

Automated Social Science: Language Models as Scientist & Subjects

Benjamin S. Manning^{1*}

Kehang Zhu^{2*}

John J. Horton^{1, 3}

¹MIT, ²Harvard, ³NBER

*Equal Contribution

Literal
crap



What do we think of this idea
of “Automated Social Science”
(as interpreted by the reader)?



Best
thing
ever

Literal
crap

What do we think of this idea
of “Automated Social Science”
(as interpreted by the reader)?

Best
thing
ever



Judea Pearl ✓
@yudapearl

Fascinating and ambitious paper, but I couldn't go beyond these two statements:

"We know that:

1. Machine learning can be used for automated hypothesis generation (e.g., 1; 2)
2. Large Language Models (LLMs) can simulate human subjects for testing hypotheses (e.g., 1; 2; 3; 4, and many others)

Do we really know that?

Literal
crap

What do we think of this idea
of “Automated Social Science”
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Best
thing
ever



Ethan Mollick
@emollick

This paper suggests a potential massive revolution in social science.

It develops a system where LLMs automatically generate scientific hypotheses, and then test those hypotheses with simulated AI human agents. Even at this early stage, it works surprisingly well. Exciting atuff



tylercower 🔵 @tylercower · Apr 20

There is a very good chance it goes down as one of the important papers of our time.



4



172



Literal
crap

What do we think of this idea
of “Automated Social Science”
(as interpreted by the reader)?

Best
thing
ever



M.J. Crockett @mollycrockett

the enshittification of everything 🤔

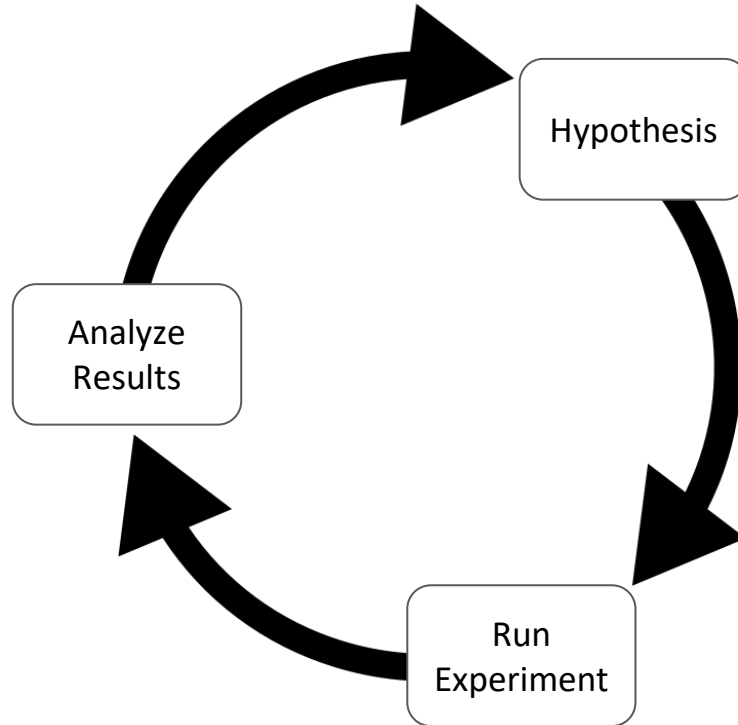


saudade 🇸🇦
@clairvoidn

Follow

getting diarrhea and then deciding to eat
it so you get more diarrhea faster, over
and over again. [x.com/emollick/statu...](https://x.com/emollick/status/1781111111111111111)

LLMs, AI, Automation, & Social Science



LLMs, AI, & Social Science

Large Language Models for Automated Open-domain Scientific Hypotheses Discovery

Zonglin Yang¹, Xinya Du², Junxian Li¹, Jie Zheng³, Soujanya Poria⁴, Erik Cambria¹

¹ Nanyang Technological University ² University of Texas at Dallas

³ Huazhong University of Science and Technology ⁴ Singapore University of Technology and Design

{zonglin001, junxian001, cambria}@ntu.edu.sg, xinya.du@utdallas.edu

jie.jay.zheng@gmail.com, sporia@sutd.edu.sg

Abstract

Hypothetical induction is recognized as the main reasoning type when scientists make observations about the world and try to propose hypotheses to explain those observations. Past research on hypothetical induction has a limited setting that (1) the observation annotations of the dataset are not raw web corpus but are manually selected sentences (resulting in a close-

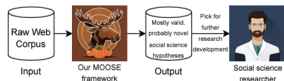


Figure 1: Overview of the new task setting of hypothetical induction and the role of our proposed MOOSE framework.

ResearchAgent: Iterative Research Idea Generation over Scientific Literature with Large Language Models

Jinheon Baek¹ Sujay Kumar Jauhar² Silviu Cucerzan² Sung Ju Hwang^{1,3}

KAIST¹ Microsoft Research² DeepAuto.ai³

{jinheon.baek, sjhwang82}@kaist.ac.kr {sjauhar, silviu}@microsoft.com

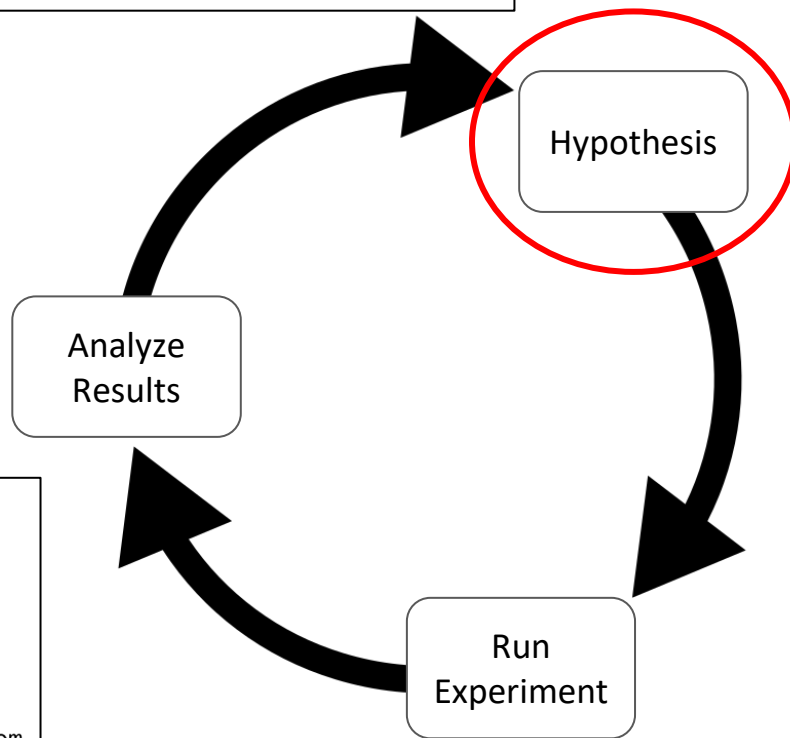
SCIMON  : Scientific Inspiration Machines Optimized for Novelty

Qingyun Wang¹, Doug Downey², Heng Ji¹, Tom Hope^{2,3}

¹ University of Illinois at Urbana-Champaign ² Allen Institute for Artificial Intelligence (AI2)

³ The Hebrew University of Jerusalem

{tomh, doug}@allenai.org, {qingyun4, hengji}@illinois.edu



LLMs, AI, & Social Science

MACHINE LEARNING AS A TOOL FOR HYPOTHESIS GENERATION

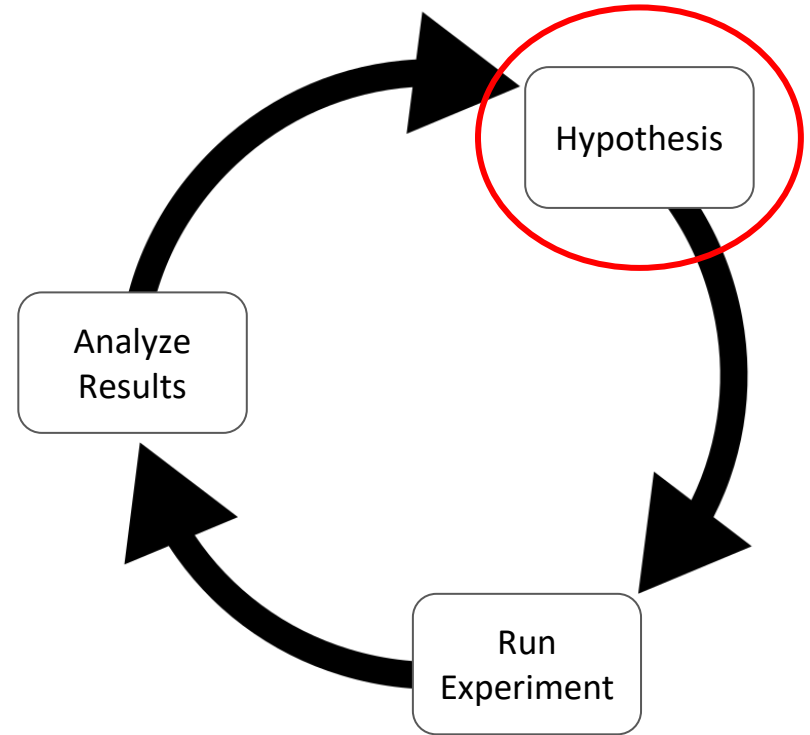
Jens Ludwig
Sendhil Mullainathan

Working Paper 31017
<http://www.nber.org/papers/w31017>

From Predictive Algorithms to Automatic Generation of Anomalies*

Sendhil Mullainathan Ashesh Rambachan[†]

May 5, 2023



LLMs, AI, & Social Science

Social Simulacra: Creating Populated Prototypes for Social Computing Systems

Joon Sung Park
Stanford University
Stanford, USA
joonspk@stanford.edu

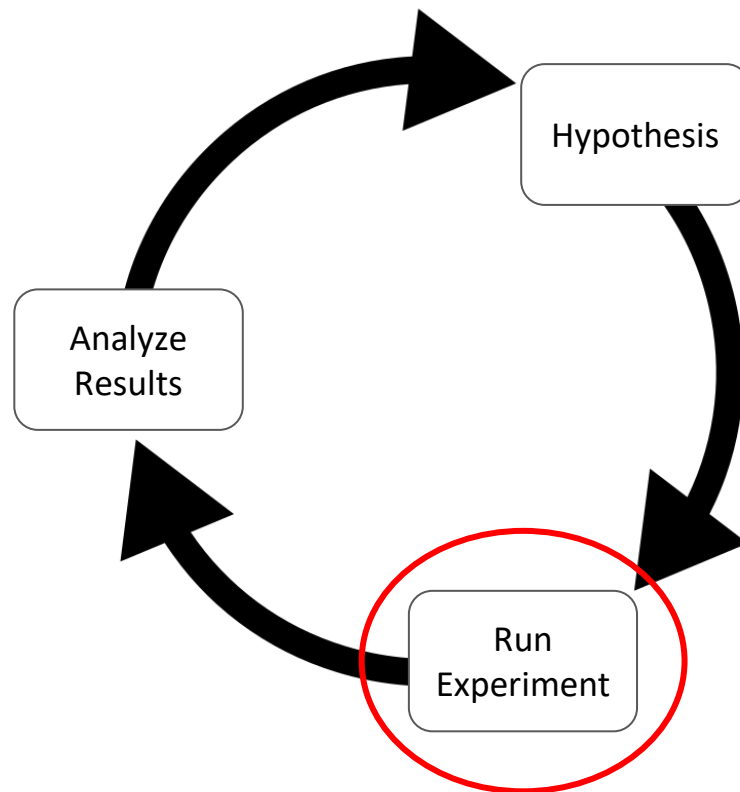
Lindsay Popowski
Stanford University
Stanford, USA
popowski@stanford.edu

Carrie J. Cai
Google Research
Mountain View, CA, USA
cjcai@google.com

Meredith Ringel Morris
Google Research
Seattle, WA, USA
merrie@google.com

Percy Liang
Stanford University
Stanford, USA
pliang@cs.stanford.edu

Michael S. Bernstein
Stanford University
Stanford, USA
msb@cs.stanford.edu



LLMs, AI, & Social Science

Large Language Models as Simulated Economic Agents: What Can We Learn from *Homo Silicus*?*

Apostolos Filippas
Fordham

John J. Horton
MIT & NBER

Benjamin S. Manning
MIT

April 23, 2024

Abstract

Large language models (LLM)—because of how they are trained and designed—are implicit computational models of humans—a *homo silicus*. LLMs can be used like economists use *homo economicus*: they can be given endowments, information, preferences, and so on, and then their behavior can be explored in scenarios via simulation. Experiments using this approach, derived from [Charness and Rabin \(2002\)](#), [Kahneman et al. \(1986\)](#), and [Samuelson and Zeckhauser \(1988\)](#) show qualitatively similar results to the original, but it is also easy to try variations for fresh insights. LLMs could allow researchers to pilot studies via simulation, first improving their experimental design and searching for novel social science insights to test in the real world.

Using GPT for Market Research*

James Brand[†]

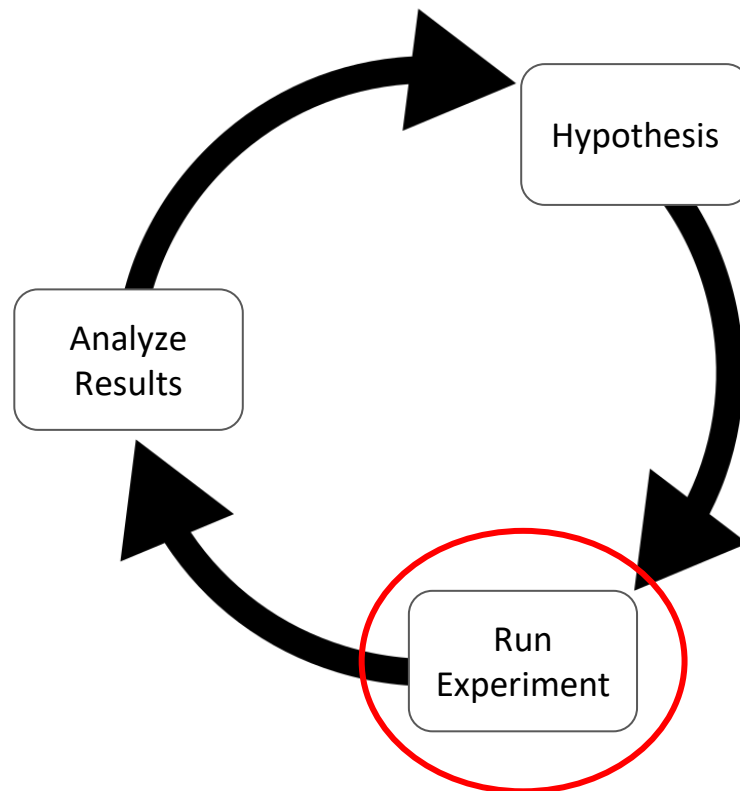
Ayelet Israeli[‡]

Donald Ngwe[†]

July 7, 2023

Abstract

Large language models (LLMs) have quickly become popular as labor-augmenting tools for programming, writing, and many other processes that benefit from quick text gener-



LLMs, AI, & Social Science

Turning large language models into cognitive models

Marcel Binz

MPRG Computational Principles of Intelligence
Max Planck Institute for Biological Cybernetics, Tübingen, Germany
marcel.binz@tue.mpg.de

Eric Schulz

MPRG Computational Principles of Intelligence
Max Planck Institute for Biological Cybernetics, Tübingen, Germany



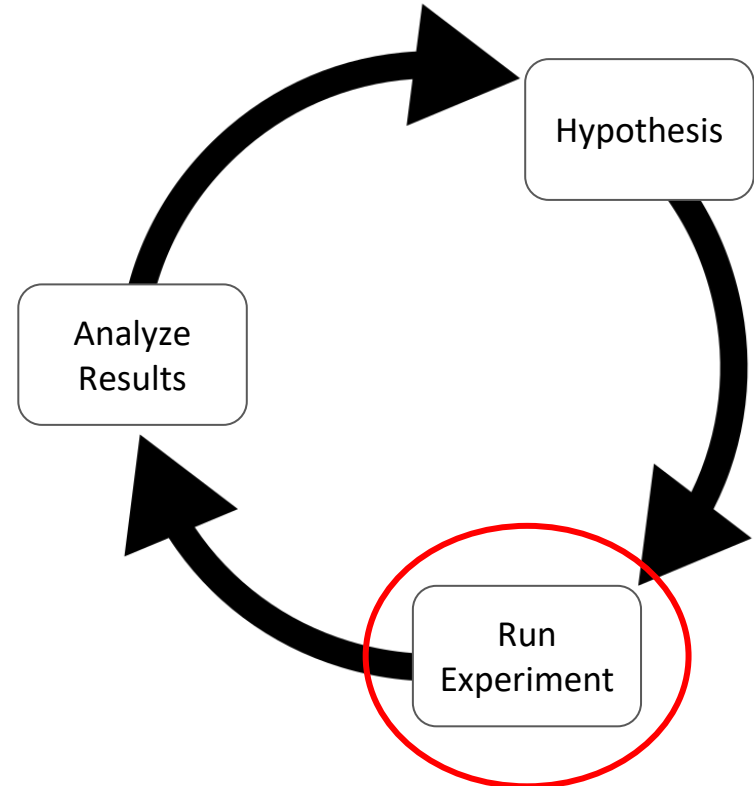
<https://pubsonline.informs.org/journal/mksc>

MARKETING SCIENCE

Articles in Advance, pp. 1–13
ISSN 0732-2399 (print), ISSN 1526-548X (online)

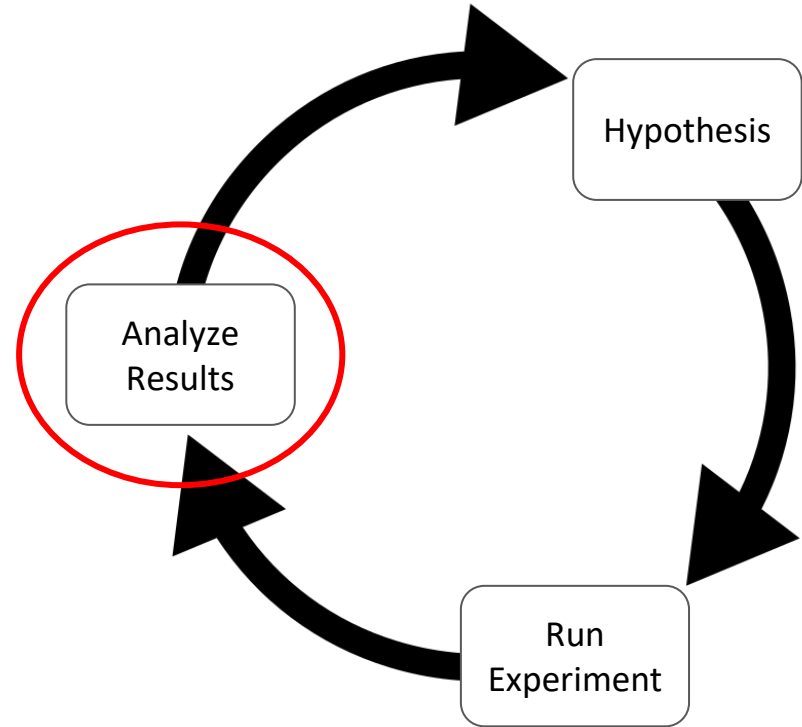
Frontiers: Determining the Validity of Large Language Models for Automated Perceptual Analysis

Peiyao Li,^a Noah Castelo,^b Zsolt Katona,^{a,*} Miklos Sarvary^c

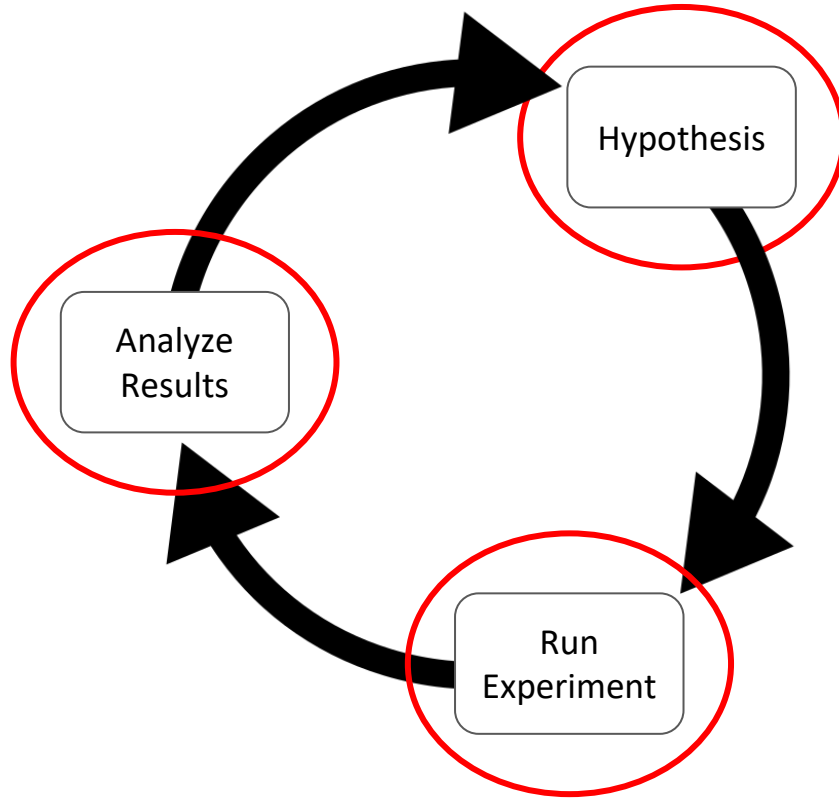


LLMs, AI, & Social Science

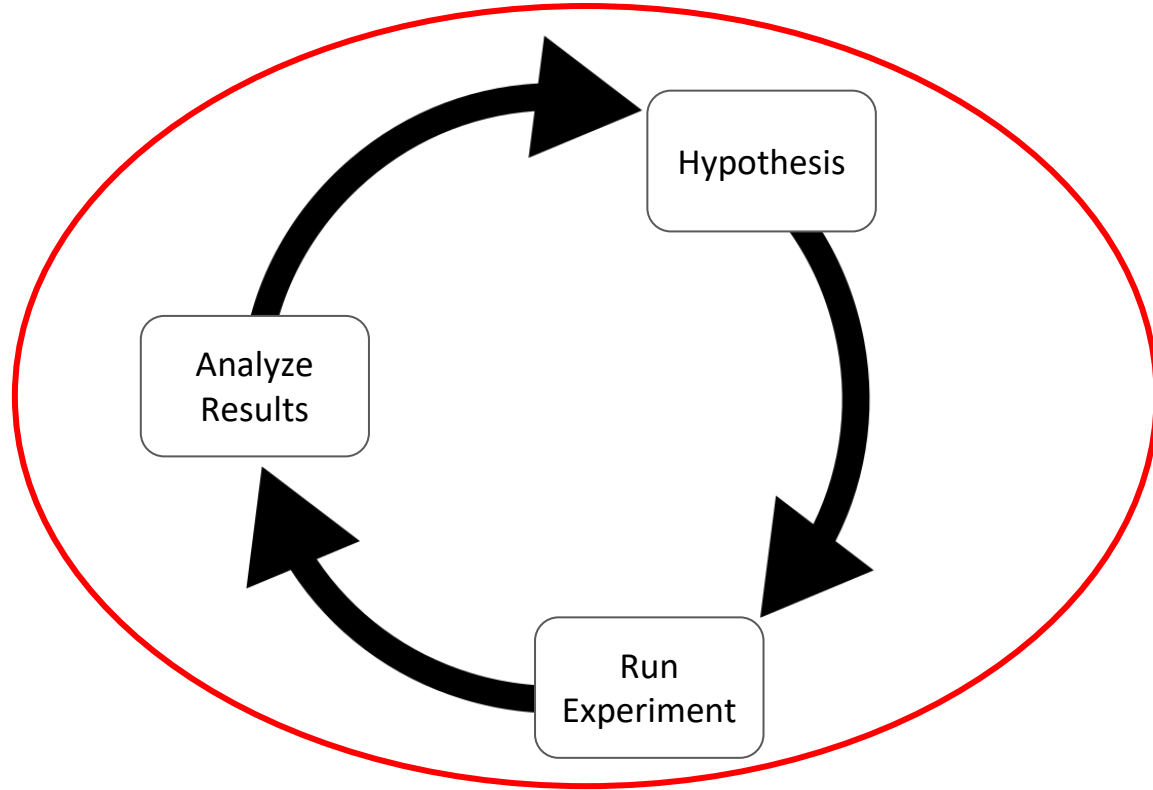
- Don't need AI to automate analysis
- Can condition analysis based on the hypothesis
- I.e, pre-registration



LLMs, AI, & Social Science



LLMs, AI, & Social Science



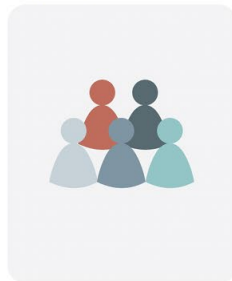
How far can we push automation of the scientific process?

Our Goal/Contribution

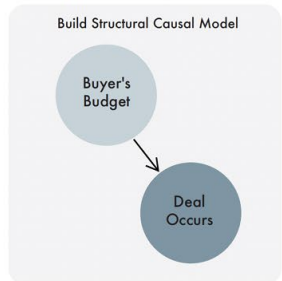
- Give LLM topic
- Have it generate ideas
- Design experiment to test ideas
- Run experiment on independent LLM subjects
- Collect the data
- Analyze the results; rinse and repeat
- **Now possible, no human at any step**

Computational System

1. Specify Social Scenario



2. Hypothesis Generation



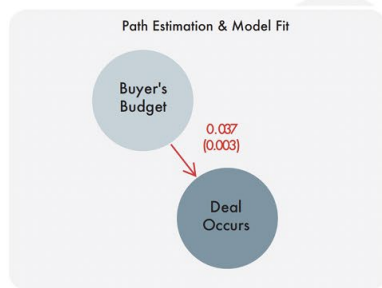
3. Agent Building



4. Design Interaction



7. Model Estimation



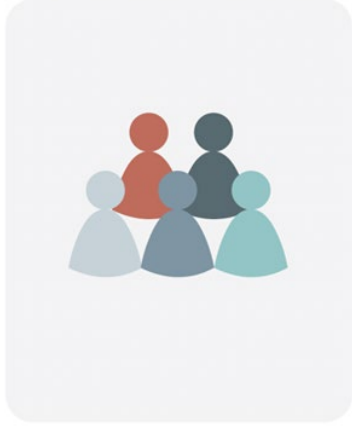
6. Data Collection



5. Experiment Running



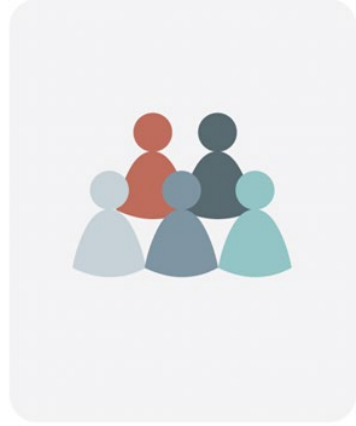
1. Specify Social Scenario



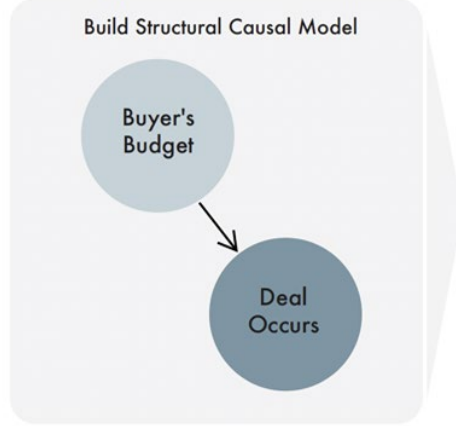
A user-provided open-ended description of some social scenario of interest, e.g.,

- Two people bargaining over an item
- A job interview
- A legal proceeding
- An auction
- Anything else you can think of!

1. Specify Social Scenario



2. Hypothesis Generation



Hypothesis as Structural Causal Model (SCM)

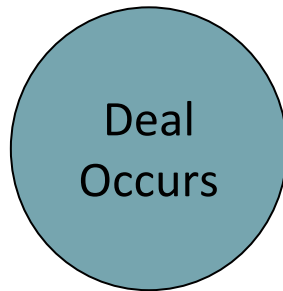
- Mathematical model of cause and effect
- Tells us exactly how to design experiment to test hypothesis
- And exactly what data analysis to do after experiment

Example

Two people bargaining
over a mug

Example

Two people bargaining
over a mug

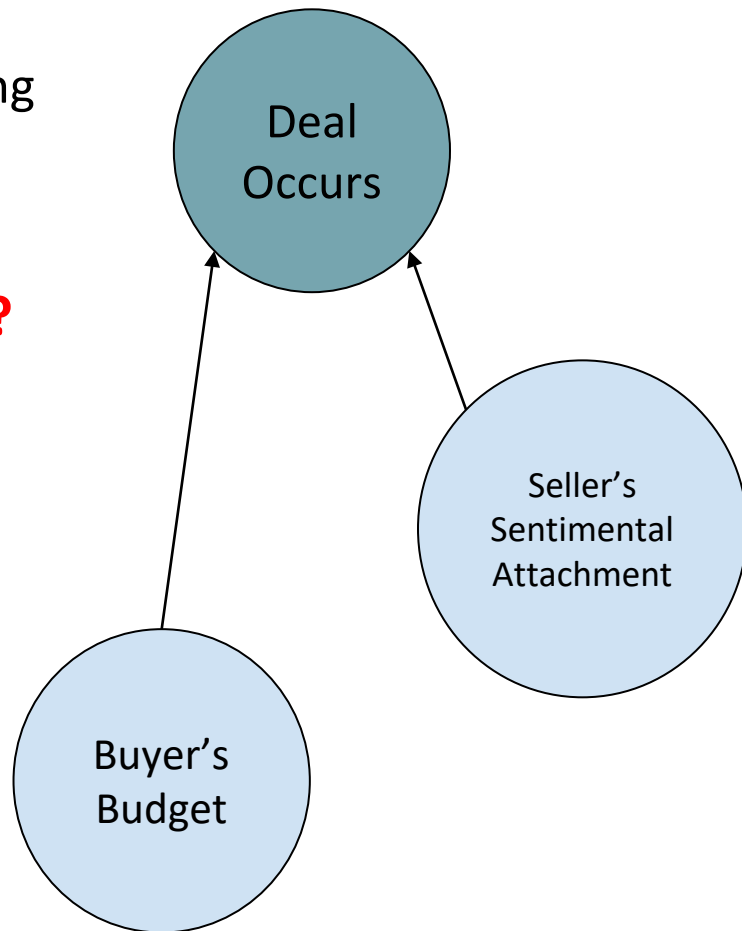


**What is an outcome
we might care about?**

Example

Two people bargaining
over a mug

**What causes might
affect this outcome?**



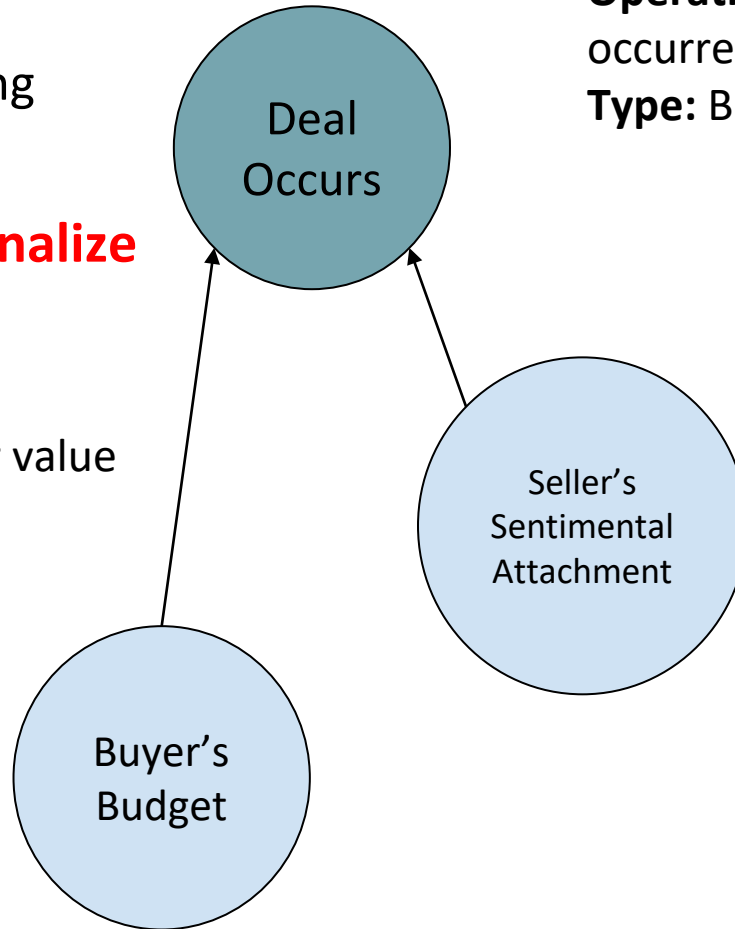
Example

Two people bargaining
over a mug

**How do we operationalize
these variables?**

Operationalization: Dollar value
willing to pay

Type: Continuous



Operationalization: 1 if a deal
occurred, otherwise 0

Type: Binary

Operationalization: How the
mug was acquired

Type: Categorical

Example

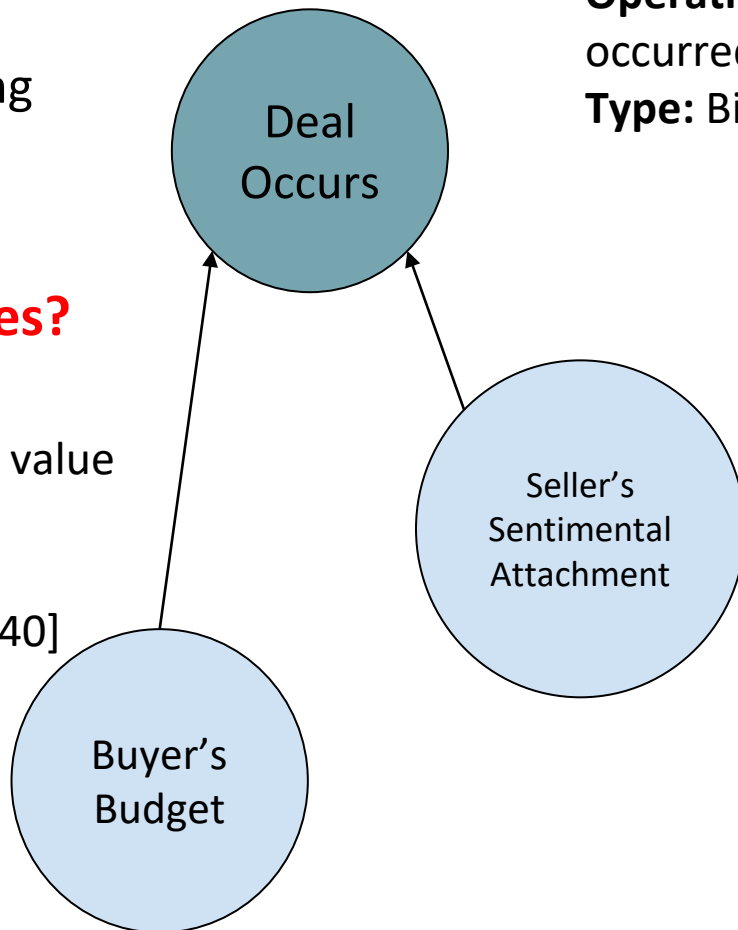
Two people bargaining
over a mug

**How do we induce
variation in the causes?**

Operationalization: Dollar value
willing to pay

Type: Continuous

Variation: [\$5, \$10, \$20, \$40]



Operationalization: 1 if a deal
occurred, otherwise 0

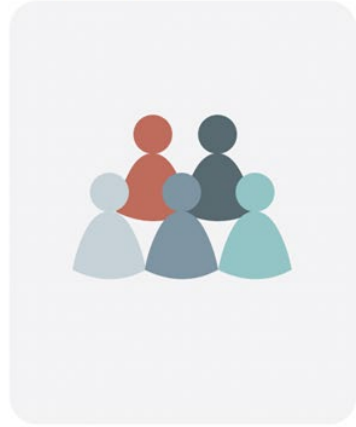
Type: Binary

Operationalization: How the
mug was acquired

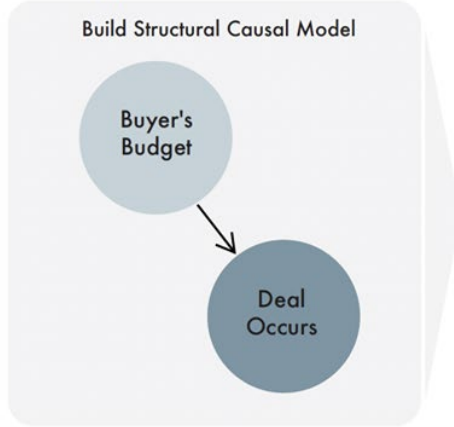
Type: Categorical

Variation: [indifferent, low
attachment, medium
attachment, highly attached]

1. Specify Social Scenario



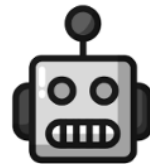
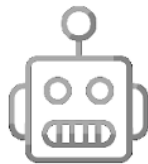
2. Hypothesis Generation



3. Agent Building



Using model from Step 2 create agents with instructions on their roles, the situation and their attributes



Basic
Information

Your role is: Seller

Your role is: Buyer

Your name: Samuel

Your name: Beatrice

Goals &
Constraints

Goal: Your goal is to sell the mug at the highest price possible

Goal: Try to purchase the mug at the lowest price possible

Constraint: Must not accept a price below your minimum selling price

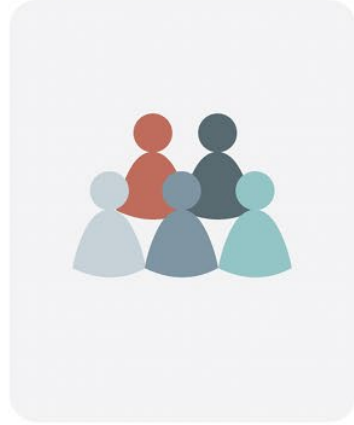
Constraint: Do not offer a price higher than your maximum budget

Exogenously
Varied
Attributes

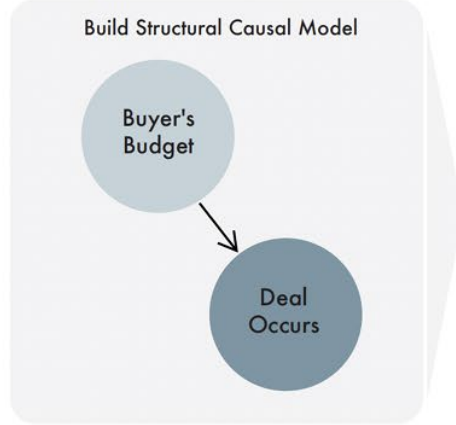
Your sentimental attachment: [no attachment, ..., extreme attachment]

Your budget: [\$5, \$10, \$20, \$40]

1. Specify Social Scenario



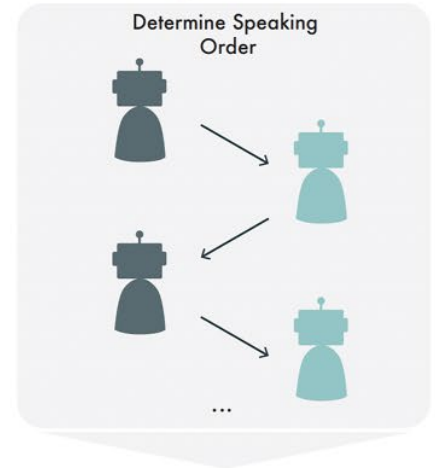
2. Hypothesis Generation



3. Agent Building



4. Design Interaction



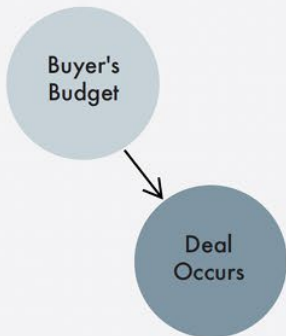
- System determines how the agents will interact
- Each agent **sends output** and **receives inputs** from other agents.
 - In bargaining scenario, 2 agents alternate, making offers and counter-offers

1. Specify Social Scenario



2. Hypothesis Generation

Build Structural Causal Model



3. Agent Building

Instantiate LLM Agents with Relevant Attributes



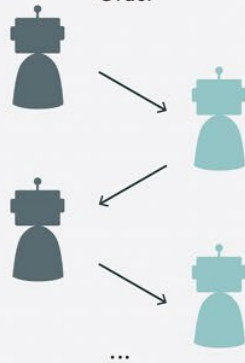
Role: Buyer
Name: Sarah
Budget: [\$3,\$5,\$8]
Goal:
...



Role: Seller
Name: Sam
Goal: ...
Constraint: ...
...

4. Design Interaction

Determine Speaking Order



5. Experiment Running

Run in Parallel

Variation 1

"Nice mug Sam!
How much..."

"Hey Sarah I'd
sell it for..."

Variation 2

"Nice mug Sam!
How much..."

"Hey Sarah I'd
sell it for..."

Variation 3

"Nice mug Sam!
How much..."

"Hey Sarah I'd
sell it for..."

- The system then launches hundreds or thousands of simulated conversations between independent agents

Buyer's Budget: \$10

"Hello Beatrice, I see you're interested in this mug. It's unique, I can let it go for \$15."

"Hello Samuel, it's a unique piece, but, I was hoping to spend around \$7 for it."

...

"Samuel, \$10 is really the best I can do. Can we meet at this price point?"

"Beatrice, I must stick to my minimum price of \$15. This mug's worth every penny. I'm sure you understand."

Buyer's Budget: \$40

"Hi Beatrice, I see you want this mug. It's a unique, and I'm asking for \$15 for it."

"Samuel, it's a nice mug indeed. Would you consider selling it for \$10?"

...

"Beatrice, I understand your position, but I must insist on a price of \$15 due to the mug's rarity and excellent condition."

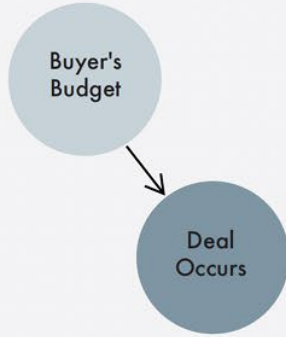
"Samuel, I appreciate your stance. Considering your insistence on the price, I'll agree to purchase the mug for \$15."

1. Specify Social Scenario



2. Hypothesis Generation

Build Structural Causal Model



3. Agent Building

Instantiate LLM Agents with Relevant Attributes



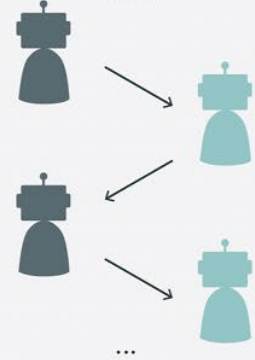
Role: Buyer
Name: Sarah
Budget: [\$3,\$5,\$8]
Goal:
...



Role: Seller
Name: Sam
Goal: ...
Constraint: ...
...

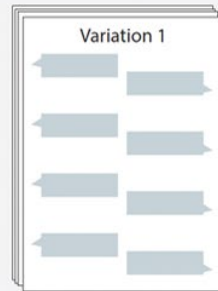
4. Design Interaction

Determine Speaking Order



6. Data Collection

Survey Agents to Get Data



Did a deal happen?
Buyer: Yes

5. Experiment Running

Run in Parallel

Variation 1

"Nice mug Sam!
How much..."

"Hey Sarah I'd
sell it for..."

Variation 2

"Nice mug Sam!
How much..."

"Hey Sarah I'd
sell it for..."

Variation 3

"Nice mug Sam!
How much..."

"Hey Sarah I'd
sell it for..."

- Data is collected by simply asking the agents what happened
- (they have memory).

Buyer's Budget: \$10

"Hello Beatrice, I see you're interested in this mug. It's unique, I can let it go for \$15."

"Hello Samuel, it's a unique piece, but, I was hoping to spend around \$7 for it."

...

"Samuel, **\$10 is really the best I can do.** Can we meet at this price point?"

"Beatrice, **I must stick to my minimum price of \$15.** This mug's worth every penny. I'm sure you understand."

- Did you buy the mug?
- Buyer: "No"

Buyer's Budget: \$40

"Hi Beatrice, I see you want this mug. It's a unique, and I'm asking for \$15 for it."

"Samuel, it's a nice mug indeed. Would you consider selling it for \$10?"

...

"Beatrice, I understand your position, **but I must insist on a price of \$15** due to the mug's rarity and excellent condition."

"Samuel, I appreciate your stance. Considering your insistence on the price, **I'll agree to purchase the mug for \$15.**"

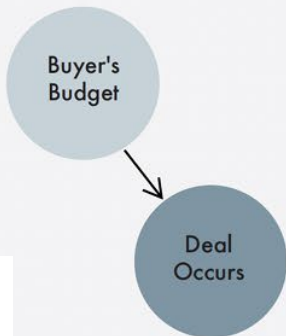
- Did you buy the mug?
- Buyer: "Yes"

1. Specify Social Scenario



2. Hypothesis Generation

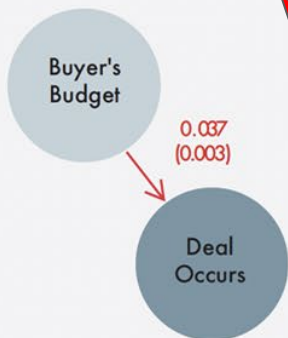
Build Structural Causal Model



Fit the model to the data

7. Model Estimation

Path Estimation & Model Fit



3. Agent Building

Instantiate LLM Agents with Relevant Attributes



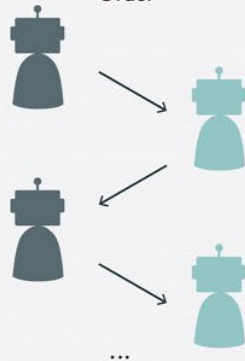
Role: Buyer
Name: Sarah
Budget: [\$3,\$5,\$8]
Goal:
...



Role: Seller
Name: Sam
Goal: ...
Constraint: ...
...

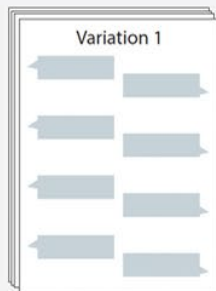
4. Design Interaction

Determine Speaking Order



6. Data Collection

Survey Agents to Get Data



Did a deal happen?
Buyer: Yes

5. Experiment Running

Run in Parallel

Variation 1

"Nice mug Sam!
How much..."

"Hey Sarah I'd
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Variation 2

"Nice mug Sam!
How much..."

"Hey Sarah I'd
sell it for..."

Variation 3

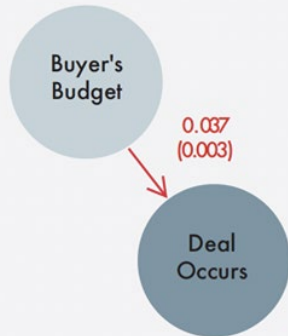
"Nice mug Sam!
How much..."

"Hey Sarah I'd
sell it for..."

- If totally unfamiliar with SEM/SCM, think of as equivalent to linear regression
- For a simple linear SCM (no mediators)
 - “Path estimate = coefficient estimate”
- $DealOccurs = 0.37 \times BuyerBudget$

7. Model Estimation

Path Estimation & Model Fit



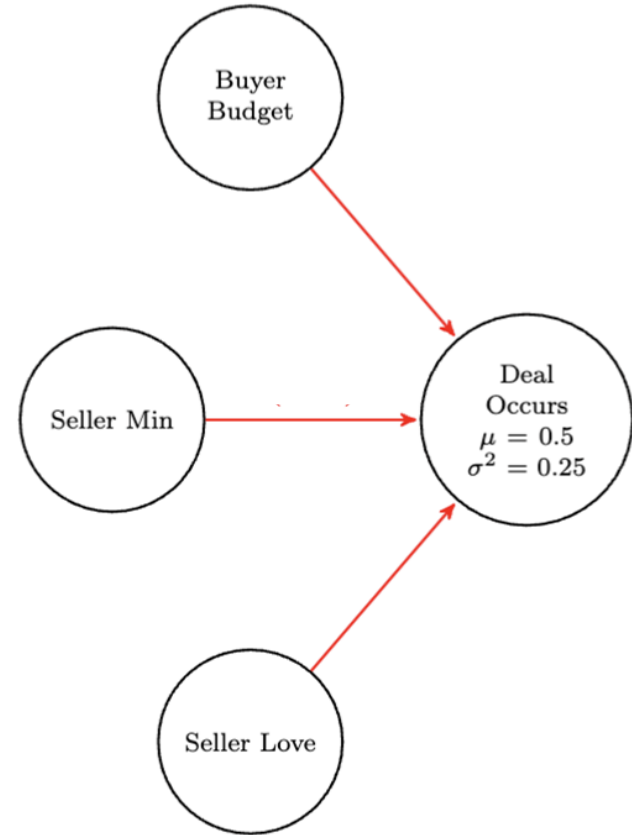
Now the real thing

Input: “Two people bargaining over a mug”

Two people bargaining over a mug

SIMULATION DETAILS

Agents: Buyer, Seller



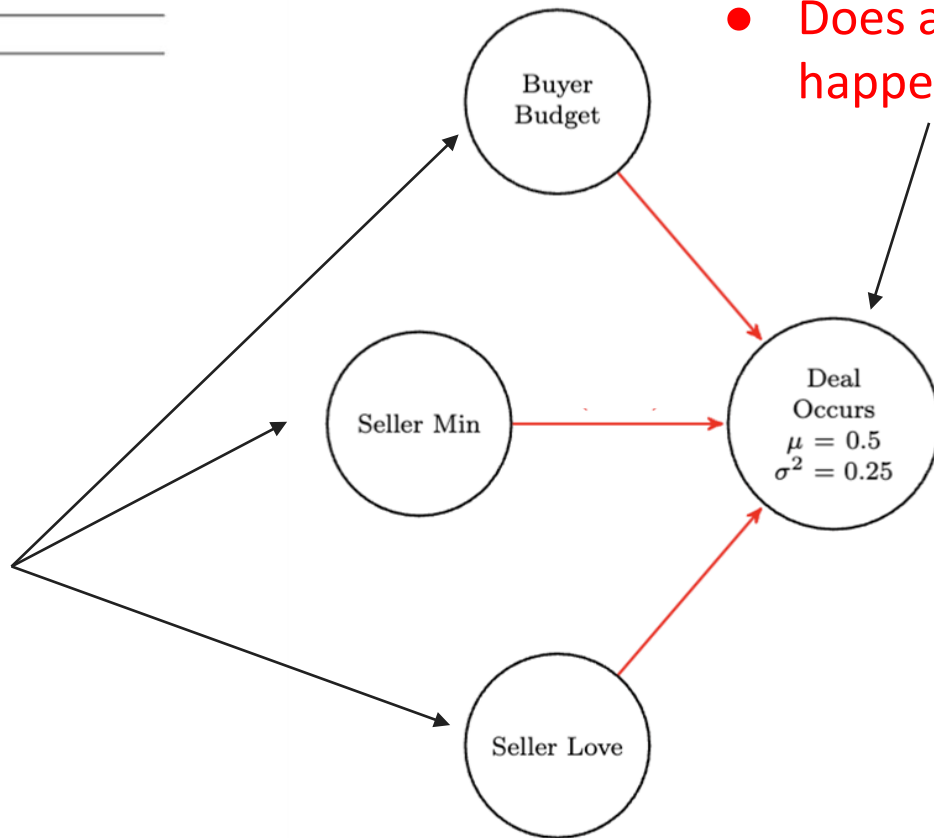
Two people bargaining over a mug

SIMULATION DETAILS

Agents: Buyer, Seller

Causes

- Buyers budget
- Seller's minimum price,
- Seller's love for the mug



Outcome

- Does a deal happen?

Two people bargaining over a mug

SIMULATION DETAILS

Agents: Buyer, Seller

Simulations Run: $9 \times 9 \times 5 = 405$

Speaking Order: Buyer, Seller, Buyer, ...repeat

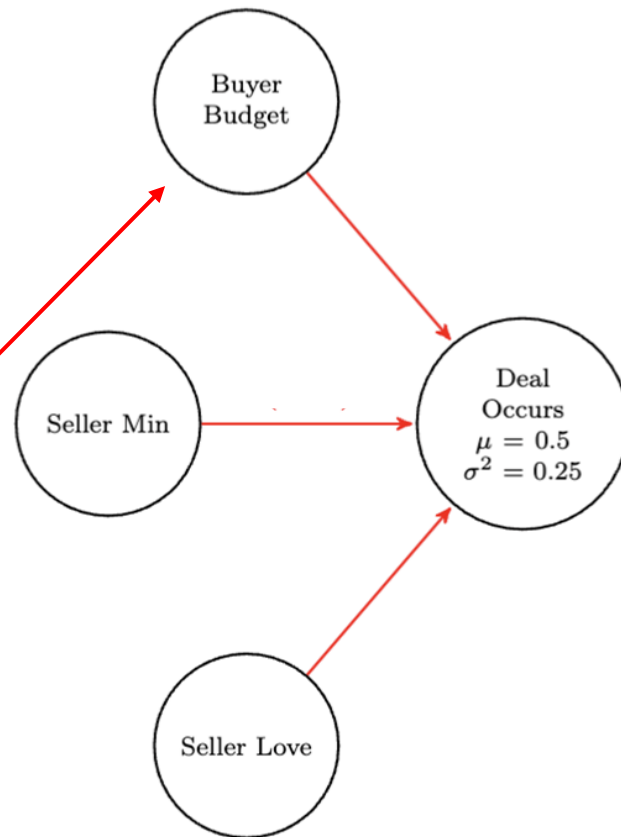
VARIABLE INFORMATION

Buyer's Budget

Attribute Treatment Variations: ['3', '6', '7', '8', '10', '13', '18', '20', '25']

Proxy Attribute: Your budget for the mug

Variable Type: Continuous



“Treatment” values for
cause

Two people bargaining over a mug

SIMULATION DETAILS

Agents: Buyer, Seller

Simulations Run: $9 \times 9 \times 5 = 405$

Speaking Order: Buyer, Seller, Buyer, ...repeat

VARIABLE INFORMATION

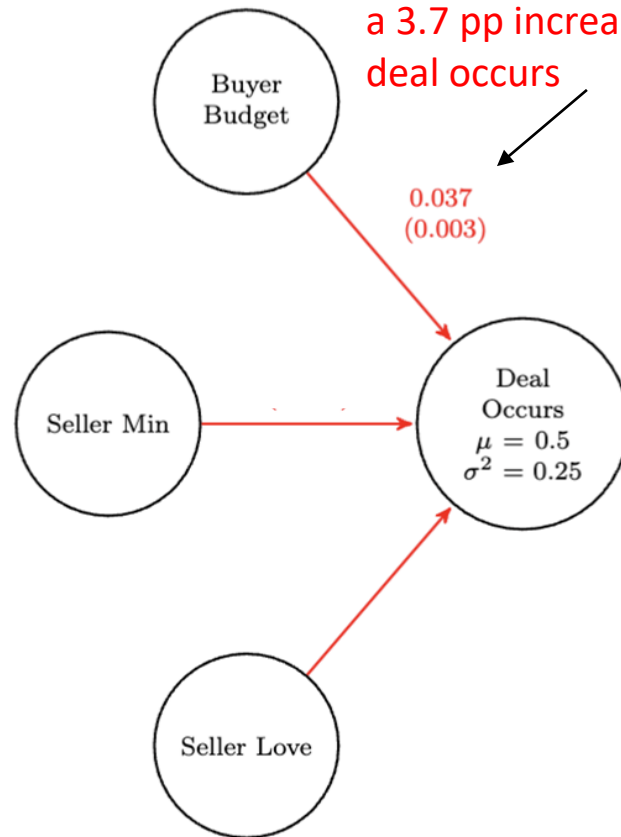
Buyer's Budget

Attribute Treatment Variations: ['3', '6', '7', '8', '10', '13', '18', '20', '25']

Proxy Attribute: Your budget for the mug

Variable Type: Continuous

In simulation, the answer is... \$1 increase leads to a 3.7 pp increase in Prob. deal occurs



Two people bargaining over a mug

SIMULATION DETAILS

Agents: Buyer, Seller

Simulations Run: $9 \times 9 \times 5 = 405$

Speaking Order: Buyer, Seller, Buyer, ...repeat

VARIABLE INFORMATION

Buyer's Budget

Attribute Treatment Variations: ['3', '6', '7', '8', '10', '13', '18', '20', '25']

Proxy Attribute: Your budget for the mug

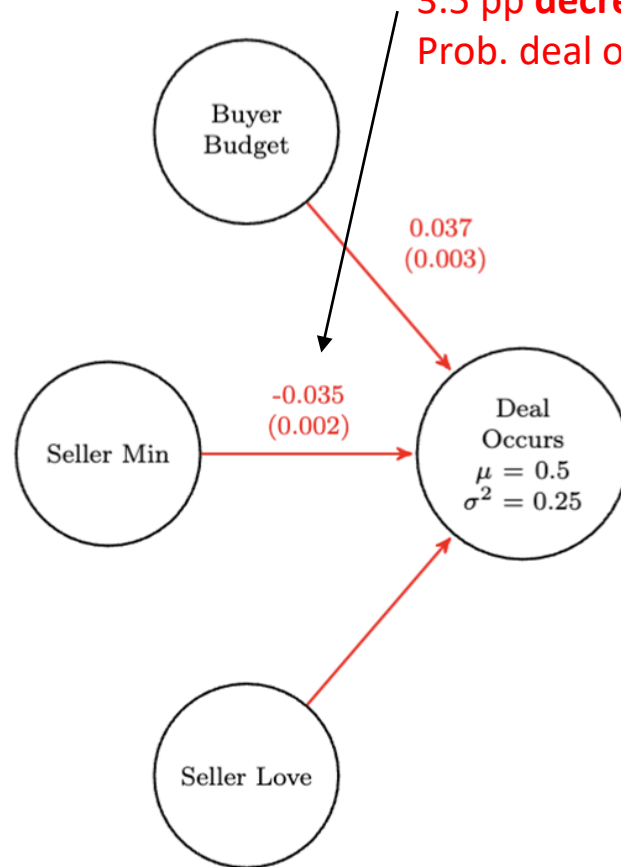
Variable Type: Continuous

Seller's minimum acceptable price

Attribute Treatment Variations: ['3', '5', '7', '8', '10', '13', '18', '20', '25']

Proxy Attribute: Your minimum acceptable price for the mug

Variable Type: Continuous



\$1 increase leads to a
3.5 pp **decrease** in
Prob. deal occurs

Two people bargaining over a mug

SIMULATION DETAILS

Agents: Buyer, Seller

Simulations Run: $9 \times 9 \times 5 = 405$

Speaking Order: Buyer, Seller, Buyer, ...repeat

VARIABLE INFORMATION

Buyer's Budget

Attribute Treatment Variations: ['3', '6', '7', '8', '10', '13', '18', '20', '25']

Proxy Attribute: Your budget for the mug

Variable Type: Continuous

Seller's minimum acceptable price

Attribute Treatment Variations: ['3', '5', '7', '8', '10', '13', '18', '20', '25']

Proxy Attribute: Your minimum acceptable price for the mug

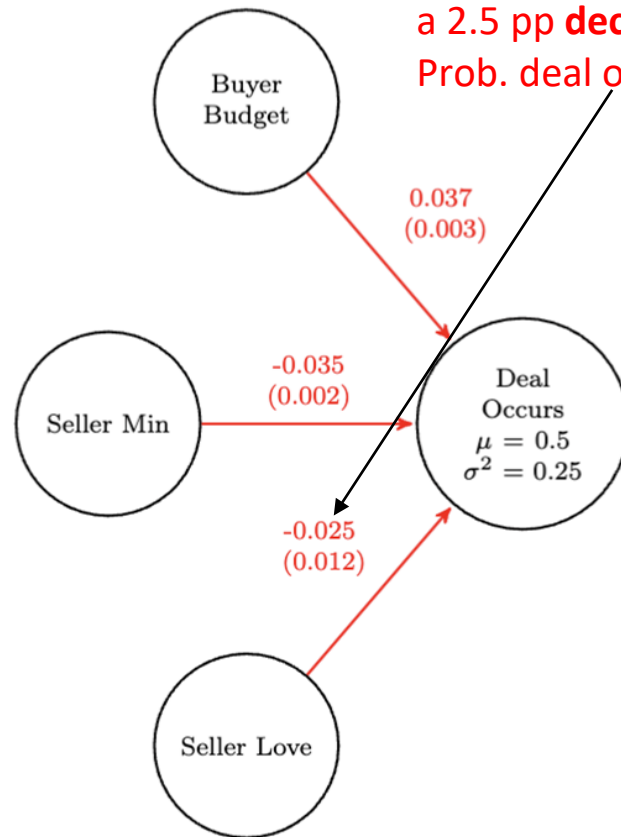
Variable Type: Continuous

Seller's feelings of love towards the mug

Attribute Treatment Variations: ['no emotional attachment', 'slight emotional attachment', 'moderate emotional attachment', 'high emotional attachment', 'extreme emotional attachment']

Proxy Attribute: Your feelings of love for the mug

Variable Type: Ordinal



1-unit increase on ordinal scale leads to a 2.5 pp **decrease** in Prob. deal occurs

**Do these simulations
match the "real world"?**

**Let's take a domain where economists
are confident they know what happens:
auctions.**

**Input: "Three bidders participating in an auction
for a piece of art starting at fifty dollars."**

3 bidders participating in an auction for a piece of art starting at \$50

SIMULATION DETAILS

Agents: Bidder 1, Bidder 2, Bidder 3, Auctioneer

Simulations Run: $7 \times 7 \times 7 = 343$

Speaking Order: Auctioneer, Bidder 1, Auctioneer,
Bidder 2, Auctioneer, Bidder 3, ... repeat

VARIABLE INFORMATION

Bidder 1's maximum budget

Attribute Treatment Variations: ['\$50', '\$100', '\$150', '\$200', '\$250', '\$300', '\$350']

Proxy Attribute: Your max budget for the art

Variable Type: Continuous

Bidder 2's maximum budget

Attribute Treatment Variations: ['\$50', '\$100', '\$150', '\$200', '\$250', '\$300', '\$350']

Proxy Attribute: Your max budget for the art

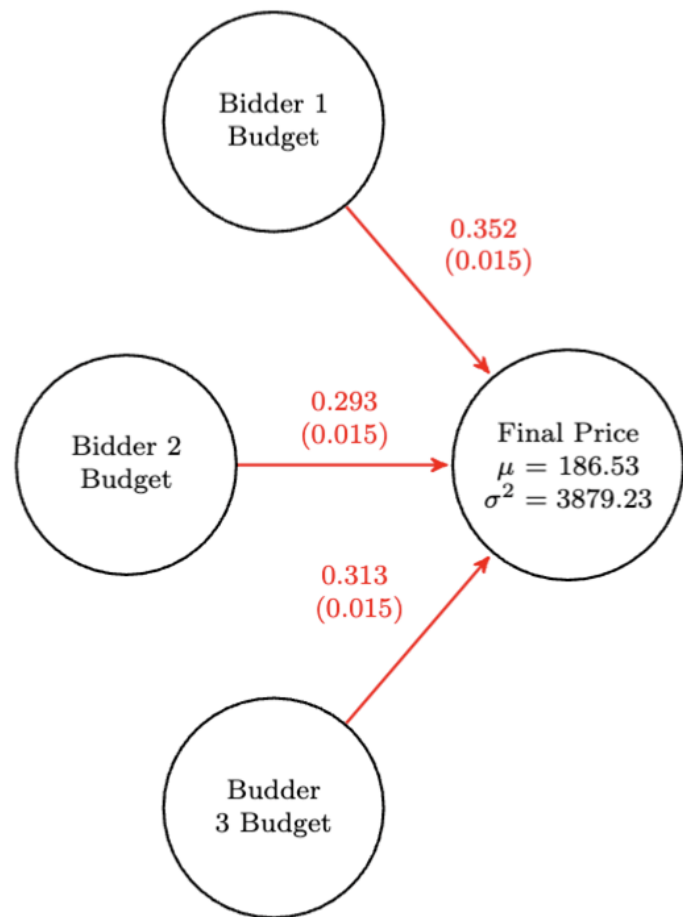
Variable Type: Continuous

Bidder 3's maximum budget

Attribute Treatment Variations: ['\$50', '\$100', '\$150', '\$200', '\$250', '\$300', '\$350']

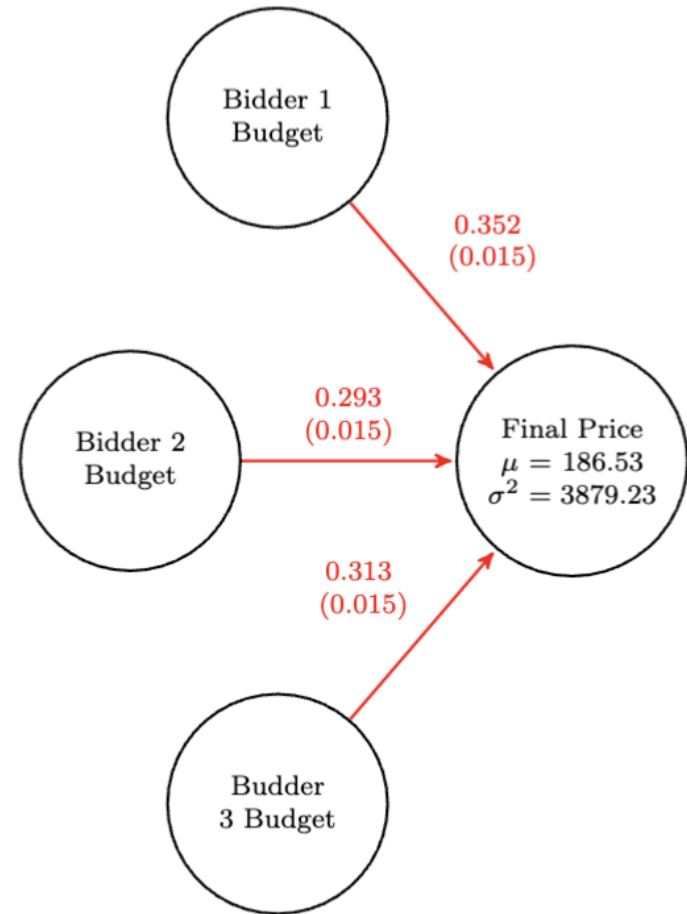
Proxy Attribute: Your max budget for the art

Variable Type: Continuous



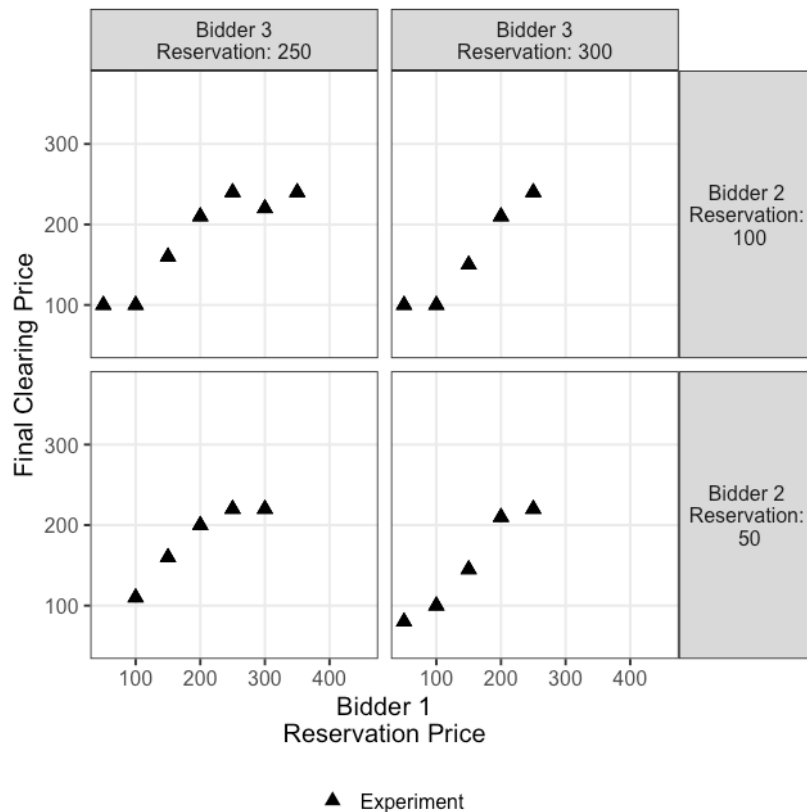
3 bidders participating in an auction for a piece of art starting at \$50

Note that coefficient of $\sim \frac{1}{3}$ on valuation is sensible, each bidder has a $\frac{1}{3}$ chance of being marginal (i.e. having the second highest valuation)



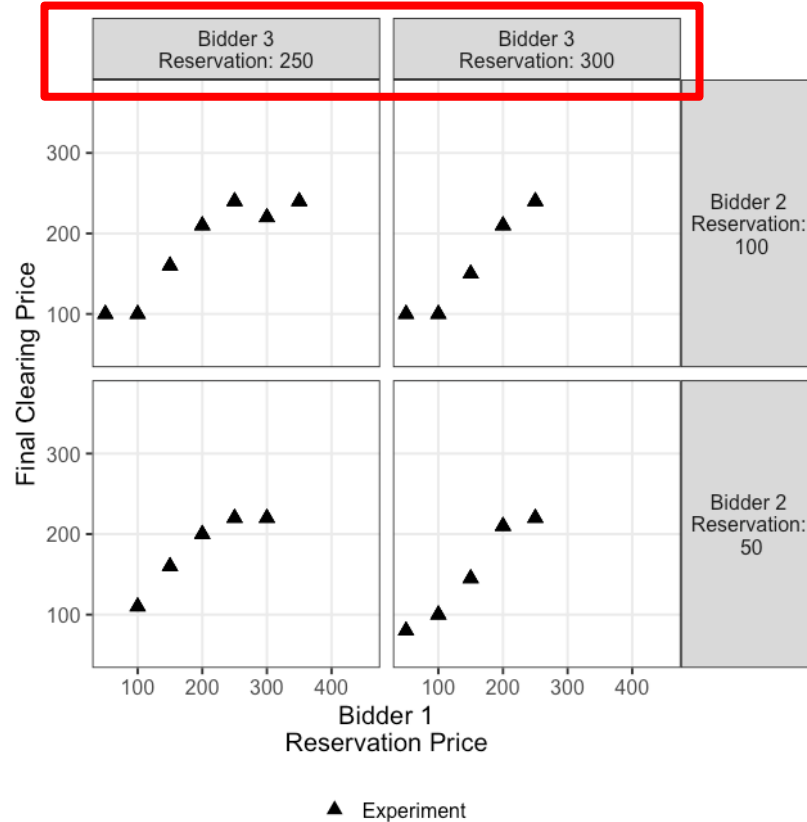
Auction Experimental Results

Subset of Bidding
simulation results



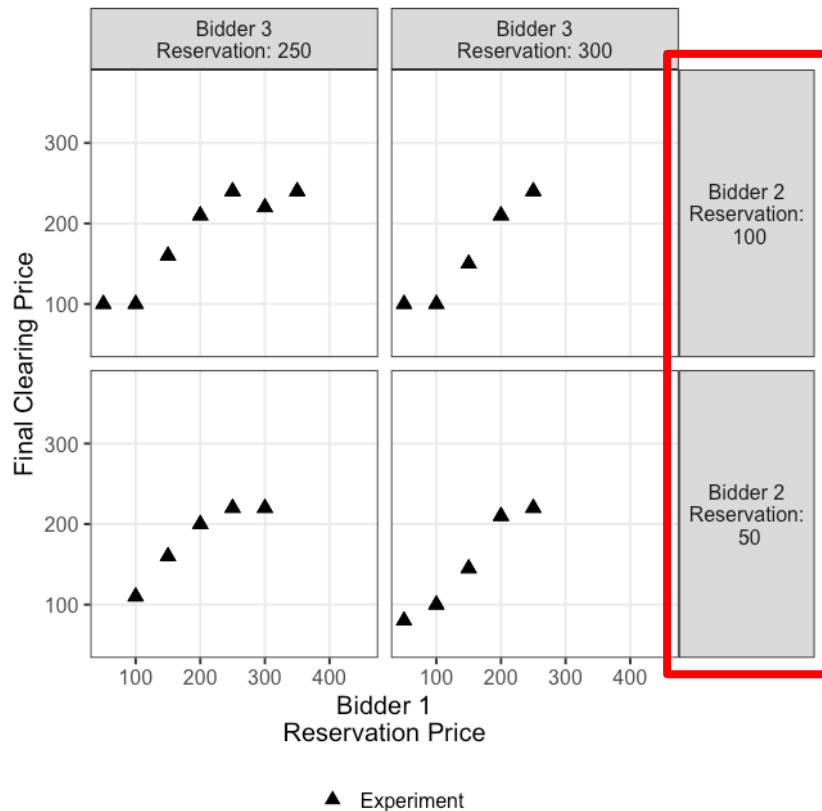
Auction Experimental Results

Columns are Bidder 3's
value



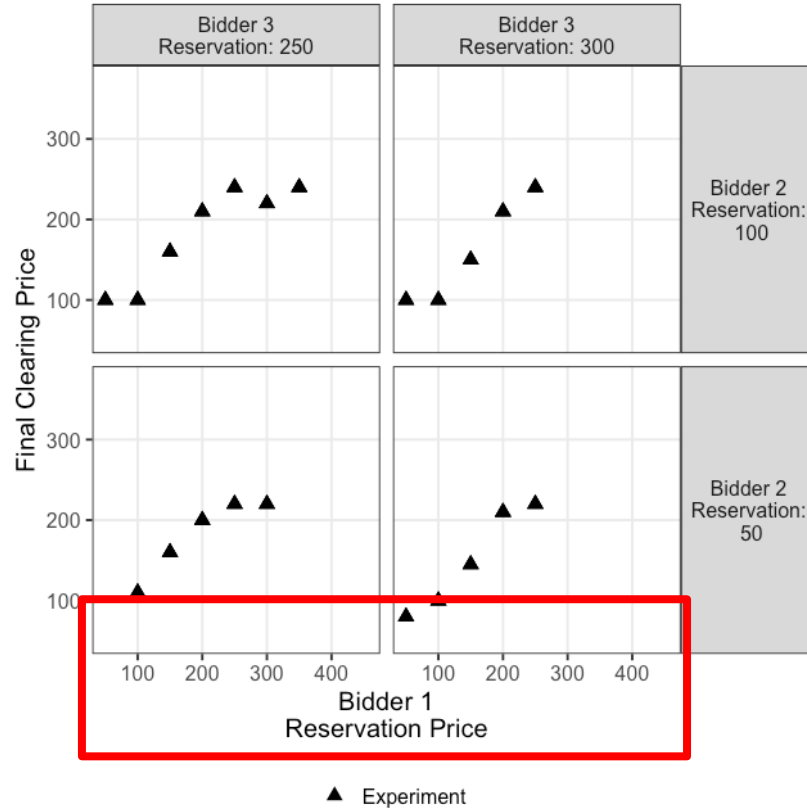
Auction Experimental Results

Row are Bidder 2's value



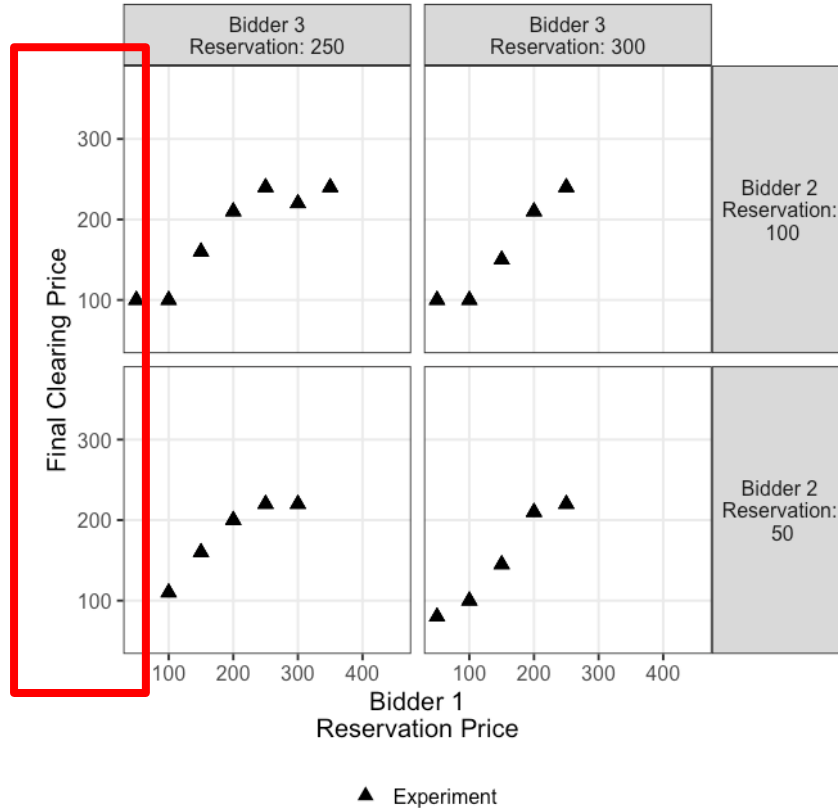
Auction Experimental Results

x-axis is Bidder 1's value

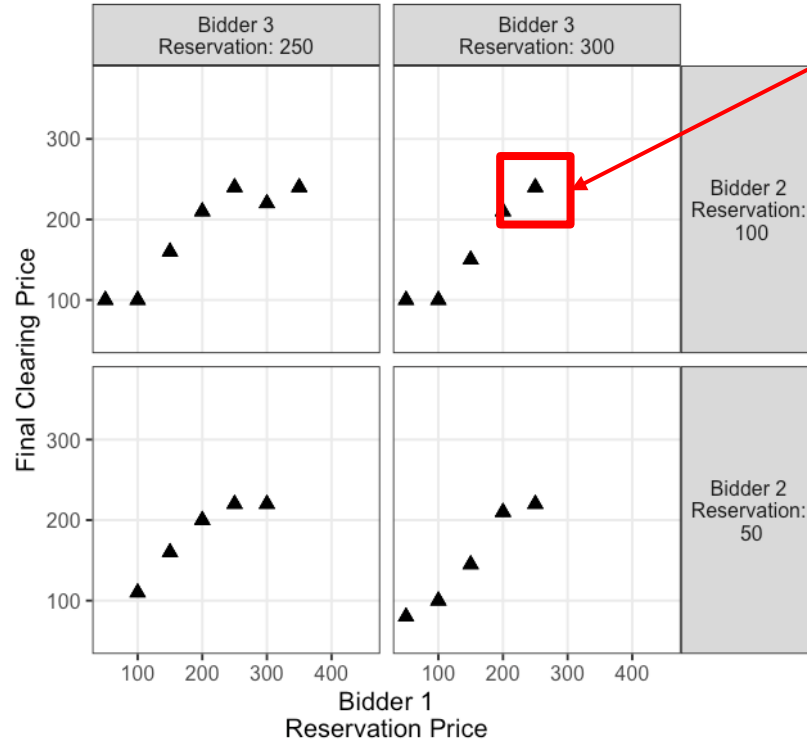


Auction Experimental Results

y-axis is final clearing price



Auction Experimental Results



Bidder 1 value: 250

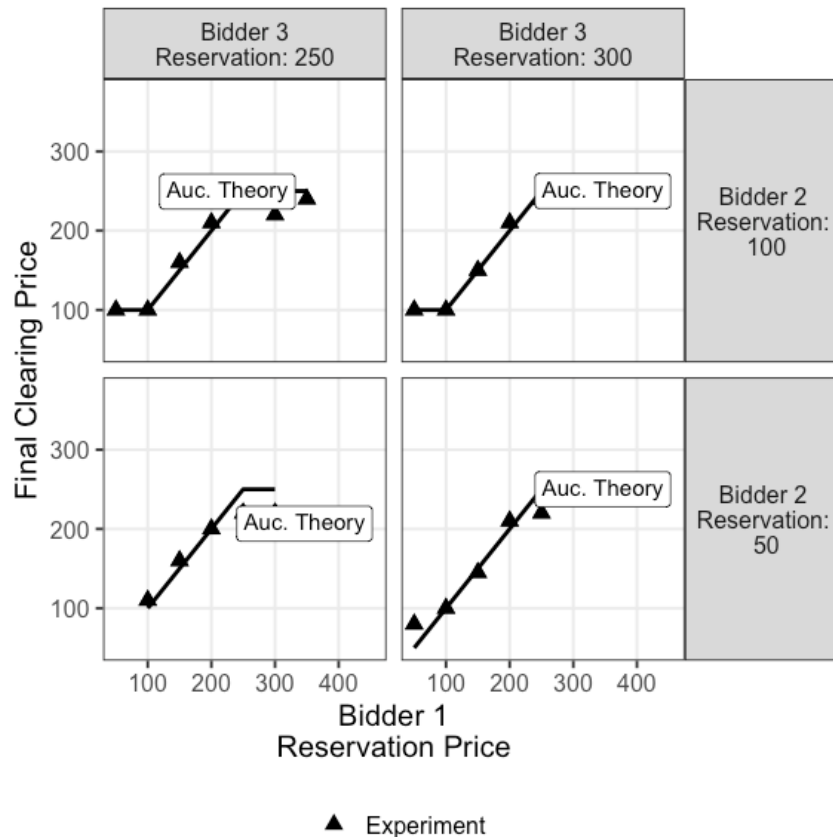
Bidder 2 value: 100

Bidder 3 value: 300

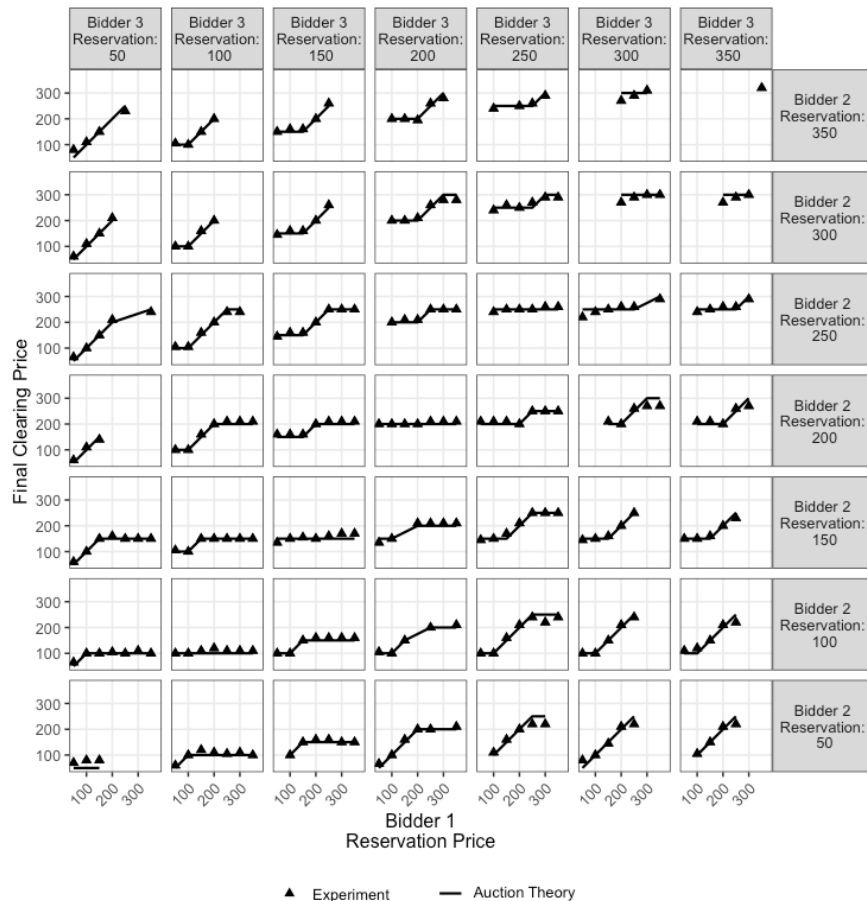
Clearing Price ~ 250

Auction Experimental Results - Theory Predictions

- Open-ascending price auction with private values
- Clearing price = Second highest value
- Why? Intuitively, once 2nd highest valuation is hit, highest bidder won't bid against themselves, takes that price



Auction Experimental Results - Theory Predictions



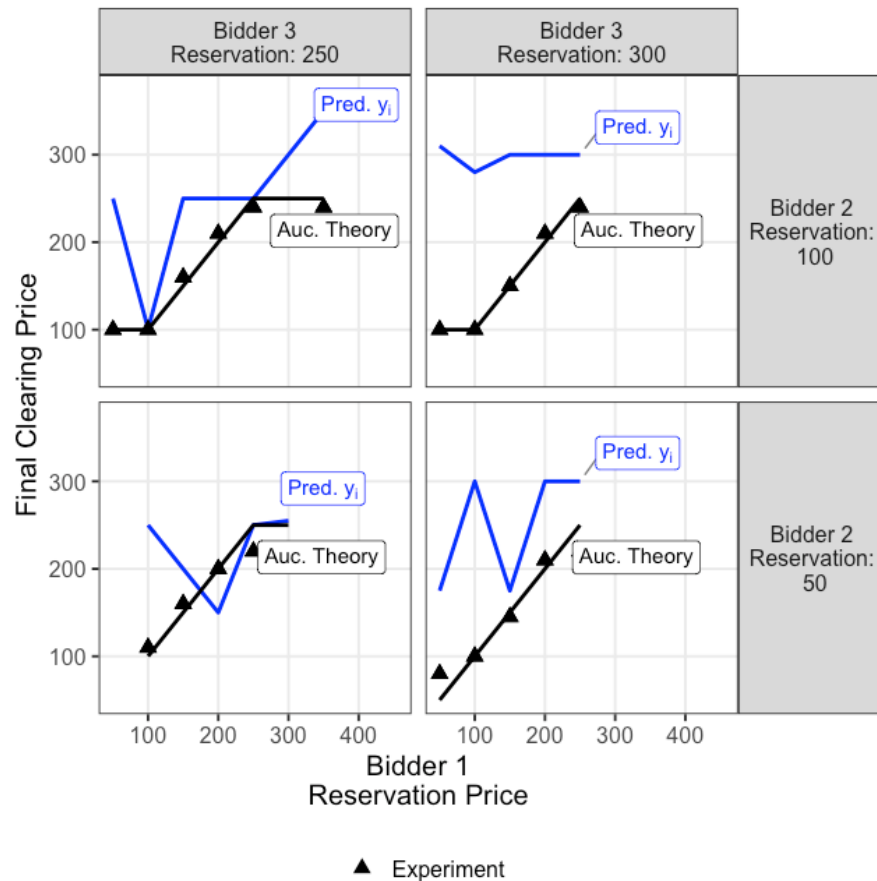
Very good agreement
between simulation and theory.

But does the LLM just "know" what will happen?
Is all this simulation necessary?

Directly asking the LLM to make a prediction

- **To LLM:** “Bidder 1 has a reservation price of $\{\{XX\}\}$, bidder 2 has a reservation price of $\{\{XY\}\}$, bidder 3 has a reservation price of $\{\{XZ\}\}$. Given the experimental setup, what do you think the final clearing price will be?”

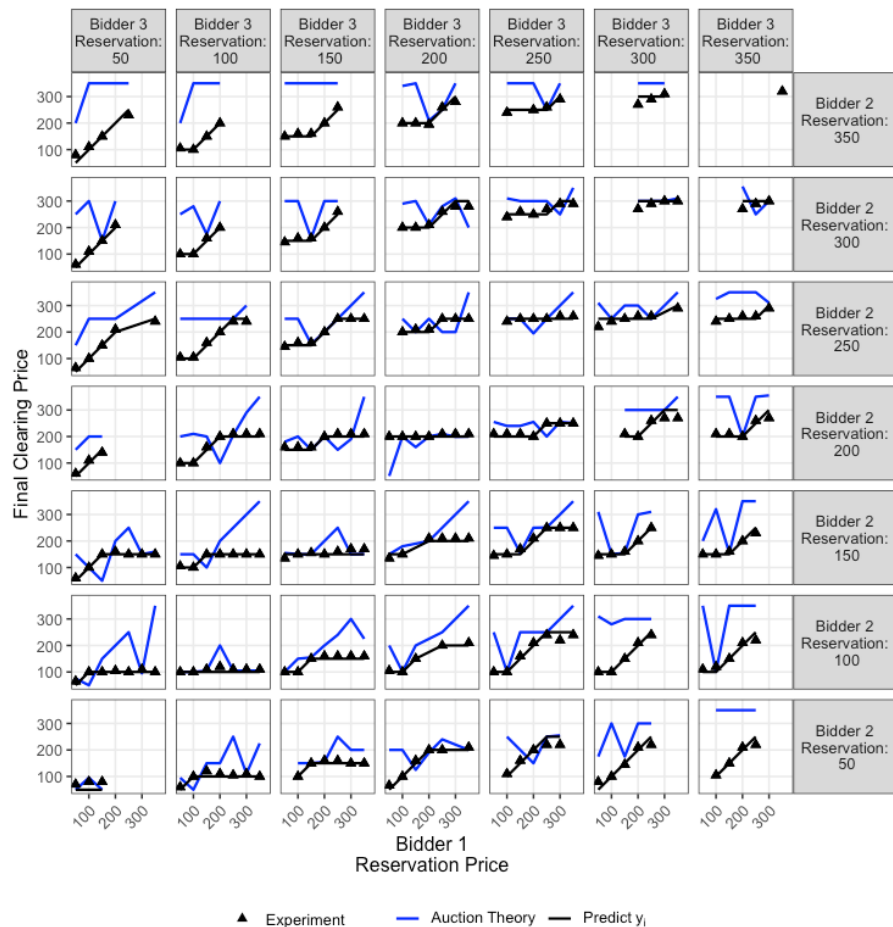
LLM Prediction (in Blue)



LLM Prediction (in Blue)

MSE for prediction: 8628

MSE for theory: 128



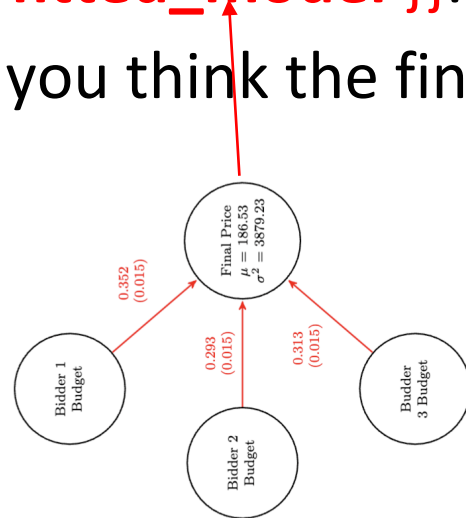
Very good agreement
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But does the LLM just "know" what will happen?
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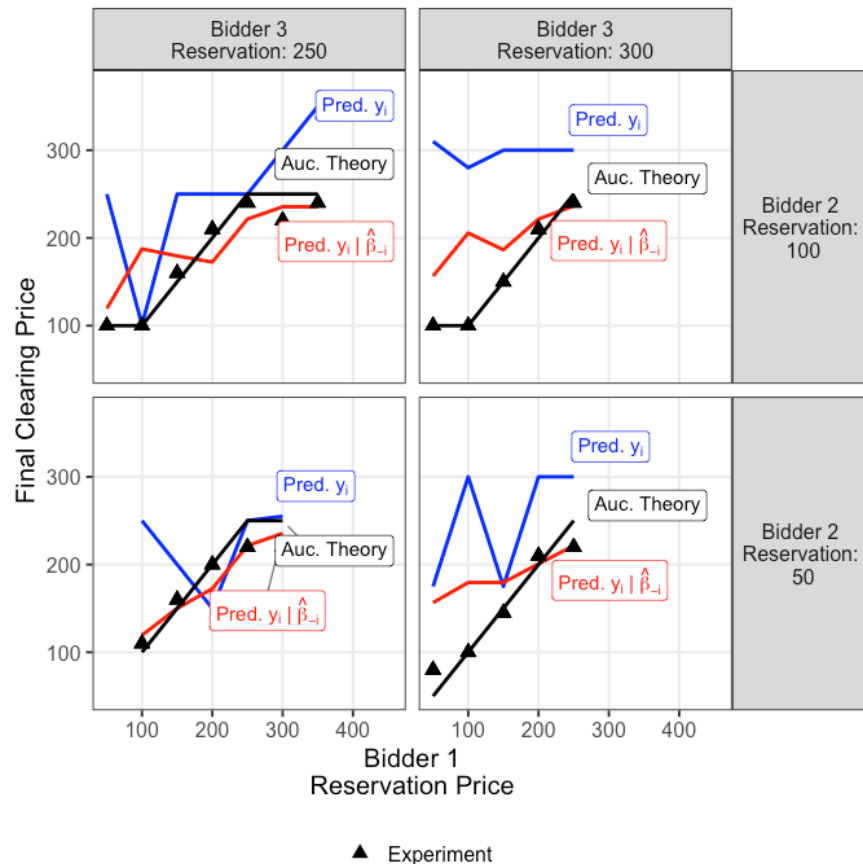
The LLM doesn't know, but can it
"learn" from the fitted model

What if we give the LLM access to the fitted model describing the situation...

- **To LLM:** “Bidder 1 has a reservation price of $\{\{XX\}\}$, bidder 2 has a reservation price of $\{\{XY\}\}$, bidder 3 has a reservation price of $\{\{XZ\}\}$. Here’s the fitted SCM: $\{\{ \text{fitted_model} \}\}$. Given the experimental setup, what do you think the final clearing price will be?”



Augmented predictions (in red) are much improved



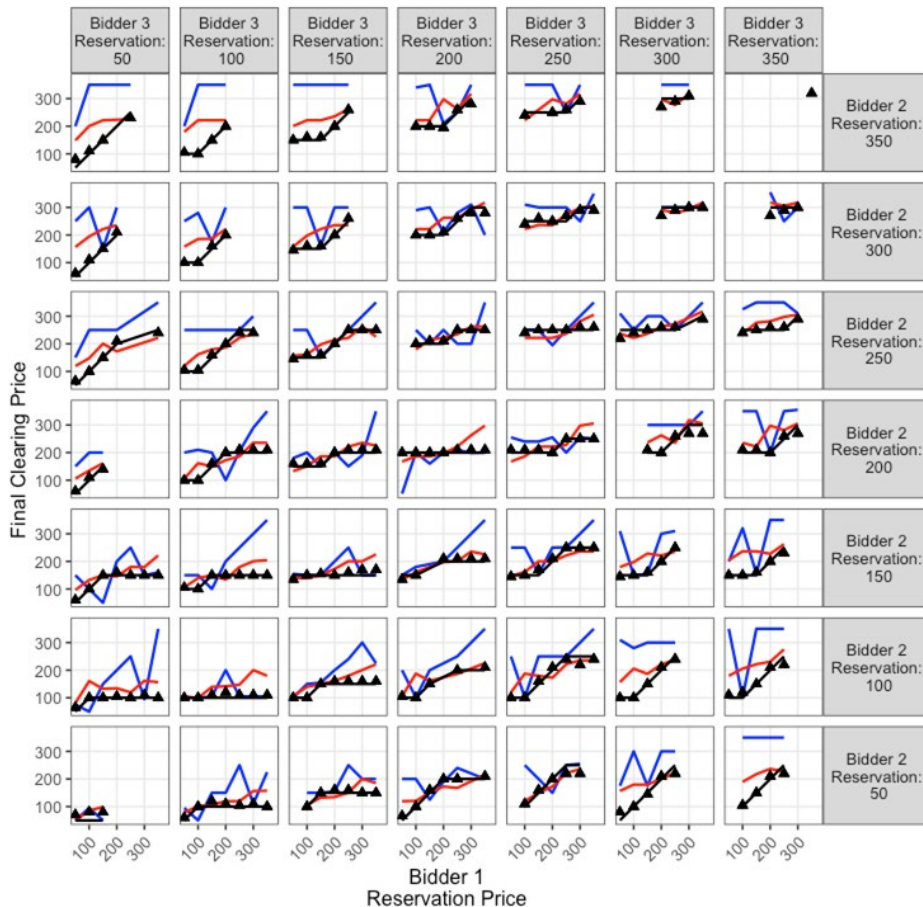
Augmented predictions (in red) are much improved

MSE pred: **8628**

MSE pred w/ SCM: **1505**

MSE for theory: **128**

Self-experimentation
was helpful for in-
context learning



Why might this be useful for social science?

- Trained to predict the next token in a sequence of text from a *massive* human-generated corpus
 - There is Latent information in these models and they are only getting better
- Imagine simulating **1000s of experiments** while you sleep
 - querying LLMs for interesting patterns learned in training
 - Easy to interpret and design replications

Next Research Questions

- How can we build a **better LLM scientist**?
 - Make systems that propose **novel hypotheses**
 - Make systems that **construct more complicated experiment**?
- Can we figure out when these **LLMs are good (and bad) proxies for humans**?
 - Iteratively explore their behavior en masse
- **Make predictions** with LLM agents and **verify on Human**.
 - Example: after intervention for 10 days, the outcome will change by $+30 \pm 3\%$

Thank you!

Link to Paper

bmannings@mit.edu
benjaminmanning.io
@BenSManning



kehangzhu@gmail.com
Kehang-Zhu.github.io

Raw data



<https://bit.ly/49xFsFR>

Experiment Details

Bidder1: oliver - Value: \$50

Bidder2: emma - Value: \$100

Bidder3: liam - Value: \$250

Auctioneer: mason

Chat History

- mason: I'll start the bidding at fifty dollars for the piece of art.
- oliver: I'll bid fifty dollars for the piece of art.
- mason: Thank you, Oliver. The current bid is fifty dollars. Do I hear a higher bid? Emma, Liam, what do you say?
- emma: I'll raise the bid to fifty-five dollars.
- mason: Thank you, Emma. The current bid is now fifty-five dollars. Can anyone offer a higher bid? Oliver, Liam, do you want to raise the bid?
- liam: I'll raise the bid to sixty dollars.
- mason: Thank you, Liam. The current bid is now sixty dollars. Emma, Oliver, can either of you offer a higher bid?
- oliver: I'm sorry, but I can't raise my bid any further.
- mason: I understand, Oliver. So, the current bid is sixty dollars from Liam. Emma, would you like to raise the bid?
- emma: I'll raise the bid to sixty-five dollars.
- mason: Thank you, Emma. The current bid is now sixty-five dollars. Liam, would you like to raise the bid?
- liam: I'll raise the bid to seventy dollars.
- mason: Thank you, Liam. The current bid is now seventy dollars. Emma, would you like to raise the bid?
- oliver: I'll have to pass, the bid is beyond my budget.
- mason: I understand, Oliver. The current bid is seventy dollars from Liam. Emma, are you interested in raising the bid further?
- emma: I'll raise the bid to seventy-five dollars.
- mason: Thank you, Emma. The current bid is now seventy-five dollars. Liam, would you like to raise the bid?
- liam: I'll raise the bid to eighty dollars.
- mason: Thank you, Liam. The current bid is now eighty dollars. Emma, would you like to raise the bid?
- oliver: I'm afraid I can't participate further, the bid has exceeded my budget.
- mason: I understand, Oliver. The current bid is eighty dollars from Liam. Emma, are you interested in raising the bid further?
- emma: I'll raise the bid to eighty-five dollars.
- mason: Thank you, Emma. The current bid is now eighty-five dollars. Liam, would you like to raise the bid?
- liam: I'll raise the bid to ninety dollars.
- mason: Thank you, Liam. The current bid is now ninety dollars. Emma, would you like to raise the bid?
- oliver: I cannot raise the bid, it's beyond my budget.