GRAPHS
The Next Frontier of GenAI Explainability

Michelle Yi & Amy Hodler

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Michelle Yi

Applied AI, Artist, Speaker
Board Member, Women in Data
Michelle@generationship.ai

Amy Hodler

Graph Evangelist, Author, Speaker
Founder of GraphGeeks
Amy@GraphGeeks.org

Today

Background

Terminology
Landscape

Hands On

Hypothesis & Tools
Collab Notebook

Tips

Learnings
Resources

Questions

What did
we miss?

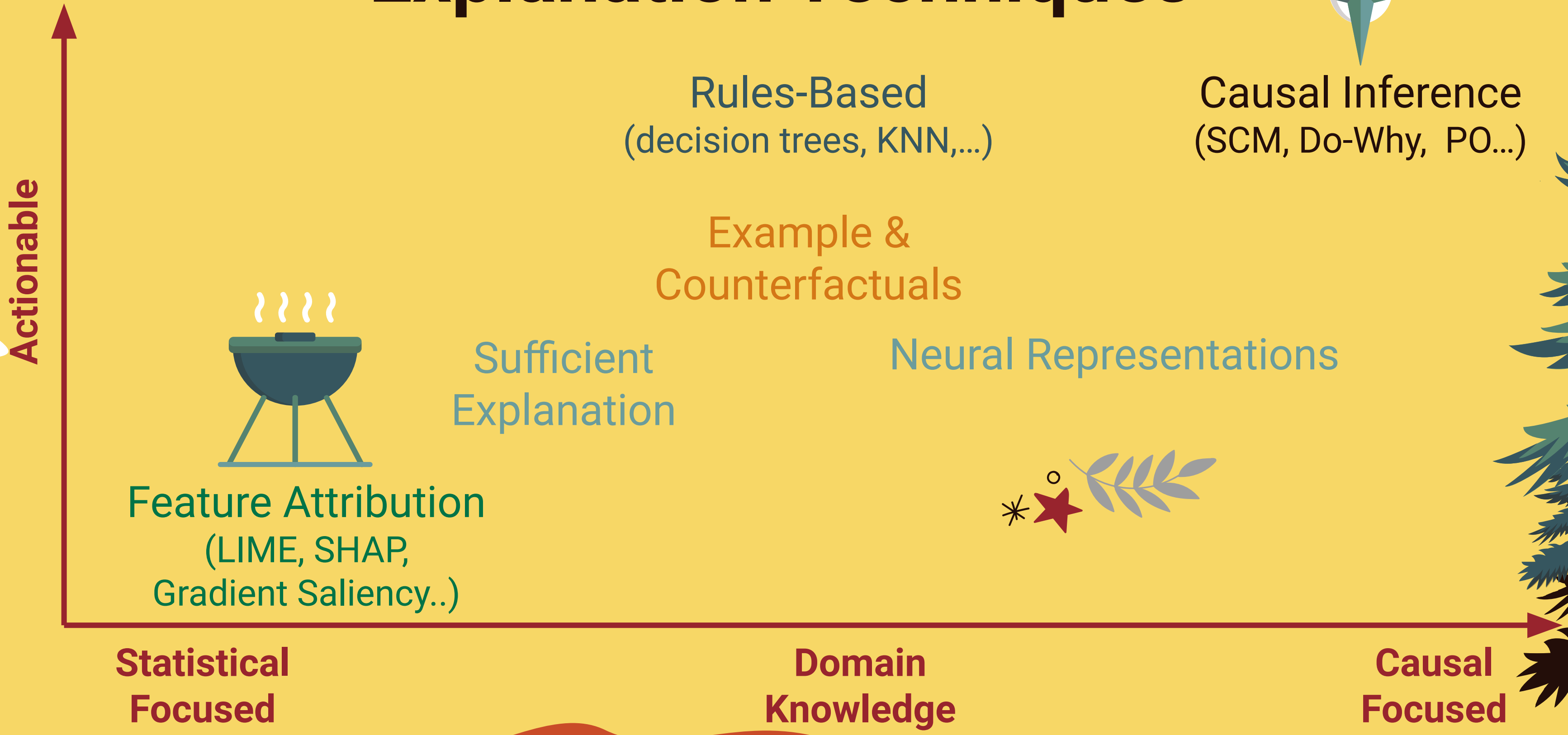
Quick Review

Explainable AI (XAI) Today

Why is this model giving me this prediction?

- Uncovers strong co-occurrences in data
- Good at finding feasible actions that would change a prediction
- Quick diagnosis of problems in data
- Not great with data drift
- It doesn’t actually explain anything

Explanation Techniques

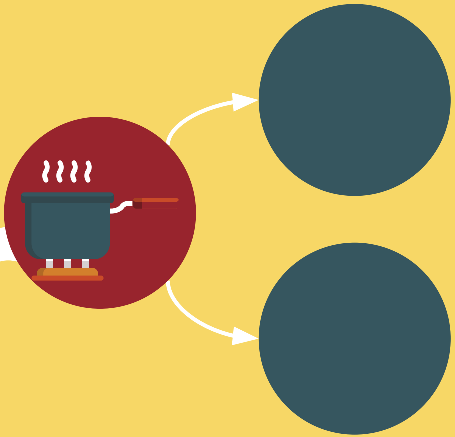


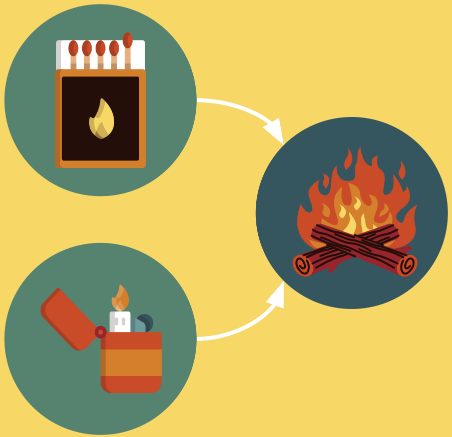
Causality: Another Layer of Explainability

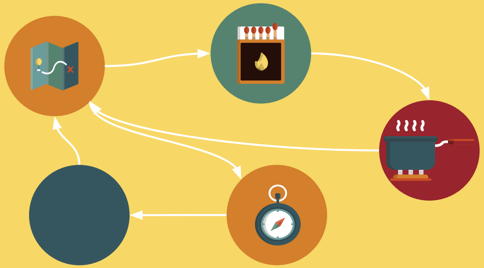
Why does this outcome happen?

- Finds how a change in one variable causes a change in another
- Causality is inferred using the difference between outcomes

Different Types



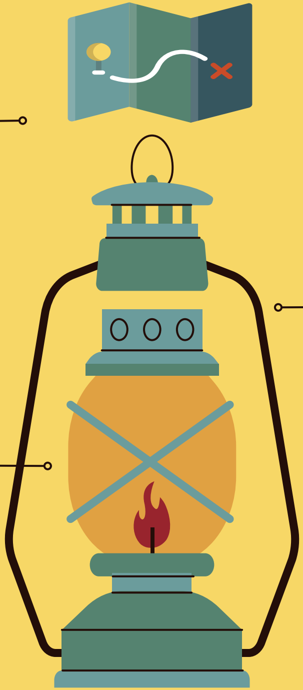




We Need Causal Inference

Answering Why

What changes outcomes?
Overall effect of intervention?
Inherent explainability



Better Results

Improve accuracy
More actionable results
Supports decision intelligence

Detecting Problems

Uncover poor associations
Is more data needed?
Highlight biased features

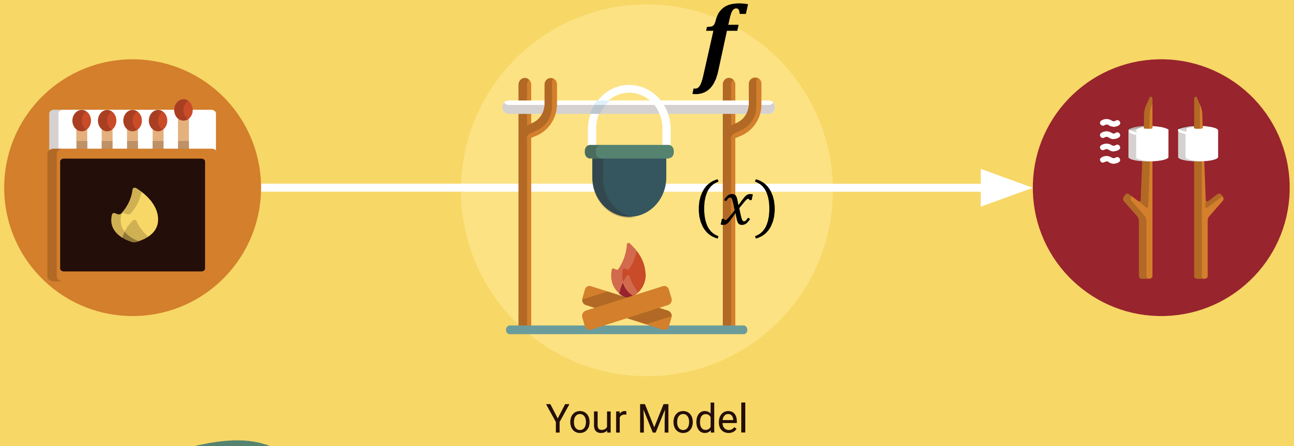
Human-in-the-Loop

Closest to human inference
Integrates domain knowledge
Emphasize human action

When To Use Causality vs Machine Learning?

Causality when your actions will impact the variables

ML when your actions depend on the outcome



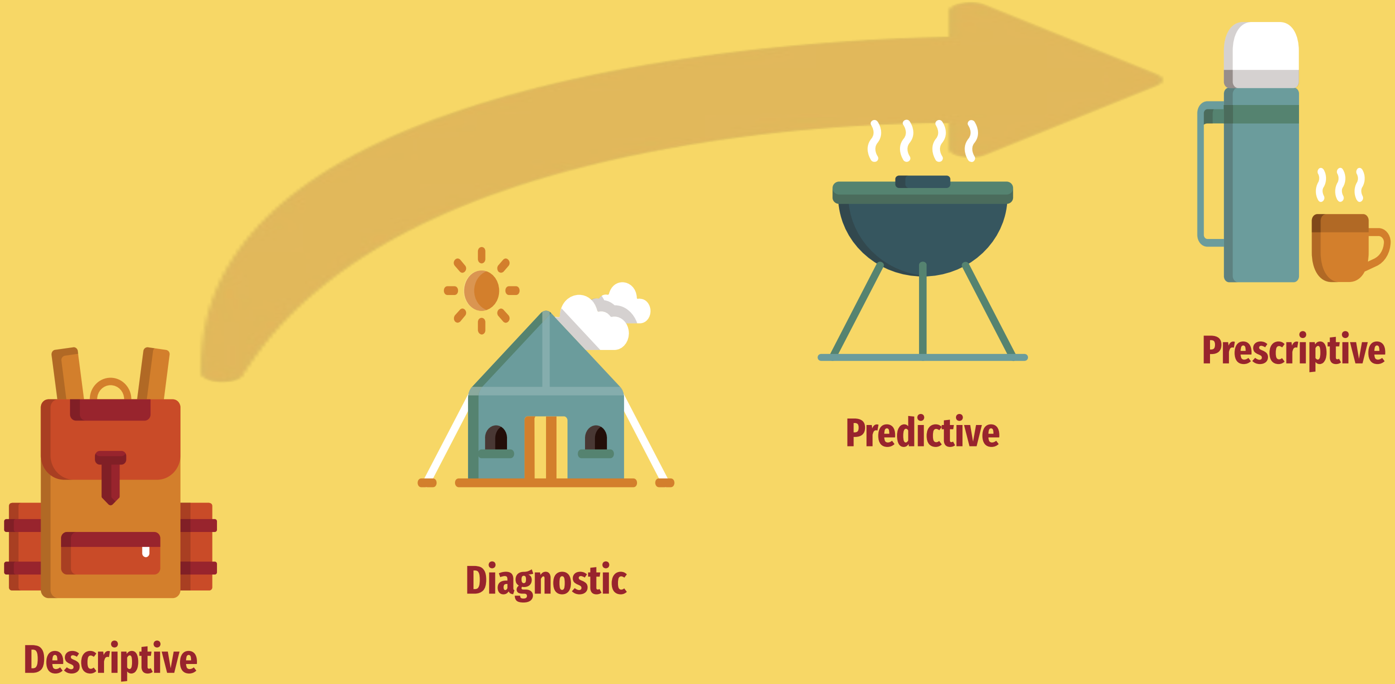
When To Use Causality vs Machine Learning?

Causality when y… ns will impact th…

ML … ur actions depend on … outcome

Your Model

Is Causality a Progression?



Causal + Statistical Approaches Are Complementary

Statistical Analysis	Casual Analysis	Statistical ML	Casual Inference

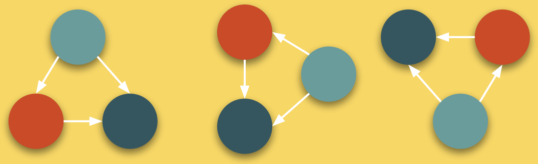
Descriptive	Diagnostic	Predictive	Prescriptive

Putting it all together

Breakthrough and Turning Point

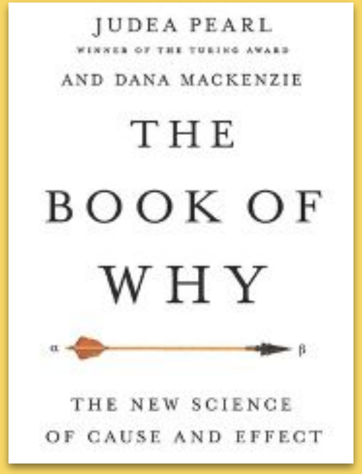
Accessible arguments on causation

Using graphs to model relationships changed the way we think about interventional questions



Creation of a *do*-calculus provided a mathematical way to calculate causal strength of *"doing"* something

Megapost summary:
https://engineeringideas.substack.com/p/megapost-about-causality-the-summary



$P(Y|X)$

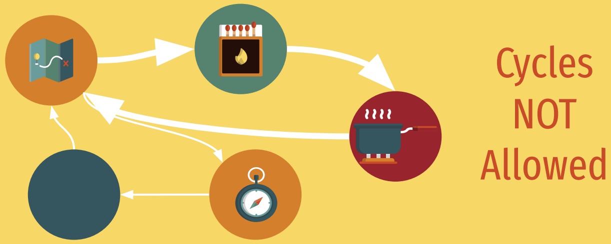
to

$P(Y|do(X))$

Causal Graphs as a Unifying Model

Directed Acyclic Graphs (**DAG**) ONLY
No feedback loops: no intervention can cause itself!

Arrow direction illustrates causal influence



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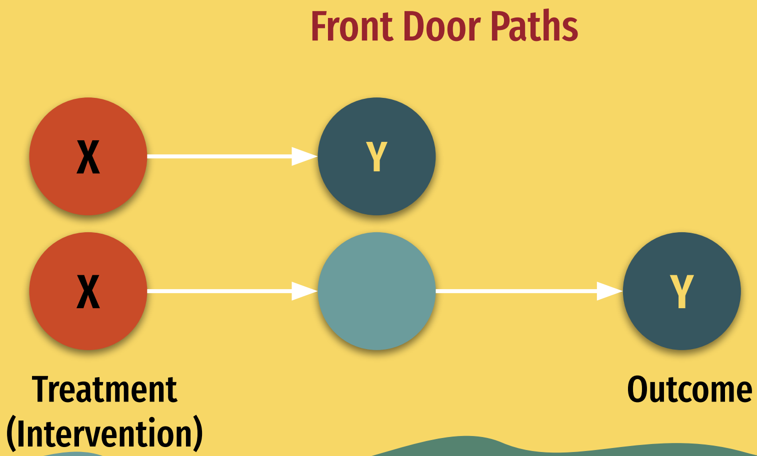

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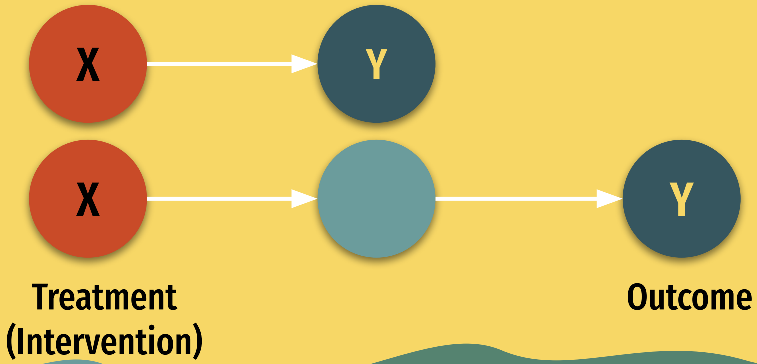
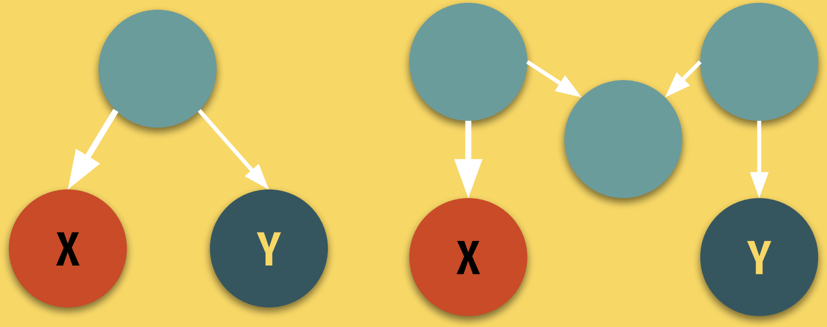
Front Door Paths

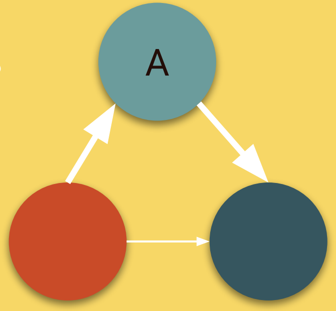


Back Door Paths

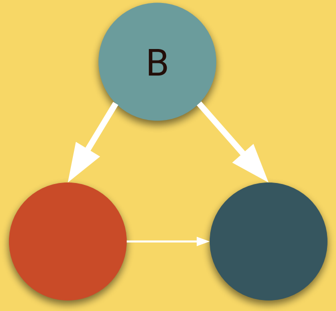


Causal Graphs as a Unifying Model

Basic structures

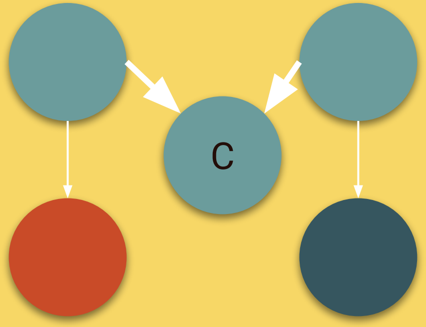


A mediator



B confounder

Often Controlled
if pointing to
treatment & outcome

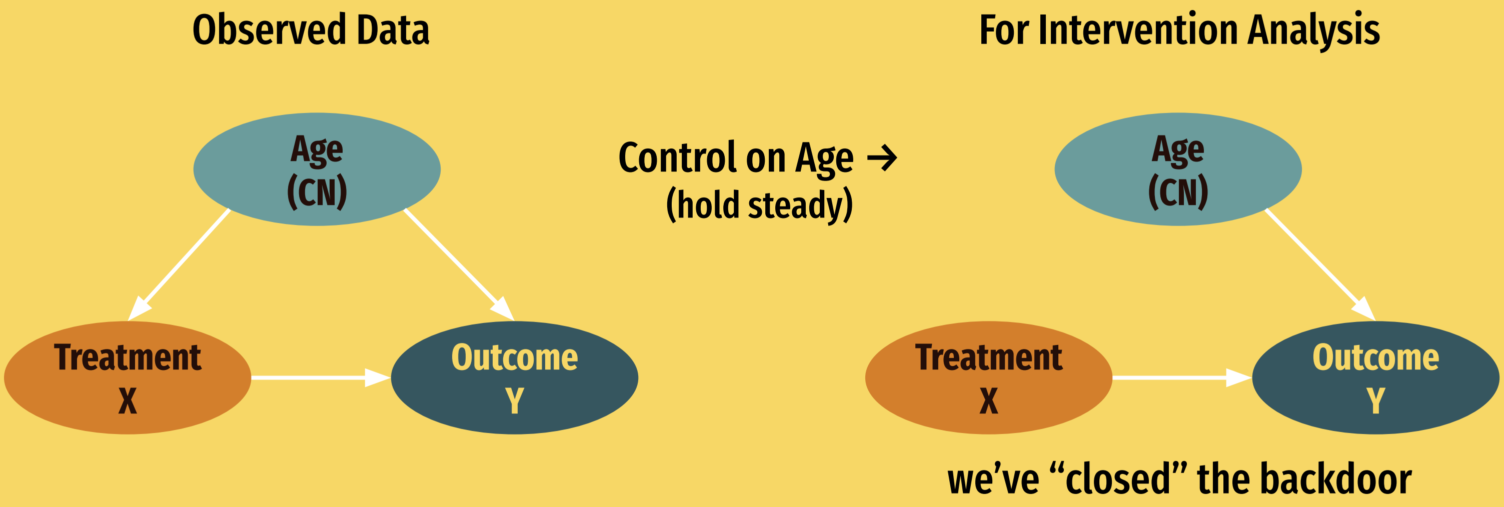


C collider

Avoid Controlling
As it introduces correlations
that require further controls

Confounders - Back Door Adjustments

Control Node (CN) Criteria: 1) CN must not be a child of the treatment your estimating and 2) CN must block the path between treatment and outcome.

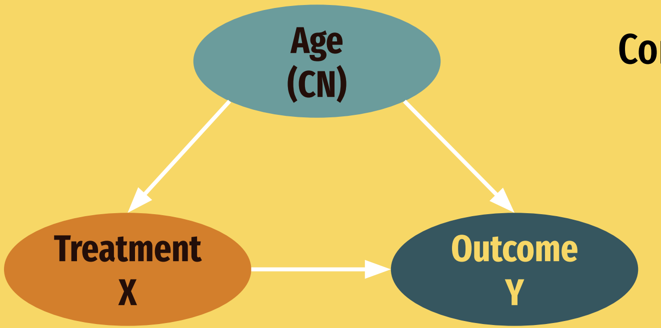


do-calculus

$P(Y|do(X)) - P(Y)$

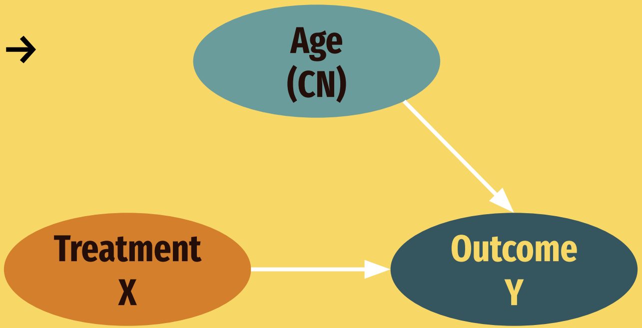
Replaces probability formulas with constant variables to simulate the change in a controlled manner

Interventions & counterfactuals are represented by the operator, **do(x)**, which "erases" the function while keeping the rest of the model unchanged



$P[Y|X]$

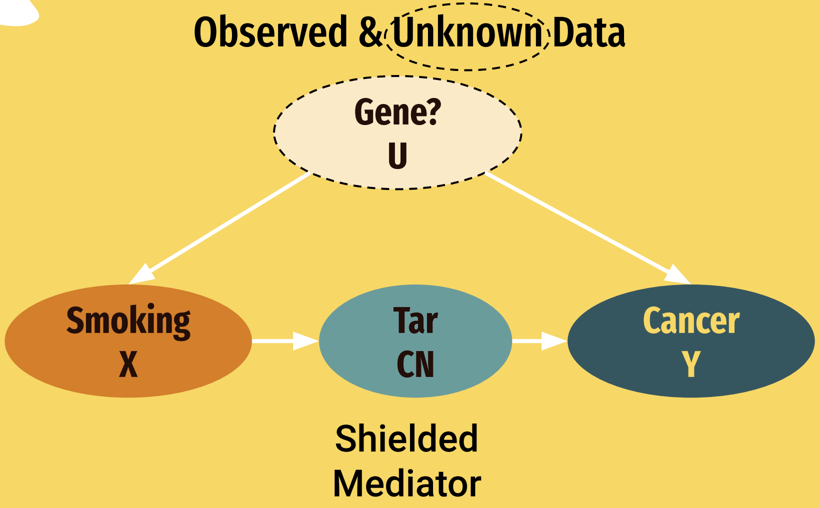
Control on Age →
(hold steady)

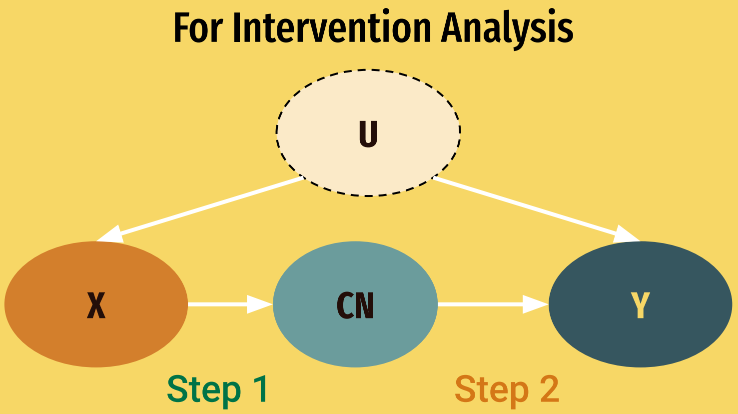


$P[Y|\mathbf{do(X)}]$

Front Door Adjustments (if you can't do a back door)

Control Node (CN) Criteria: 1) CN must intercept all directed paths from treatment to outcome 2) no unblocked backdoor path from treatment to CN and 3) all backdoor paths from CN to outcome are blocked by the treatment.





Step 3 - Sum over Mediator and chain together

$$\sum_z P[Z|do(X)]\, P[Y|do(Z)]$$

DoWhy for Causal Inference

Model causal mechanisms	**Identify** target estimand	**Estimate** causal effect	**Refute** estimate

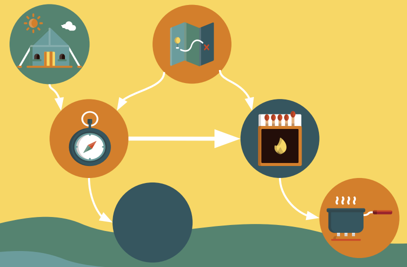
Input Data
Domain Knowledge

Causal Graphs and
do-calculus

Statistical and
Potential Outcomes

Sensitivity and
Robustness Checks

Formula for describing
(estimating) the impact!



PyWhy – Brings It All Together

LLM API

LLM API

LLM API

Model	Identify	Estimate	Refute
DoWhy	**DoWhy**	**DoWhy (basic)**	**DoWhy**
Casual Learn (discovery & investigation)		EconML (deeper)	

ShowWhy 😢😢😢

CausalML (deeper)

Today's Scenario

Camping Supply Vendor Wants to Increase Sales

We have lots of data and experience…and even more opinions!

Branded Designs!

Get on Shelves Sooner!

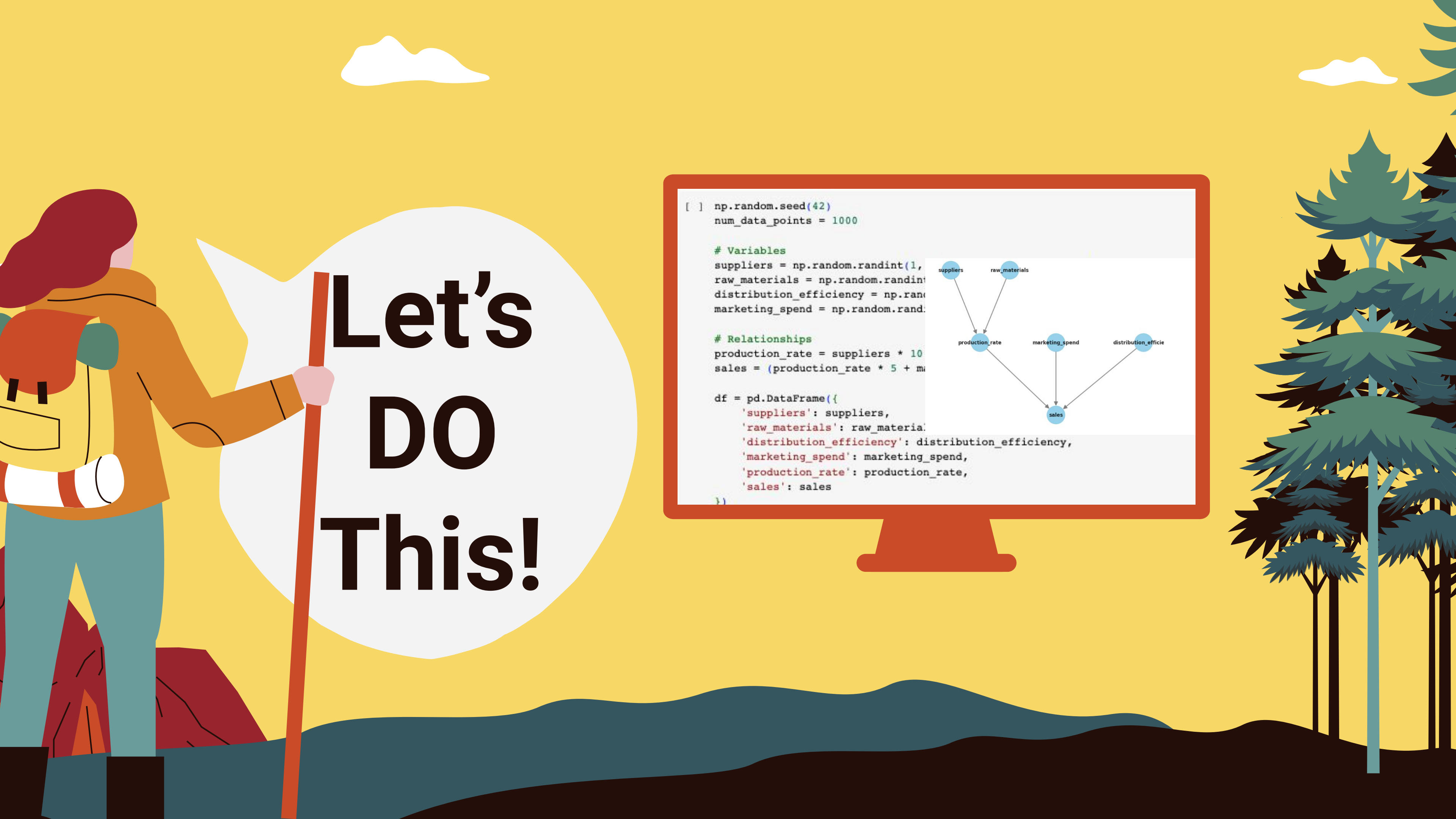
Let’s Ask an LLM!

Images from: https://www.backcountry.com/

We're Data Scientists: We Can Help Settle the Argument

What if we changed where we focus our resources this year?
What changes have the most impact to sales?

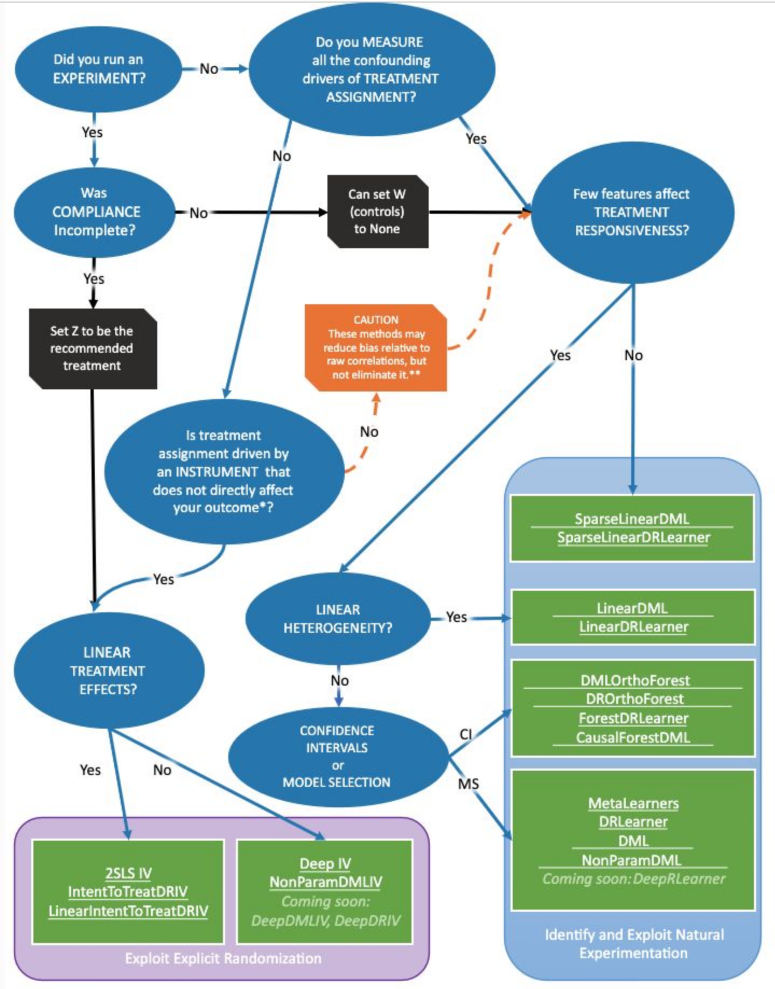
Model	Identify	Estimate	Refute
Costume Supplier (branded/not) Costume variety Production rate Material (quality) Pricing Sales (output)	Use ATE (ave. treatment effect) to measure the effect of these variables on sales. SME input → Updates	Find the causal strength of interventions on sales using linear regression. Then use EconML for Causal Forest	Test robustness of findings by adding randomness, checking new vs estimated effect and the p values. Present Results!


Let's
DO
This!
[ ] np.random.seed(42)
num_data_points = 1000
# Variables
suppliers = np.random.randint(1,
raw_materials = np.random.randin
distribution_efficiency = np.ran
marketing_spend = np.random.rand
# Relationships
production_rate = suppliers * 10
sales = (production_rate * 5 +
df = pd.DataFrame({
'suppliers': suppliers,
'raw_materials': raw_materia
'distribution_efficiency': distribution_efficiency,
'marketing_spend': marketing_spend,
'production_rate': production_rate,
'sales': sales
suppliers
raw_materials
production_rate
marketing_spend
sales

https://github.com/yulleyi/odsc_east_2024_graphs_explainability

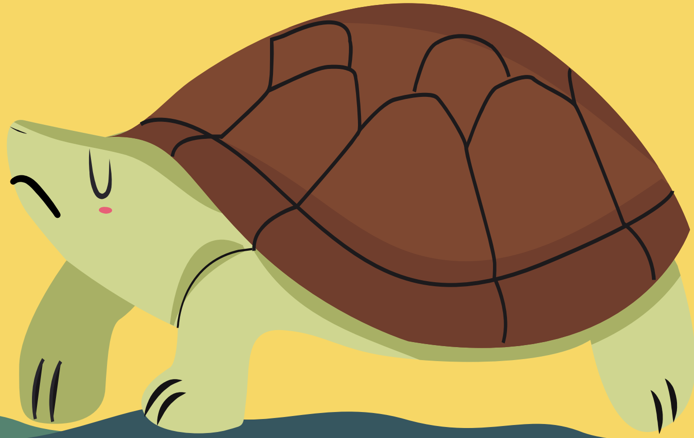
copy or download the notebook

What We Learned

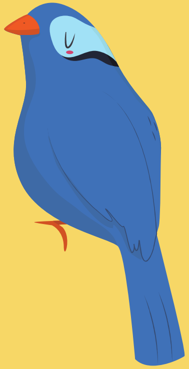


Um…Yeah, This Isn't Helpful

(maybe for more advanced?)



Start Simple and Add Layers!



DoWhy

- Find the strength of different relationships
- Simple models (linear regression)
- Limited to averages, not a lot of tuning

EconML

- Play with other models (🌲🌲, DML, +)
- More & deeper controls, cross validation
- No robustness testing → So fit the log back in DoWhy

Causality Limitations / Considerations

Missing Data

Missing confounders or other data left out can cause spurious correlations

One Outcome at a Time

Can’t observe someone having the treatment and not having a treatment in one pass

Domain Expertise

Need to confirm your causal links, possible missing data, and confounder assumptions

Graph Model

No auto-magical creation, use your SME!
Causal Learn can help

Final Tips and Resources

- Don’t be intimated, the math and implementations are done for you!
- Finding good data is a challenge but DoWhy has some curated data
  - Synthetic Healthcare Data Example - Synthea
- There are multiple ways to do things, just try it out

Slides and Notebook - **https://github.com/yulleyi/odsc_east_2024_graphs_explainability**
Causal Resources

- PyWhy pywhy.org/ (with links to DoWhy and EconML)
- Another causal inference guide tinyurl.com/5e4auenh
- Discord community is very helpful! tinyurl.com/365d7e37

GraphGeeks.org

New Graph Community: GraphGeeks.org &
Discord tinyurl.com/hrjanc3p

Real Use Cases??

tinyurl.com/48dk6bmm

Questions?

Thank You

Patrick Blöbaum

Jason Grafft

Michelle@generationship.ai

Amy@GraphGeeks.org

Amit Sharma, Emre Kiciman. DoWhy: An End-to-End Library for Causal Inference. 2020. https://arxiv.org/abs/2011.04216

Patrick Blöbaum, Peter Götz, Kailash Budhathoki, Atalanti A. Mastakouri, Dominik Janzing. DoWhy-GCM: An extension of DoWhy for causal inference in graphical causal models. 2022. https://arxiv.org/abs/2206.06821

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