Putting It All Together

Nick Eubank



1. Move from problems to questions	

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- 2. Recognize the type of question you are asking

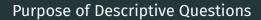
- 1. Move from problems to questions
- 2. Recognize the type of question you are asking
- 3. Understand how to choose the right tool to answer the question you are asking

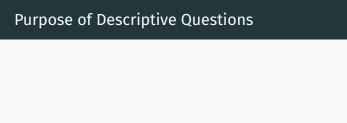
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Help identify areas for further investigation / prioritization

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- · Formally: PCA
- Informally: picking what variables to plot, summary statistics to include, etc.

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- Ensure what you present faithfully represents the patterns in the underlying data.
- You make sure to look for ethically-salient patterns (differences by race, ethnicity, gender, etc.)

df	df.head()						
	example1_x	example1_y	example2_x	example2_y	example3_x	example:	
0	32.331110	61.411101	51.203891	83.339777	55.993030	79.2772	
1	53.421463	26.186880	58.974470	85.499818	50.032254	79.013	
2	63.920202	30.832194	51.872073	85.829738	51.288459	82.4359	

48.179931

41.683200

85.045117

84.017941

51.170537

44.377915

79.1652

78.1646

3

4

70.289506

34.118830

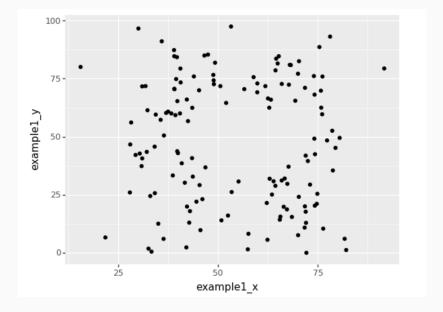
5 rows × 26 columns

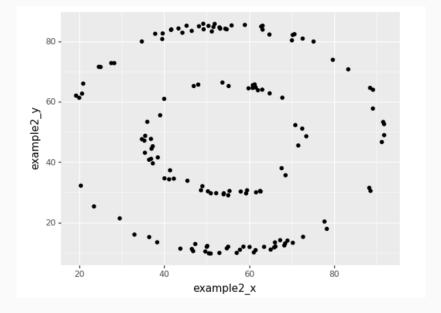
82.533649

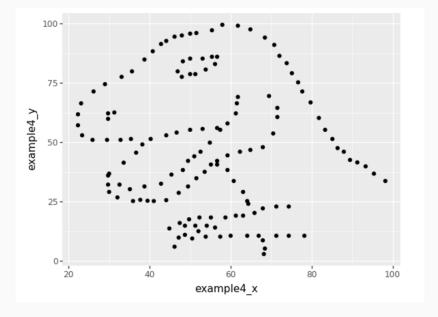
45.734551

DATA SET 1 Mean x: 54.27 Mean y: 47.83 Std Dev x: 16.77 Std Dev y: 26.94 Correlation: -0.06	DATA SET 2 Mean x: 54.27 Mean y: 47.83 Std Dev x: 16.77 Std Dev y: 26.94 Correlation: -0.07
DATA SET 3	DATA SET 4
Mean x: 54.27	Mean x: 54.26
Mean y: 47.84	Mean y: 47.83
Std Dev x: 16.76	Std Dev x: 16.77
Std Dev y: 26.93	Std Dev y: 26.94
Correlation: -0.07	Correlation: -0.06

D 4 T 4







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But if you had only reported those summary statistics, you would not have been faithfully representing the data.

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Purpose of Causal Questions

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ightarrow Generally asked in anticipation of undertaking some action.

Causal Inference



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- 2. When X is not present, we don't see Y

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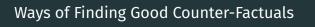
- 1. When X is present, we see Y
- 2. When X is not present, we don't see Y

To know if X causes Y, we would have to see both a world with X, and a world without X, and that's impossible.

Because we can never see both a world with X, and a world without X,

Because we can never see both a world with X, and a world without X, we need to find settings that approximate one of these states of the world.

Counter-factuals: settings with same potential outcomes, but different realizations of treatment.



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4. Differences-in-Differences

Adjust for pre-existing baseline differences \rightarrow same potential outcomes in trends

Assumptions

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Fundamentally unverifiable, so evaluation requires critical thinking!

Applies both to your projects, but also anything else you read!

Validity

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- External Validity: Do I think these causal effects would generalize?

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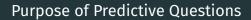
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 when certain assumptions are met, correlation does imply causation.

And now you know those assumptions and how to evaluate them!

Types of Questions

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Purpose of Predictive Questions

 Anticipate outcomes for subsequent intervention (e.g. high value customers, expensive patients)
 Supervised Machine Learning

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- Anticipate outcomes for subsequent intervention (e.g. high value customers, expensive patients)
 Supervised Machine Learning
- Predict result of your actions

 (e.g. advertisements, sales, web design)
 Causal inference tools

 Parameter values beyond our training data Out-of-sample extrapolations

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- 2. New settings
 Different places, different products
- 3. Different dynamics
 Adversarial users

Bias

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- · What constitutes bias is context dependent
- Bias doesn't come from ML models malfunctioning If training data biased, ML is designed to replicate!
- Interpretable models can help make bias visible
 Often with no performance cost, and benefits to maintainability

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- articulate a question whose answer will help address their need,
- 2. depending on the type of question, you can reach for the right tool,
- 3. know the types of conceptual problems to bear in mind when answering the question.