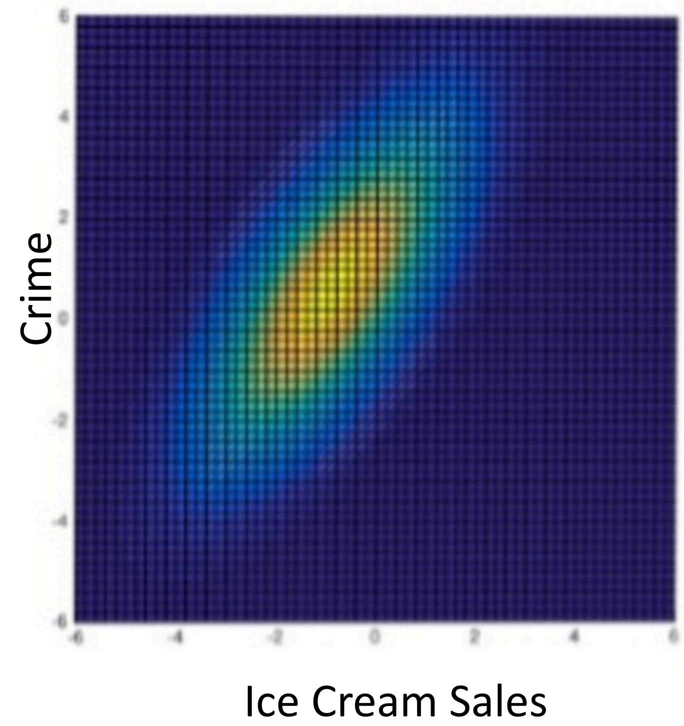
Associative Models

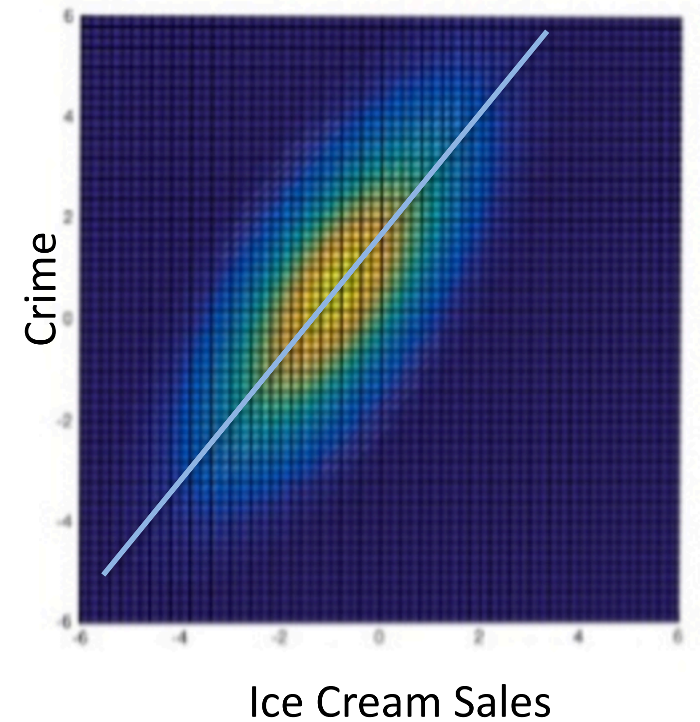
Causal versus Associative Models

- In this class, we want you to start thinking from a causal modeling perspective
  - Unfortunately, you will very commonly encounter omitted variables
  - Still, we want you to practice identifying those omitted variables and thinking about them.
  - Wooldridge follows a causal perspective from beginning to end.
- Useful to contrast causal modeling with associative modeling
  - What if you really don't care about causality?
  - You're purely interested in population averages.



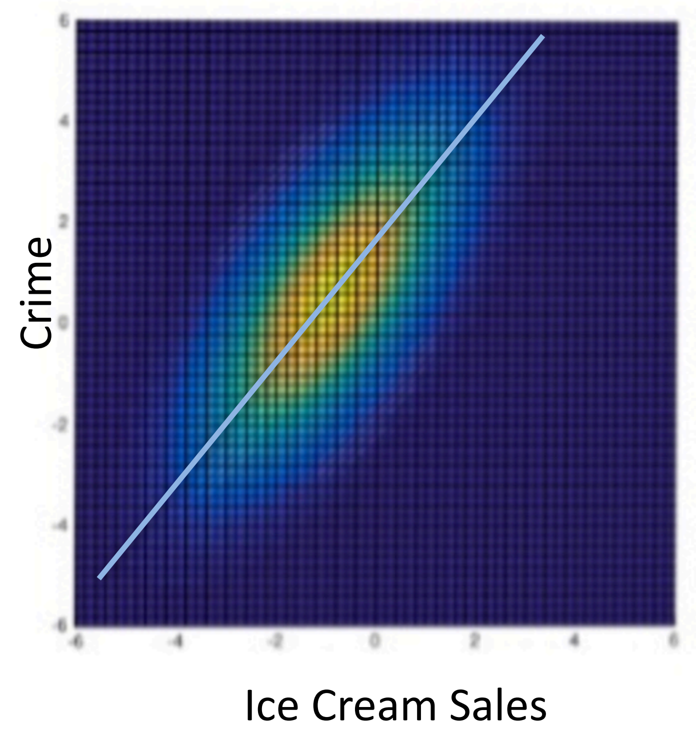
Building an Associative Model

- Let's see how to summarize a joint distribution without regard to causality.
- Choose β_0 and β_1 to minimize $E[\ (\text{crime} - \beta_0 - \beta_1\ \text{sales})^2\ ]$
  - This is similar to the way we derived the ols coefficients, here we have distances to the actual joint distribution, instead of a sample of data.
- This is what we call the **population best fit line.**
  - Now, I'm just going to define the error, $u = \text{crime} - \beta_0 - \beta_1\ \text{sales}$



Building an Associative Model

- If I do all that, it turns out that the best fit line always fulfills two properties:
  - $E(u) = 0$
  - $cov(x_i, u) = 0$
- You will recognize that the second property is exactly the exogeneity assumption.
- This means that OLS will estimate the population best fit line consistently.
  - This is important.
- The problem: we're redefined the errors to make this happen.
- But if you're a causal modeler, the errors aren't there for you to redefine.
  - They represent actual real world effects!
  - E.g. the effect of temperature on crime.



Building an Associative Model

Remember two things:

- OLS will consistently find the population best fit line.
- When we do causal modeling, the population best fit line isn't always the line we want.