus, are ineffective and at times even harmful
- Instead, enable end-users to explore capabilities and limitations of AI (and AI-based systems) through interaction that is tailored for them

WHAT ARE SOME EXAMPLES OF XAI?

Even code: #2426146
https://app.sli.do/event/ut4dDWikQr64YLzNqBDHVr

You have 120 seconds…

DONE!

EXAMPLE XAI: LIME

- Local Interpretable Model-agnostic Explanations
- Let's watch a quick video: https://youtu.be/hUnRCxnydCc

Ribeiro et al. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. In KDD '16, 1135–1144. https://doi.org/10.1145/2939672.2939778

EXAMPLE XAI: LIME

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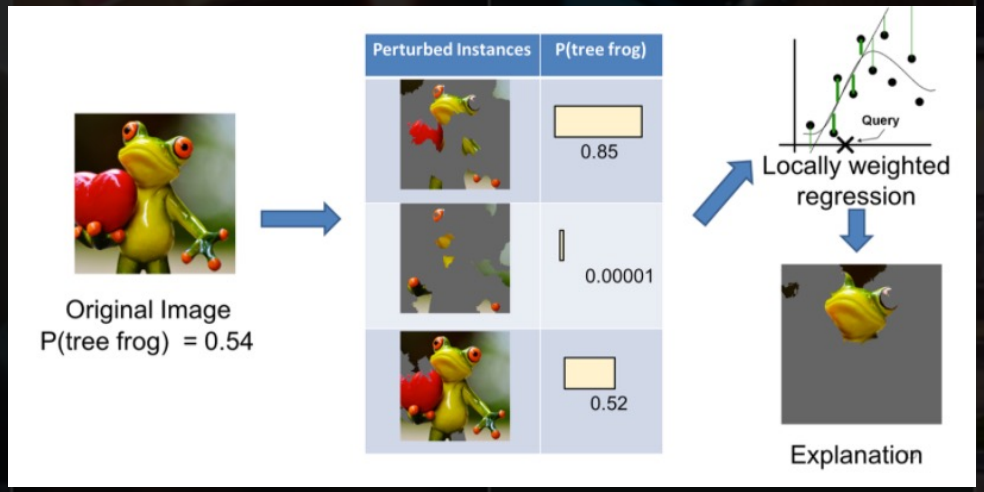

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WHAT IS HUMAN-CENTERED XAI?

WHAT IS HUMAN-CENTERED XAI?

"XAI methods and tools that are implemented using a human-centered design method."

ALGORITHMIC AUDIT DETECTS ERRORS IN E-GOVERNMENT SYSTEMS

Escher & Banovic. 2020. Exposing Error in Poverty Management Technology: A Method for Auditing Government Benefits Screening Tools. In *PACM HCI (CSCW)* 2020.

INTERACTIVE IMAGE GALLERIES ENABLE EXPLORATION OF GAN MODELS

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

AUDIT BASED XAI (OR WHEN AI CANNOT BE TRUSTED TO EXPLAIN ITSELF)

ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

- E-Government
  - Provision of state services through technological communication devices
- May improve access
- May reduce administrator workload

Escher & Banovic. 2020. Exposing Error in Poverty Management Technology: A Method for Auditing Government Benefits Screening Tools. In *PACM HCI (CSCW)* 2020.

ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

- Huge impact for affected people
- Can be hard to detect
- Can be hard to contest

Escher & Banovic. 2020. Exposing Error in Poverty Management Technology: A Method for Auditing Government Benefits Screening Tools. In *PACM HCI (CSCW)* 2020.

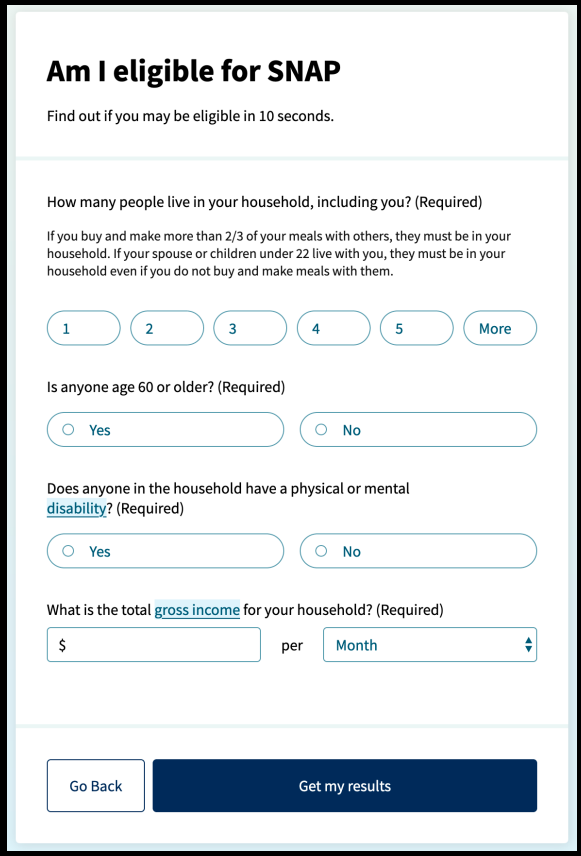
ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

- Detect errors before they affect people
- Make embedded errors visible
- Allow organizations and individuals to articulate demands for change

Escher & Banovic. 2020. Exposing Error in Poverty Management Technology: A Method for Auditing Government Benefits Screening Tools. In *PACM HCI (CSCW)* 2020.

ELIGIBILITY SCREENING TOOLS

- Accepts estimated information about a household, then predicts whether they will qualify for benefits
  - Eligibility handbooks can stretch hundreds of pages, often written in complex legal language



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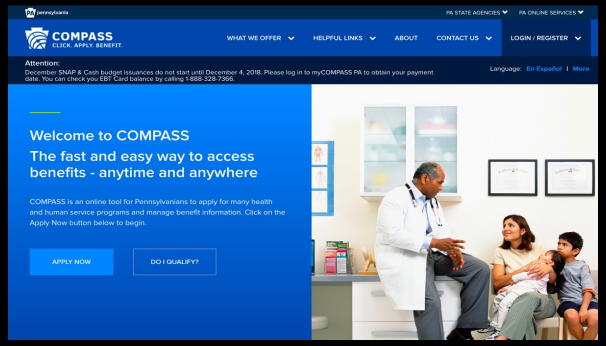
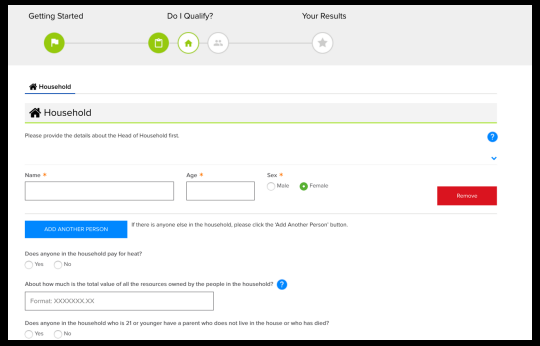
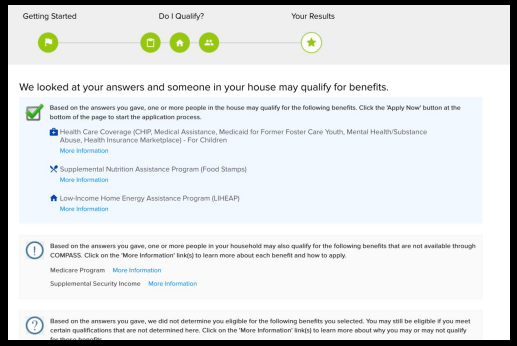
ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

- Method for auditing Screening Tools
  - Locate embedded errors, i.e., incorrect application of the legal rules
  - Illustrated on the Pennsylvania “Do I Qualify?” screening tool







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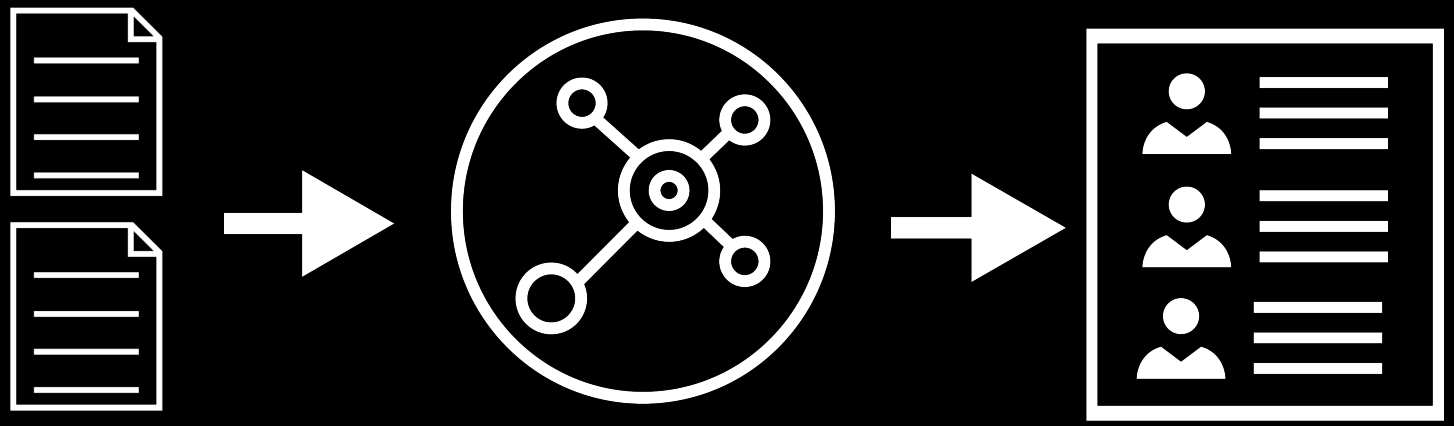
ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

1. Generate Test Households

External Data Sets

Data Transformation and Merge Scripts

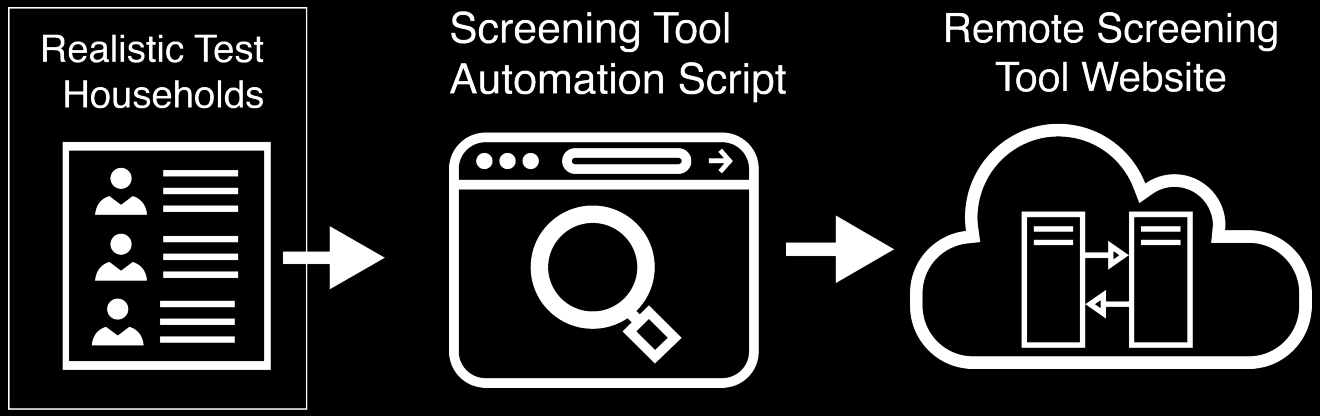
Realistic Test Households



Escher & Banovic. 2020. Exposing Error in Poverty Management Technology: A Method for Auditing Government Benefits Screening Tools. In *PACM HCI (CSCW)* 2020.

ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

2. Retrieve Test Determinations



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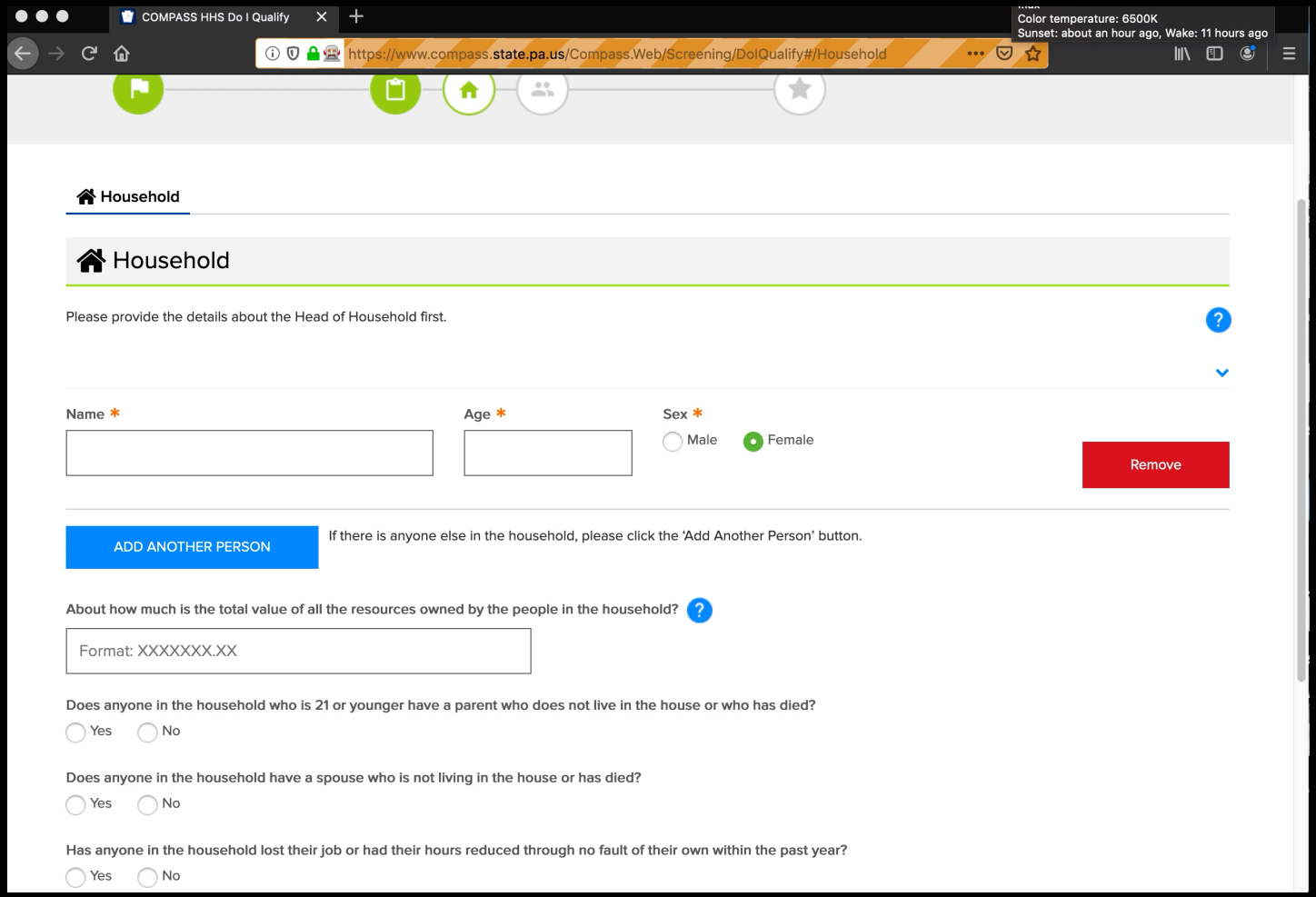

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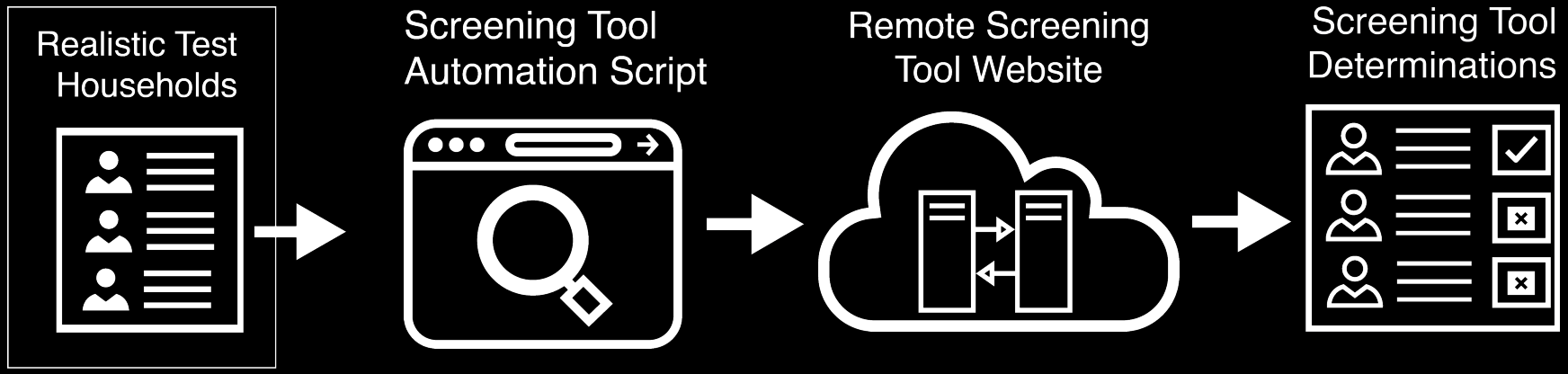

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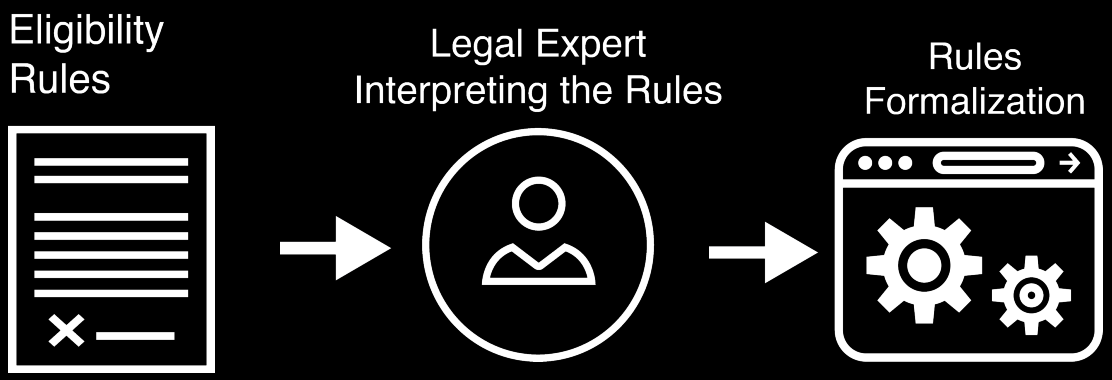
3. Translate Legal Text to Code



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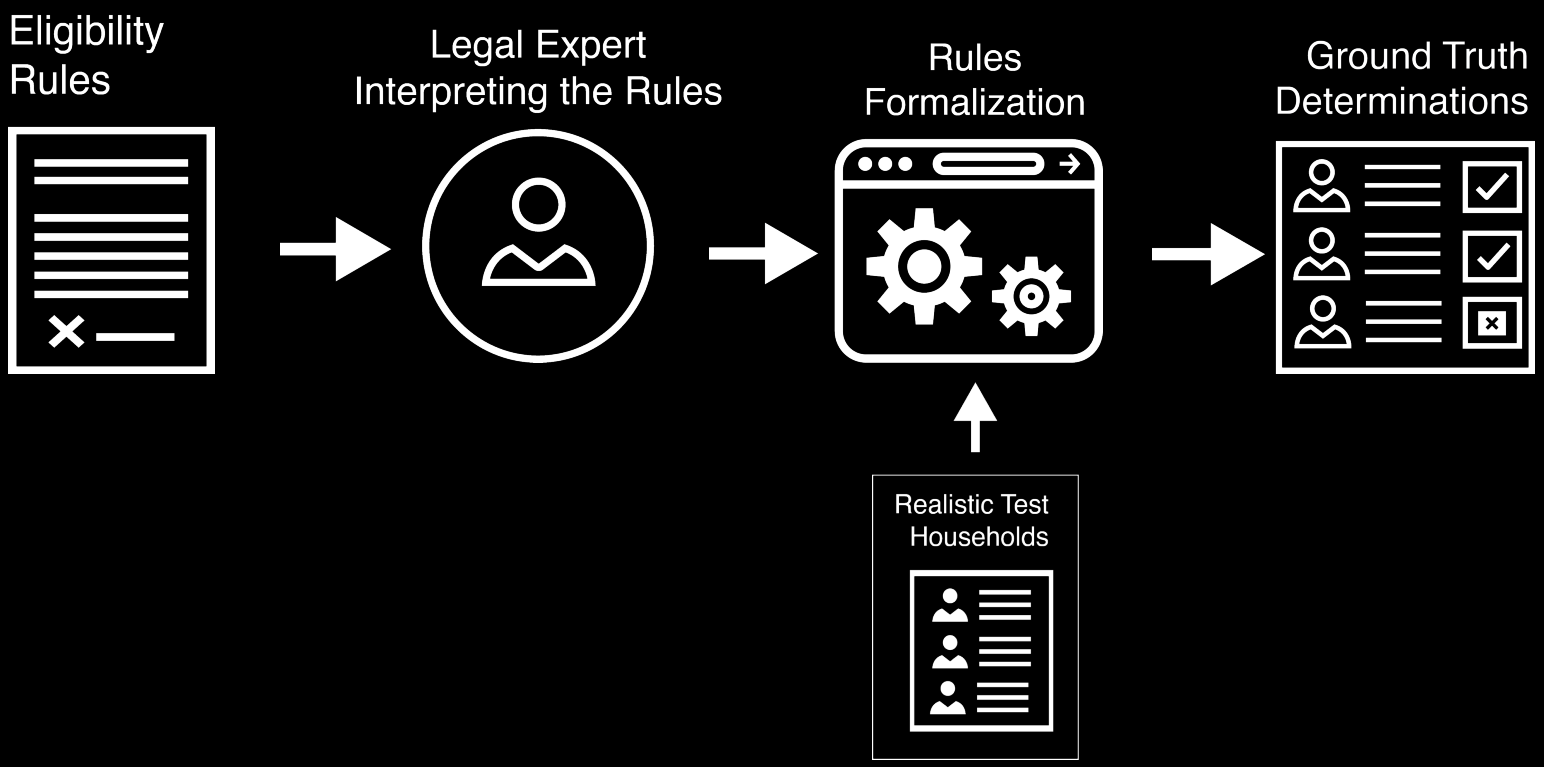

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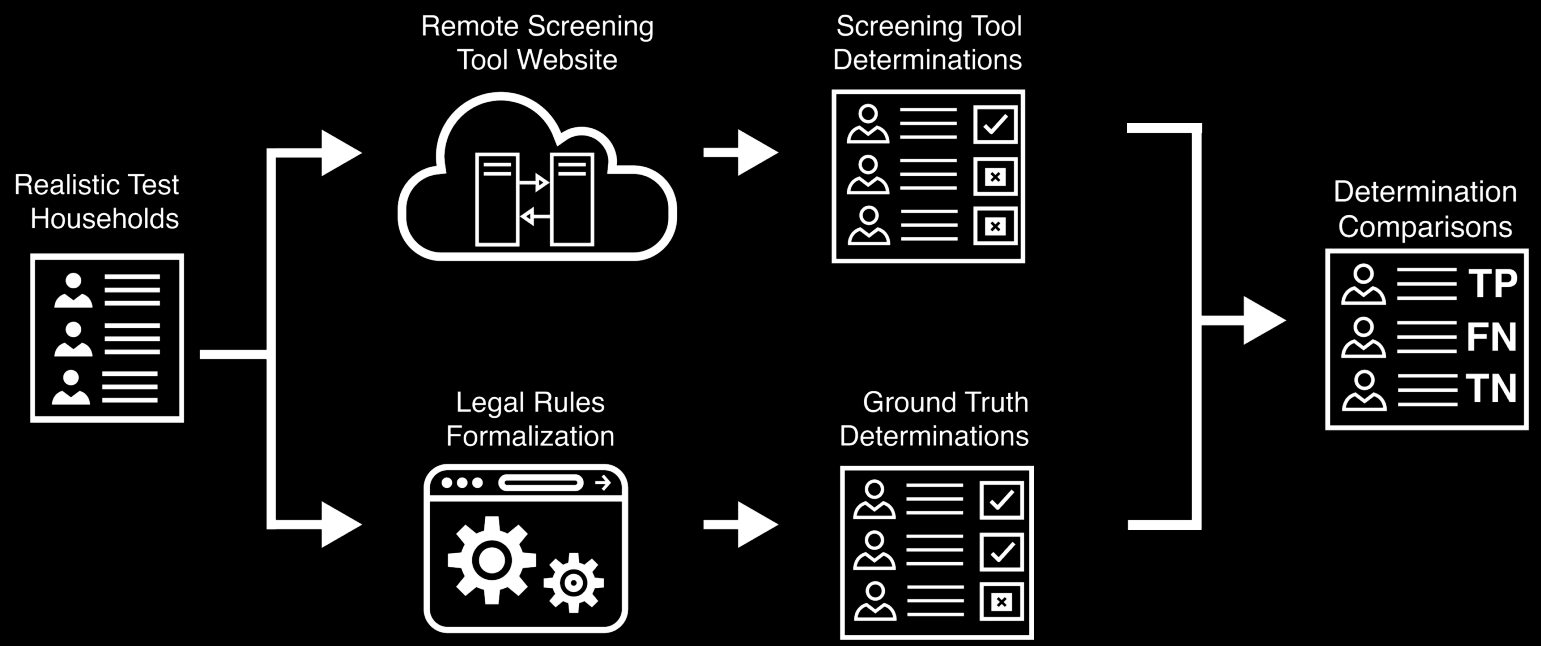
ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

4. Identify Conflicting Determinations



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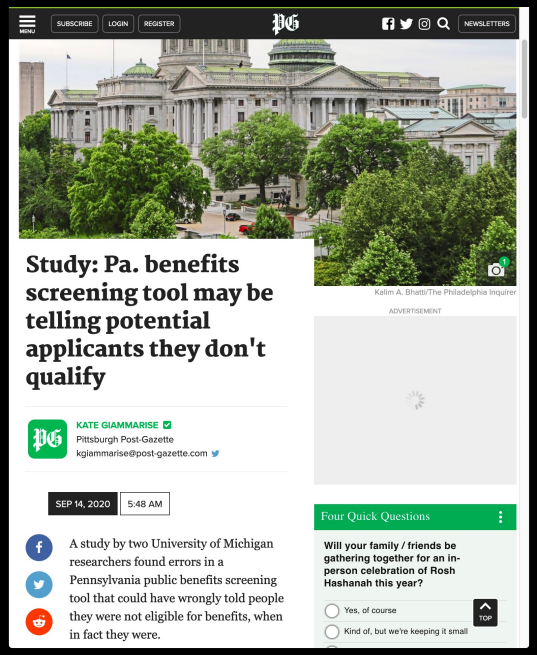
ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

- Example Results: Subsidized Child Care
  - Program described in Pennsylvania Code Title 55, Chapter 3041
    - Families with a child who needs supervision and whose income falls below 200% of the Federal Poverty Income Guidelines (FPIG) are eligible
  - No families predicted eligible for the subsidized child care benefit
    - Our formalization marked at least 4.6% of families as eligible

Escher & Banovic. 2020. Exposing Error in Poverty Management Technology: A Method for Auditing Government Benefits Screening Tools. In *PACM HCI (CSCW)* 2020.

ALGORITHMIC AUDIT: E-GOVERNMENT SYSTEMS

- Some of the errors we exposed have been corrected in the “Do I Qualify?” Screening Tool
- Suggests that coordination between interested groups & public attention required to correct errors



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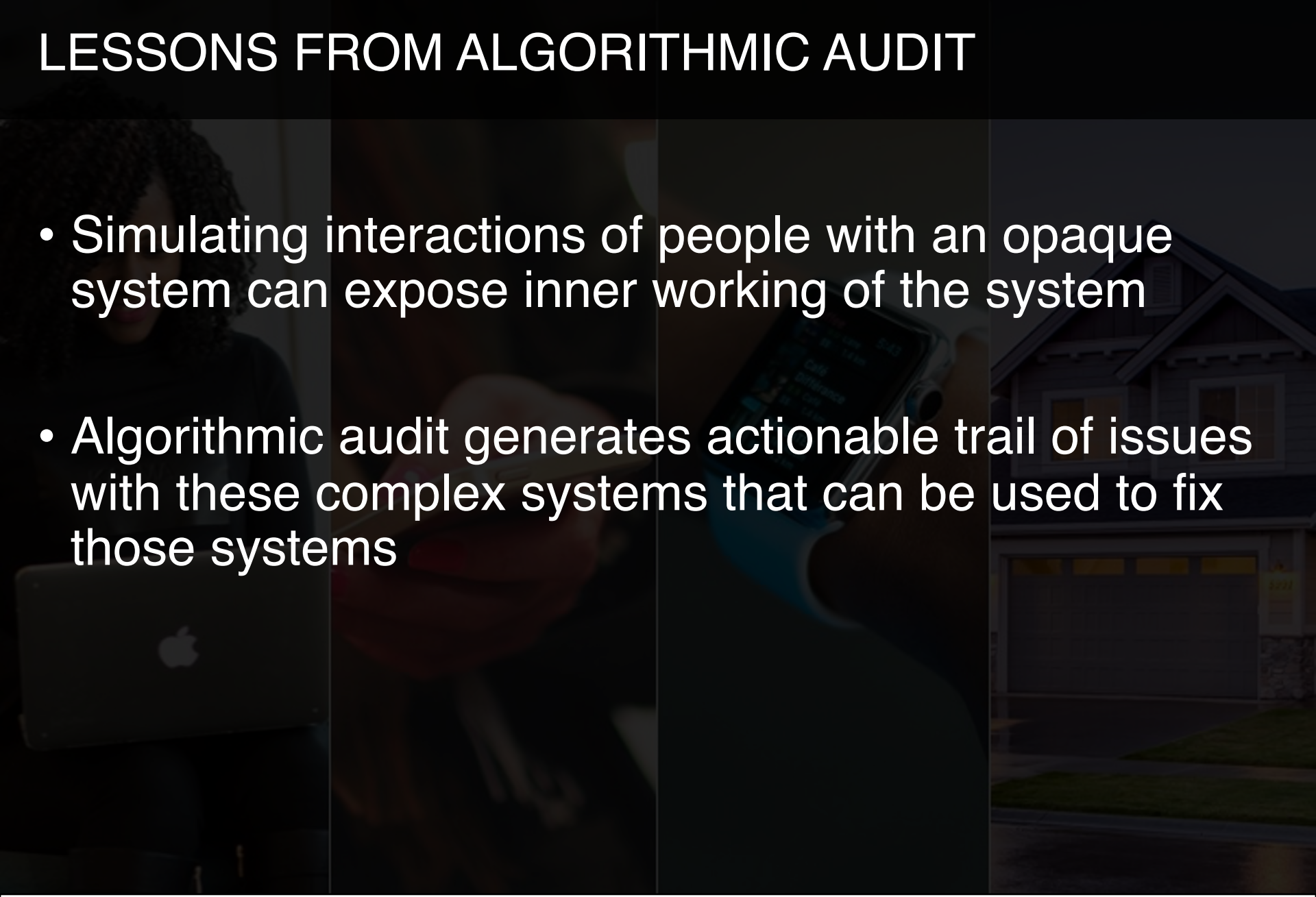
LESSONS FROM ALGORITHMIC AUDIT



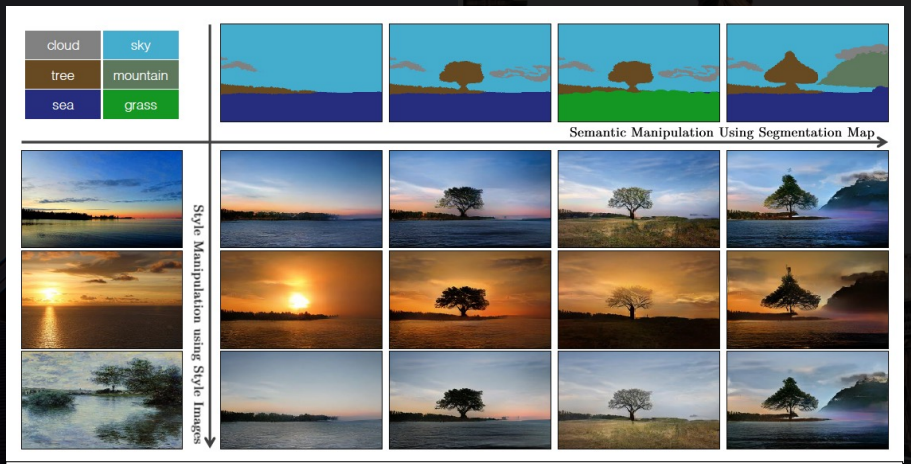
- Simulating interactions of people with an opaque system can expose inner working of the system

- Algorithmic audit generates actionable trail of issues with these complex systems that can be used to fix those systems

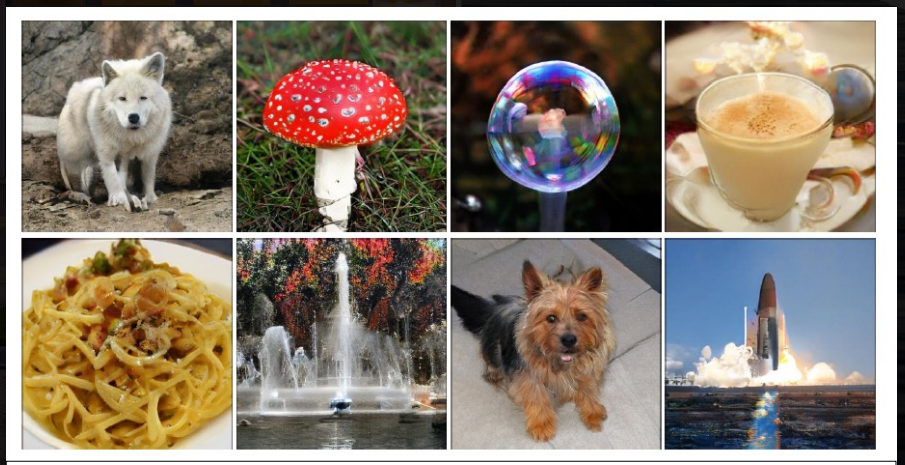
Escher & Banovic. 2020. Exposing Error in Poverty Management Technology: A Method for Auditing Government Benefits Screening Tools. In *PACM HCI (CSCW)* 2020.

EXPLORATION BASED XAI INTERFACES

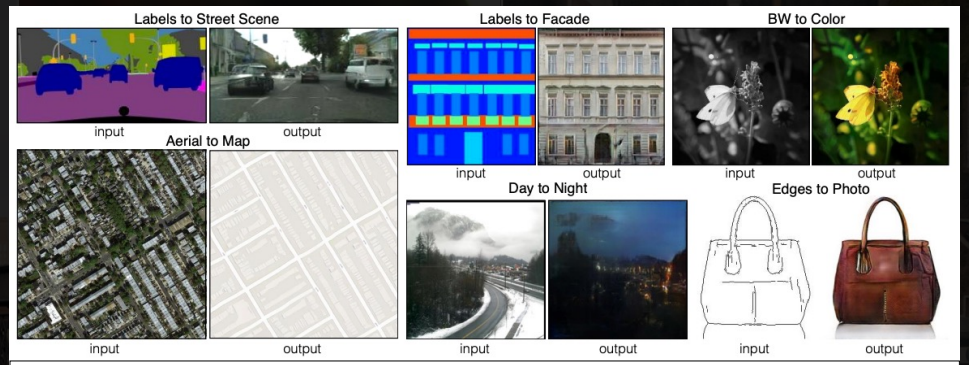
INTERACTING WITH GANs



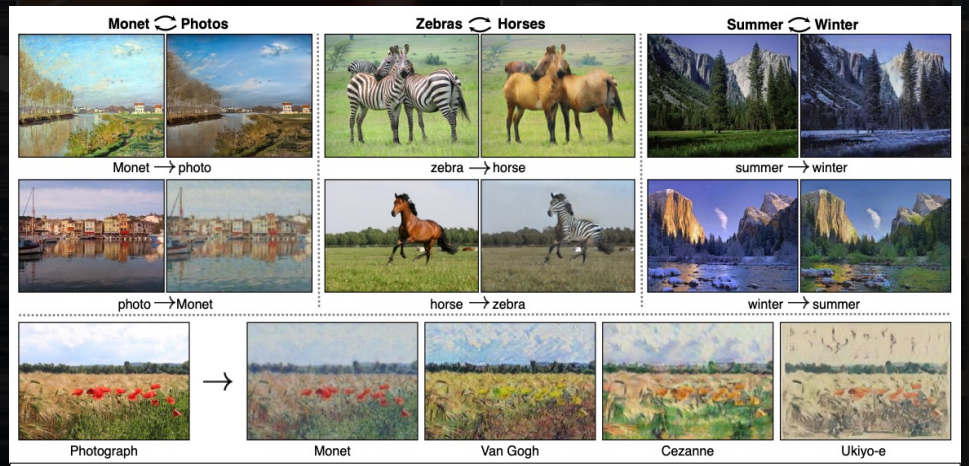
Park et al. 2019. Semantic image synthesis with spatially-adaptive normalization. In *Proc.* CVPR 2019.



Brock et al. 2018. Large scale GAN training for high fidelity natural image synthesis. arXiv preprint arXiv:1809.11096.



Isola et al. 2017. Image-to-image translation with conditional adversarial networks. In *Proc.* CVPR 2017.



Zhu et al. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proc.* ICCV. 2017.

INTERACTING WITH GANs

- Training a GAN involves two networks:
  1. a Generator that takes in a vector of latent variables z = (z1, ..., zn) ∈ R n and outputs the corresponding image
  2. a Discriminator that is used to distinguish between generated images and real images (training data).

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

INTERACTING WITH GANs

- Training a GAN involves two networks:
  1. a Generator that takes in a vector of latent variables z = (z1, ..., zn) ∈ R n and outputs the corresponding image
  2. a Discriminator that is used to distinguish between generated images and real images (training data).

- The Generator is trained to maximize the probability of fooling the Discriminator

Goodfellow et al. 2014. Generative Adversarial Nets. In *Advances in Neural Information Processing Systems*.

INTERACTING WITH GANs

- Training a GAN involves two networks:
  1. a Generator that takes in a vector of latent variables z = (z1, ..., zn) ∈ R n and outputs the corresponding image
  2. a Discriminator that is used to distinguish between generated images and real images (training data).

- The Generator is trained to maximize the probability of fooling the Discriminator

- The Discriminator is trained to discriminate training data from the images created by the Generator.

Goodfellow et al. 2014. Generative Adversarial Nets. In *Advances in Neural Information Processing Systems*.

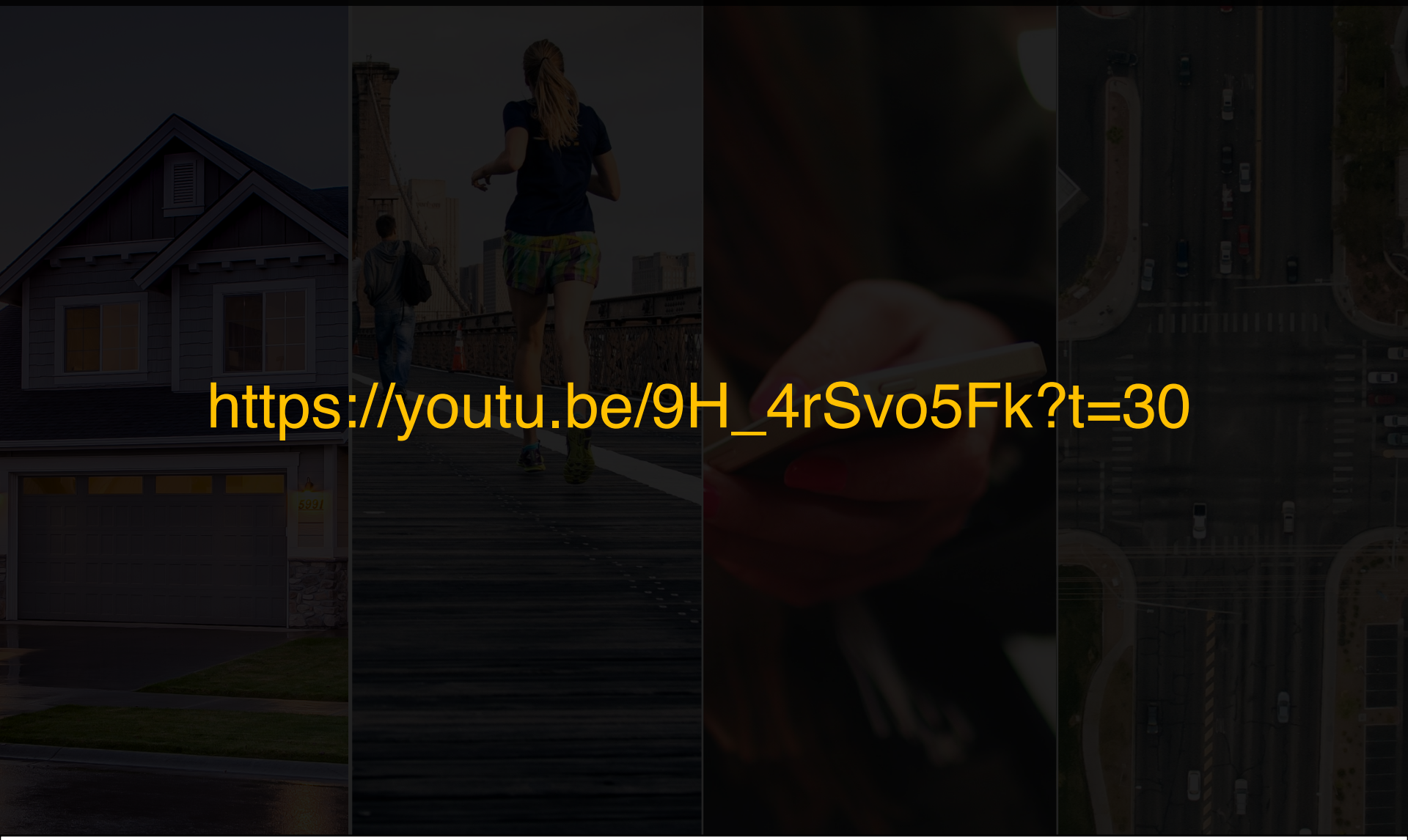
INTERACTING WITH GANs

- Challenging to evaluate quality of images that a GAN can generate (e.g., ability to generate a diverse set of photo-realistic images)

- Often using tedious visual examination of image galleries generated from narrow probability distributions

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

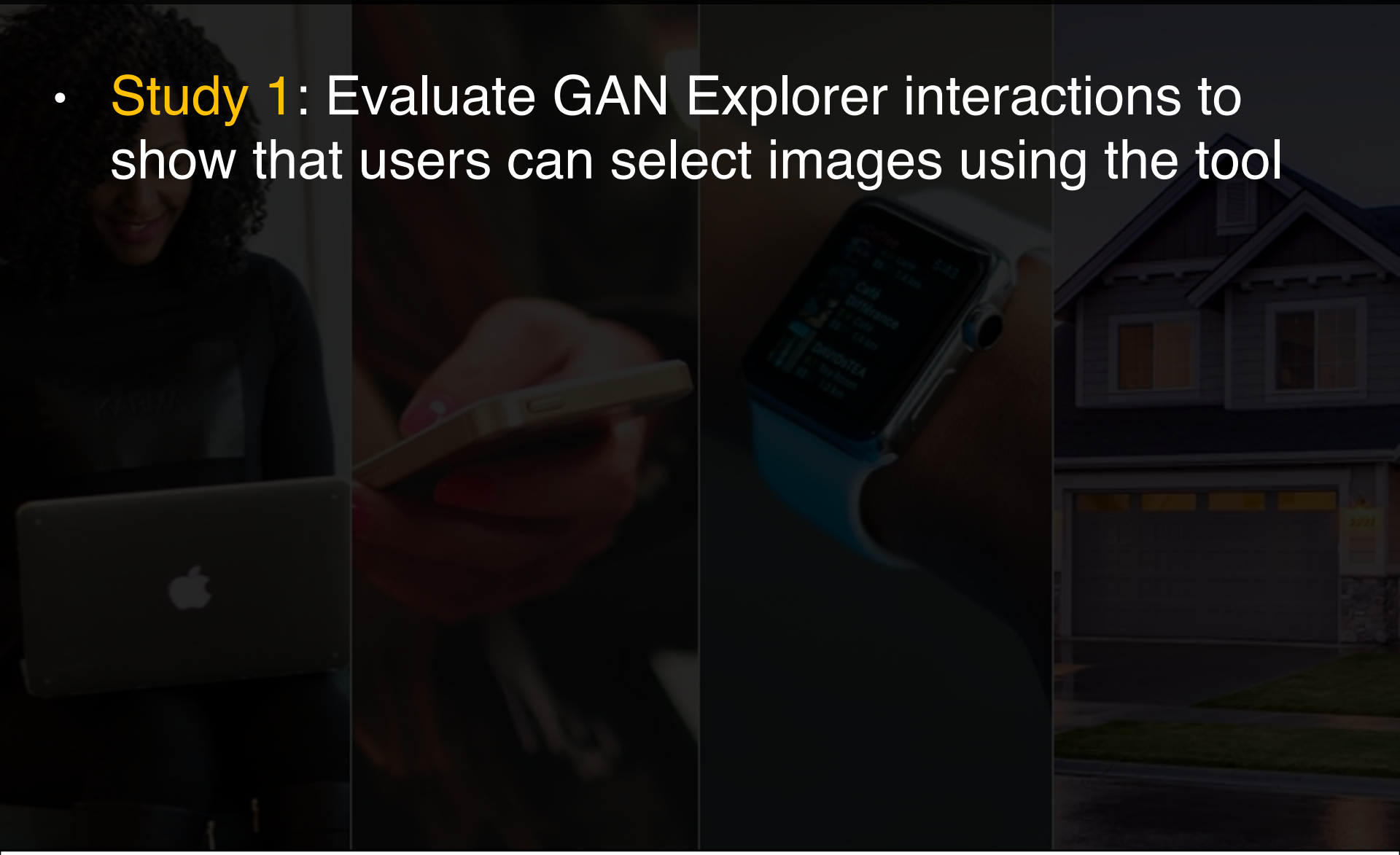
GAN EXPLORER



Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

EVALUATING GAN EXPLORER

- Study 1: Evaluate GAN Explorer interactions to show that users can select images using the tool



Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

STUDY 1: EVALUATING GAN EXPLORER

- Amazon MTurk study with 367 participants
- Task: select photo-realistic images generated from the BigGAN model using our interactive tool
- Participants selected images from 10 BigGAN categories.
- We measured how many images participants selected and what tools they used to select them

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

STUDY 1: EVALUATING GAN EXPLORER

- Participants interacted with:

Tool	# times	Tool	# times
Pan	2,138	Randomize	679
Zoom in	969	Undo	97
Zoom out	107	Redo	15
Zoom into region	210	Take snapshot	200
Pivot	150	Revert to previous snapshot	34

- Participants selected 10,026 GAN-generated images using our prototype

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

EVALUATING GAN EXPLORER

- Study 1: Evaluate GAN Explorer interactions to show that users can select images using the tool

- Study 2: Validate that images that the participants in Study 1 selected are photo-realistic

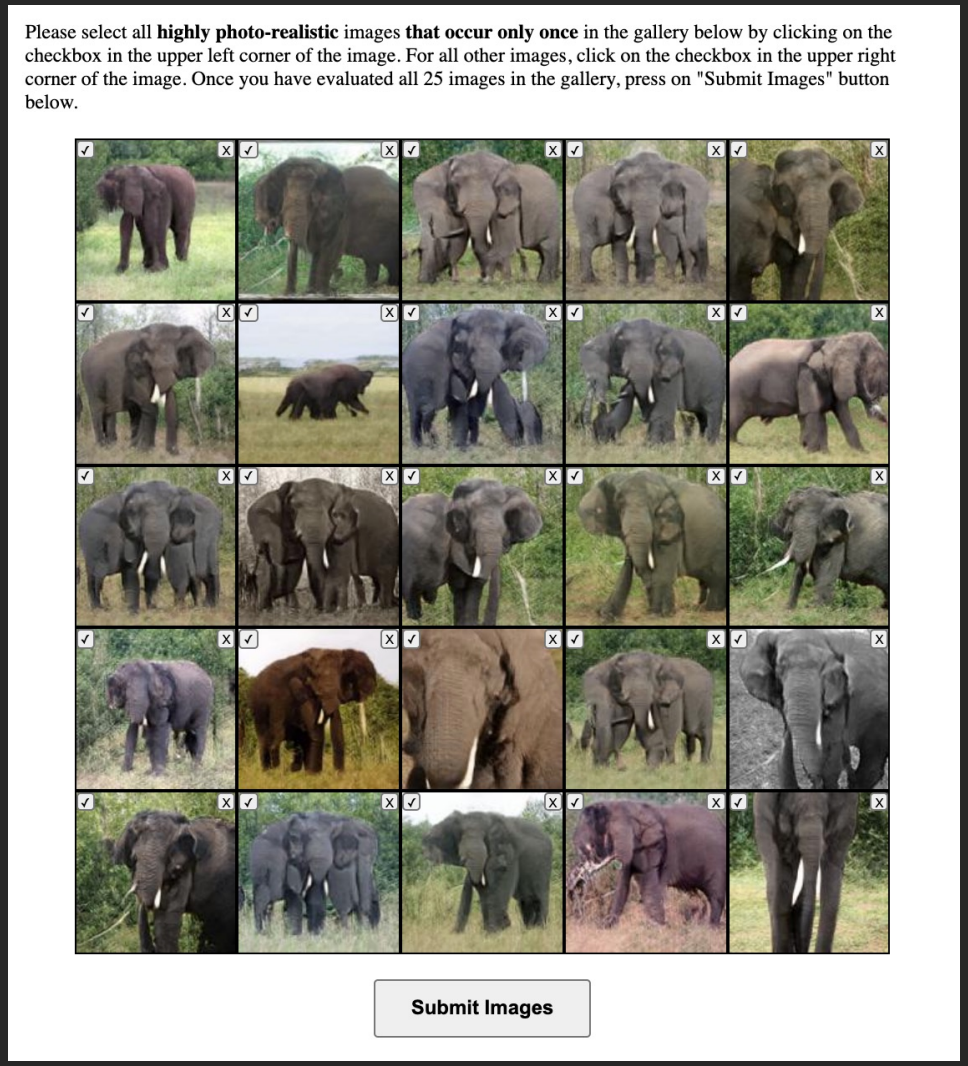
Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

STUDY 2: VALIDATING IMAGE QUALITY

- Amazon MTurk study with 1,622 participants
- Task: select only photo-realistic images from an image gallery
- We measured how many images from Study 1 were photo-realistic

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

STUDY 2: VALIDATING IMAGE QUALITY



Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

STUDY 2: VALIDATING IMAGE QUALITY

- Out of 10,026 images generated in Study 1, 8,015 images (79.94%) were rated as photo-realistic by at least one participant in Study 2
- We observed a lot of ambiguity in ratings, and low inter-rater agreement
- Visual examination of images rated as photo-realistic by at least 75% of participants uncovered a diverse set of photo-realistic images

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

EVALUATING GAN EXPLORER

- Study 1: Evaluate GAN Explorer interactions to show that users can select images using the tool
- Study 2: Validate that images that the participants in Study 1 selected are photo-realistic
- Study 3: Compare our image galleries with galleries sampled and generated using existing methods

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

AUTOMATICALLY GENERATED IMAGE GALLERIES

- Our method: Using MCMC to sample from the posterior probability distribution of latent vector z, given user-selected photo-realistic images
- Baseline: sampling the latent vector z from a truncated normal distribution

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

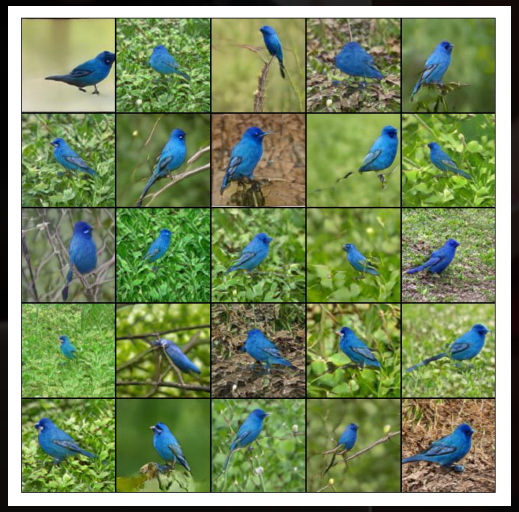
STUDY 3: EVALUATING IMAGE GALLERIES

- Amazon MTurk study with 1,000 participants
- Randomly assigned participants into one of 50 (*Method x Category*) conditions
  - *Method*: our method and four baselines
  - *Category*: one of 10 BigGAN image categories
- Task: select photo-realistic images that occur only once in the assigned gallery containing 25 images
- We measured number of photo-realistic images per *Method*

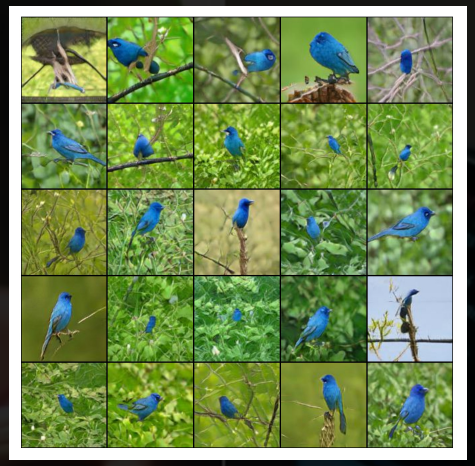
Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

STUDY 3: EVALUATING IMAGE GALLERIES

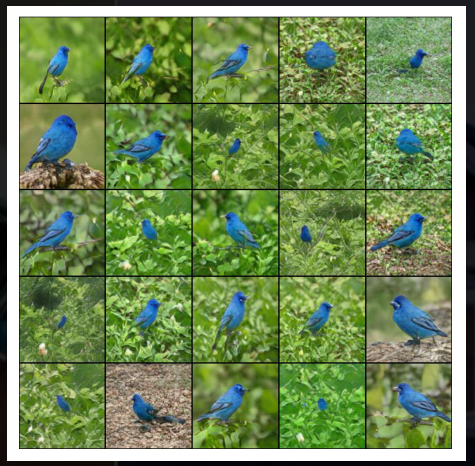
Our method



BigGAN heuristic-based thresholds



Truncated at 2



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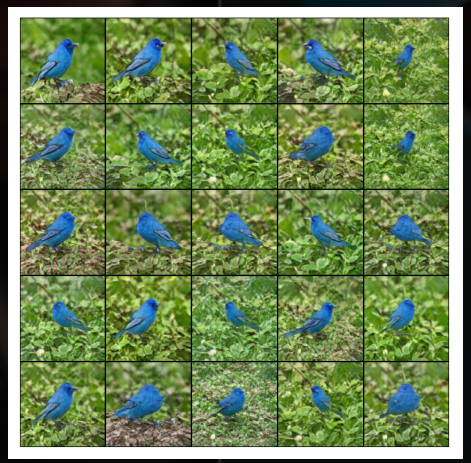
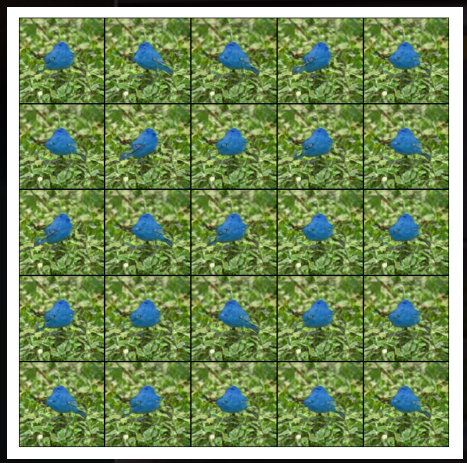


Truncated at 0.5

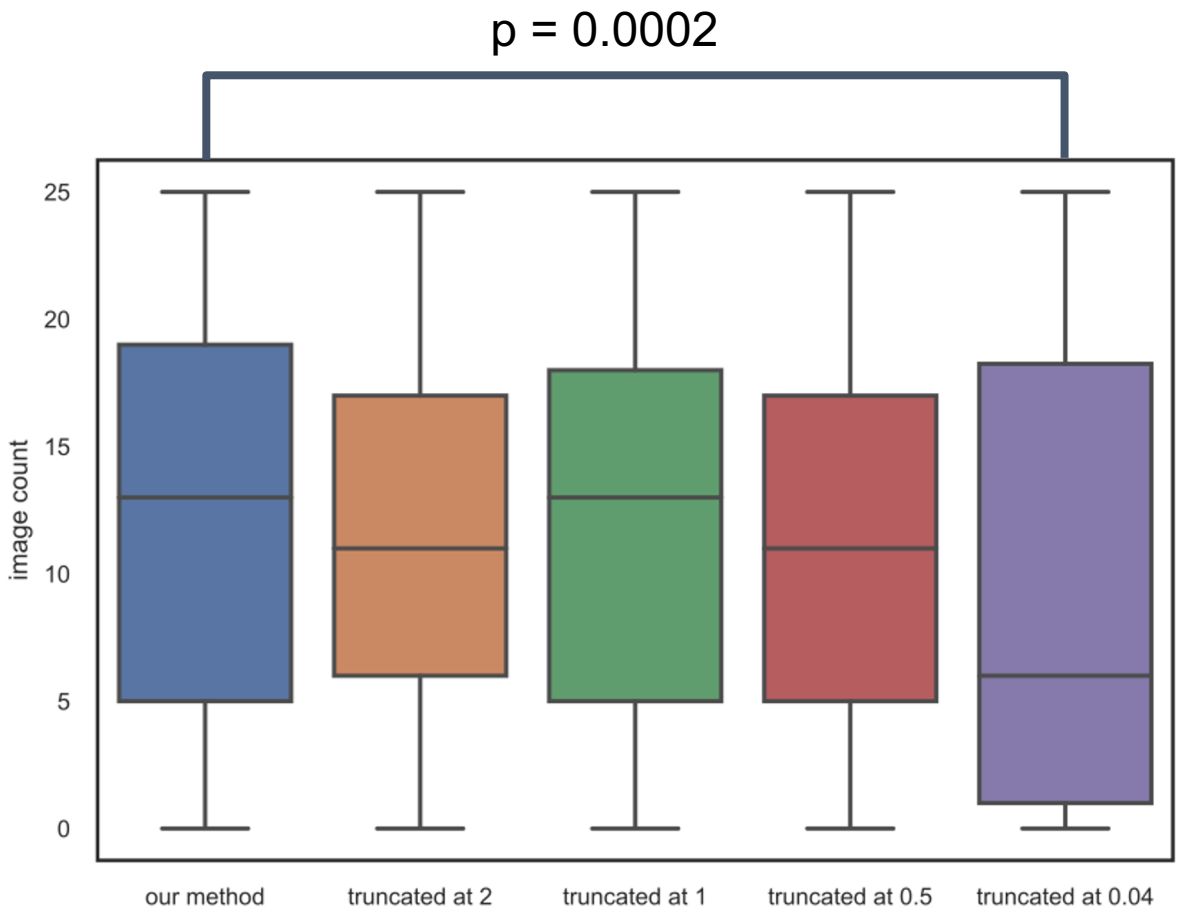


Truncated at 0.04

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

STUDY 3: EVALUATING IMAGE GALLERIES

- Our tests found significant main effect of *Method* on the number of selected images (p=0.0006).



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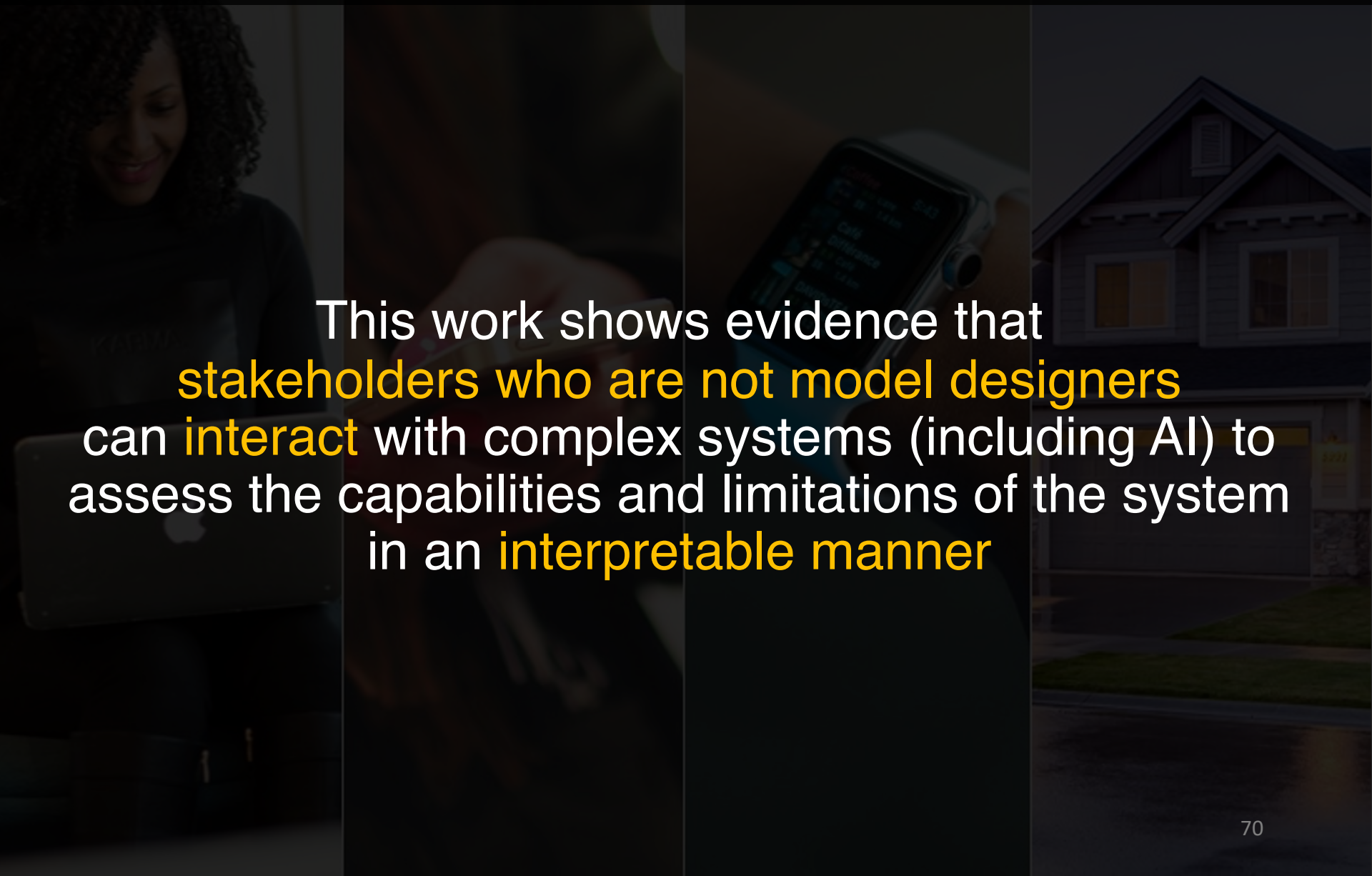
INTERACTING WITH GANs

- Our interactive tool enables qualitative GAN exploration via interactive visual examination
- Our automated image gallery generation method enables quick creation of many diverse, photo-realistic image galleries to support interactive qualitative evaluation of GANs
- GAN Explorer demo: https://comphcithree.eecs.umich.edu:8040/intro/

Zhang & Banovic. 2021. Method for Exploring Generative Adversarial Networks (GANs) via Automatically Generated Image Galleries. In *Proc.* CHI 2021.

HUMAN-CENTERED XAI THROUGH INTERACTION



This work shows evidence that
stakeholders who are not model designers
can interact with complex systems (including AI) to
assess the capabilities and limitations of the system
in an interpretable manner

FUTURE DIRECTIONS

- Explore variety of interaction techniques to identify promising threads of research

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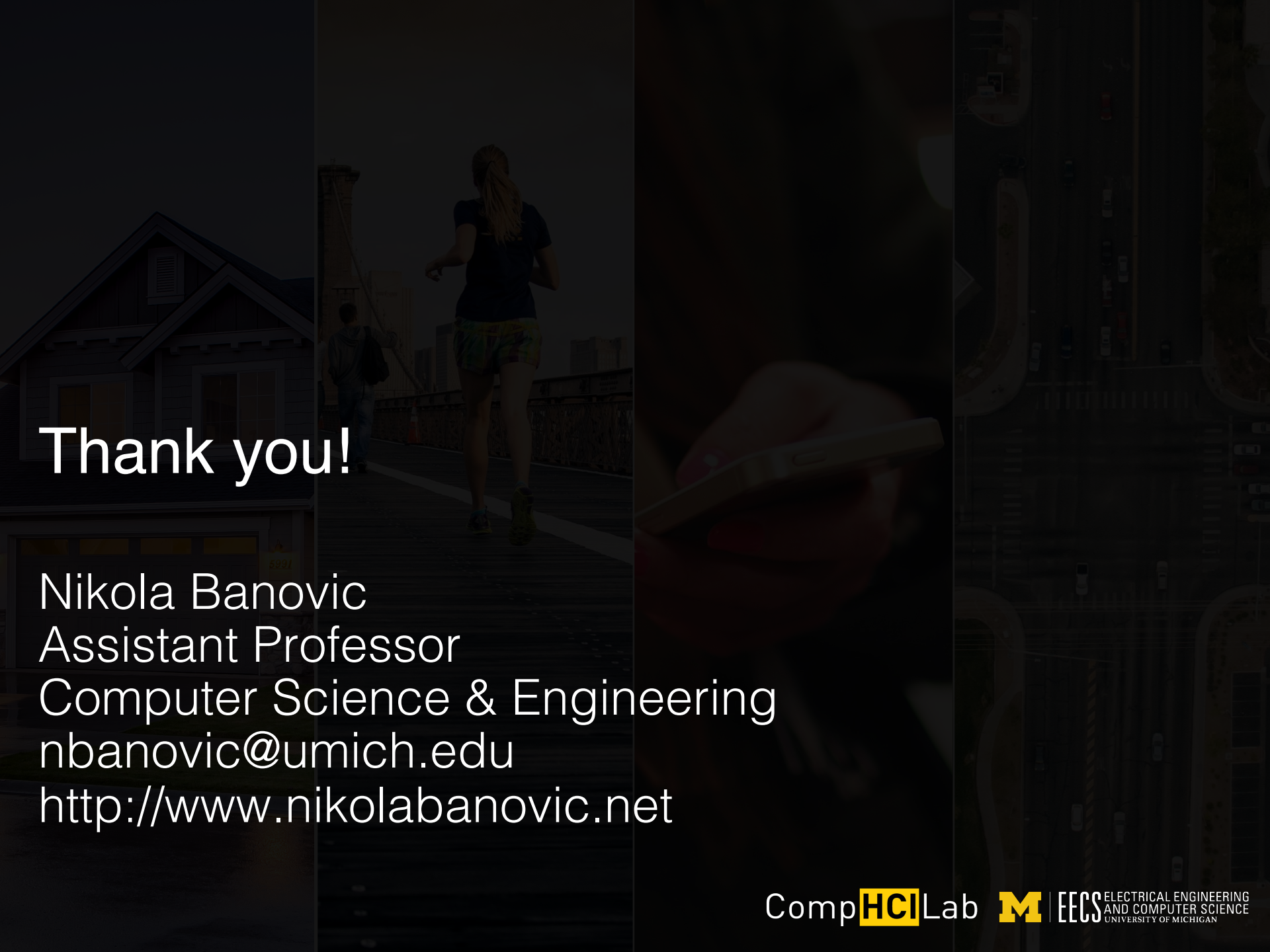
- Explore variety of interaction techniques to identify promising threads of research
- Formulate the interactive model exploration as an optimal sequential experimental design problem
- Go beyond identifying capabilities and limitations of models to include other factors that impact people and our society more broadly (e.g., ethics, fairness)



Thank you!

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Next up, let's implement interactions for model exploration

INTERACTIVE & EXPLAINABLE AI

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The 6th Summer School on Computational Interaction – Day 4

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