Week 2

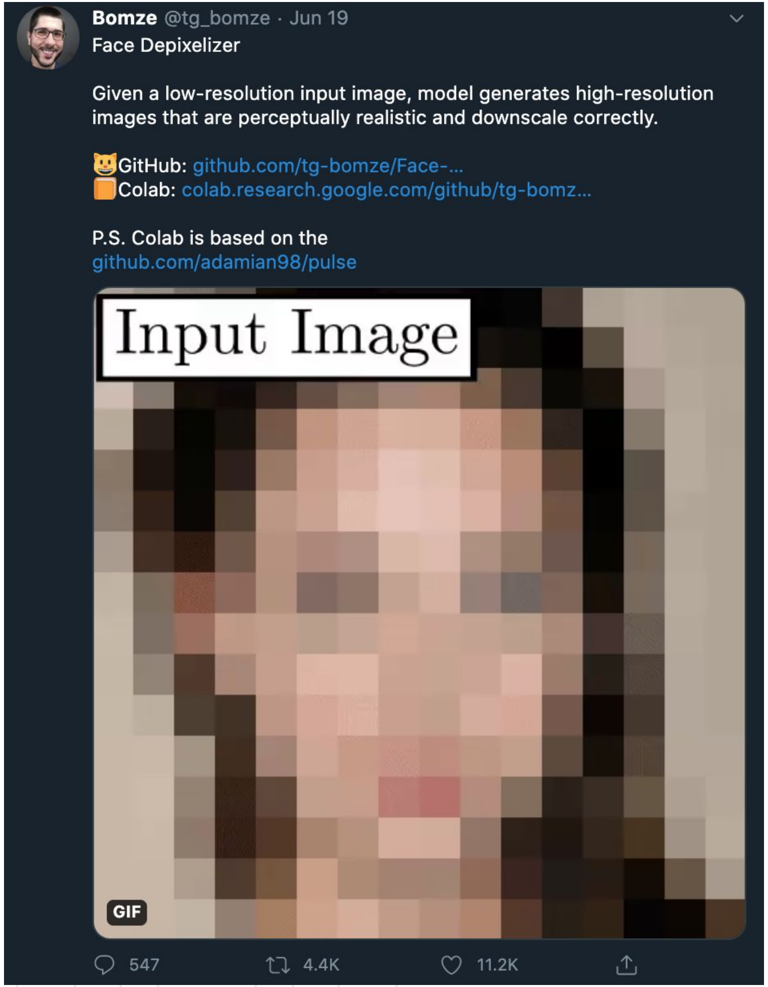
MORPH Algorithmic Fairness

Catherine Yeo

Agenda:
Fairness in Classification

- Feedback
- This week in fairness
- Individual fairness
    - Aware & unaware
- Group fairness
- Looking ahead to week 3

This Week in Fairness



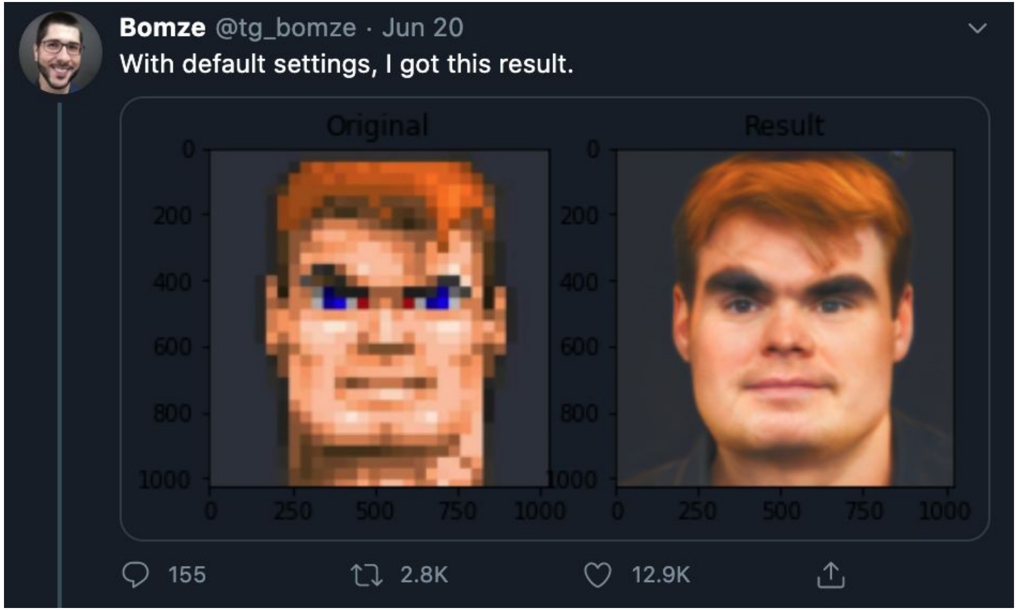
Bomze @tg_bomze · Jun 19

Face Depixelizer

Given a low-resolution input image, model generates high-resolution images that are perceptually realistic and downscale correctly.

😺GitHub: github.com/tg-bomze/Face-...
🟧Colab: colab.research.google.com/github/tg-bomz...

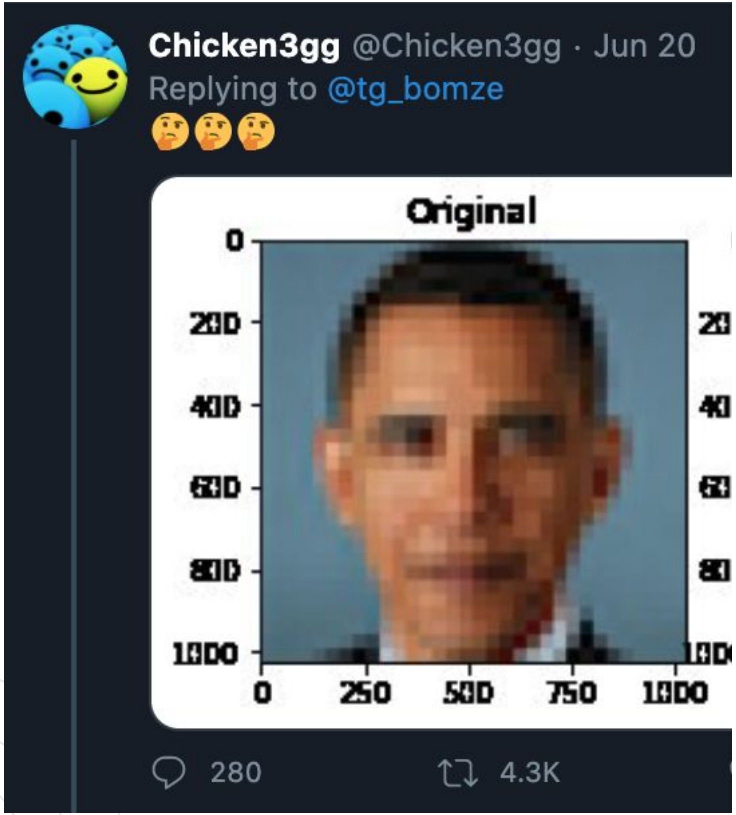
P.S. Colab is based on the github.com/adamian98/pulse



Bomze @tg_bomze · Jun 20

With default settings, I got this result.

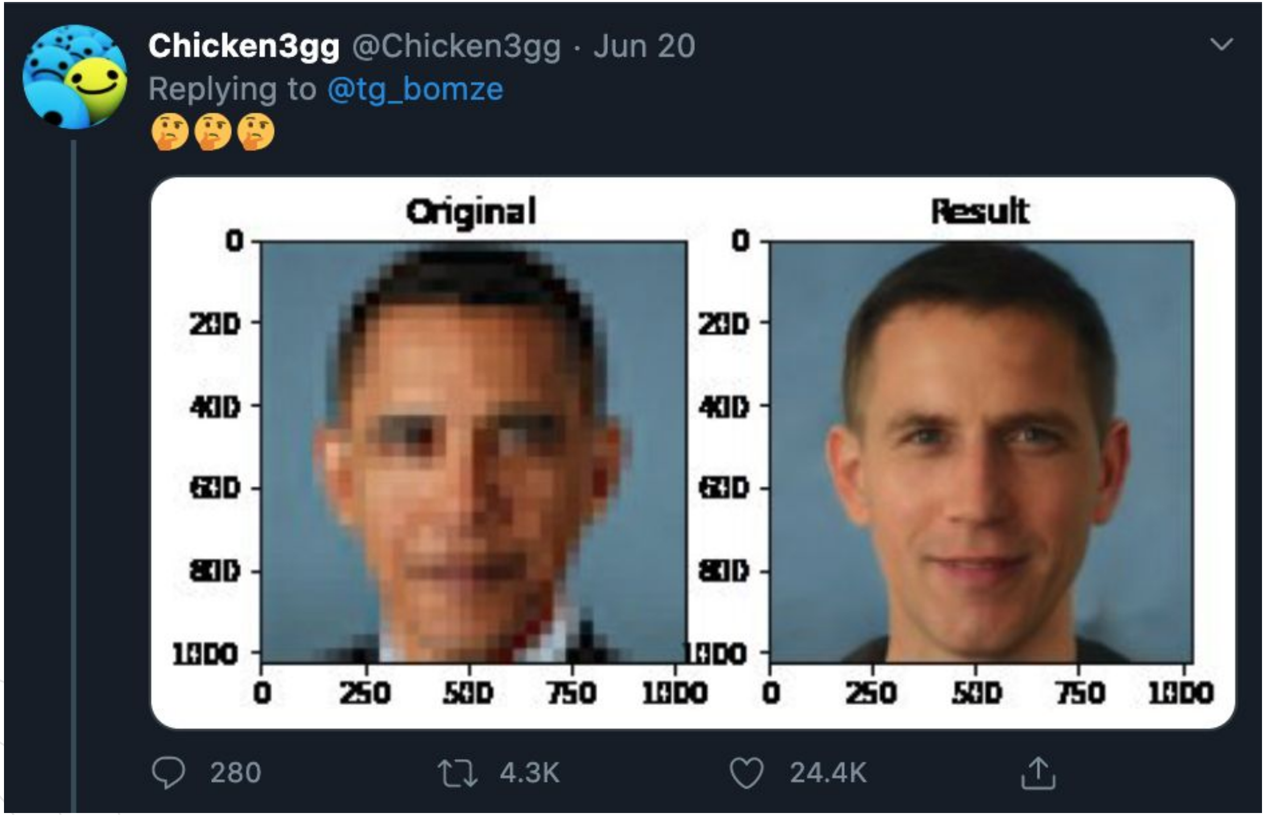
But then people realized...



Chicken3gg @Chicken3gg · Jun 20

Replying to @tg_bomze

🤔🤔🤔



Chicken3gg @Chicken3gg · Jun 20

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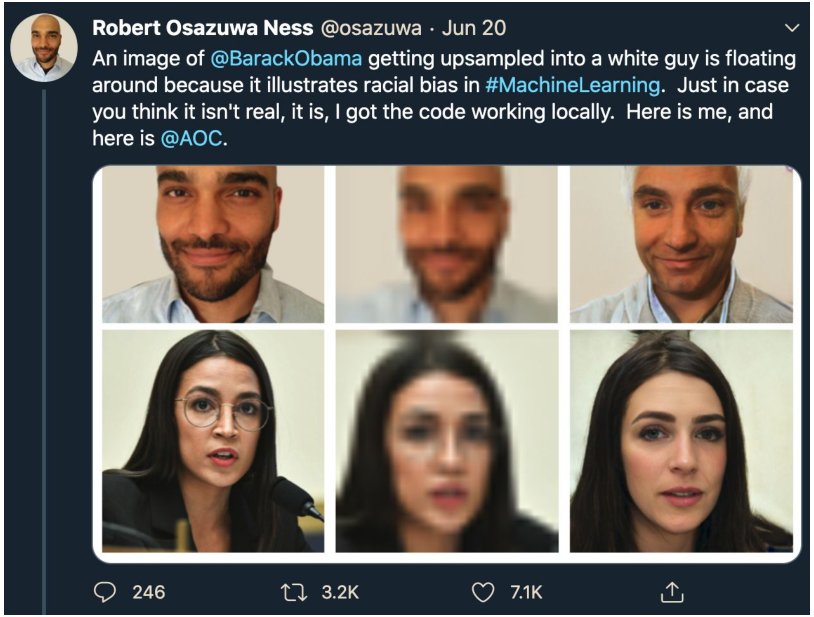
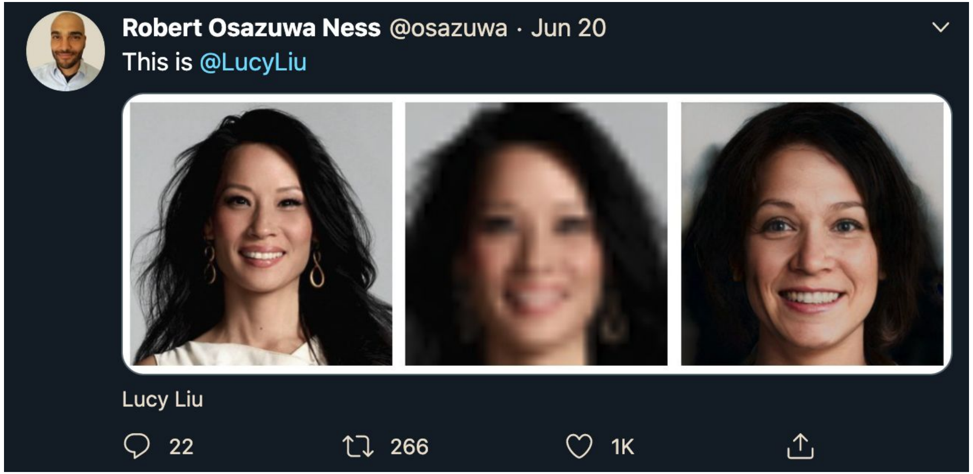
🤔🤔🤔



Robert Osazuwa Ness @osazuwa · Jun 20

An image of @BarackObama getting upsampled into a white guy is floating around because it illustrates racial bias in #MachineLearning. Just in case you think it isn't real, it is, I got the code working locally. Here is me, and here is @AOC.

246 3.2K 7.1K

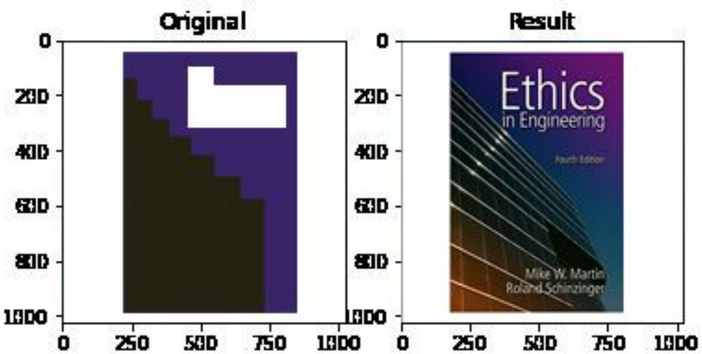


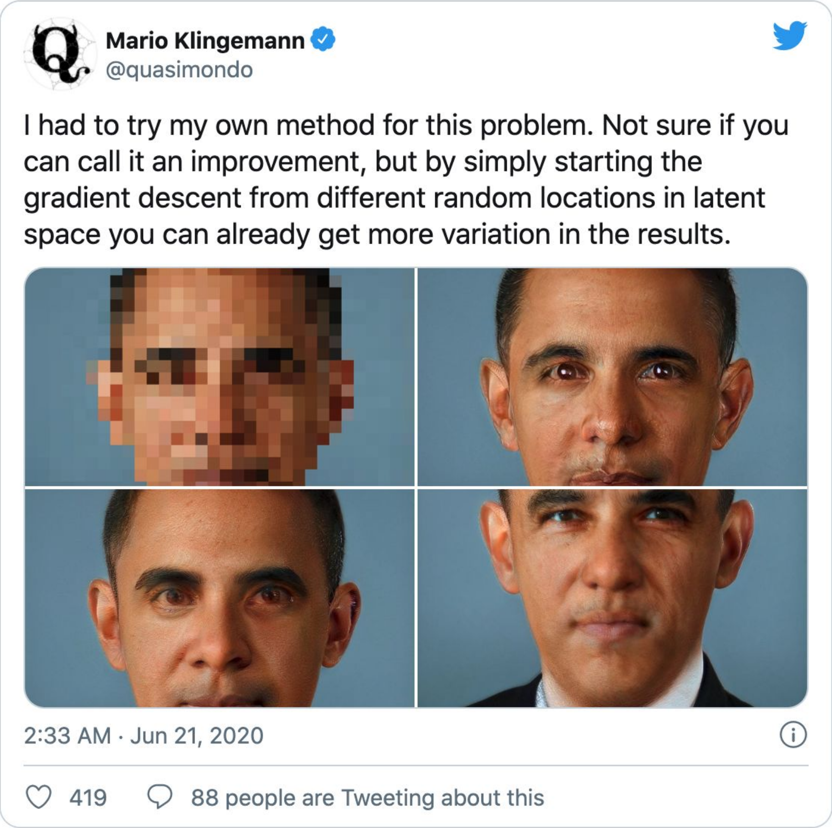
Robert Osazuwa Ness @osazuwa · Jun 20

This is @LucyLiu

Lucy Liu

22 266 1K





Mario Klingemann
@quasimondo

I had to try my own method for this problem. Not sure if you can call it an improvement, but by simply starting the gradient descent from different random locations in latent space you can already get more variation in the results.

2:33 AM · Jun 21, 2020

419 88 people are Tweeting about this

Someone tried a quick improvement(?)... so there are definitely many ways to improve and mitigate such cases.

What are your immediate reactions? thoughts?

If you're interested in reading more:

News:
https://www.theverge.com/21298762/face-depixelizer-ai-machine-learning-tool-pulse-stylegan-obama-bias

Great piece summarizing the takeaways, discourse, and researchers' response:

https://thegradient.pub/pulse-lessons/

Individual Fairness

What is “fairness”?
How do we define it?

Law

- Law is a natural starting point
- Two main notions:
  - **Disparate treatment**
    - Focuses on process
    - Unfair if decision was made w.r.t. to sensitive attribute
  - **Disparate impact**
    - Focuses on outcome
    - Unfair if outcome harms/benefits specific people

And many other definitions in...

- Philosophy — equality, distributive justice
- Economics — how do you divide and assign resources to people fairly
- etc.

→ What about in algorithms?

Fairness through Unawareness

- To not include sensitive attributes in consideration / data / algorithm at all
- Similar to idea of disparate treatment
- Problem: proxy features

- So let’s try fairness through awareness!

Key Idea:

Similar individuals should be treated similarly.

Treating Similar Individuals Similarly

- Binary classification algorithm
  - Positive or negative / 1 or 0 / accept or reject
- Any 2 individuals who are similar <u>with respect to a particular task</u> should be classified similarly

Dwork et al. (2006)

Similarity

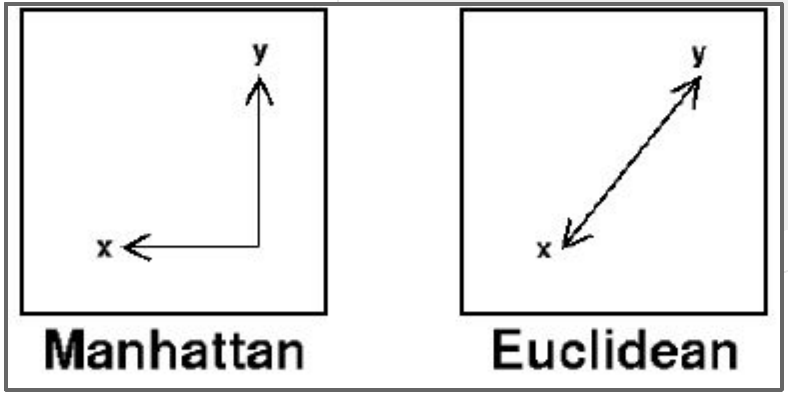
- How do we define **similarity**?
- We assume a **distance metric**
  - Similarity metric between individuals $d(x, y)$
    - # of features
    - Graphical distance (like word embeddings paper)
    - Many more ideas
  - Similarity measure between distributions of outcomes $D(x, y)$

Any 2 individuals who are similar with respect to a task should be classified similarly

Dwork et al. (2006)

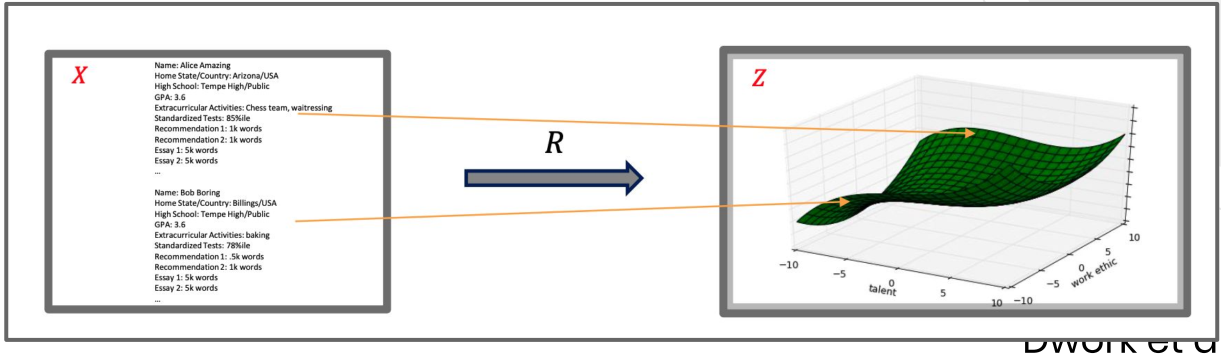
Distance Metric

- In math, a **distance function/metric** is a function that defines the distance between each pair of elements in a set
- Properties to uphold:
  - $d(x, y) = 0$ iff $x = y$
  - $d(x, y) = d(y, x)$
  - $d(x, y) \leq d(x, z) + d(z, y)$
- Many ways to choose or define a metric



Parameters

- Universe
- Outcome space
- A **representation mapping** between them:
  - Map from individuals to distributions over outcomes



Name: Alice Amazing
Home State/Country: Arizona/USA
High School: Tempe High/Public
GPA: 3.6
Extracurricular Activities: Chess team, waitressing
Standardized Tests: 85%ile
Recommendation 1: 1k words
Recommendation 2: 1k words
Essay 1: 5k words
Essay 2: 5k words
...

Name: Bob Boring
Home State/Country: Billings/USA
High School: Tempe High/Public
GPA: 3.6
Extracurricular Activities: baking
Standardized Tests: 78%ile
Recommendation 1: .5k words
Recommendation 2: 1k words
Essay 1: 5k words
Essay 2: 5k words
...

Dwork et al. (2006)

Lipschitz Condition

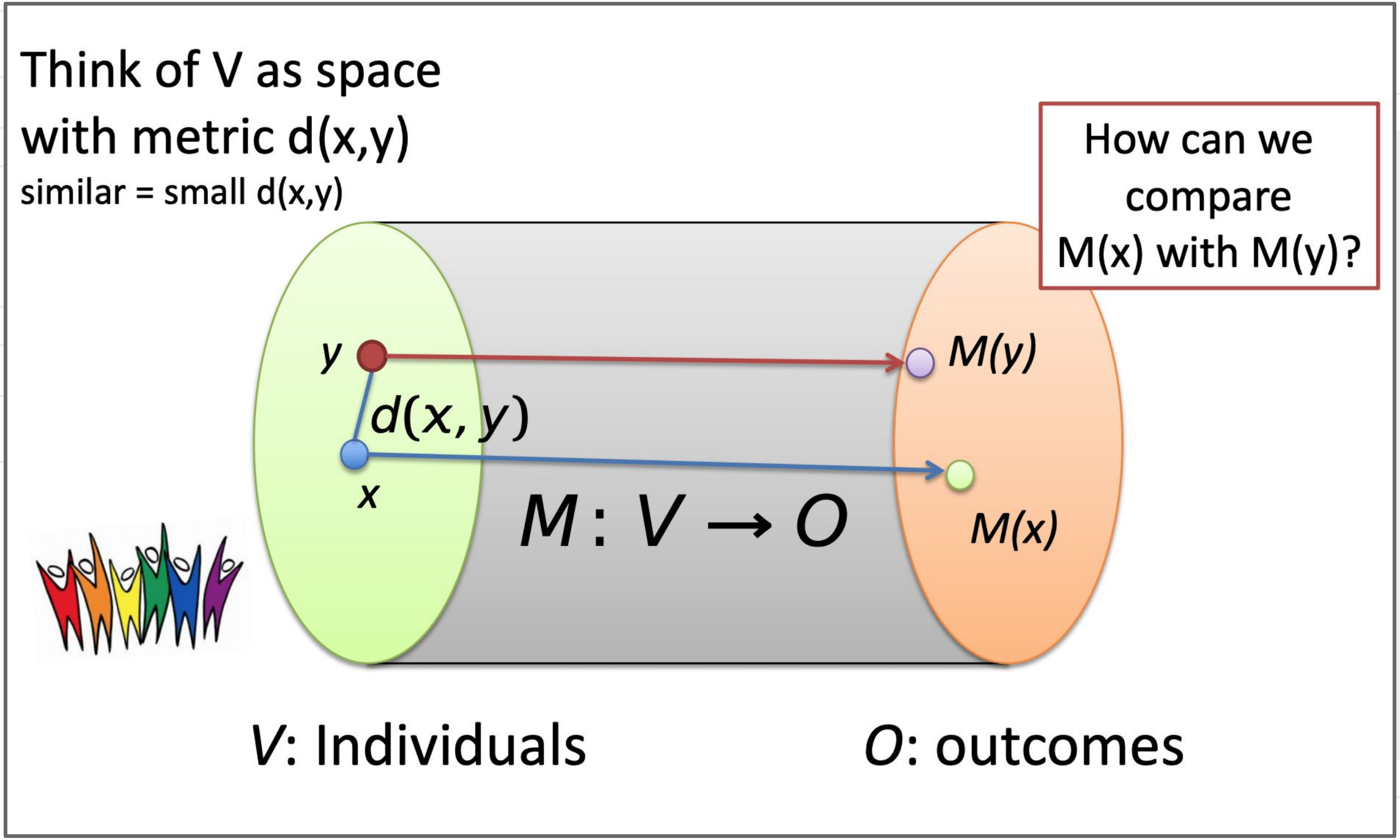
“Any two individuals x, y that are at distance *d(x, y)* ∈ [0, 1] map to distributions *M(x)* and *M(y)*, respectively, such that the statistical distance between *M(x)* and *M(y)* is at most *d(x, y)*.”

Big picture idea:

difference in outputs ≤ difference in inputs

$$\mathbf{D(M(x), M(y)) \leq d(x, y)}$$

Dwork et al. (2006)



Think of V as space
with metric d(x,y)
similar = small d(x,y)

How can we compare M(x) with M(y)?

V: Individuals

O: outcomes

Slide taken from here

Loss Function

- Some classifiers are more fair than others
- To capture this, we have the idea of **loss**
    - Minimizing loss = better and fairer!

- Thus, our goal becomes:
  Find a mapping from individuals to distributions over outcomes that minimizes expected loss subject to the Lipschitz condition.

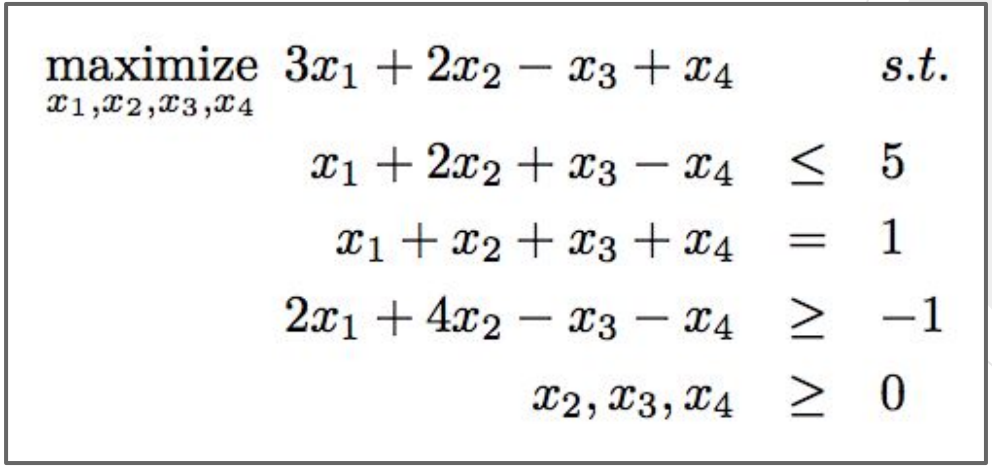
Dwork et al. (2006)

Linear Program

A way to achieve best outcome (ex: max profit, min cost) with requirements or constraints represented by linear relationships

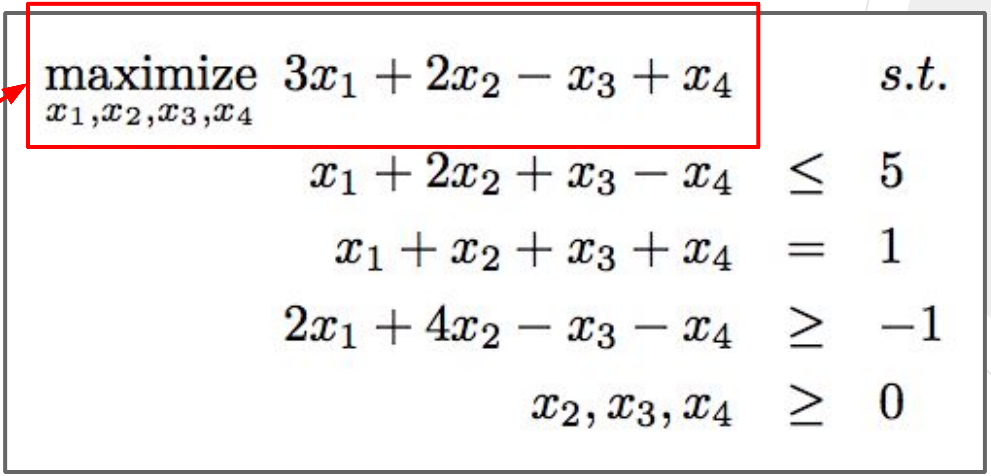
→ **Optimization**

Linear Program



$$\begin{array}{rcl}
\underset{x_1,x_2,x_3,x_4}{\text{maximize}} \;\; 3x_1 + 2x_2 - x_3 + x_4 & & s.t. \\
x_1 + 2x_2 + x_3 - x_4 & \leq & 5 \\
x_1 + x_2 + x_3 + x_4 & = & 1 \\
2x_1 + 4x_2 - x_3 - x_4 & \geq & -1 \\
x_2, x_3, x_4 & \geq & 0
\end{array}$$

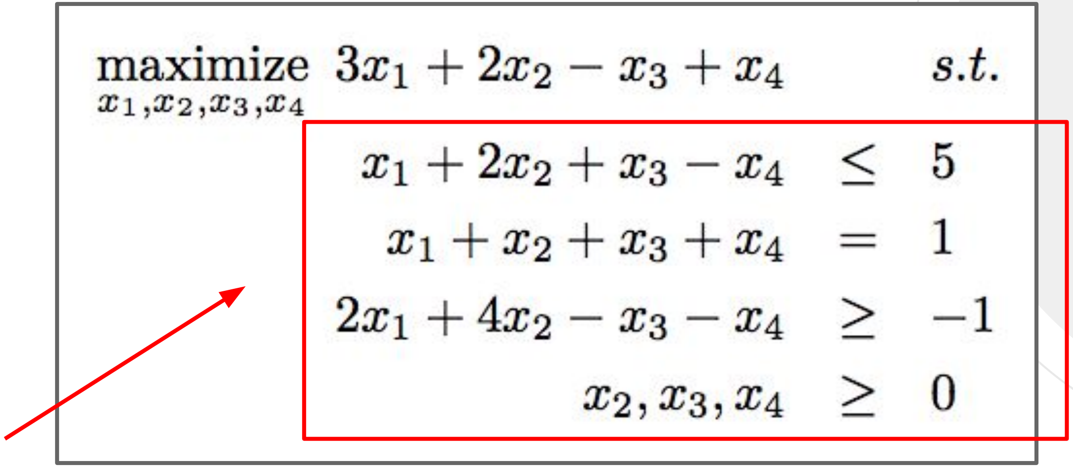
Linear Program



$$\begin{array}{rcl} \boxed{\underset{x_1,x_2,x_3,x_4}{\text{maximize}}\ \ 3x_1+2x_2-x_3+x_4} & & s.t. \\ x_1+2x_2+x_3-x_4 & \leq & 5 \\ x_1+x_2+x_3+x_4 & = & 1 \\ 2x_1+4x_2-x_3-x_4 & \geq & -1 \\ x_2,x_3,x_4 & \geq & 0 \end{array}$$

Optimization Objective

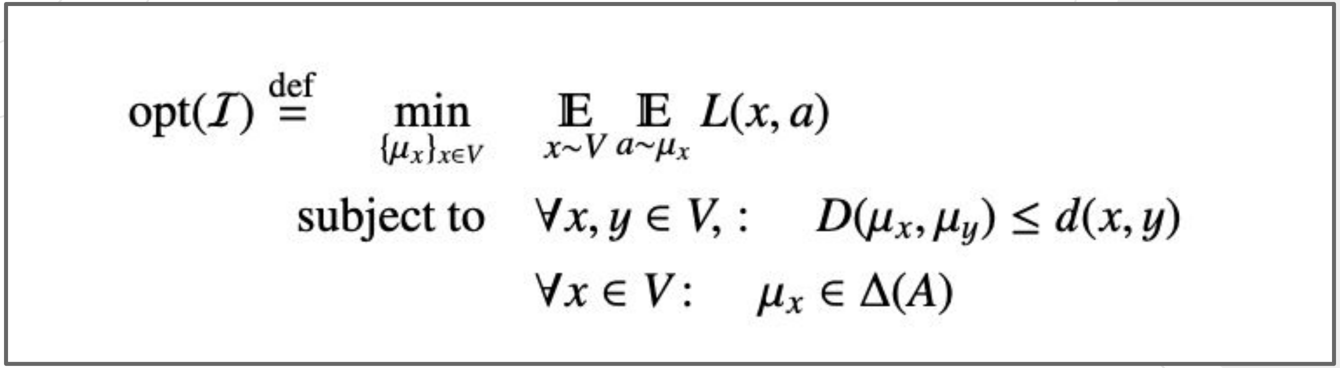
Linear Program



$$\begin{aligned} \underset{x_1,x_2,x_3,x_4}{\text{maximize}} \quad 3x_1 + 2x_2 - x_3 + x_4 & \qquad & s.t. \\ x_1 + 2x_2 + x_3 - x_4 & \leq & 5 \\ x_1 + x_2 + x_3 + x_4 & = & 1 \\ 2x_1 + 4x_2 - x_3 - x_4 & \geq & -1 \\ x_2, x_3, x_4 & \geq & 0 \end{aligned}$$

Constraints we must follow

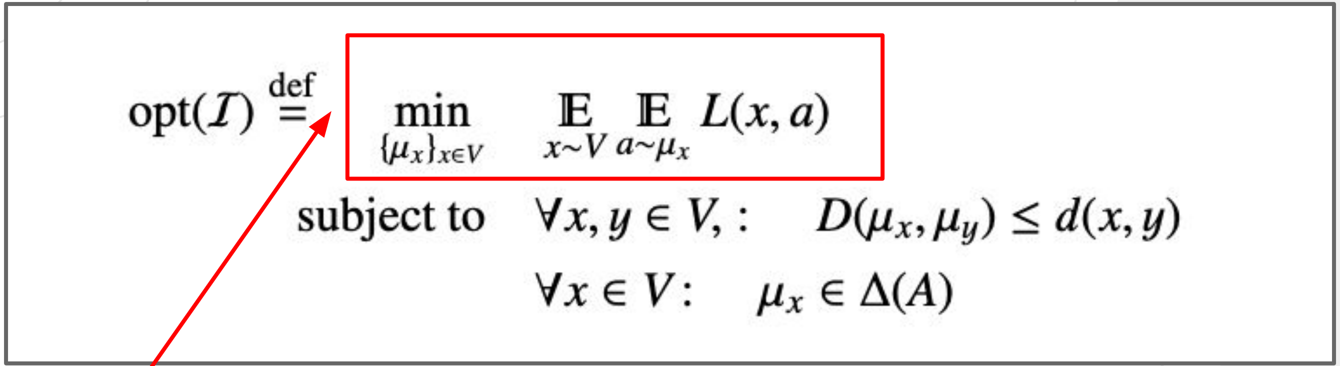
Fairness LP



$$
\begin{aligned}
\mathrm{opt}(\mathcal{I}) \overset{\mathrm{def}}{=} \quad & \min_{\{\mu_x\}_{x\in V}} \quad \mathop{\mathbb{E}}_{x\sim V}\ \mathop{\mathbb{E}}_{a\sim\mu_x} L(x,a) \\
\text{subject to} \quad & \forall x, y \in V, : \quad D(\mu_x, \mu_y) \le d(x,y) \\
& \forall x \in V : \quad \mu_x \in \Delta(A)
\end{aligned}
$$

Dwork et al. (2006)

Fairness LP

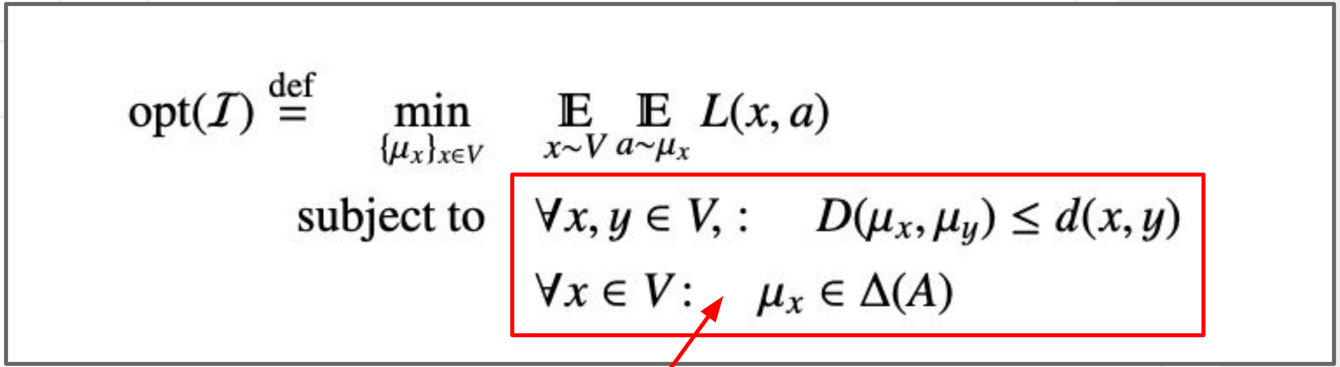


$$
\begin{aligned}
\mathrm{opt}(\mathcal{I}) \overset{\mathrm{def}}{=} & \boxed{\min_{\{\mu_x\}_{x\in V}} \quad \mathop{\mathbb{E}}_{x\sim V} \mathop{\mathbb{E}}_{a\sim\mu_x} L(x,a)} \\
\text{subject to} \quad & \forall x, y \in V, : \quad D(\mu_x, \mu_y) \leq d(x,y) \\
& \forall x \in V : \quad \mu_x \in \Delta(A)
\end{aligned}
$$

Optimization objective:
minimize expected loss over
all individuals & outcomes

Dwork et al. (2006)

Fairness LP



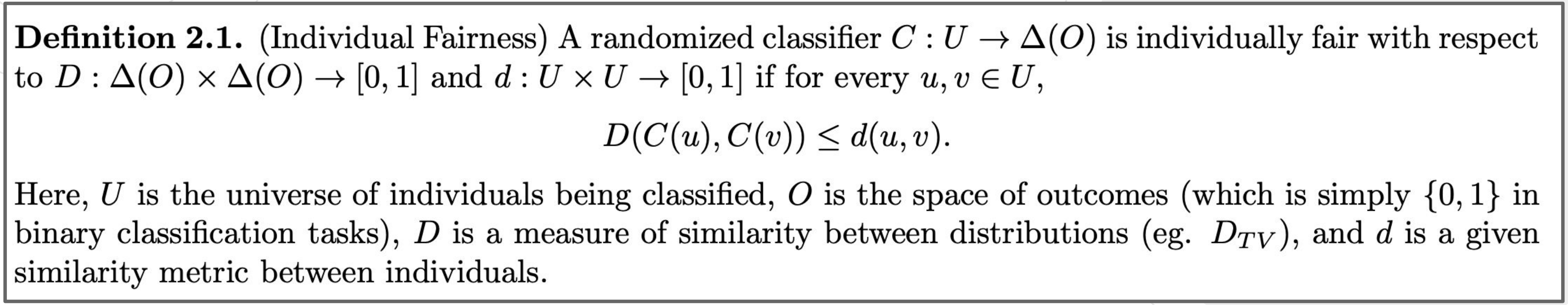
$$\begin{aligned} \operatorname{opt}(\mathcal{I}) \overset{\text{def}}{=} \quad & \min_{\{\mu_x\}_{x\in V}} \quad \mathop{\mathbb{E}}_{x\sim V}\, \mathop{\mathbb{E}}_{a\sim\mu_x} L(x,a) \\ \text{subject to} \quad & \boxed{\begin{aligned} &\forall x, y \in V, : \quad D(\mu_x, \mu_y) \leq d(x,y) \\ &\forall x \in V: \quad \mu_x \in \Delta(A) \end{aligned}} \end{aligned}$$

Constraints:

1) Lipschitz condition
2) Mapping outcomes are valid

Dwork et al. (2006)

To Sum Up:
Individual Fairness



Definition 2.1. (Individual Fairness) A randomized classifier $C : U \to \Delta(O)$ is individually fair with respect to $D : \Delta(O) \times \Delta(O) \to [0, 1]$ and $d : U \times U \to [0, 1]$ if for every $u, v \in U$,

$$D(C(u), C(v)) \leq d(u, v).$$

Here, U is the universe of individuals being classified, O is the space of outcomes (which is simply $\{0, 1\}$ in binary classification tasks), D is a measure of similarity between distributions (eg. D_{TV}), and d is a given similarity metric between individuals.

Dwork et al. (2006)

Group Fairness

Statistical Parity

- % of people classified positive/negative matches the % demographic of general population
- Hire the same % of people in both groups

Pr[outcome | person in S] = Pr[outcome | person in T]

Statistical Parity

- Sometimes desirable, but can be abused! (How so?)
- Outcome might be “fair” but individuals can still be discriminated
  - In S, most skilled students study CS
  - In T, most skilled students study finance
  - Company hiring students interested in economics would hire wrong subset of S
- Self-fulfilling prophecy
  - When unqualified members of S are hired to justify future discrimination against S

Dwork et al. (2006)

Equalized Odds (Equality of Opportunity)

- Hiring analogy:
  - C = the decision made (hire or reject)
  - Y = the true standard of whether a person was qualified enough or not to be hired.
  - Ex: One can be rejected (C=0) but be capable enough for the job (Y=1).
- Hire equal % of individuals from the qualified subset of each group

$$\boxed{Pr_1[C = c \mid Y = y] = Pr_2[C = c \mid Y = y]}$$

Predictive Rate Parity

- Equal chance of success given hired/accepted
- Hiring analogy:
  - C = the decision made (hire or reject)
  - Y = the true standard of whether a person was qualified enough or not to be hired.
  - Ex: One can be rejected (C=0) but be capable enough for the job (Y=1).

$$\boxed{\Pr_1[Y = y \mid C = c] = \Pr_2[Y = y \mid C = c]}$$

Which group fairness notion do you agree with the most?