Is Algorithmic Fairness Possible?

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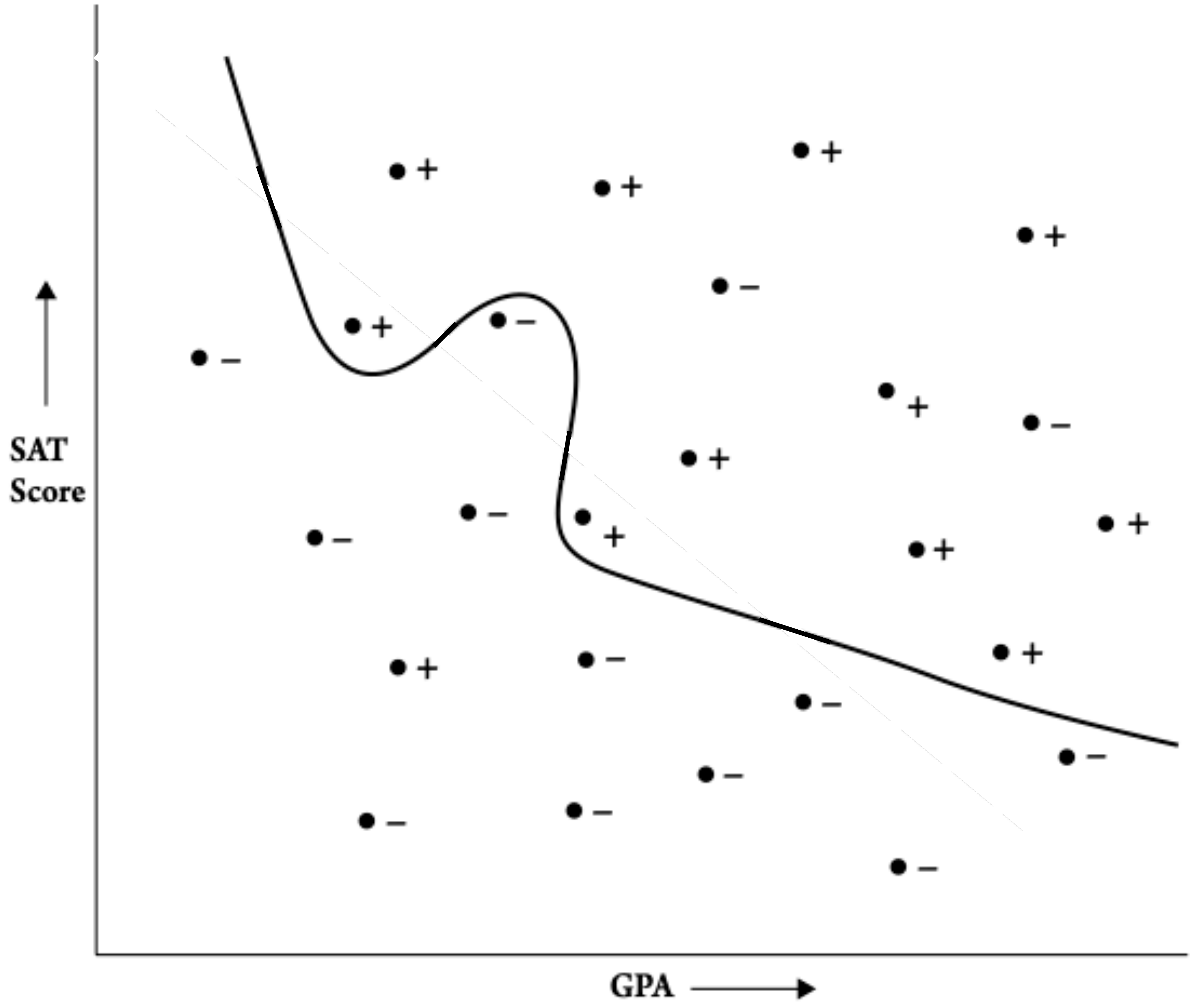
0. Background

Predictive Models (*binary case*)



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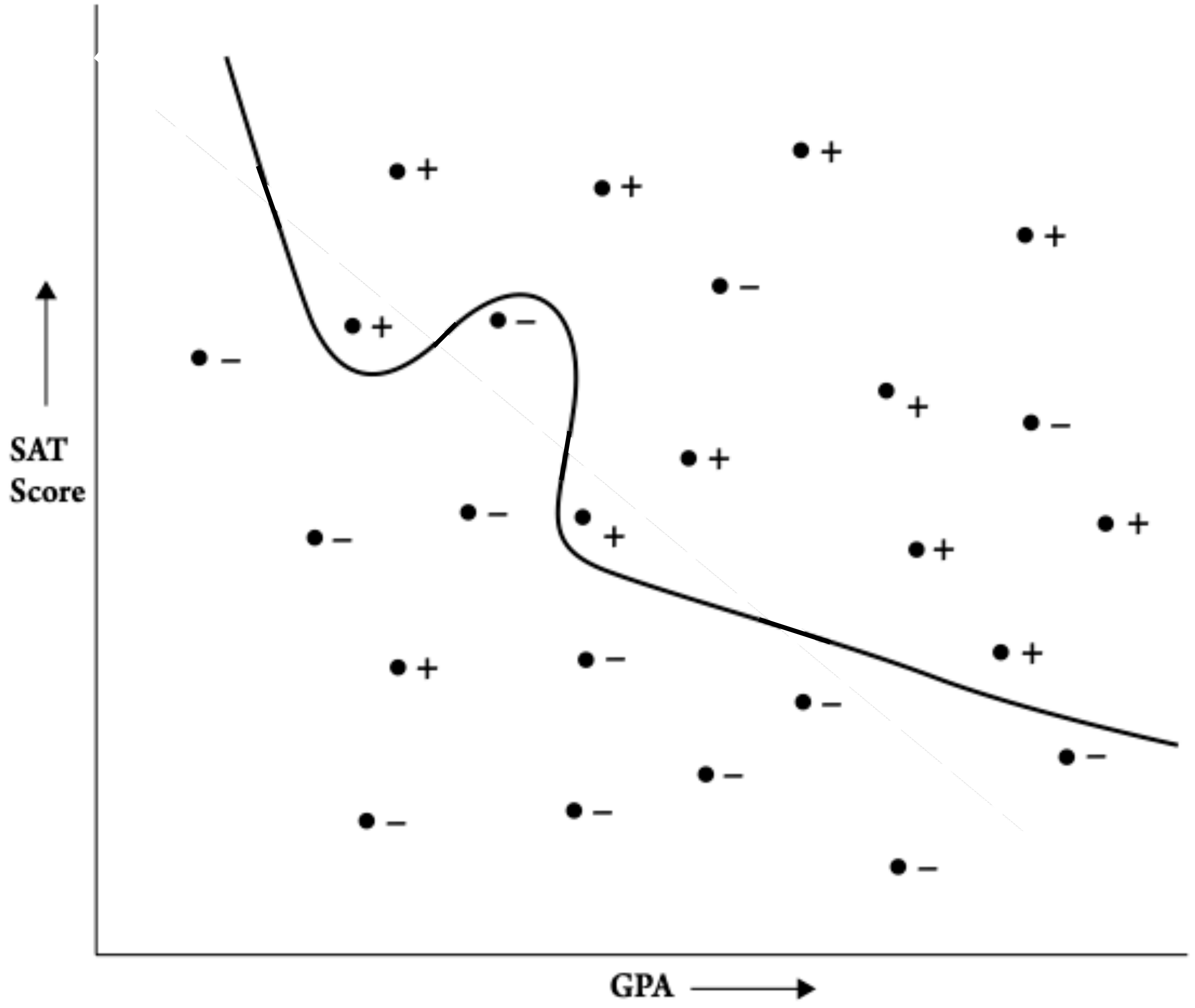

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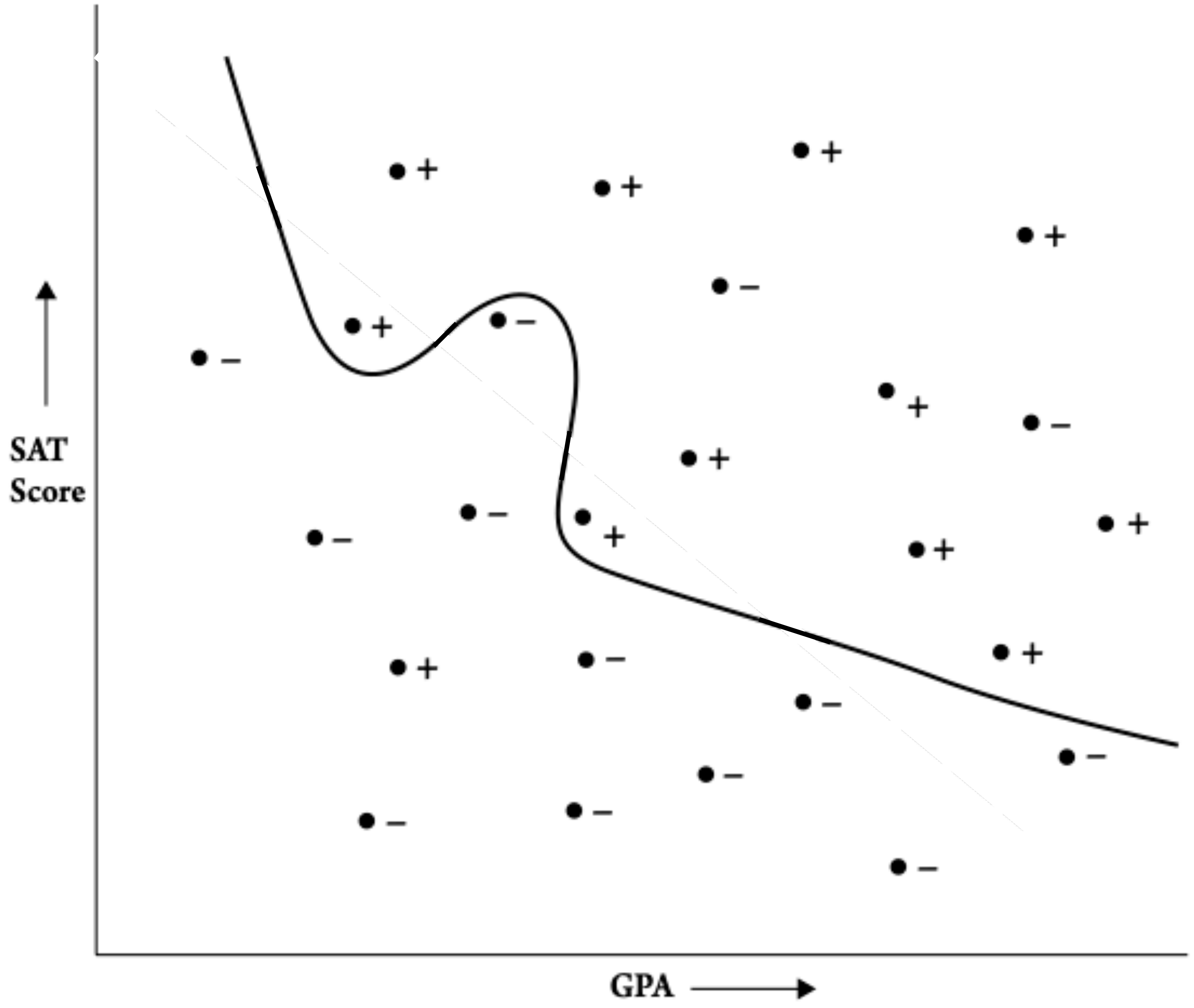

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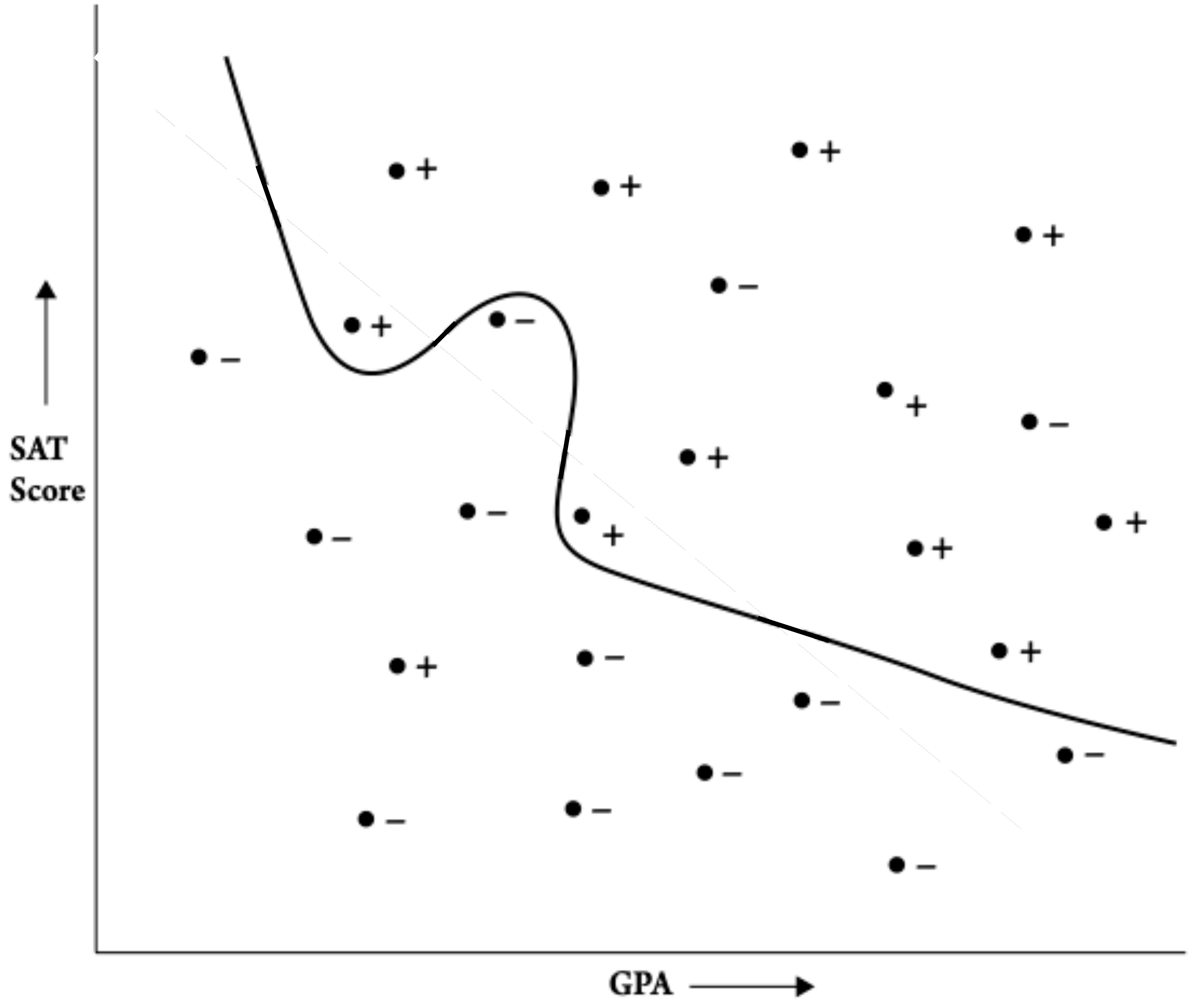

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Based on the features one possesses, the **predictive model classifies** individuals as **C=1** or **C=0**

Predictive Models Can Make Mistakes

Dichotomous Accuracy/Error Metrics

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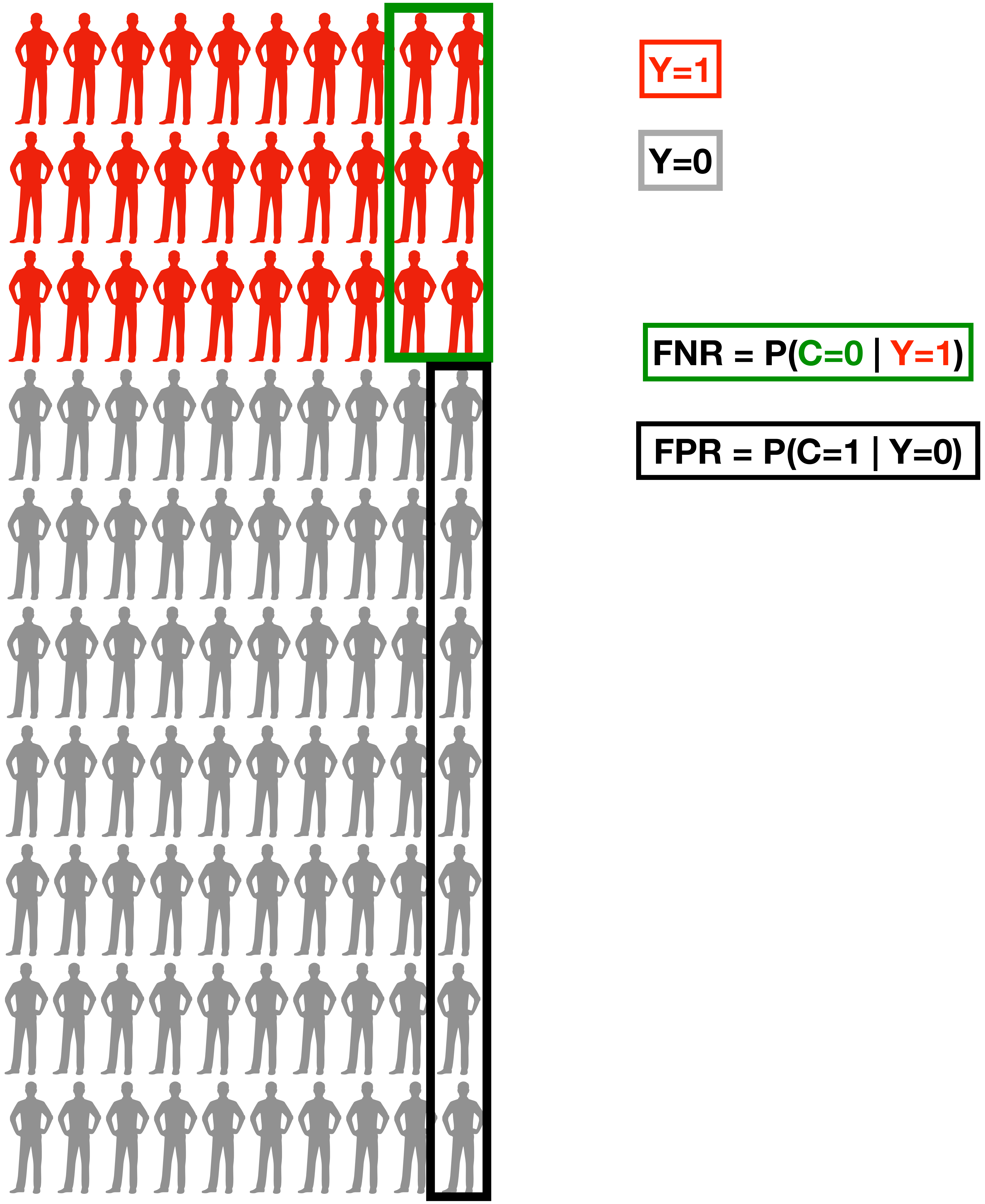
False negative rate (**FNR**)
P(C=0 | Y=1)

False positive rate (**FPR**)
P(C=1 | Y=0)

Y is the *actual* outcome
C is the *classified* outcome



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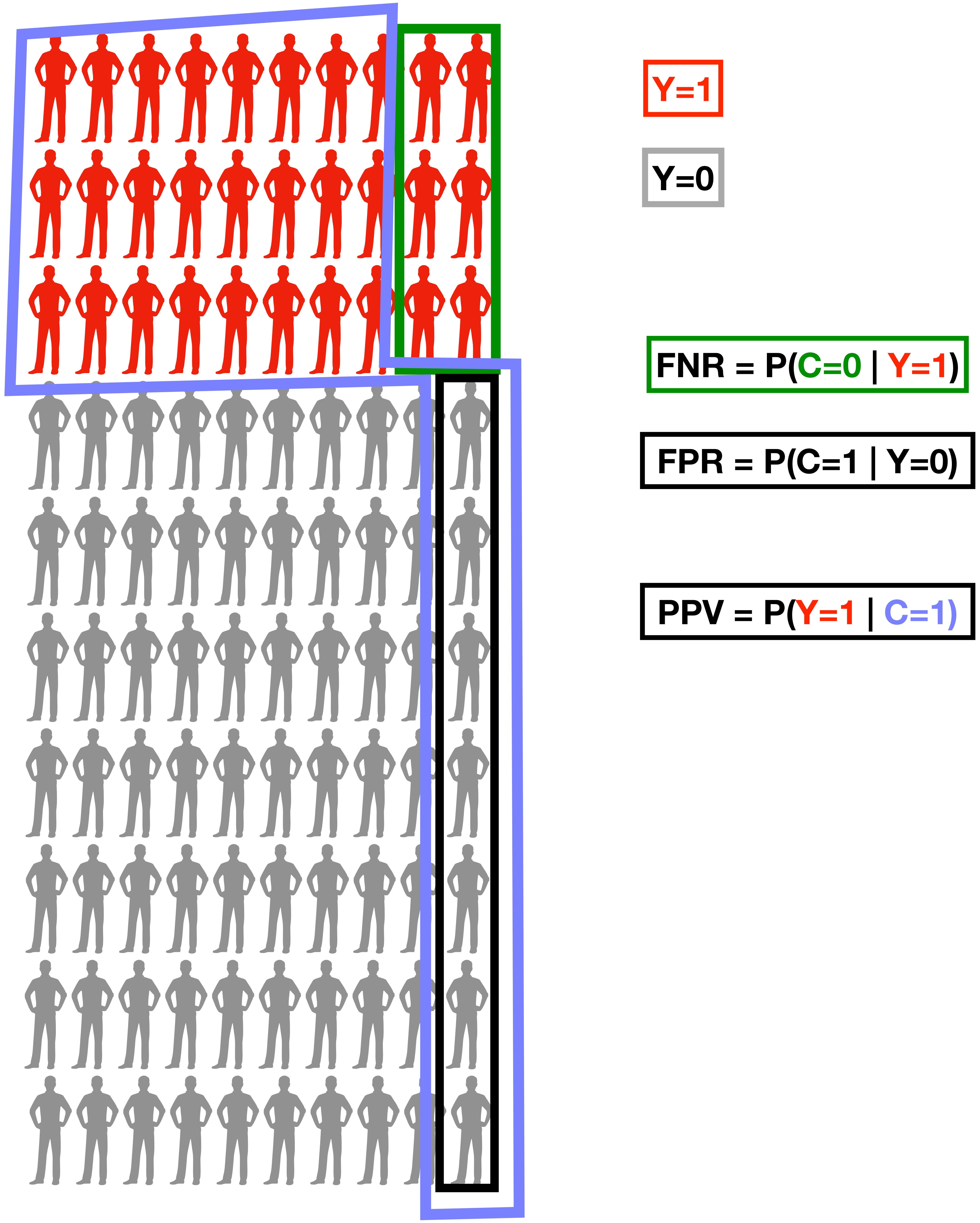
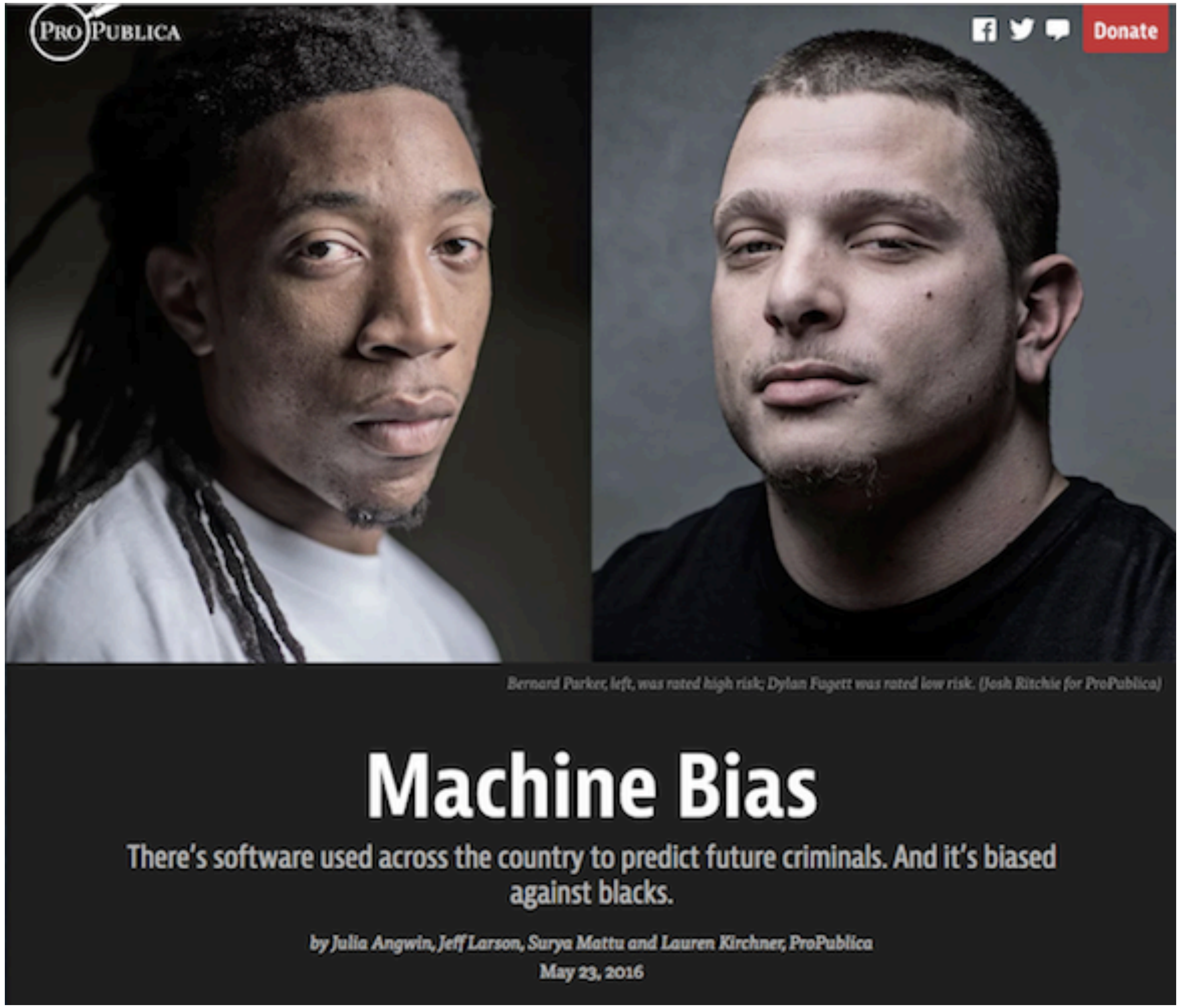


Predictive Models Can Be Unfair

COMPAS Algorithm



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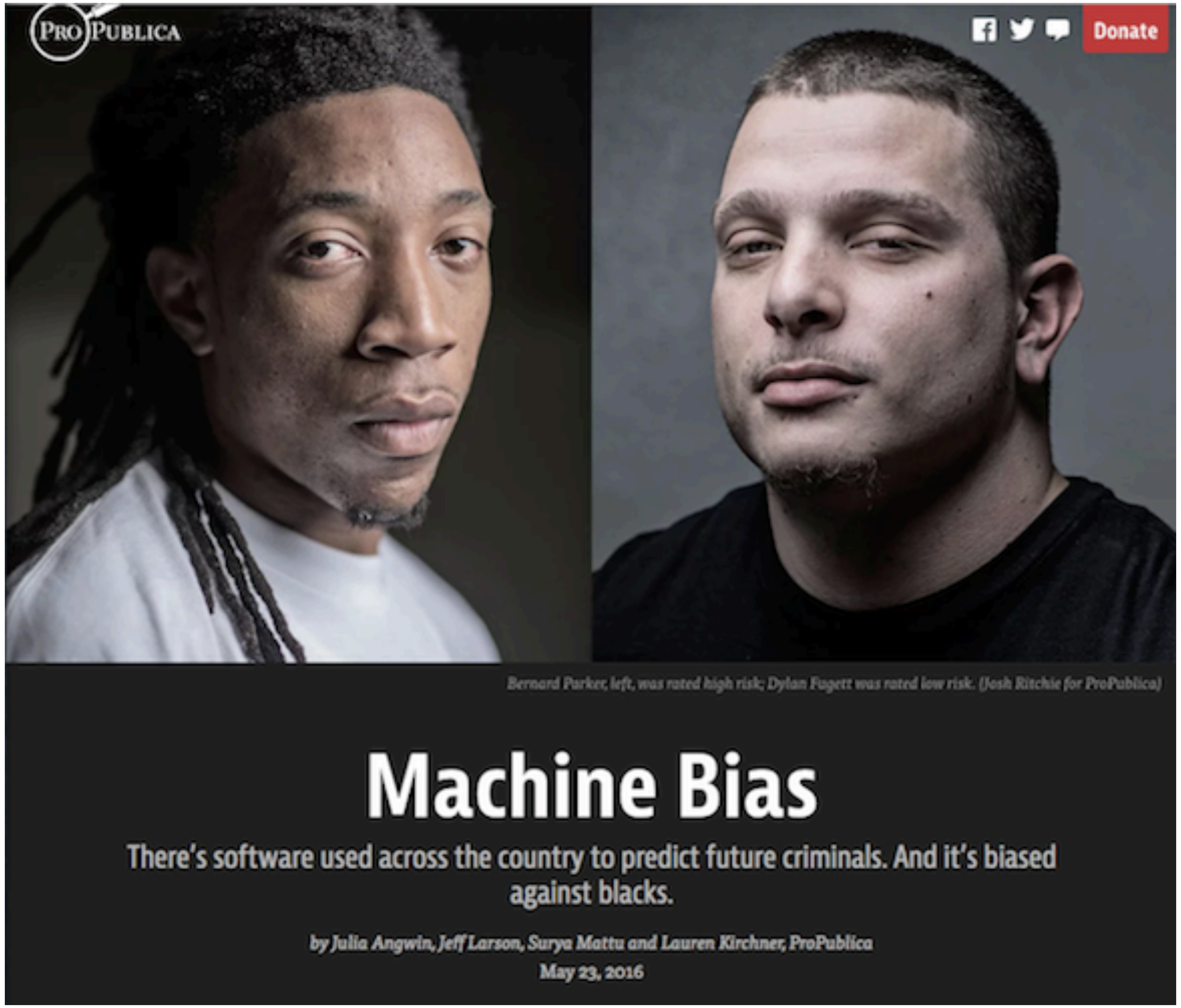

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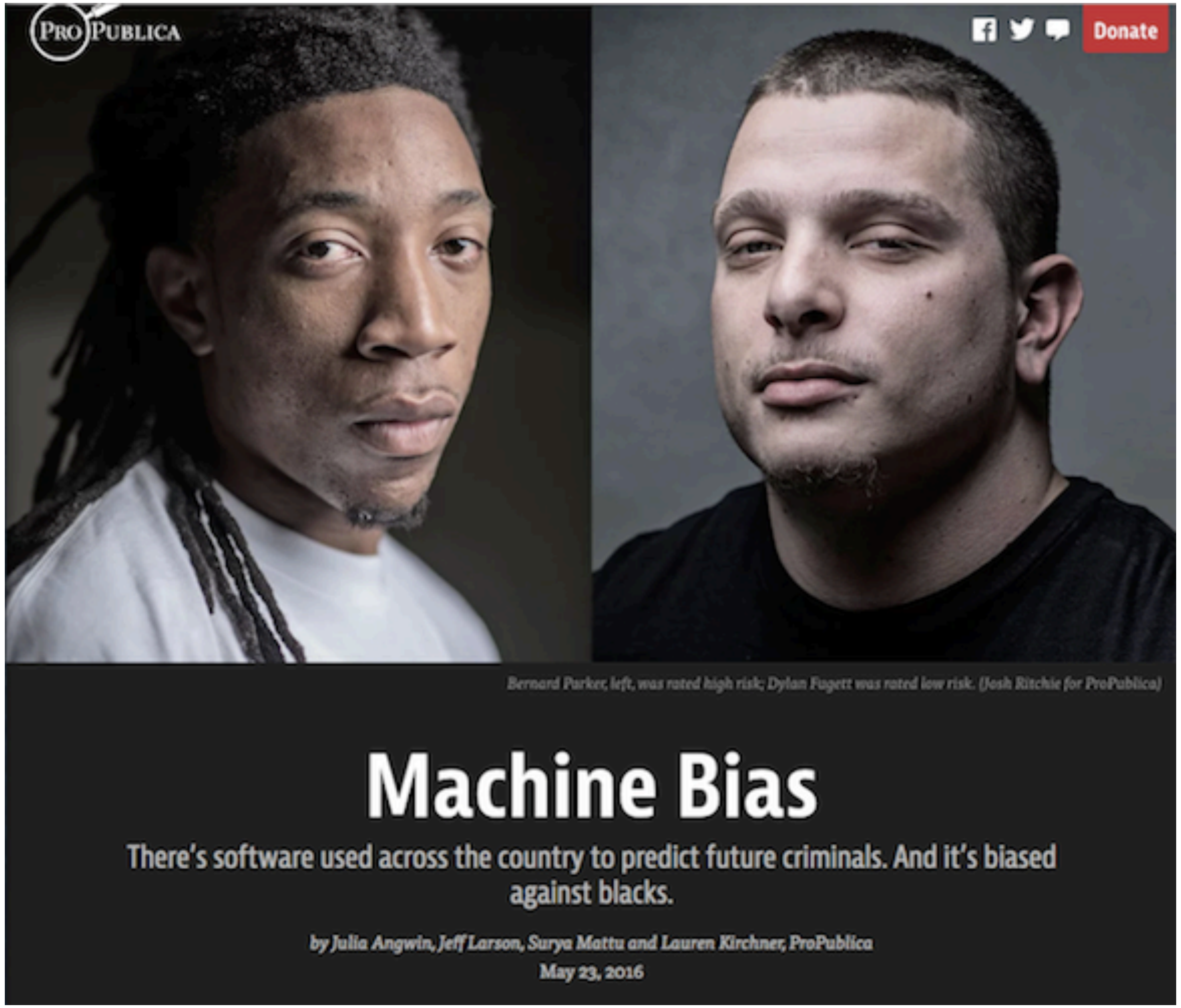

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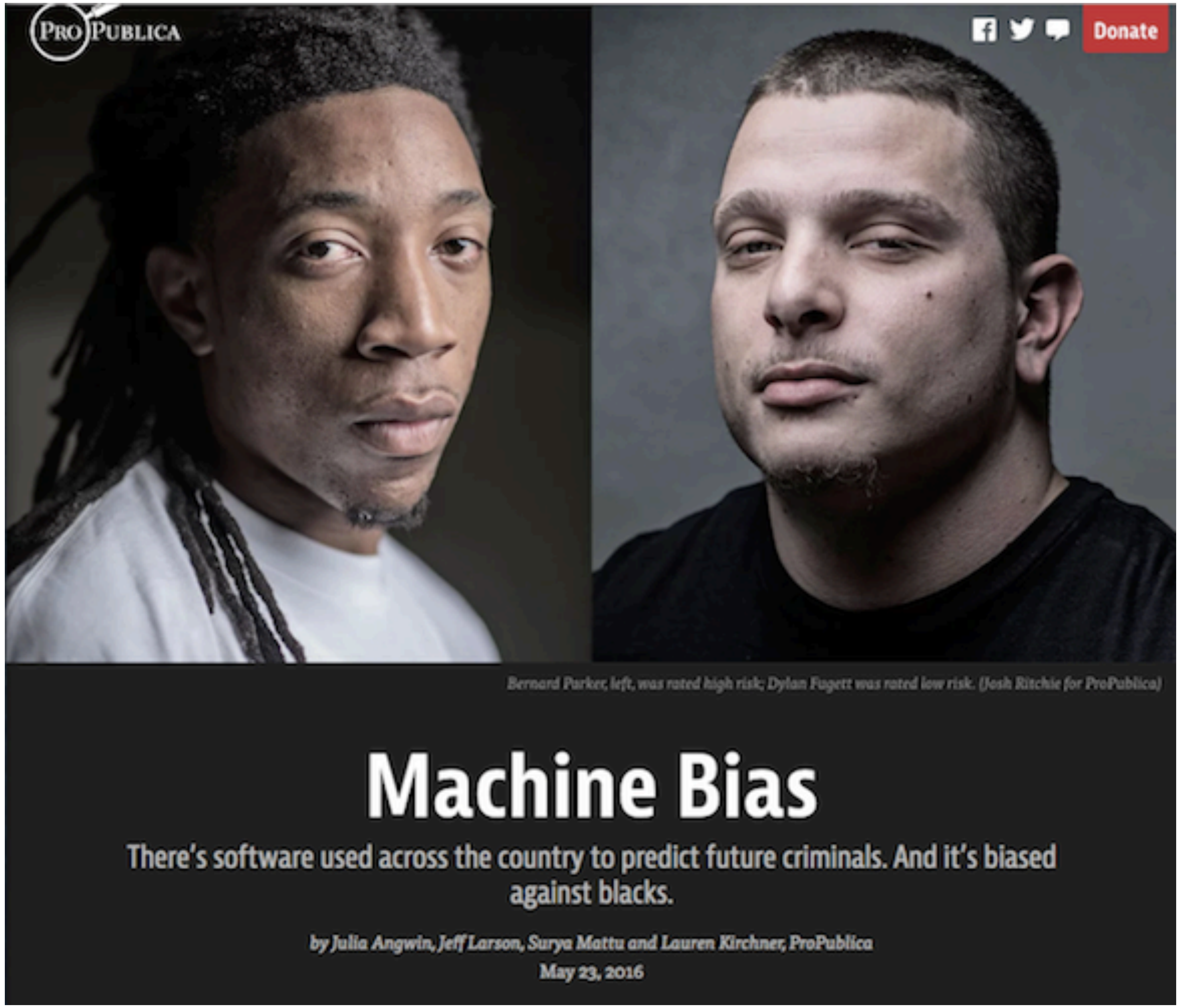

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Even if ‘race’ was not among the predictive features used:

- False positive rate (**FPR**) was **higher for blacks** than whites

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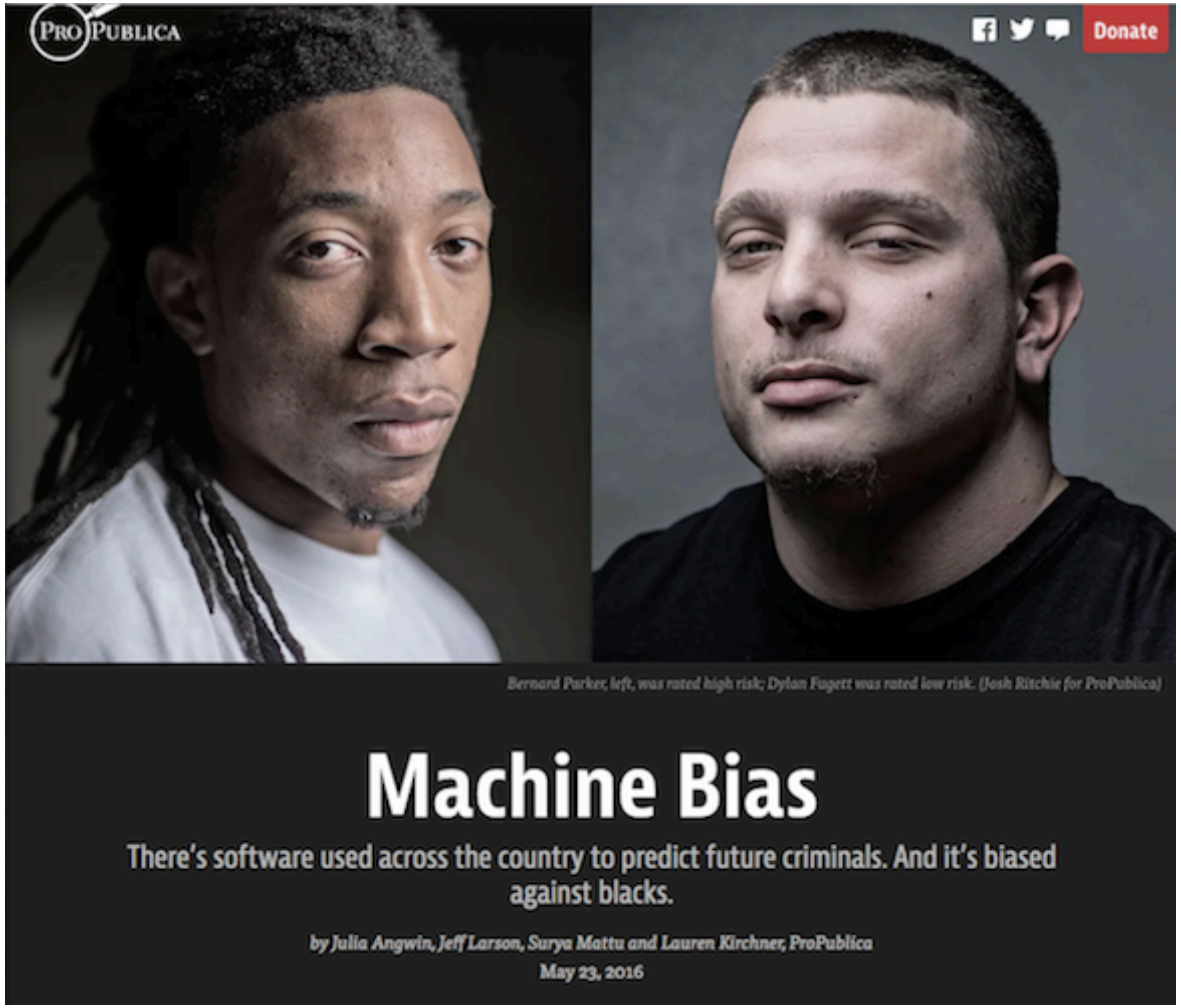
- The positive predictive value (**PPV**) was the **same** for the two racial groups



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Predictive parity

Classification parity

1. Impossibility Theorems

Chouldechova's Impossibility Theorem

No predictive model or algorithm can concurrently satisfy

- same **FP** and **FN** rate (`classification parity`)
- same **PPV** (`predictive parity`)

Provided

1. the groups have different prevalence rates
2. the model or algorithm is not infallible

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$$\frac{P(Y=1 \mid C=1)}{P(Y=0 \mid C=1)} = \frac{P(C=1 \mid Y=1)}{P(C=1 \mid Y=0)} \times \frac{P(Y=1)}{P(Y=0)}$$

$$\frac{PPV}{1-PPV} = \frac{1-FN}{FP} \times \text{prevalence ratio}$$

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How Broadly Do Impossibility Theorems Apply?

Theorems such as Chouldechova's are usually formulated in the literature on predictive algorithms (Kleinberg, Mullainathan, Raghavan 2016) and in the literature about the fairness of test scores (Borsboom, Romeijn, Wicherts, 2008)

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Shall we assume these impossibility theorems *only* apply to:

1. predictive evidence
2. quantitative evidence

They Apply Broadly

Impossibility theorems about algorithmic fairness **generalize to any dichotomous evidence-based decisions** (in fact, any dichotomous decision), whether or not the decision is aided by a predictive model.

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Thus, any dichotomous decision would seem unfair one way or another.

2. Are All Decisions Unfair?

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It is tricky to draw the distinction. In the medical context, the distinction is formulated in terms of **screening** v. **diagnostic tests**

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Using Bayes' theorem, the doctor combines

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Suppose the doctor makes decisions based *solely* on diagnostic tests (that is, **T=1 iff C=1** and **T=0 iff C=0**).

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Using Bayes' theorem, jurors combine

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However, if crime prevalence is different across groups, profiling evidence will tend to incriminate more members of higher prevalence groups than lower prevalence groups.

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Given the same body of evidence, people in group H are more likely to have Y=1 than people in group L since prevalence of Y=1 is higher in H than in L

3. A Way Out

Question: If the impossibility theorems generalize to any evidence-based decision, *might* the underlying conception of fairness — i.e. classification parity *plus* predictive parity — be too demanding?

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- No identifiable group can make a complaint. The group of those convicted or left untreated does not exist *ex ante* of the decision. Anyone could be in it. This group can voice no complaint as it does not exist in a socially stable way.
- Instead, the innocent or sick form well-defined groups that exist *ex ante* of the decision being made.

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`Calibration`

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`Predictive parity`

Classification Parity and *Predictive Parity*

$$G \leftarrow Y \rightarrow C$$
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Classification parity:
G and C are independent given Y

$$G \leftarrow C \rightarrow Y$$
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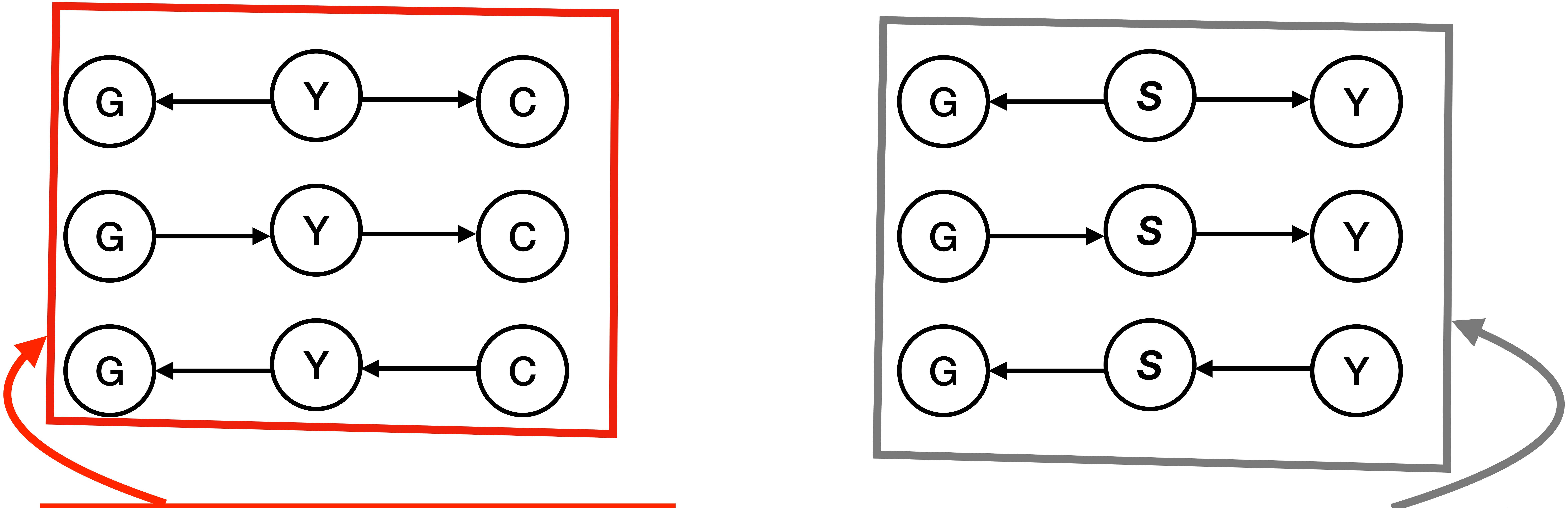
Predictive parity:
G and Y are independent given C

No causal diagram can guarantee both no matter the kind of evidence used

Classification Parity and Calibration



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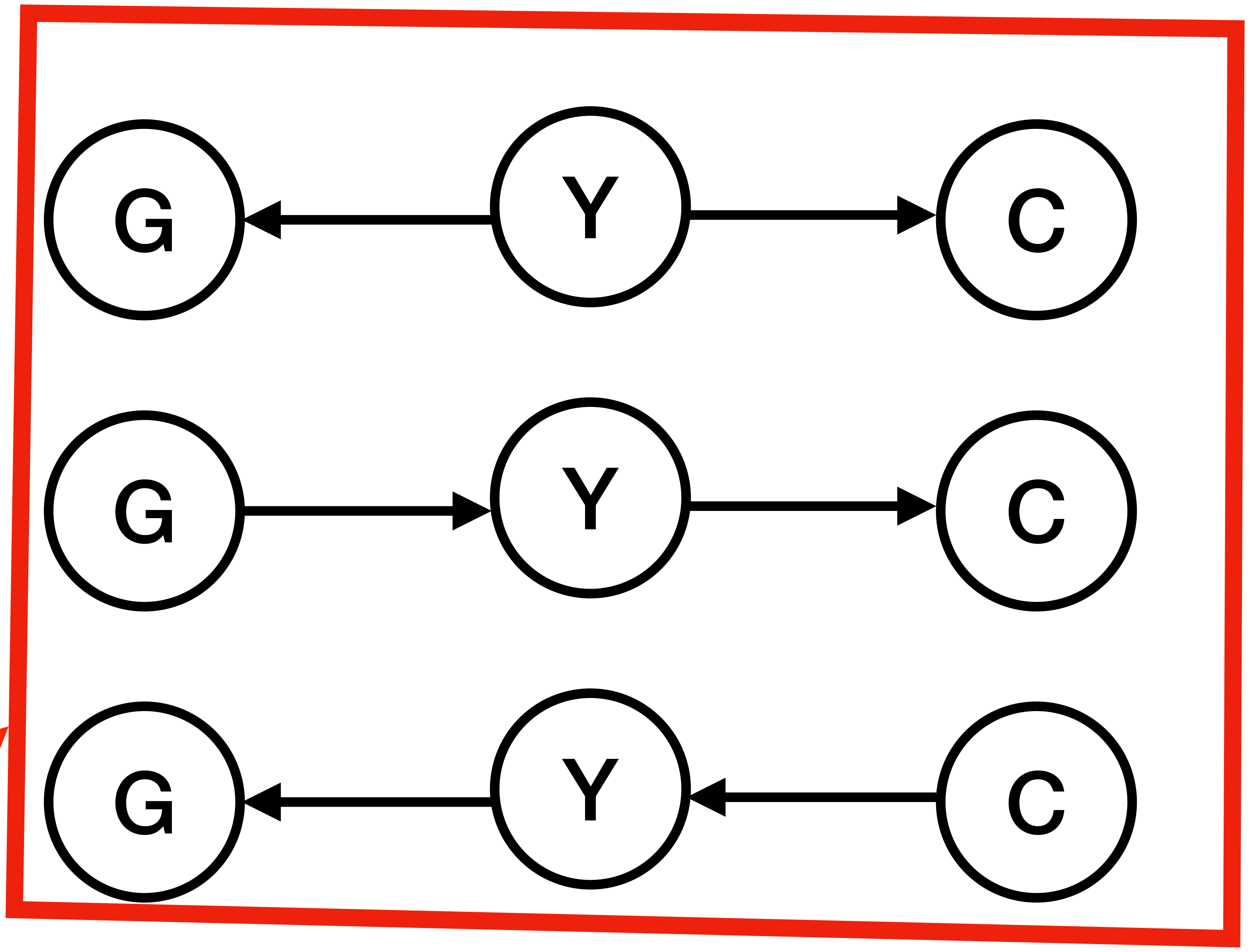

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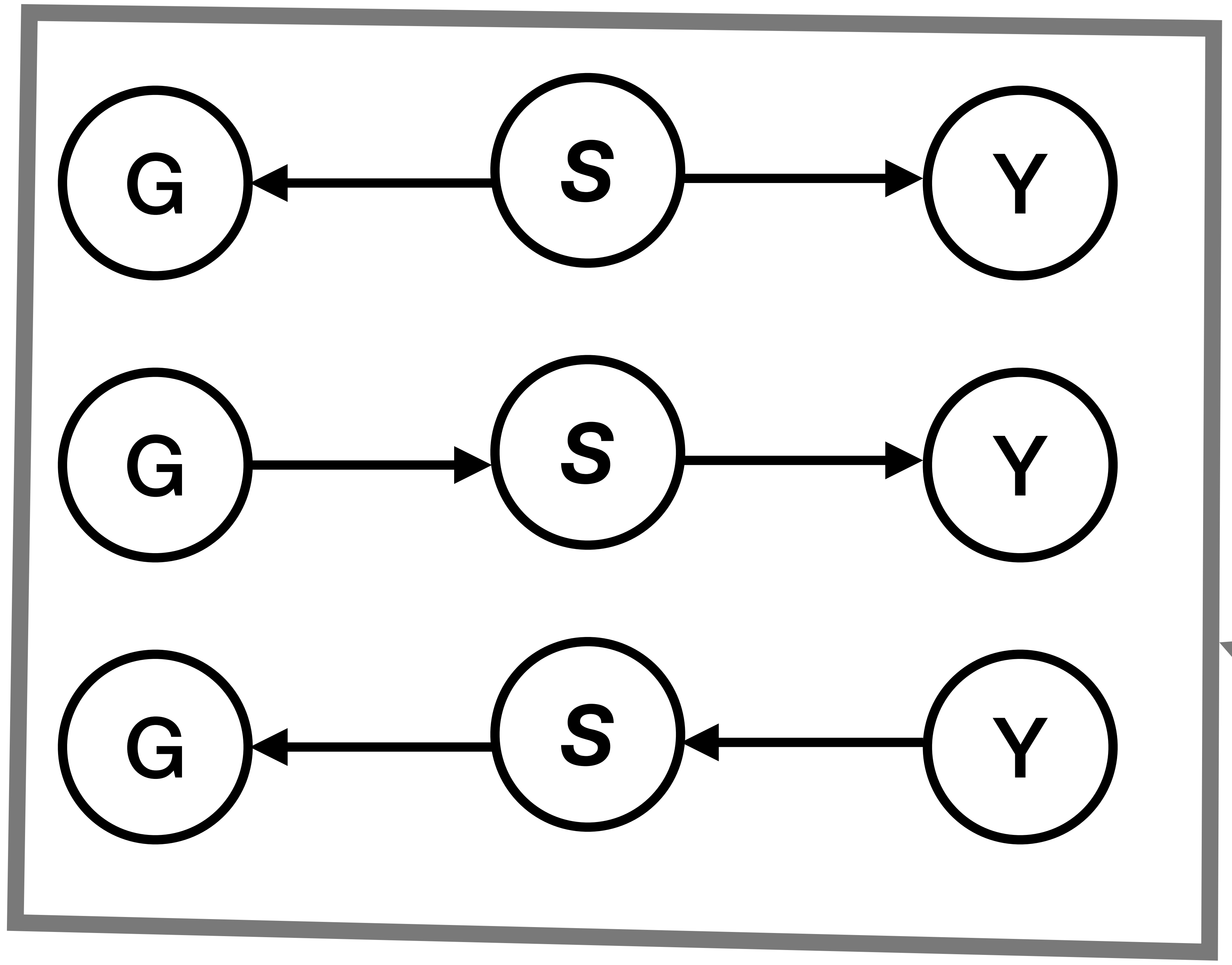

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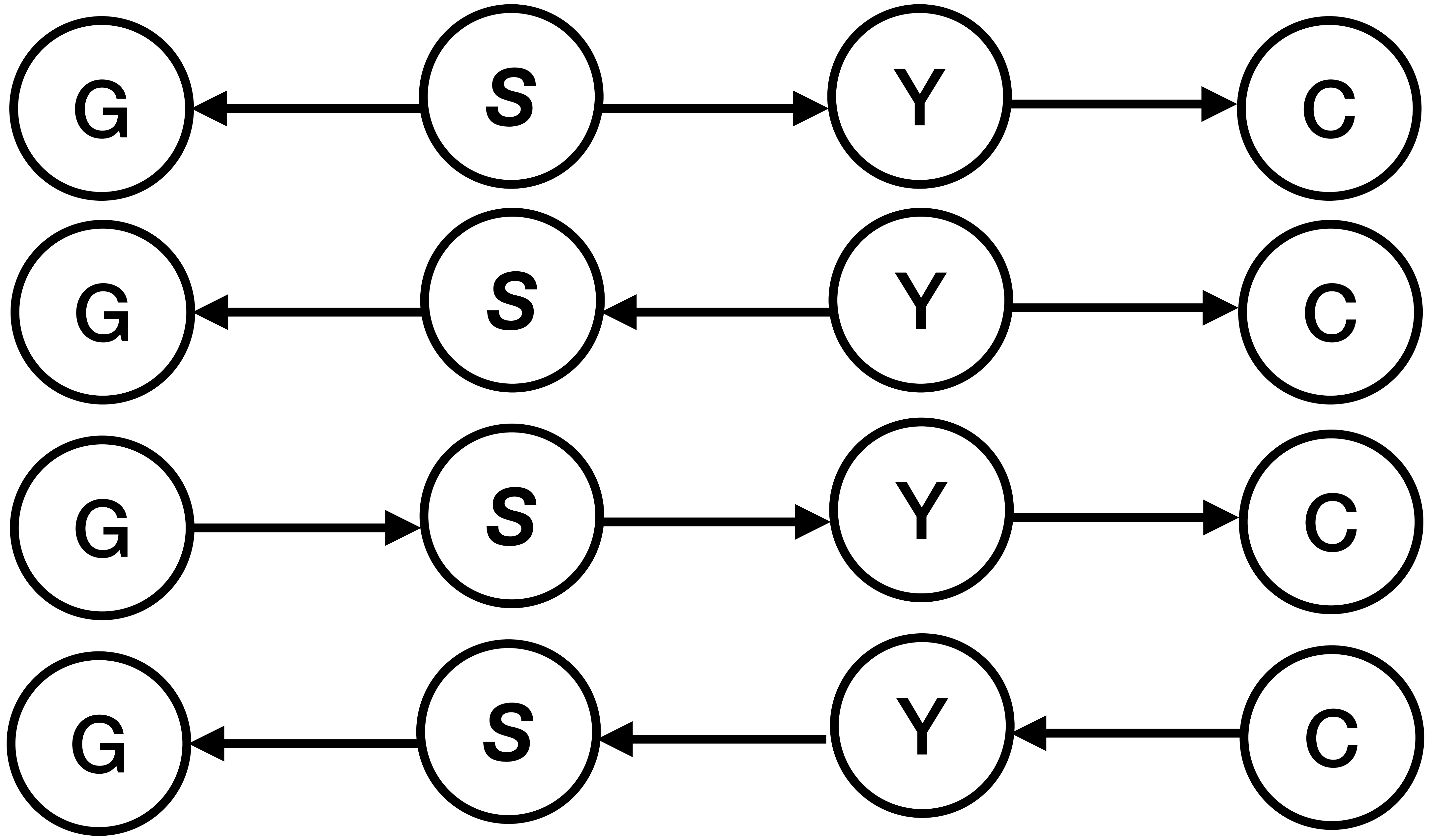

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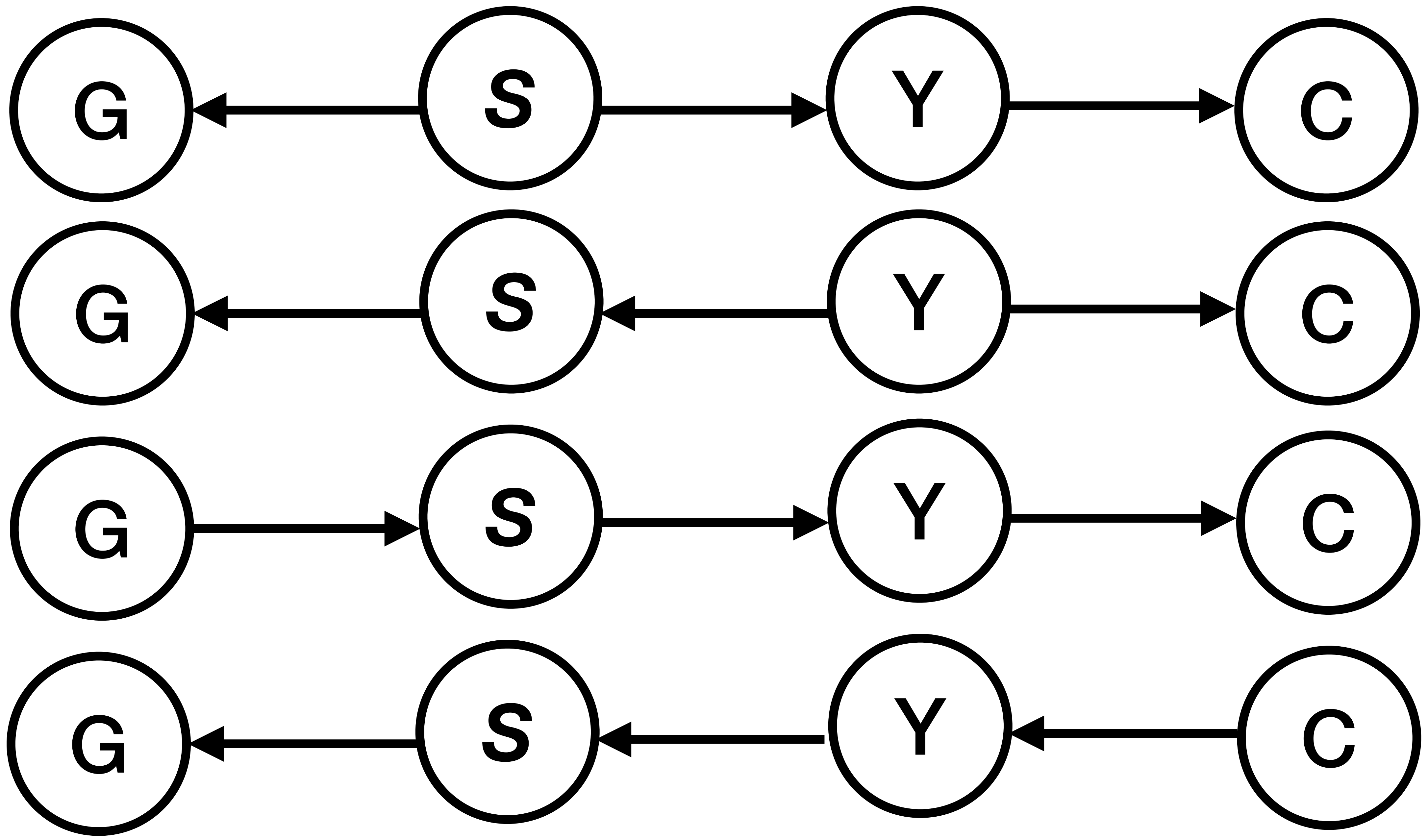

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Classification Parity and Calibration

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4. Conclusion

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These impossibility theorems underscore the unfairness of **any** evidence-based decisions.

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These impossibility theorems underscore the unfairness of **any** evidence-based decisions.

(2) But *perhaps* we can be content with a compromise:

- satisfy **classification parity** together with **calibration** (a close cousin of predictive parity)

Thank you!