the Advertising Research Foundation

AUDIENCE xSCIENCE 2024

A Clean Room Incrementality Experiment – An Indeed Case Study

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Indeed

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#ARFAxS

Data Clean Room Experimentation: Assessing Incrementality

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indeed

Outline

- Indeed and Our Goals
- Bias in Online Experiments
- Managing Bias with Experimental Design
- Conclusion: Comparing Tests and Results

What is Indeed?

Indeed is the world's number one job site and leading matching and hiring platform. We strive to make a positive impact on society by connecting people to better work to create better lives.

We must regularly engage with new employers *and* jobseekers to balance the market

Employers → ← ***Jobseekers***

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What are we trying to achieve?

1. Measurement of the *incremental* impact of advertising on KPIs.

2. High quality continuous reporting with actionable analytics and insights.

Major Considerations for Experimentation at Indeed

- **New customer focus**

  For current customers, retargeting would be straightforward

- **Cookie-free**

  Deprecation in process

- **Privacy forward**

  Doesn't allow us to see individual customer data

- **Ability to verify advertiser data**

  Allows for "checks" on delivery and efficacy

  Rules out most "walled gardens"

Experimentation through Data Clean Rooms

Fragmented Landscape: Indeed uses multiple vendors to measure incrementality, but the process remains the same.

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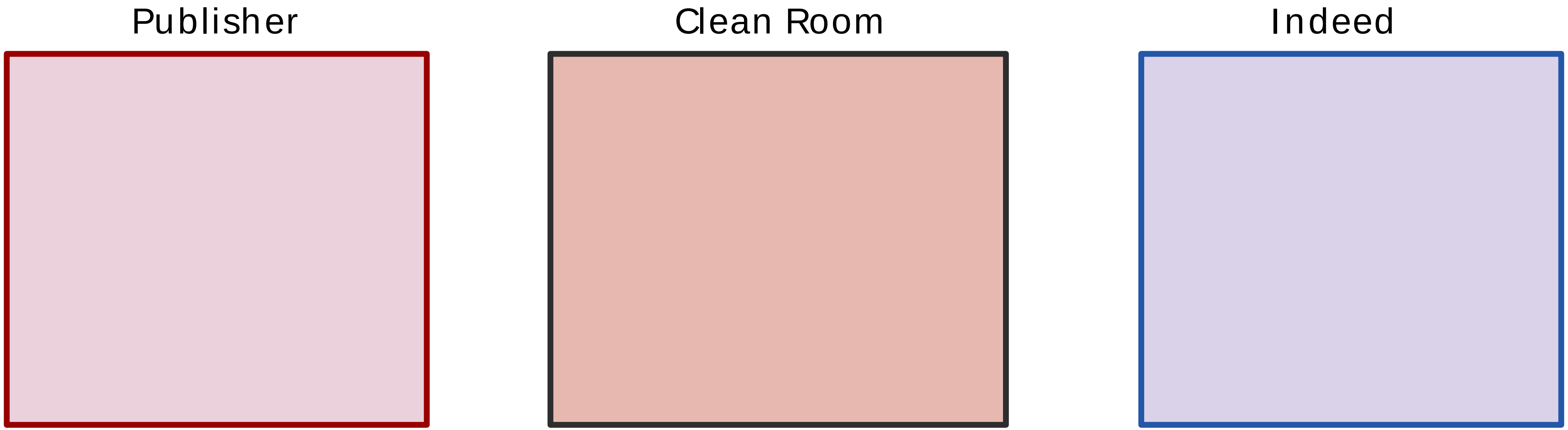

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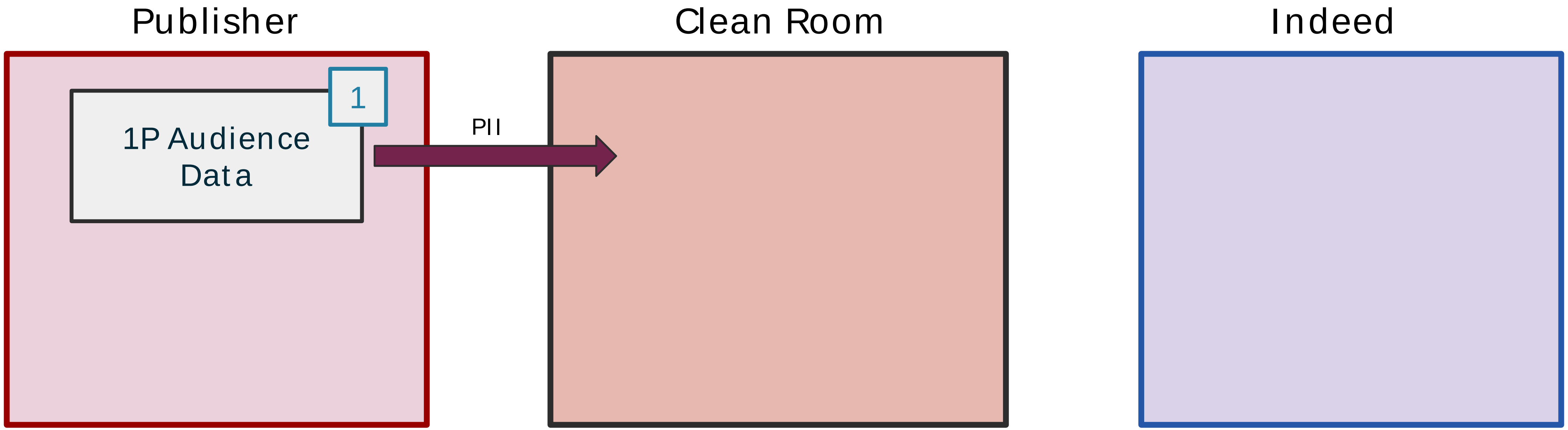

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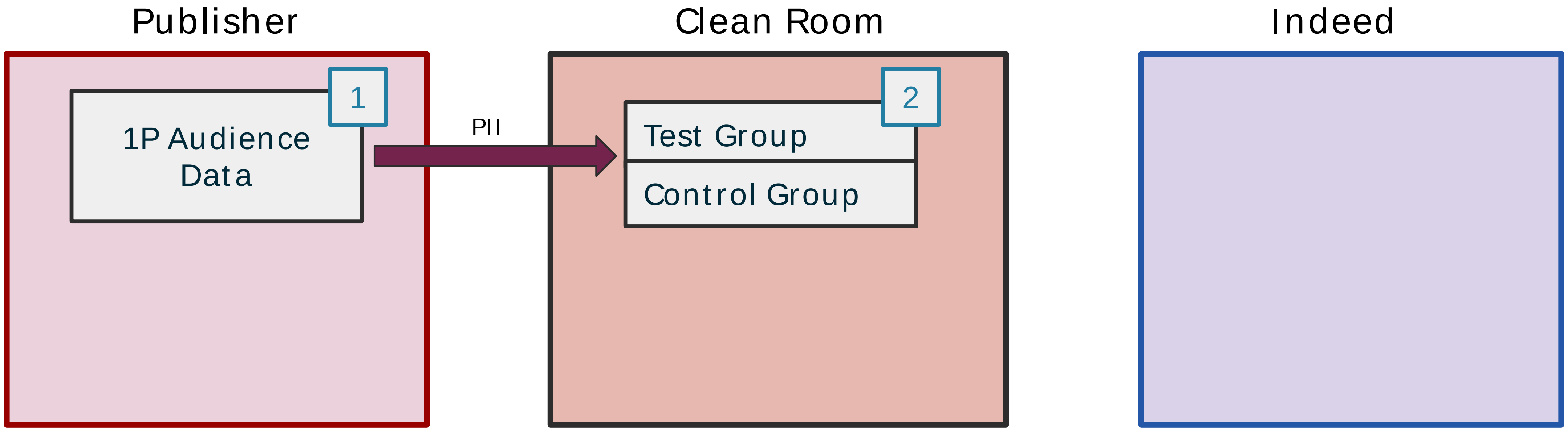

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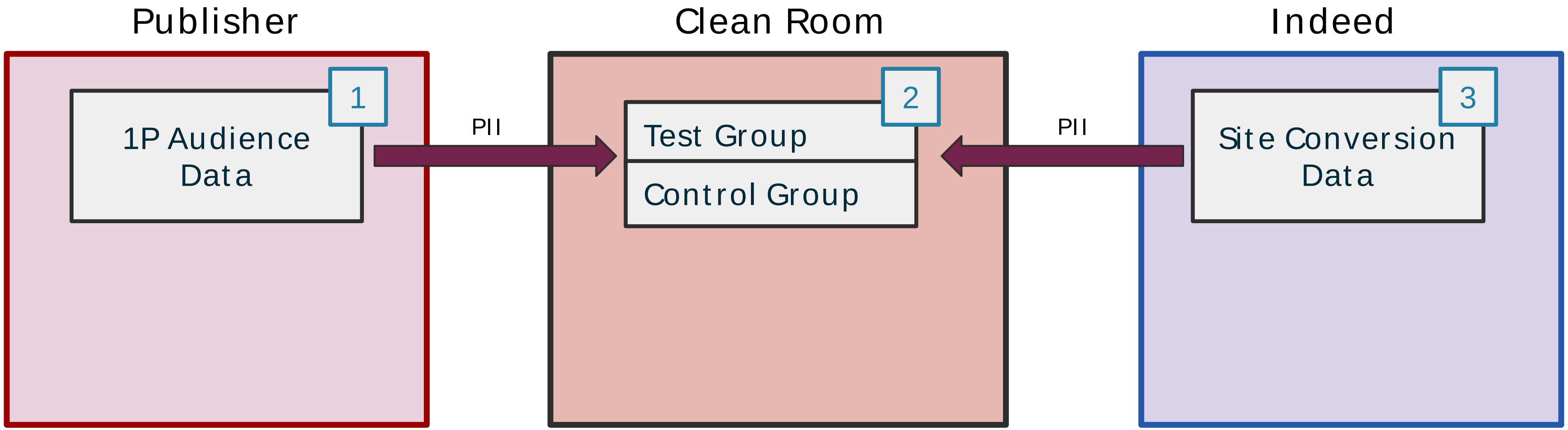

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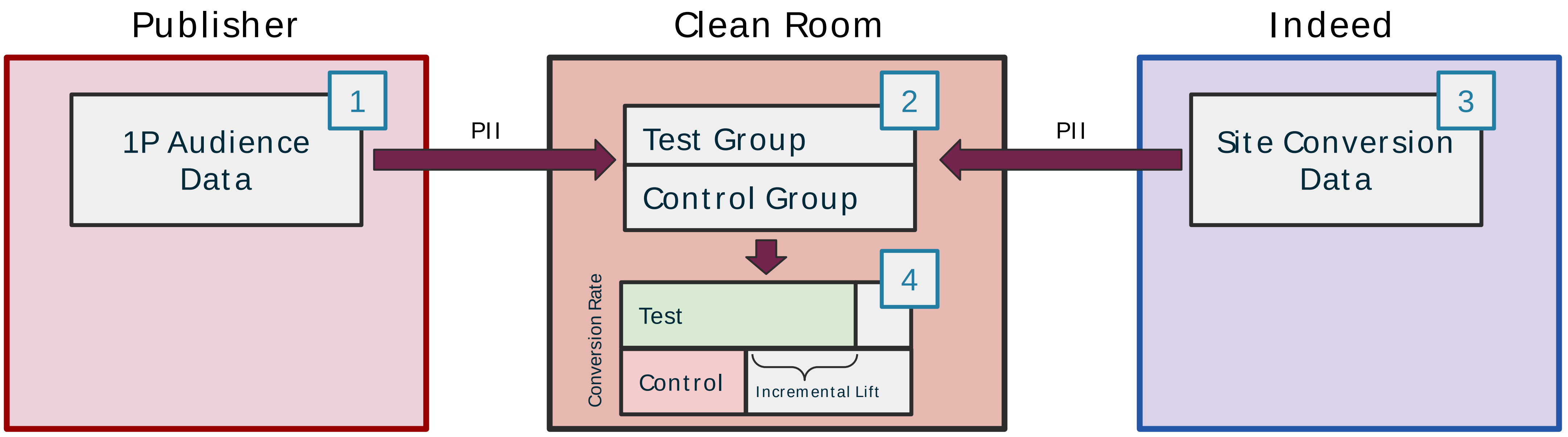

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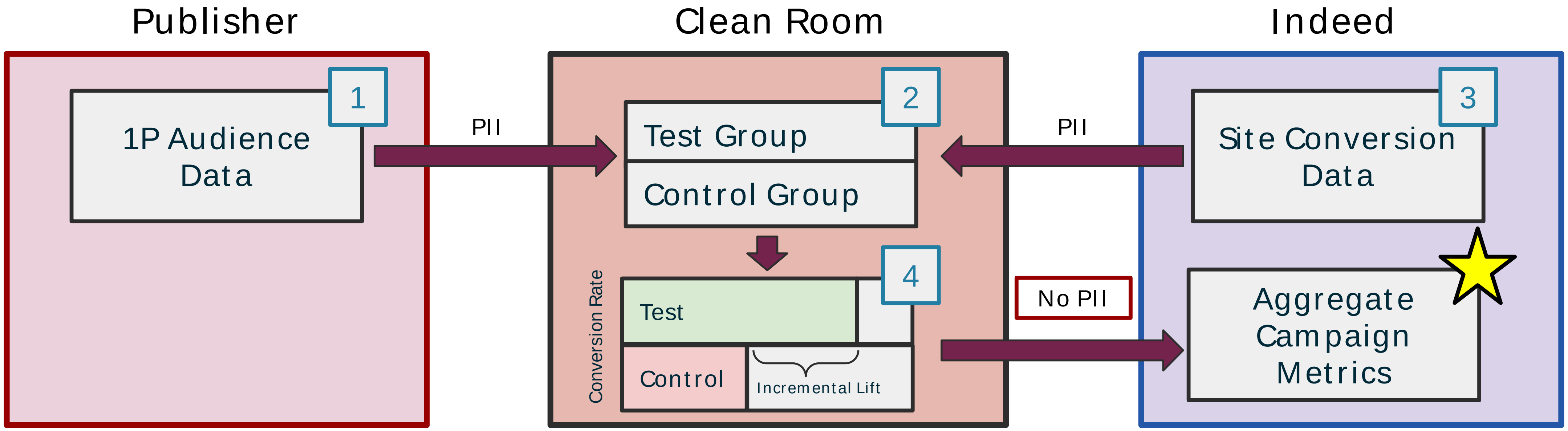

Clean Room Experimentation in Practice

Bias in Online Experimentation

Clean experiments in an online marketplace is difficult due to a complex marketplace.

- **Activity Bias**

  Test users may be more active on the publisher's platform than control users

  Experiment may measure "Activity", rather than ad effects

- **Ad Server Bias**

  Ad servers optimize to specific behaviour (i.e. clicks) and may serve PSA/House ads to a different type of user than the test group

- **Base Rate Bias**

  Baseline conversion rates of different methods (Ghost Ads, Suppression, etc.) may be dissimilar, causing incorrect lift estimates against a test population in unpredictable ways

Experimental Design: Five Variations

Creating of the control group can be achieved in multiple ways

Ghost Ads	→ *Control users are served ads normally, but log when test ads would have won the auction*
High Technical Set Up	

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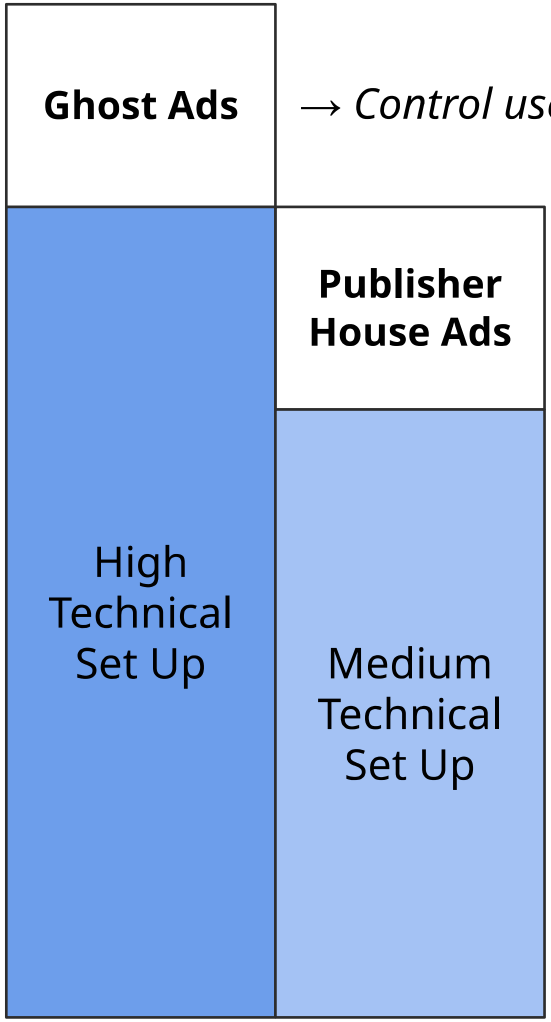

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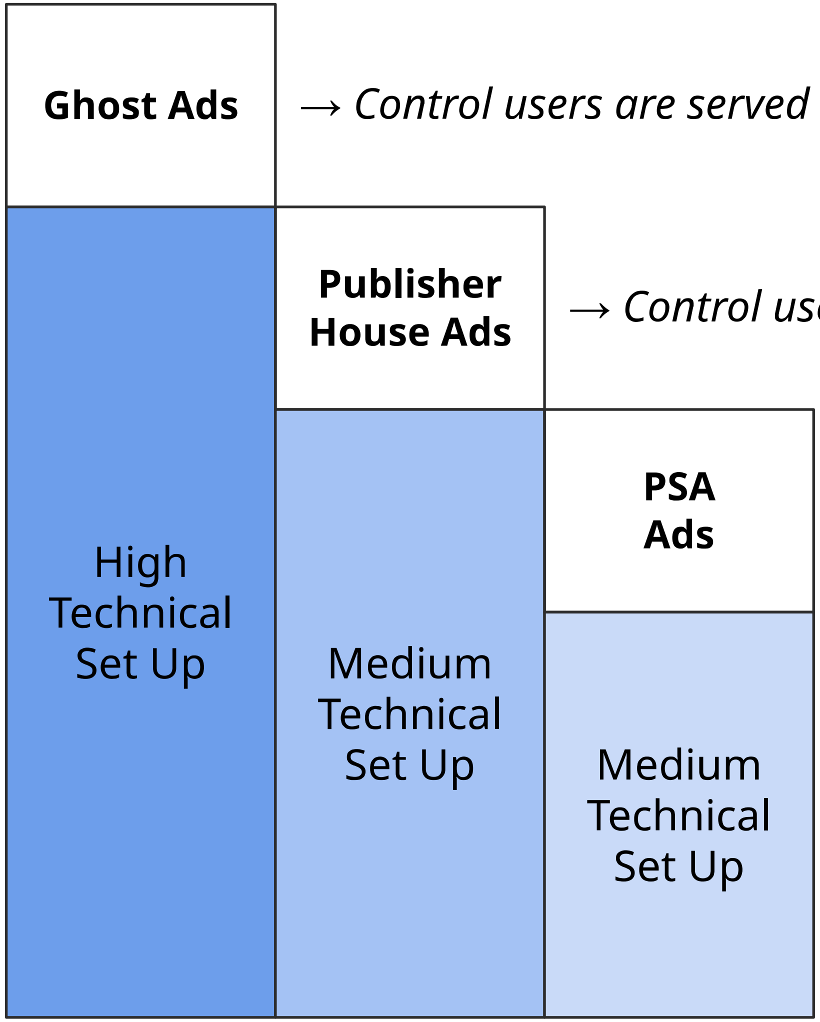

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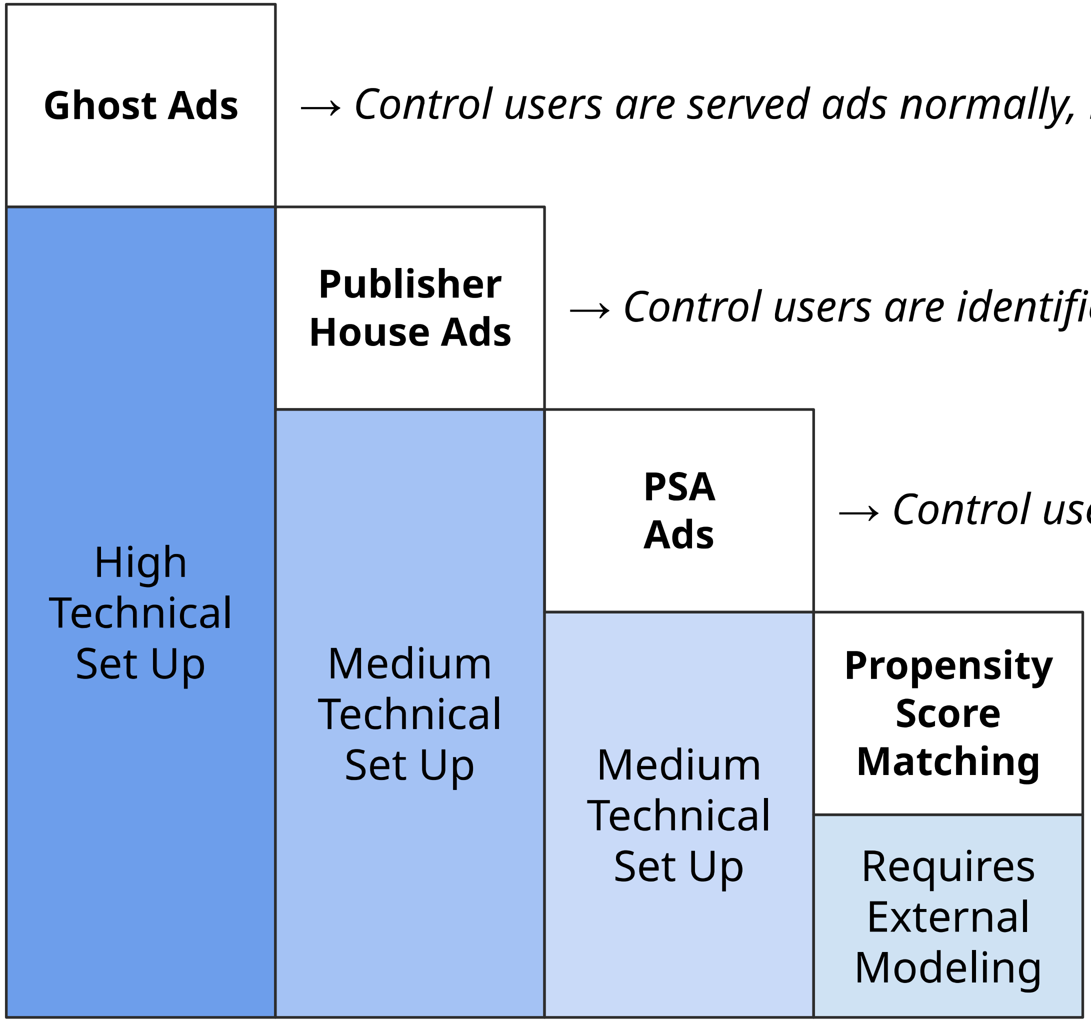

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→ *(Pairwise Comparison) Control users matched to test users via propensity score modeling*

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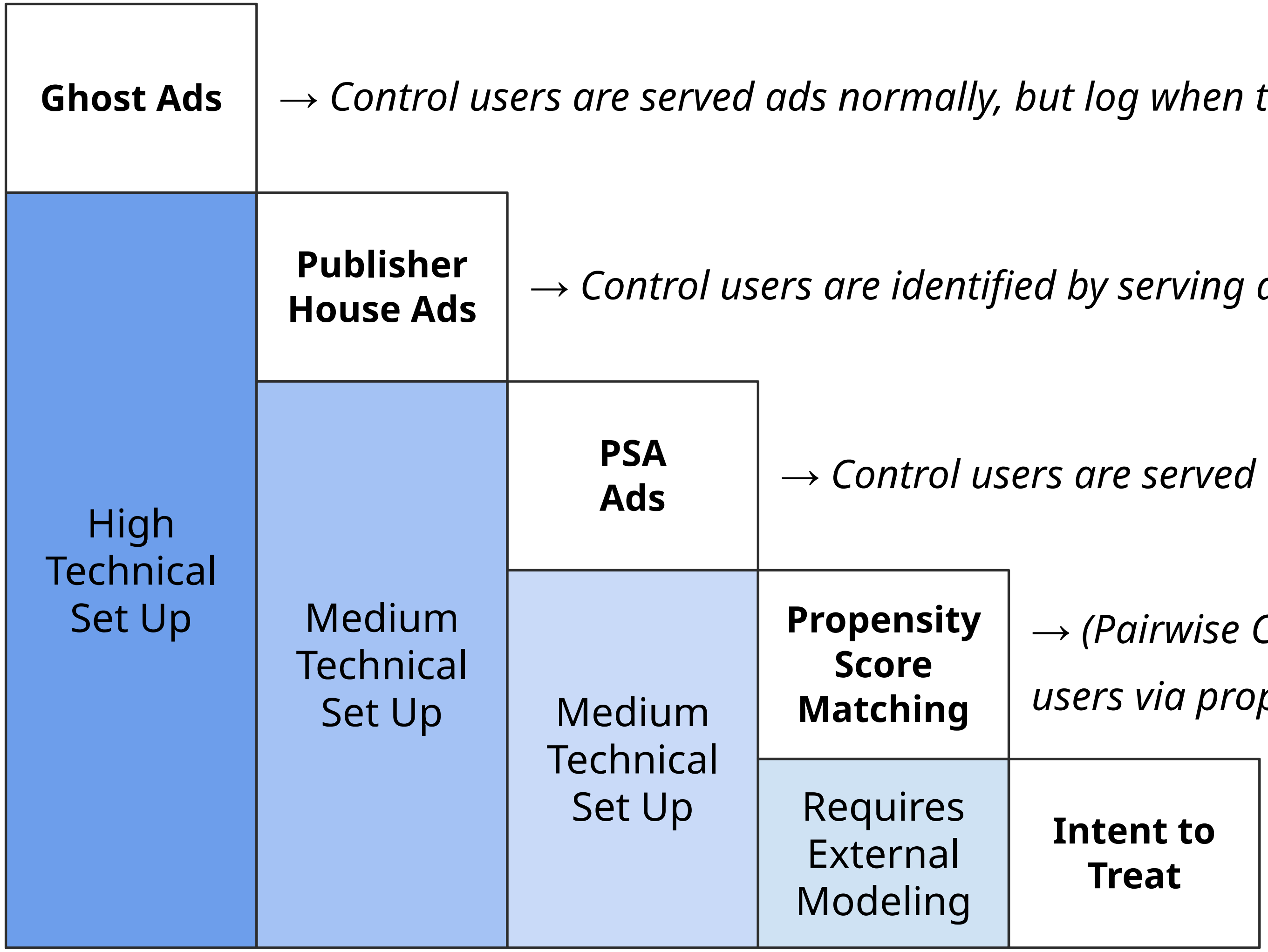

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→ *(Pairwise Comparison) Control users matched to test users via propensity score modeling*

→ *(Suppression) Control users are identified and suppressed from the test campaign*

Interpreting Experiment Results

Comparing the Options: There is No Free Lunch

Experiment Design	Activity Bias	Ad/Context Bias	Base Rate Bias	Pros	Cons
Ghost Ads	✅	✅	✅	Best mimics real world for control users No cost to advertiser	Few publishing partners have this capability Low control over the analysis

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Propensity Score Matching	tbd	❎	✅	• Potentially strips away noise in unexposed users	• Requires additional data to model high quality matches

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Propensity Score Matching	tbd	☒	✅	• Potentially strips away noise in unexposed users	• Requires additional data to model high quality matches
Intent to Treat	tbd	✅	tbd	• Clean analysis IF there is access to unexposed test population data	• Requires publisher support • Lower statistical power due to additional “noise”

Challenges with Interpreting Experiment Results

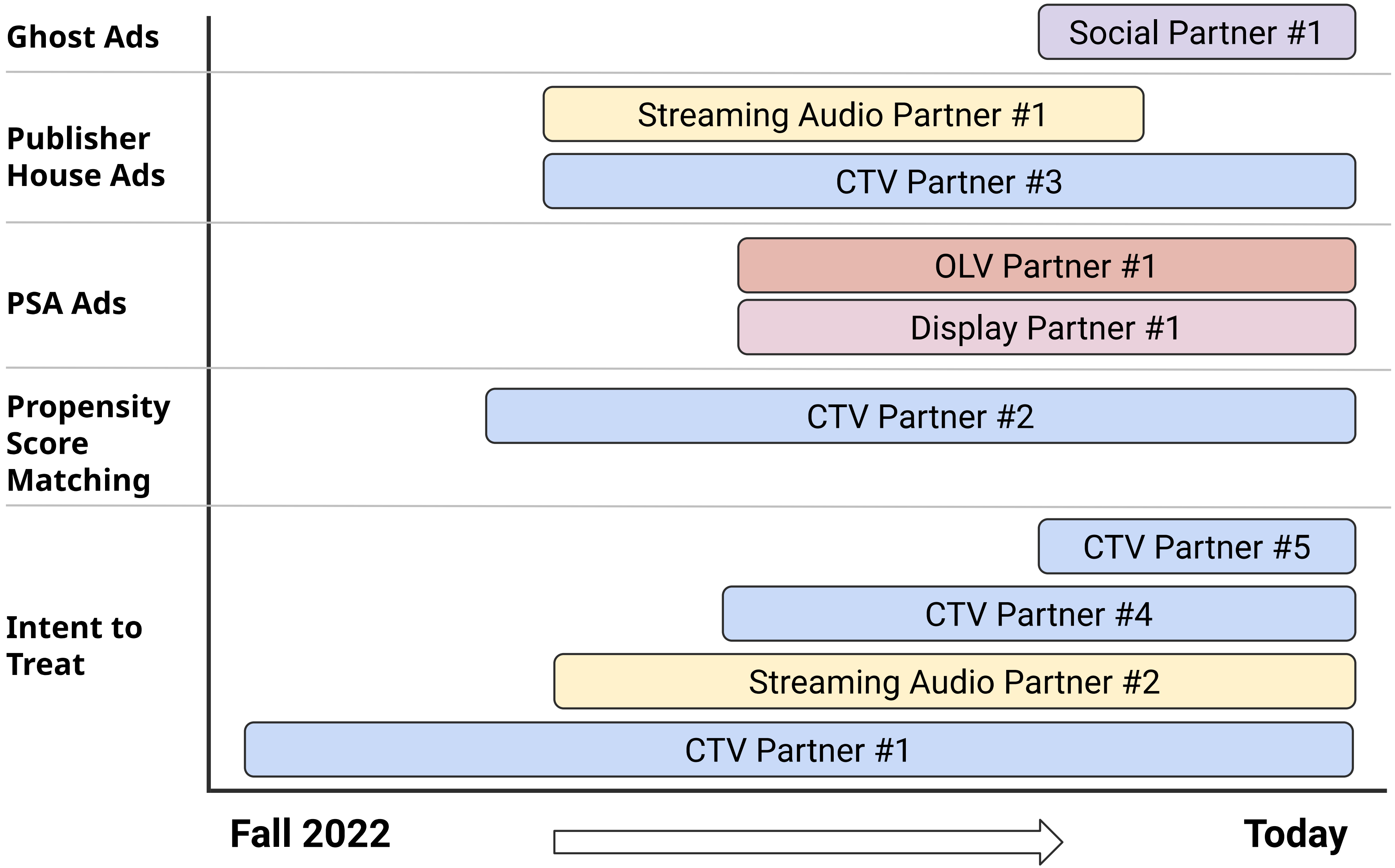
Low Match/Conversion Rates

1. **Narrow definition of a “match”**
2. **Match rates can be low and variable**
    a. Is the advertising ineffective or is there significant loss in matching?
3. **Resolving personal and corporate email accounts is a challenge**

Comparing Results

1. **Household identity graphs (one to many) vs individual identity graphs (one to one)**
    a. Relative lift is comparable, but attributed conversions can be very different.
2. **How comparable are experiments with different control group construction?**

Clean Room Experimentation: A Success Story



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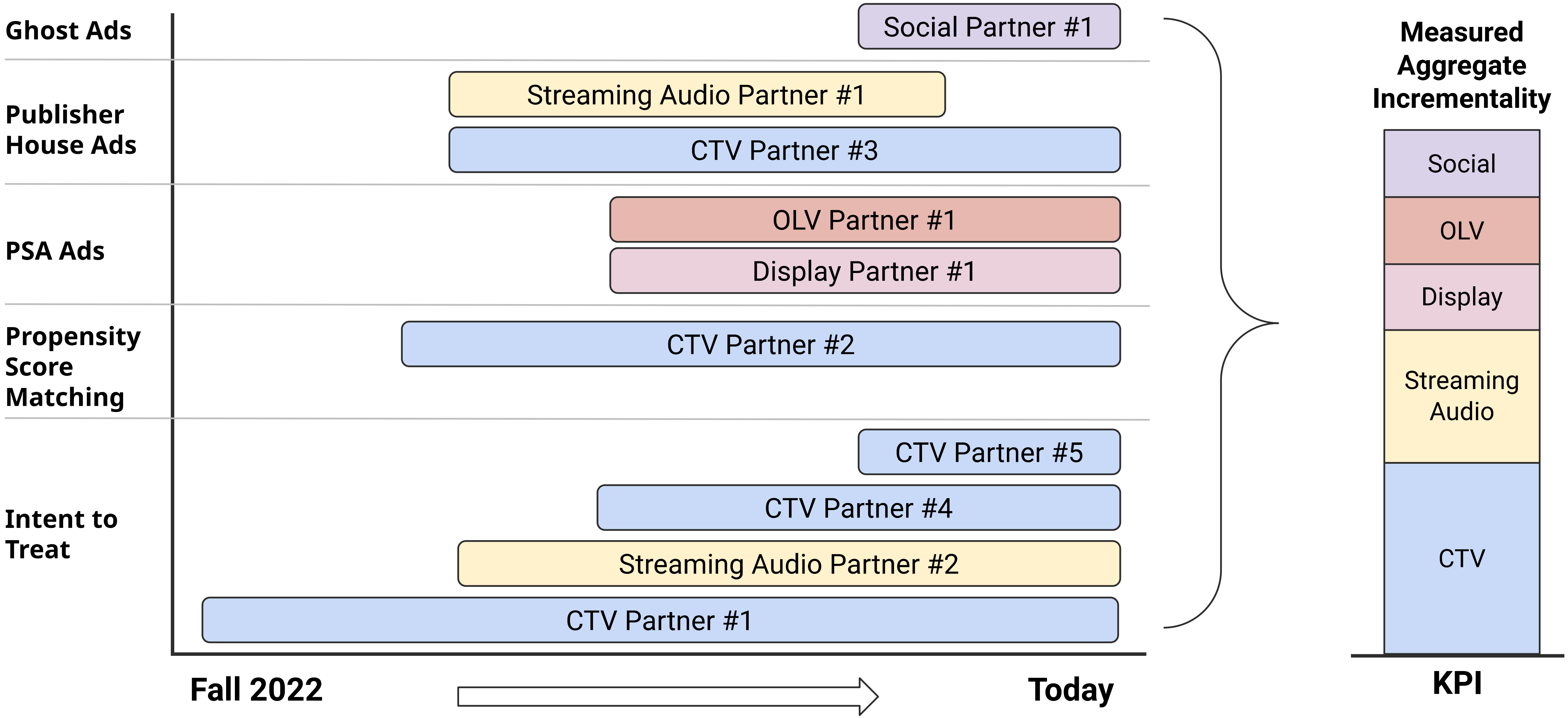

Q&A