# APPLIED MECHANISM DESIGN FOR SOCIAL GOOD


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Lecture #22 – 04/12/2022

CMSC498T
Mondays & Wednesdays
2:00pm – 3:15pm

COMPUTER SCIENCE
UNIVERSITY OF MARYLAND

# ANNOUNCEMENTS

Due tonight: Fair Allocation Quiz

Due on Monday, 4/25: Project Checkup

- Kind of like the project proposal, but regarding the current state of things
- Will be graded in a similar manner
- Remember that proposal comments are up!

# WHAT IS MACHINE LEARNING?

**"The study of computer algorithms that can improve automatically through experience and by the use of data."**

**- Wikipedia**

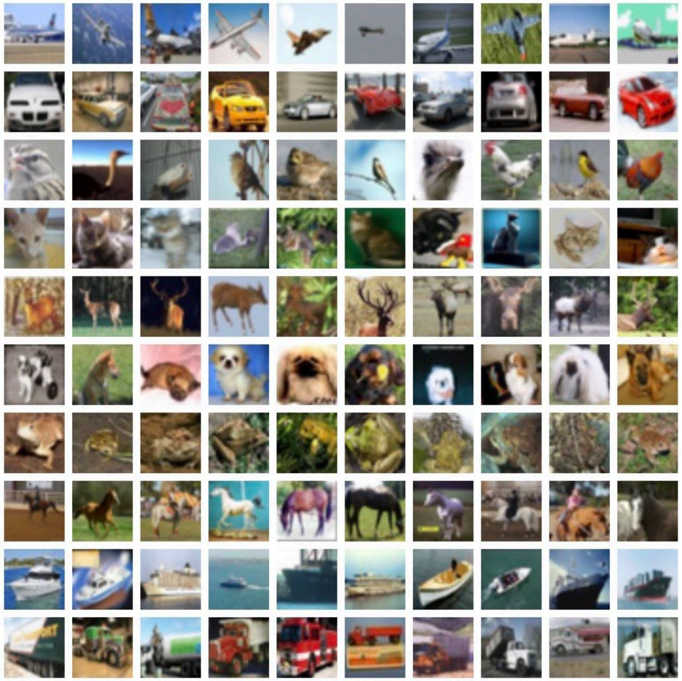
Let P be data. Let A be a set of labels.

Find a mapping M : P → A in an attempt to most accurately identify the labels.

We want to estimate the label as best as possible under *constraints*.

A: P:

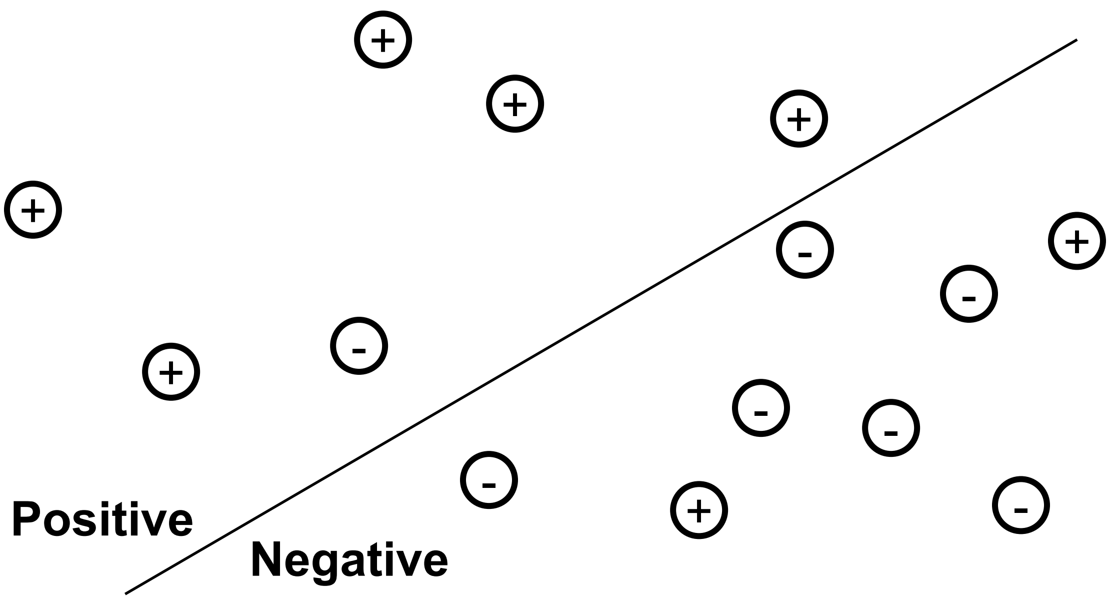
**airplane**
**automobile**
**bird**
**cat**
**deer**
**dog**
**frog**
**horse**
**ship**
**truck**



# CONSTRAINT: LINEAR SEPARATOR

A constraint is any restriction on the solution map M.

Example: M must be a linear separator.



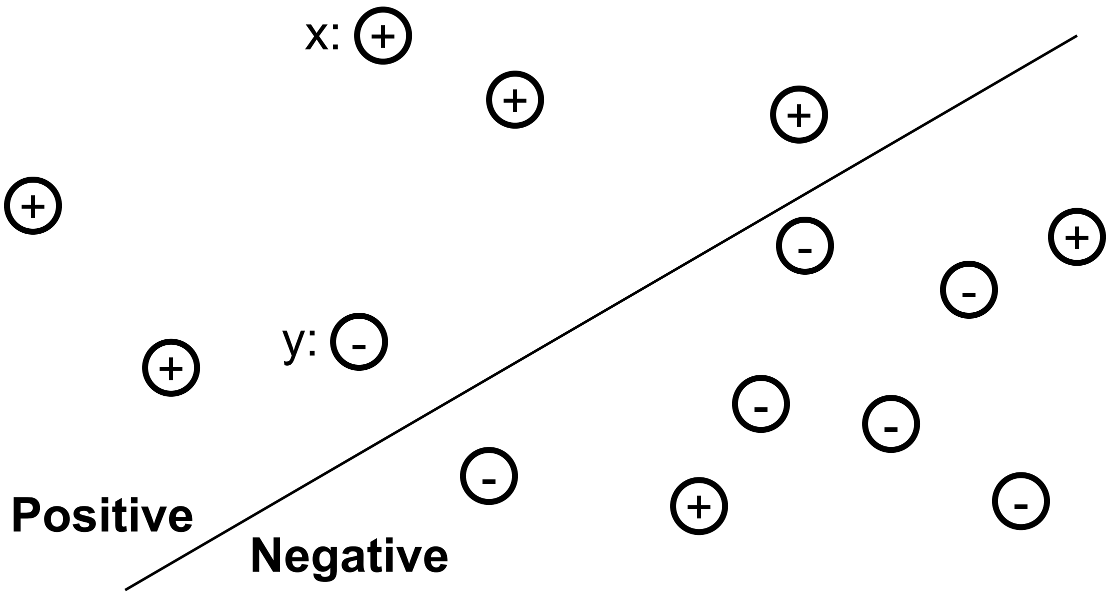

False Positives: 1

False Negatives: 2

This may be the best linear separator

# LOSS FUNCTION AND LINEAR PROGRAMS

**Loss function:** A function L : P x A → R which tells you "how far away you are from a solution.

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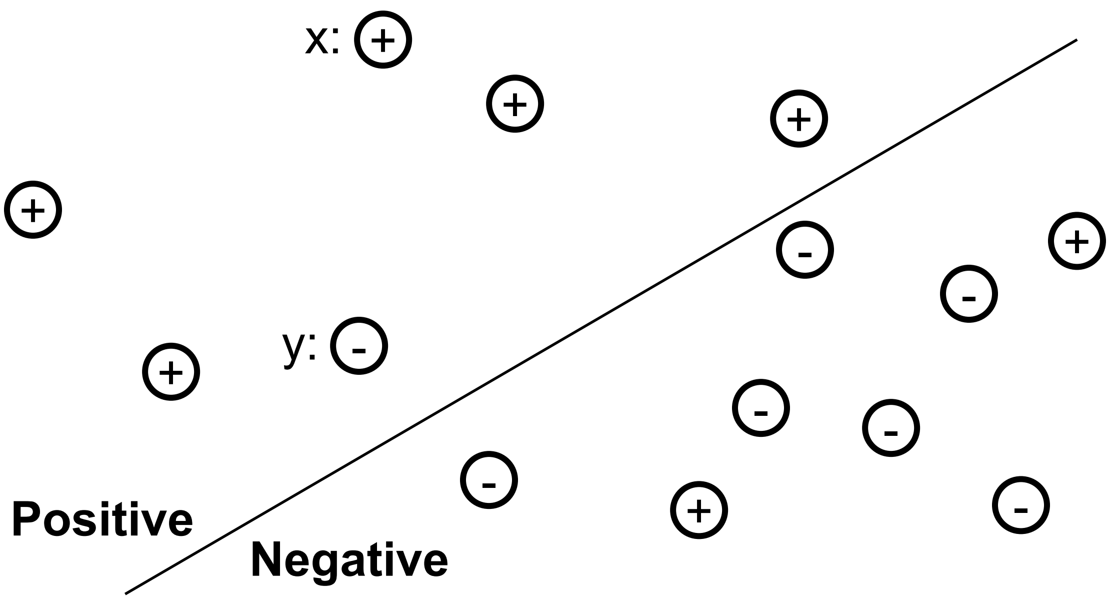

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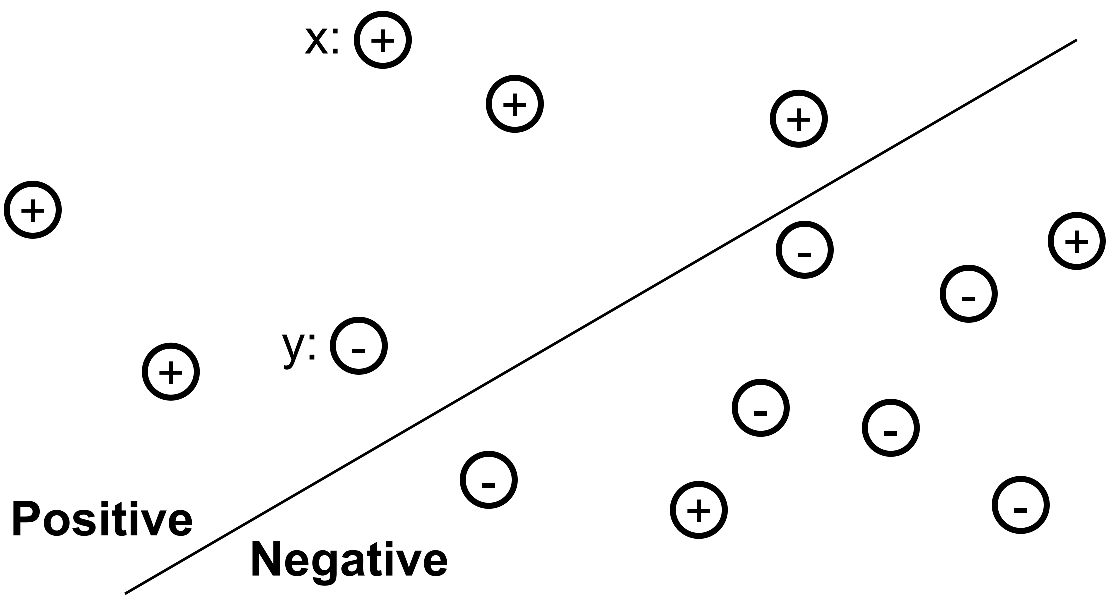



Say L(p, a) is 0 if x's label is a, 1 otherwise (0-1 loss).

L(x, +) = 0

L(y, +) = 1

Thus y is a bad label, x is a good label.

Goal: minimize total loss.

# IF IT AIN'T BROKE, DON'T FIX IT

Unfortunately, it is broken

# IF IT AIN'T BROKE, DON'T FIX IT

Unfortunately, it is broken in lots of ways.

But let's focus on a few.

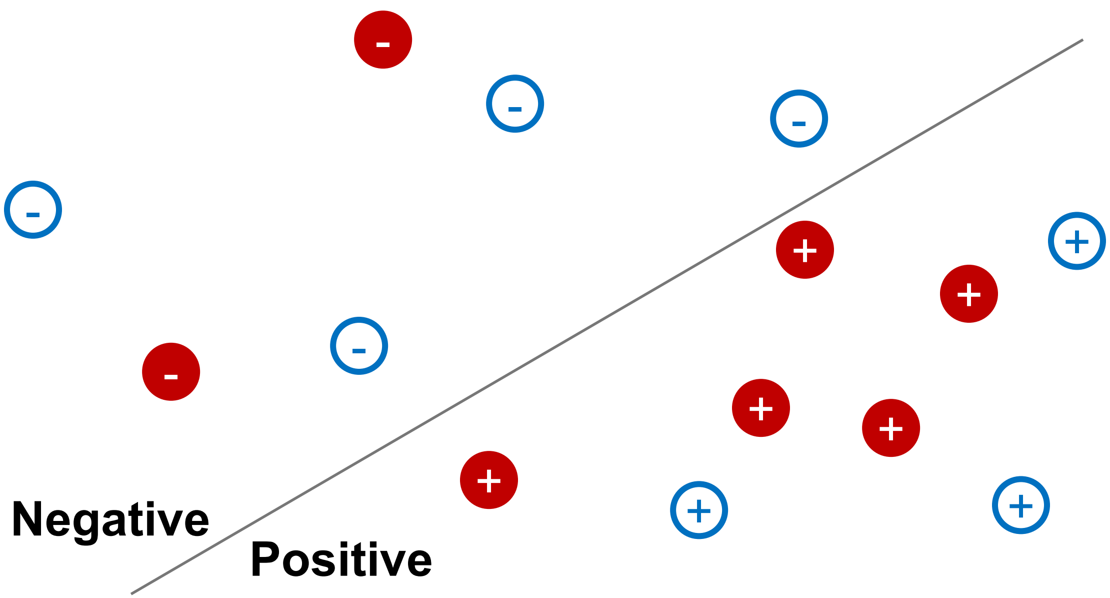
**Many machine learning projects that we rely on today discriminate against real people.**

- Credit card advertisements
- Google Ad selection
- Google name advertisements
- Recidivism risk
- Others: hiring decisions, school admission, etc.

# GROUP FAIRNESS

**“Group fairness” or “statistical parity”:** demographics in the positive group and negative group are the same as the whole distribution.

Say our demographics are blue and red points.




50% of the points are red, 50% are blue.

To be fair, 50% of the positive points must be red, 50% must be blue. Same with negative points.

This is not fair.

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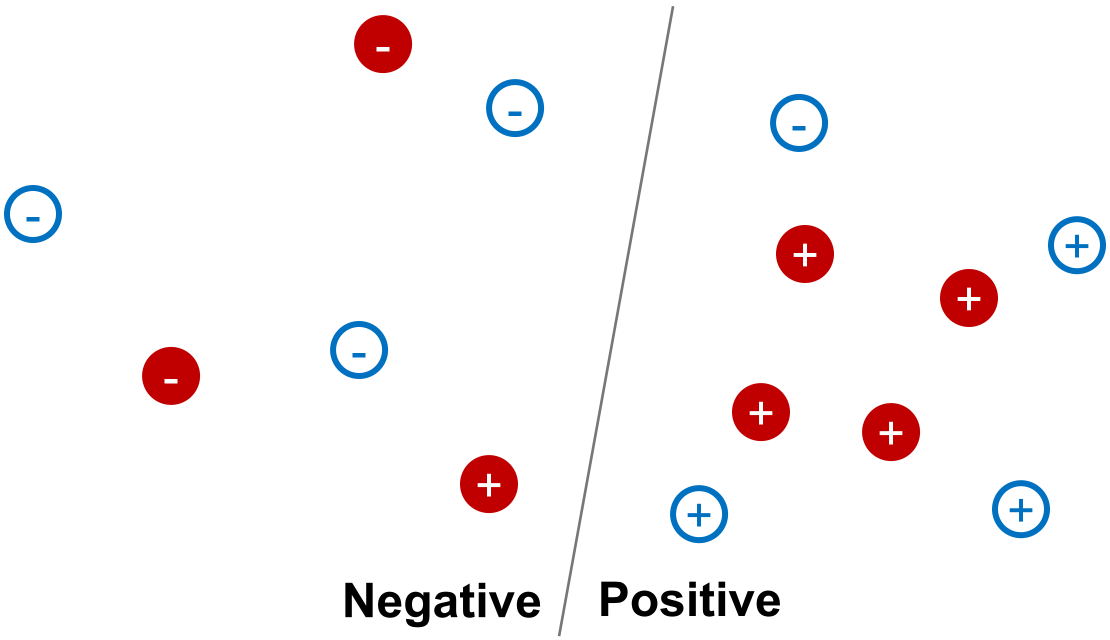


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# EXAMPLE: LOAN DECISIONS

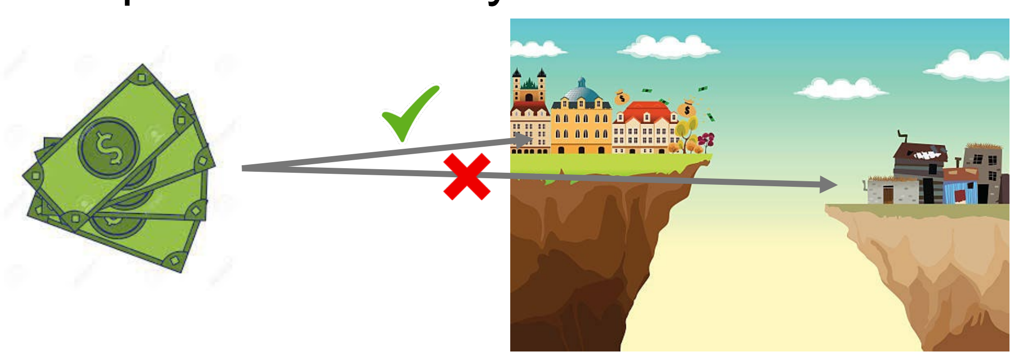
http://research.google.com/bigpicture/attacking-discrimination-in-ml/

# DISCRIMINATORY PRACTICES

We are running a classification task on a point set P with labels A. Say S is a protected class (i.e., a racial minority).

Discriminatory practices:

- **Blatant discrimination:** membership in S is explicitly used to give a worse outcome.
- **Redundant encoding:** blatant discrimination but you use a "proxy" metric.
  - **Redlining:** discriminating against neighborhoods because occupants are mostly minorities and/or low-income



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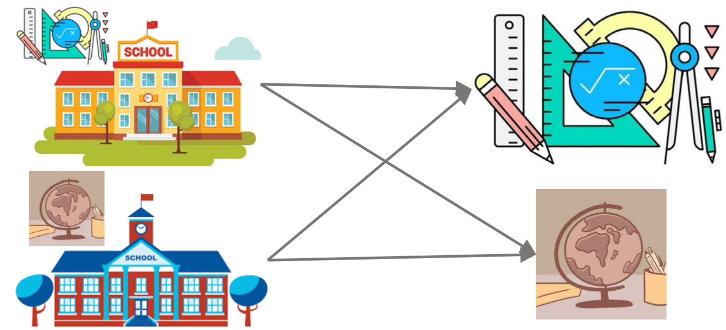
Discriminatory practices:

- **Disproportionate discrimination:** discriminating against groups because occupants are *disproportionately* minorities and/or low-income.
- **Self-fulfilling prophecy:** deliberately choosing a specific subset of S to discriminate against S.
- **Reverse tokenism:** excusing discrimination against S by citing a “good” member of $S^c$ who is denied service.

# LIMITATIONS OF GROUP FAIRNESS

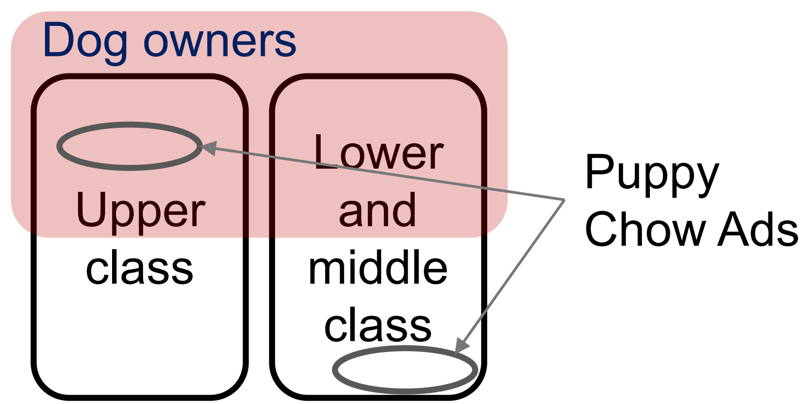
**Reduced utility:** statistical parity can yield low-utility solutions.




**Self-fulfilling prophecy:** you can select sub-optimal example and use that as a basis to discriminate.

| | | |
|---|---|---|
| Kent IQ: 145 | Mark IQ: 115 | Zak IQ: 95 |
| Kate IQ: 145 | Eve IQ: 115 | Rose IQ: 95 |

**Subset targeting:** you can target irrelevant individuals in S, thereby catering more to $S^c$.

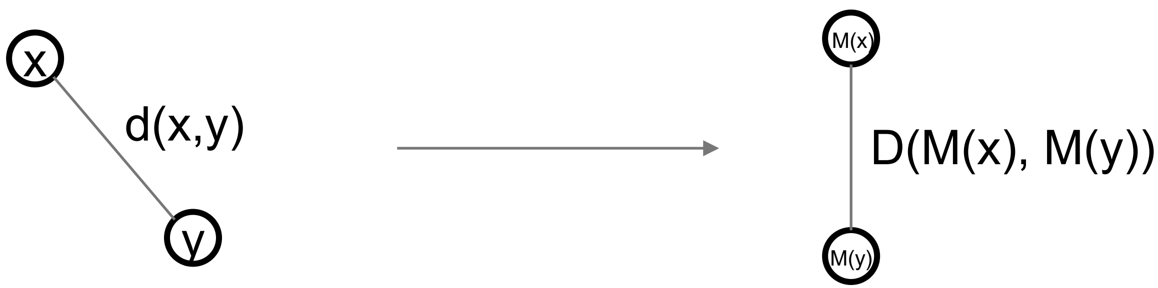


# INDIVIDUAL FAIRNESS

**“Lipschitz fairness”** or **“individual fairness”**: The closer two points are together, the closer their labels should be.

Recall our classifier is M, and M(x) is the label of a point x. Let d,D be a distance function. M is Lipschitz if for any x,y in P:

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




*Point space, distance function: d*

*Label space, distance function: D*

# WHY WE LIKE INDIVIDUAL FAIRNESS

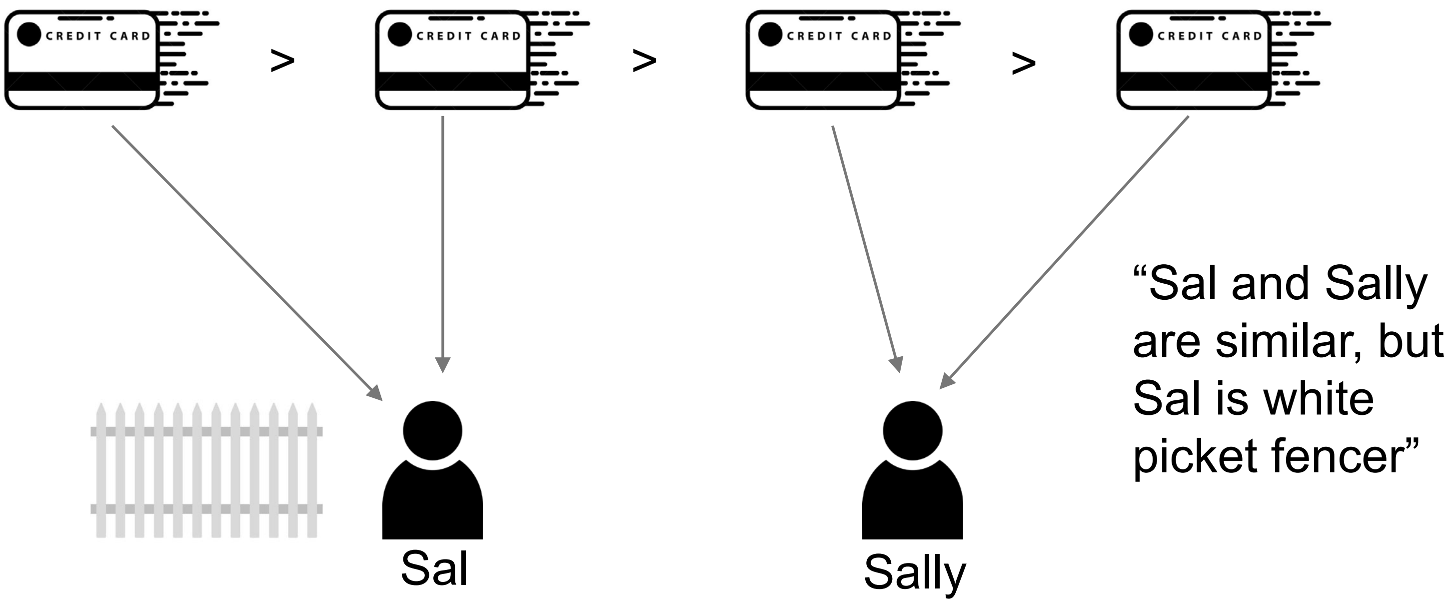
**Theorem:** In certain circumstances (i.e., certain distance measures), individual fairness implies group fairness.

- In other cases, you can force group fairness while retaining some individual fairness.

**Property:** Individual fairness is a generalization of *differential privacy.*

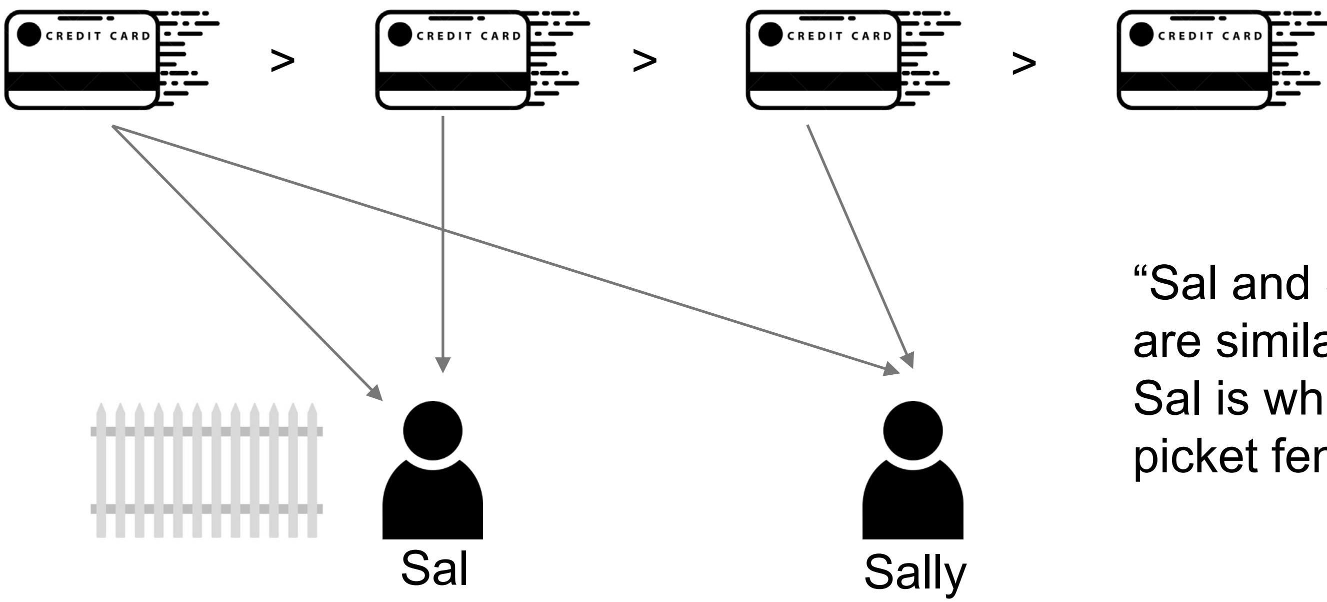
**Property:** Individual fairness prevents reverse tokenism, the self-fulfilling prophecy, and redundant encodings.

# EXAMPLE: AD NETWORK




Individual fairness guarantees that Sally and Sal are expected to have similar classifications. Prevents reverse tokenism and self-fulfilling prophecy (have them guess!)

# EXAMPLE: AD NETWORK




“Sal and Sally are similar, but Sal is white picket fencer”

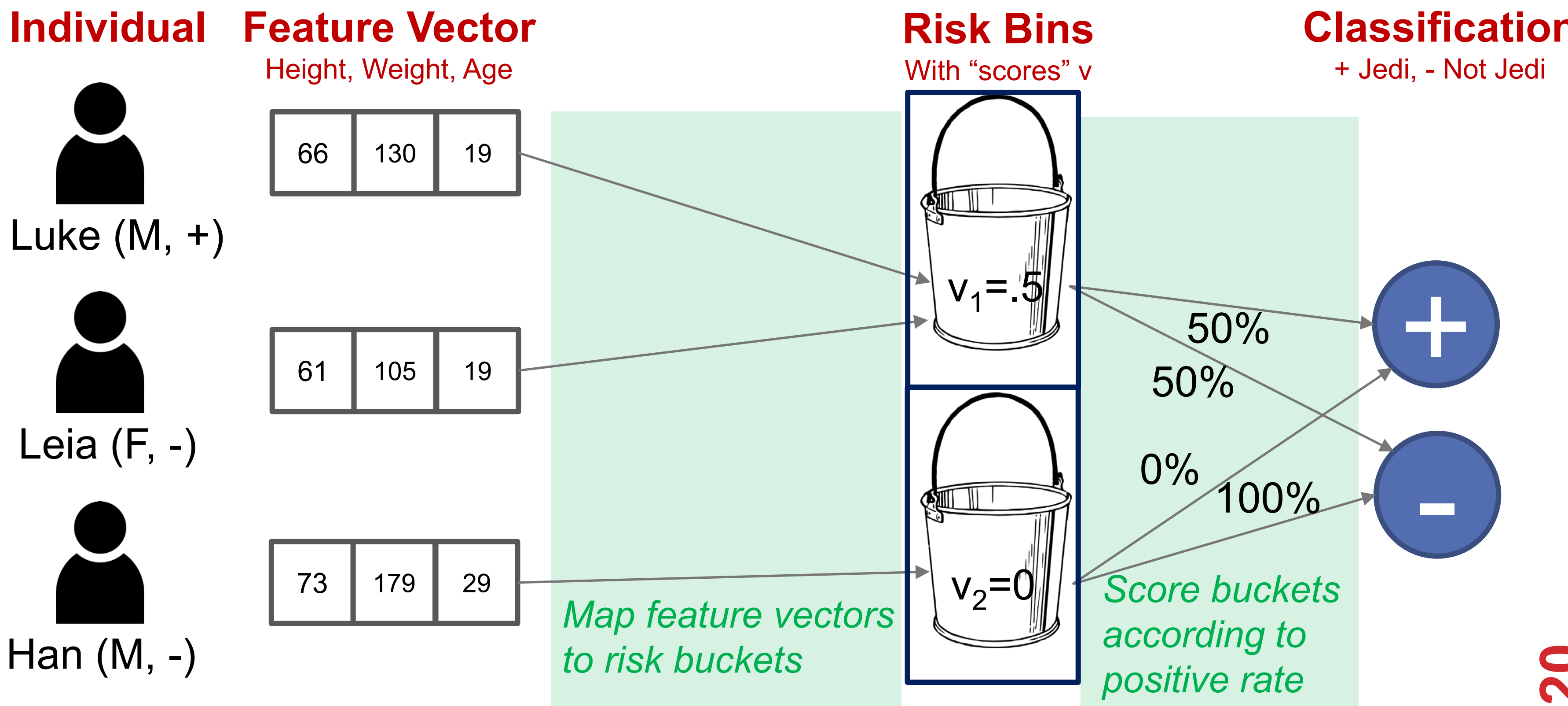
Individual fairness guarantees that Sally and Sal are expected to have similar classifications. Prevents reverse tokenism and self-fulfilling prophecy (have them guess!)

# RISK ASSIGNMENTS

**Warning**: For simplicity purposes, this uses binary gender labels, which may not reflect all possible groups in the data. The issue of datasets using binary gender labels is common and a current topic of interest in fair data collection.

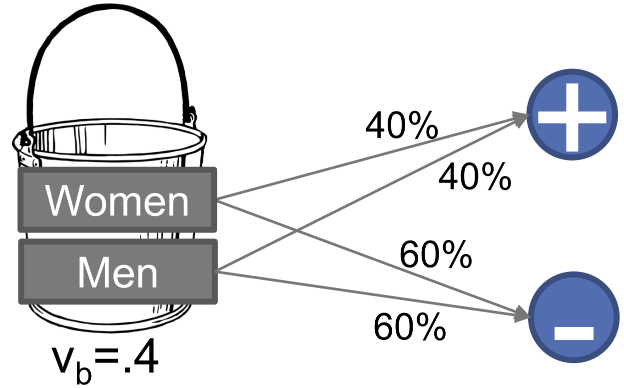
**We can also quantify fairness through *risk assignments*.**

Task: output a probability someone is a jedi. Protect for gender.

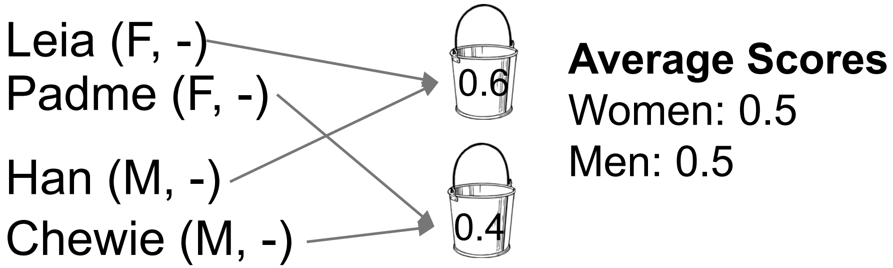


# FAIRNESS BY RISK ASSIGNMENT

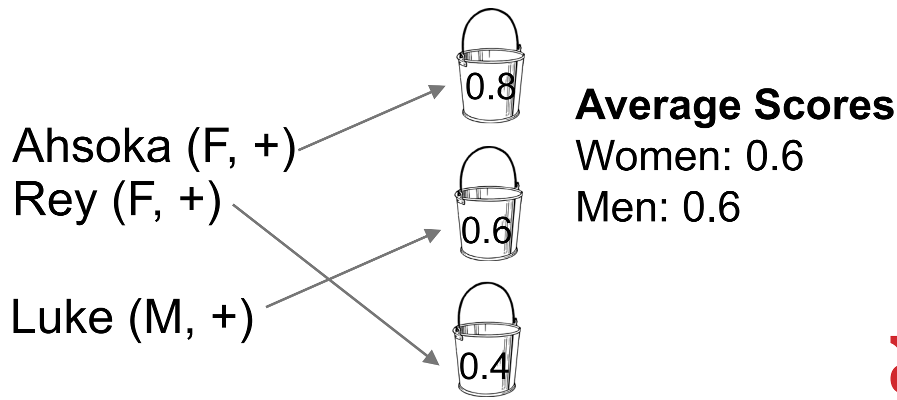
**Calibration within groups:** in any bin, men and women have the same chance of jedi classification.




**Negative class balance:** the average scores of non-jedi men and women are equal




**Positive class balance:** the average score of jedi men and women are equal.



# A PERPLEXING CASE: RECIDIVISM PREDICTION

**COMPAS risk tool:** an intelligent system used by the criminal justice system to assign an estimated chance of convicted criminals to commit reoffenses.

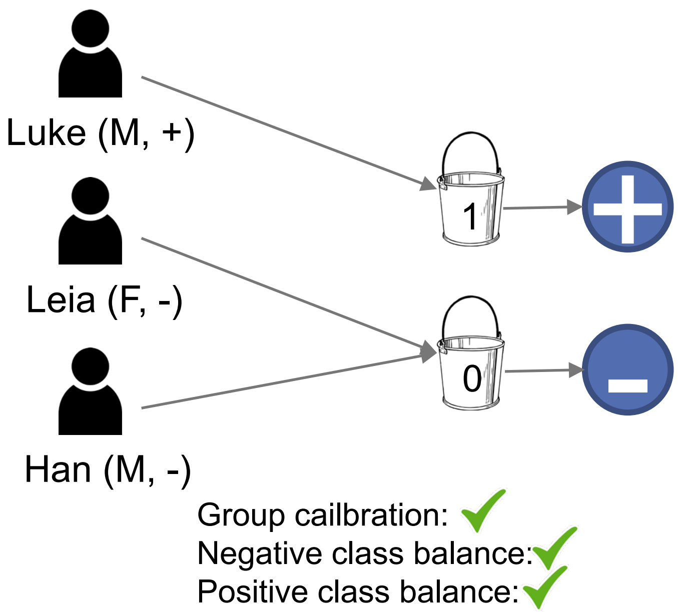
**Angwin et al.:** claimed that COMPAS discriminated against race because it failed to achieve both *negative class balance* and *positive class balance.*

**Counter:** claimed COMPAS does not discriminate because it achieves *calibration within groups*.

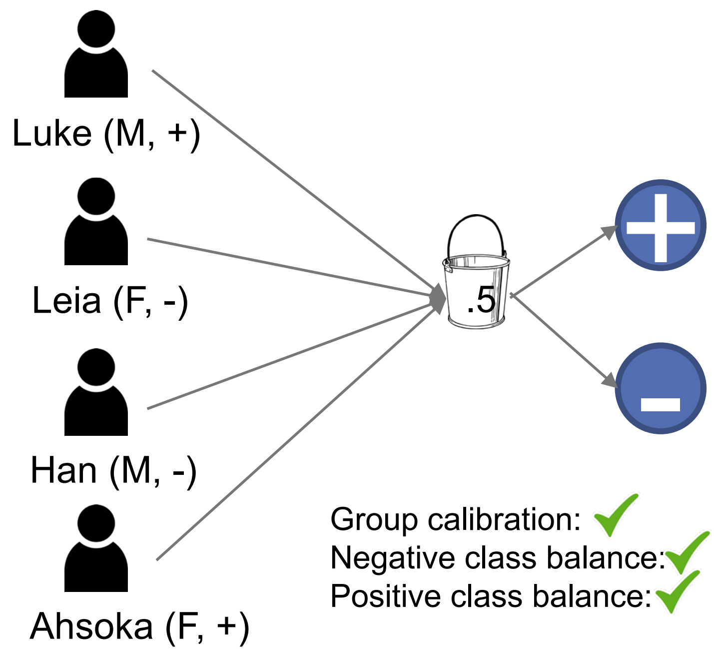
*Does that mean it's okay or bad?*

# HOW MANY CONDITIONS CAN WE GET SIMULTANEOUSLY?

**Perfect prediction:** We are given who is a jedi.

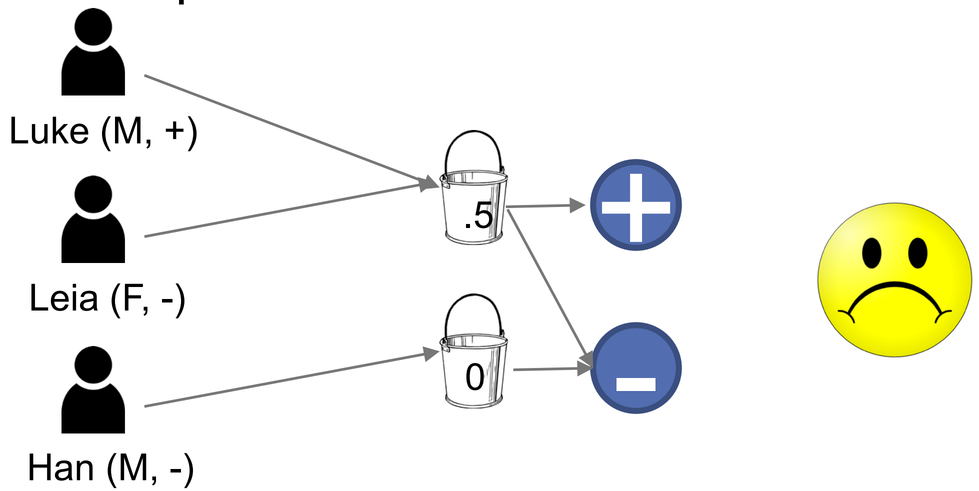



**Equal base rates:** Men and women are equally likely to be jedis.



# BEYOND SPECIAL CASES

**Theorem:** group calibration, negative class balance, and positive class balance can be achieved all together if and only if there is perfect prediction or equal base rates.




**COMPAS:** Never could have achieved all 3! But maybe could have done 2.

# ETHICAL GUIDE TO FAIR MACHINE LEARNING

**Keep in mind:** algorithmic fairness inherently interacts with vulnerable and marginalized communities.

**Big question:** How do we ensure that we serve and give back to these communities

- Do not exploit fair algorithms

**Other big question:** How do we avoid harming these communities?

Some groups have codes for this, including **the AAAI code of ethics**.

# FAIR ALGORITHMS CAN CAUSE HARM!

**Consider:** We know employers discriminate against applicant's criminal history. Since the criminal justice system exhibits racial discrimination, this issue can propagate to hiring.

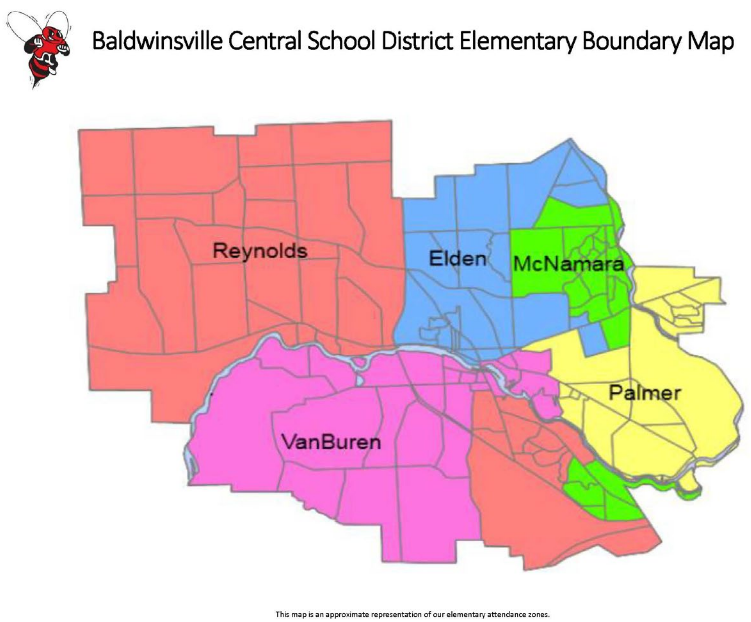
- Solve this by banning employers from asking about criminal history?
- No: we know that employers then use race as a proxy for unknown criminal history. This *increases* racial discrimination.

**"Imposing a fairness constraint can make the disadvantaged group worse off if the fairness constraint and utilities of the population mismatch."**

# EXAMPLE: SCHOOL DISTRICTING

In the US, the population is divided (“clustered”) into geographic districts. People in the same district use the same school system.

- Funding and resources are not distributed equitably
- Districts are segregated

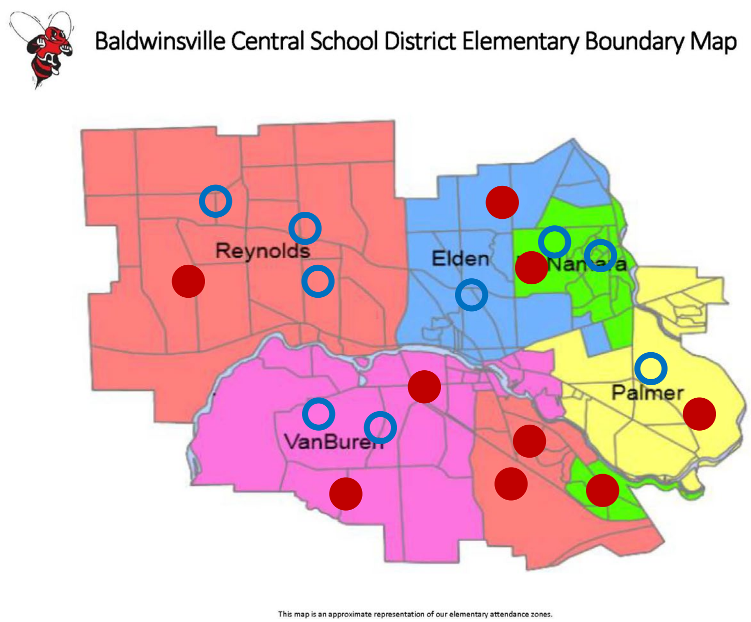


# EXAMPLE: SCHOOL DISTRICTING

What if we impose fairness on this clustering problem?

- Ensure the clustering is group fair

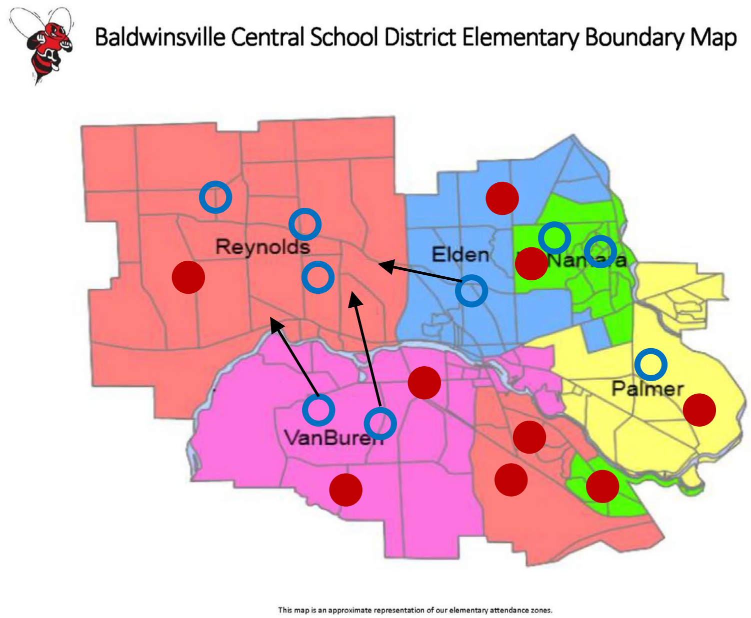
Consider: Who are we serving, and how does this impact them?



# EXAMPLE: SCHOOL DISTRICTING

Important considerations:

- Logistics and cost
- People move for schools!



# WHEN YOU ARE TRYING TO APPLY FAIRNESS...

Applications and context matter

- Define and model fairness for specific social problems
- General abstractions are useful but often over-sold
- Use caution mapping ideas from fair classification to other fair problems (i.e., fair clustering…)

Fairness interventions do not act in a vacuum

- Broader context and upstream/downstream effects are important
- Different bad inputs require different fair algorithms
- How the algorithm's output is used must also be considered

# WHEN YOU ARE TRYING TO APPLY FAIRNESS...

Interdisciplinary research is the best way to use fairness well

- Know your limitations as a researcher, programmer, etc.
- Know relevant work in related areas
- Understand what compromises are most acceptable when ideals can't be achieved
- Establish what is/isn't allowed in practice (i.e., code of ethics)

Real people are involved!

- Who is this for?
- Who are we being fair to?
- What do they want?
- How do they want fairness defined?