Algorithm FATE (Fairness, Accountability, Transparency, & Ethics)

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Review

- Last week:
 - Machine Learning for Sequential Data
 - Recurrent Neural Networks (RNNs)
 - Training Deep Neural Networks: Hardware & Software
- Assignments (Canvas):
 - Project outline due tonight
 - Prototype of final project ML system due at tomorrow's meeting
 - Final project submission with video due in two weeks
- Questions?

Final Project Video Suggestions

- Video creation/editing resources:
 - https://docs.google.com/document/d/1jBZ1fU1CKDLw1y2ZVM5LvYHjv3iFZoA YPz947_0f2Bs/edit?usp=sharing

- Attributions:
 - Creative commons license generator: https://creativecommons.org/choose/

Plagiarism: Definition

• Material from: https://legacy.lib.utexas.edu/services/instruction/avoidplagiarism.html

University of Texas Definition of Plagiarism:

"the appropriation of, buying, receiving as a gift, or obtaining by any means material that is

attributable in whole or in part to another source, including words, ideas, illustrations, structure,

or media, and presenting that material as one's own academic work being offered for credit."

Plagiarism: Definition

• Material from: https://legacy.lib.utexas.edu/services/instruction/avoidplagiarism.html

Plagiarism in Plain English:

Using someone else's work in your own academic work without giving proper credit. Click a button below to see some examples.

Intentional Plagiarism

Unintentional Plagiarism

Material from: https://legacy.lib.utexas.edu/services/instruction/avoidplagiarism.html

Intentional Plagiarism:

- Copying a friend's or classmate's work
- Buying or horrowing papers
- Cutting and pasting blocks of text without providing documentation of the original source
- Borrowing images and other media without documentation of the original source
- Publishing work on the Web without the permission of the creator

Material from: https://legacy.lib.utexas.edu/services/instruction/avoidplagiarism.html

Unintentional Plagiarism:

- Careless paraphrasing
- Poor documentation of sources
- Quoting excessively
- Failure to use your own ideas or words

• Material from: https://legacy.lib.utexas.edu/services/instruction/avoidplagiarism.html

During the course of your research, you come across an idea that you use in your paper. You don't use the author's exact words or even paraphrase -- just the idea. Cite it?

Other people's words aren't the only thing you need to cite. You also need to cite ideas. So in this case, you should give the author credit for the idea by citing them.

• Material from: https://legacy.lib.utexas.edu/services/instruction/avoidplagiarism.html

You are doing a presentation for your Chemistry class and use an image of the Periodic Table you found on a government web site. Cite it?

You should cite images. Even government websites in the public domain need to be cited.

- What can happen if you are accused of plagiarism?
 - Redo assignment
 - Receive a failing grade
 - Be suspended
 - Be expelled
- What resources can help you to avoid plagiarism?
 - Review: https://legacy.lib.utexas.edu/services/instruction/avoidplagiarism.html
 - Review: https://legacy.lib.utexas.edu/d7/sites/default/files/services/instruction/AvoidingPlagiarism guide.pdf
 - Visit writing center: http://uwc.utexas.edu/
- Neither you (I believe) nor I have any desire to talk about plagiarism ©
- Play it safe and give credit generously!!!

Give Credit Generously

- Idea: add credit page to your presentation for resources used
 - e.g., Microsoft Azure
 - e.g., freely-shared code/libraries
 - e.g., links to all images
 - •

Today's Topics

Machine Learning Algorithms that Discriminate

• FAT (Fair, Accountable, & Transparent) Algorithms

Ethics in Machine Learning

• Guest: Dr. Mehrnoosh Sameki from Microsoft

Today's Topics

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Observation: World Population is Diverse



Image Source: https://www.rocketspace.com/corporate-innovation/why-diversity-and-inclusion-driving-innovation-is-a-matter-of-life-and-death

Algorithms Discriminate: Google Search



Safiya U. Noble; Algorithms of Oppression: How Search Engines Reinforce Racism

Algorithms Discriminate: Google Search

A search for "Jew" returned many anti-Semitic web pages:

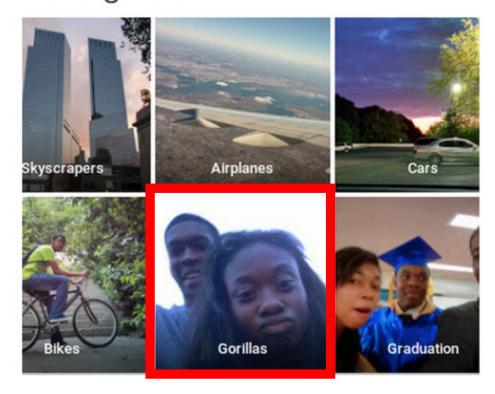


Safiya U. Noble; Algorithms of Oppression: How Search Engines Reinforce Racism

Algorithms Discriminate: Image Tagging



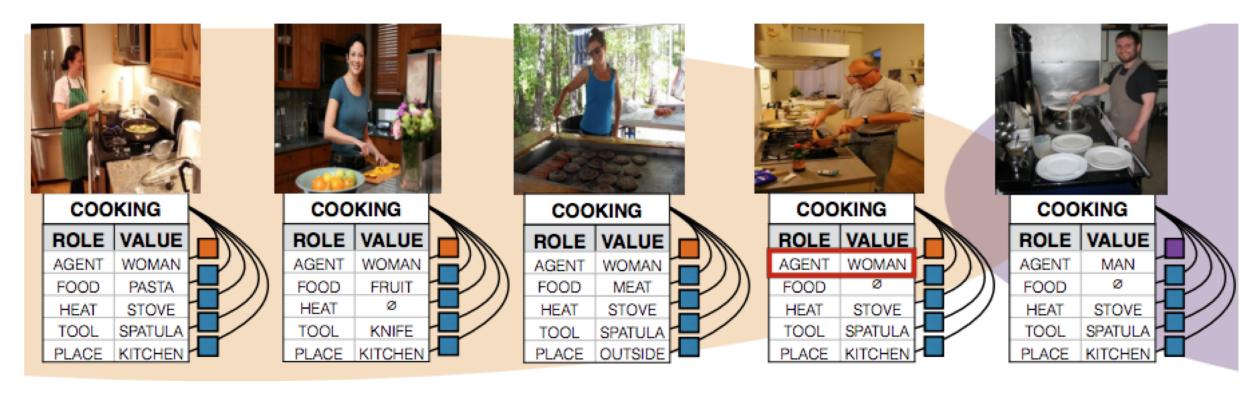
Google Photos, y'all fucked up. My friend's not a gorilla.



Using Twitter to call out Google's algorithmic bias

https://www.theverge.com/2015/7/1/8880363/google-apologizes-photos-app-tags-two-black-people-gorillas

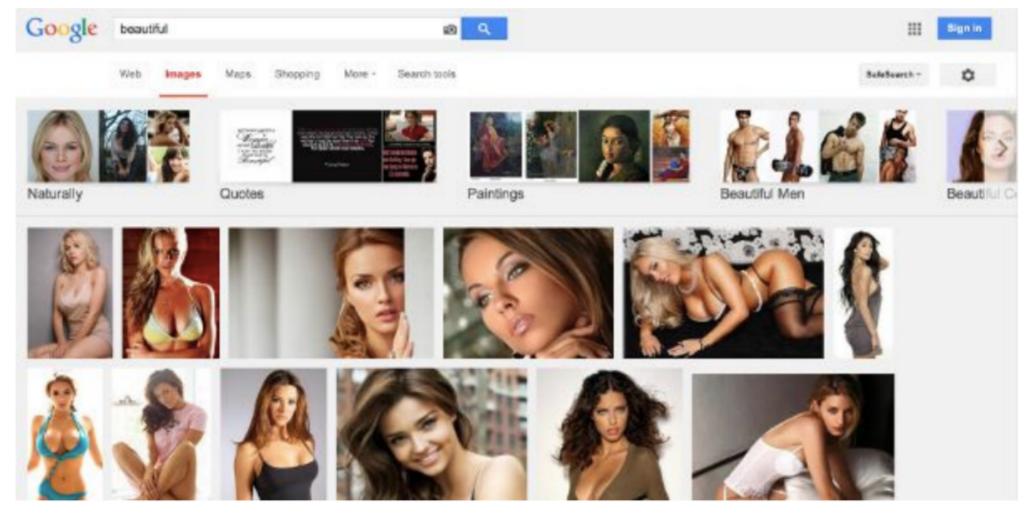
Algorithms Discriminate: Image Tagging



Algorithm identifies men in kitchens as women. Learned this example from given dataset. (Zhao, Wang, Yatskar, Ordonez, Chang, 2017)

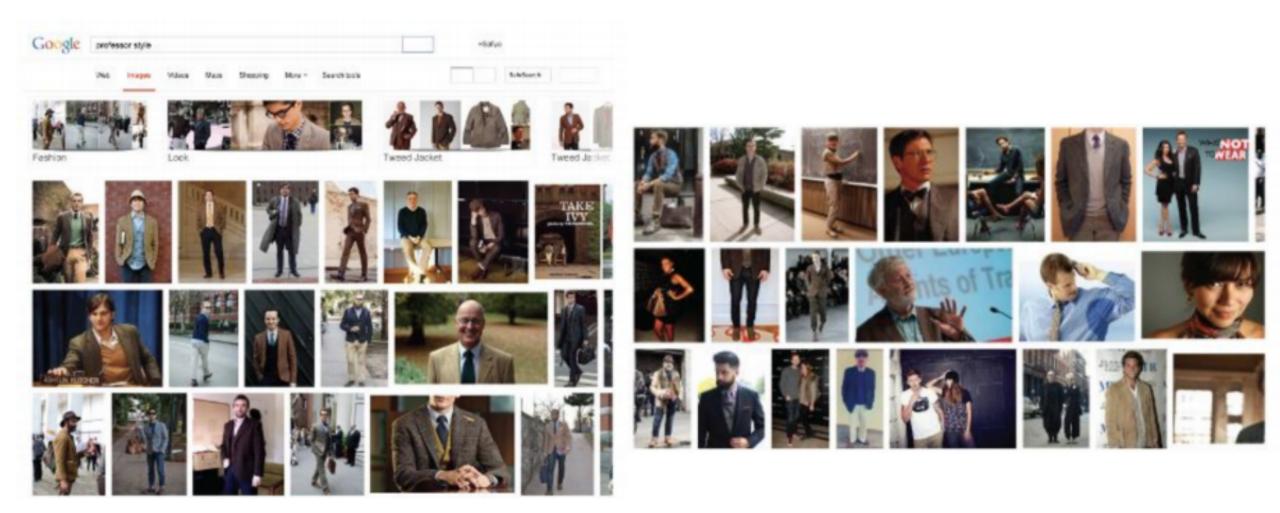
https://www.wired.com/story/machines-taught-by-photos-learn-a-sexist-view-of-women/ç

Algorithms Discriminate: Image Tagging ("beautiful"; 2014)



Safiya U. Noble; Algorithms of Oppression: How Search Engines Reinforce Racism

Algorithms Discriminate: Image Tagging ("professor style"; 2014)



Safiya U. Noble; Algorithms of Oppression: How Search Engines Reinforce Racism

Algorithms Discriminate: Image Tagging



```
"age": {
    "min": 20,
    "max": 23,
    "score": 0.923144
},
"face_location": {
    "height": 494,
    "width": 428,
    "left": 327,
    "top": 212
"gender": {
    "gender": "FEMALE",
    "gender_label": "female",
    "score": 0.9998667
```

```
"class": "woman".
"score": 0.813,
"type_hierarchy": "/person
/female/woman"
"class": "person",
"score": 0.806
"class": "young lady (heroine)",
"score": 0.504,
"type_hierarchy": "/person/female
/woman/young lady (heroine)"
```

Person identifies as agender (gender-less, and so non-binary)

Morgan Klaus Scheurman, Jacob M. Paul, and Jed R. Brubaker, "How Computers See Gender: An Evaluation of Gender Classification in Commercial Facial Analysis and Image Labeling Services." CSCW 2019.

Algorithms Discriminate: "Hotness" Photo-Editing Filter

FaceApp apologizes for building a racist Al

Natasha Lomas @riptari / 2 years ago

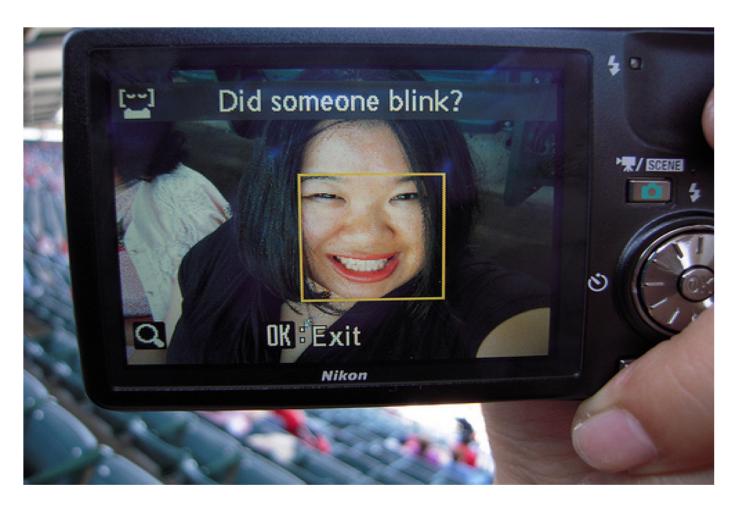




https://techcrunch.com/2017/04/25/faceapp-apologises-for-building-a-racist-ai/

Algorithms Discriminate: Nikon Blink Detection

Two kids bought their mom a Nikon Coolpix S630 digital camera for Mother's Day... when they took portrait pictures of each other, a message flashed across the screen asking, "Did someone blink?"



http://content.time.com/time/business/article/0,8599,1954643,00.html

Algorithms Discriminate: Face Recognition

Software engineer at company: "It got some of our Asian employees mixed up," says Gan, who is Asian. "Which was strange because it got everyone else correctly."



Gfycat's facial recognition software can now recognize individual members of K-pop band Twice, but in early tests couldn't distinguish different Asian faces.

Algorithms Discriminate: Book Shopping



Anti-Semitic Bias:

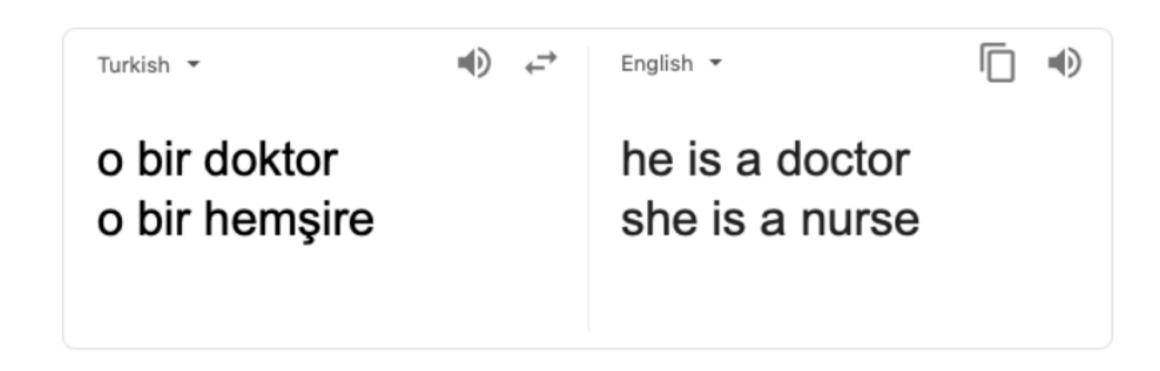
Algorithms Discriminate: Job Recruiting

Amazon's algorithm learned to systematically downgrade women's CVs for technical jobs such as software developer.

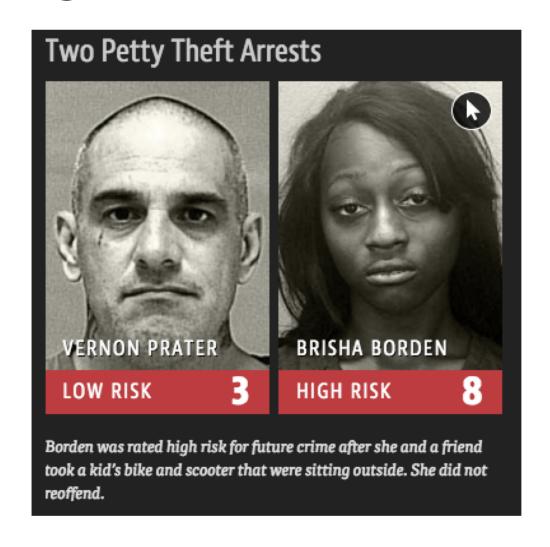


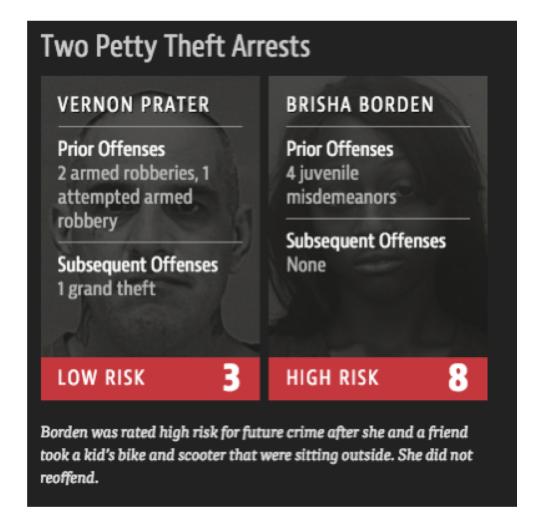
https://phys.org/news/2018-11-amazon-sexist-hiring-algorithm-human.html

Algorithms Discriminate: Language Translation



Algorithms Discriminate: Criminal Sentencing





Algorithms Discriminate: And MANY more...

• e.g.,

Awful Al

Awful AI is a curated list to track current sca

Artificial intelligence in its current state is un Often, Al systems and predictions amplify ex more and more concerning the uses of Al te hope that *Awful Al* can be a platform to spur fight back!).

Discrimination

Al-based Gaydar - Artificial intelligence can their faces, according to new research that s [summary]

Infer Genetic Disease From Your Face - Dee photograph of a patient's face. This could le

https://github.com/daviddao/awful-ai

Gender, Race, and Power in Al

A Playlist

Al Now Institute Apr 17, 2019 · 6 min read



Gender, Race, and Power in AI is the product of a year-long survey of literature at the nexus of gender, race, and power in the field of artificial intelligence. Our study surfaced some astonishing gaps, but it also made clear that scholars of diverse gender and racial backgrounds have been sounding the alarm about inequity and discrimination in artificial intelligence for decades.

We are concerned that in the rush to diagnose and solve 'new' problems, this critical scholarship is deserving of greater attention. So, we're offering up what we like to think of as a playlist — some of the greatest hits and deep cuts from the literature on gender, race and power in AI — by sharing the work that has inspired us, we hope that others might read along with us.

Algorithms Discriminate

How would you try to fix issues like these?

Today's Topics

Biased Machine Learning Algorithms

• FAT (Fair, Accountable, & Transparent) Algorithms

Ethics in Machine Learning

Guest: Dr. Mehrnoosh Sameki from Microsoft

We know that algorithms are not perfect.

How can we alleviate the issue that ML algorithms that discriminate?

FAT Machine Learning: In Vague, Lay Terms

• Fairness: treat people fairly

• Accountability: mimic infrastructure to oversee human decision makers (e.g., policymakers, courts) for algorithm decision-makers

 Transparency: clearly communicate algorithms' capabilities and limitations

FAT Machine Learning: Fairness

- How to make more fair methods?
 - Pre-processing:
 - Training data: modify it
 - Optimization at training:
 - Algorithm: e.g., add regularization term to objective function to penalize unfairness
 - Features: remove those that reflect bias; e.g., gender, race, age, education, sexual orientation, etc.
 - Post-process predictions
 - Counterfactual assumption: check impact of modifying single feature

FAT Machine Learning: Fairness

- Fairness how to define this mathematically?
 - e.g., group fairness (proportion of members in protected group receiving positive classification matches proportion in the population as a whole)
 - e.g., individual fairness (similar individuals should be treated similarly)

e.g., IBM's AI Fairness 360 Open Source Toolkit

70+ fairness metrics and 10+ bias mitigation algorithms

Optimized Preprocessing

Use to mitigate bias in training data. Modifies training data features and labels.

→

Learning Fair Representations

Use to mitigate bias in training data. Learns fair representations by obfuscating information about protected attributes.

Prejudice Remover

Reweighing

examples.

Use to mitgate bias in training data. Modifies the

weights of different training

Use to mitigate bias in classifiers. Adds a discrimination-aware regularization term to the learning objective.

Calibrated Equalized Odds Post-processing

Adversarial Debiasing

Use to mitigate bias in

techniques to maximize

accuracy and reduce

evidence of protected

attributes in predictions.

classifiers. Uses adversarial

Use to mitigate bias in predictions. Optimizes over calibrated classifier score outputs that lead to fair output labels.

Equalized Odds Post-processing

Use to mitigate bias in predictions. Modifies the predicted labels using an optimization scheme to make predictions fairer.

Reject Option

Classification

Use to mitigate bias in

predictions from a classifier

predictions, Changes

to make them fairer.

Disparate Impact Remover

Use to mitigate bias in training data. Edits feature values to improve group fairness.

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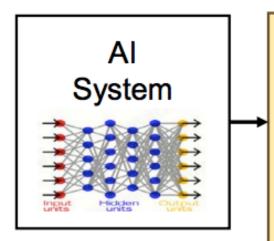
Meta Fair Classifier

Use to mitigate bias in classifier. Meta algorithm that takes the fairness metric as part of the input and returns a classifier optimized for that metric.

FAT Machine Learning: Accountability

- Accountability: who is accountable for ML algorithm behavior?
 - e.g., developers who must design algorithms so that oversight authorities meet pre-defined rules ("procedural regularity")?
 - e.g., data providers?
 - e.g., regulators who determine scope of oversight (e.g., require describing and explaining failures in ML systems)?

FAT Machine Learning: Transparency



- We are entering a new age of AI applications
- Machine learning is the core technology
- Machine learning models are opaque, non-intuitive, and difficult for people to understand

Watson



AlphaGo



Sensemaking



Operations



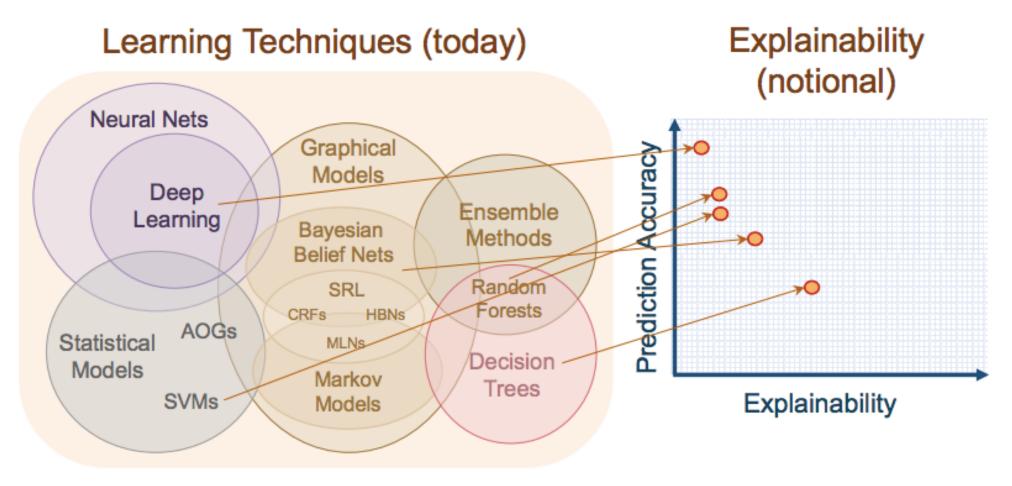


- Why did you do that?
- Why not something else?
- When do you succeed?
- When do you fail?
- When can I trust you?
- How do I correct an error?

FAT Machine Learning: Transparency

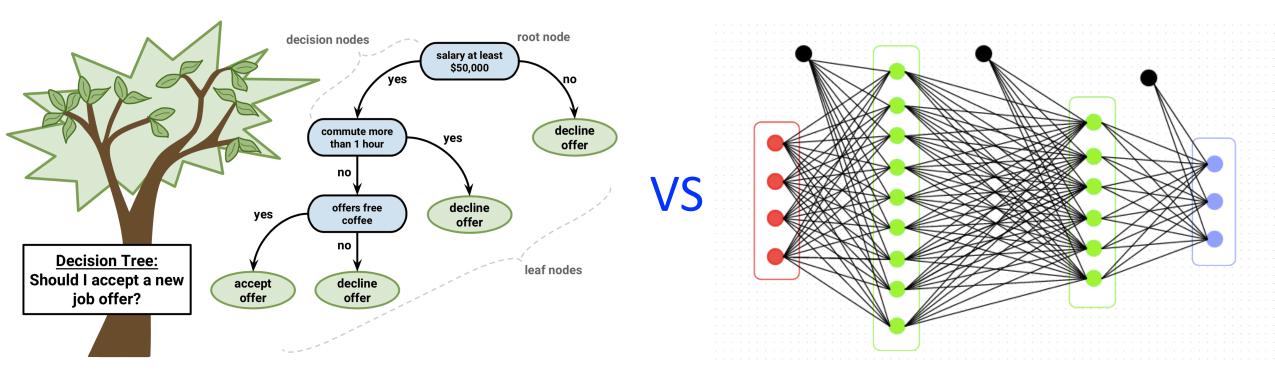
New Approach

Create a suite of machine learning techniques that produce more explainable models, while maintaining a high level of learning performance



FAT Machine Learning: Transparency

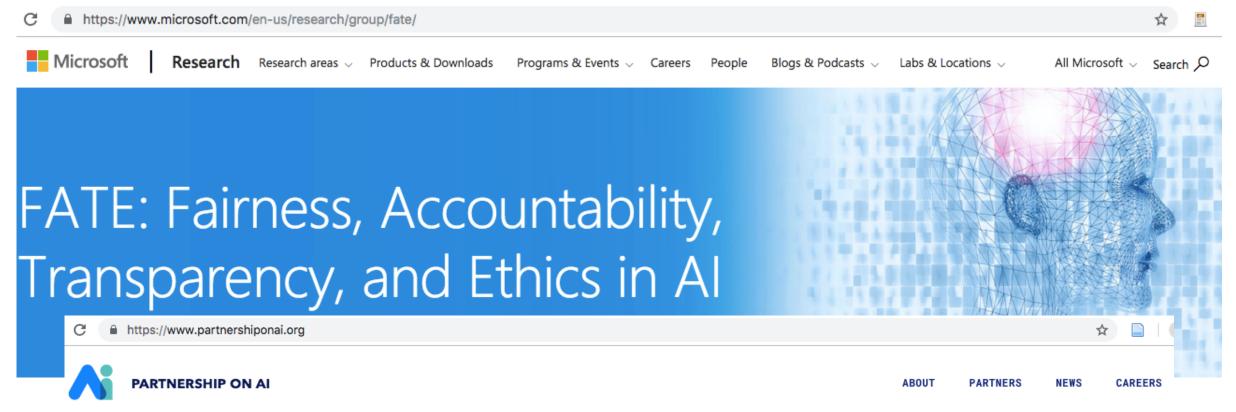
- Transparency: how are predictions made by black box ML algorithms?
 - e.g.,



Source: http://dataaspirant.com/2017/01/30/how-decision-tree-algorithm-works/

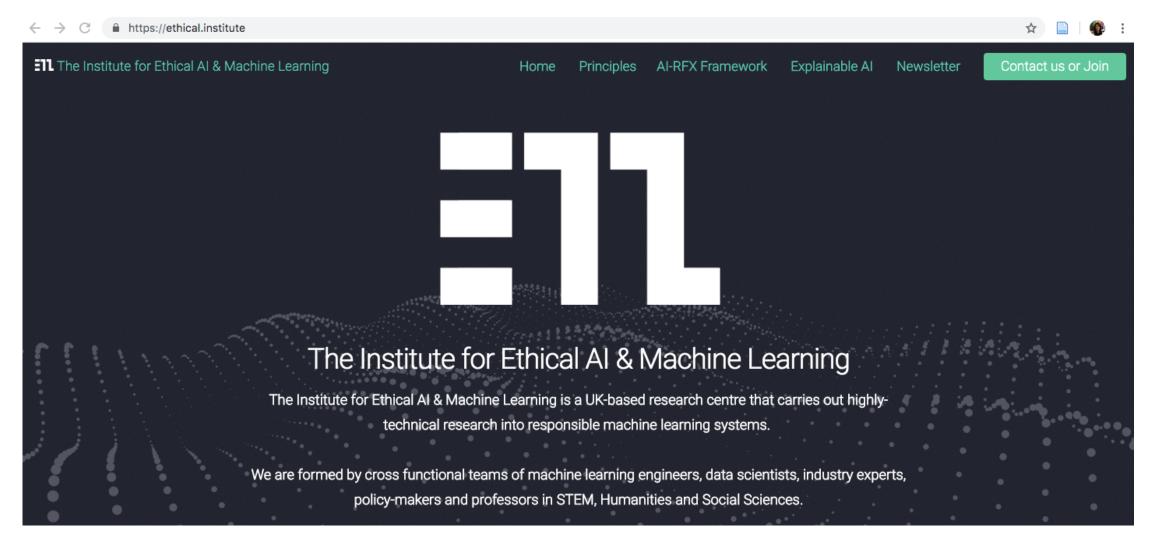
Source: https://towardsdatascience.com/build-your-first-deep-learning-classifier-using-tensorflow-dog-breed-example-964ed0689430

Industry (Facebook, Google, Uber, & more...)



"We need the best and the brightest involved in conversations to improve trust in AI and to benefit

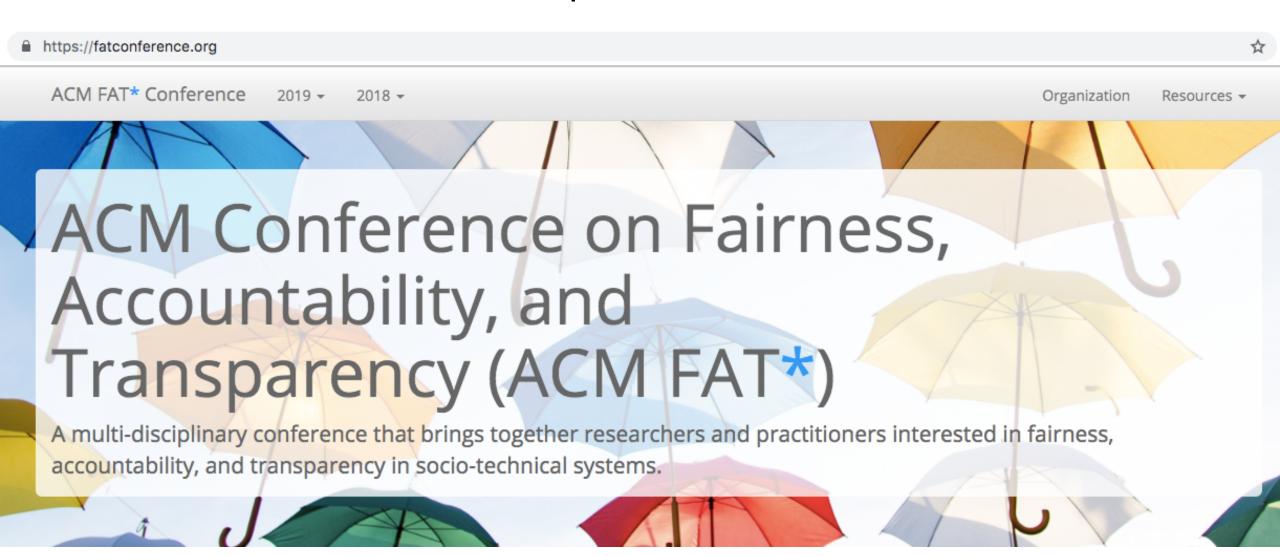
Institutes



Academia: Workshops



Academia: Workshops



Academia: Workshops

Not Secure | fairware.cs.umass.edu/agenda.html



Academia: Annual Workshop Since 2014...



Scope

This interdisciplinary workshop will consider issues of fairness, accountability, and transparency in machine learning. It will address growing anxieties about the role that machine learning plays in consequential decision-making in such areas as commerce, employment, healthcare, education, and policing.

Academia: Annual Workshop Scope...

Questions to the machine learning community include:

- How can we achieve high classification accuracy while eliminating discriminatory biases? What are meaningful formal fairness properties?
- How can we design expressive yet easily interpretable classifiers?
- Can we ensure that a classifier remains accurate even if the statistical signal it relies on is exposed to public scrutiny?
- Are there practical methods to test existing classifiers for compliance with a policy?

Academia: And Many More Resources...

https://fatconference.org/resources.html

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We know that algorithms are not perfect. Algorithms can be biased.

Are they ethical to use?

Time for a group activity!

Unacceptable to acceptable: Using ML to sentence people for a crime

Unacceptable to acceptable: Using ML to diagnose diseases

Unacceptable to acceptable: Using ML to filter resumes for jobs

Unacceptable to acceptable: Using ML to determine eligibility for a loan

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Google Form: Guest Speaker

- Guest: Dr. Mehrnoosh Sameki, Senior Technical Program Manager at Microsoft (https://www.linkedin.com/in/mehrnoosh-sameki-a2a02245/)
 - Share one question for her for tomorrow's visit