Big Data and Economics

Causal Effects of Neighborhoods

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Bates College | ECON/DCS 368

Table of contents

Prologue

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- We saw in the Opportunity Atlas that neighborhood income mobility is correlated with many outcomes
- But are any of these correlations causal?
- If so, we should be able to change neighborhood characteristics to change outcomes
- How do we know if a correlation is causal?

Prediction vs. causation

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For the rest of the term, we will focus on **causally estimating** β_j.

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Causality requires us to **hold all else constant** (*ceterus paribus*).

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Generally, ***causal*** relationships are complex and challenging to answer, *e.g.*,

- What causes some countries to grow and others to decline?
- What caused the capital riot?
- Did lax regulation cause Texas's recent energy problems?
- How does the number of police officers affect crime?
- What is the effect of better air quality on test scores?
- Do longer prison sentences decrease crime?
- How did cannabis legalization affect mental health/opioid addiction?

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New saying:

> Correlation plus exogeneity is causation.

Let's work through a few examples.

Causation

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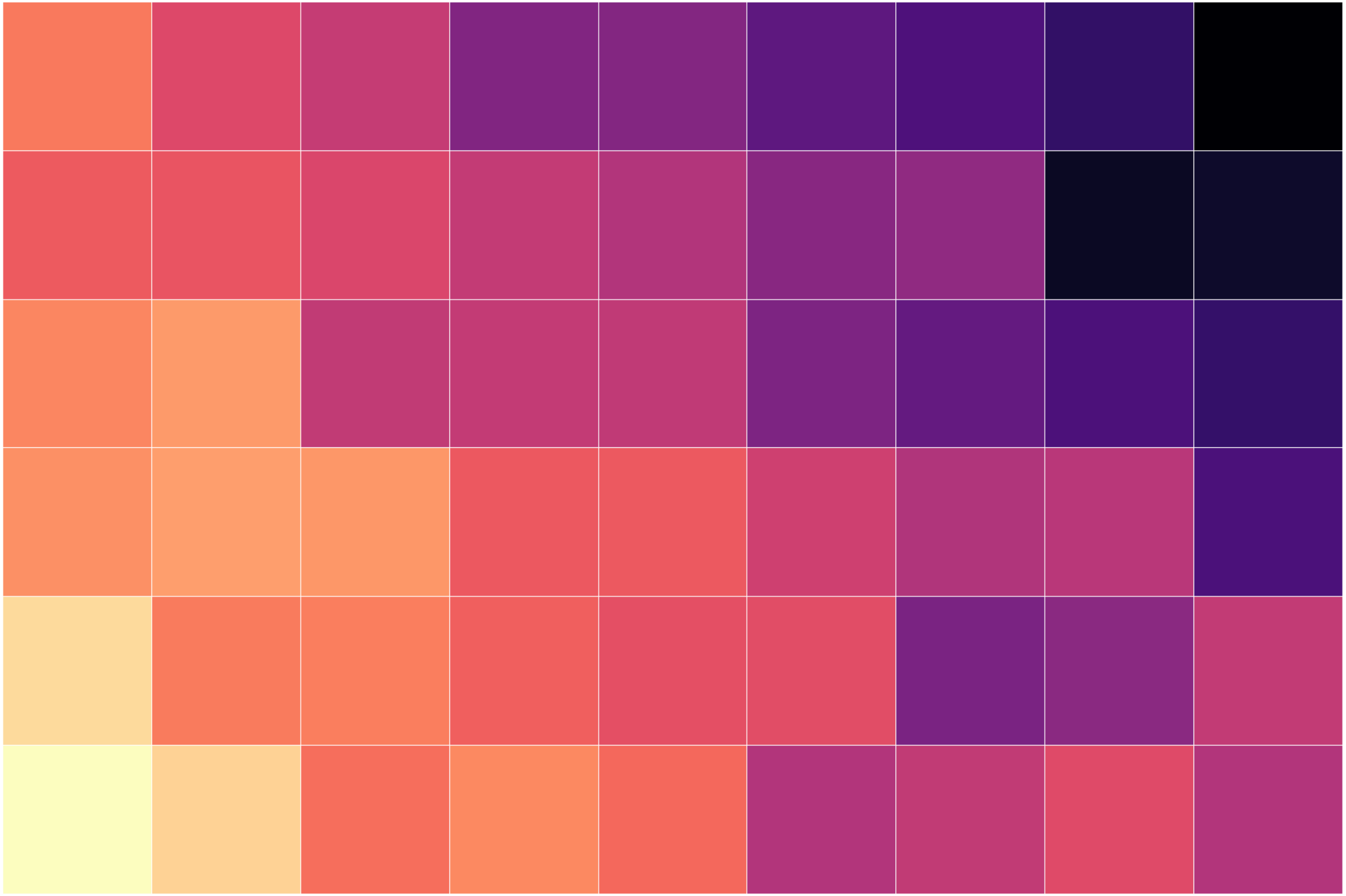
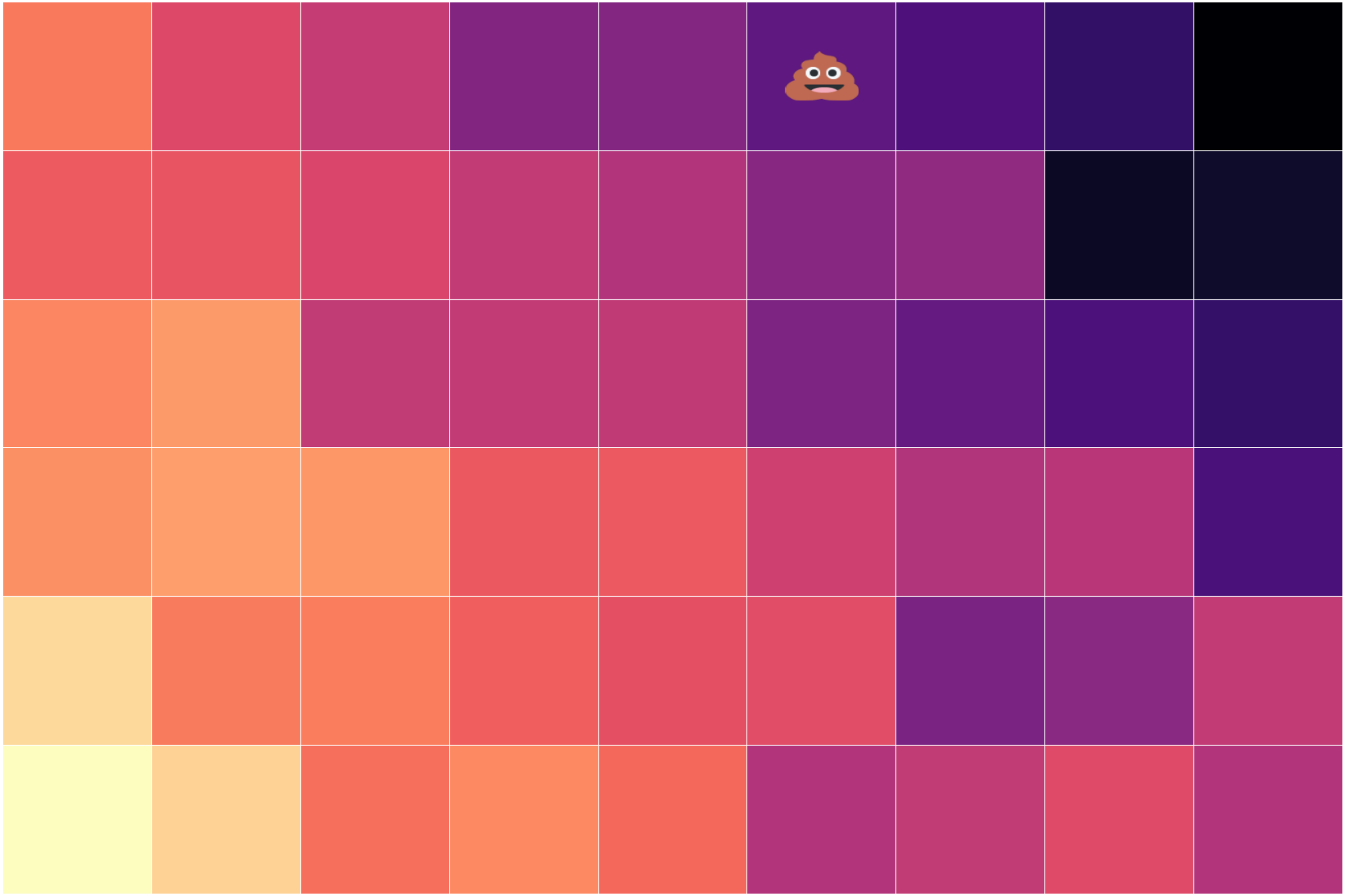
54 equal-sized plots

01	02	03	04	05	06	07	08	09
10	11	12	13	14	15	16	17	18
19	20	21	22	23	24	25	26	27
28	29	30	31	32	33	34	35	36
37	38	39	40	41	42	43	44	45
46	47	48	49	50	51	52	53	54

54 equal-sized plots of varying quality



54 equal-sized plots of varying quality plus randomly assigned treatment



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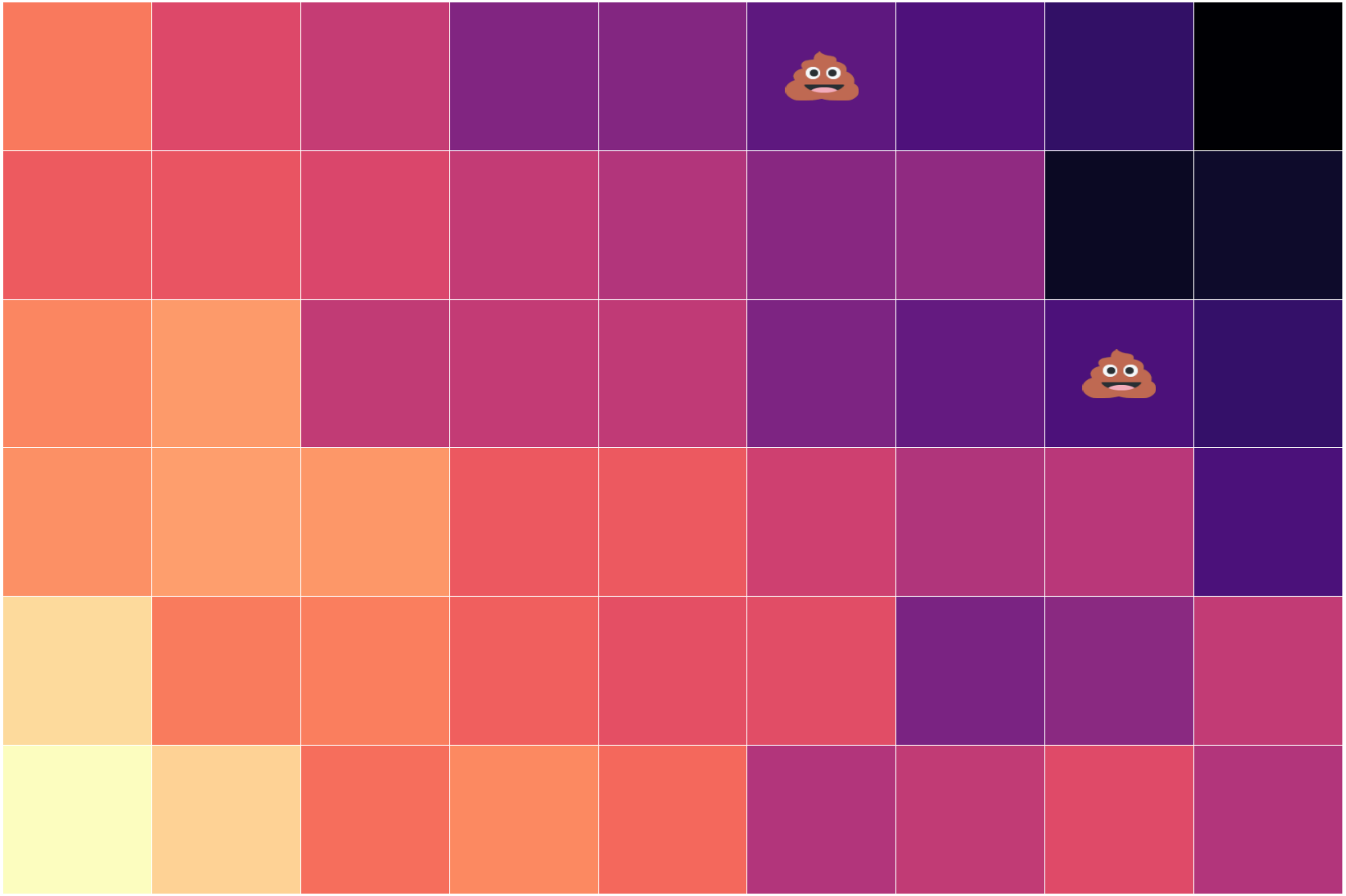

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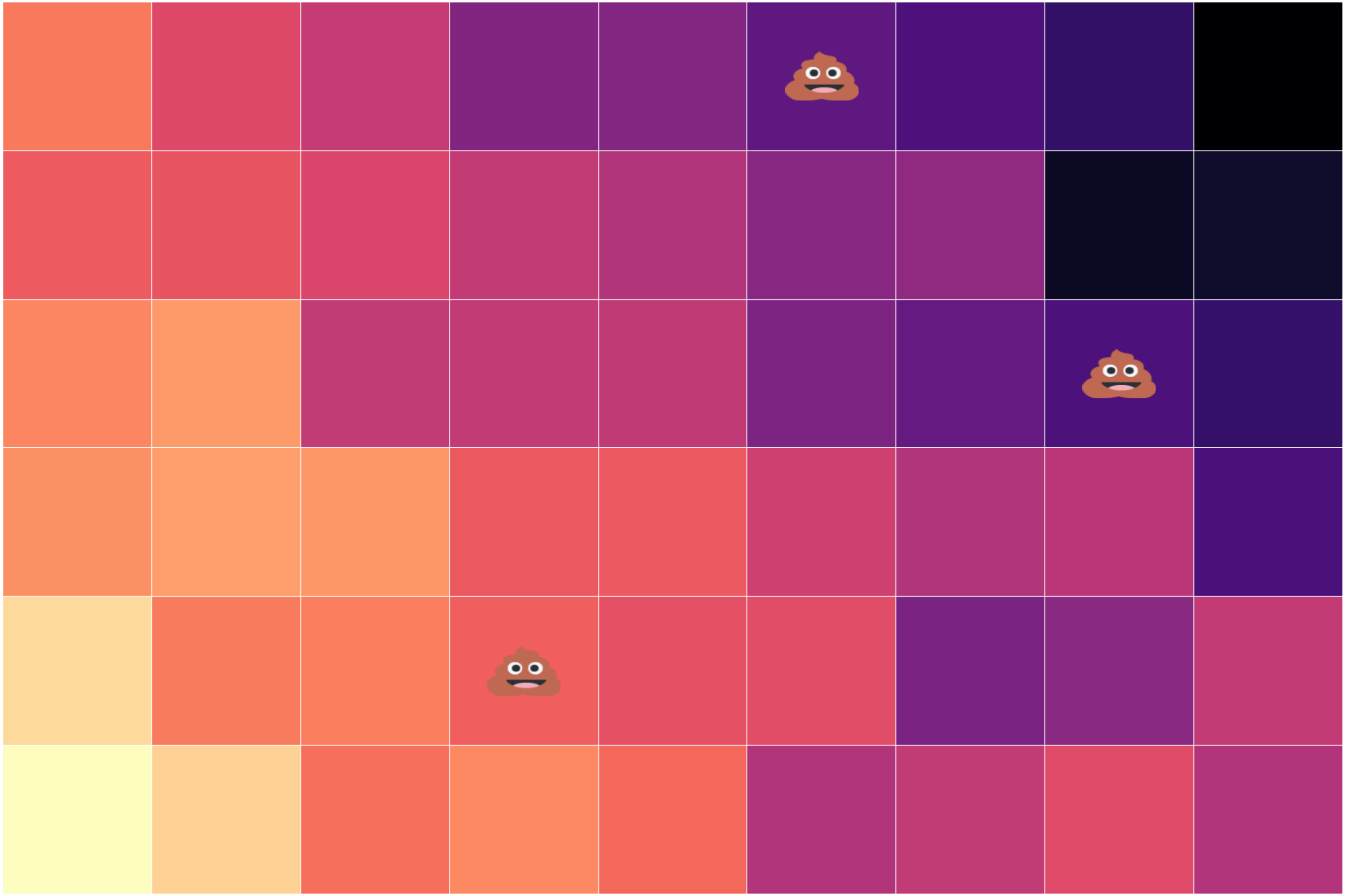

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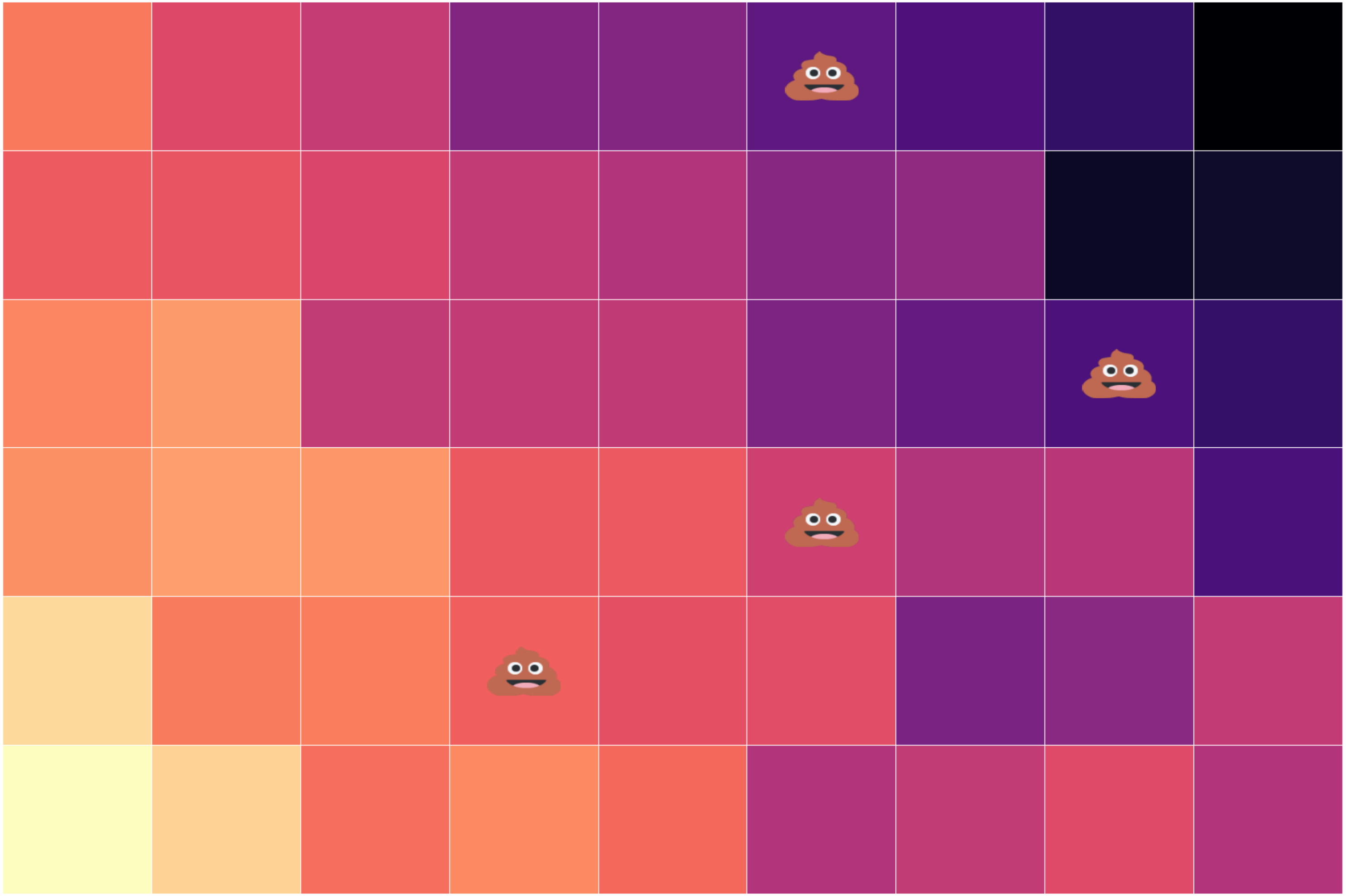

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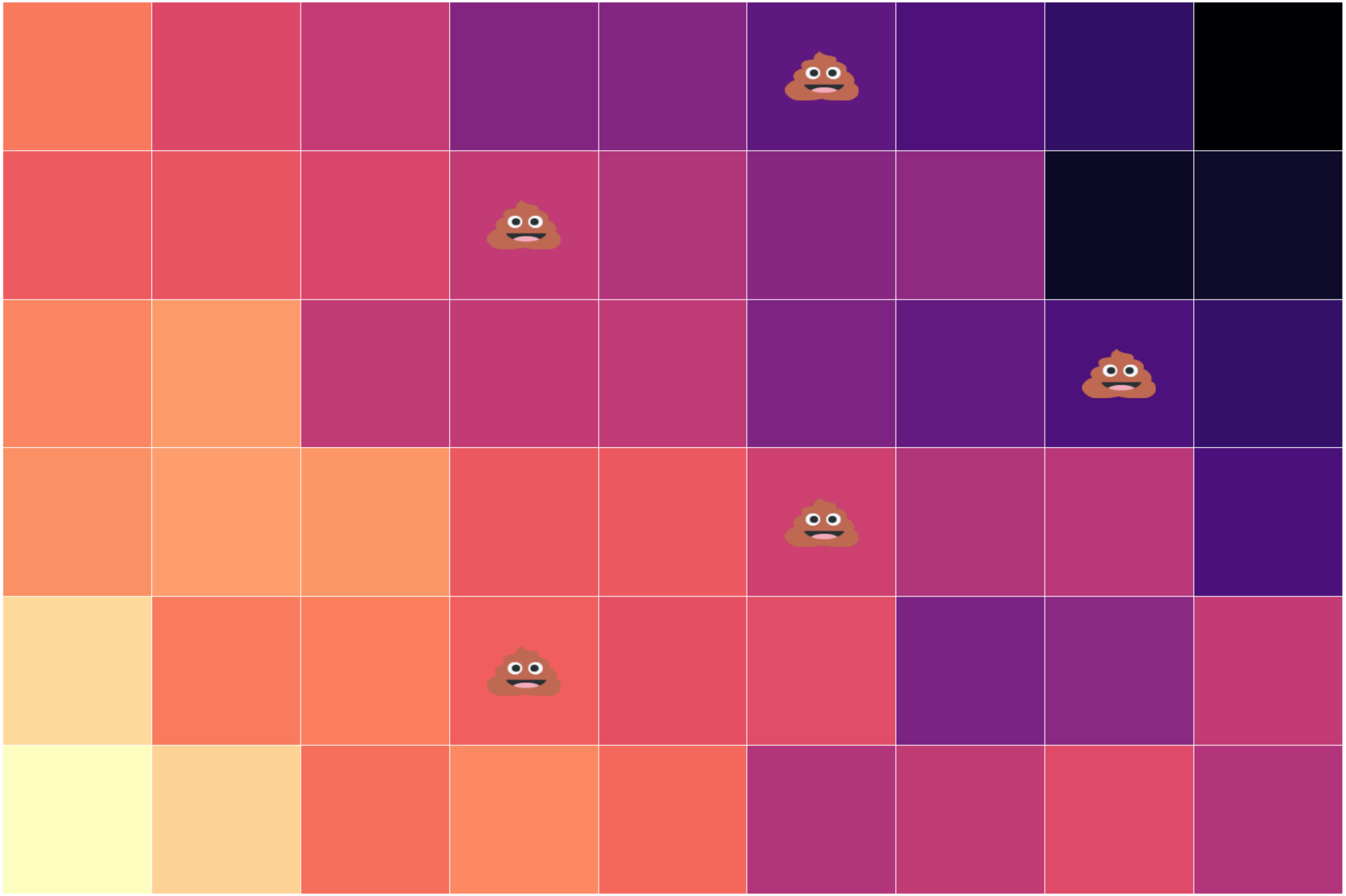

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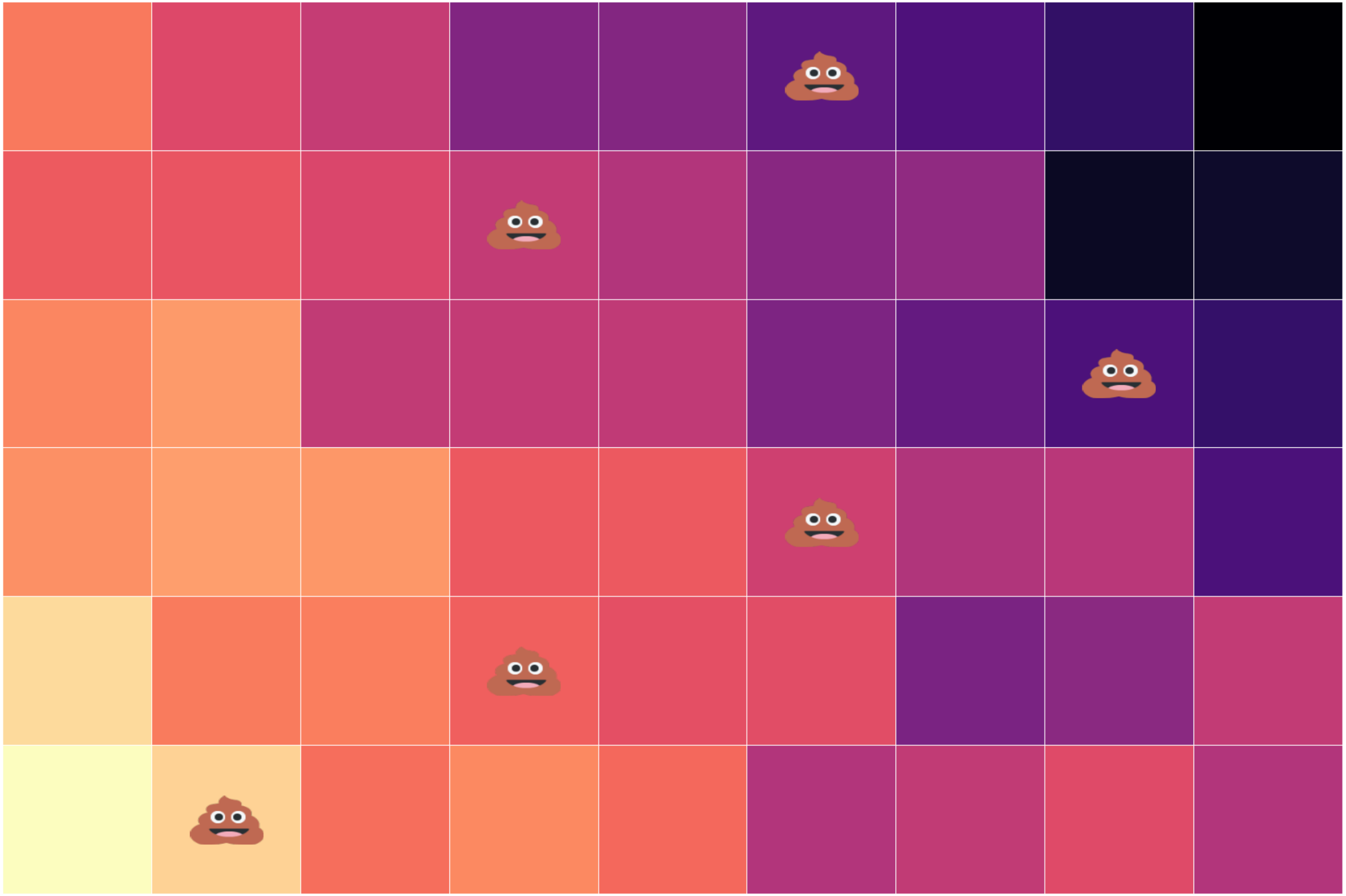

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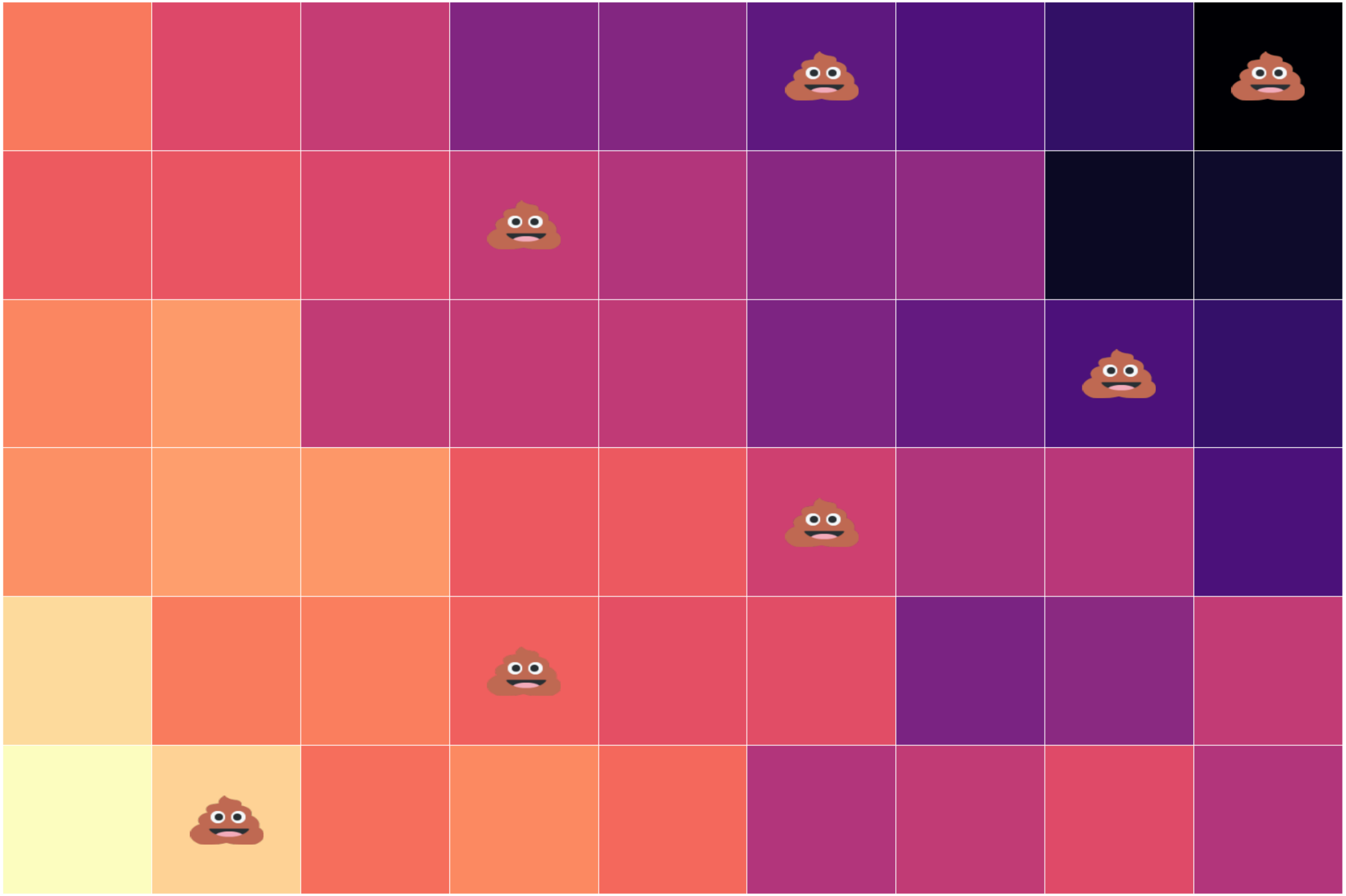

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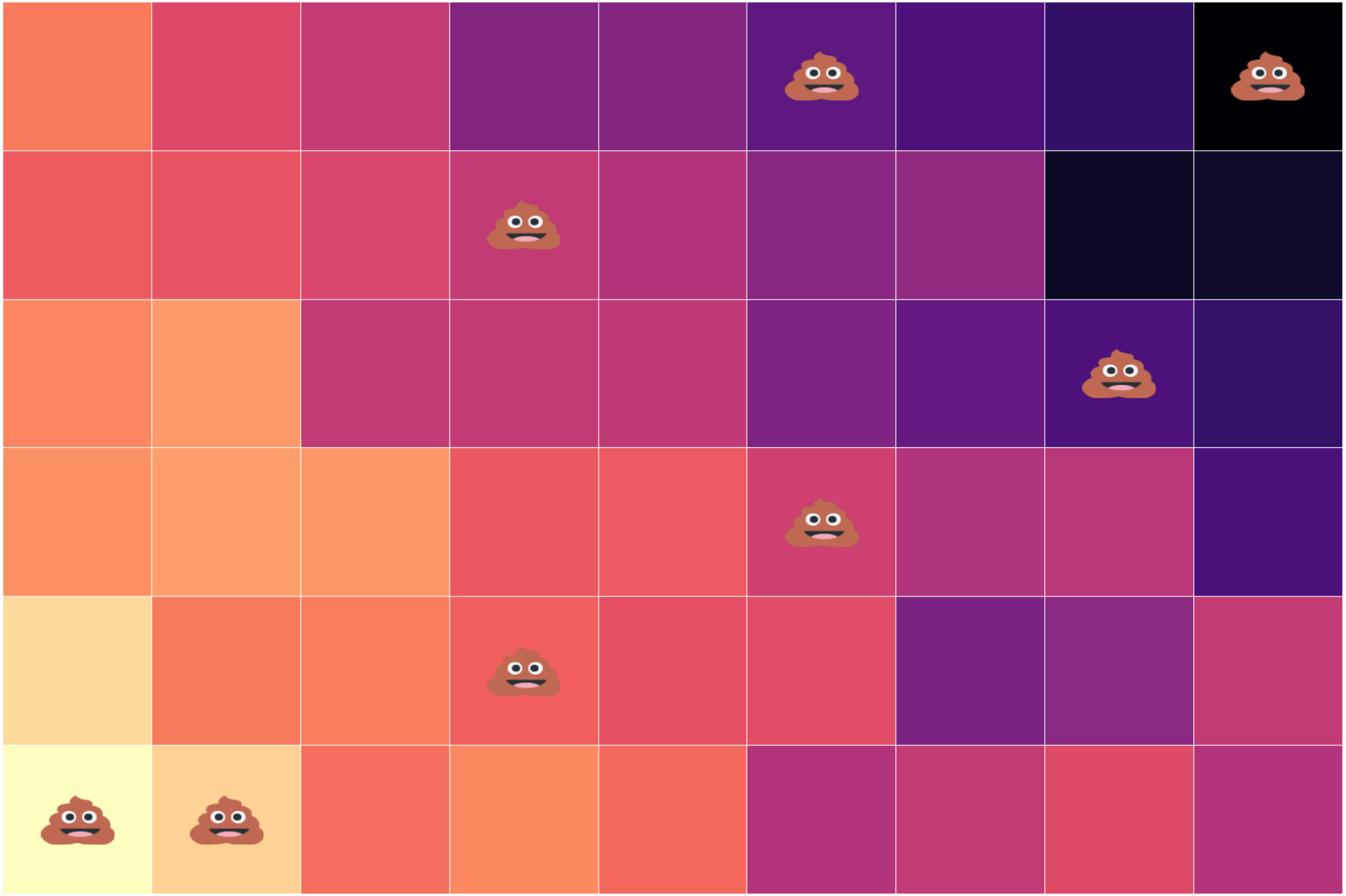

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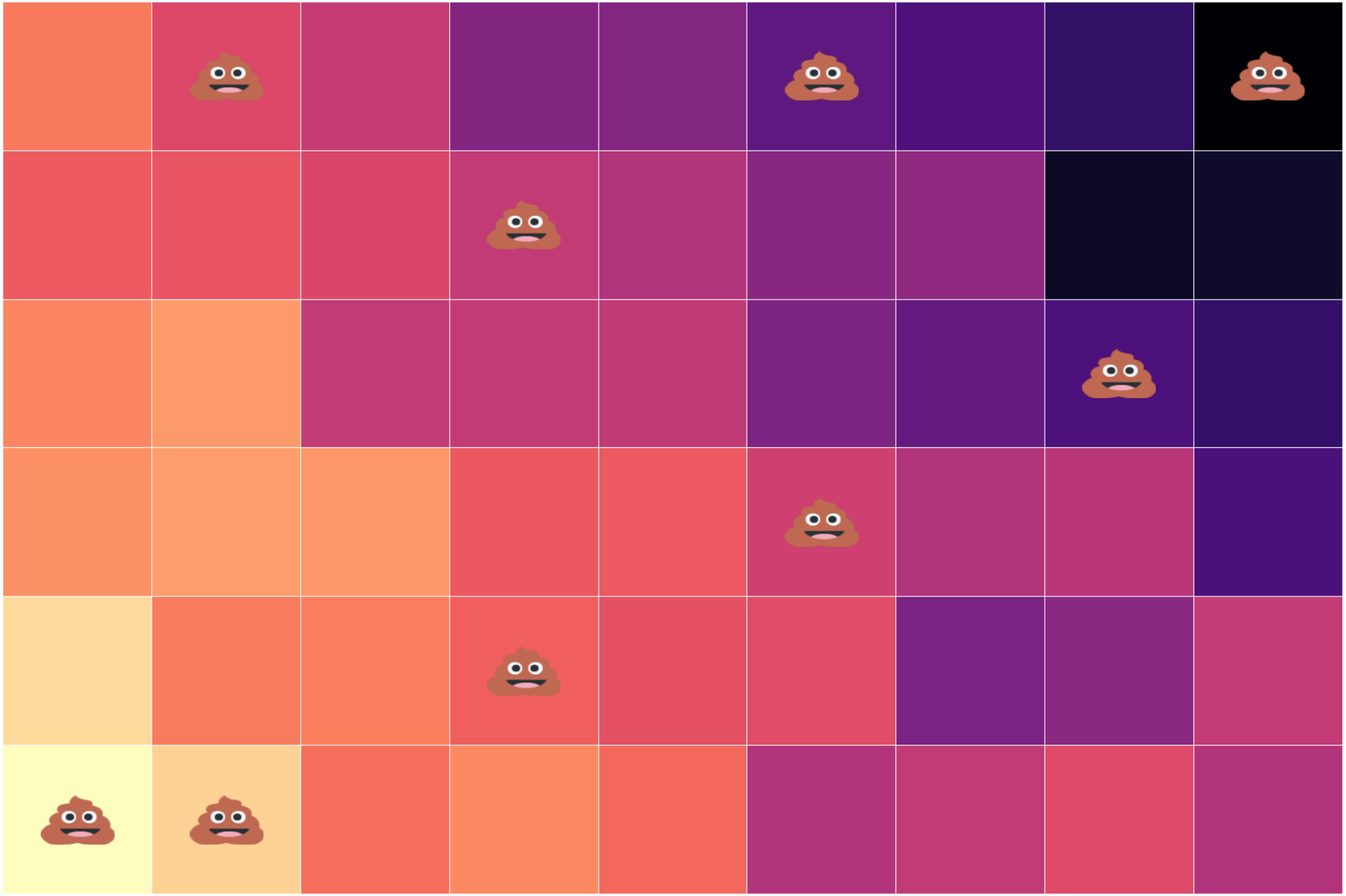

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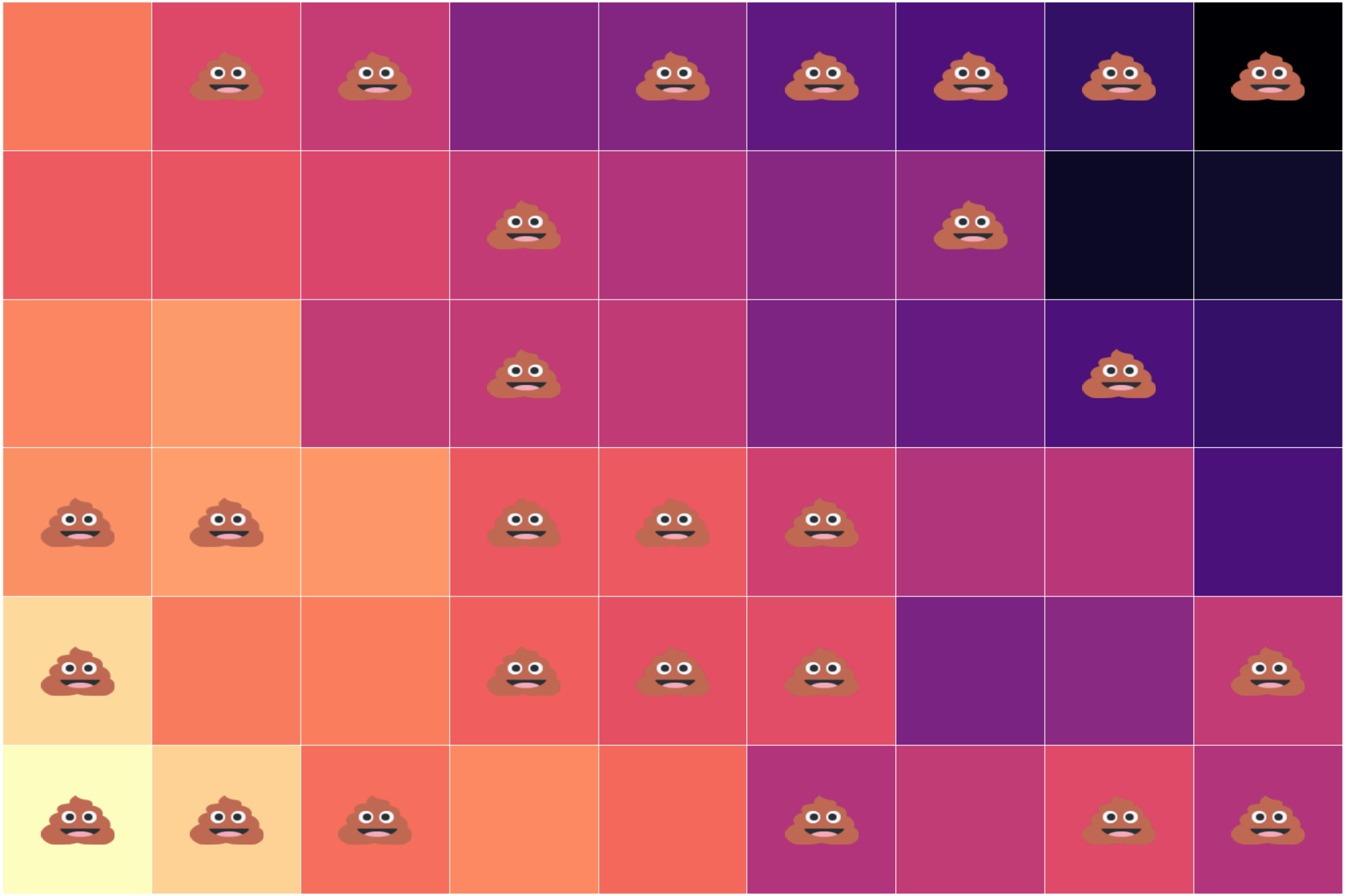

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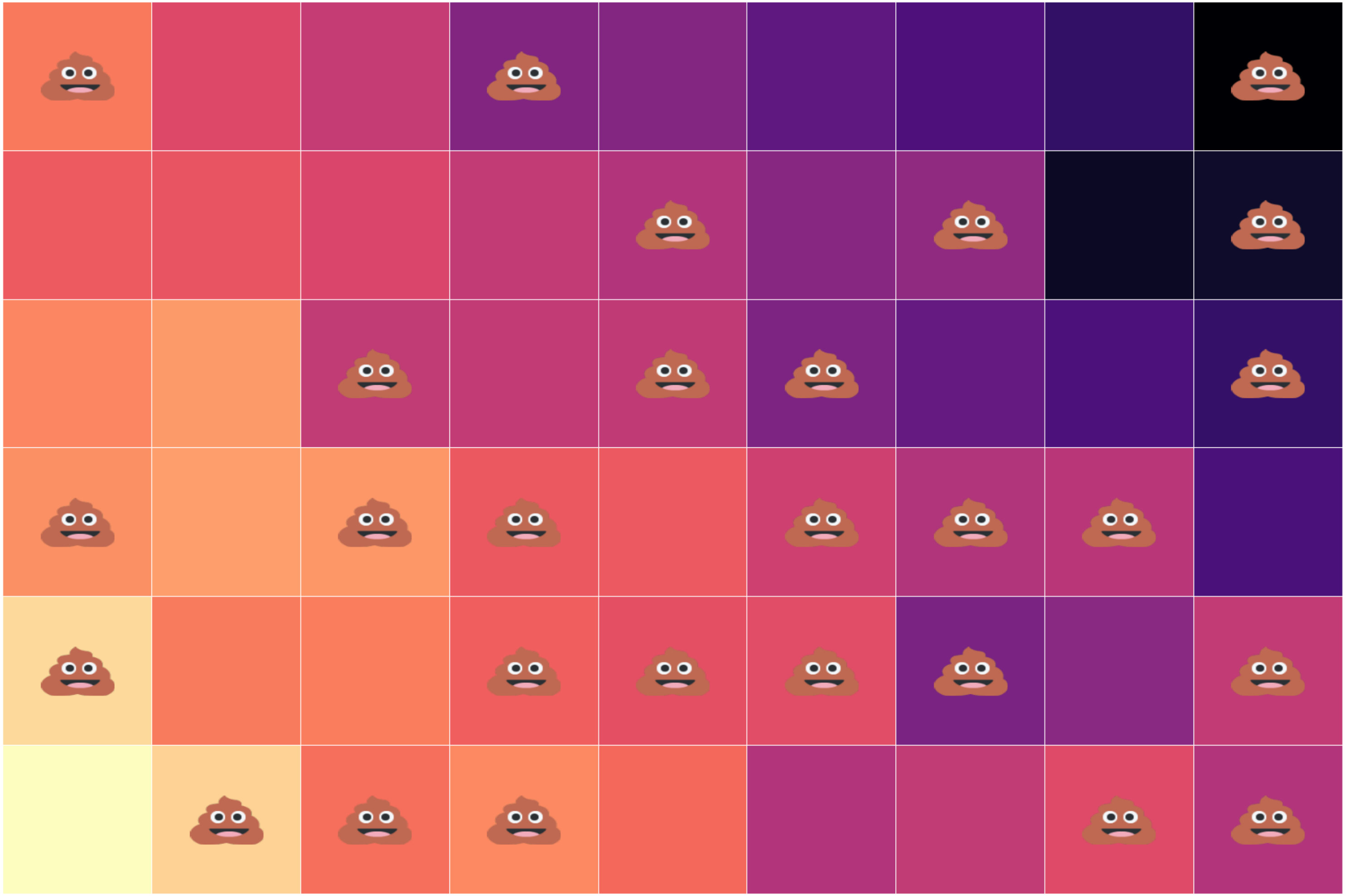

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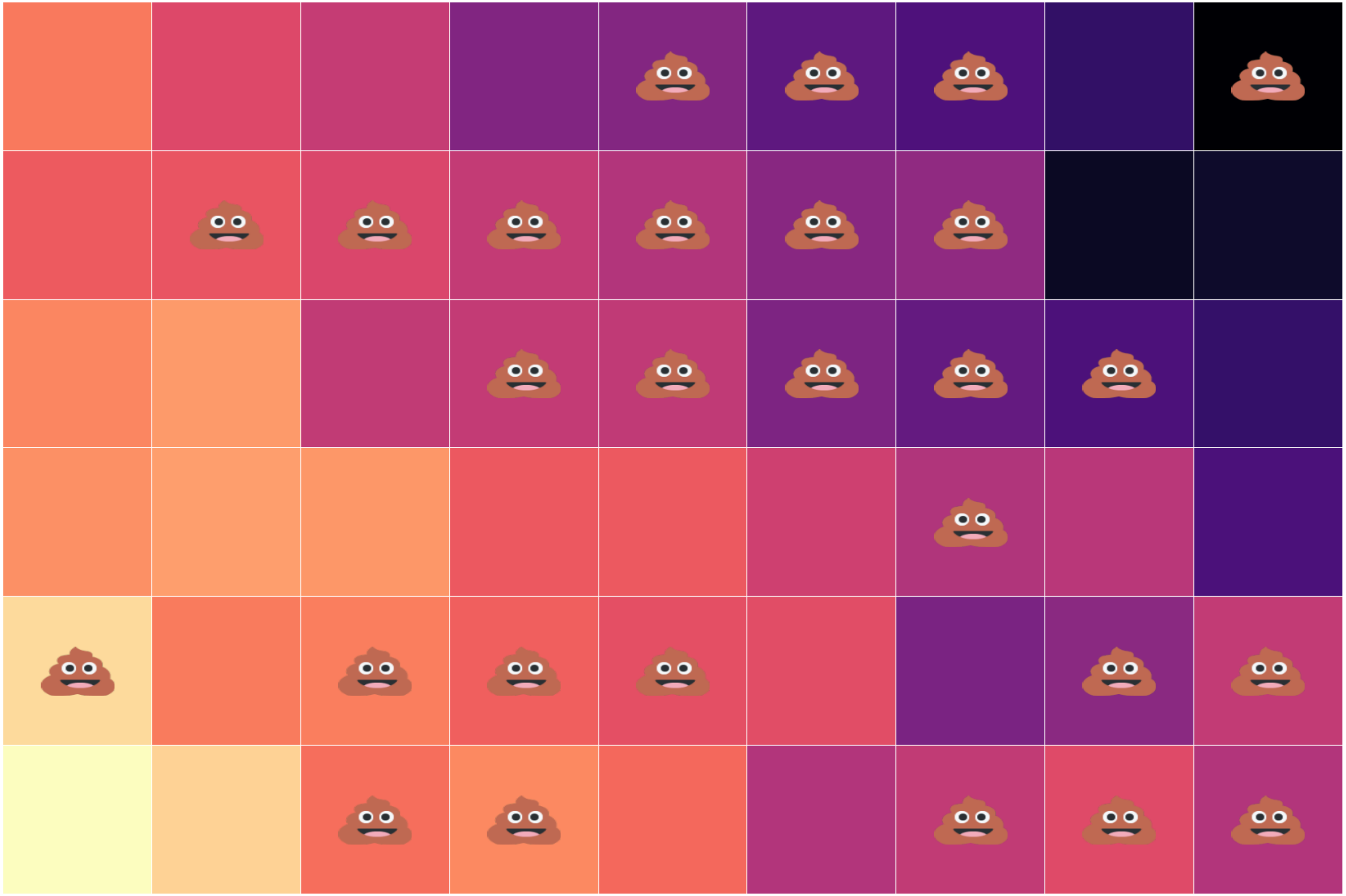

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We can estimate the **causal effect** of fertilizer on crop yield by comparing the average yield in the treatment group (💩) with the control group (no 💩).

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A: On average, **randomly assigning treatment should balance** trt. and control across the other dimensions that affect yield (soil, slope, water).

Causal Effects of Neighborhoods vs. Sorting

- Two very different explanations for variation in children's outcomes across areas

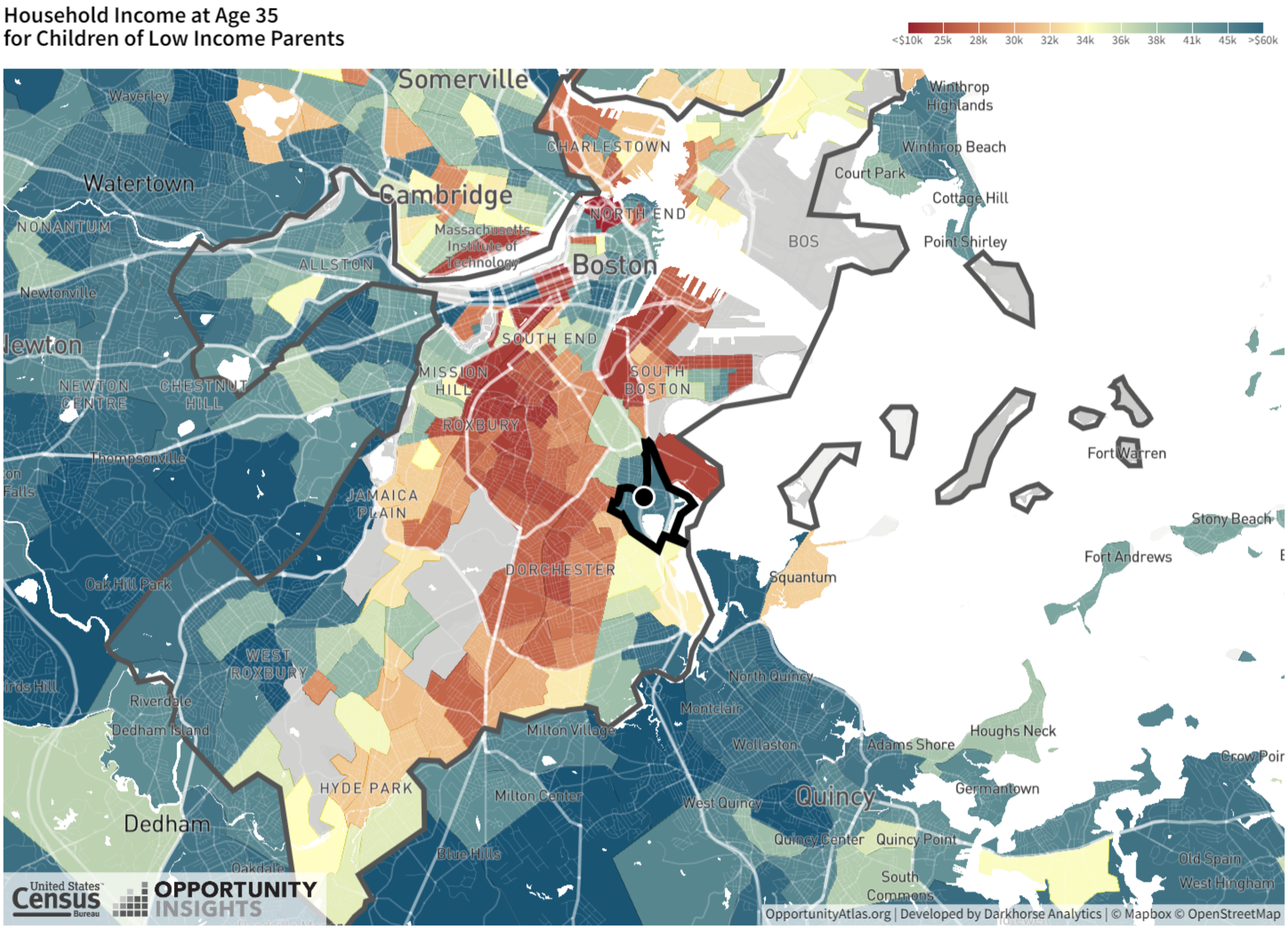
  1. Sorting: different people live in different places

  2. Causal effects: places have a causal effect on upward mobility for a given person

Identifying Causal Effects of Neighborhoods

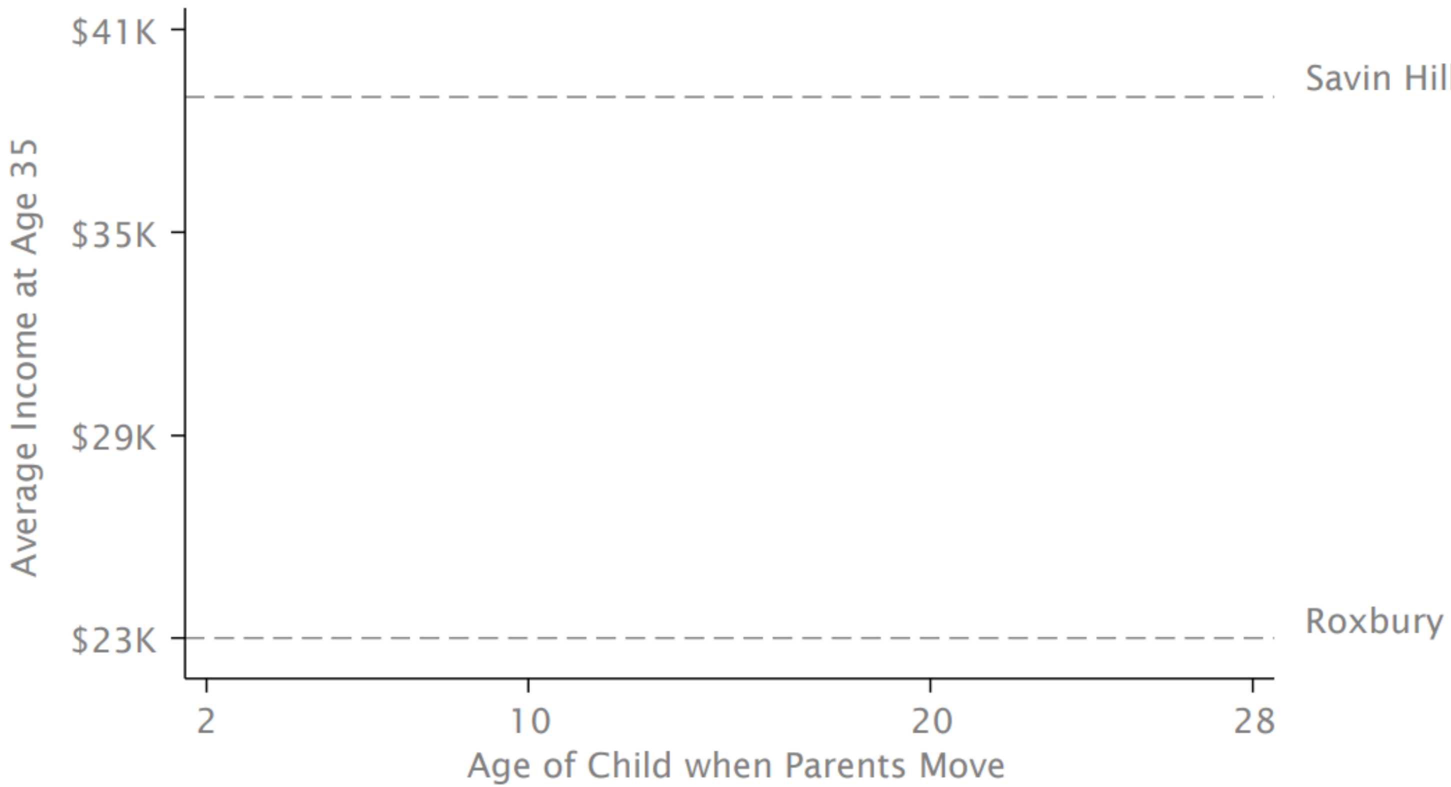
- Ideal experiment: randomly assign children to neighborhoods and compare outcomes in adulthood
  - Any issues with this?
- How can we approximate this same thing?
- Chetty and Hendren (2018) use a **quasi-experimental** design:
  - Sample of 3 million families that move across Census tracts
  - Key idea: exploit variation in the *age of child* when the family moves to identify causal effects of neighborhood

Moving a short distance in Boston



Opportunity Atlas of MA: Savin Hill outlined, Roxbury nextdoor.

Moving to a Higher Mobility Neighborhood and Income



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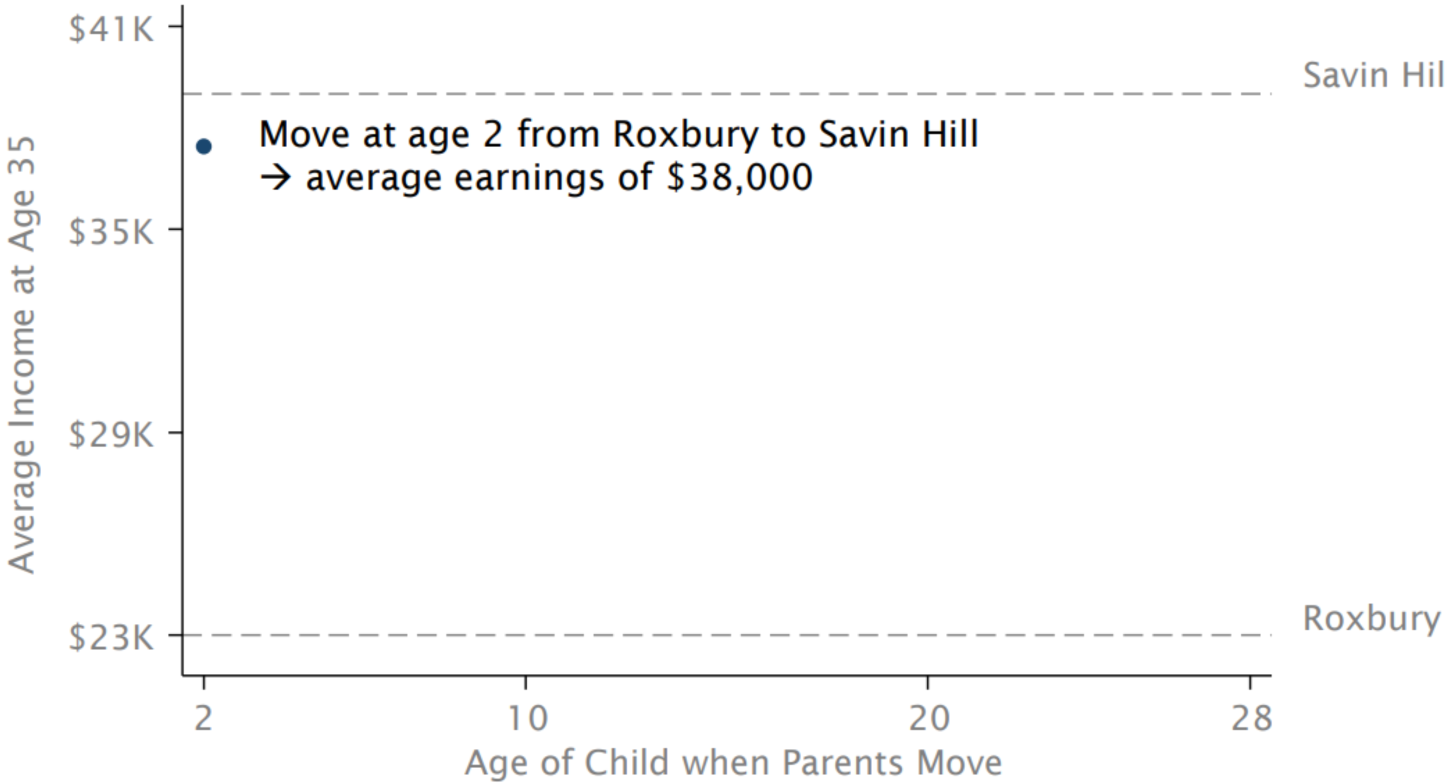

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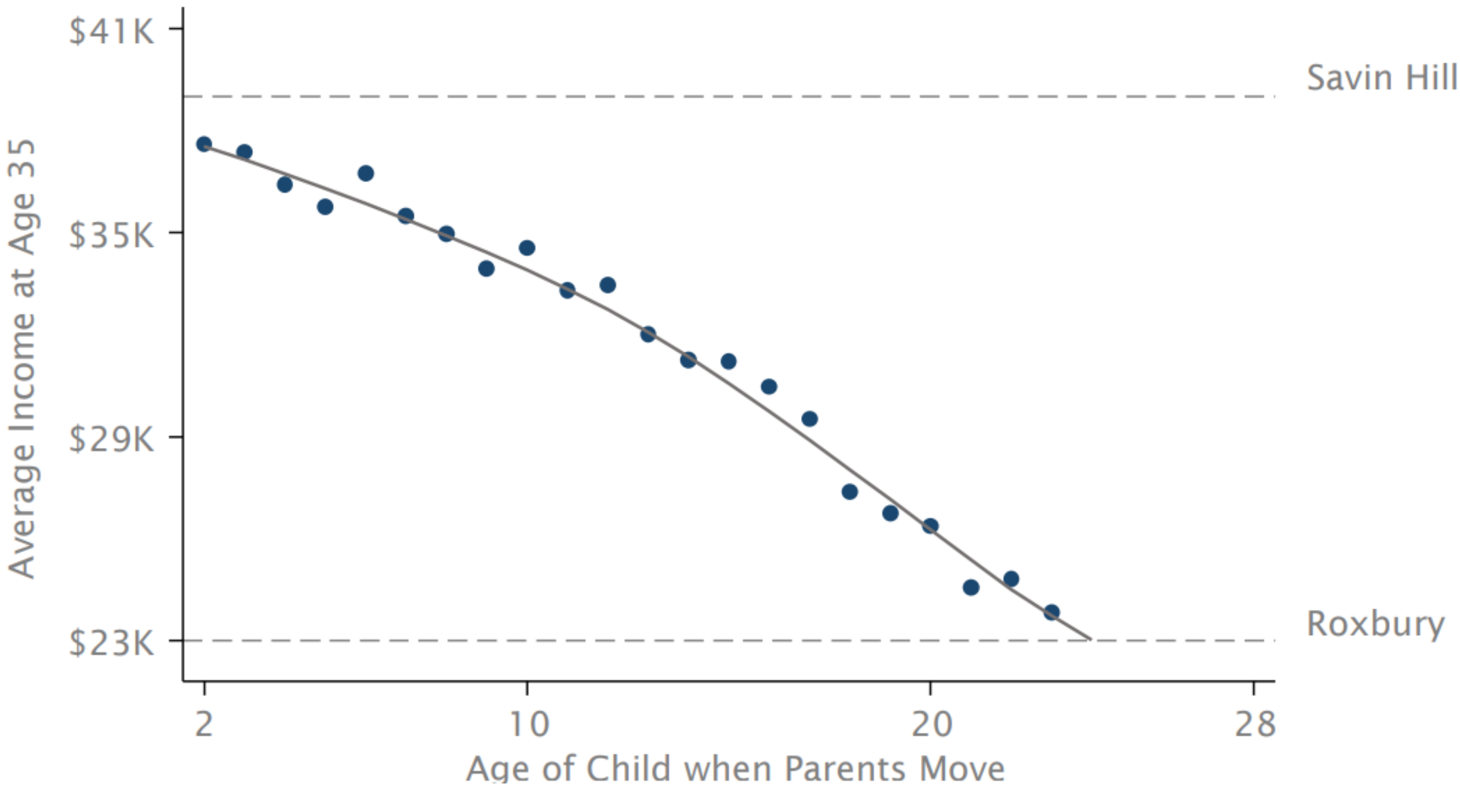

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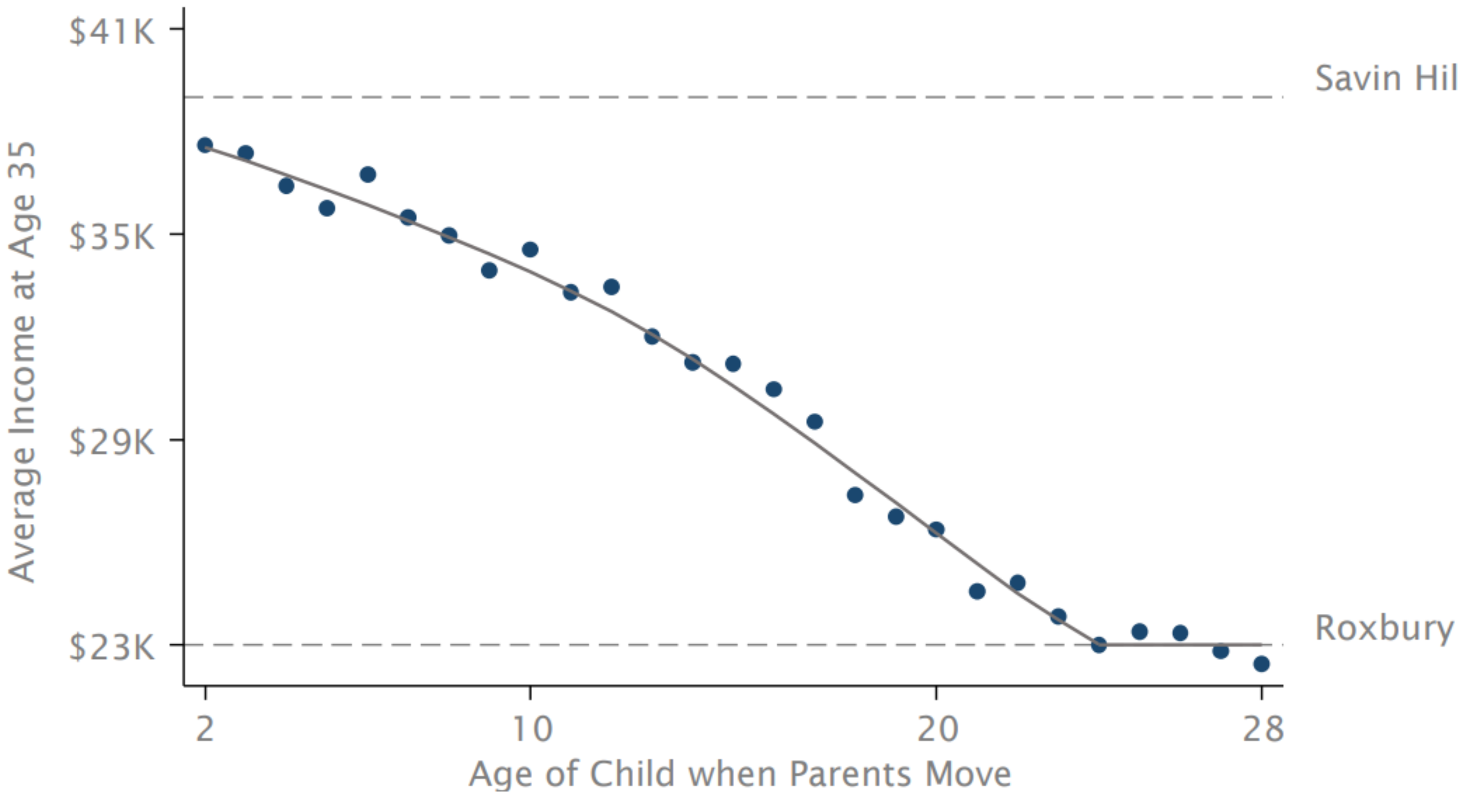

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- Key assumption: *timing* of moves between areas is unrelated to other determinants of a child's outcomes
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    1. Parents who move to good areas when their children ar young might be different from those who move later
    2. Moving may be related to other factors (e.g., change in parents' job) that affect children directly

"Testing" assumptions

- You cannot fully test assumptions, but you can look for evidence they are violated

- Two approaches to evaluate validity of timing of move assumption:

  1. Compare siblings' outcomes to control for family "fixed" effects

  2. Use differences in neighborhood effects across subgroups to implement "placebo" tests

  - Ex: some places (e.g. low-crime areas) have better outcomes for boys than girls

  - Move to place where boys have higher earnings --> son improves in proportion to exposure, but not daughter

- Conclude that ~2/3 of variation in upward mobility across areas is due to causal effects of neighborhoods

Next lecture: Fixed effects and difference-in-differences