Assumption-Lean Analysis of Cluster Randomized Trials in Infectious Diseases for Intent-to-Treat Effects and Network Effects

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EuroCIM2021

CRTs with interference and noncompliance

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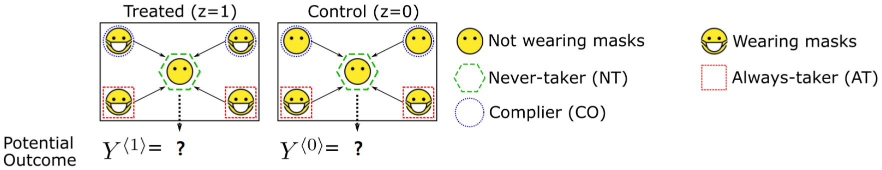
- **Today's Talk**: Do individuals not using face masks and hand sanitizer (i.e. never-takers) benefit from peers' using them (i.e. spillover effect among NTs)?

Spillover Effect Among Never-Takers τ_{NT}

- Graphical illustration of τ_{NT}: Consider a household having 5 members:



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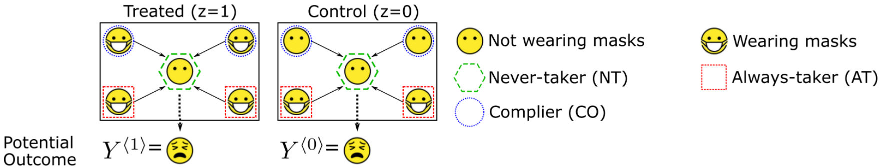

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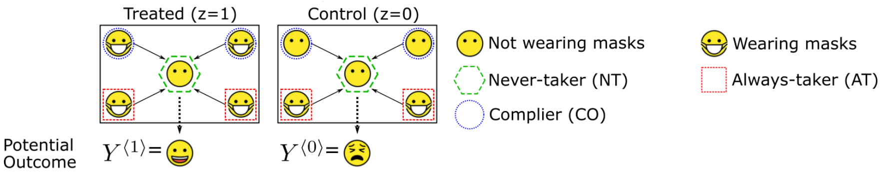

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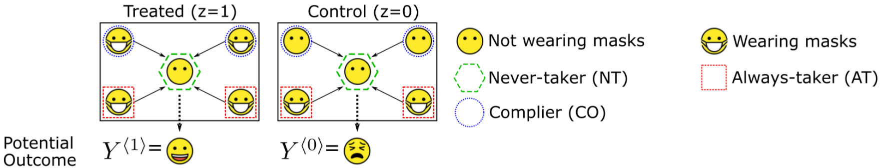

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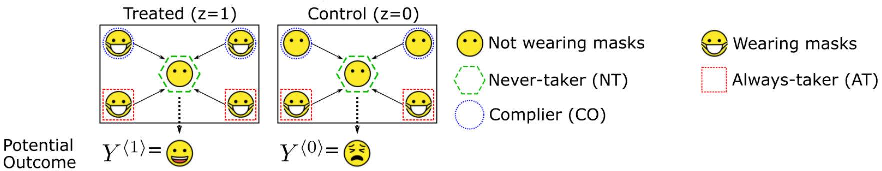

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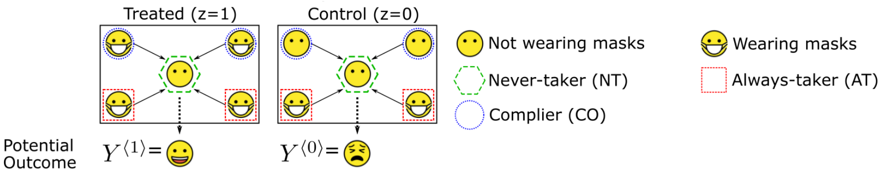

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- **Our "Assumption-Lean" Approach**: Make only "standard" assumptions in CRTs and obtain sharp bound of network effects using machine learning (ML) and linear programming (LP).

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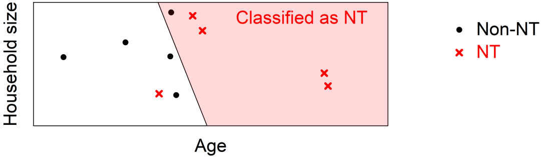

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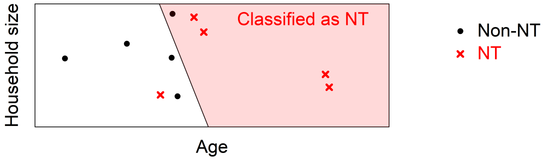

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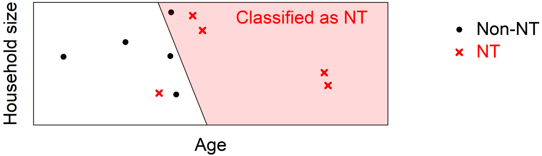

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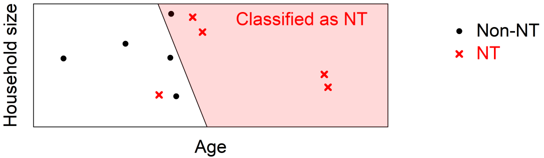

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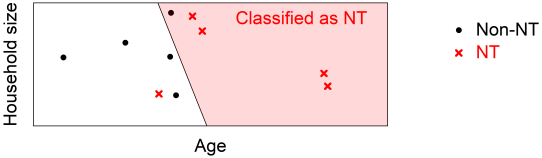

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  - The bounds are based on using linear programming (LP).
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  - Our approach is similar (in spirit) to Balke and Pearl (1997)'s LP bounds in IV settings, but our approach (i) targets subgroup network effects and (ii) uses covariates adjusted via ML to further sharpen bounds.

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- **Property 4**: Under some mild conditions on classifiers (e.g. smoothness of loss function),
  our bounds can be consistently estimated.
- For inference, we use resampling approaches of Efron and Tibshirani (1993) and Romano and Shaikh (2010), modified for cluster-level resampling.

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τ_{CO}	Bound	$[0.000, 0.146]$	$[0.000, 0.146]$	$[0.000, 0.186]$	$[0.000, 0.146]$
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- There is no significant network effect at $\alpha = 0.05$ level.

Conclusion and Key Takeaways

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- Thank you! Check the paper (**arXiv: 2012.13885**) for details.

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