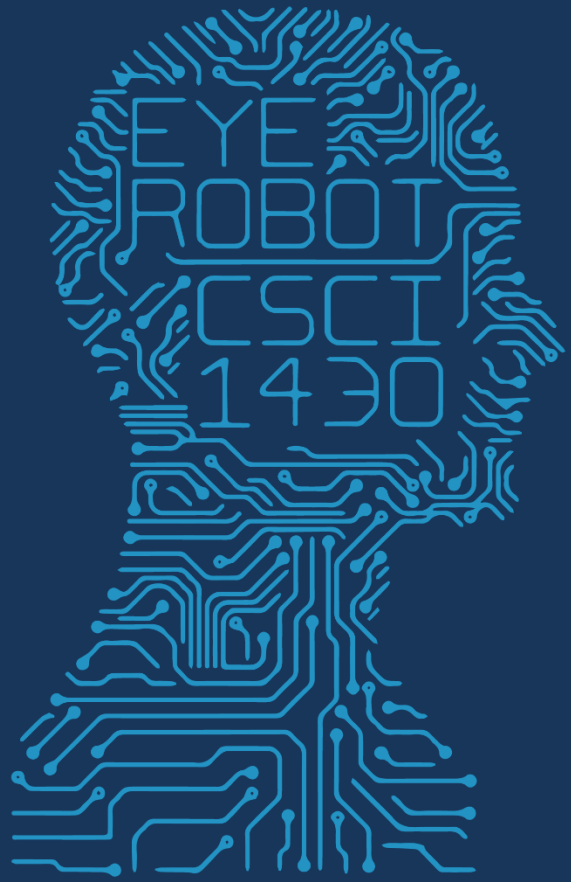
1950

Future Vision



2020

Computer Vision

Newsflash: ML Drama

NeurIPS (Neural Information Processing Systems) 2017.

Ali Rahimi (Google) just won a ‘test of time’ award for work on applying random functions as a basis for training; gave a speech.

“Artificial Intelligence is the new electricity” – Ng, 2017

“ML has become alchemy” – Rahimi, 2017

Rahimi, NeurIPS 2017 test of time

"If you're building photo-sharing systems, alchemy is ok, but we're beyond that now.

We're building systems that govern healthcare and mediate our civic dialog; we influence elections.

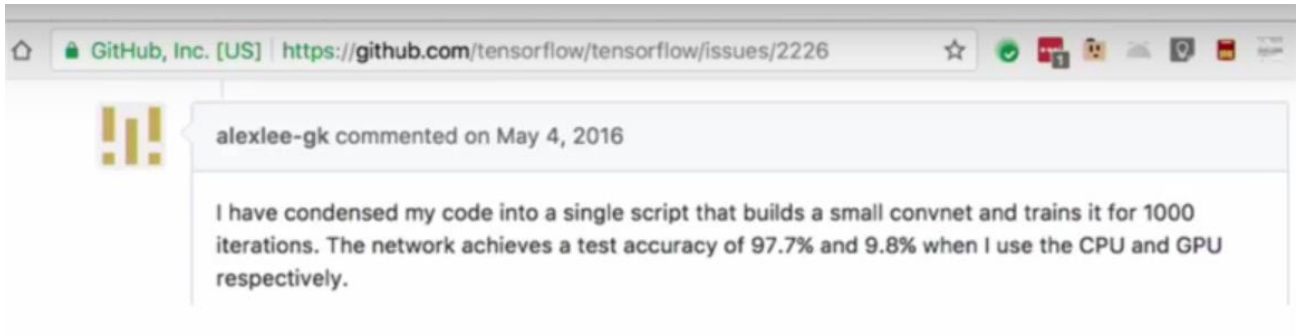
I would like to live in a society whose systems are build on verifiable, rigorous, thorough knowledge, and not on alchemy."

“This is happening because we apply brittle optimization strategies to loss surfaces we don’t understand.”

From: Boris
To: Ali

"On Friday, someone on another team changed the default rounding mode of some Tensorflow internals (from “truncate toward 0” to "round to even").

Our training broke. Our error rate went from <25% error to ~99.97% error (on a standard 0-1 binary loss)."



Yann LeCun retorts:

Yann LeCun
Yesterday at 11:57 ·

In the history of science and technology, the engineering artifacts have almost always preceded the theoretical understanding: the lens and the telescope preceded optics theory, the steam engine preceded thermodynamics, the airplane preceded flight aerodynamics, radio and data communication preceded information theory, the computer preceded computer science.
Why? Because theorists will spontaneously study "simple" phenomena, and will not be enticed to study a complex one until there a practical importance to it.

Why dangerous? It's exactly this kind of attitude that lead the ML community to abandon neural nets for over 10 years, *despite* ample empirical evidence that they worked very well in many situations.

Yoshua Bengio chimes in:

Yoshua Bengio Ali Rahimi, many of us want to make deep learning understandable, and I have worked hard for more than two decades towards that goal in a number of papers. The problem with your talk is the attitude, which could be wrongly interpreted and lead to a repetition of past mistakes, as Yann wrote. Using the word Alchemy was not a good idea. However, I agree with you that I would like to see more science, more specifically more experimental science by opposition to engineering (see Yann's distinction above). Both have their role, but focusing the experiments on testing hypotheses which help us understand phenomena is not getting as much rewarded (by reviewers) as beating some benchmark. And THAT is unfortunate and needs a cultural change.

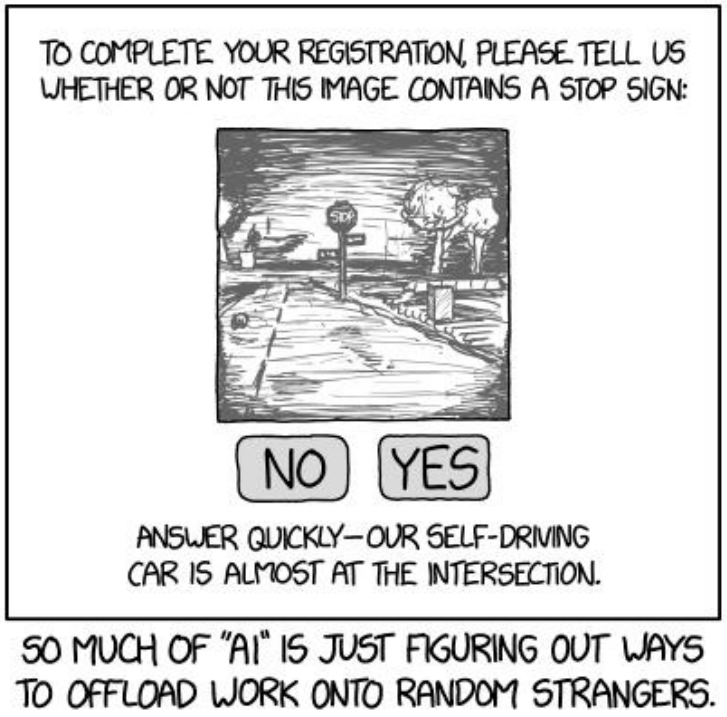
Like · Reply · 33 · 18 hrs

Compute cost / human cost

- Recent CVPR best paper: 50,000 GPU hours
- Google's commercial object recognizer: continually training for _years_.

"JFT is an internal Google dataset that has 100 million labeled images with 15,000 labels. When we did this work, Google's baseline model for JFT was a deep convolutional neural network that had been trained for about six months using asynchronous stochastic gradient descent on a large number of cores."

XKCD; thanks to **Iuliu Balibanu**



Alt-text: "Crowdsourced steering" doesn't sound quite as appealing as "self driving".

Fast.ai – Aug 8th 2018

"…managed to train ImageNet to 93% accuracy in just 18 minutes, using 16 machines each with 8 NVIDIA V100 GPUs, running the fastai and PyTorch libraries. This is a new speed record for training Imagenet to this accuracy…"

NVIDIA V100 -> $8500k

16*8*8500 = $$$ a million bucks

"… on publicly available public AWS cloud instances infrastructure, and costs around $40 to run."

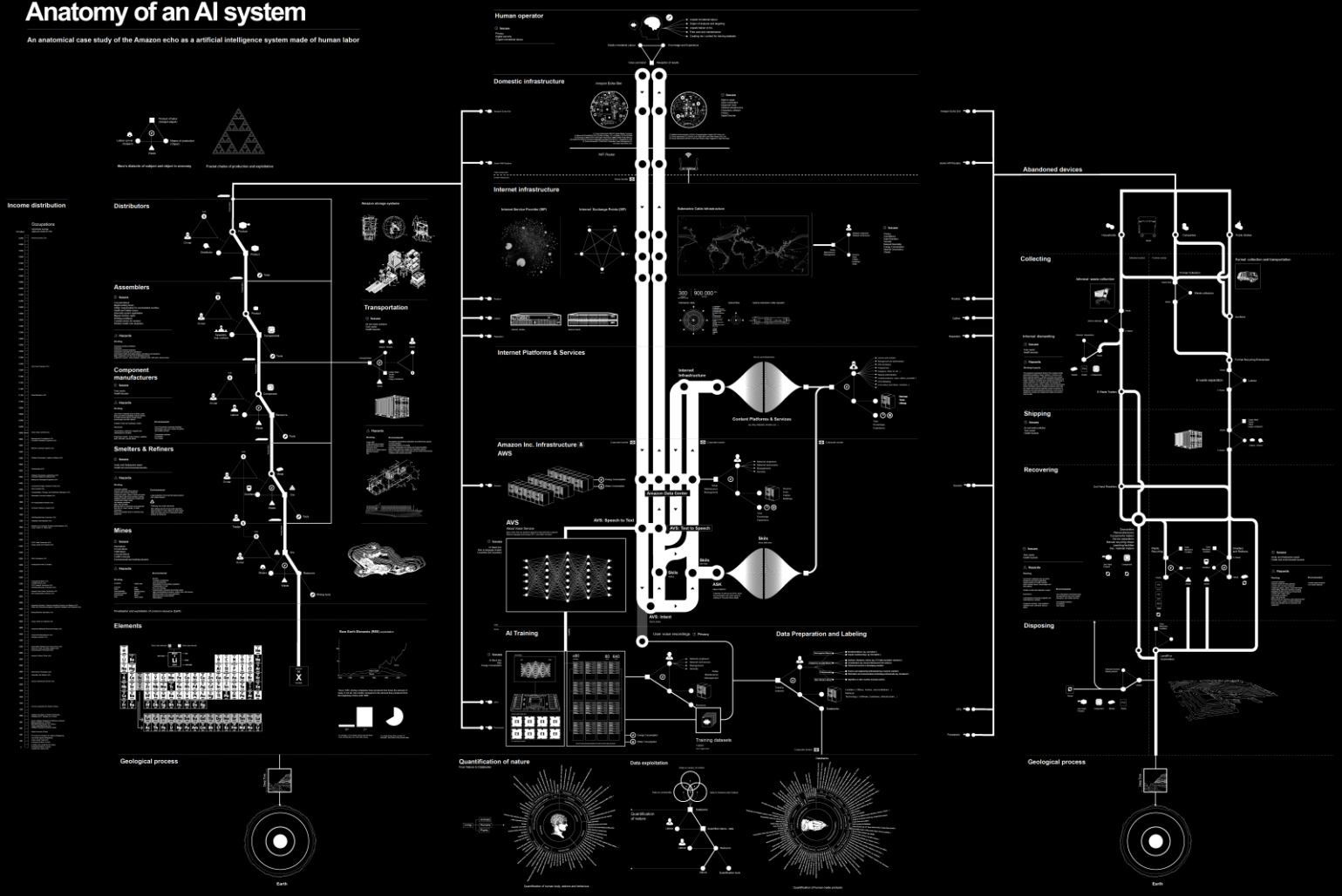
Anatomy of an AI System

- https://anatomyof.ai/

By Kate Crawford [1] and Vladan Joler [2]
(2018)

Anatomy of an AI system

An anatomical case study of the Amazon echo as a artificial intelligence system made of human labor



Rodney Brooks – The Mistakes We Make

- https://rodneybrooks.com/the-seven-deadly-sins-of-predicting-the-future-of-ai/

- Quote in PPTX notes.

Rodney Brooks – Artificial General Intelligence Tests

2, 4, 6, 8 year old competency tasks:
object recognition, language understanding, manual dexterity, social understanding.

"A two year old child can know that something is deliberately meant to function as a chair even if it is unlike any chair they have seen before. It can have a different number of legs, it can be made of different material, its legs can be shaped very oddly, it can even be a toy chair meant for dolls. A two year old child is not fazed by this at all. Despite having no visual features in common with any other chair the child has ever seen before the child can declare a new chair to be a chair. This is completely different from how a neural network is able to classify things visually."

"But wait, there is more! A two year old can do one-shot visual learning from multiple different sources. Suppose a two year old has never been exposed to a giraffe in any way at all. Then seeing just one of a hand drawn picture of a giraffe, a photo of a giraffe, a stuffed toy giraffe, a movie of a giraffe, or seeing one in person for just a few seconds, will forever lock the concept of a giraffe into that two year old's mind. That child will forever be able to recognize a giraffe as a giraffe, whatever form it is represented in. Most people have never seen a live giraffe, and none have ever seen a live dinosaur, but the are easy for anyone to recognize."

But James…

…I thought we could treat machine learning like a magical black box? I like black boxes.

Deep learning is:
- a black box
- *also a black art*.

- Grad student
  gradient descent : (

CV and society

CV / ML is a tool

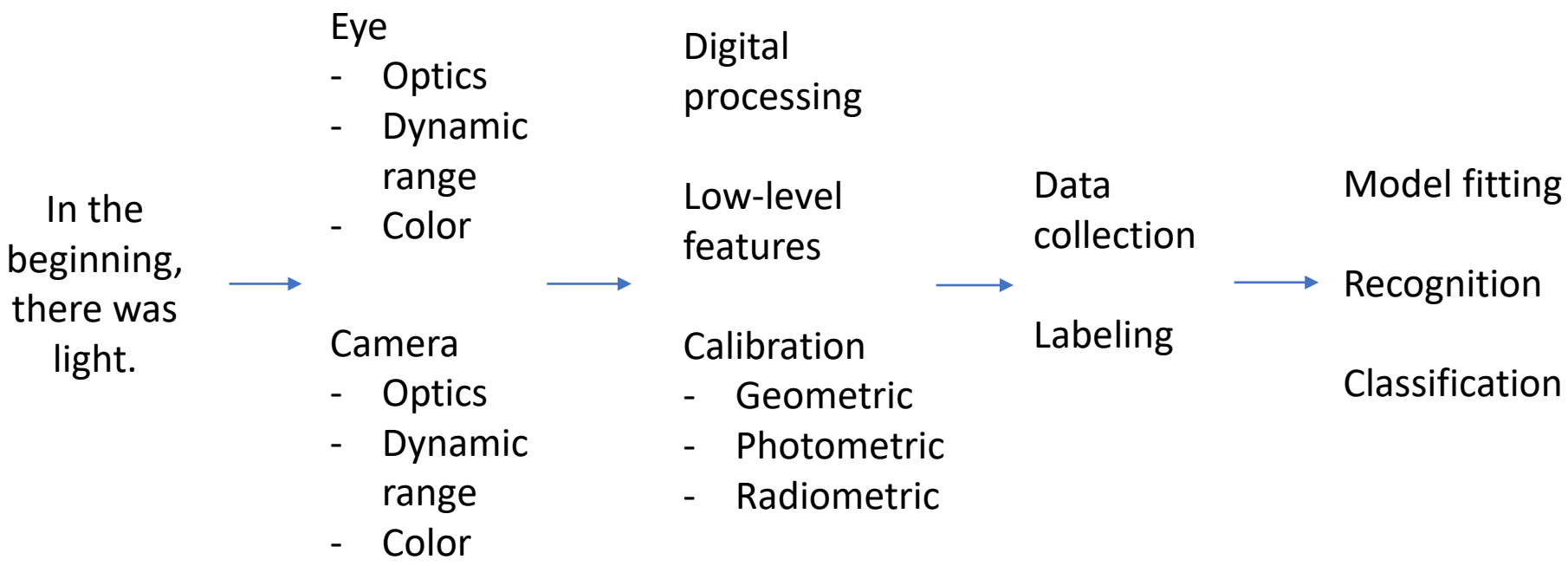
Any tool can be used for good or bad.

- Definition of good/bad *can* vary with point of view.

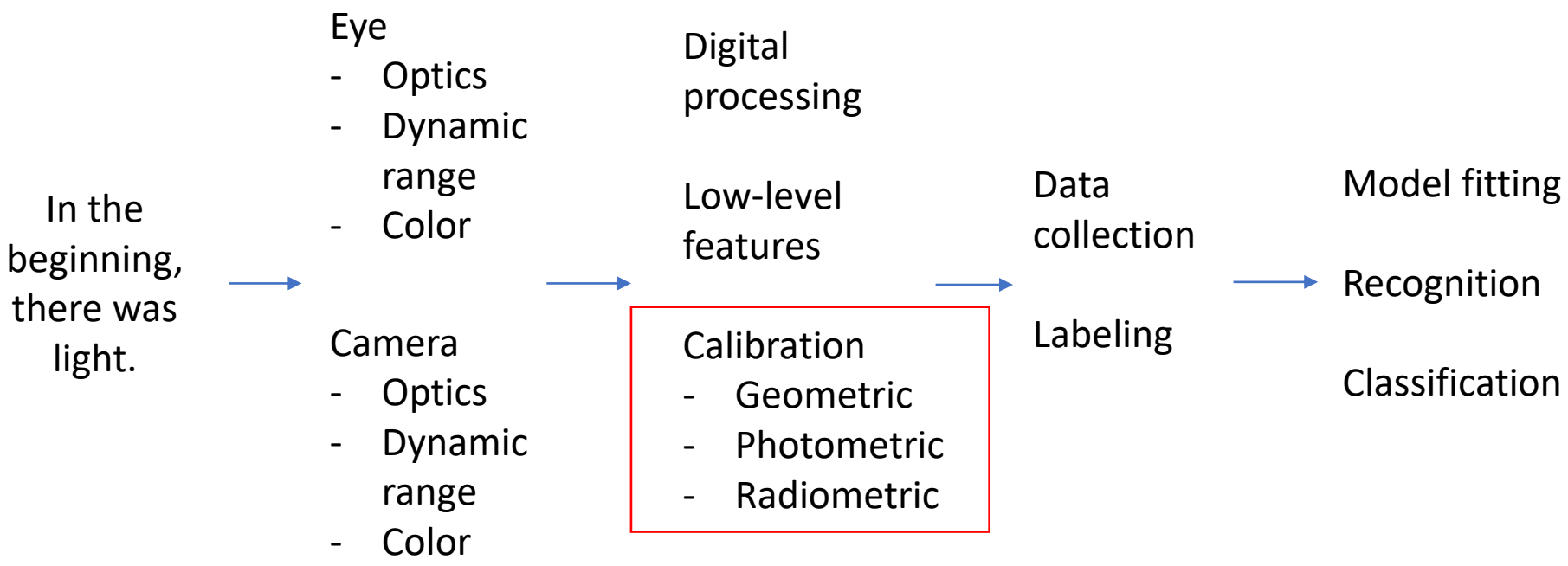
Tools are created and used in the real world.

- Time/money trade-offs
- Different agendas
- Advertent or inadvertent
- With or without awareness

Computer vision domain

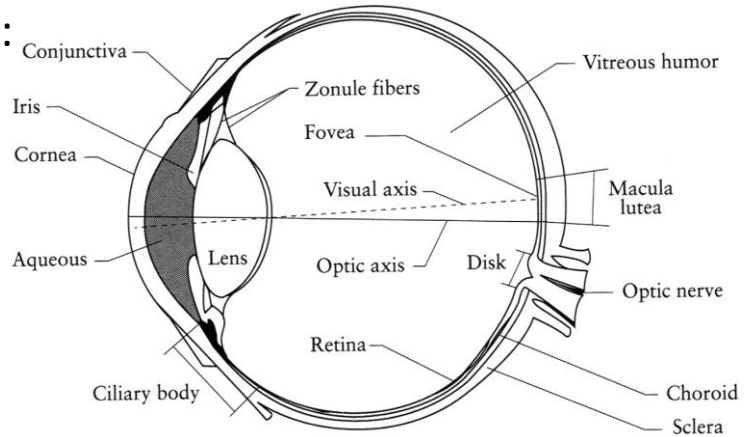


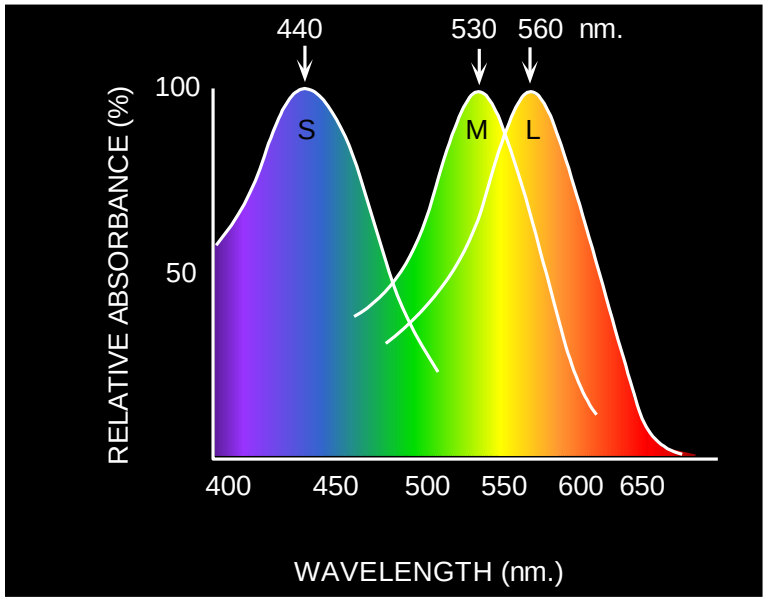
Computer vision domain



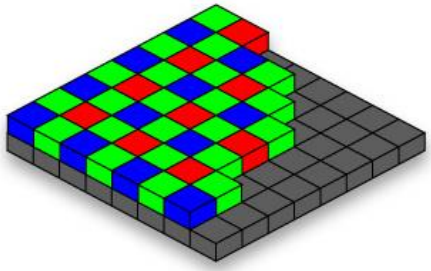
Light response curves

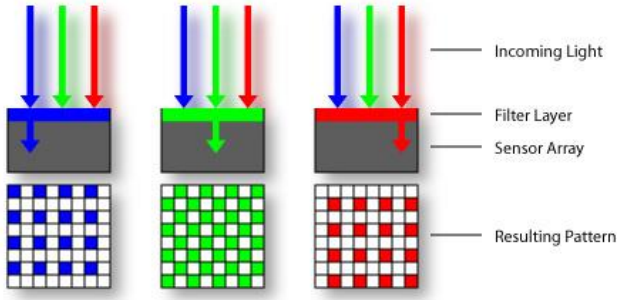
Eye Sensor:

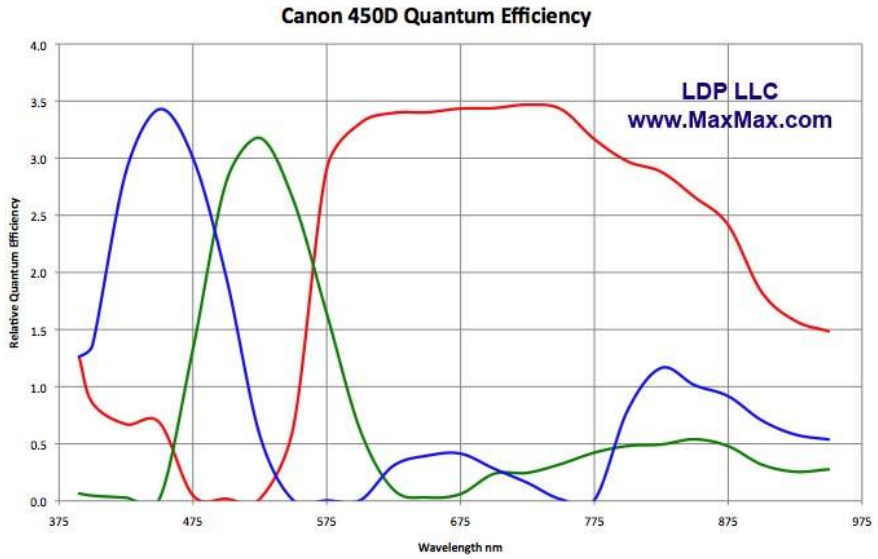




Camera Sensor:

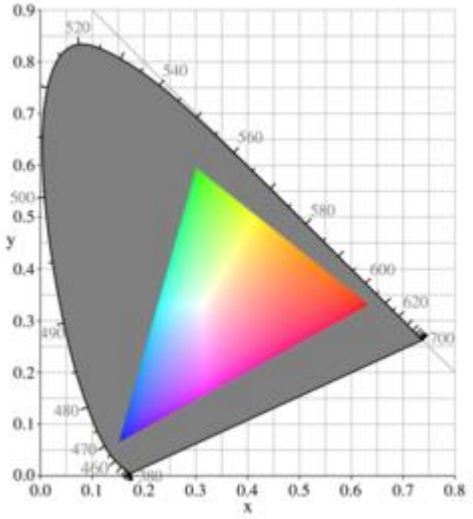






Light/reflectance output curves

250-500:1 contrast ratio (OLED = inf.)
6 / 8 / 10 bit dynamic range
3 / 4 additive primaries (RGB, rarely +yellow)
Defines a gamut



50-150:1 contrast ratio
??? dynamic range
4 subtractive primaries (CYMK)
Defines a gamut

We want:

Colors we see with our eyes in the world

=

Colors we see with our eyes in the reproduction

How do we calibrate these?

Time Warp: Photo Film processing

Price of film roll included film development costs.
Actually a monopoly!
1954 – broken up; independent film developers.

http://www.picture-newsletter.com/kodak/

Not actually a Kodak shop…

An independent chain!

New problem:
How to control quality of output across these different developers?

[Don Henderson – Flickr]

Here's the process:

1. Kodak produces a photosensitive chemical film.
    - Different compounds gave different spectral responses.
    - Kodak calibrates these responses using photometers and using test scenes.

2. You buy Kodak film from the store and put it in your camera.
    - Play with your family in the park
    - Take photos.

3. You take the film back to the store/lab for development.
    - Kodak needs the lab to reproduce the film's intended spectral response
    - Needs to *calibrate* the chemical development/printer to a target

Solution:
Kodak sends test negatives and test prints to printer technicians to check that their output matches the intended response of the film!

Kodak's test input + output

- 'Shirley cards' – 1950s/60s

- Shirley was photographed hundreds of times by Kodak.
- One negative was processed as per Kodak specifications.

- A new unexposed negative + processed output was sent to each printer lab.
- Colors were calibrated on site to match the target Shirley card.

Circa 1960

Kodak's test input + output

- 'Shirley cards' – 1950s/60s
- Any issues with this approach?

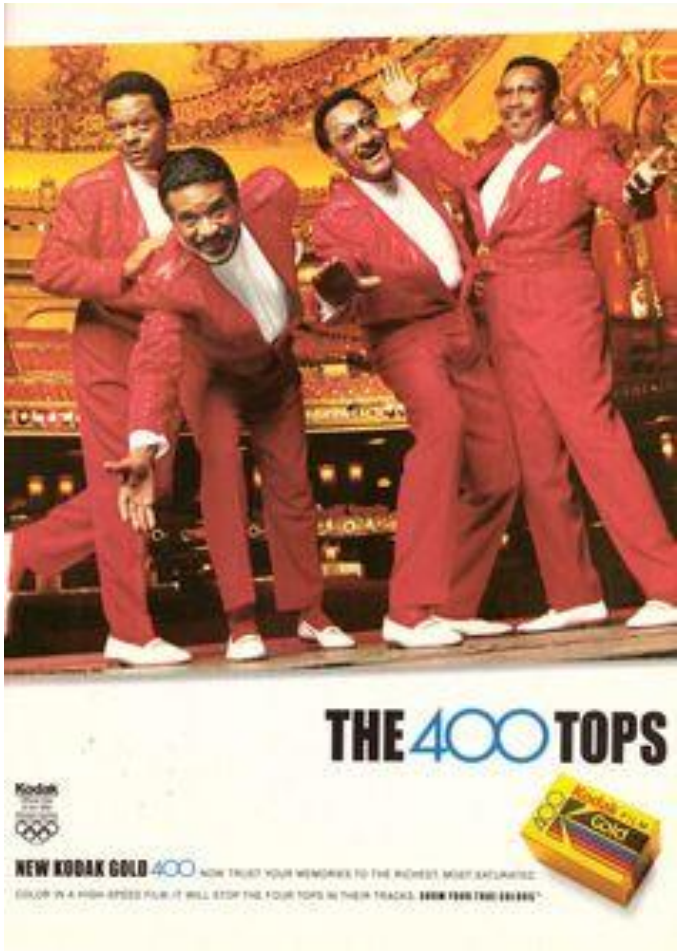
Circa 1960

Over time

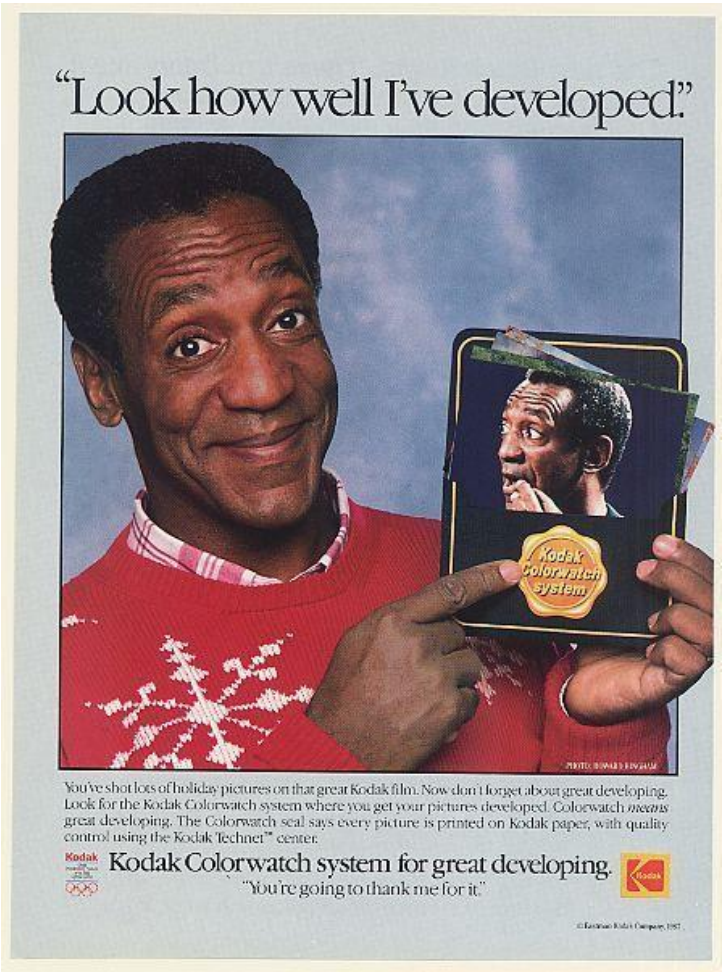
- 1978: Filmmaker Jean-Luc Godard refuses to use Kodachrome film in Mozambique.
- 1980s: Chocolate and furniture manufacturers complain.
- 1986: Kodacolor VR-G (or Gold) – film for dark browns.
  - “Photograph the details of a dark horse in low light.”

Shirley card, 1996

1980s – adverts



The Four Tops!



Bill Cosby!
Some other issues here now too : (

What are the underlying technical problems?

How do they relate to egalitarianism

…and how might we overcome them?

Think-pair-share.

Issues

- Dynamic range: not enough!
- Color balance:

So digital fixes this, right?

- Well…

"The hardest part of being in a biracial relationship is taking a picture together."

whatthecaptcha

So digital fixes this, right?

…it’s a lot better.

- 14-bit sensors (≈ eye’s static range)
- High-dynamic range by combining low-dynamic range
- Digital post-processing for color balance

References

Canadian Journal of Communication:

Roth et al., Looking at Shirley, the Ultimate Norm: Colour Balance, Image Technologies, and Cognitive Equity

http://www.cjc-online.ca/index.php/journal/article/view/2196

http://www.npr.org/2014/11/13/363517842/for-decades-kodak-s-shirley-cards-set-photography-s-skin-tone-standard/

https://priceonomics.com/how-photography-was-optimized-for-white-skin/

https://www.buzzfeed.com/syreetamcfadden/teaching-the-camera-to-see-my-skin/

Word of warning

- Around 2013/2014 there were a lot of articles about this issue.
- Many articles rewrite the same few sources.
- Some do not have a technical background, and sometimes technical issues are confused.
- ‘Internet comments’ warning.

- ‘Take care.’

CV as making bank

- Intel buys Mobileye!
- $15 billion

- Mobileye:
  - Spin-off from Hebrew University, Israel
  - 450 engineers
  - 15 million cars installed
  - 313 car models

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Intel buys driverless car technology firm Mobileye

2 hours ago | Business | 138 | Share

US chipmaker Intel is taking a big bet on driverless cars with a $15.3bn (£12.5bn) takeover of specialist Mobileye.

Intel will pay $63.54 a share in cash for the Israeli company, which develops "autonomous driving" systems.

Mobileye and Intel are already working together, along with German carmaker BMW, to put 40 test vehicles on the road in the second half of this year.

Intel expects the driverless market to be worth as much as $70bn by 2030.

Technology companies are racing to launch driverless cars.

June 2016 - Tesla left Mobileye

- Fatal crash – car ‘autopilot’ ran into a tractor trailer.

“What we know is that the vehicle was on a divided highway with Autopilot engaged when a tractor trailer drove across the highway perpendicular to the Model S. Neither Autopilot nor the driver noticed the white side of the tractor trailer against a brightly lit sky, so the brake was not applied.” – Tesla blog.

What computer vision problems
does this sound like?

Tesla crash: how it happened

A preliminary investigation into 25,000 Tesla Model S cars has been opened after a driver of one of the vehicles was killed while operating in Autopilot mode in a crash in Williston, Florida. Here is how the fatal accident occurred according to authorities.

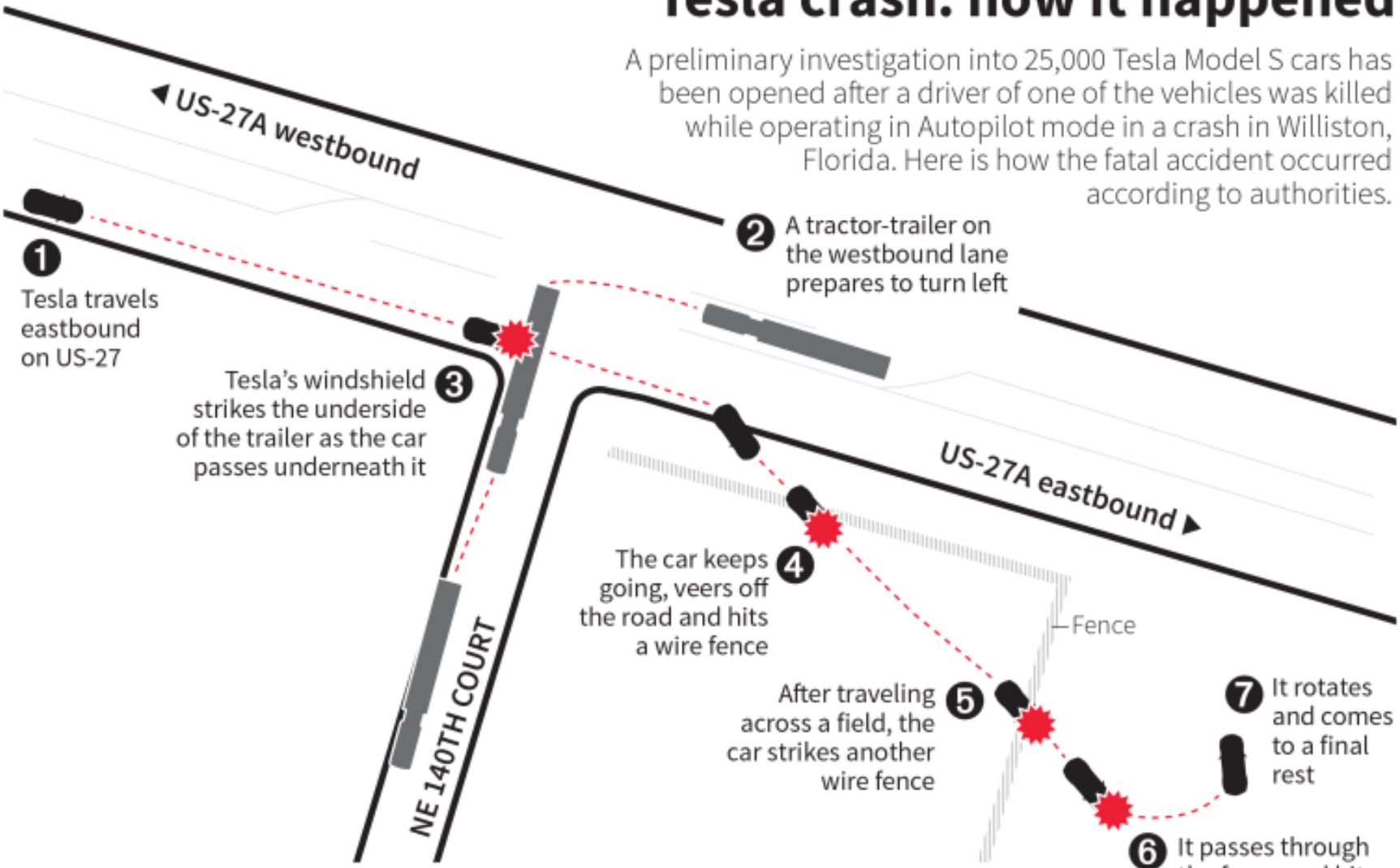


Diagram not to scale.

Sources: Florida Highway Patrol Troop; U.S. National Highway Traffic Safety Administration

C. Chan, 30/06/2016

REUTERS


0:07 / 0:16

June 2016 - Tesla left Mobileye

- Fatal crash – car ‘autopilot’ ran into a tractor trailer.

“What we know is that the vehicle was on a divided highway with Autopilot engaged when a tractor trailer drove across the highway perpendicular to the Model S. Neither Autopilot nor the driver noticed the white side of the tractor trailer against a brightly lit sky, so the brake was not applied.” – Tesla blog.

What computer vision problems does this sound like?

What HCI problems does this sound like?

Autosteer

U.S. Department of Transportation
National Highway Traffic Safety Administration

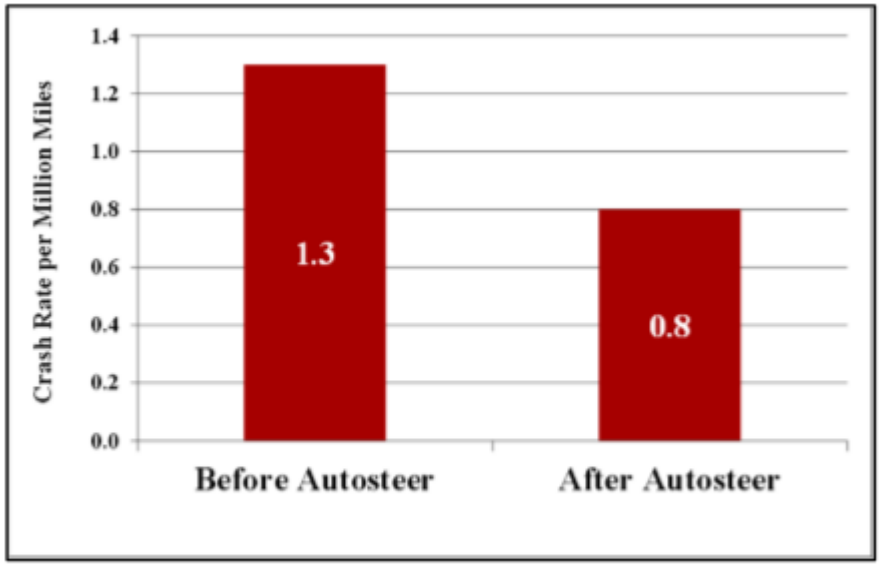


Figure 11. Crash Rates in MY 2014-16 Tesla Model S and 2016 Model X vehicles Before and After Autosteer Installation.

- https://www.bbc.com/news/technology-47468391
- **Uber 'not liable' for self-driving death**

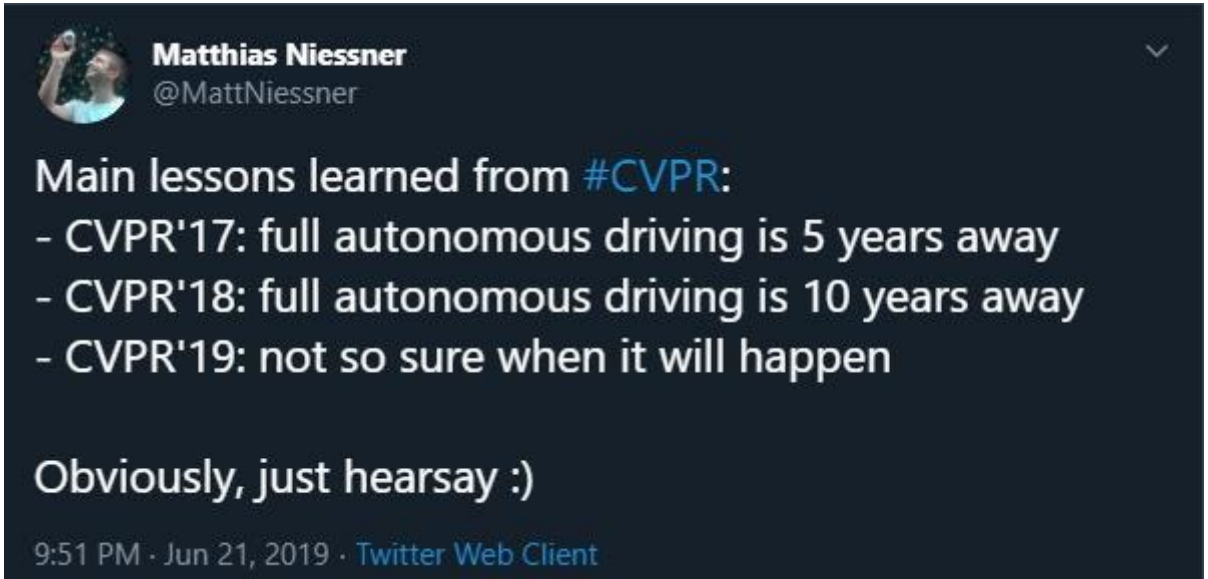
Full self driving example

- https://youtu.be/tlThdr3O5Qo

State of Self-driving Cars

- NYTimes: https://www.nytimes.com/2019/07/17/business/self-driving-autonomous-cars.html

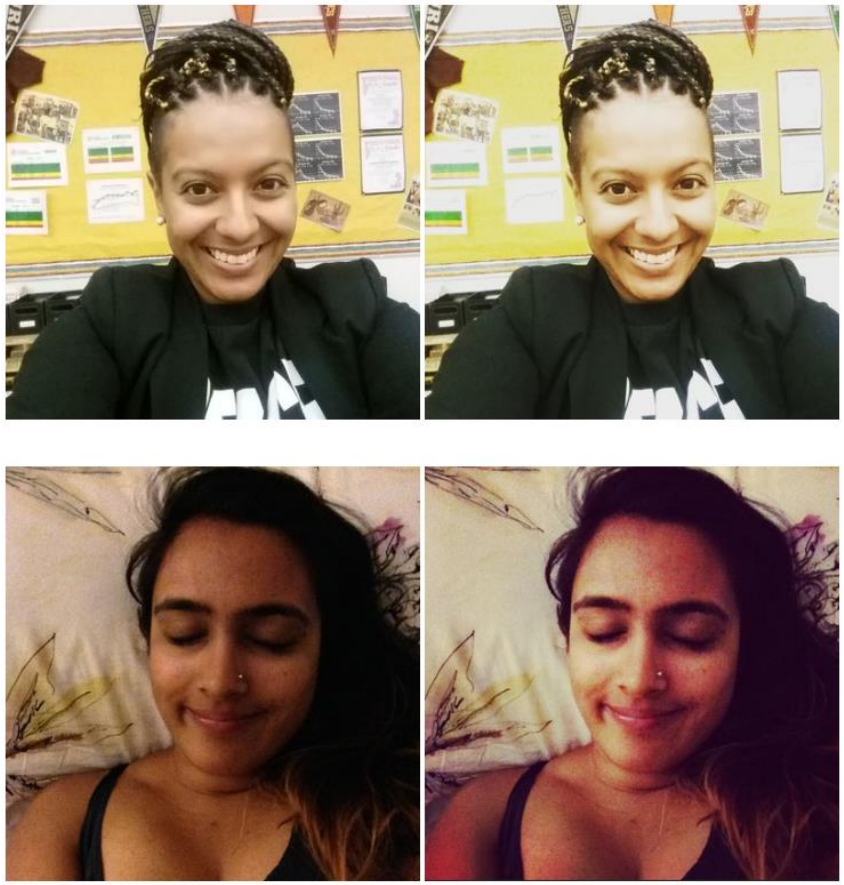
- Matthias Niessner:



Instagram filters

- Filters that brighten
- Filters that darken

- Filters can do anything!



Snapchat

"Anime inspired"

FaceApp

- Learning-based face transformations

neural networks
FaceApp
algorithmic bias
algorithmic accountability
Artificial Intelligence

FaceApp apologizes for building a racist AI

Posted 45 minutes ago by ***Natasha Lomas*** *(@riptari)*

2017/04/25

If only all algorithmic bias were as easy to spot as this: FaceApp, a photo-editing app that uses a neural network for editing selfies in a photorealistic way, has apologized for building a racist algorithm.

The app lets users upload a selfie or a photo of a face, and offers a series of filters that can then be applied to the image to subtly or radically alter its appearance — its appearance-shifting effects include aging and even changing gender.

The problem is the app also included a so-called "hotness" filter, and this filter was racist. As users pointed out, the filter was lightening skin tones to achieve its mooted "beautifying" effect. You can see the filter pictured above in a before and after shot of President Obama.

In an emailed statement apologizing for the racist algorithm, FaceApp's founder and CEO Yaroslav Goncharov told us: "We are deeply sorry for this unquestionably serious issue. It is an unfortunate side-effect of the underlying neural network caused by the training set bias, not intended behaviour. To mitigate the issue, we have renamed the effect to exclude any positive connotation associated with it. We are also working on the complete fix that should arrive soon."

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5 days ago

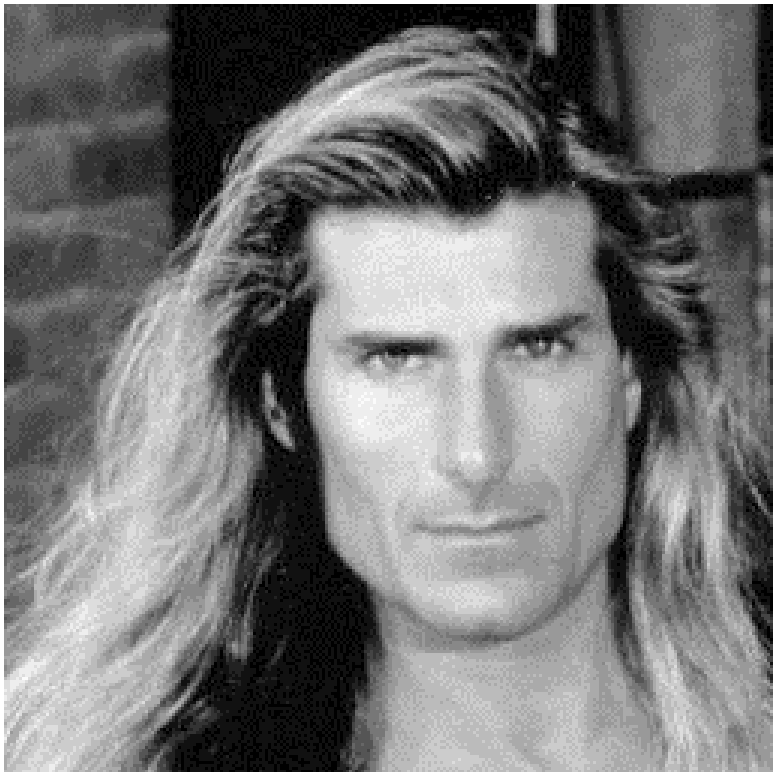

Uber gets sued over alleged 'Hell' program to track Lyft drivers
a day ago

Lena and Fabio

Examples: Controversy and Appropriateness

‘Lena’

Alexander Sawchuk @ USC, 1973



‘Fabio’

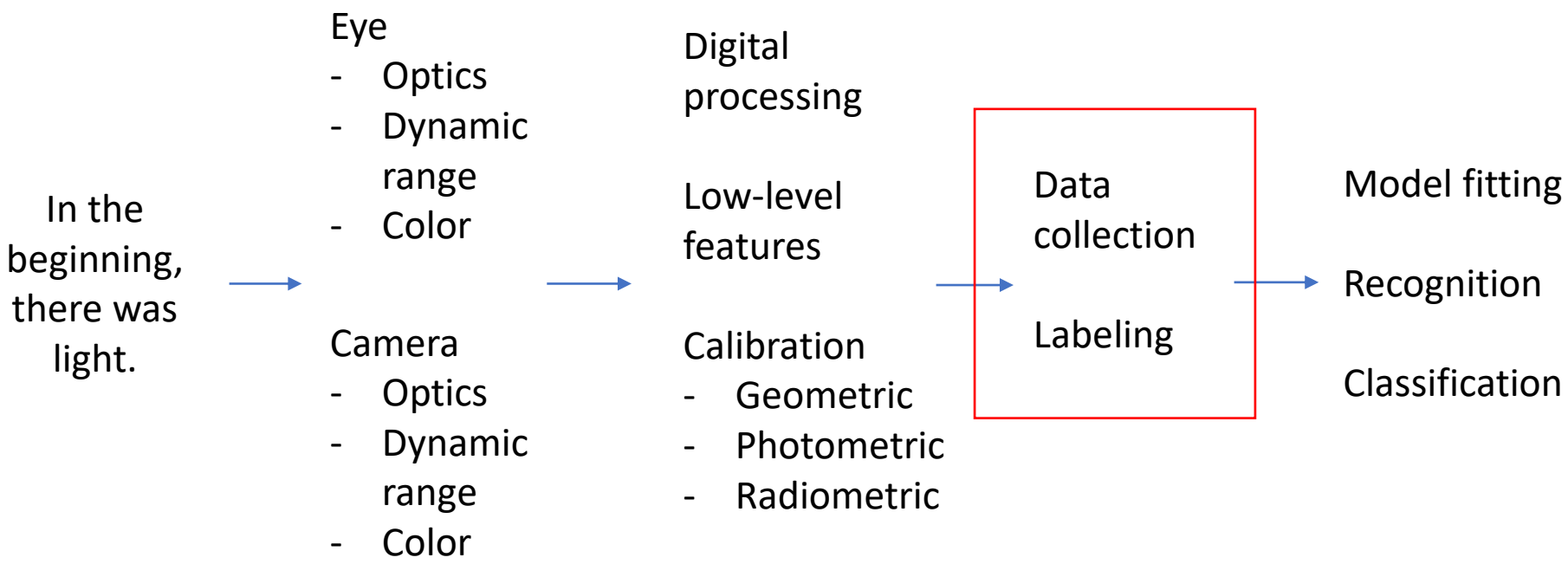
Deanna Needell @ Claremont McKenna, 2012

Wired article explaining it all

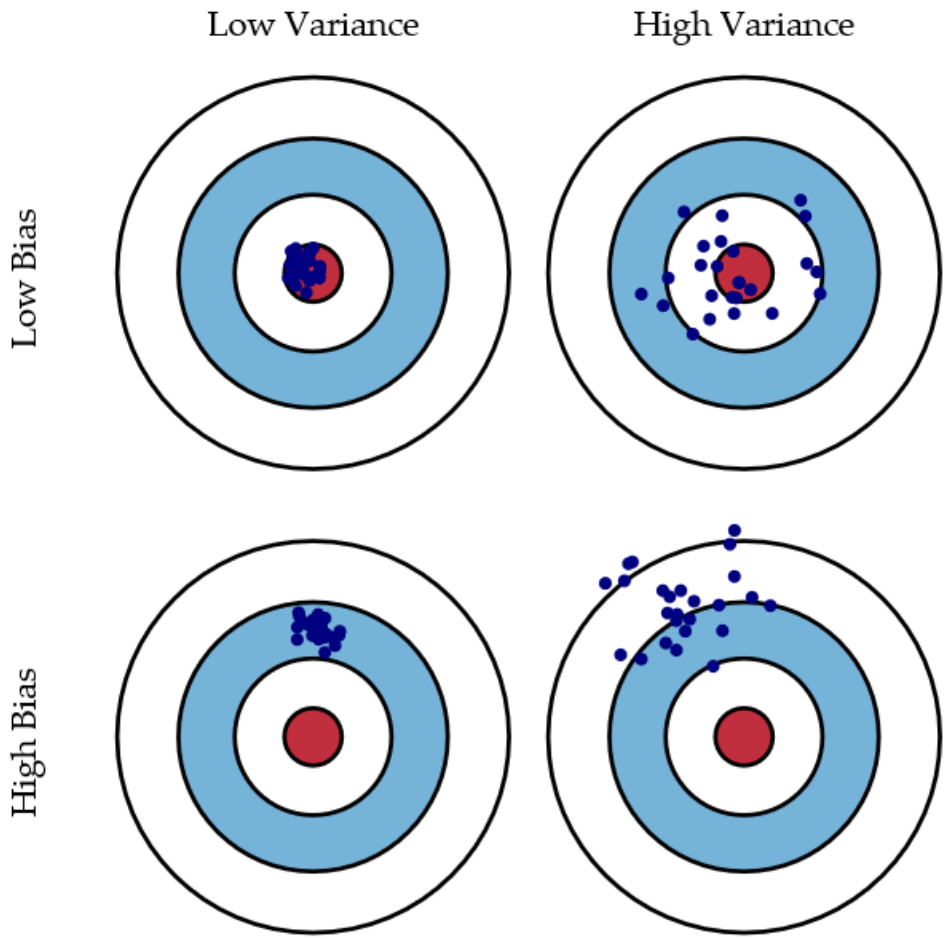
https://www.wired.com/story/finding-lena-the-patron-saint-of-jpegs/

Dataset Bias

Computer vision domain



Bias/variance trade-off



Bias = accuracy
Variance = precision

Unbiased Look at Dataset Bias

Torralba and Efros, CVPR 2011

“The authors would like to thank the Eyjafjallajokull volcano as well as the wonderful kirs at the Buvette in Jardin du Luxembourg for the motivation (former) and the inspiration (latter) to write this paper.“

Next few slide contents are from the paper

Progression of dataset complexity

- COIL-100:

- 15 scenes: Out of the lab, backgrounds
- Caltech-101: Google-mined, single object in middle.
- LabelMe: Multiple objects, anywhere
- PASCAL VOC: More rigorous testing standards
- ImageNet: Internet-scale, real-world

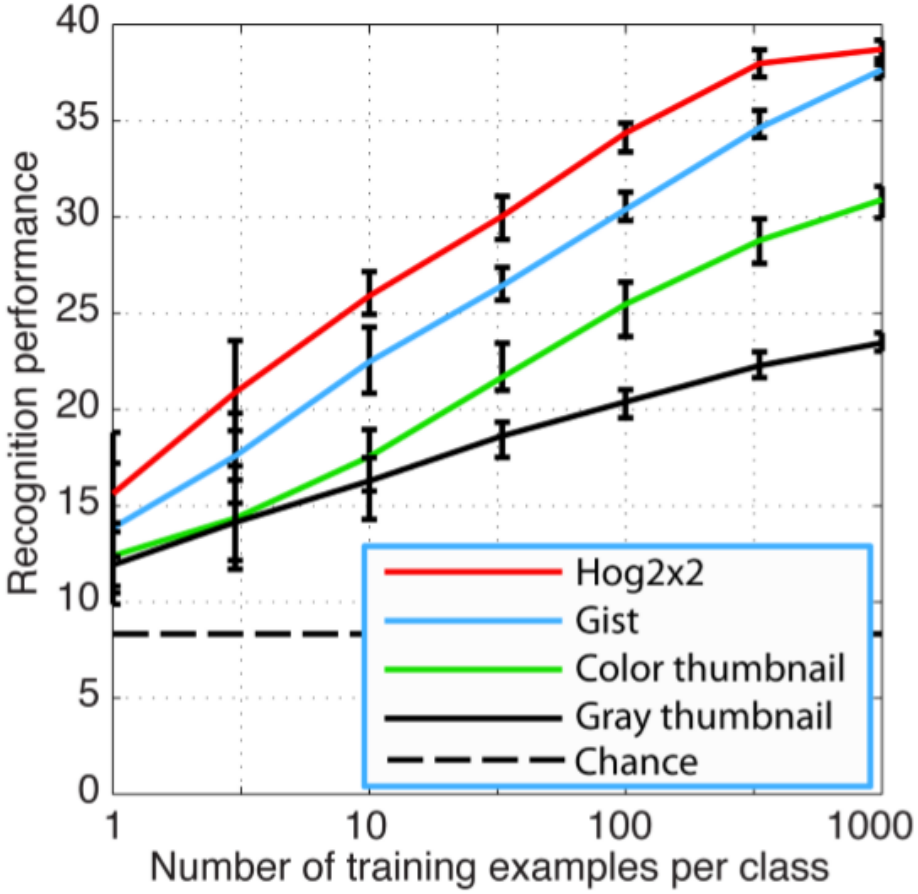
Caltech101 ____ Tiny ____ LabelMe ____ 15 Scenes ____

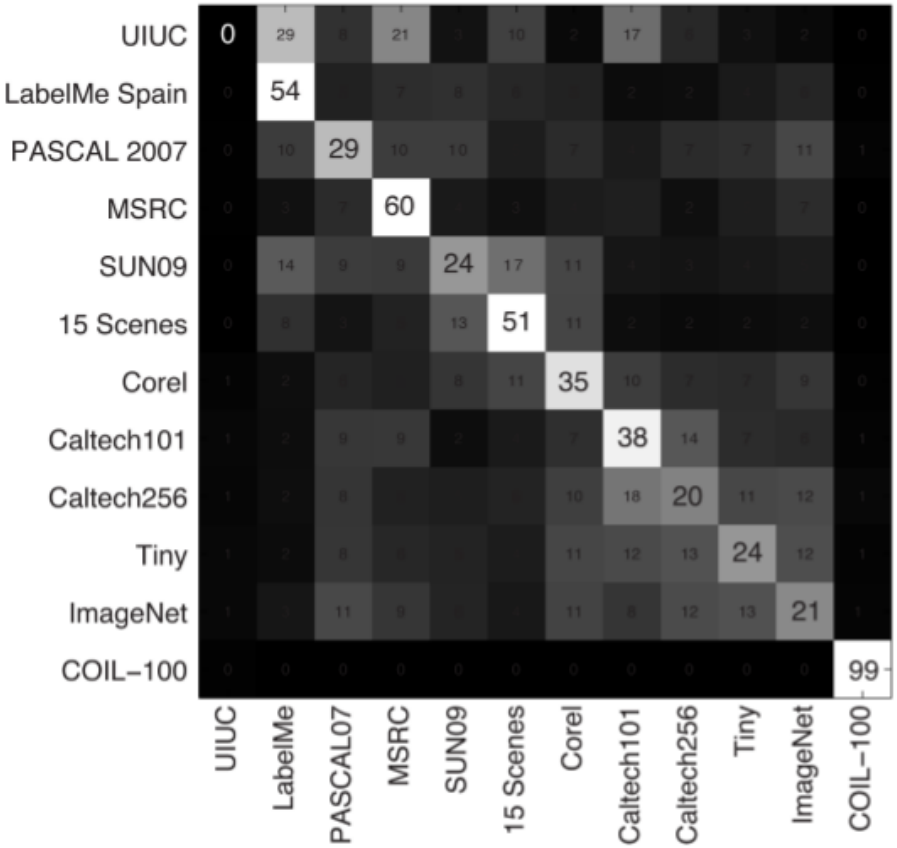
MSRC ____ Corel ____ COIL−100 ____ Caltech256 ____

UIUC ____ PASCAL 07 ____ ImageNet ____ SUN09 ____

Figure 1. Name That Dataset: Given three images from twelve popular object recognition datasets, can you match the images with the dataset? (answer key below)

CV plays name that dataset!





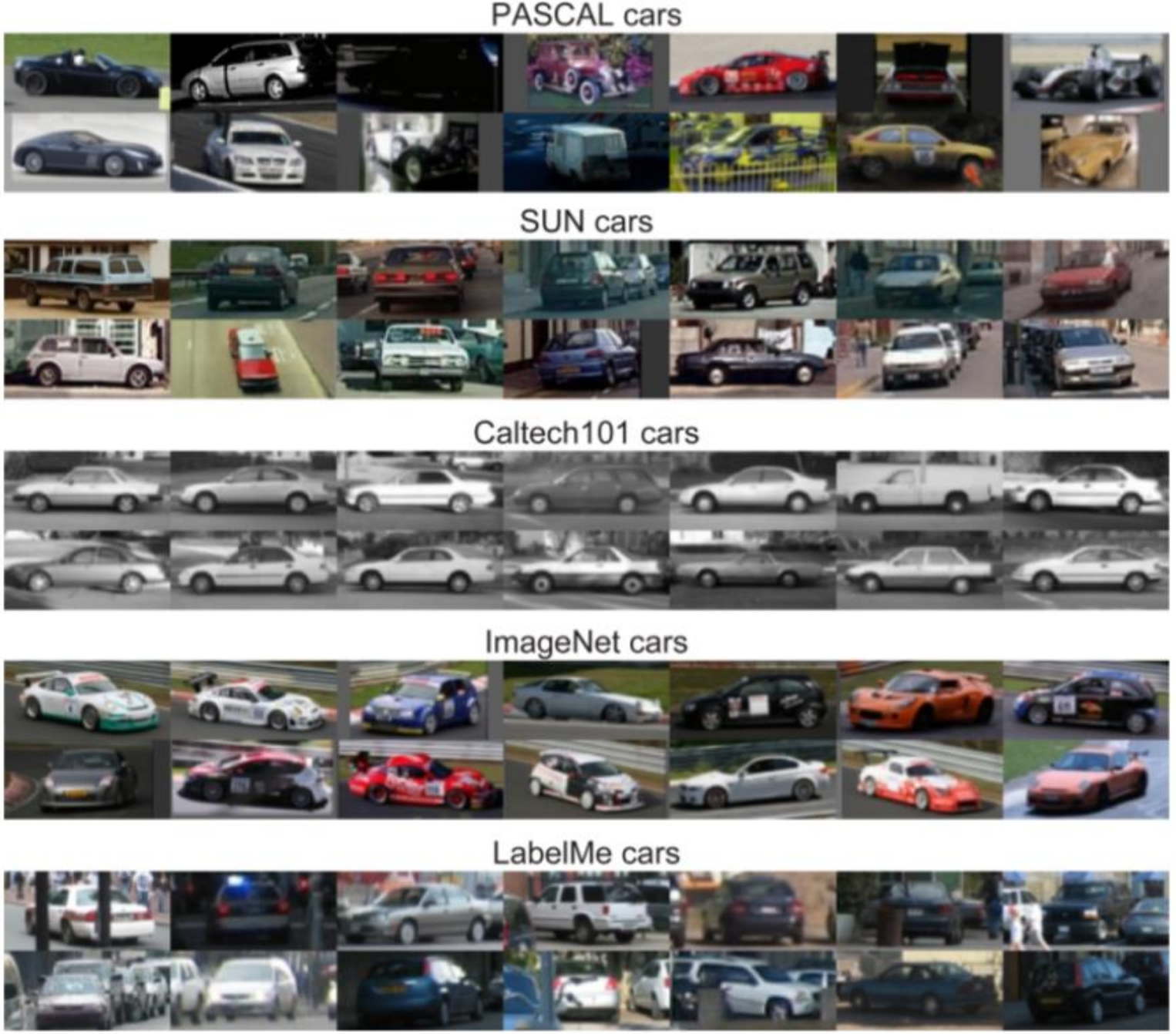


Figure 4. Most discriminative cars from 5 datasets

Measuring Dataset Bias

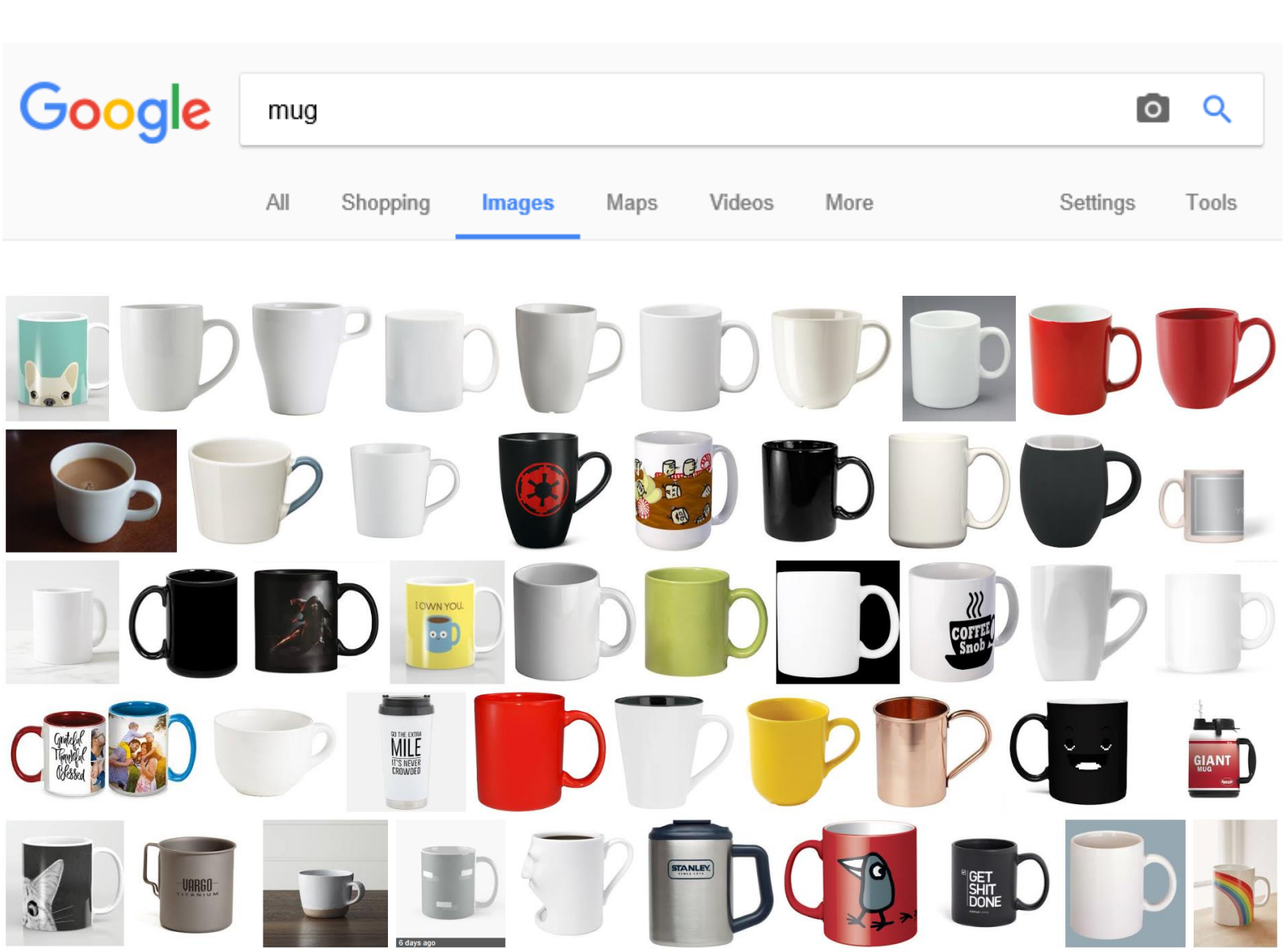
- Idea: cross-dataset generalization

- Train an object classifier on one dataset
- Test on the same object class on another dataset
- Observe performance as measure of bias

task	Test on: / Train on:	SUN09	LabelMe	PASCAL	ImageNet	Caltech101	MSRC	Self	Mean others	Percent drop
"person" detection	SUN09	**69.6**	56.8	37.9	45.7	52.1	72.7	69.6	53.0	**24%**
	LabelMe	58.9	**66.6**	38.4	43.1	57.9	68.9	66.6	53.4	**20%**
	PASCAL	56.0	55.6	**56.3**	55.6	56.8	74.8	56.3	59.8	**-6%**
	ImageNet	48.8	39.0	40.1	**59.6**	53.2	70.7	59.6	50.4	**15%**
	Caltech101	24.6	18.1	12.4	26.6	**100**	31.6	100	22.7	**77%**
	MSRC	33.8	18.2	30.9	20.8	69.5	**74.7**	74.7	34.6	**54%**
	Mean others	44.4	37.5	31.9	38.4	57.9	63.7	71.1	45.6	**36%**
"person" classification	SUN09	**16.1**	11.8	14.0	7.9	6.8	23.5	16.1	12.8	**20%**
	LabelMe	11.0	**26.6**	7.5	6.3	8.4	24.3	26.6	11.5	**57%**
	PASCAL	11.9	11.1	**20.7**	13.6	48.3	50.5	20.7	27.1	**-31%**
	ImageNet	8.9	11.1	11.8	**20.7**	76.7	61.0	20.7	33.9	**-63%**
	Caltech101	7.6	11.8	17.3	22.5	**99.6**	65.8	99.6	25.0	**75%**
	MSRC	9.4	15.5	15.3	15.3	93.4	**78.4**	78.4	29.8	**62%**
	Mean others	9.8	12.3	13.2	13.1	46.7	45.0	43.7	23.4	**47%**

Different kinds of bias

- *Selection bias*
  - Retrieve different kinds of images; keywords/search engines can bias.
- *Capture bias*
  - Objects photographed in similar ways that do not generalize, e.g., object always in center, race track car vs. street car, mugs.


Google
mug
All
Shopping
Images
Maps
Videos
More
Settings
Tools
I OWN YOU.
COFFEE Snob
Grateful Thankful Blessed
GO THE EXTRA MILE IT'S NEVER CROWDED
GIANT MUG
VARGO TITANIUM
STANLEY
GET SHIT DONE
6 days ago

Different kinds of bias

- *Selection bias*
  - Retrieve different kinds of images; keywords/search engines can bias.
- *Capture bias*
  - Objects photographed in similar ways that do not generalize, e.g., object always in center, race track car vs. street car, mugs.
- *Category/label bias*
  - Poorly-defined classes, e.g., painting vs. picture
- *Negative set bias*
  - In one vs. all classification, ‘all’ or “the rest of the world” is not well represented.
  - “Are features which helps classify ‘boat’ object really the boat, or are they the water it sits on?”
    - Low bias negative set would include many boat-free images of rivers and lakes.

Measuring Negative Set Bias

- Take negative examples from other datasets and add to superset; train against this.

task	Positive Set: / Negative Set:	SUN09	LabelMe	PASCAL	ImageNet	Caltech101	MSRC	Mean
"car" detection	self	67.6	62.4	56.3	60.5	97.7	74.5	70.0
	all	53.8	51.3	47.1	65.2	97.7	70.0	64.1
	percent drop	20%	18%	16%	-8%	0%	6%	8%
"person" detection	self	67.4	68.6	53.8	60.4	100	76.7	71.1
	all	52.2	58.0	42.6	63.4	100	71.5	64.6
	percent drop	22%	15%	21%	-5%	0%	7%	9%

- Drop in performance of 'all' suggests negative examples are being misclassified

Overcoming bias at collection time

- *Selection bias*
  - Multiple keywords, search engines, countries.
  - Collect unknown images and label them by crowd-sourcing.

- *Capture bias*
  - Better sampling
  - Different transforms: noise, flips, rotations, affine, crops.

Overcoming bias at collection time

- *Category/label bias*
  - Clear instruction to turkers; unambiguous classes (possible?)
  - Pre-label clustering, or multiple acceptable answers.

- *Negative set bias*
  - Cross-dataset mining
  - Mine for hard negatives from unlabeled set using a reliable algorithm and high threshold.

Undoing the Damage of Dataset Bias

Khosla et al., ECCV 2012

“While it remains in question whether creating an unbiased dataset is possible given limited resources, we propose a discriminative framework that directly exploits dataset bias during training.”

More info

Kate Crawford @ NIPS 2017

https://www.youtube.com/watch?v=fMym_BKWQzk

The Trouble with Bias

More examples

https://www.quora.com/What-are-examples-of-computer-vision-bugs-related-to-race

http://www.telegraph.co.uk/technology/2016/12/07/robot-passport-checker-rejects-asian-mans-photo-having-eyes/

Thank you Tiffany Chen

Viola-Jones with a bad training database

wzamen01

Google Photos (2015)

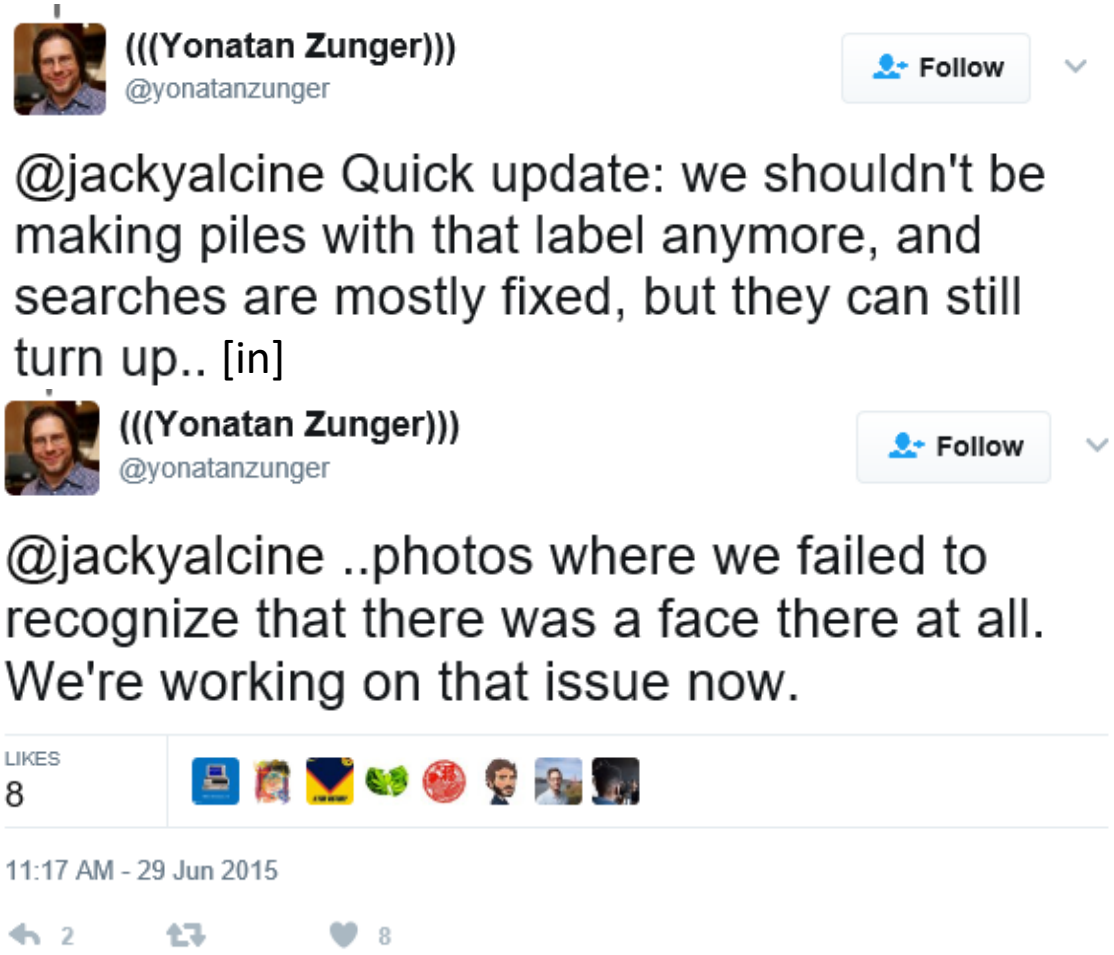
[Jacky Alciné]

Google Photos (2015)

- What do you think the problem was?
- How could you fix it?

- Has it been fixed? Anyone use Google Photos?

Google Photos (2015)



Not just a vision problem

Text embeddings also suffer:

https://gist.github.com/rspeer/ef750e7e407e04894cb3b78a82d66aed

'Sentiment analysis' ->

```
In [12]: text_to_sentiment("this example is pretty cool")
Out[12]: 3.889968926086298

In [13]: text_to_sentiment("this example is okay")
Out[13]: 2.7997773492425186

In [14]: text_to_sentiment("meh, this example sucks")
Out[14]: -1.1774475917460698
```

Rob Speer

Not just a vision problem

Text embeddings also suffer:

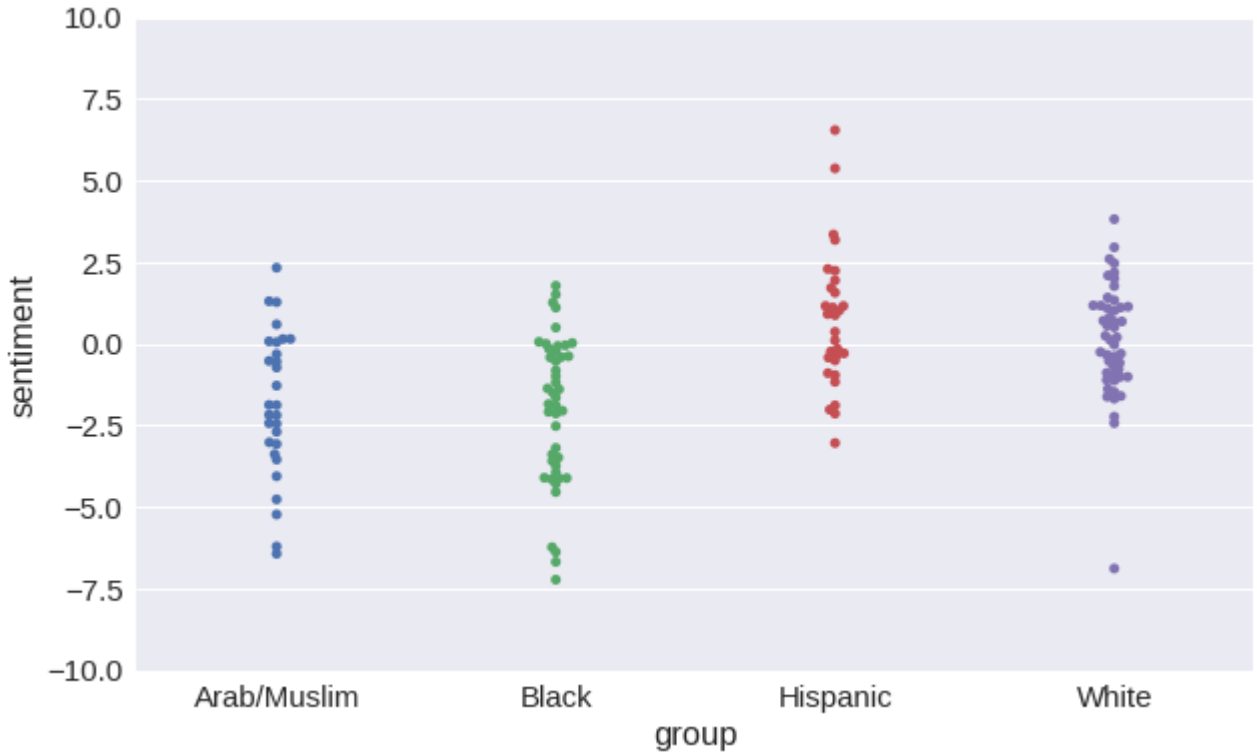
https://gist.github.com/rspeer/ef750e7e407e04894cb3b78a82d66aed

'Sentiment analysis' ->

```
In [15]: text_to_sentiment("Let's go get Italian food")
Out[15]: 2.0429166109408983

In [16]: text_to_sentiment("Let's go get Chinese food")
Out[16]: 1.4094033658140972

In [17]: text_to_sentiment("Let's go get Mexican food")
Out[17]: 0.38801985560121732
```

Word embedding trained on Google News – word2vec

```
In [20]: text_to_sentiment("My name is Yvette")
Out[20]: 0.98463802132985556

In [21]: text_to_sentiment("My name is Shaniqua")
Out[21]: -0.47048131775890656
```



AI ‘Safety’

Concrete Problems in AI Safety

- https://arxiv.org/abs/1606.06565

In context of robots, but promising ideas

  - Regularizer based on expert ‘risk’ of class confusion

Criminality

- Wu and Zhang, *Automated Inference on Criminality using Face Images*, on arXiv 2016

(a) Three samples in criminal ID photo set S_c.

(b) Three samples in non-criminal ID photo set S_n

Figure 1. Sample ID photos in our data set.

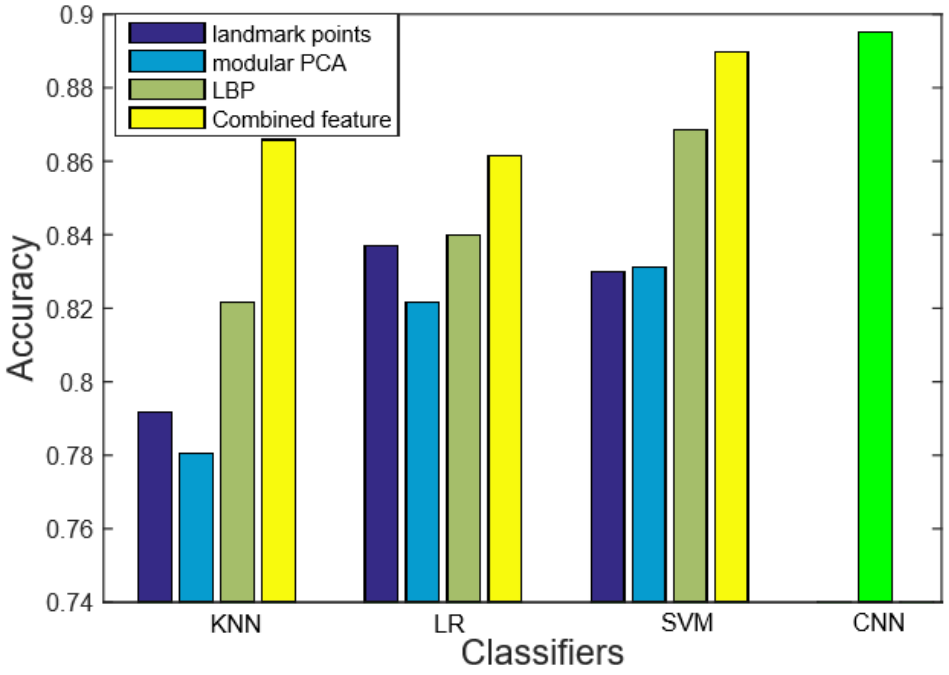
https://arxiv.org/abs/1611.04135

Slide figures from paper

“Unlike a human examiner/judge, a computer vision algorithm or classifier has absolutely no subjective baggages, having no emotions, no biases whatsoever due to past experience, race, religion, political doctrine, gender, age, etc., no mental fatigue, no preconditioning of a bad sleep or meal. The automated inference on criminality eliminates the variable of meta-accuracy (the competence of the human judge/examiner) all together.”

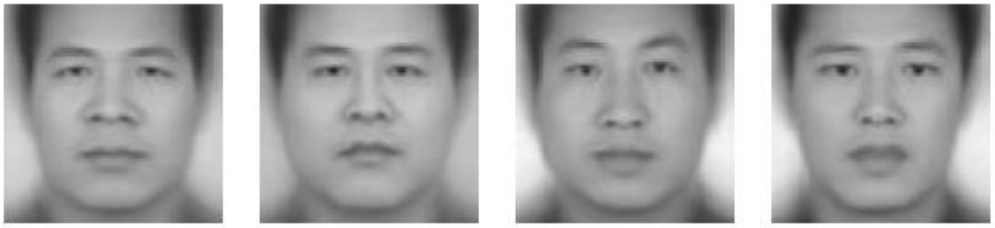
Criminality

- 1100 non-criminal, 730 criminal Chinese face photos
- Tested various features + classifiers



Criminality

K-means, averaging clusters



(a) -0.98 (b) -0.68 (c) -0.28 (d) -0.38

(e) 0.76 (f) 0.98 (g) 0.66

Figure 13. (a), (b), (c) and (d) are the four subtypes of criminal faces corresponding to four cluster centroids on the manifold of S_c; (e), (f) and (g) are the three subtypes of non-criminal faces corresponding to three cluster centroids on the manifold of S_n. The number associated with each face is the average score of human judges (-1 for criminals; 1 for non-criminals).

What biases might exist? Discuss!

- Selection bias
- Capture bias
- Category/label bias
- Negative set bias

Is this real?

Whatever the case, it needs care! Significant ramifications.

Can humans do this?

- *Small but statistically significant ability to tell criminal from non-criminal in photo.*

Valla, J., Williams, W., & Ceci, S. J. (2011).

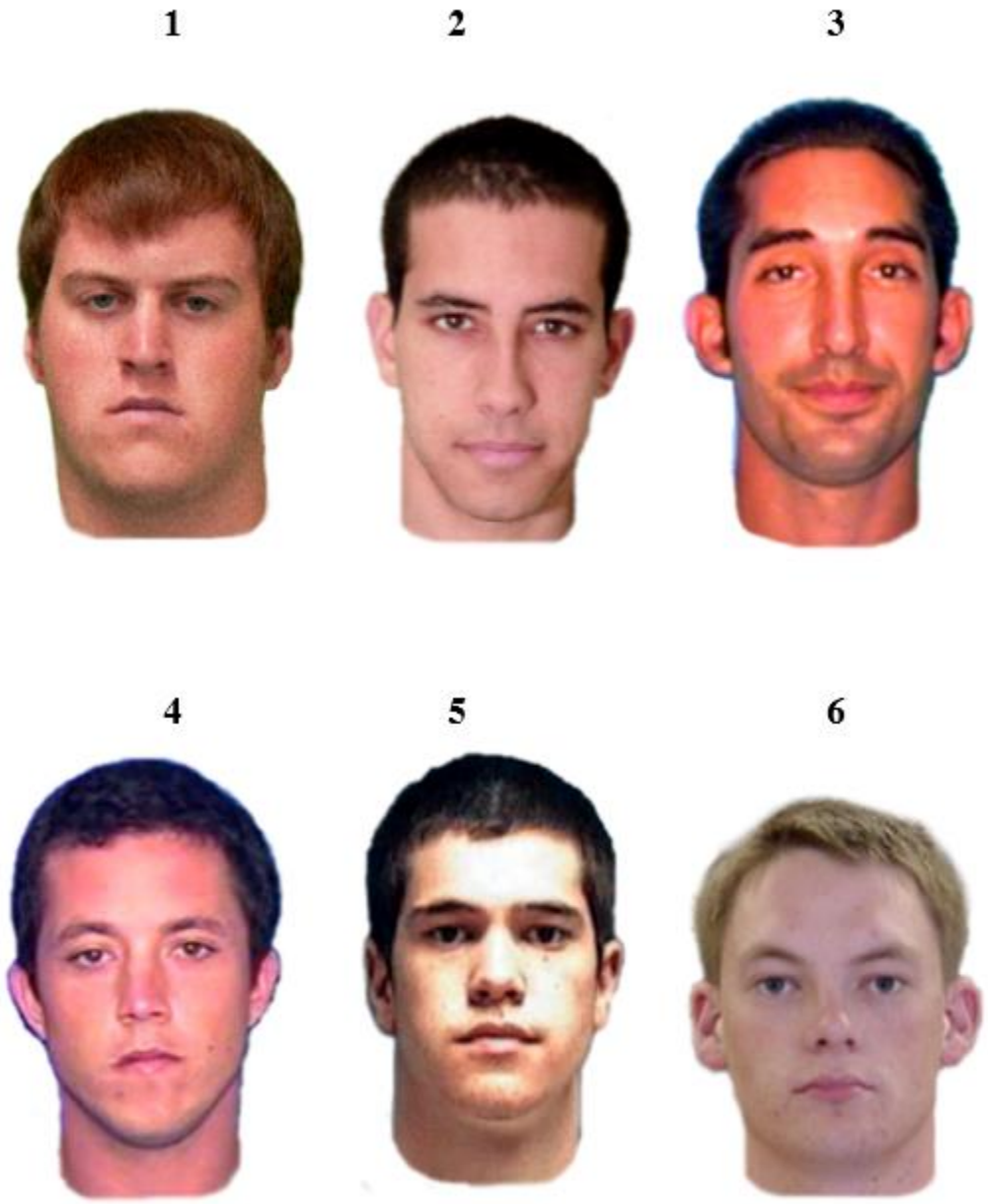
The accuracy of inferences about criminality based on facial appearance.

Journal of Social, Evolutionary, and Cultural Psychology, 5(1), 66-91.

Same biases?

MIT Technology Review has a good overview:

https://www.technologyreview.com/s/602955/neural-network-learns-to-identify-criminals-by-their-faces/



Valla, J., Williams, W., & Ceci, S. J. (2011)

FACEPTION
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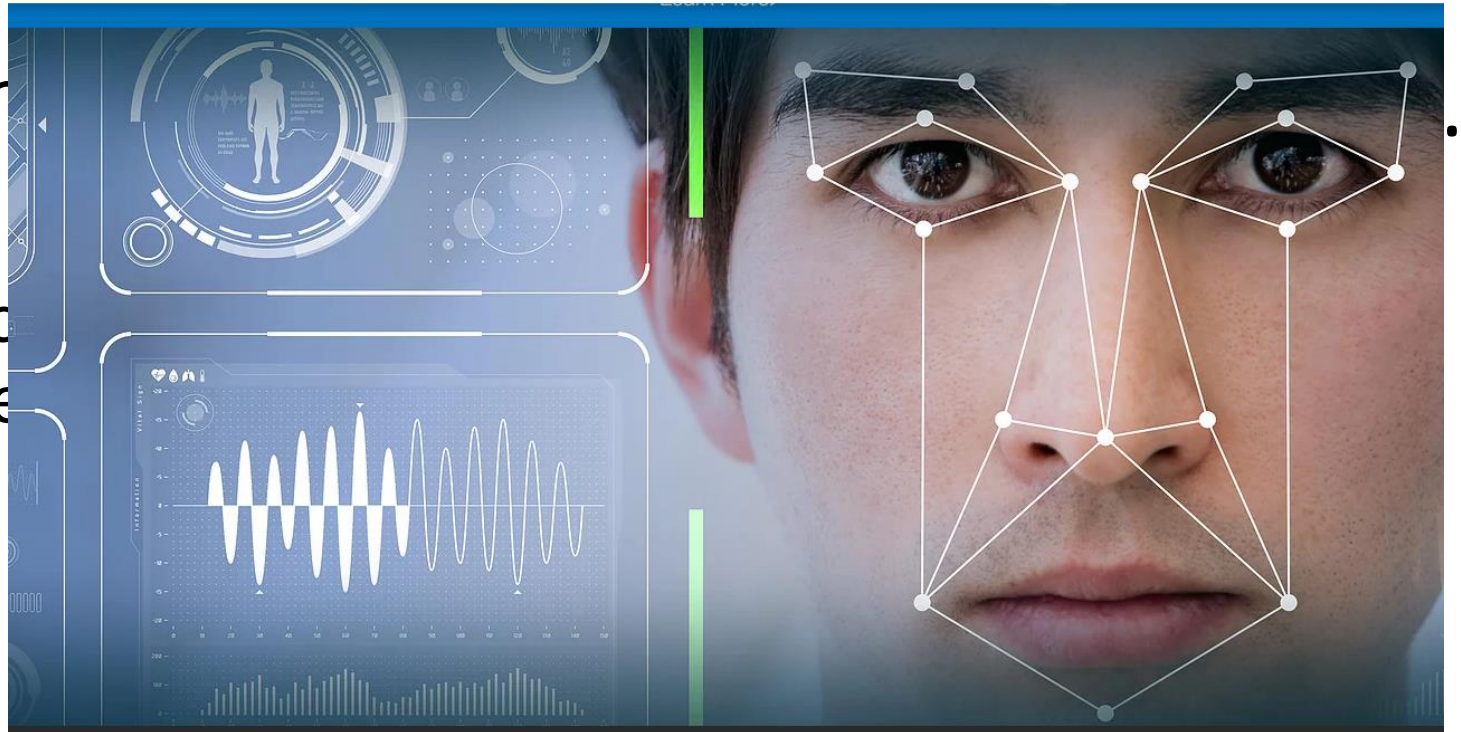


OUR CLASSIFIERS


High IQ


Academic Researcher


Professional Poker Player


Terrorist

Utilizing advanced machine learning techniques we developed and continue to evolve an array of classifiers. These classifiers represent a certain persona, with a unique personality type, a collection of personality traits or behaviors. Our algorithms can score an individual according to their fit to these classifiers.

Learn More>

individuals who could present a threat to public safety. According ...

Click Here

Facial analysis software is being used to predict sexuality and security risks
February 5, 2018

Click Here

ETHICS & FAIRNESS USAGE

The Faception Advantage: Privacy and Fairness

- **Decision Support System** - Provides actionable intelligence as predicted traits and behaviors of individuals
- **Operates anonymously** – no need for identity, phone, social media data
- **Objective** – not biased by race, class, gender, age
- We store only classifiers (like a mathematical equation), **no "big data"** on people

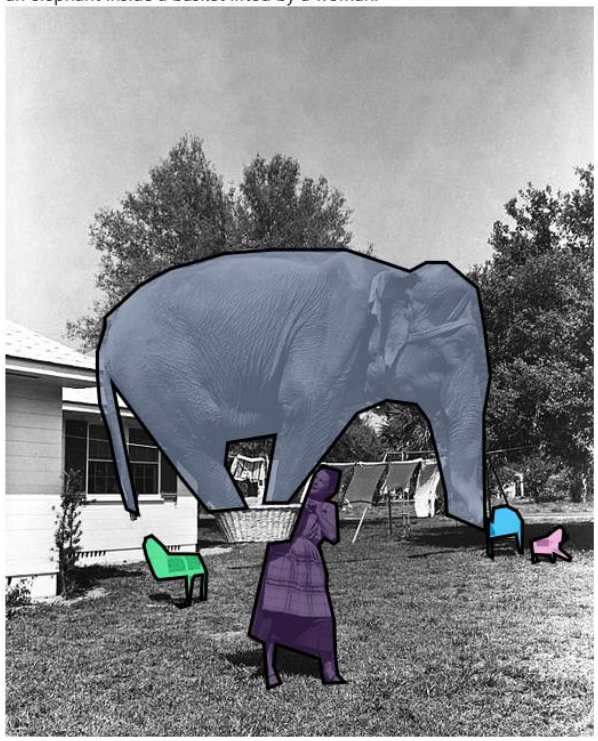
“Guns don't kill people, *people* kill people!”

“Machine learning doesn’t kill people,
training data kills people!”

- ML community, all the time.

Dataset improvement: MS COCO

an elephant standing on top of a basket being held by a woman.
a woman standing holding a basket with an elephant in it.
a lady holding an elephant in a small basket.
a lady holds an elephant in a basket.
an elephant inside a basket lifted by a woman.



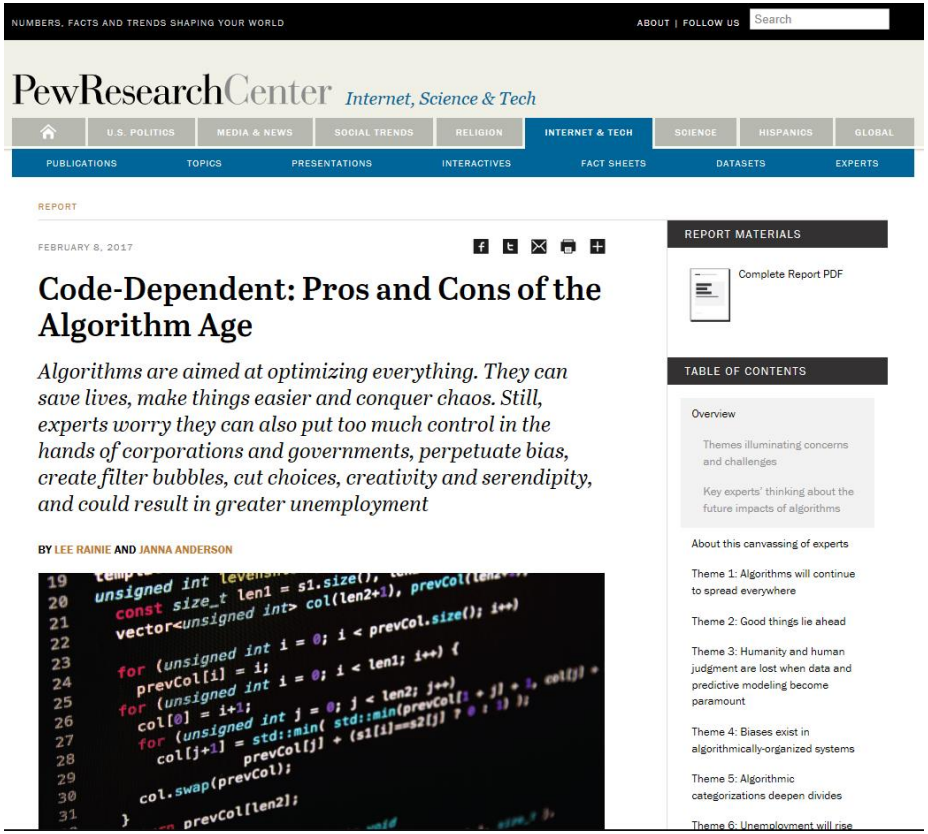
What is COCO?

COCO is a new image recognition, segmentation, and captioning dataset. COCO has several features:

- **Object segmentation**
- **Recognition in Context**
- **Multiple objects per image**
- **More than 300,000 images**
- **More than 2 Million instances**
- **80 object categories**
- **5 captions per image**
- **Keypoints on 100,000 people**

Decent Pew Overview on Big Picture

Rainie and Anderson *Code-Dependent: Pros and Cons of the Algorithm Age*



http://www.pewinternet.org/2017/02/08/code-dependent-pros-and-cons-of-the-algorithm-age/

Brookings Report

Algorithmic bias detection and mitigation: Best practices and policies to reduce consumer harms

Nicol Turner Lee, **Paul Resnick**, and **Genie Barton**

May 22, 2019

https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/

Help Do Something About It

Joy Buolamwini

https://www.theguardian.com/technology/2017/may/28/joy-buolamwini-when-algorithms-are-racist-facial-recognition-bias/

Founded ‘Algorithmic Justice League’

https://www.ajlunited.org/

Look at Joy's paper on face bias in commercial softwares

Amazon Is Pushing Facial Technology That a Study Says Could Be Biased

In new tests, Amazon's system had more difficulty identifying the gender of female and darker-skinned faces than similar services from IBM and Microsoft.

By Natasha Singer

Jan. 24, 2019

Over the last two years, Amazon has aggressively marketed its facial recognition technology to police departments and federal agencies as a service to help law enforcement identify suspects more quickly. It has done so as another tech giant, Microsoft, has called on Congress to regulate the technology, arguing that it is too risky for companies to oversee on their own.

Now a new study from researchers at the M.I.T. Media Lab has found that Amazon's system, Rekognition, had much more difficulty in telling the gender of female faces and of darker-skinned faces in photos than similar services from IBM and Microsoft. The results raise questions about potential bias that could hamper Amazon's drive to popularize the technology.

[New York Times]

Effect of public shaming on face recognition databases

https://www.engadget.com/2019/01/25/amazon-rekognition-facial-analysis-gender-race-bias-mit/

The paper: http://www.aies-conference.com/wp-content/uploads/2019/01/AIES-19_paper_223.pdf

“However, Amazon has disputed the results of MIT's tests, which took place over the course of 2018. It argued the researchers hadn't used the current version of Rekognition, and said the gender identification test used facial analysis (which picks out faces from images and assigns generic attributes to them), rather than facial recognition, which looks for a match for a specific face. It noted that they are distinct software packages.”

"Using an up-to-date version of Amazon Rekognition with similar data downloaded from parliamentary websites and the Megaface dataset of [1 million] images, we found exactly zero false positive matches with the recommended 99 [percent] confidence threshold," Matt Wood, general manager of deep learning and AI at Amazon Web Services, told *VentureBeat*.

More info on the technical issues here:
https://itif.org/publications/2019/01/27/note-press-facial-analysis-not-facial-recognition

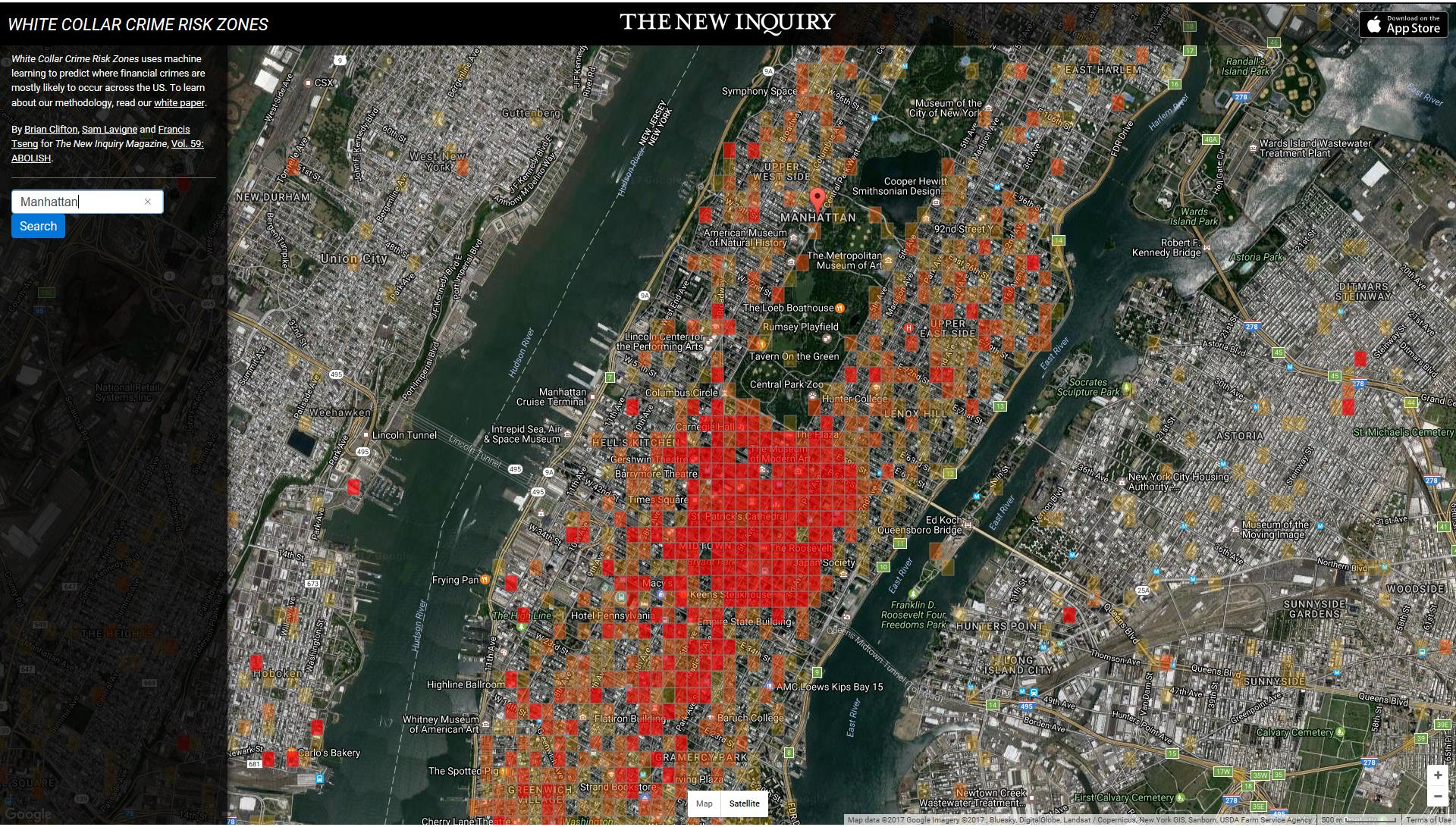
Predicting Financial Crime: Augmenting the Predictive Policing Arsenal

Brian Clifton[1], Sam Lavigne[1], and Francis Tseng[1]

[1] The New Inquiry
https://thenewinquiry.com/

Abstract. Financial crime is a rampant but hidden threat. In spite of this, predictive policing systems disproportionately target "street crime" rather than white collar crime. This paper presents the White Collar Crime Early Warning System (WCCEWS), a white collar crime predictive model that uses random forest classifiers to identify high risk zones for incidents of financial crime.

Keywords: Criminal justice; crime models; capitalism, financial malfeasance; white collar crime; police patrol.

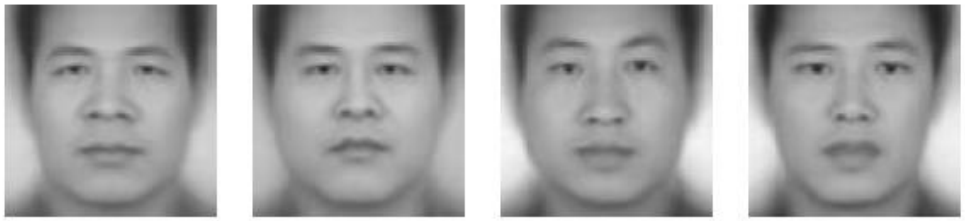


[https://whitecollar.thenewinquiry.com/]

Recently researchers have demonstrated the effectiveness of applying machine learning techniques to facial features to quantify the "criminality" of an individual[21].

---

[21] X. Wu and X. Zhang, "Automated inference on criminality using face images," *CoRR*, vol. abs/1611.04135, 2016.



(a) -0.98 (b) -0.68 (c) -0.28 (d) -0.38

(e) 0.76 (f) 0.98 (g) 0.66

Figure 13. (a), (b), (c) and (d) are the four subtypes of criminal faces corresponding to four cluster centroids on the manifold of S_c; (e), (f) and (g) are the three subtypes of non-criminal faces corresponding to three cluster centroids on the manifold of S_n. The number associated with each face is the average score of human judges (-1 for criminals; 1 for non-criminals).

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We therefore plan to augment our model with facial analysis and psychometrics to identify potential financial crime at the individual level. As a proof of concept, we have downloaded the pictures of 7000 corporate executives whose LinkedIn profiles suggest they work for financial organizations, and then averaged their faces to produce generalized white collar criminal subjects unique to each high risk zone. Future efforts will allow us to predict white collar criminality through real-time facial analysis.

Face detection + facial landmark detection + image warping + averaging/PCA!

Fig. 7: Predicted White Collar Criminal for 40.7087811, -74.0064149

WHITE COLLAR CRIME RISK ZONES

THE NEW INQUIRY

Download on the App Store

White Collar Crime Risk Zones uses machine learning to predict where financial crimes are mostly likely to occur across the US. To learn about our methodology, read our white paper.

By Brian Clifton, Sam Lavigne and Francis Tseng for *The New Inquiry Magazine*, Vol. 59: ABOLISH.

Manhattan ×

Search

Most Likely Suspect

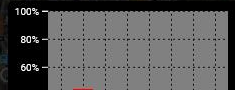
Top Risk Likelihoods

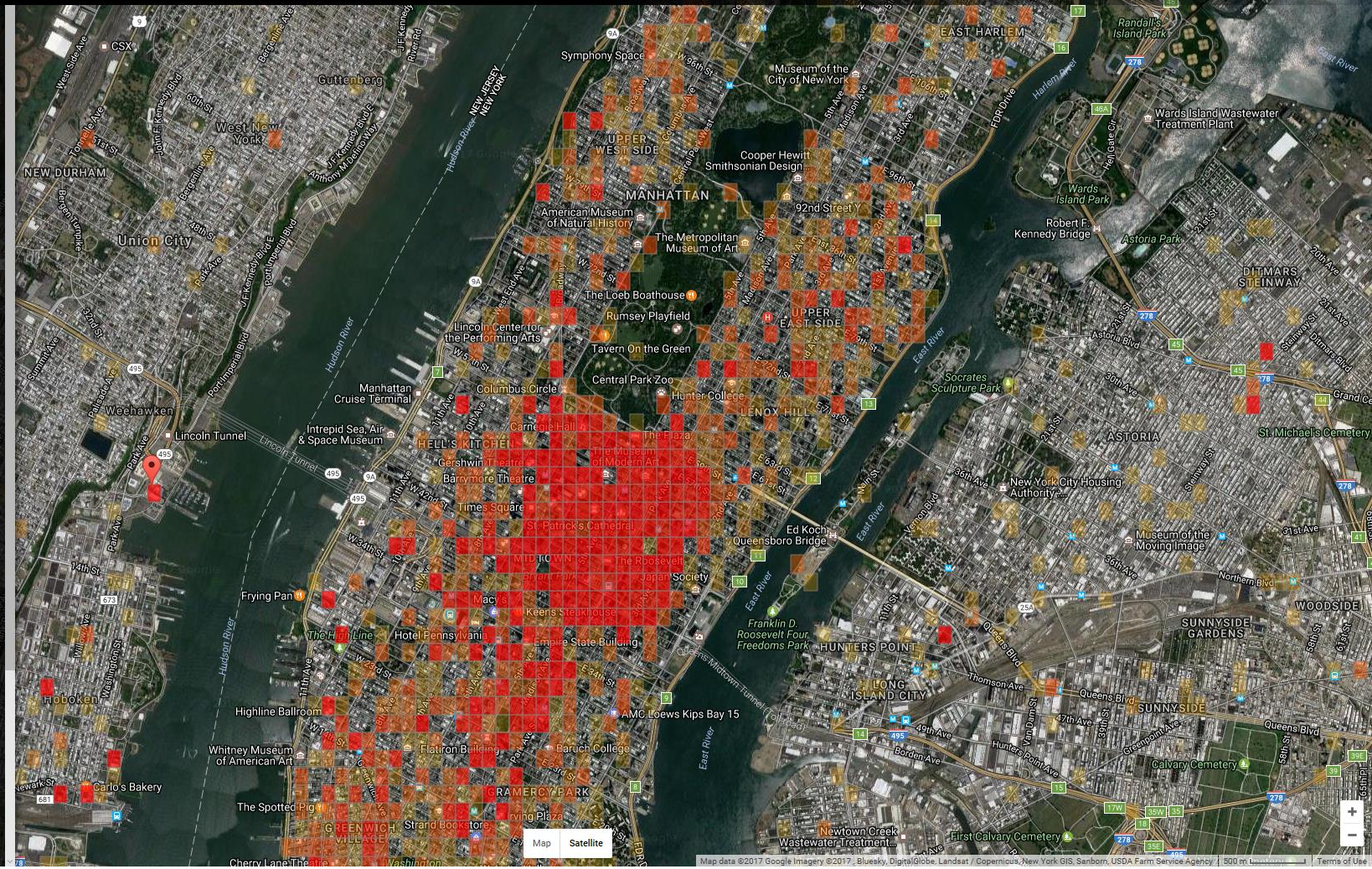
FAILURE TO SUPERVISE
(18.75%)

BREACH OF FIDUCIARY DUTY
(18.57%)

EMPLOYMENT DISCRIMINATION BASED ON AGE
(14.12%)

Approx. Crime Severity (in USD)





[https://whitecollar.thenewinquiry.com/]

[https://whitecollar.thenewinquiry.com/]

Facebook translation (+image)

HAARETZ Friday, December 01, 2017. Kislev 13, 5778 Time in Israel: 9:55 PM

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Israel Arrests Palestinian Because Facebook Translated 'Good Morning' to 'Attack Them'

No Arabic-speaking police officer read the post before arresting the man, who works at a construction site in a West Bank settlement

Yotam Berger | Oct 22, 2017 1:36 PM

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Trending Now

Flynn: Trump Transition Officials Directed My Contact With the Russians

Analysis // As Israel Issues Threats, Iran Works to Create Facts on the Ground in Syria

The Facebook post that mistranslated 'good morning' to 'hurt them'

Dataset openness

Rights on data

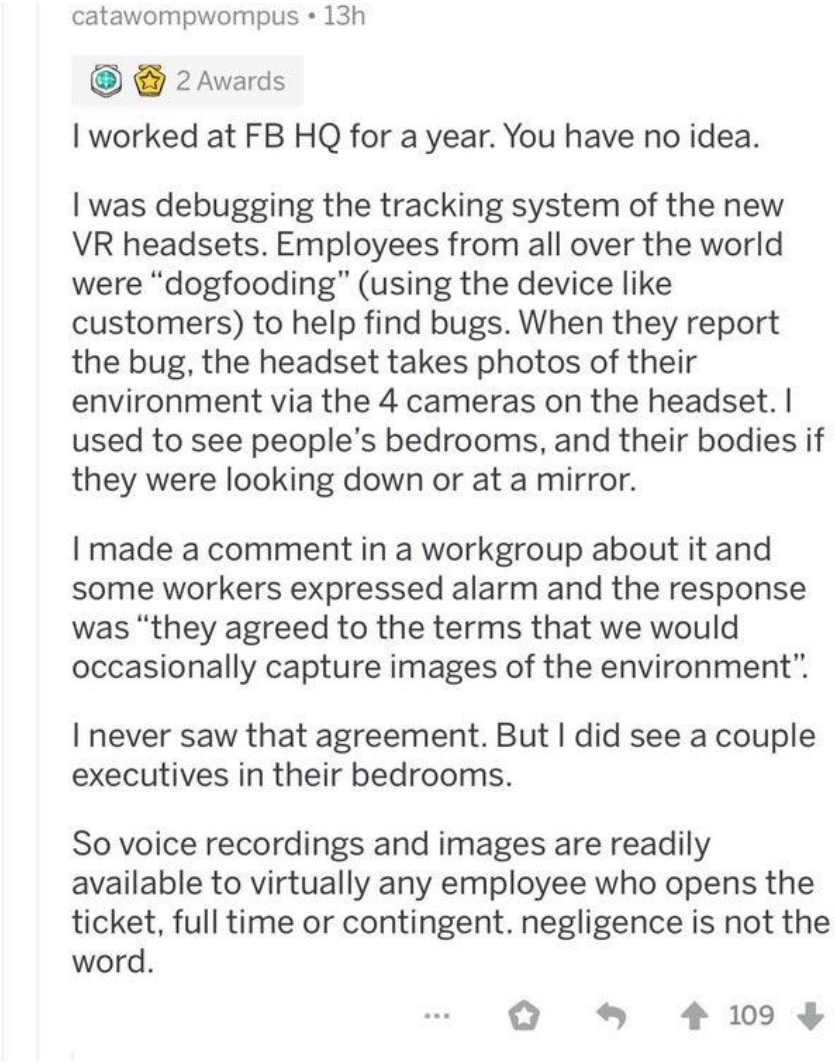
Later could be used in previously inconceivable ways

E.g., Flickr scrape for Creative Commons images is legal

https://www.theinquirer.net/inquirer/news/3072504/ibm-flicker-photos-facial-recognition-privacy-scandal

Debugging tracking

- https://www.reddit.com/r/OculusQuest/comments/cv8ayx/if_this_comment_is_true_the_potential_breach_of/?utm_source=ifttt



catawompwompus • 13h

2 Awards

I worked at FB HQ for a year. You have no idea.

I was debugging the tracking system of the new VR headsets. Employees from all over the world were "dogfooding" (using the device like customers) to help find bugs. When they report the bug, the headset takes photos of their environment via the 4 cameras on the headset. I used to see people's bedrooms, and their bodies if they were looking down or at a mirror.

I made a comment in a workgroup about it and some workers expressed alarm and the response was "they agreed to the terms that we would occasionally capture images of the environment".

I never saw that agreement. But I did see a couple executives in their bedrooms.

So voice recordings and images are readily available to virtually any employee who opens the ticket, full time or contingent. negligence is not the word.

109