Optimal matching approaches in health policy evaluations under rolling enrollment

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Based on

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Impact of falls in health system data

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- How to measure the impact of serious falls on health status or healthcare spending?
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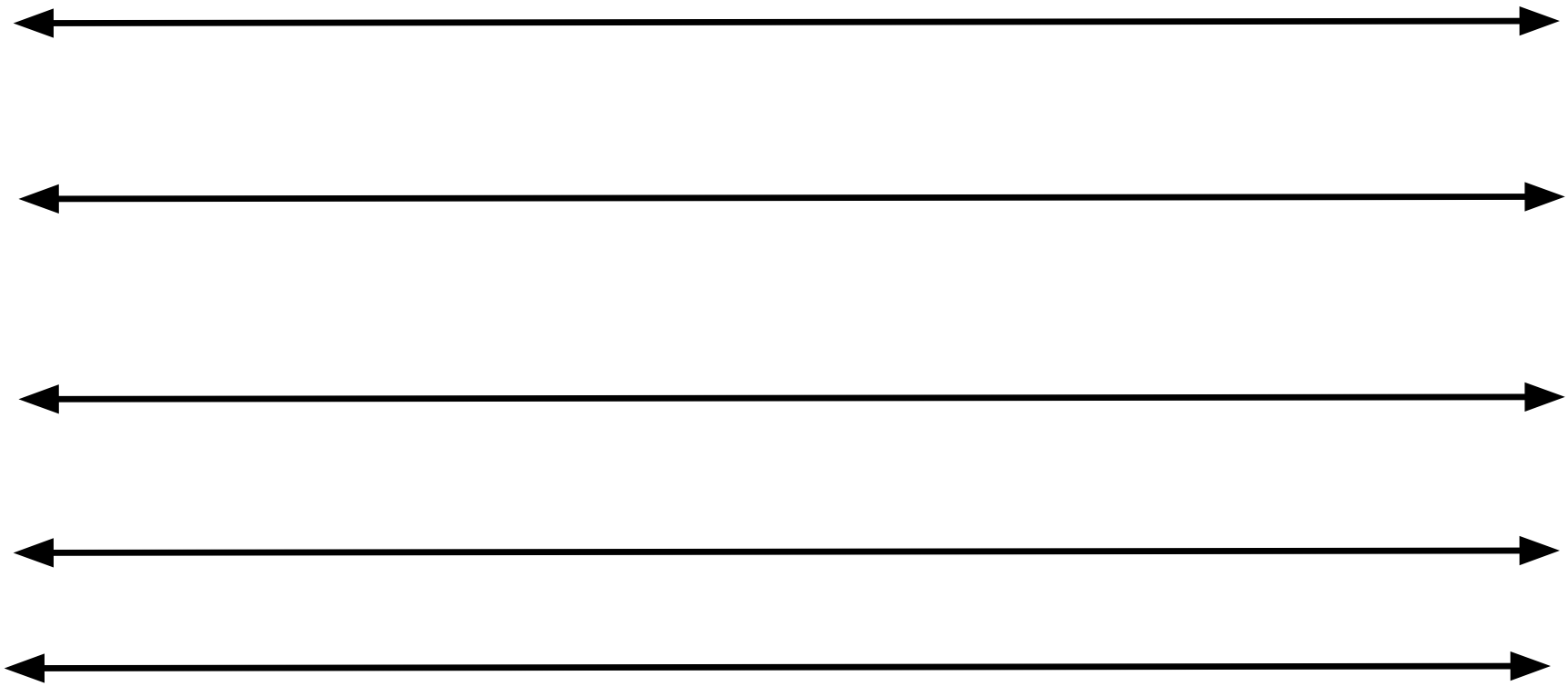
- Fallers may not be comparable to non-fallers at point of fall
- Possible confounding due to other health conditions, medications ("trigger events").
- How to do a good matched comparison?

Comparison and alignment



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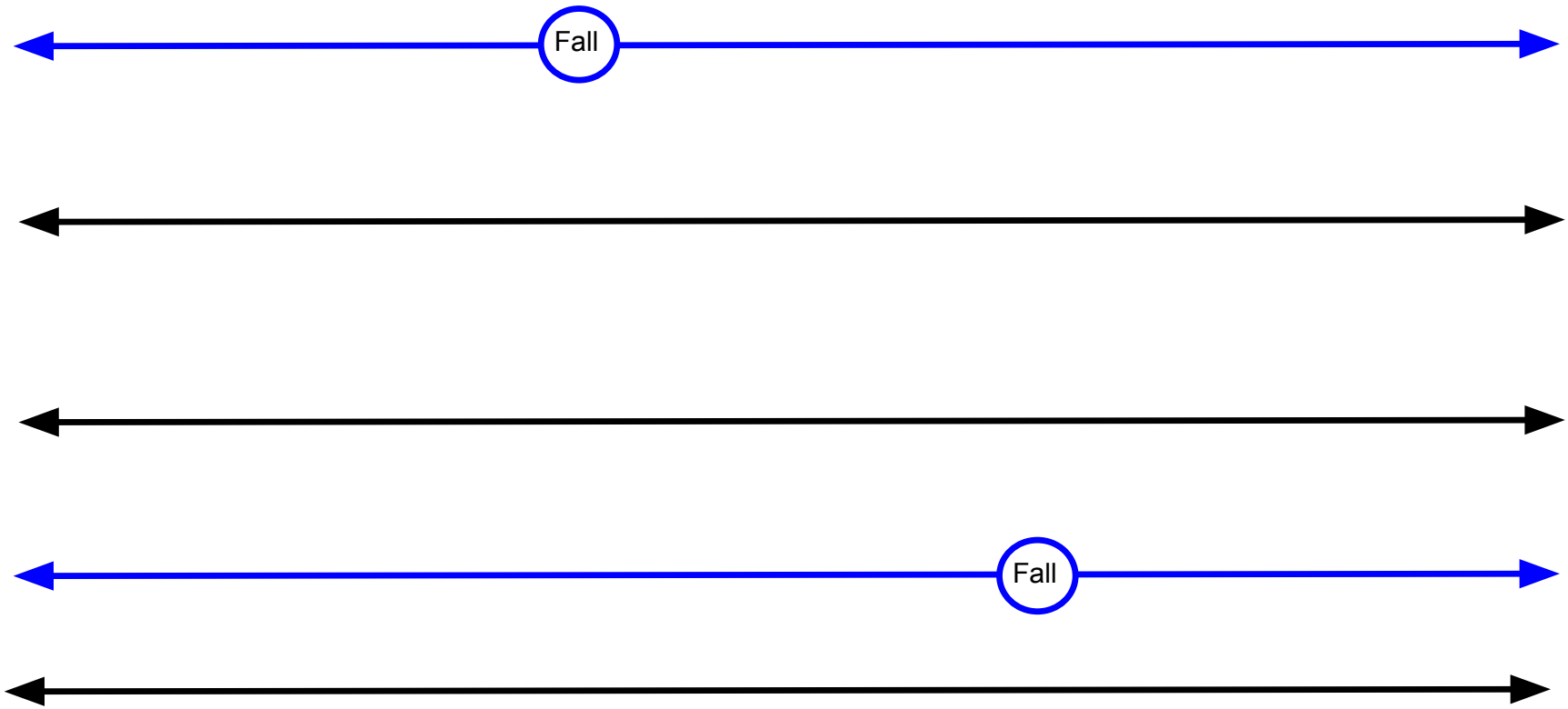

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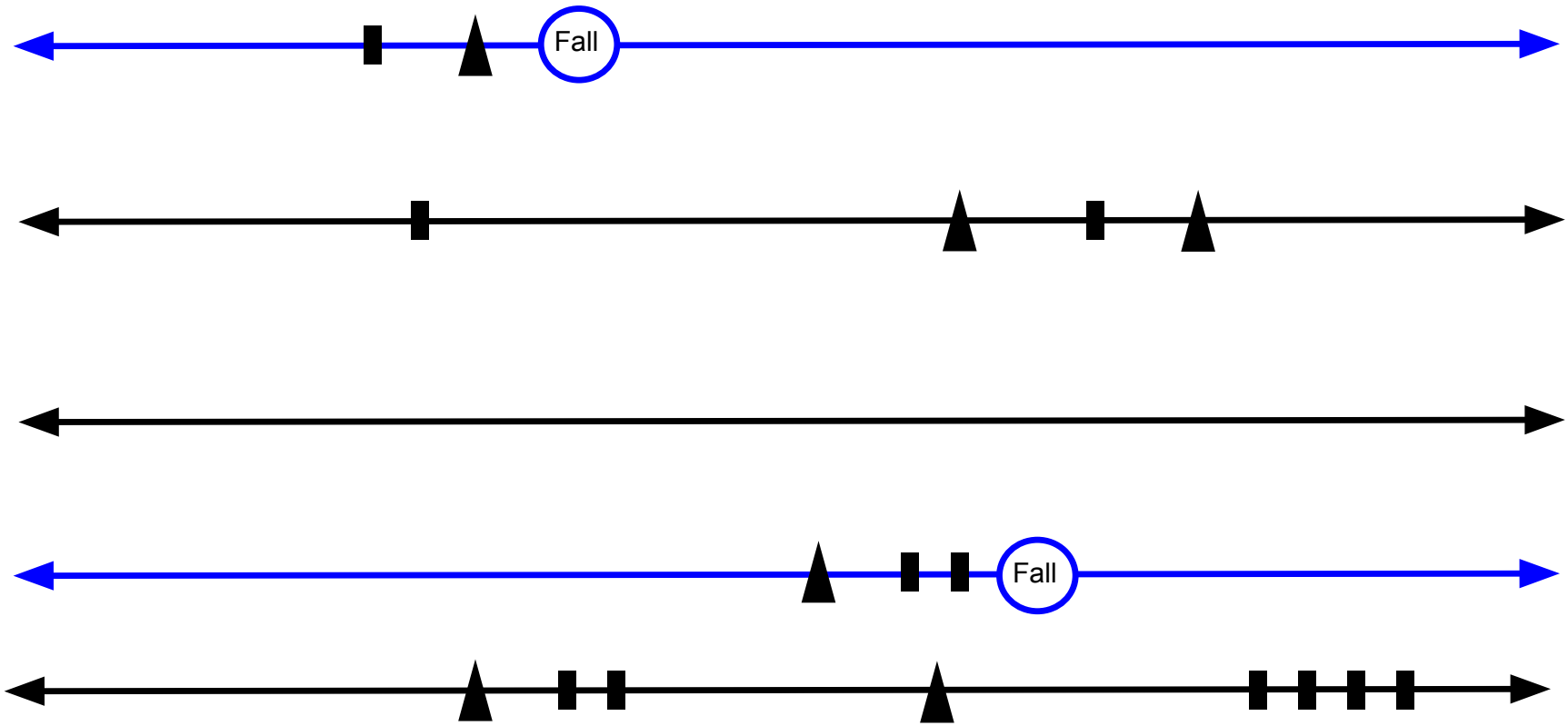

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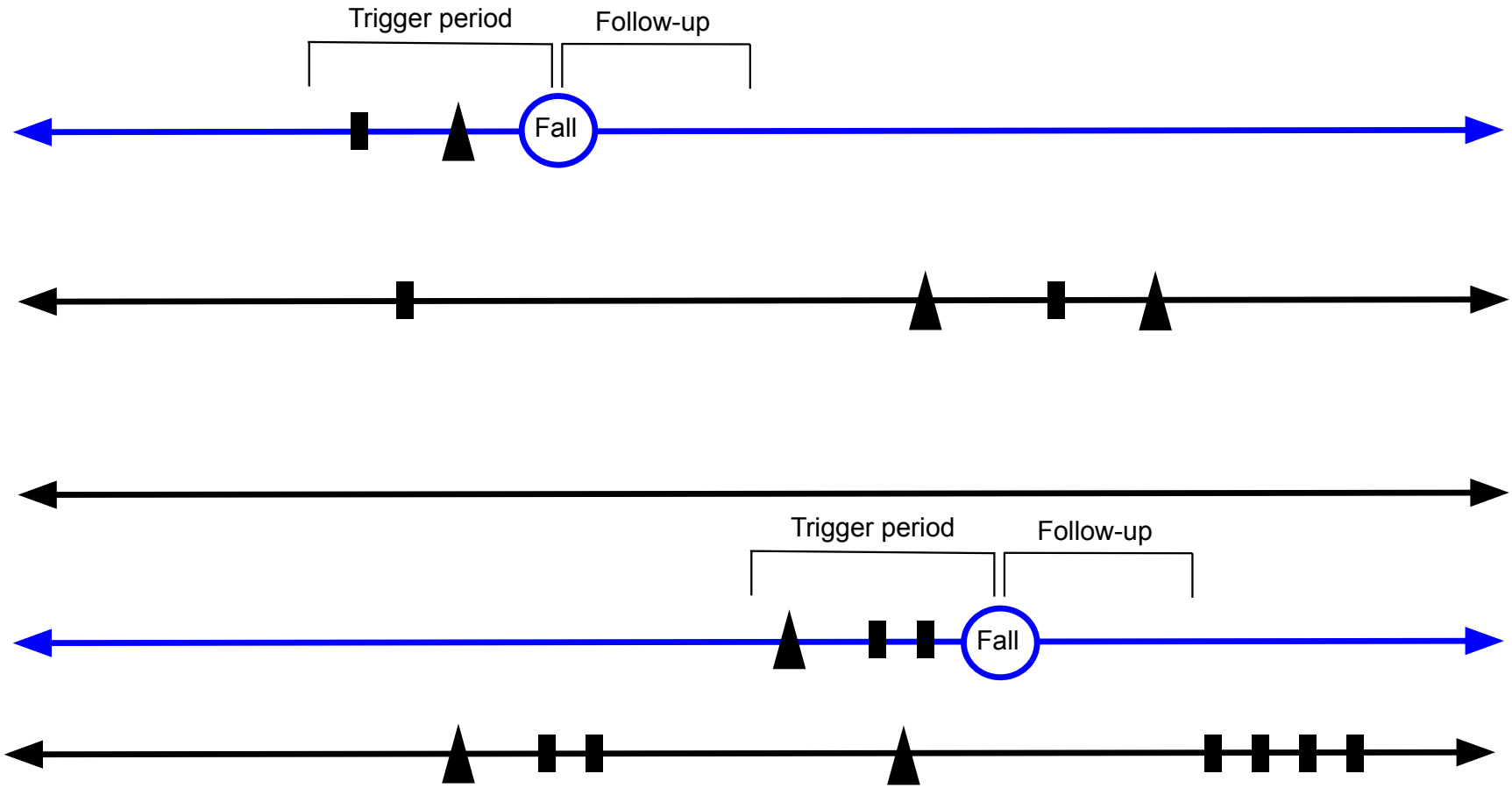

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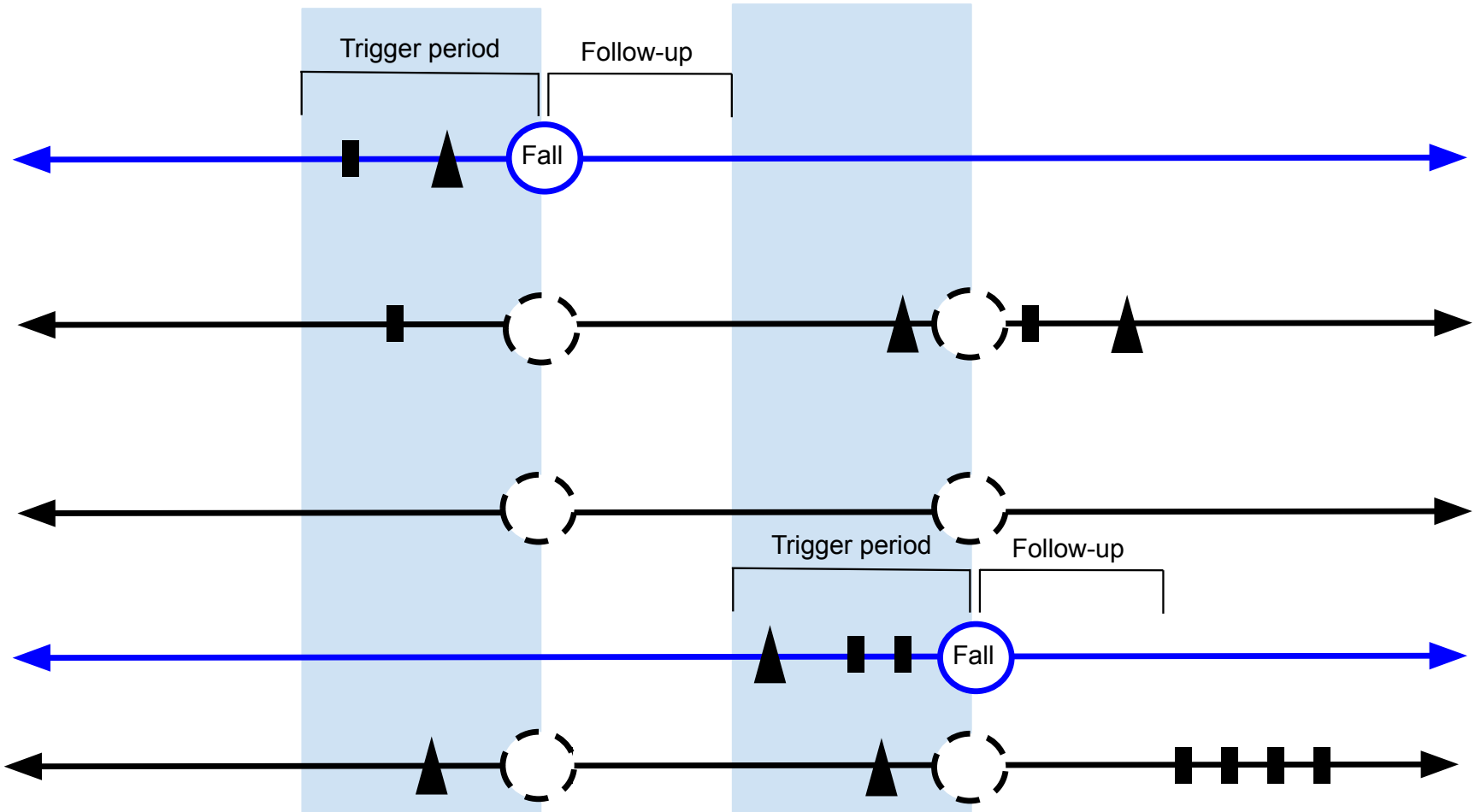

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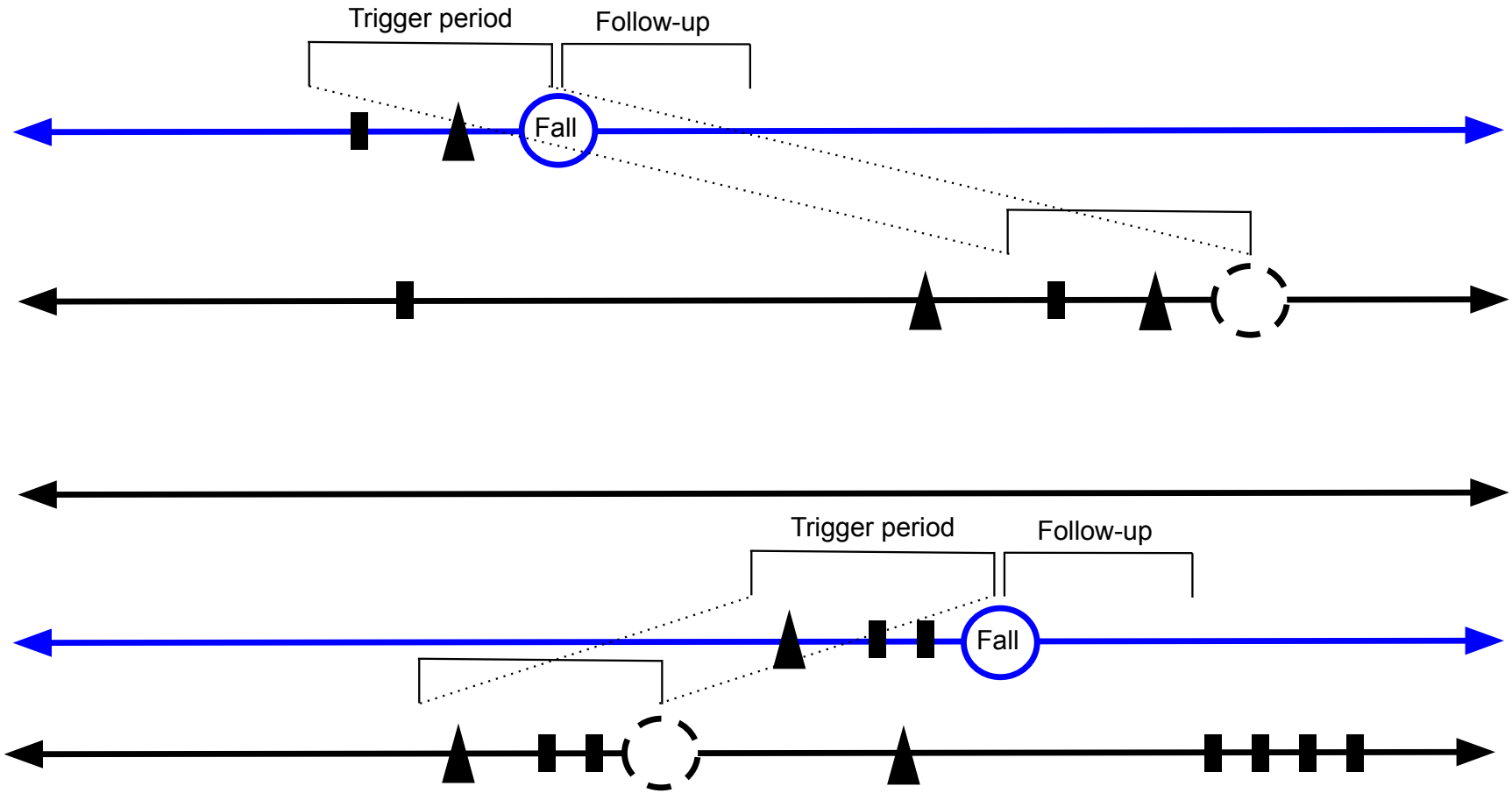

GroupMatch: matching and alignment solved together

- Our contribution: an optimization algorithm called **GroupMatch**.
- Matches treated units by searching jointly over all control individuals and all instances-in-time of those individuals to find optimal match.

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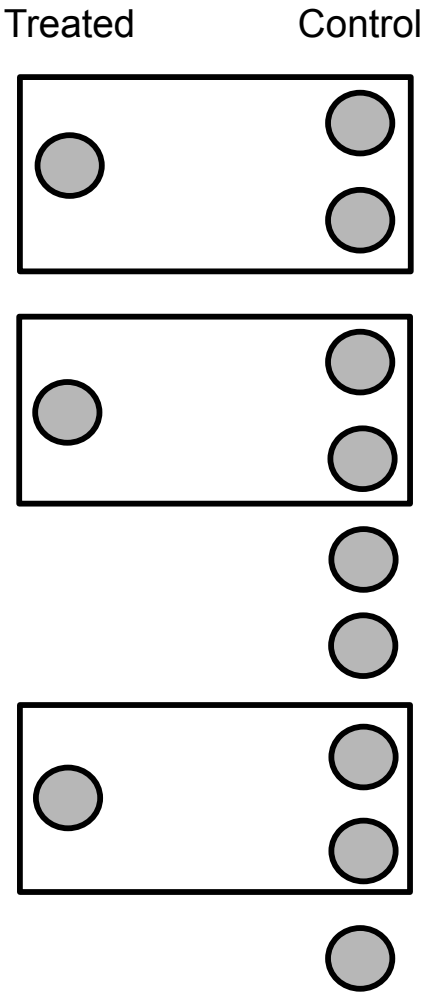
- Roadmap:
  1. Optimization approach underpinning GroupMatch.
  2. Application to Bohl et al. data, comparison to other methods.
  3. Statistical framework and areas for further work.

Review: optimal matching using a multivariate distance

- Goal is to link each treated unit to fixed number of controls K.
- In moderate/high dimensions, exact matching not usually possible.
- Instead, define distances δ_{ij} between treated and control units (e.g. Mahalanobis).
- Rosenbaum (*JASA* 1989): use network flow optimization to find configuration with minimum total within-set distance.



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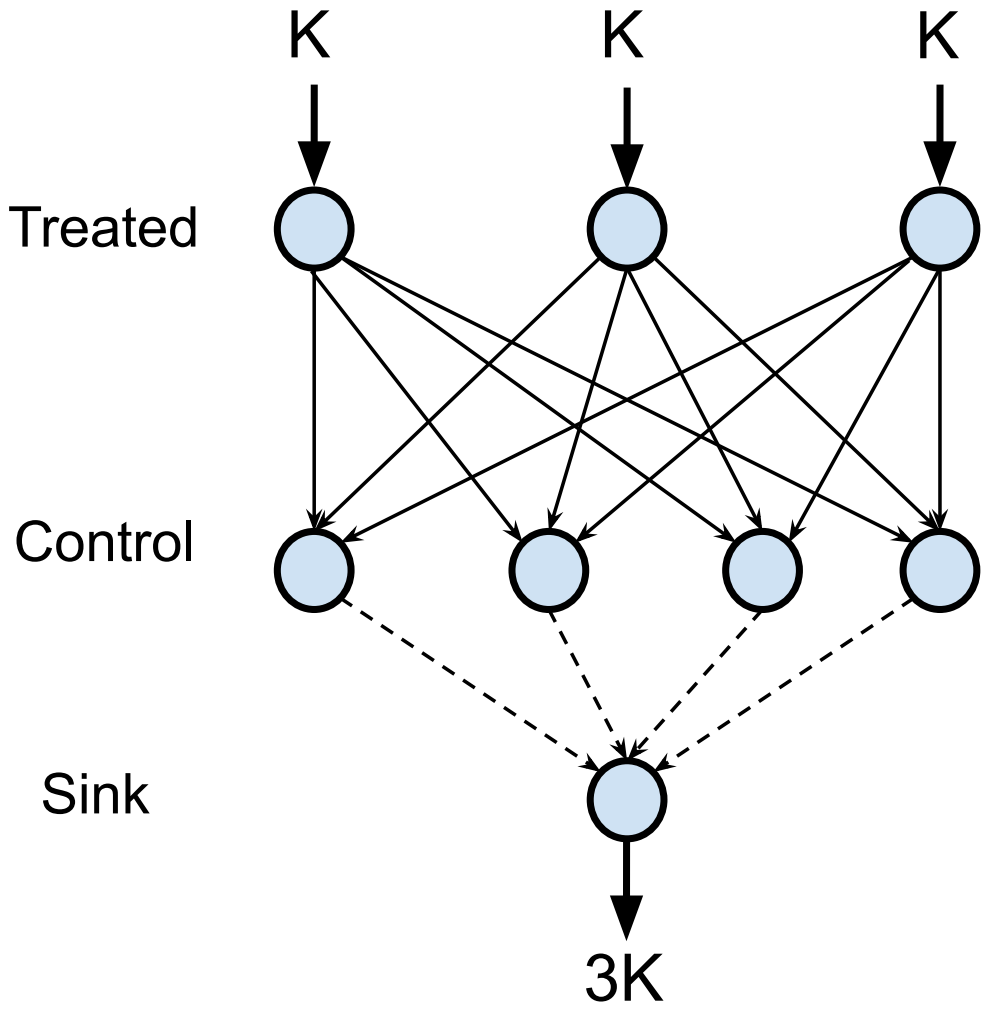
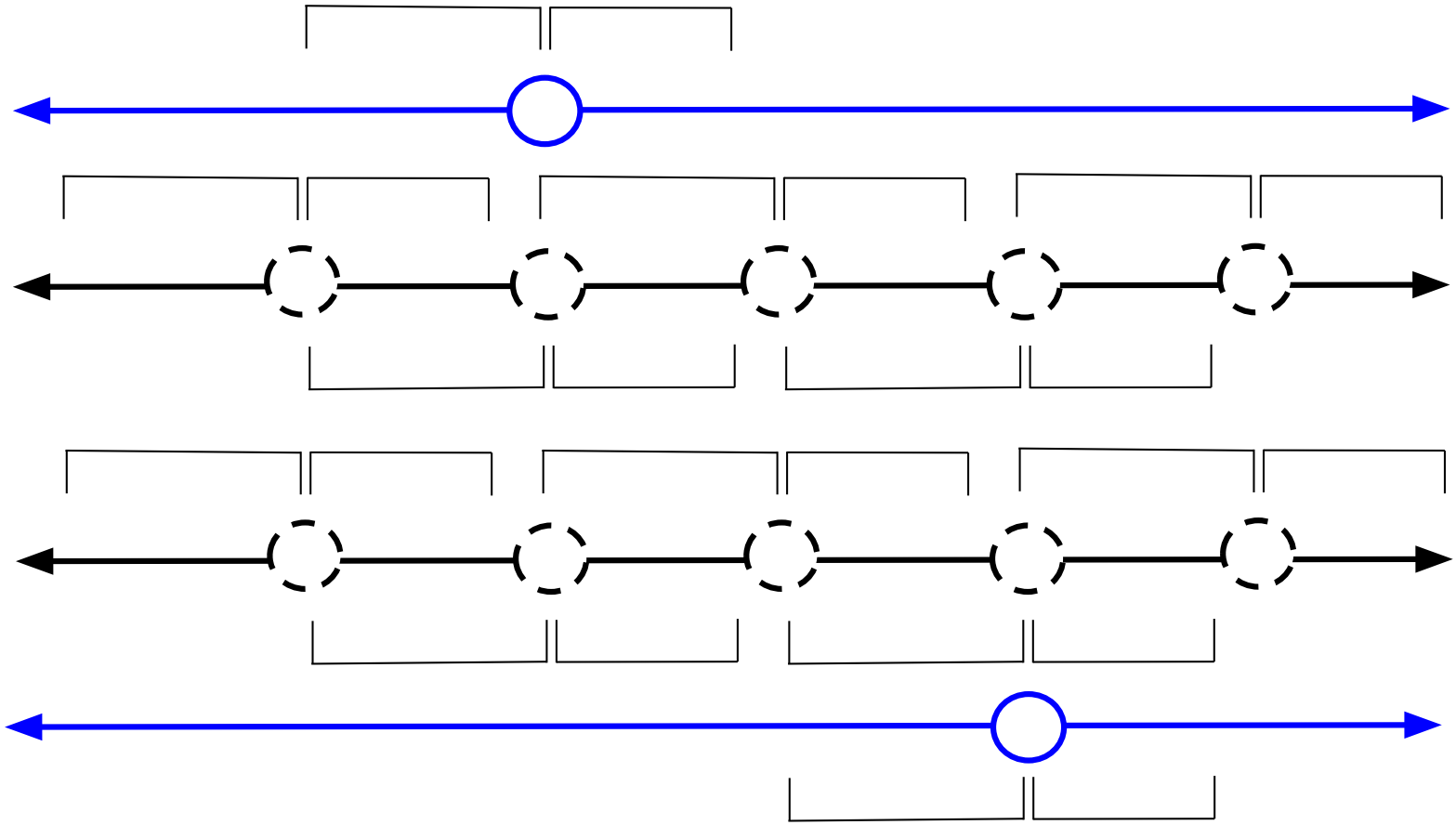


Adapting optimization framework to rolling enrollment

- Treated *trajectories i* have one *instance* of interest (at entry time).
- Control trajectories *j* have many instances *jt* of potential interest.



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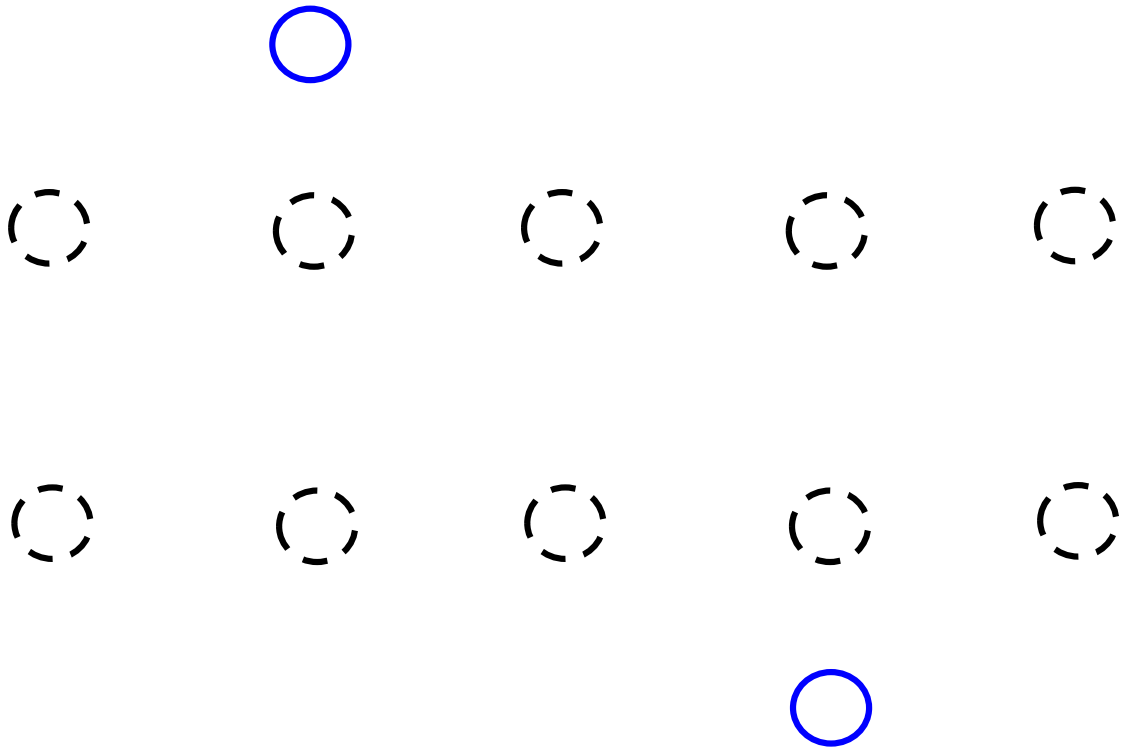
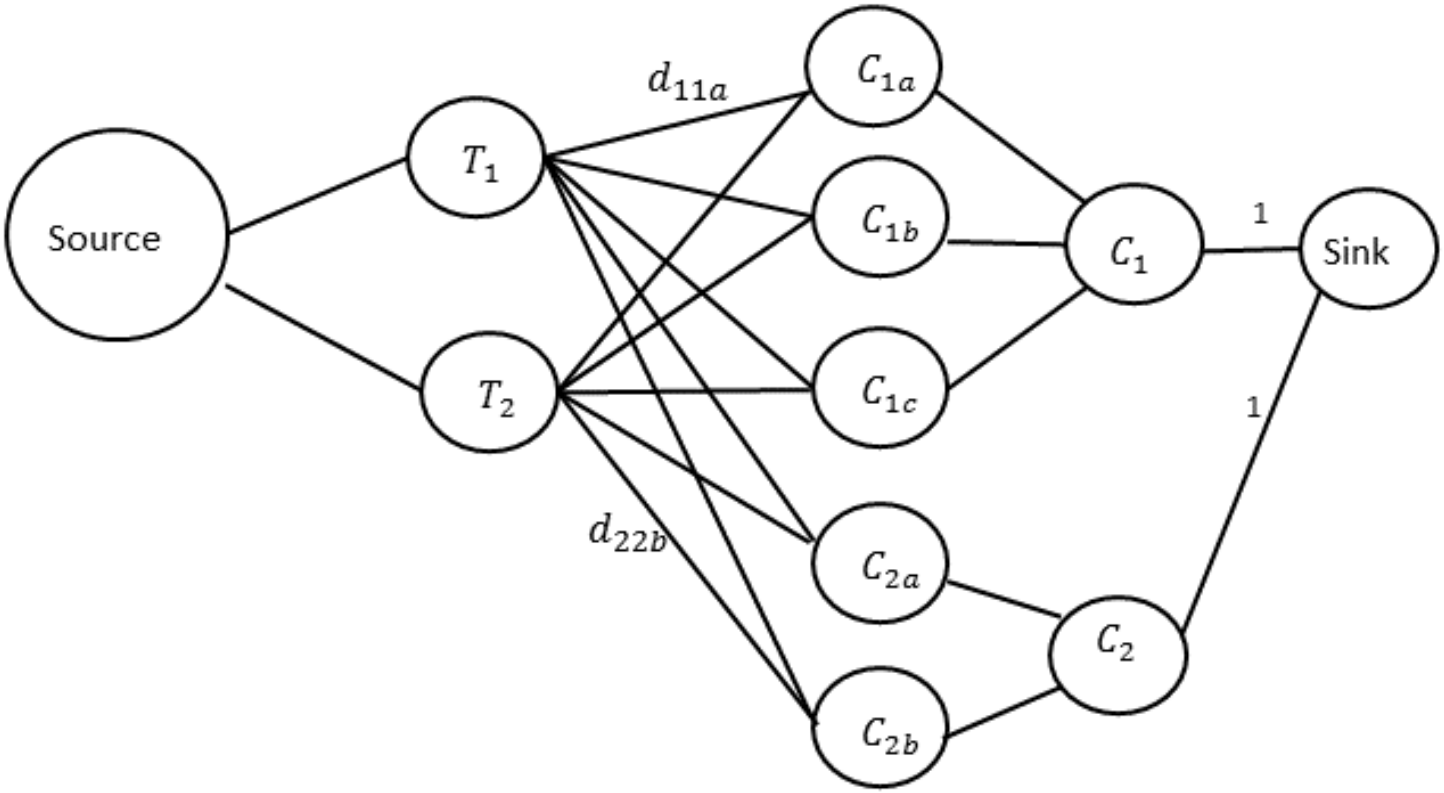


Adapting optimization framework to rolling enrollment

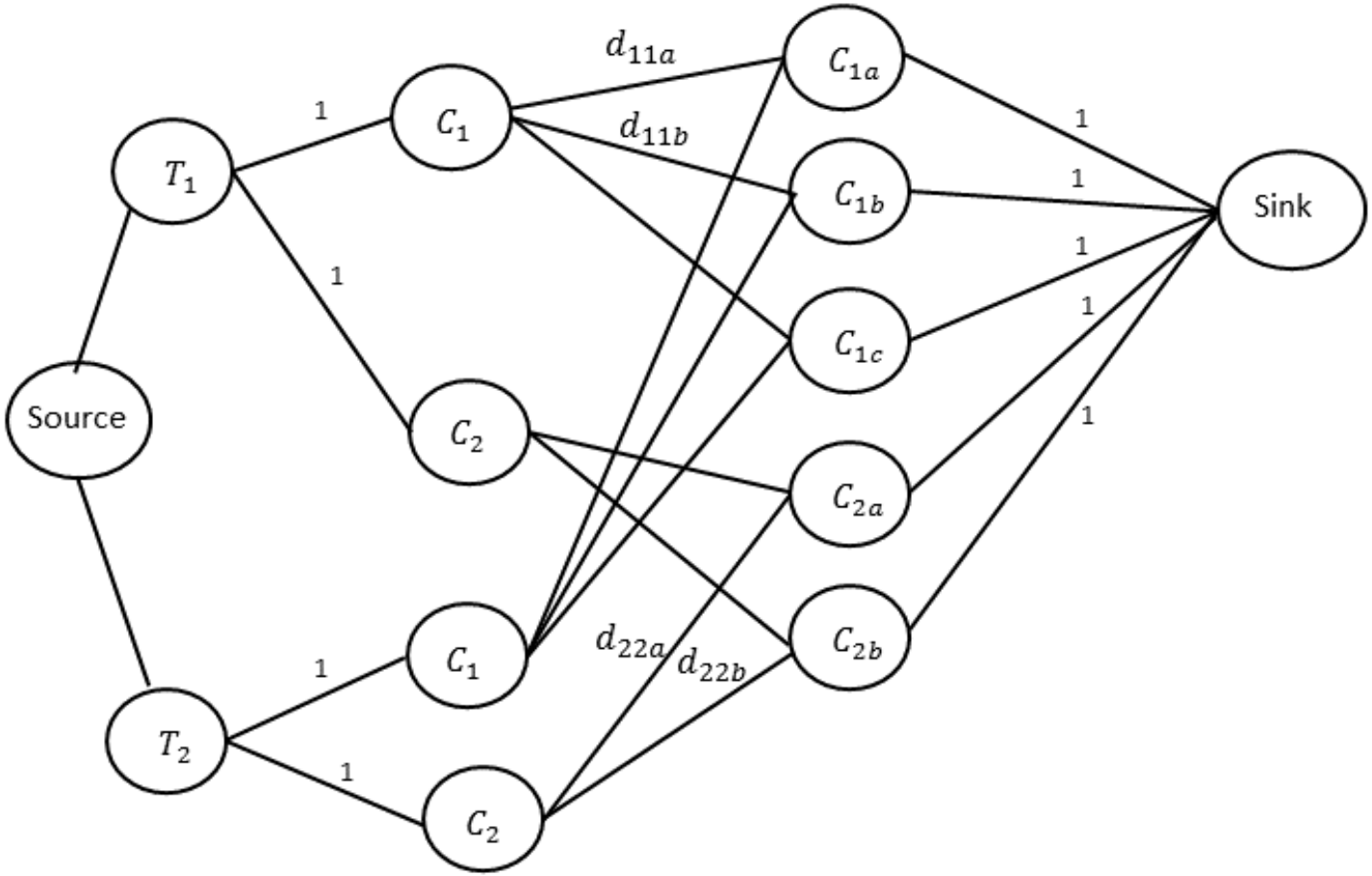
- Need to add constraints to force use of variety of controls (when $K > 1$):
- Matching *without (trajectory) replacement*: at most one instance from each control trajectory used, across entire match.
- Matching *with (trajectory) replacement* (and without instance replacement): at most one instance from each control trajectory per matched set, at most one use of each unique instance.
- How to represent these more complex constraints in a network?

Without trajectory replacement



- At most one instance from each control trajectory used, across entire match.

With trajectory, without instance replacement

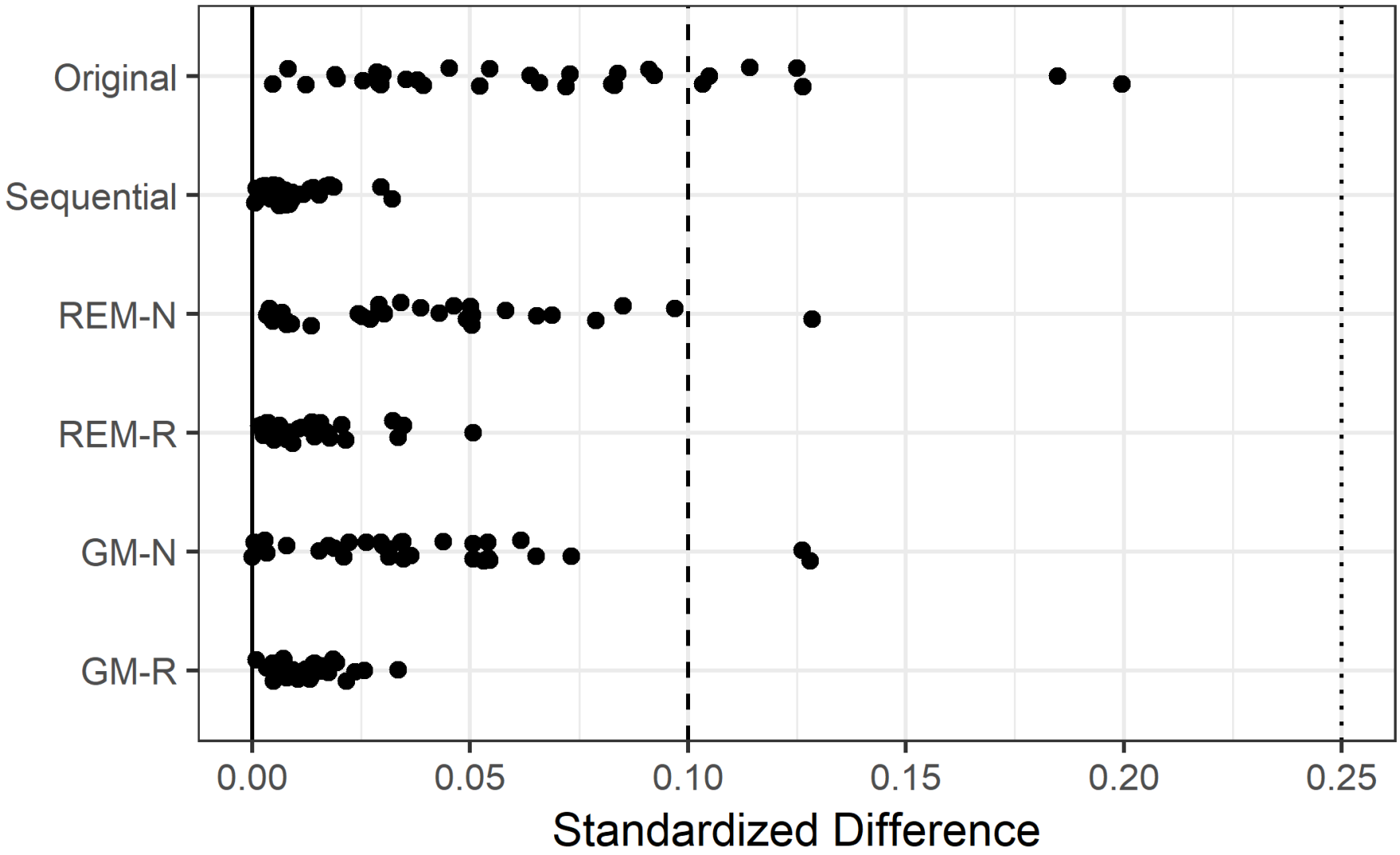


- At most one instance from each control trajectory per matched set.
- No reuse of instances across sets; reuse of trajectories OK.

Case study: Bohl et al. (2010)

- Bohl et al. data: ~3,500 treated patients, ~9,000 controls with nine timepoints each.
- No outcomes available, so reanalysis is limited to the design stage.
- Compare to relevant competitors:
  1. Randomly pick an instance for each control (Bohl et. al's original approach).
  2. Sequential: perform 1:1 matching K times, after each round dropping controls already used.
  3. Package `rollmatch` (REM) from Witman et al. (*HSR* 2019): Enforce exact matching across time and match greedily, without (N) and with (R) replacement of instances.
  4. GroupMatch (GM), without (N) and with (R) replacement.

Case study results



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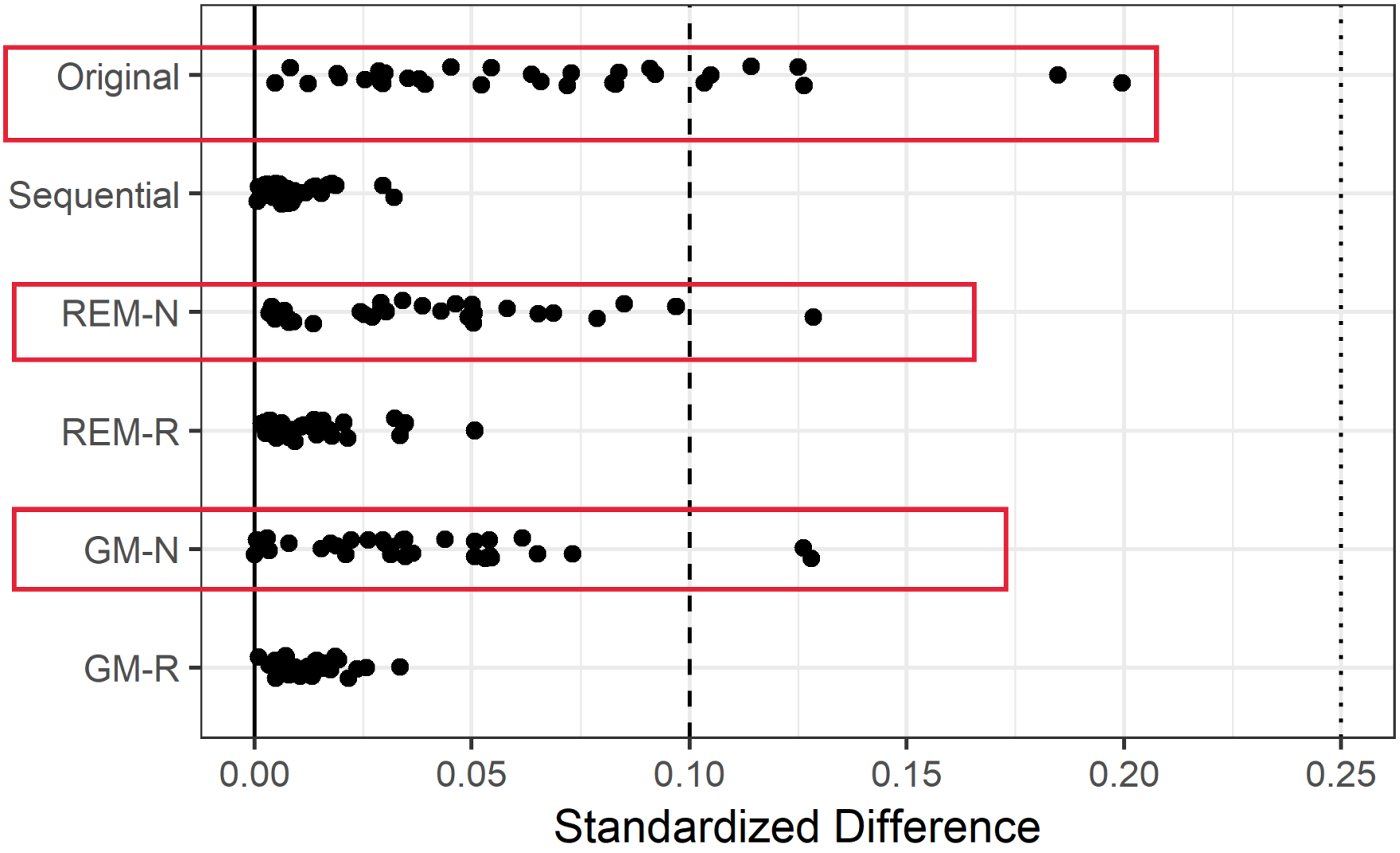

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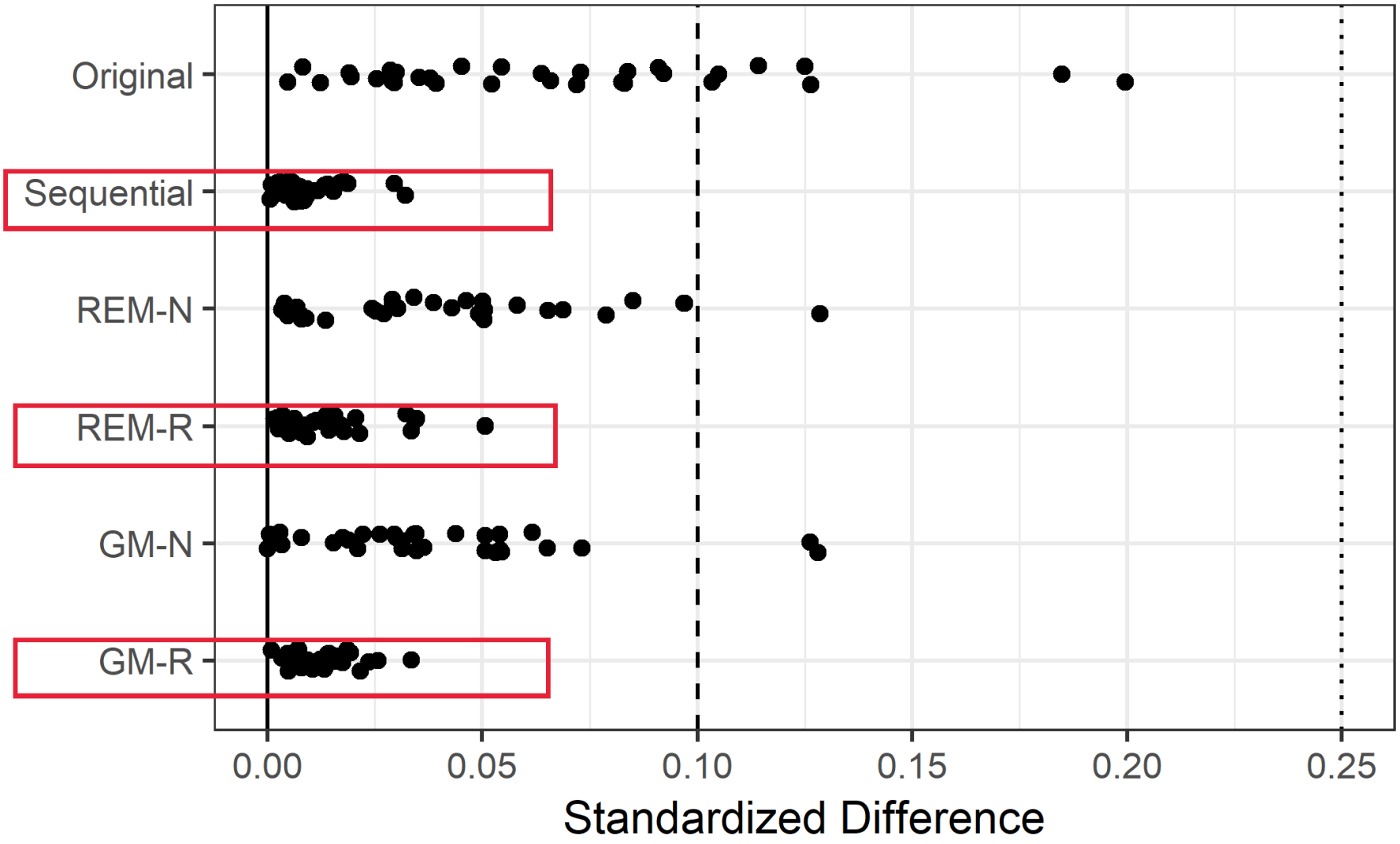

Statistical framework

- Patient trajectories i assumed sampled iid, T distinct timepoints observed for all patients.
- Treatment Z_i^t is time since first fall for patient i at time t.
- Outcomes Y_i^t (and potential outcomes $Y_i^t(z)$).

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- Wish to estimate the population ATT at fixed follow-up time $F \geq 0$:

$$\Delta_{pop} = E(Y^t(F) - Y^t(0) \mid Z^t = F)$$

Average impact, across trajectories and time, of falling F timepoints ago among population who actually fell F timepoints ago.

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Theorem 1

Suppose Assumptions 1-4 hold and matching on covariates (besides time) can be exact. Then the difference-in-means estimator for matched samples formed by GroupMatch is unbiased for Δ_{pop}.

Assumptions

1. **No unmeasured confounders**: Present/future treatment independent of potential outcome at t, given lagged treatment and covariates.
2. **Overlap**: control condition observed w/ nonzero prob. over all possible lagged covariate histories.

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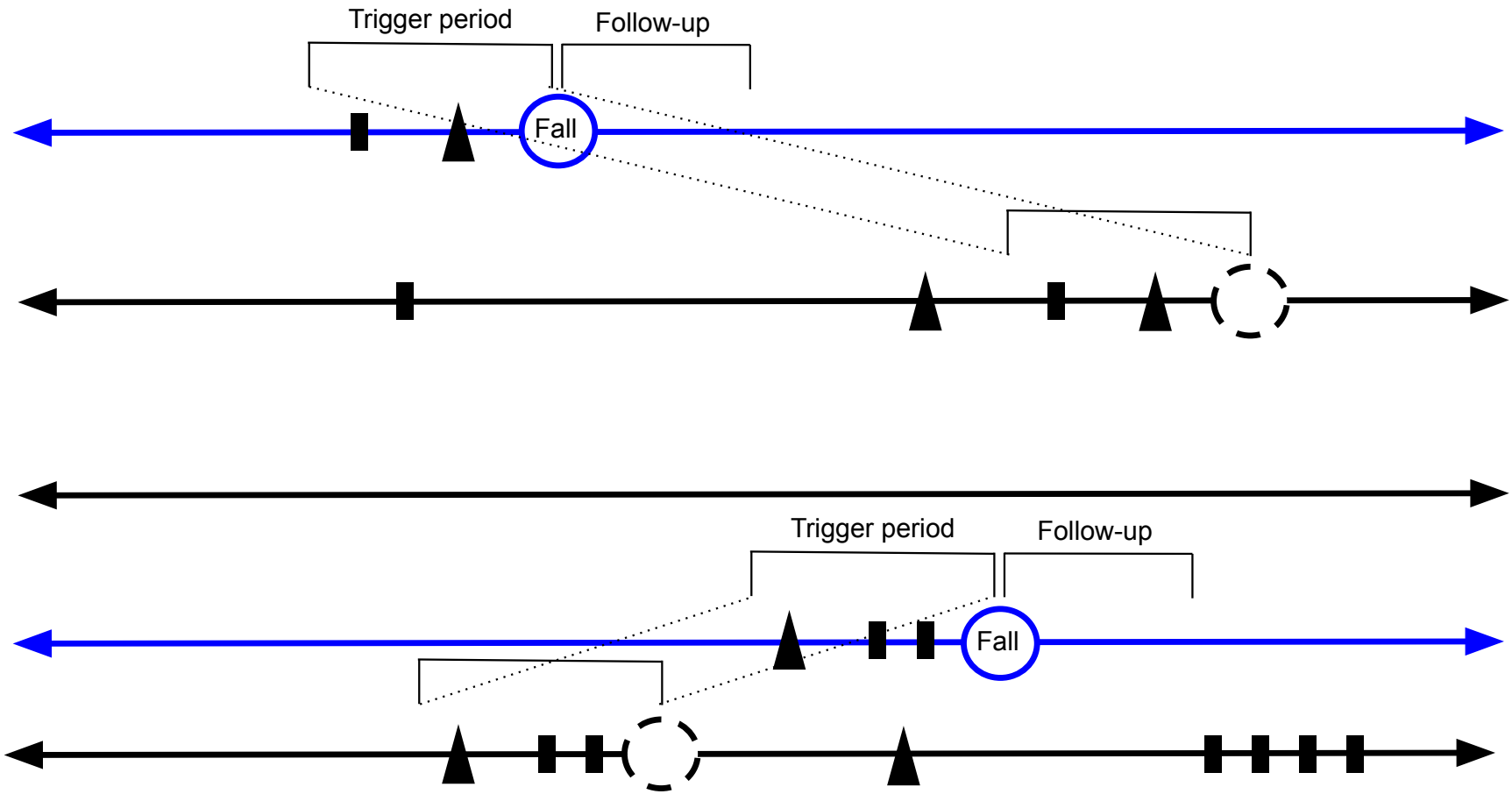
2. **Overlap**: control condition observed w/ nonzero prob. over all possible lagged covariate histories.
3. **Time agnosticism**: no time trends in potential outcome means, i.e. time is not a confounder.
4. **Covariate exogeneity**: future covariates uninformative about current potential outcomes, given lagged treatment and covariates.


Trigger period
Follow-up
Fall
Trigger period
Follow-up
Fall

Inference after matching

- Two dominant modes of inference after matching:
  1. Fisherian randomization inference (Rosenbaum 2002).
  2. Model-based sampling inference (Abadie and Imbens 2006, 2012).
- Both are possible for Problem A.
- Randomization inference is motivated by a *sequential* analogue of a paired experiment.

- Inference for Problem B is still an open problem; bootstrap approaches seem promising.

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Other open problems and extensions

- Time agnosticism has observable implications. Can we test for it effectively?
- Could we relax covariate exogeneity and independence with future treatment by matching in a sequential manner? More like risk-set matching (Li, Propert, & Rosenbaum, *JASA* 2001).
- Why not include pre-treatment instances of treated units as potential controls? Poses computational challenges when matching without trajectory replacement.

Assumptions

- Ignorability (and overlap):

$$Z_T \perp\!\!\!\perp Y_t(0) \mid (Z_{t-F}, \{X_s\}_{s=t-F-L}^{t-F})$$
$$P\left(Z^t = 0 \mid \{X_s\}_{s=t-F-L}^{t-F} = \mathbf{x}\right) > 0 \quad \forall t,\ \forall \mathbf{x} \in \mathcal{X}^L$$

- Present/future treatment independent of potential outcome at t, given treatment up to time $t - F$ and covariates from $t - F - L$ to $t - F$.
- Control condition observed w/ nonzero prob. for all possible sets of L covariate vectors $\mathbf{x}$.
- Need conditional independence with future treatment because we compare only to individuals who never receive treatment, now or later.

Assumptions, continued

- Time agnosticism: for all times t, t' and all $z \in \{0, F\}$,

$$E(Y_t(z) \mid \{X_s\}_{s=t-F-L}^{t-F} = \mathbf{x}) = E(Y_{t'}(z) \mid \{X_s\}_{s=t'-F-L}^{t'-F} = \mathbf{x})$$

- Potential outcome means, conditional on lagged covariates, are stable across time.
- Rules out time trends that would make it a bad idea to compare patients at different timepoints.
- In other words, rules out time itself as a confounder.
- Relaxing the assumption to the $z = 0$ case permits effect modification by time, but causal inference of some kind should still be possible.

Assumptions, continued

- Covariate exogeneity:

$$\{X_s\}_{s=1}^{T} \perp\!\!\!\perp Y_t(0) \mid (Z_{t-F}, \{X_s\}_{s=t-F-L}^{t-F})$$

- Future covariates are uninformative about current potential outcomes, conditional on lagged treatment and covariates.
- This is needed since we consult future covariates when deciding which version of a control to include in the match. Perhaps it could be weakened?

Case study details: Bohl et al. (2010)

- Medicare beneficiaries in Group Health Western Washington network, age 67+ with no history of falls, followed quarterly for 3 years.
- 3,517 individuals experienced a fall, 8,956 did not.
- Assign each control trajectory nine quarterly pseudo-enrollment dates.