# Why Propensity Scores Should Not Be Used For Matching

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(Talk at the International Methods Colloquium, 9/11/2015)

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  - The mathematical theorems about propensity scores

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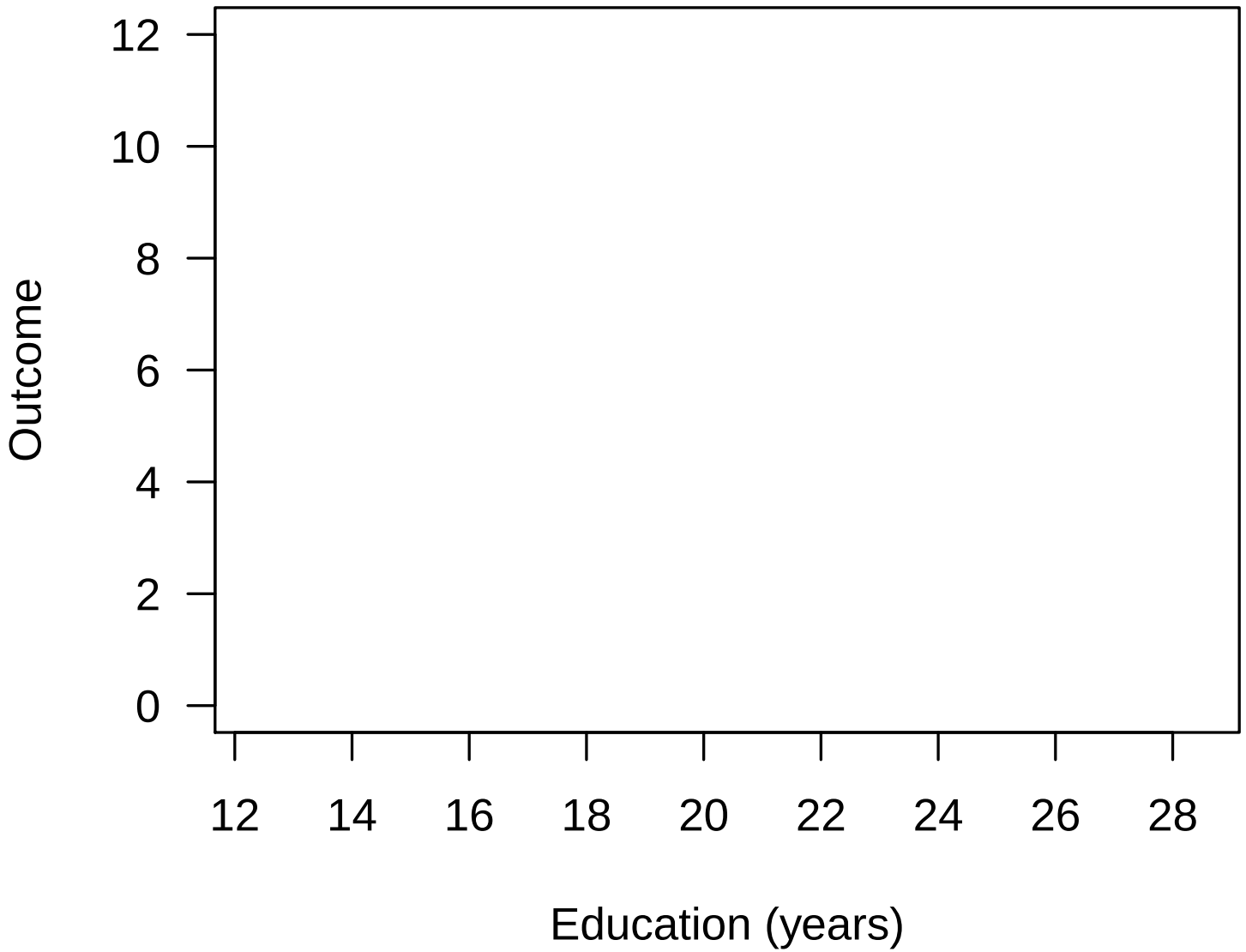

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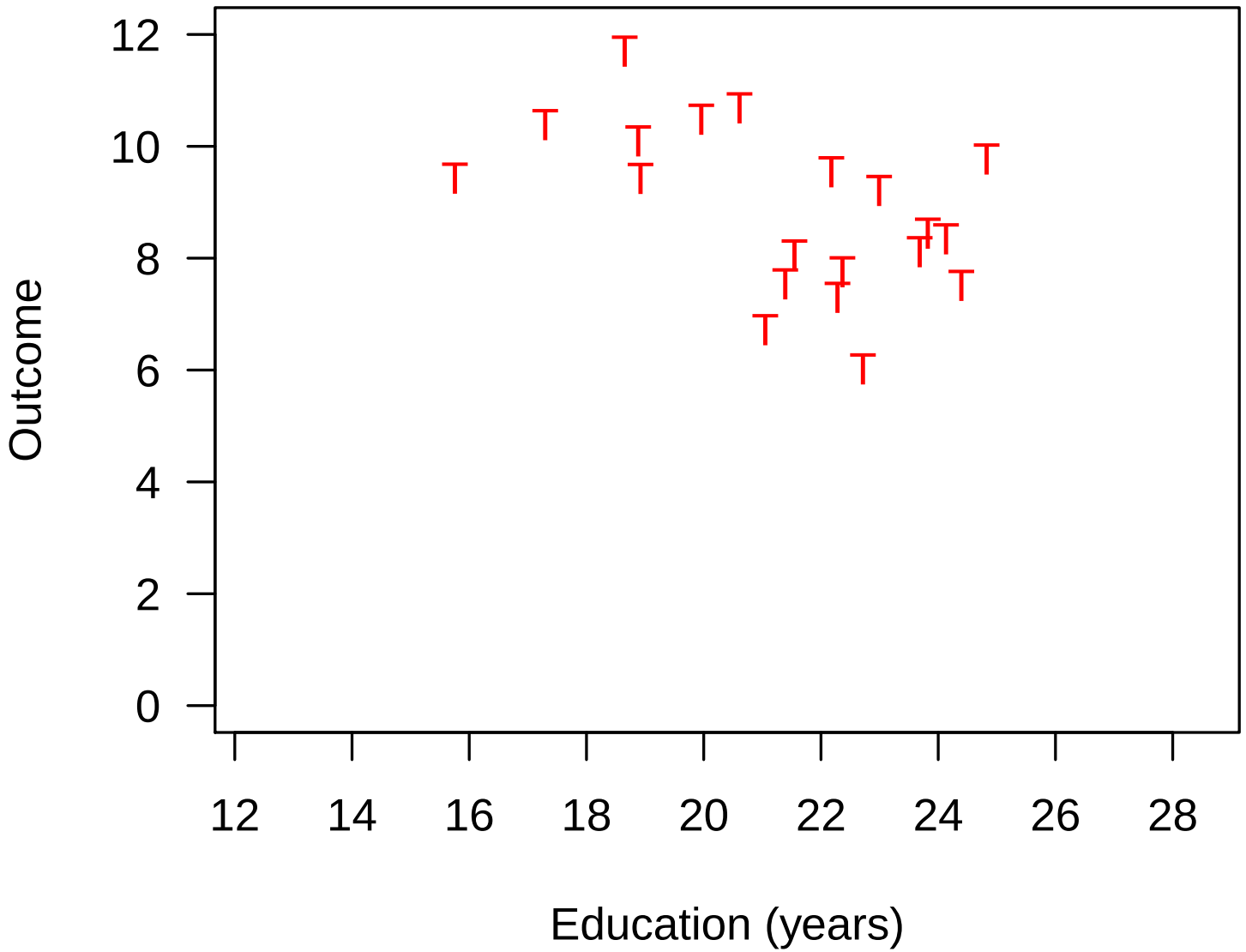

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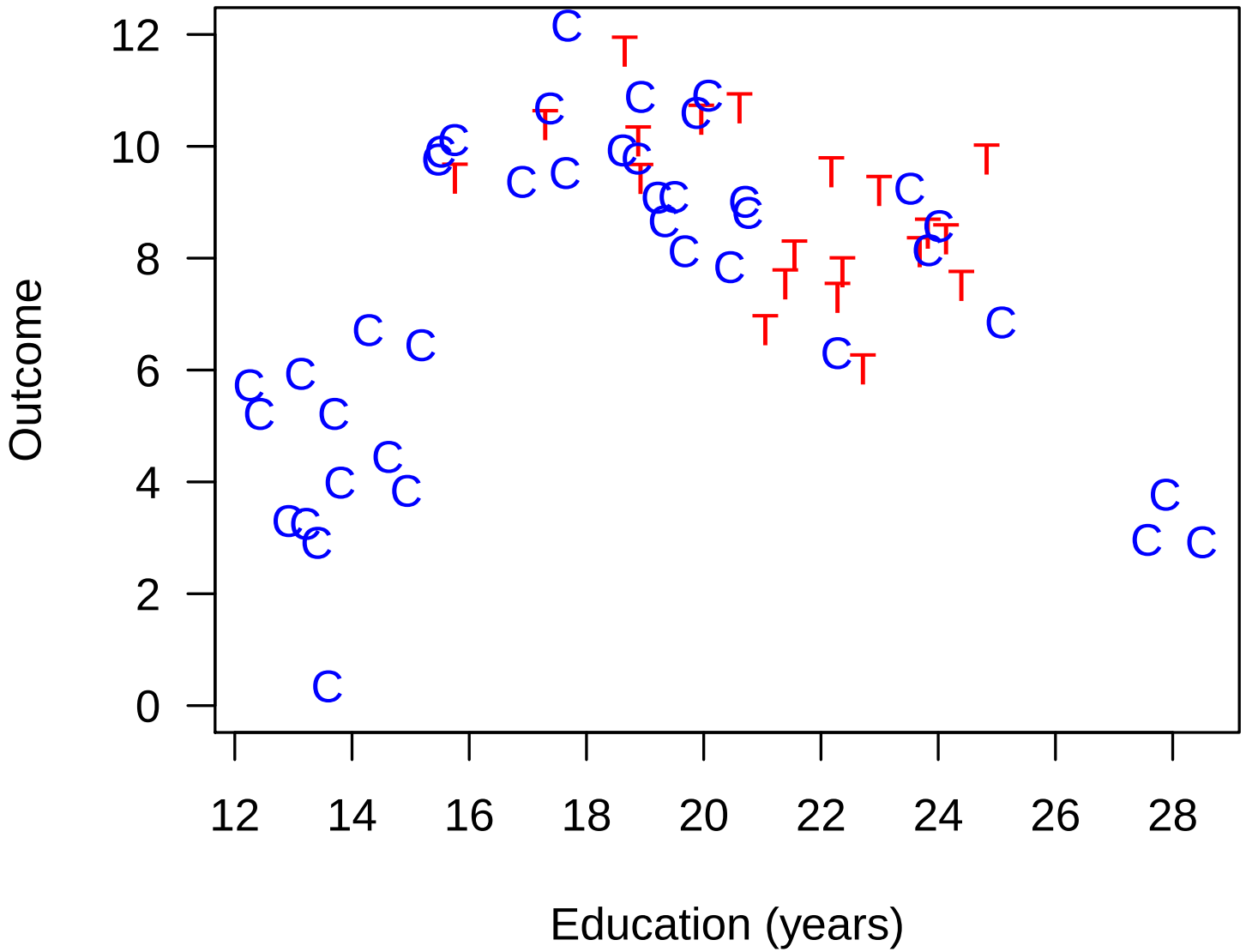

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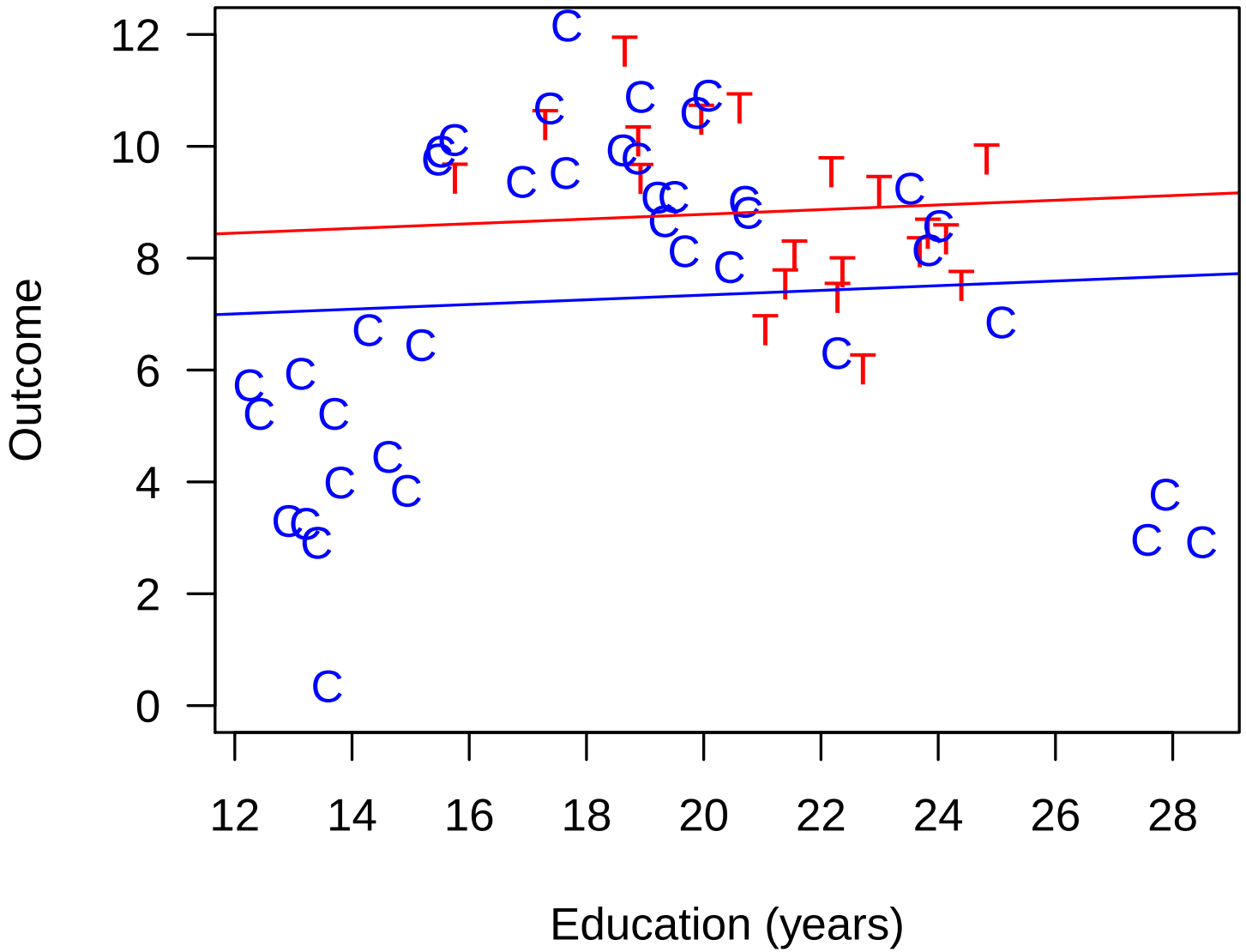

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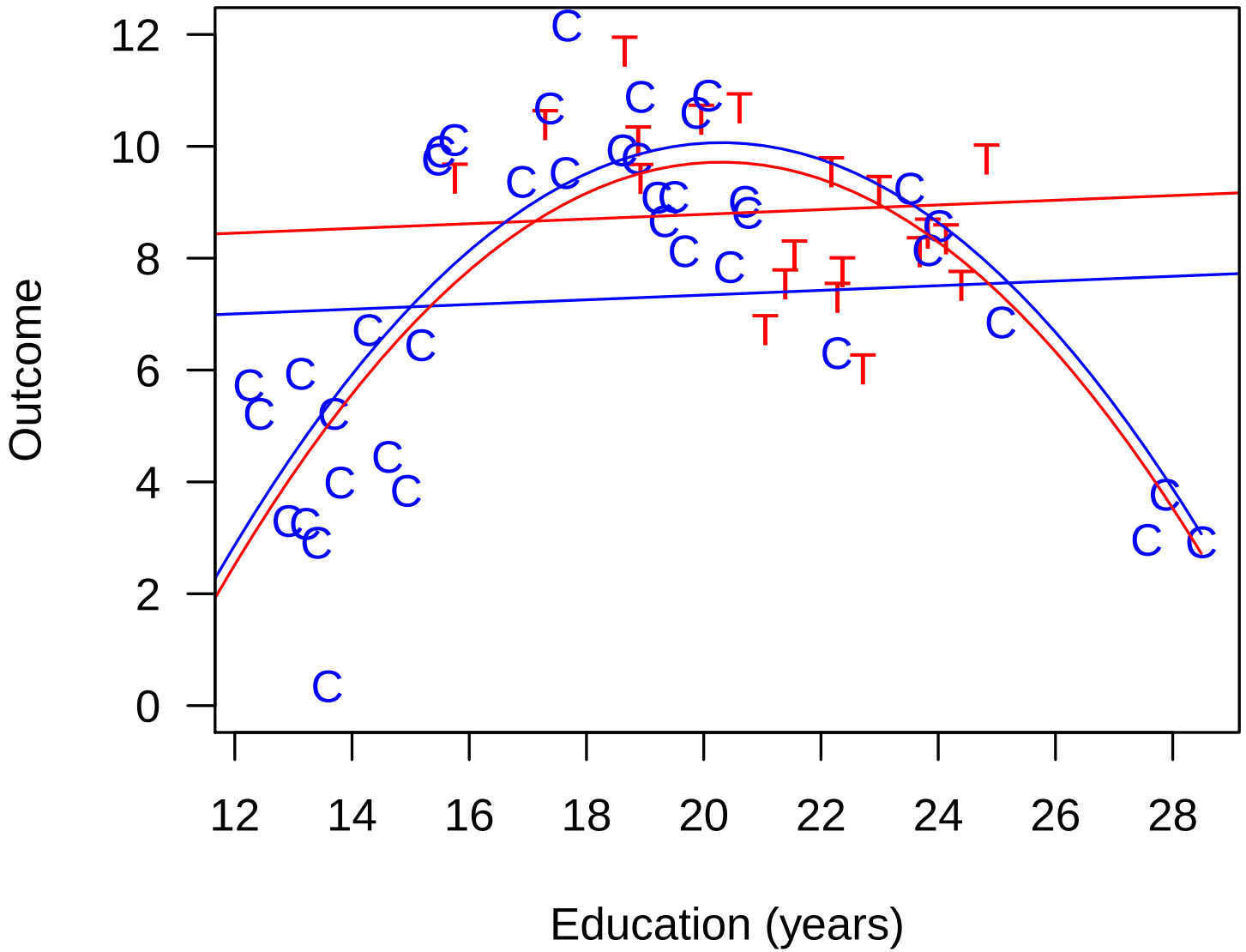

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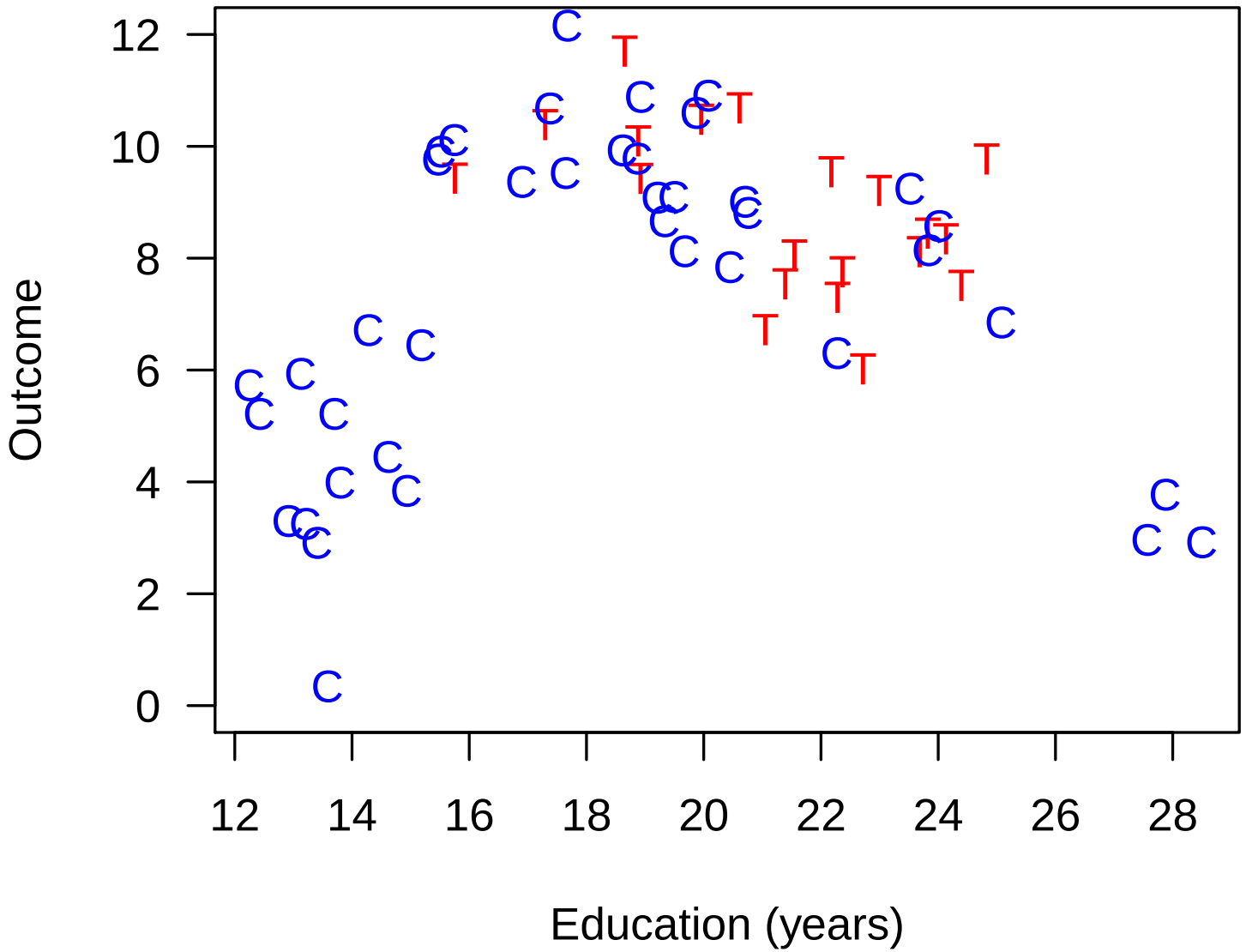

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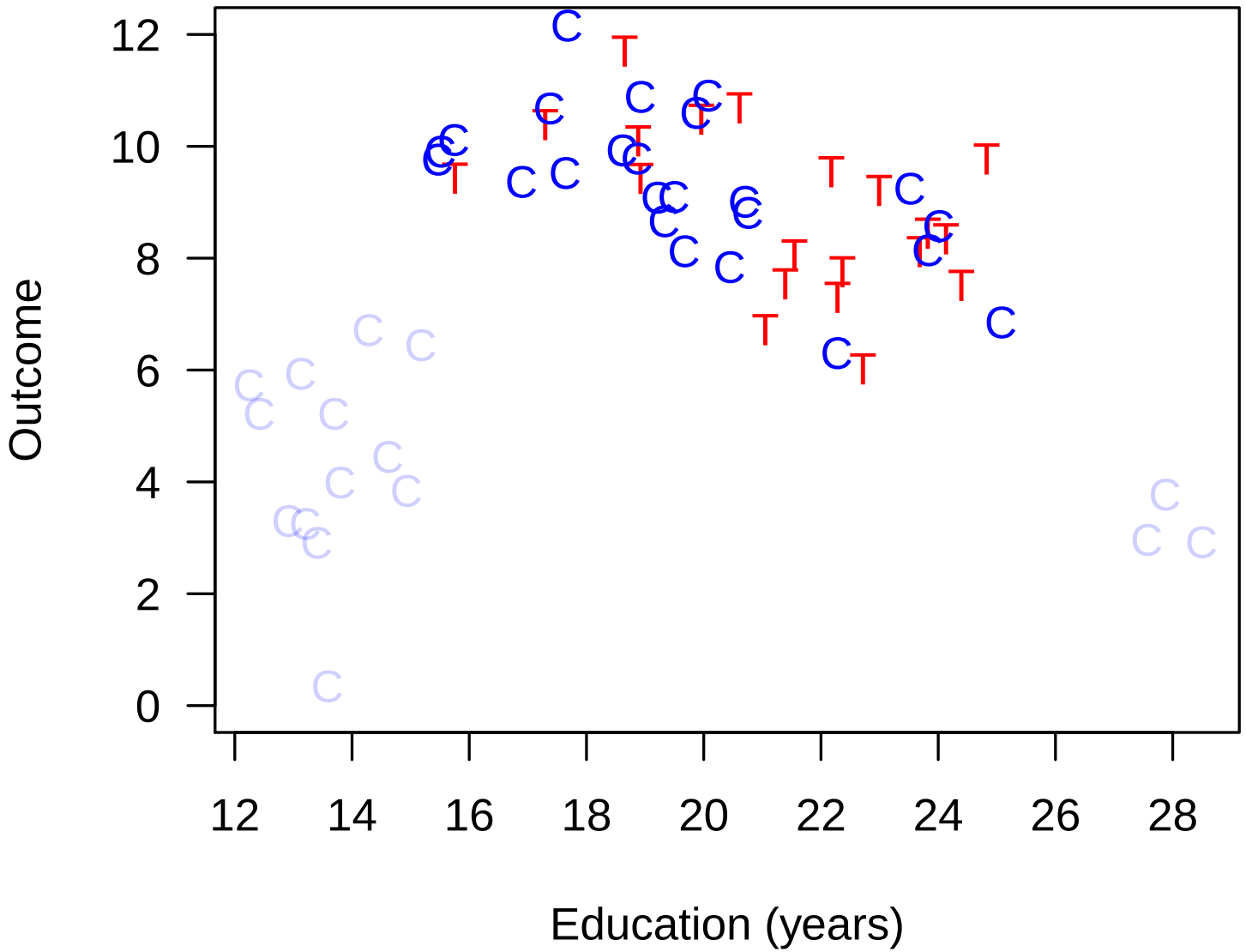

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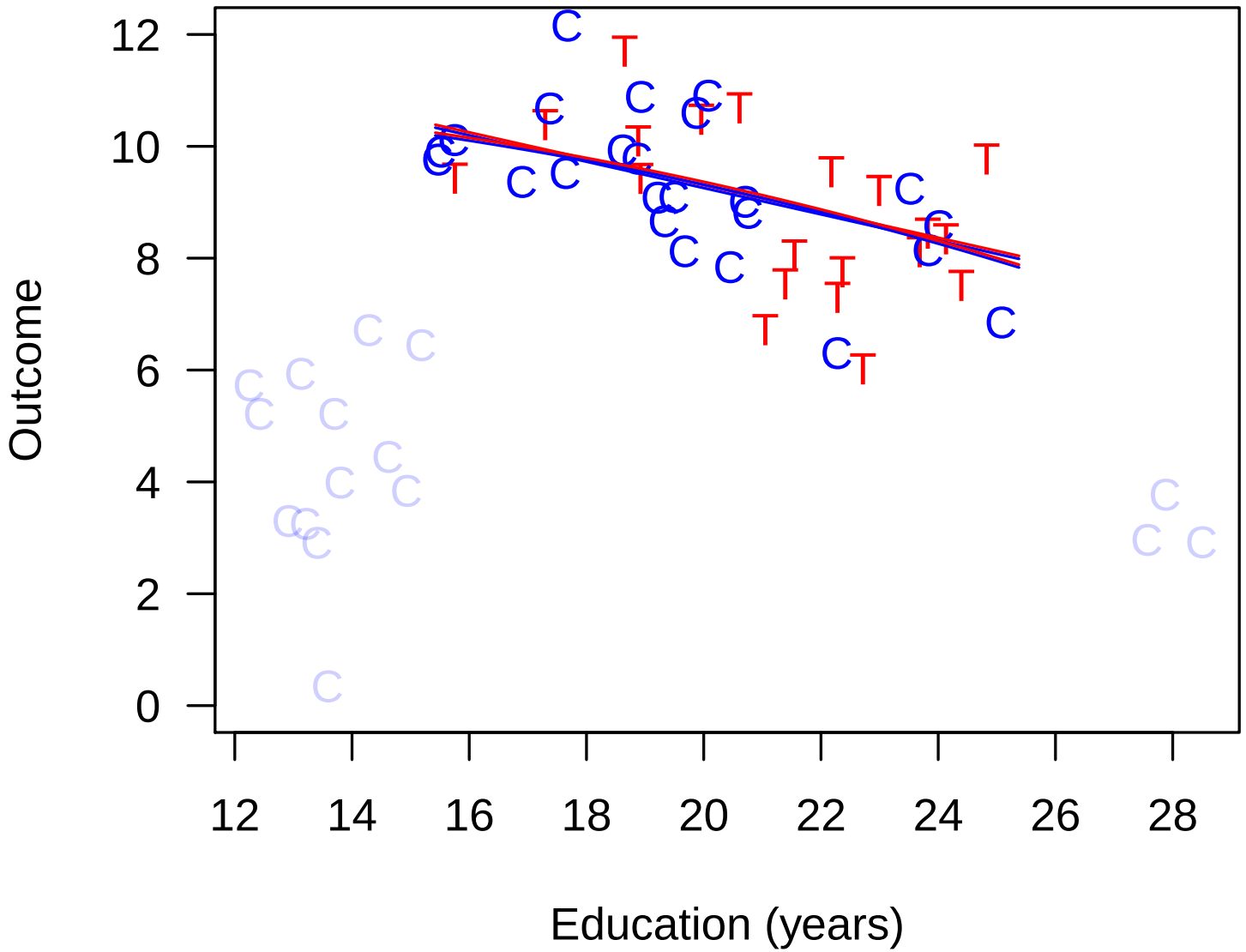

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- "Teaching psychology is mostly a waste of time" (Kahneman 2011)

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A central project of statistics: Automating away human discretion

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- Pruning nonmatches makes control vars matter less: reduces imbalance, model dependence, researcher discretion, & bias

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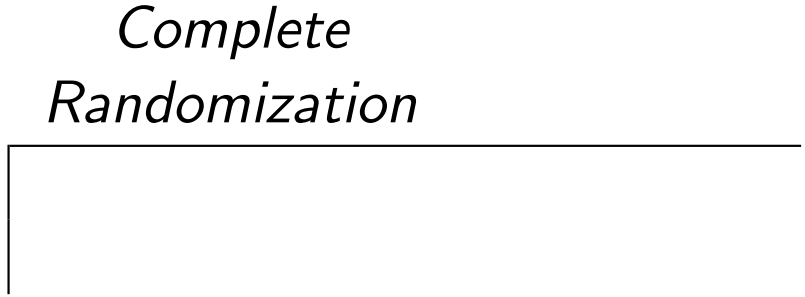

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- Other matching methods dominate PSM (wait, it gets worse)

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   - Match each treated unit to the nearest control unit

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(Approximates Fully Blocked Experiment)

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   - (Mahalanobis is for methodologists; in applications, use Euclidean!)
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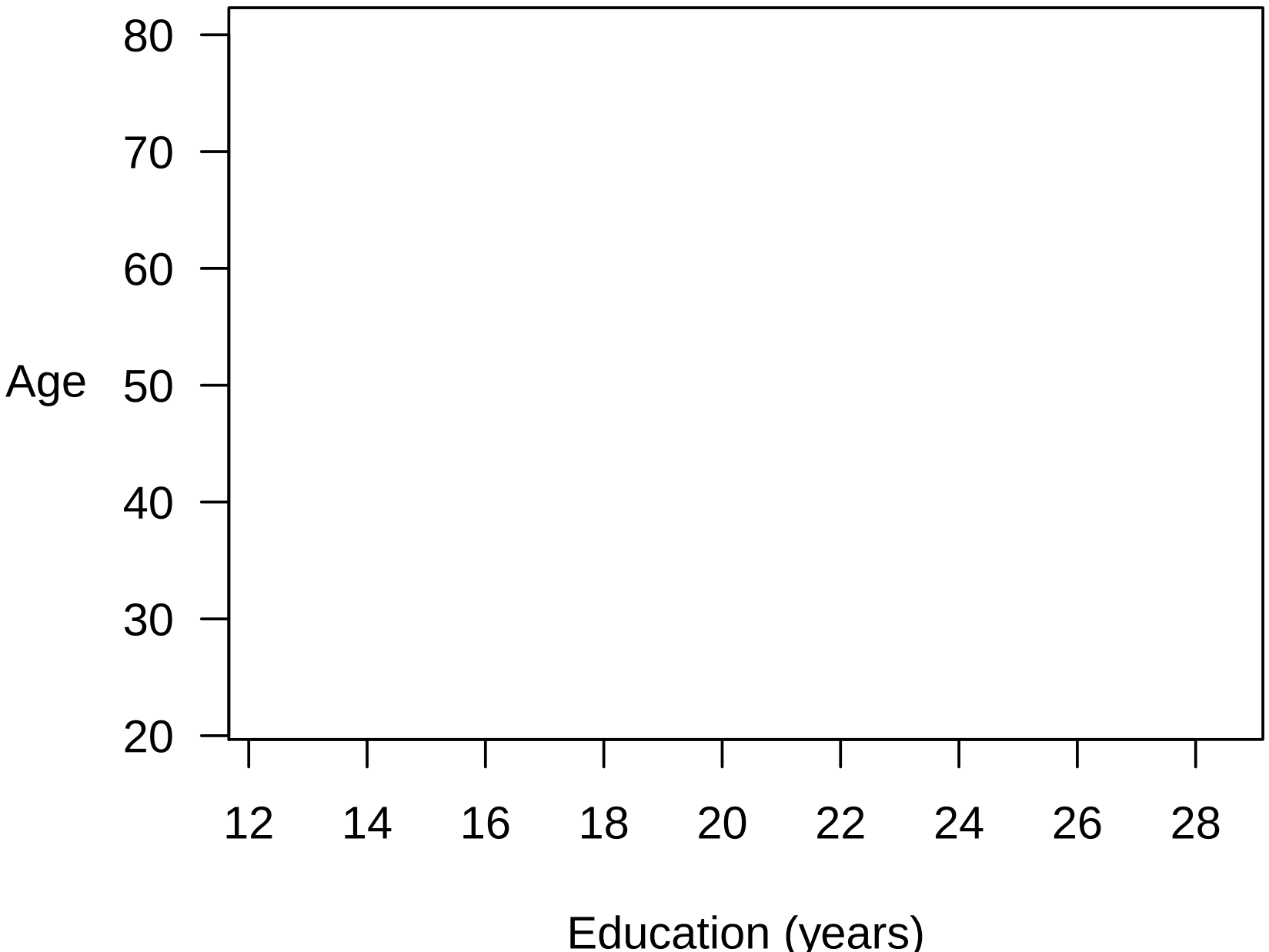

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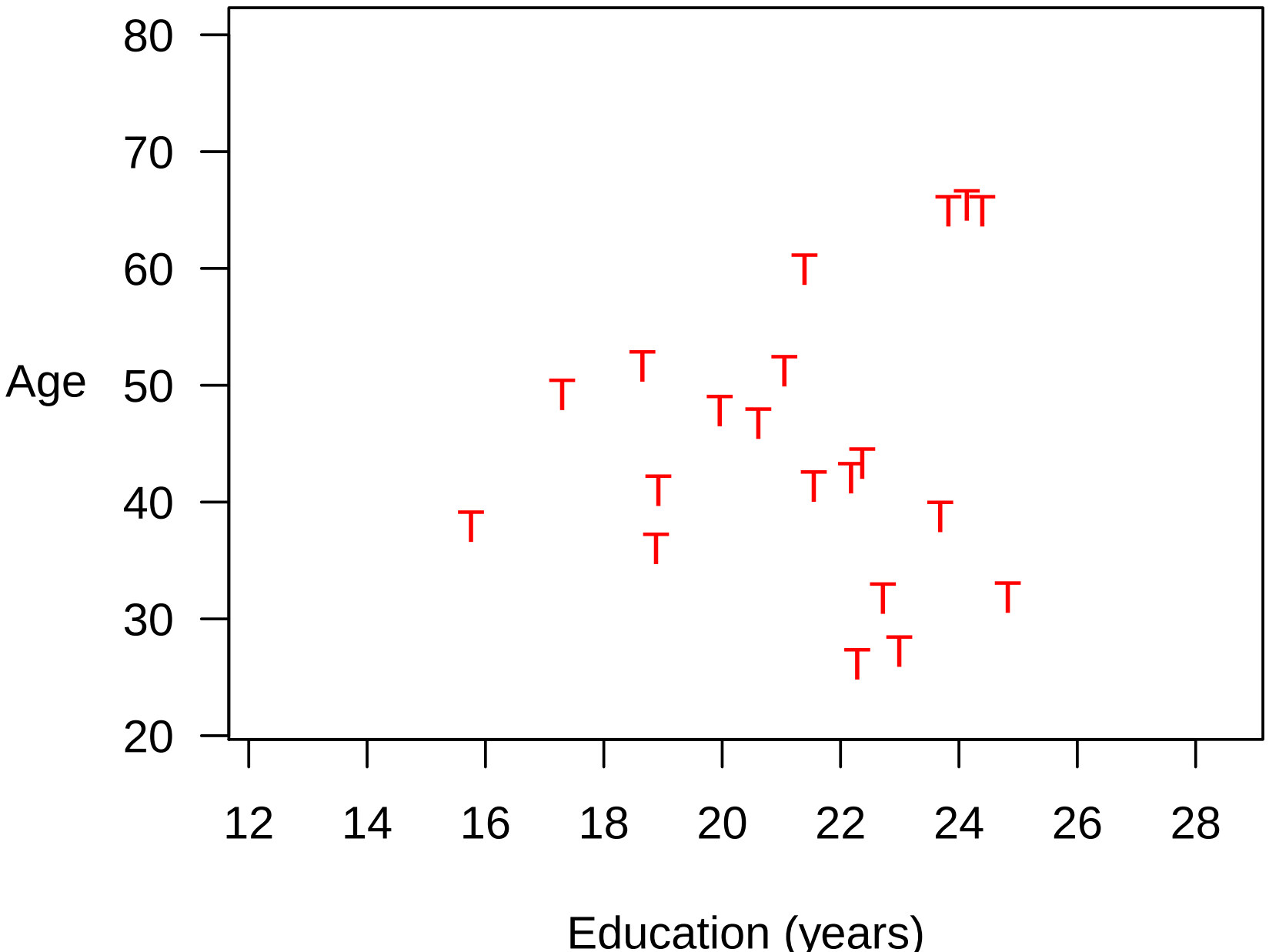

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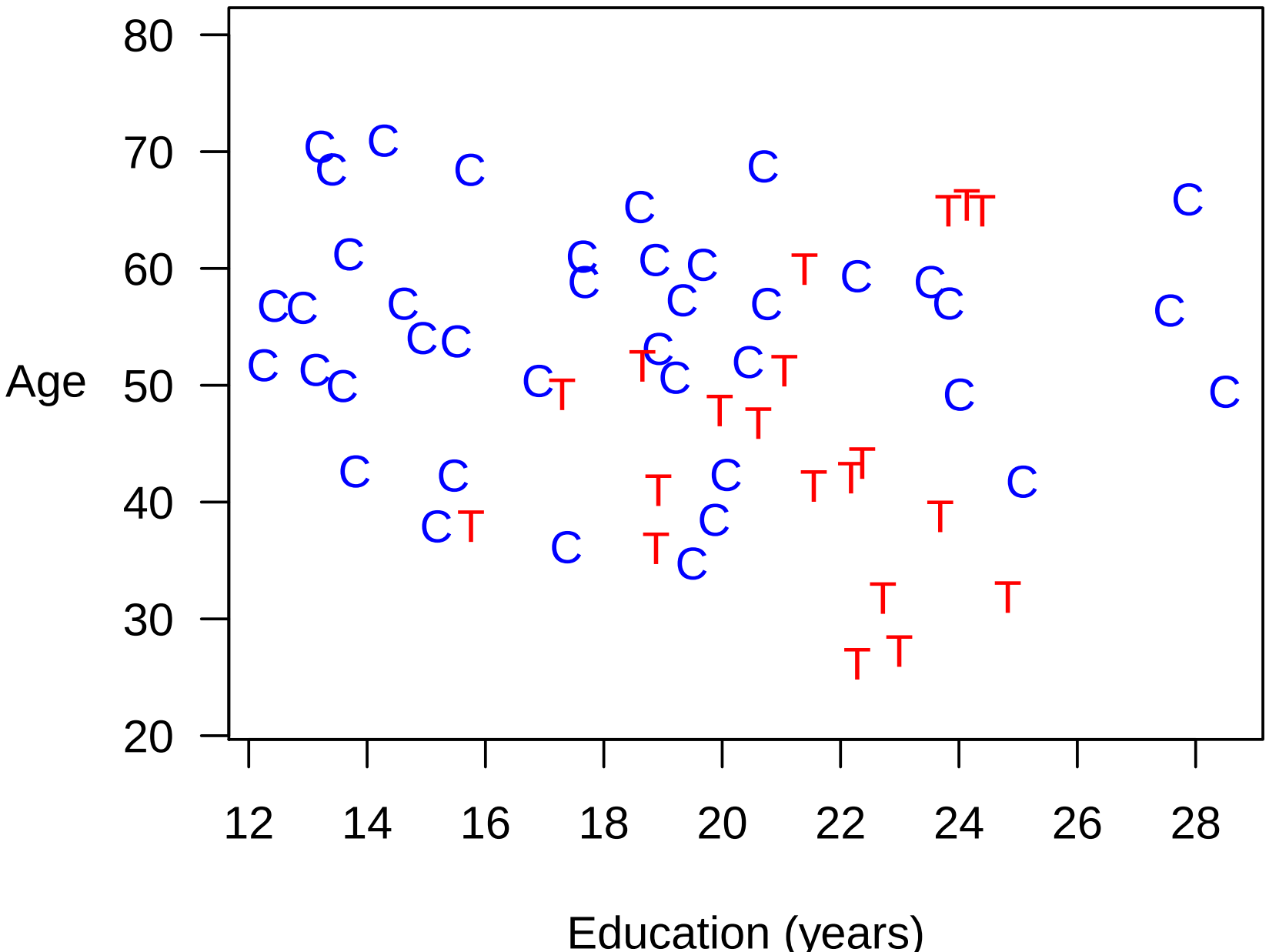

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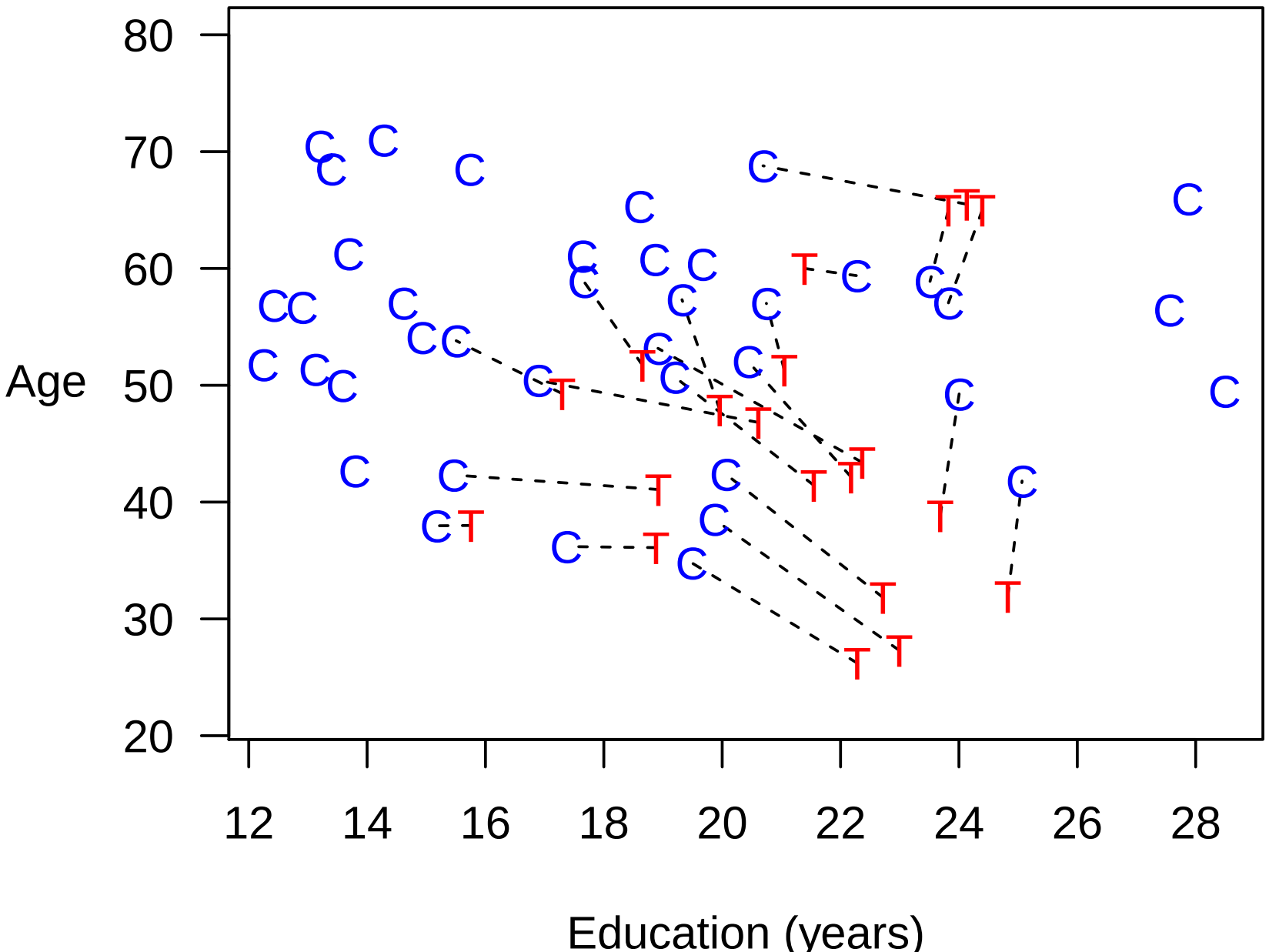

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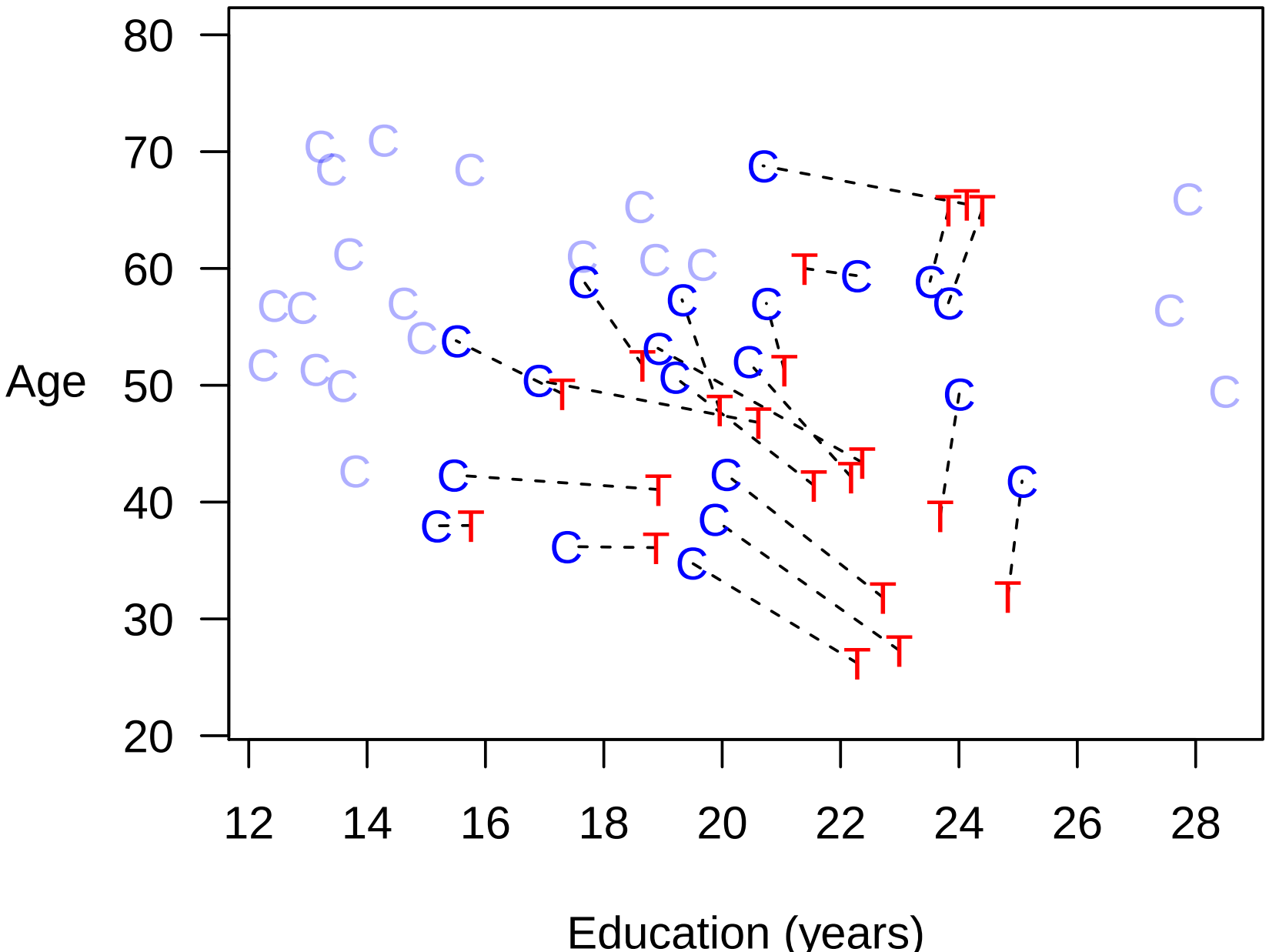

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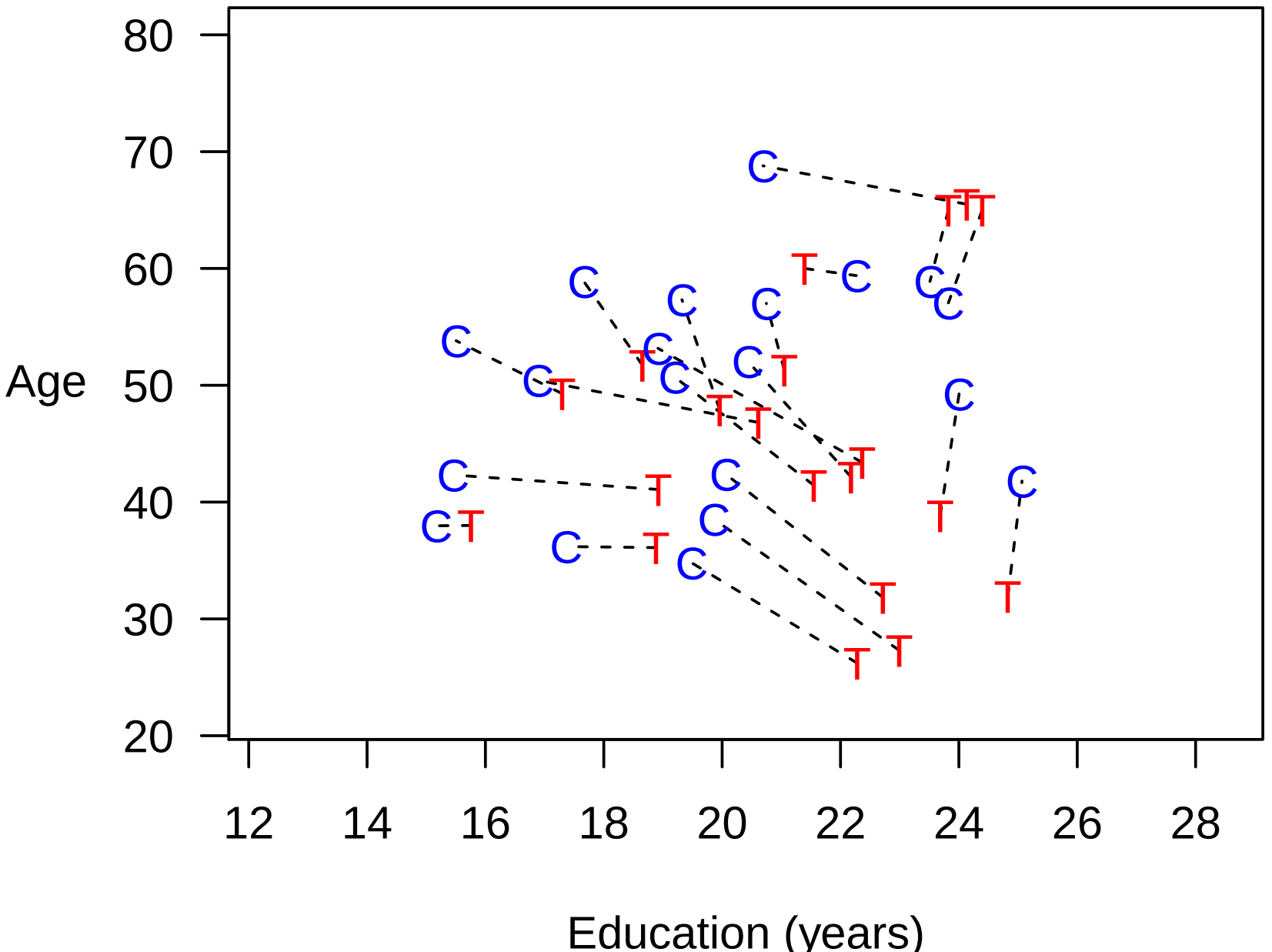

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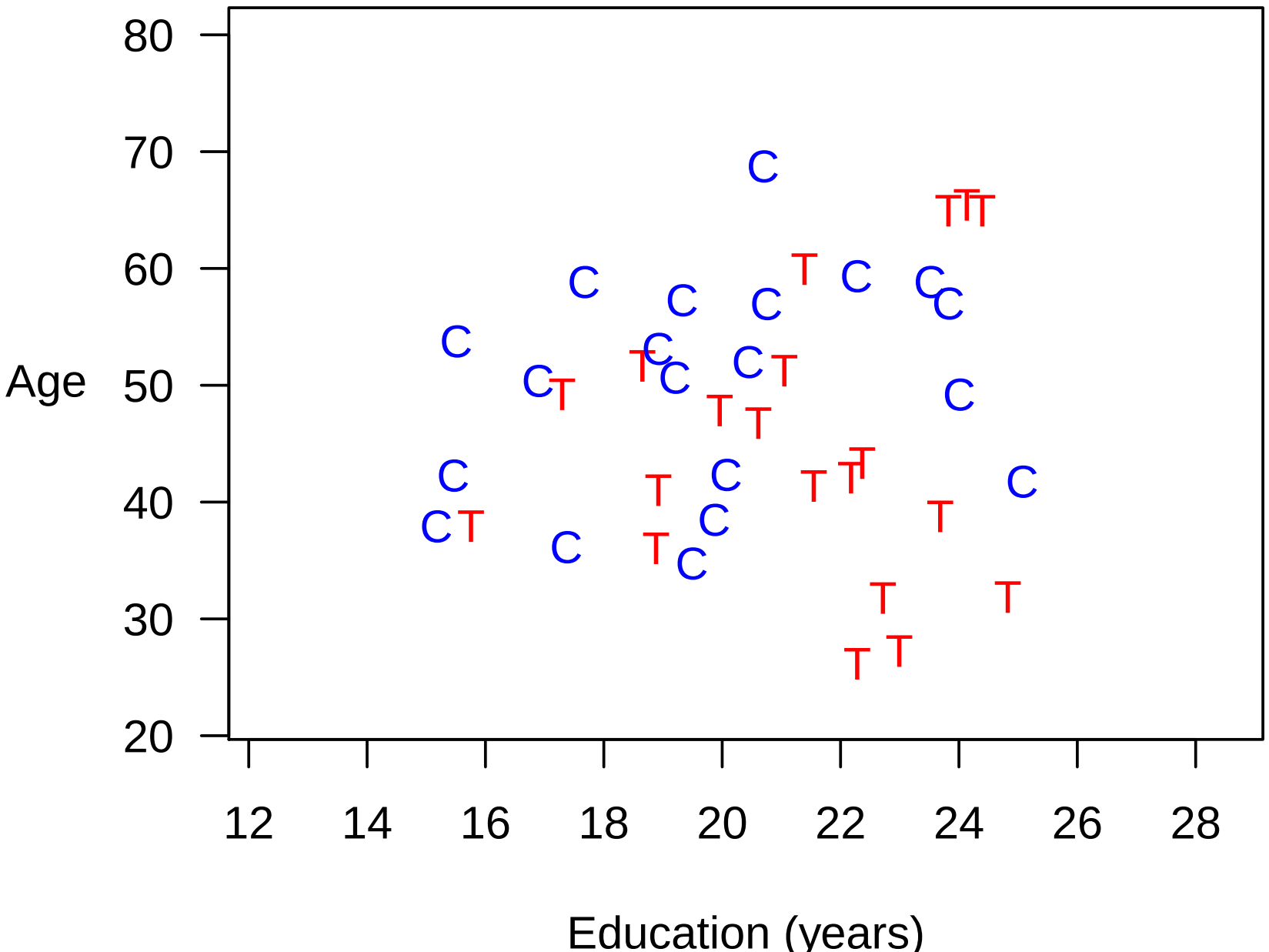

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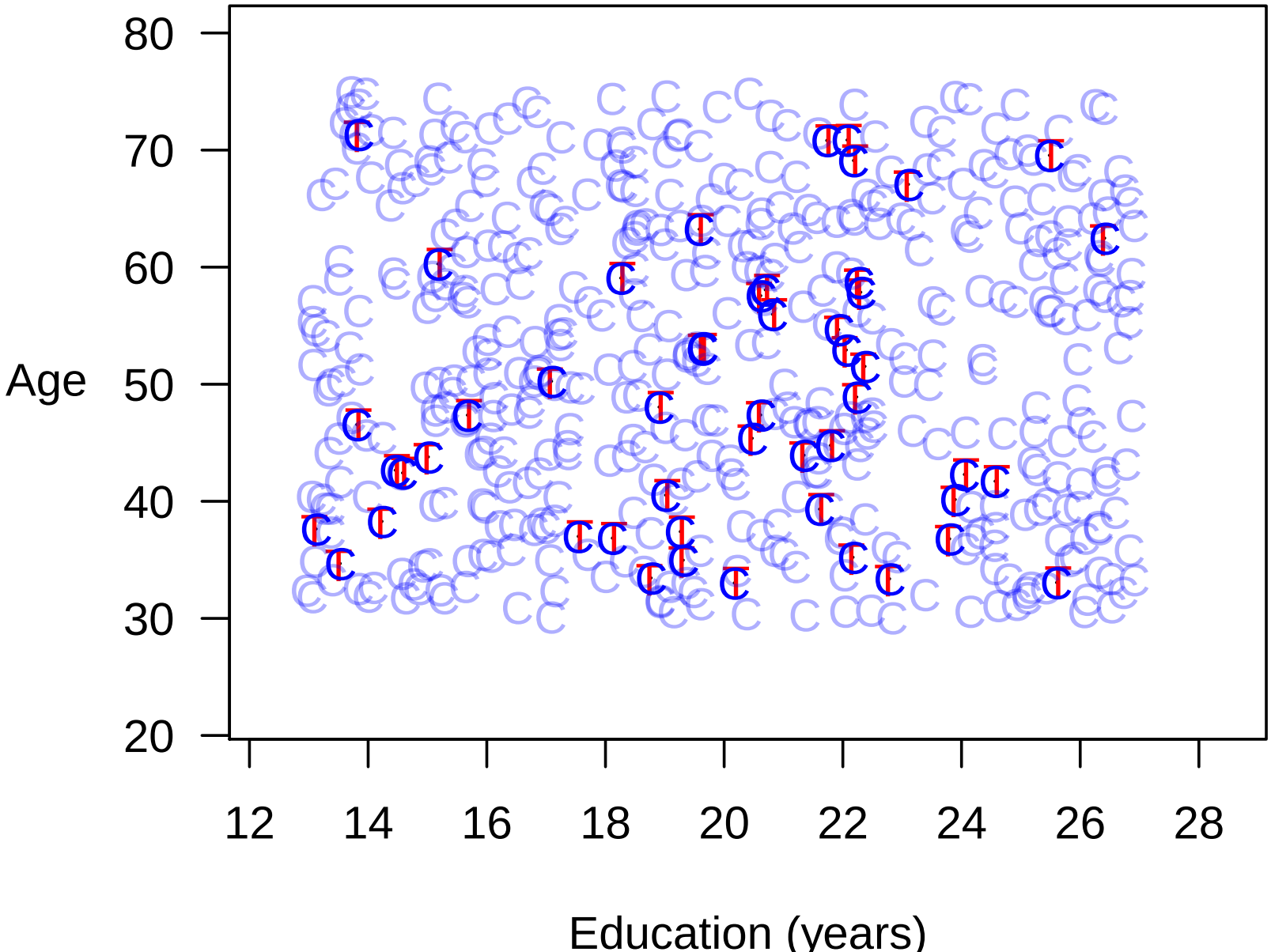

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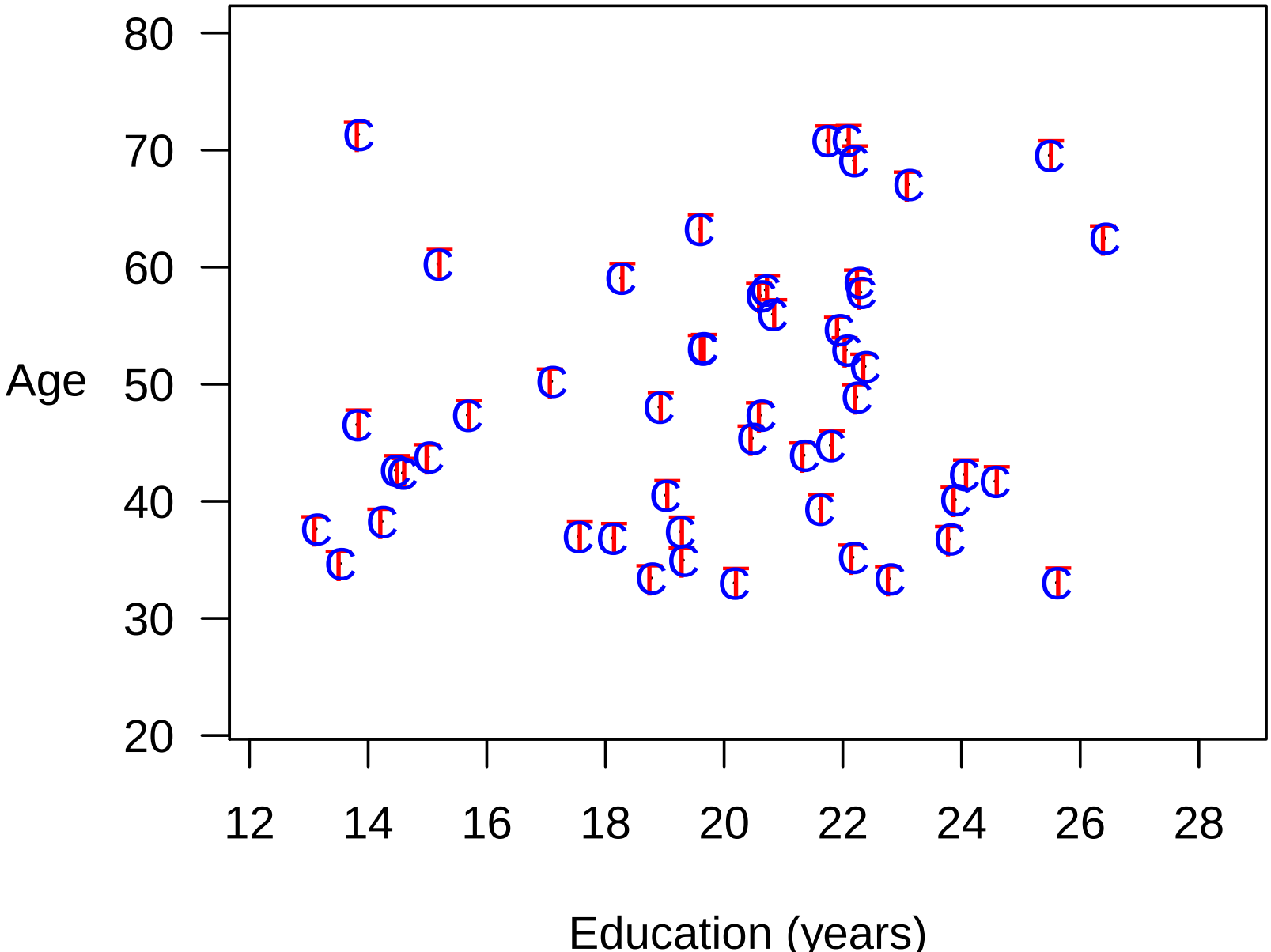

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(Approximates Fully Blocked Experiment)

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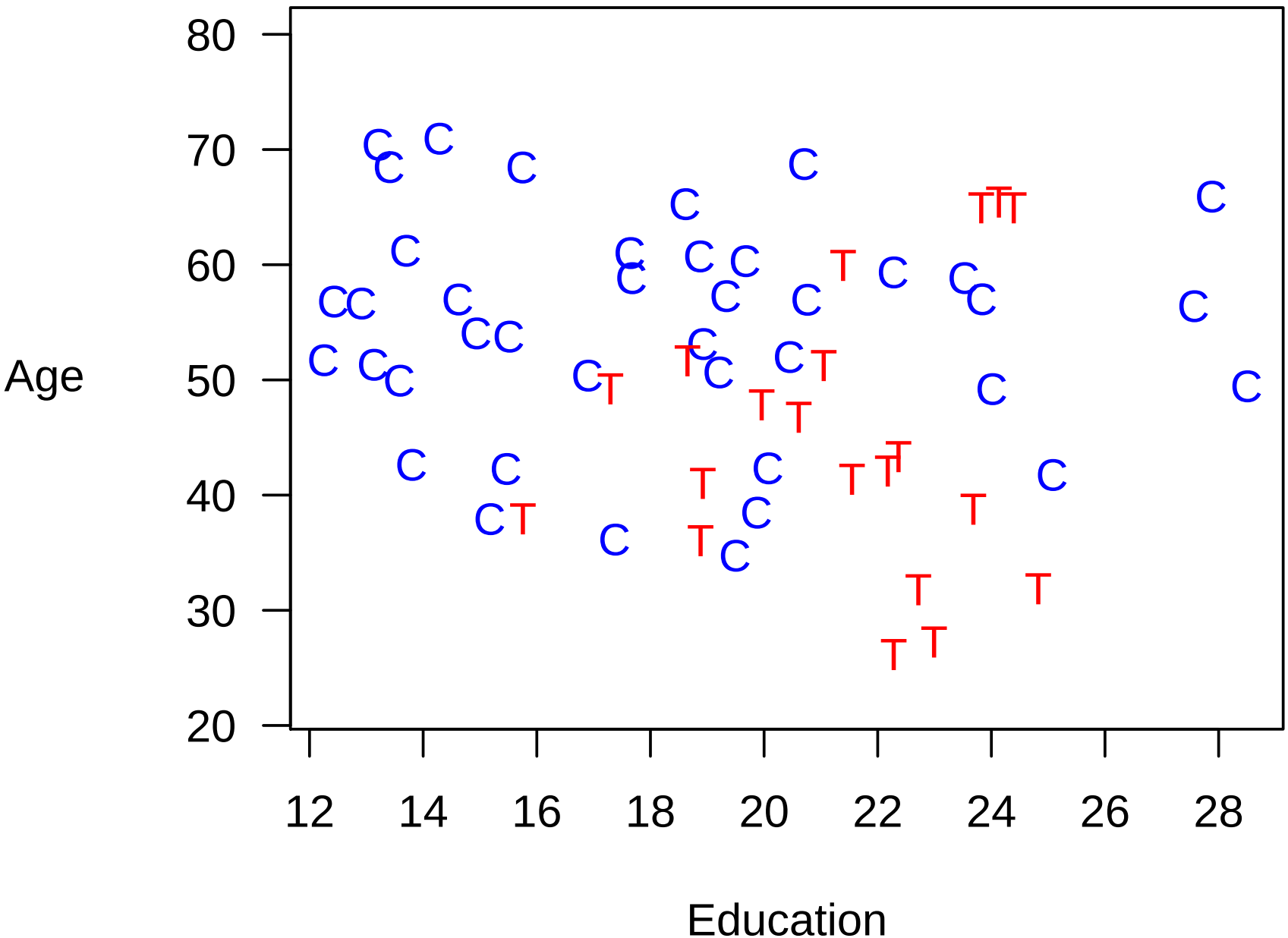

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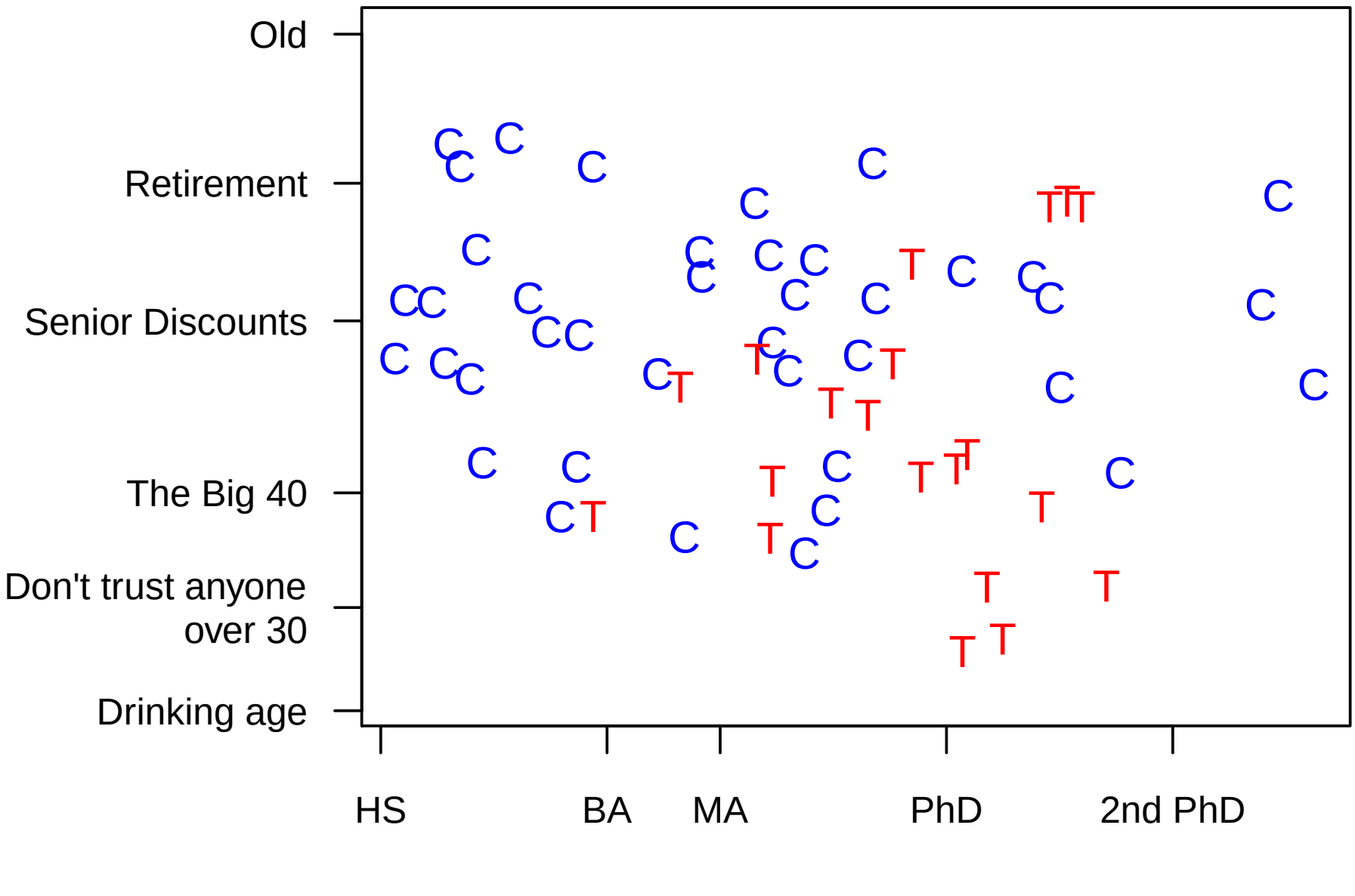

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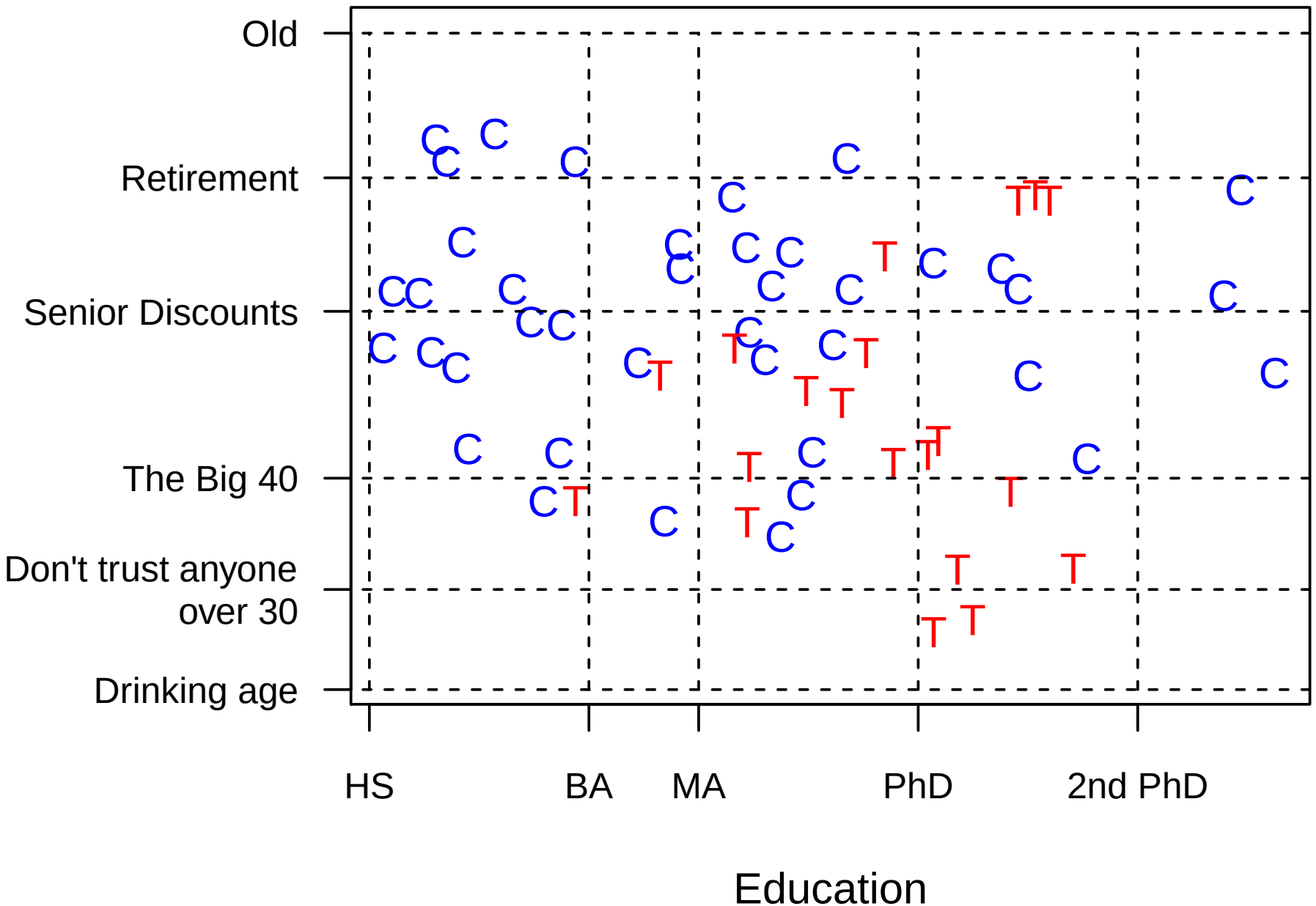

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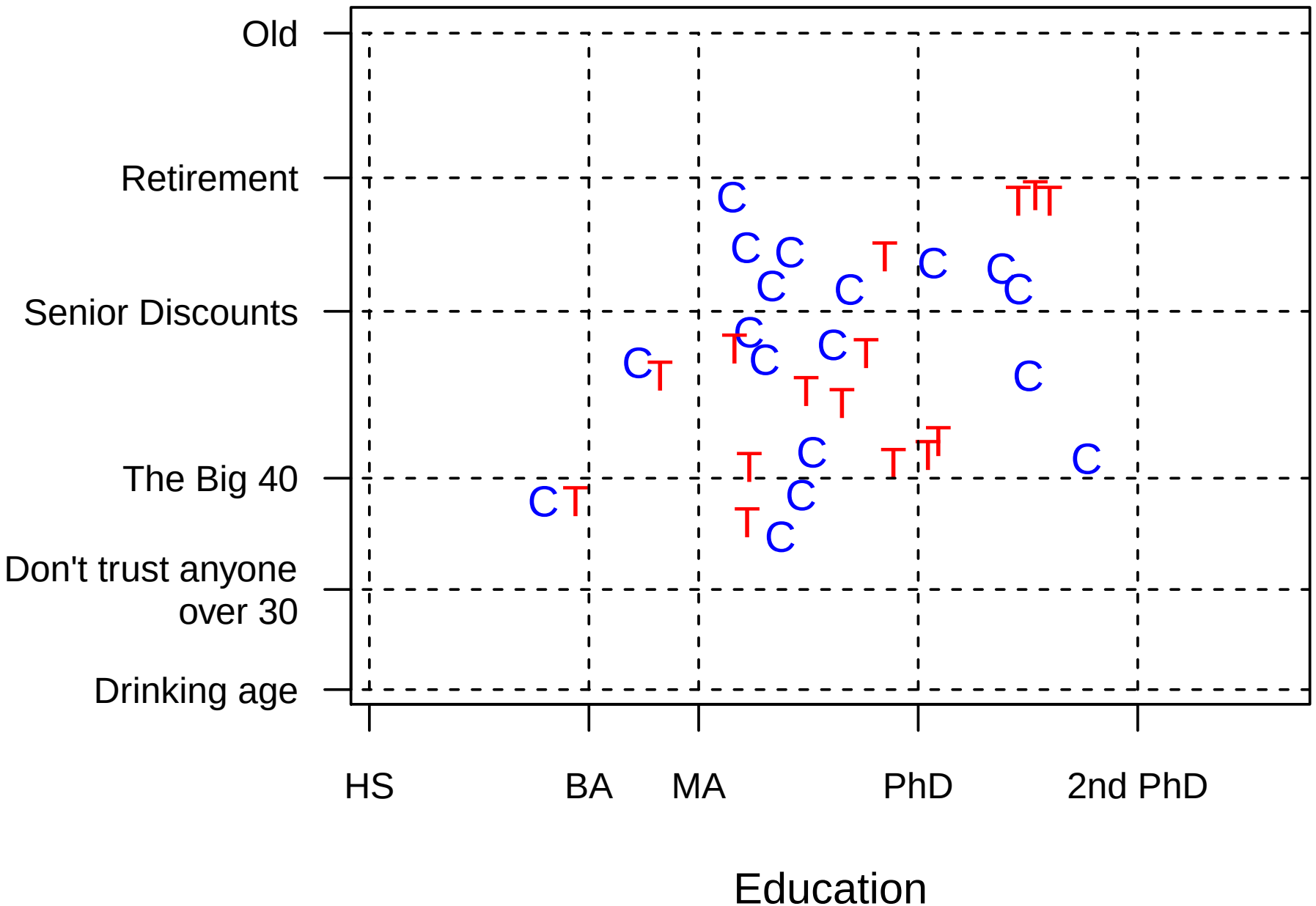

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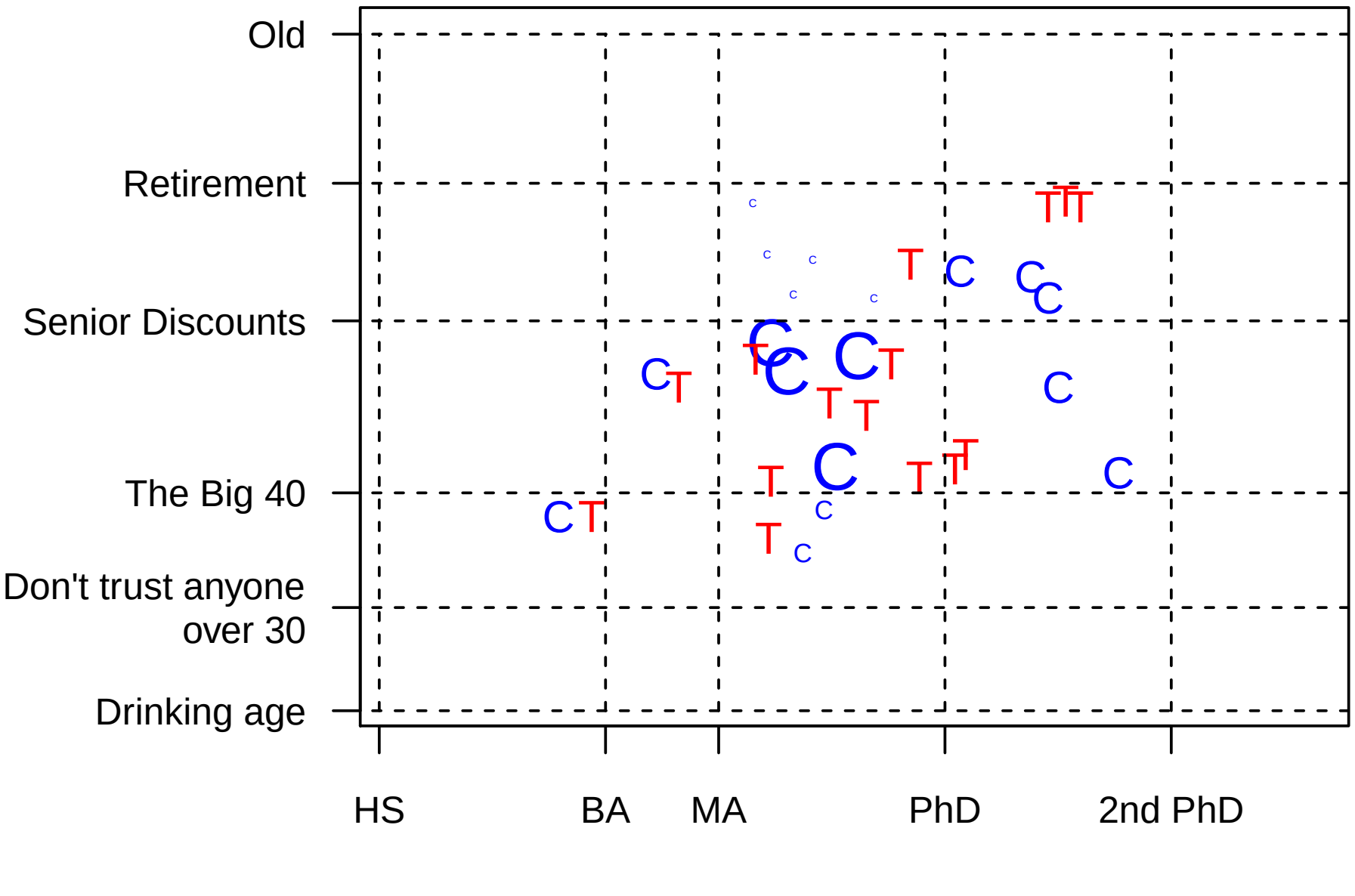

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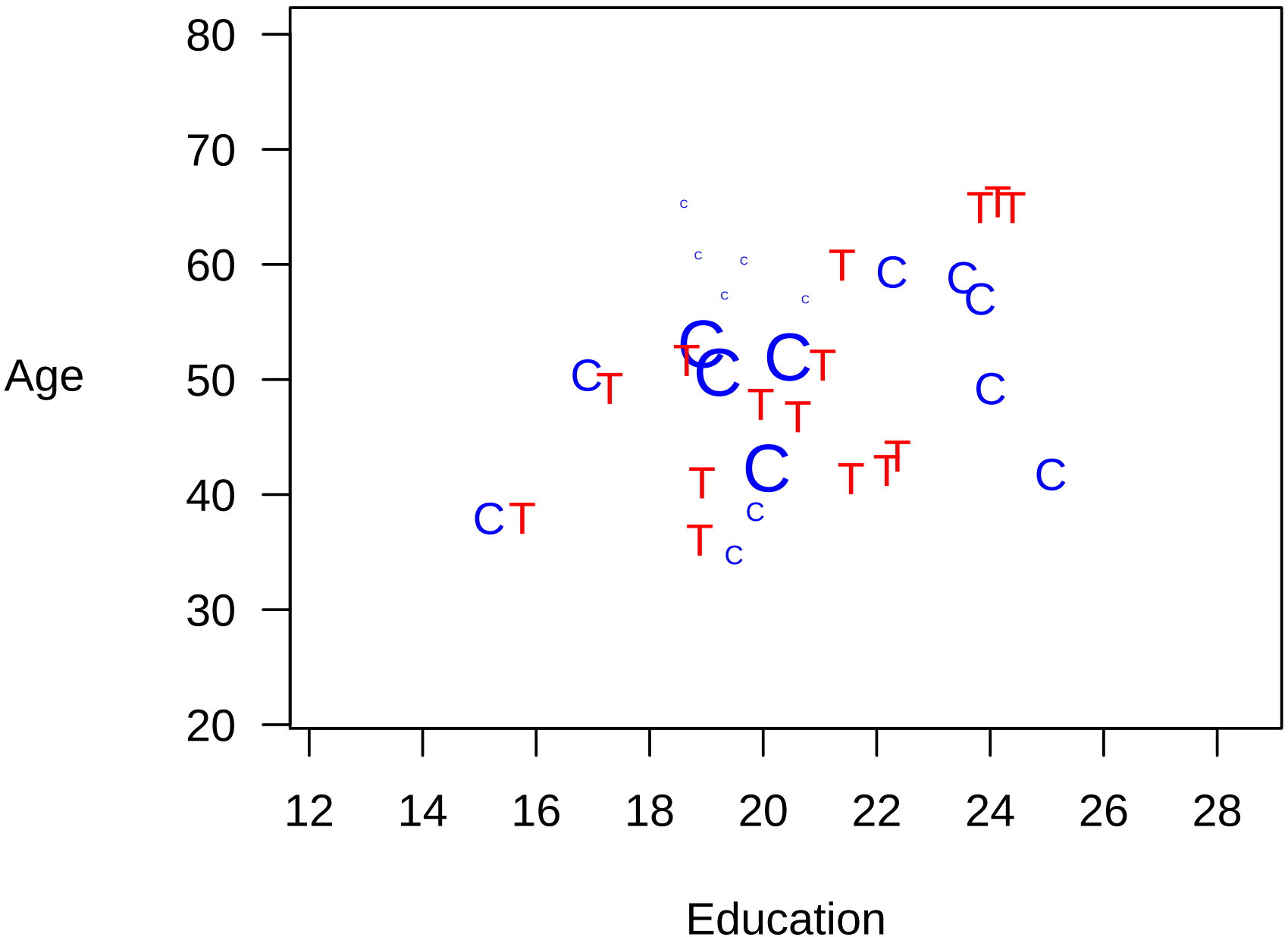

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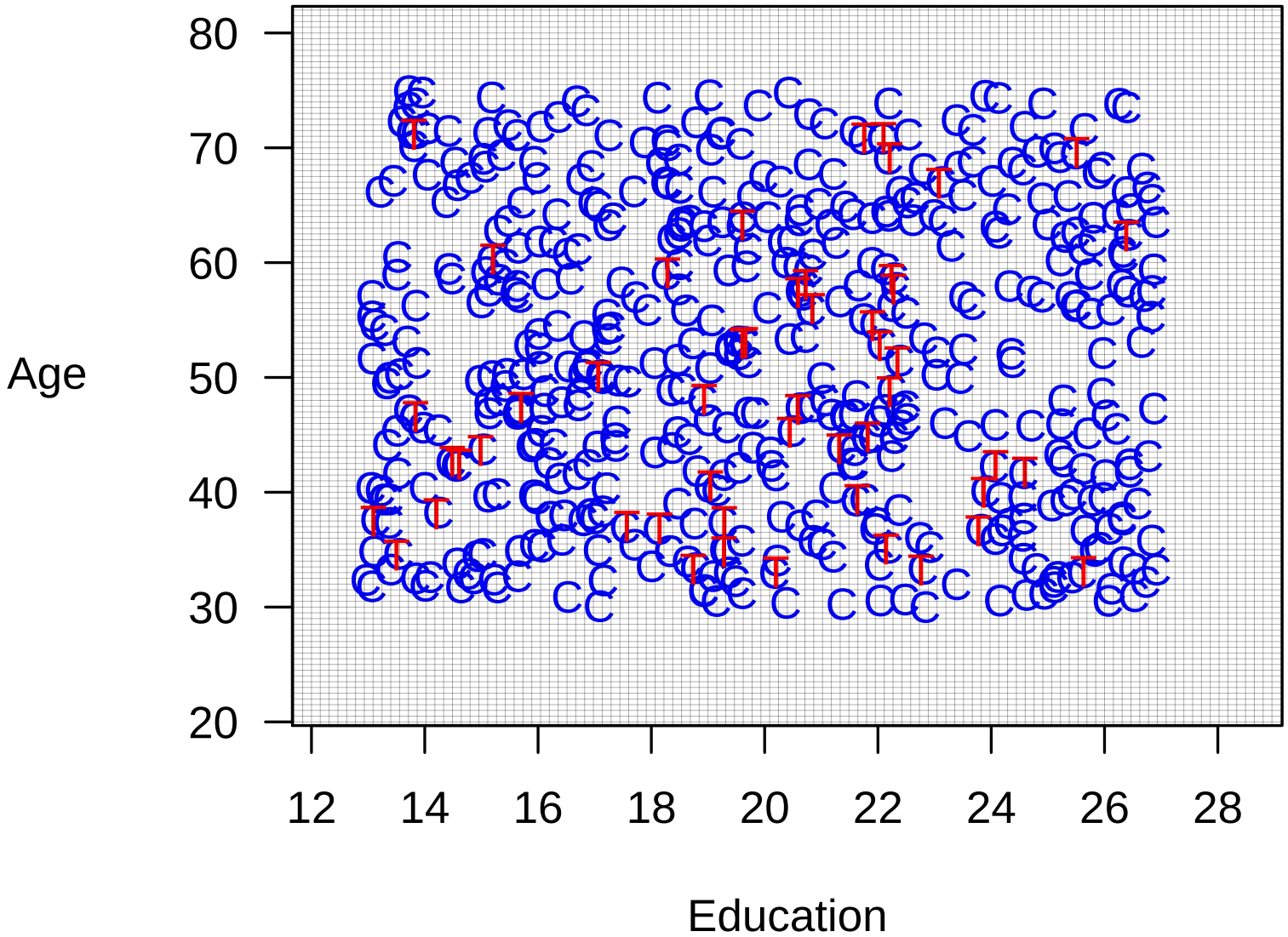

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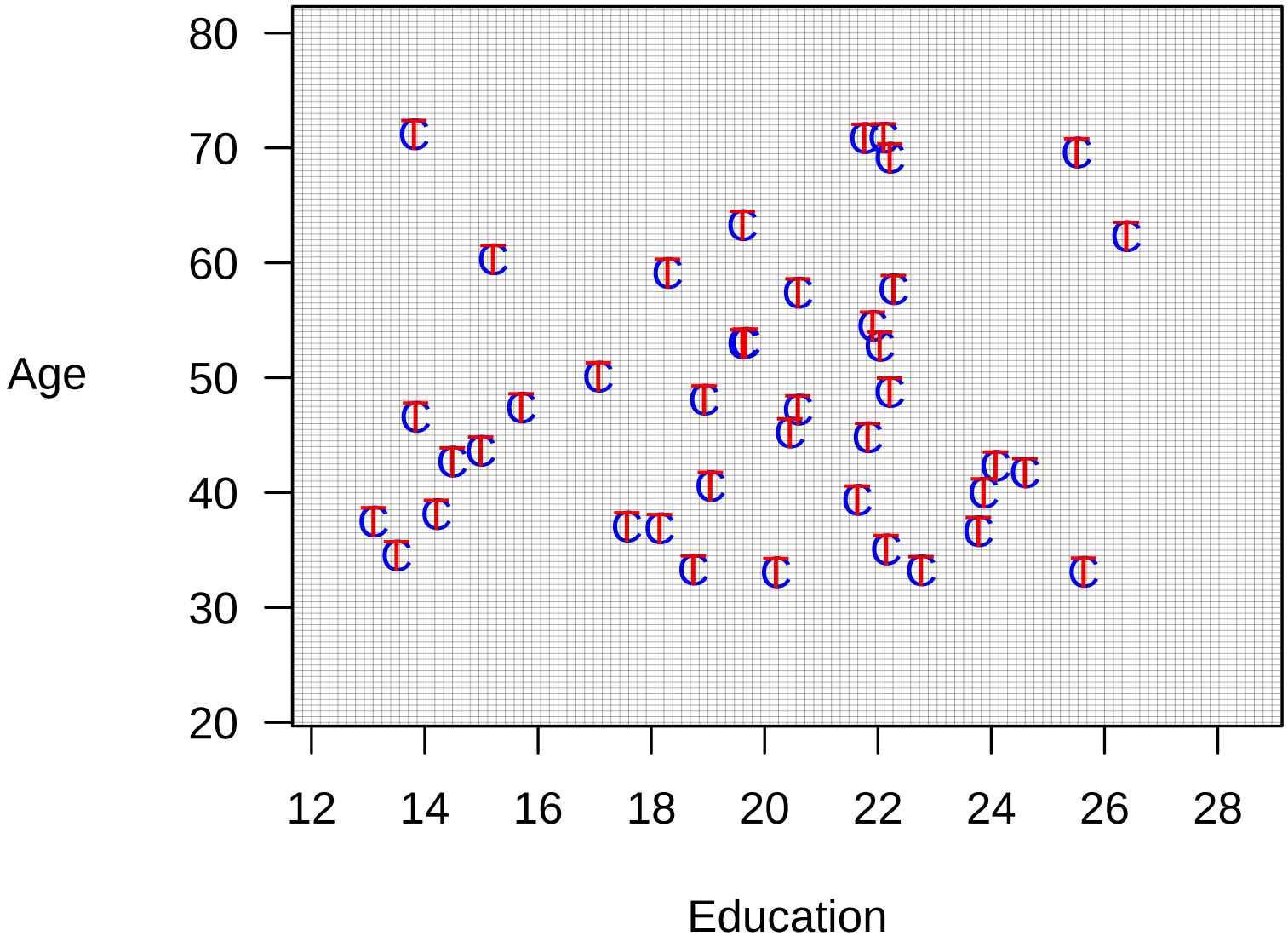

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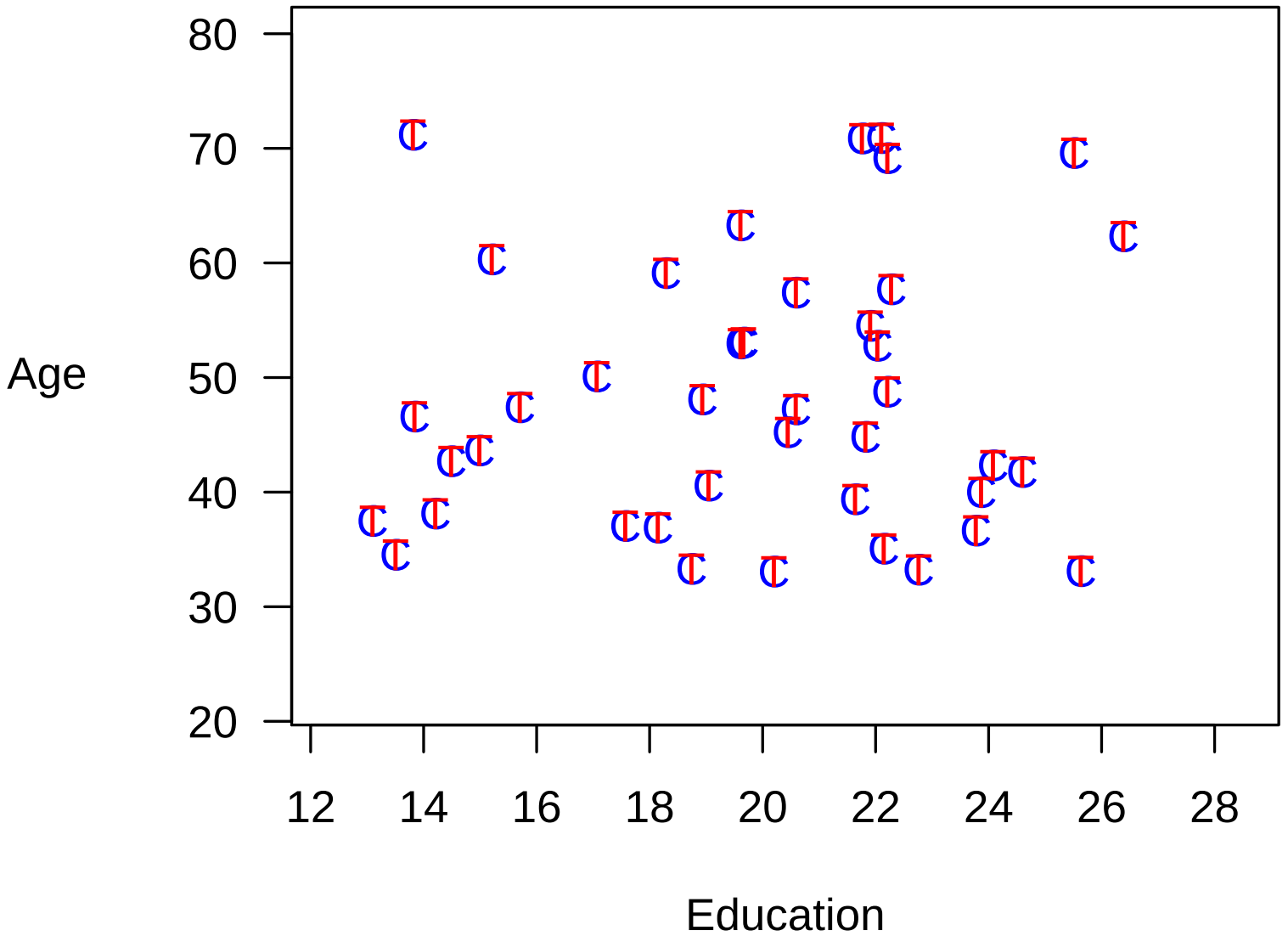

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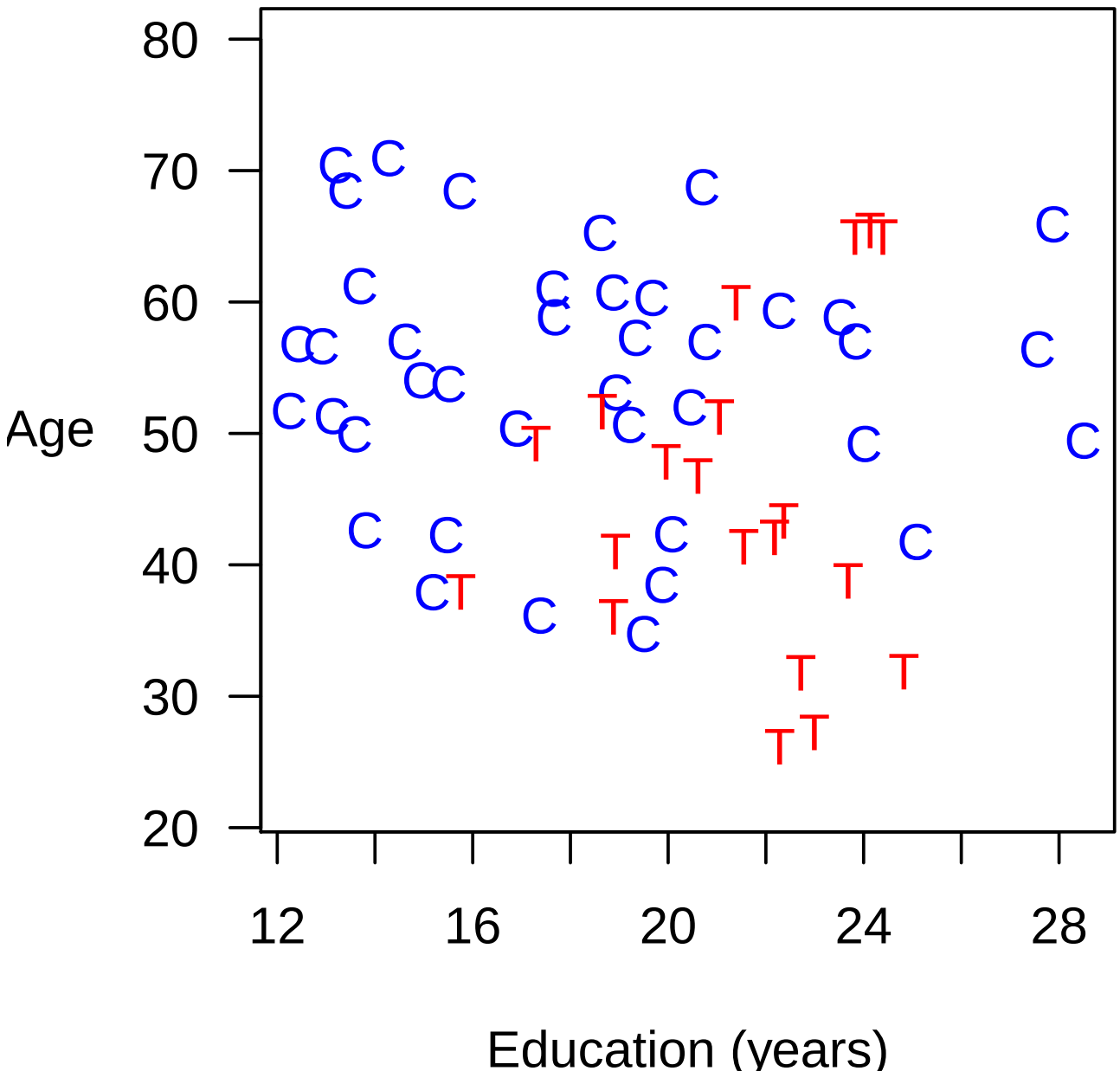

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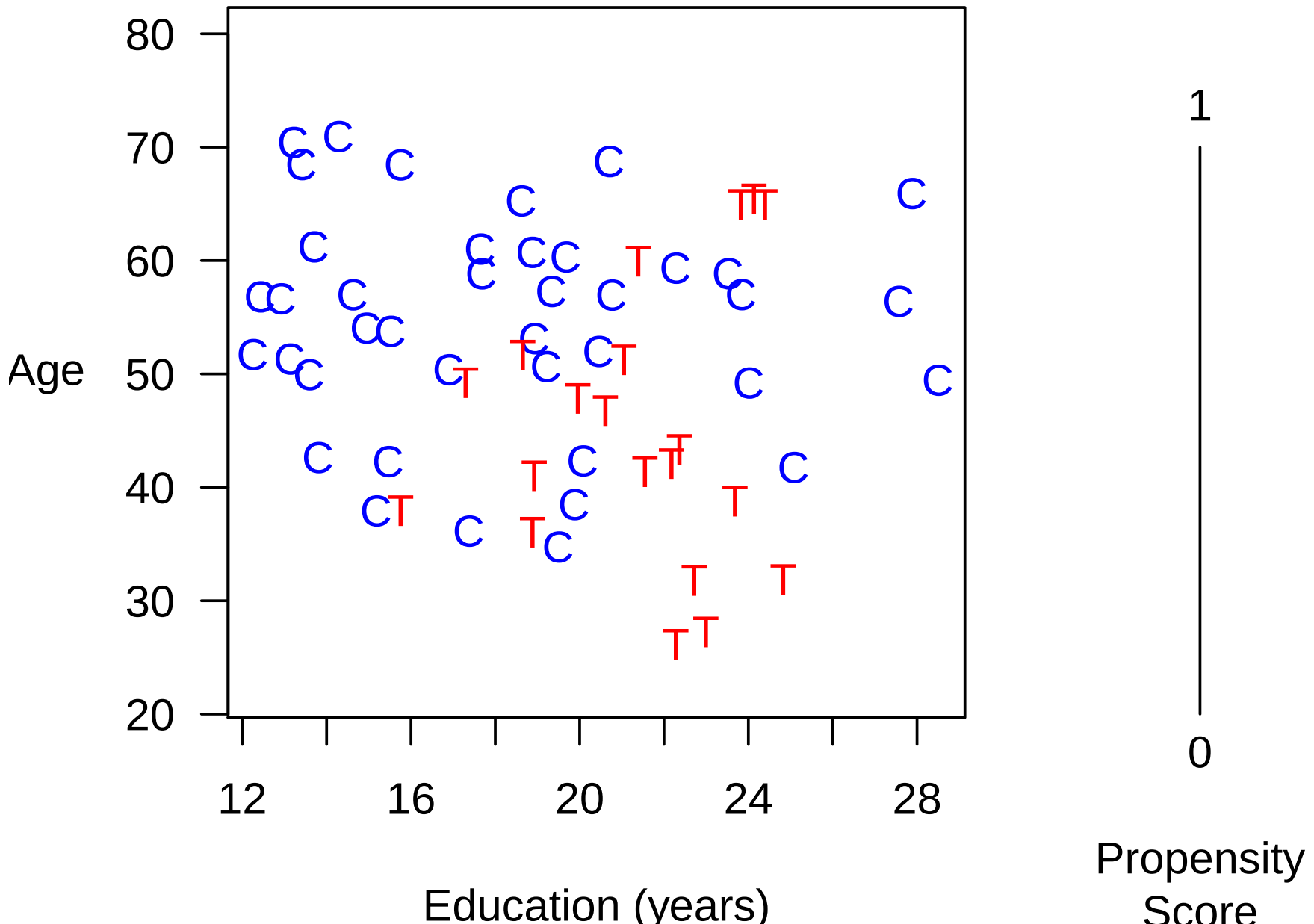

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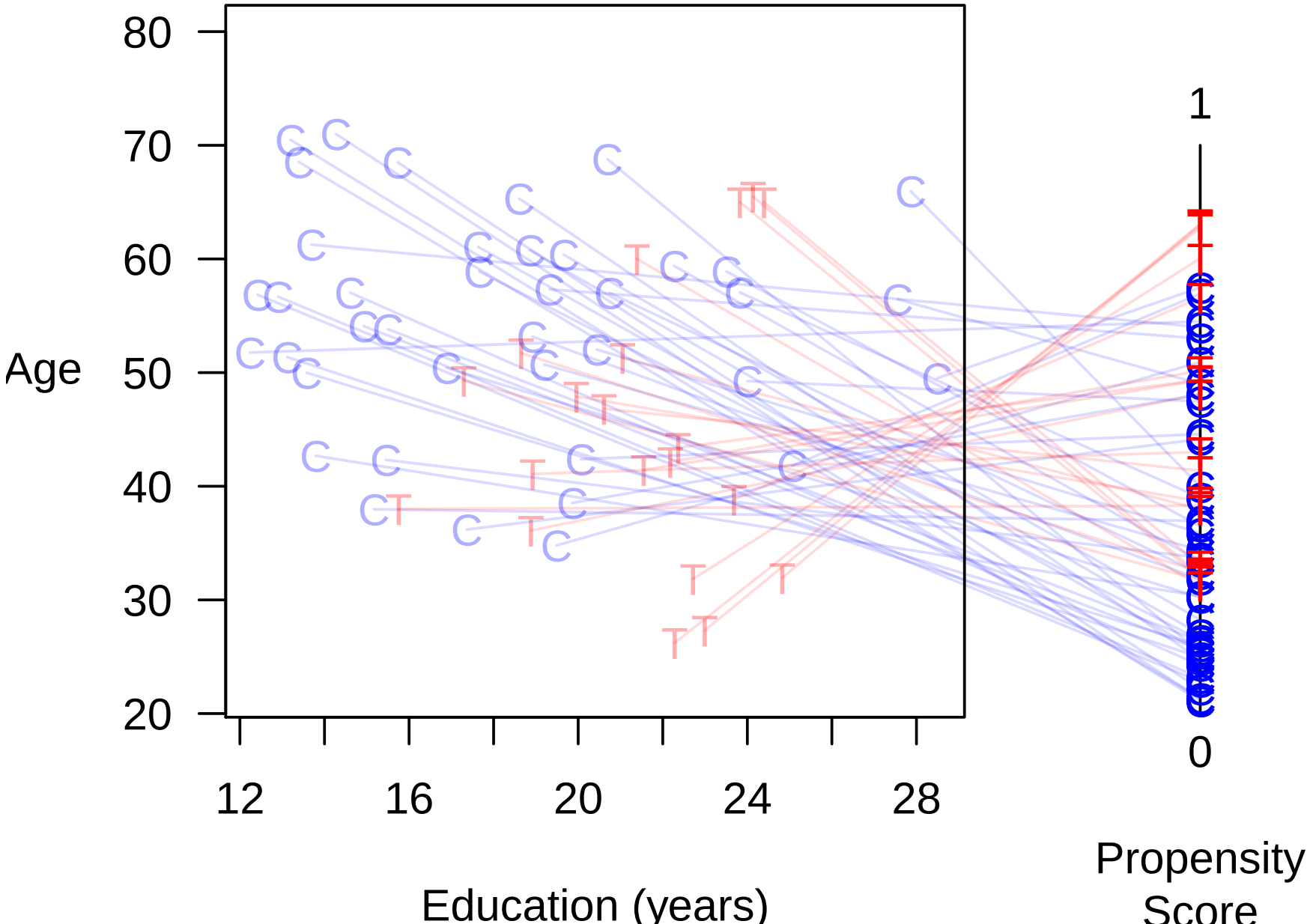

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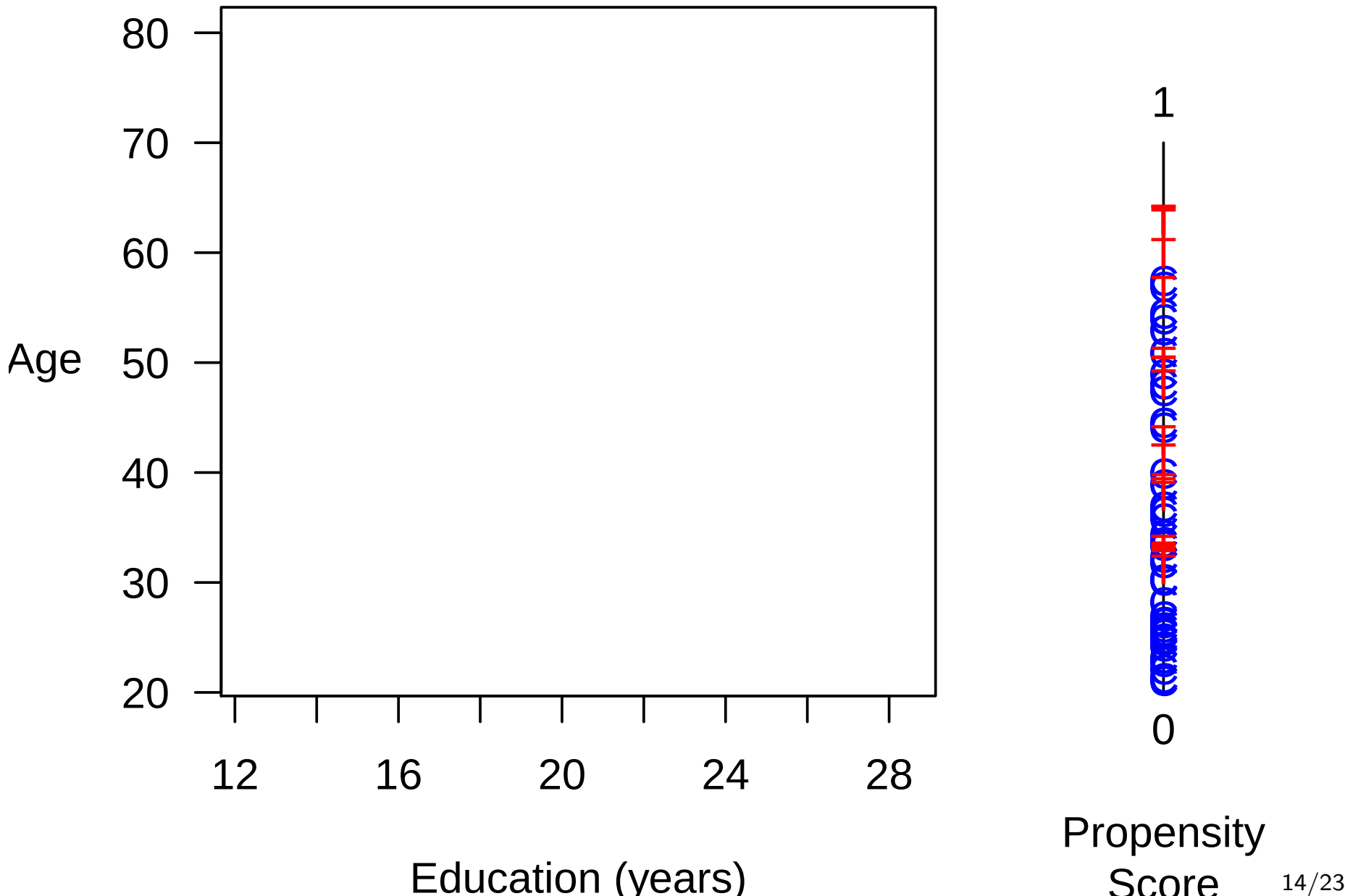

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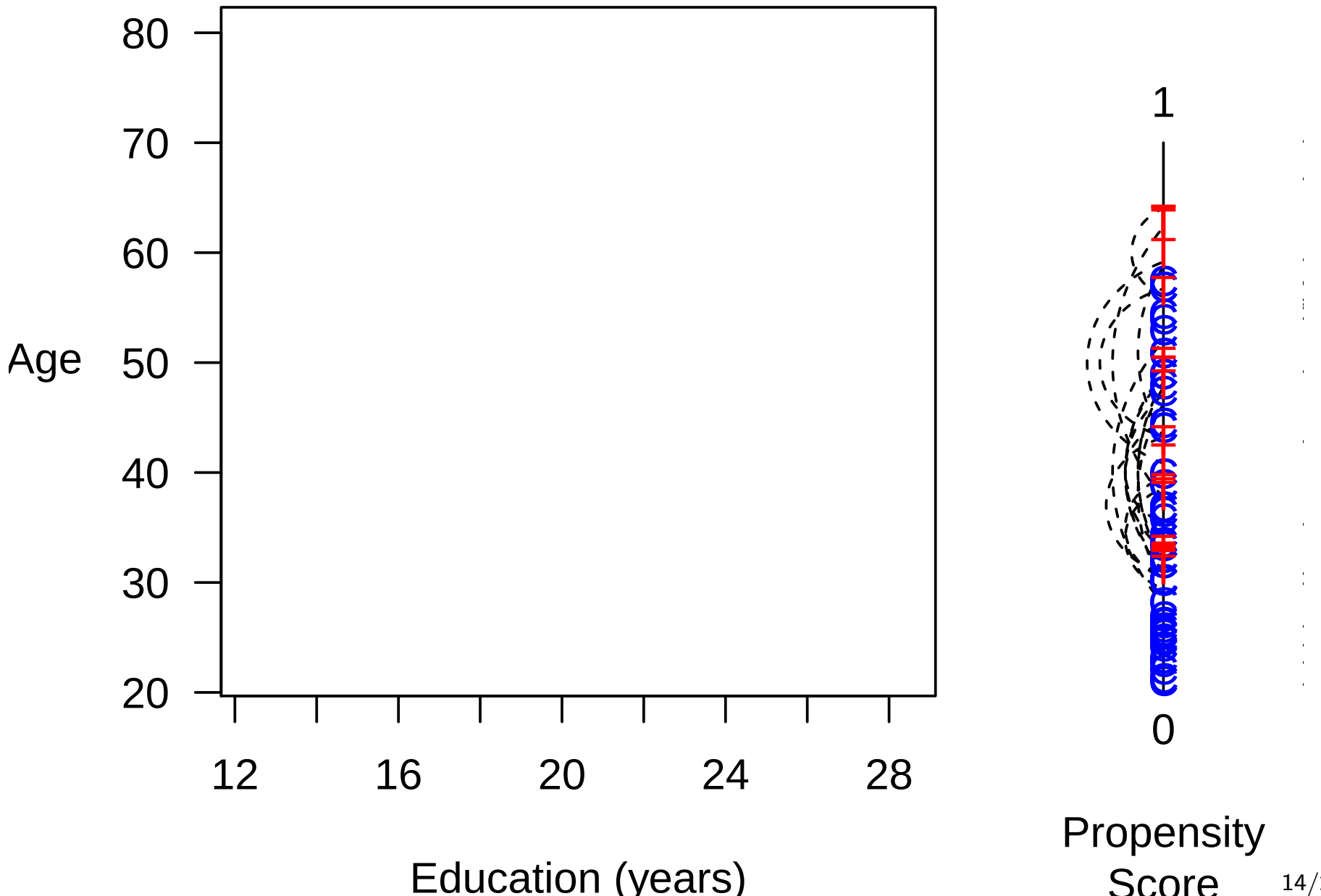

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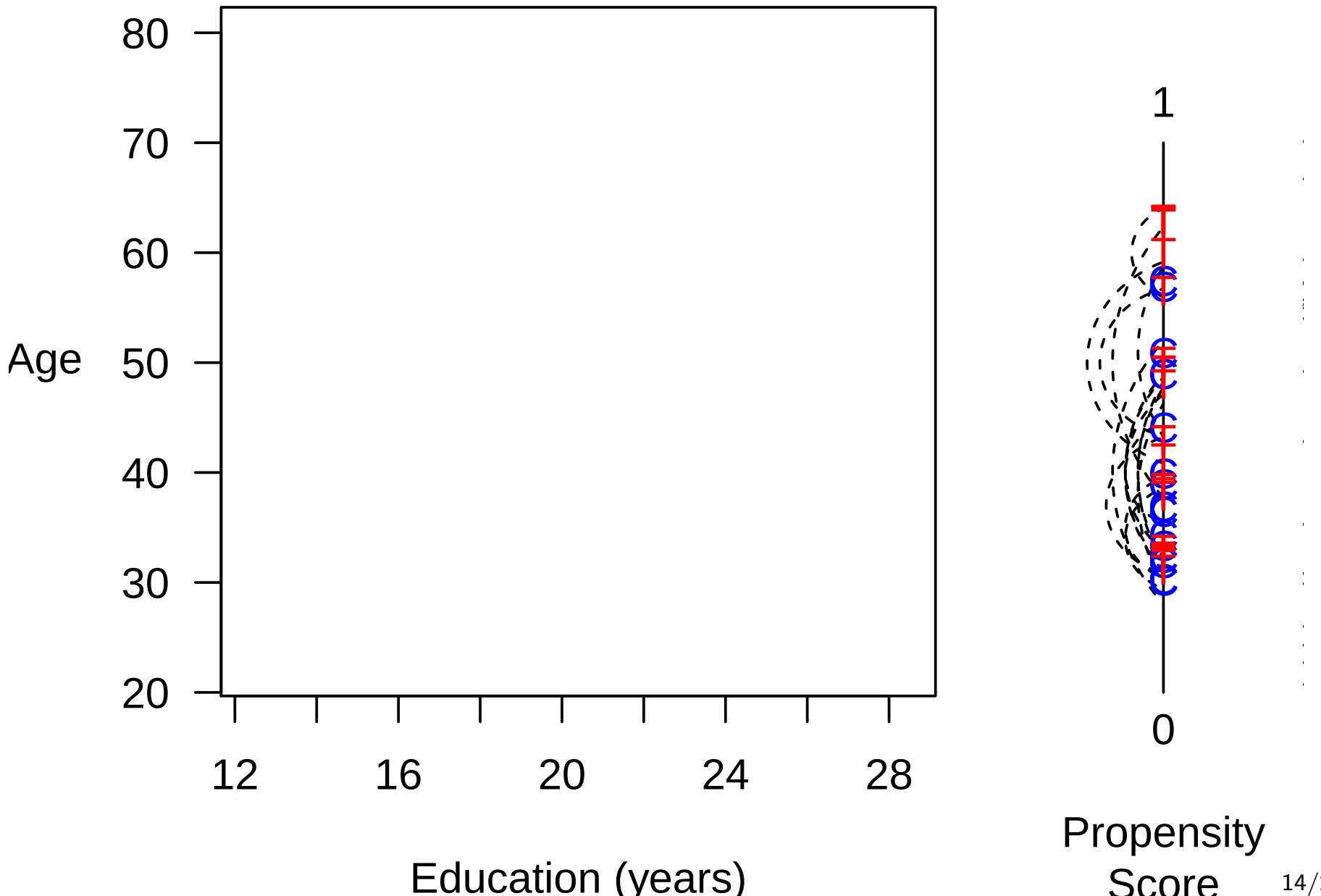

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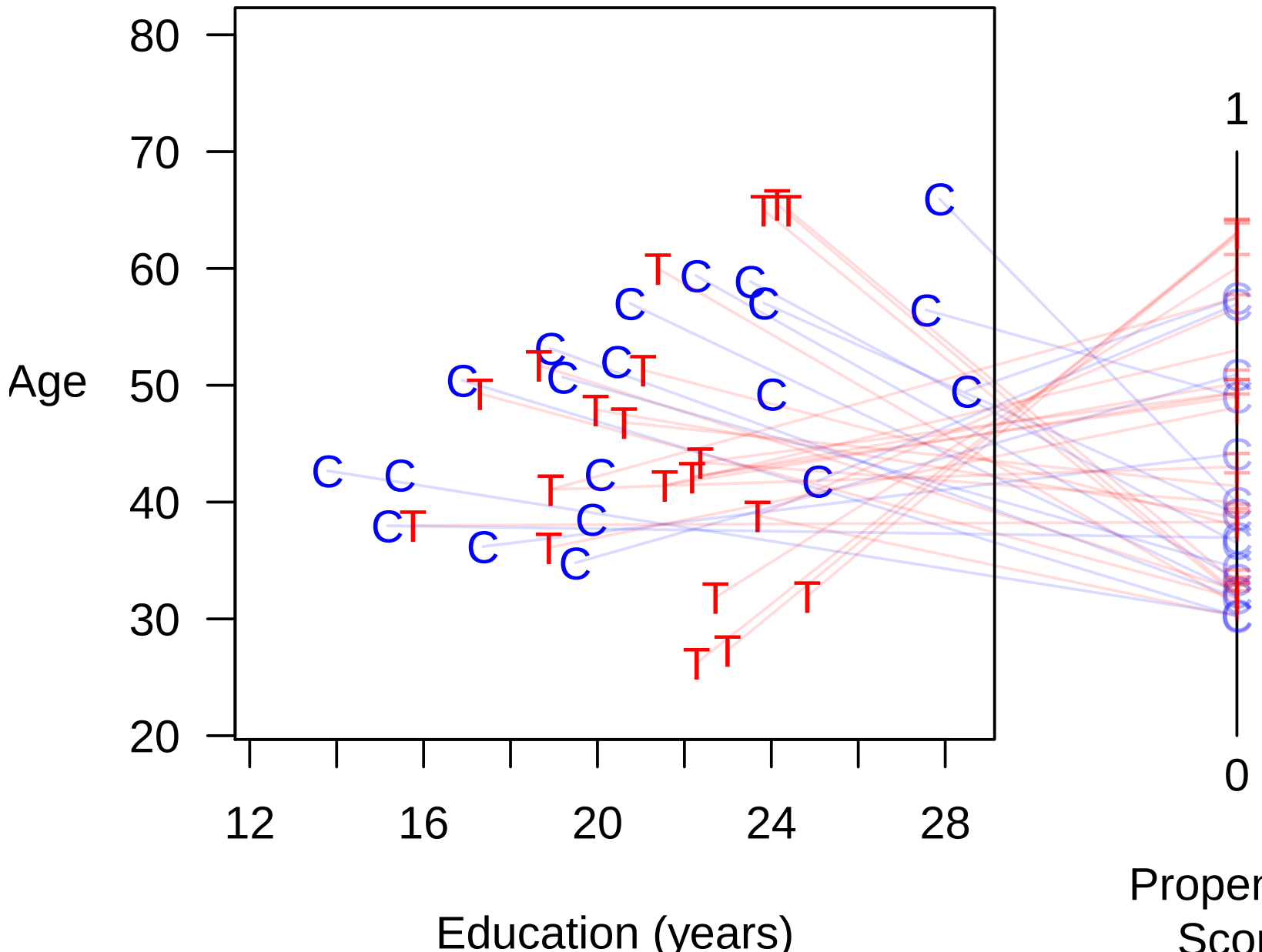

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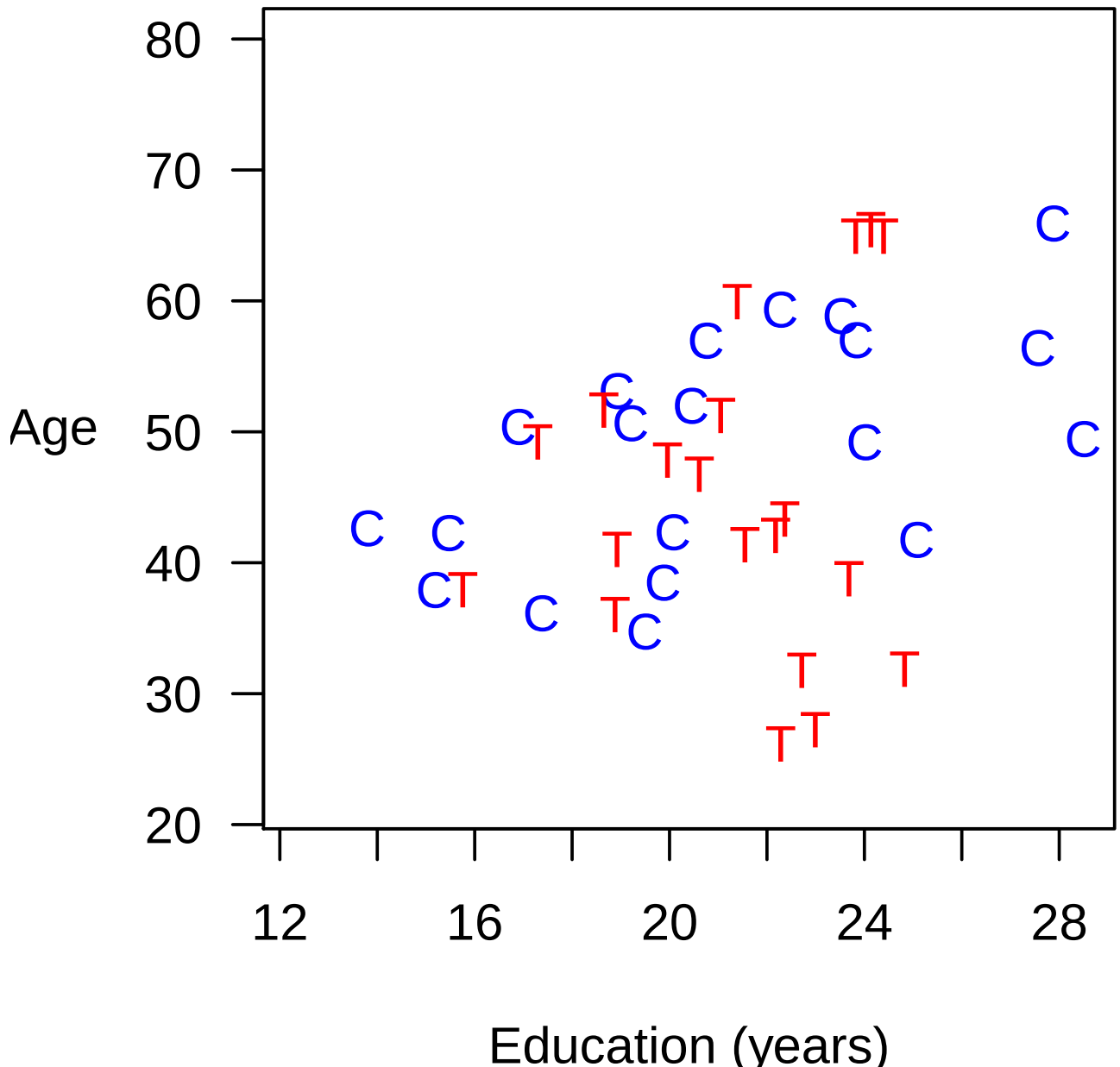

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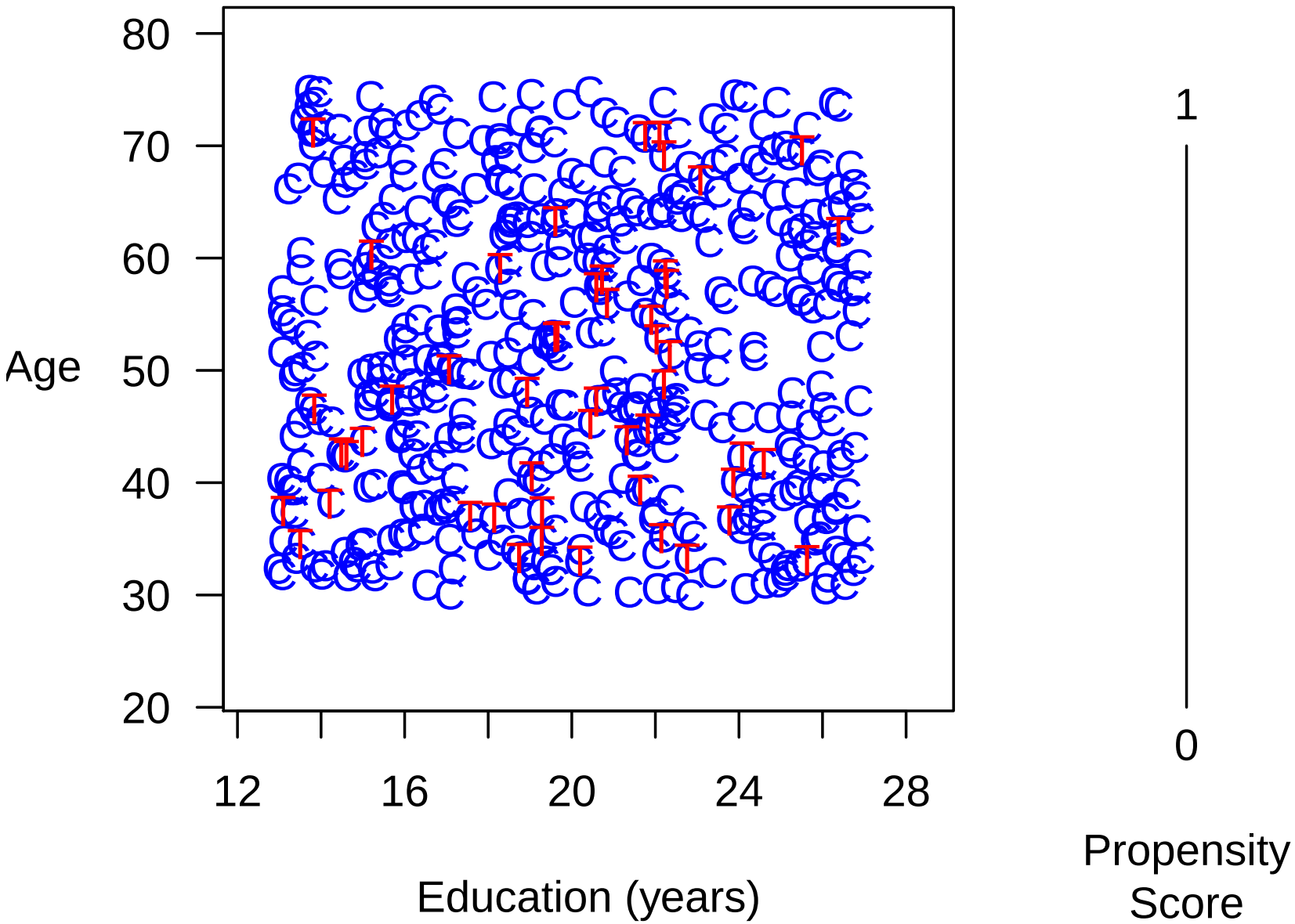

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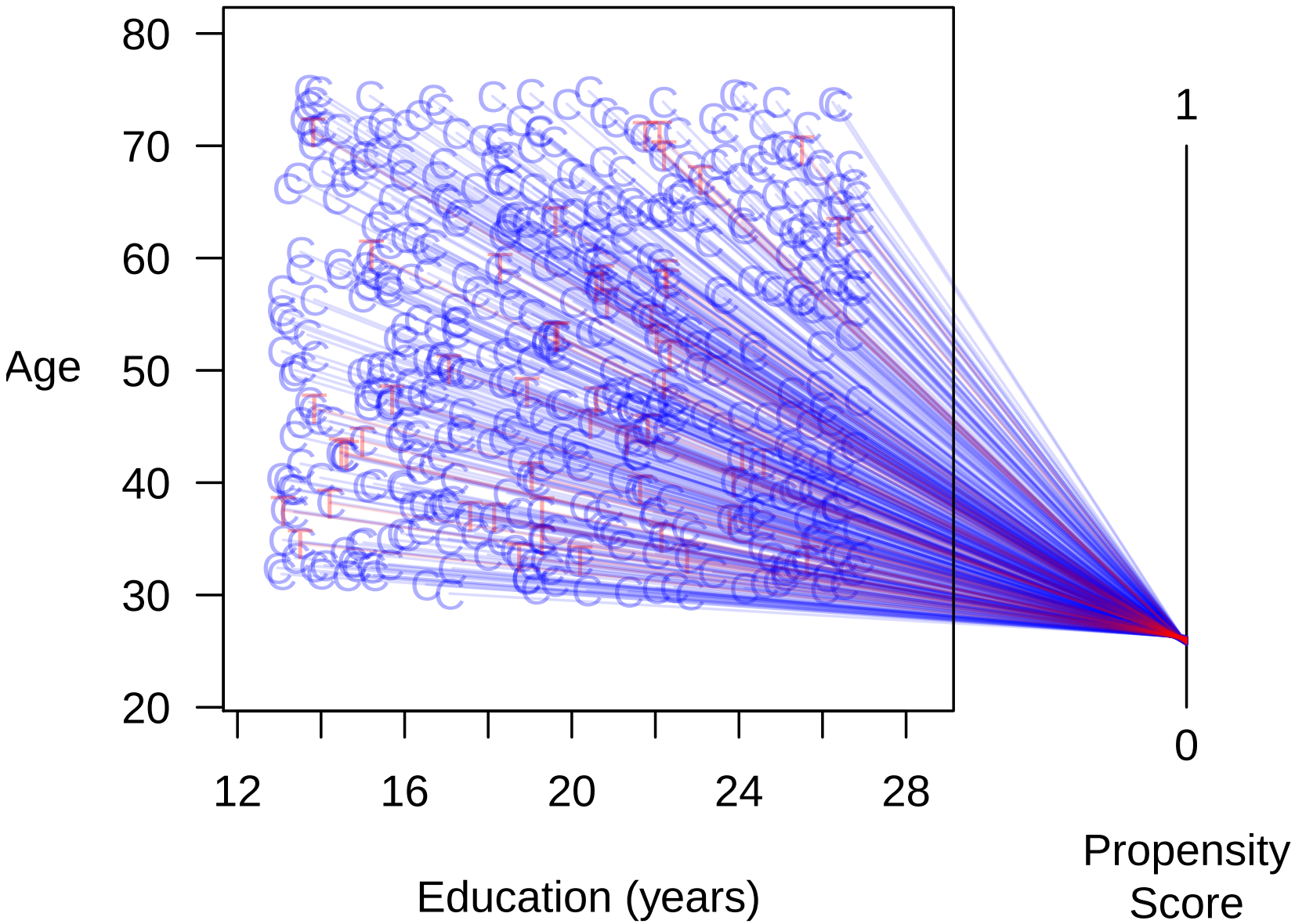

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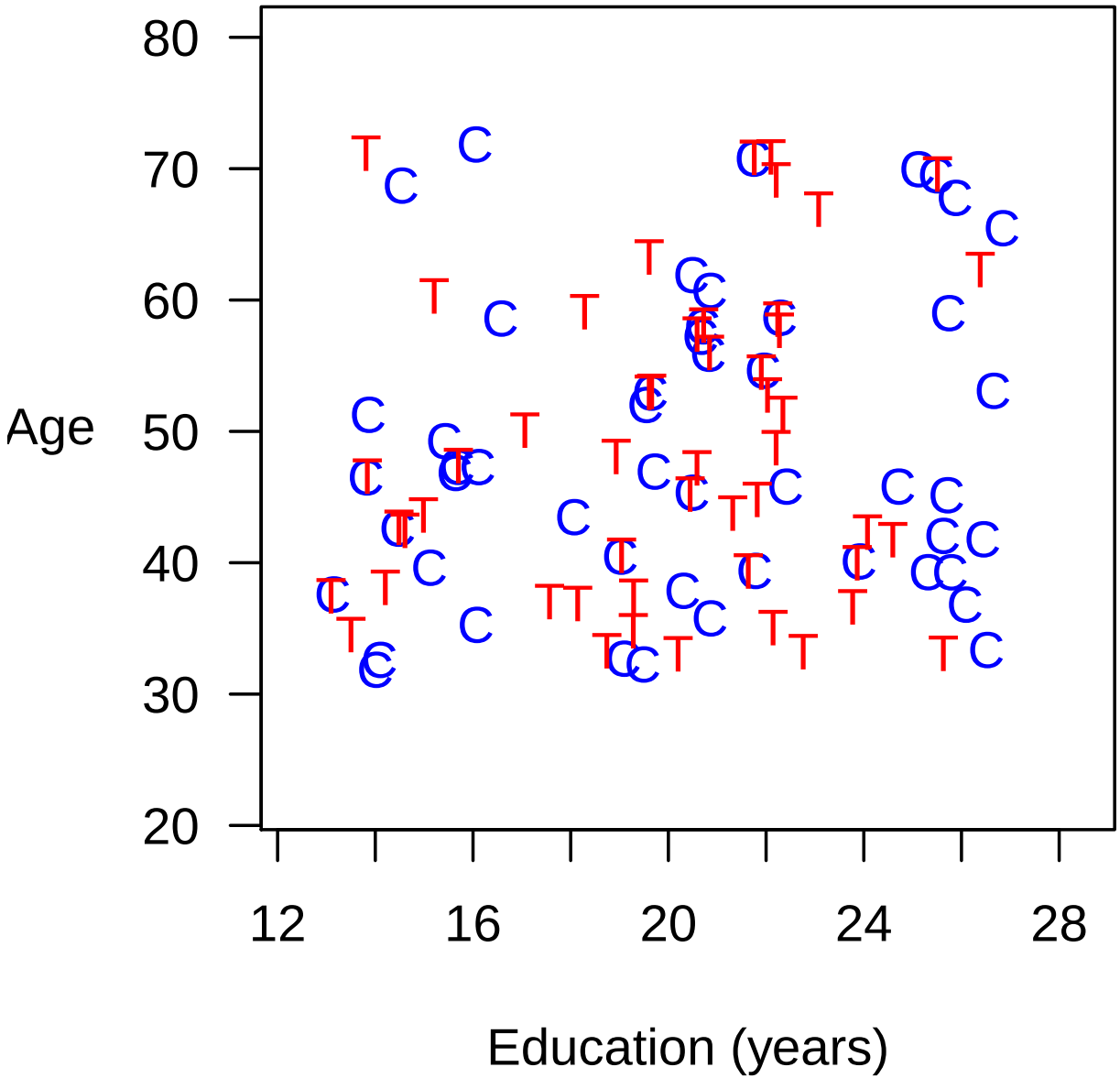

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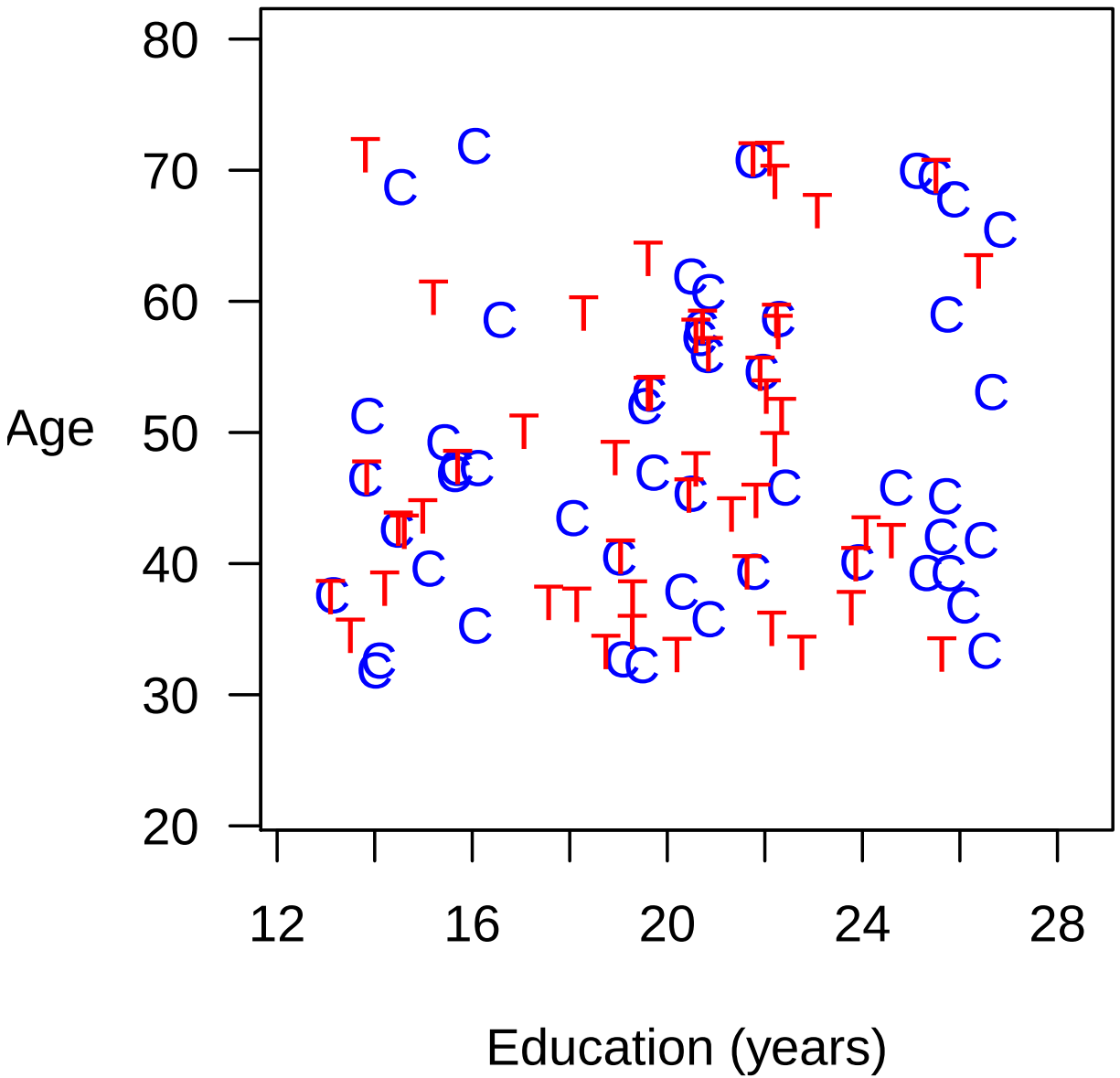

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  - Sex-balanced dataset: treateds $M_t, F_t$, controls $M_c, F_c$
  - Randomly prune 1 treated & 1 control $\rightsquigarrow$ 4 possible datasets:
    2 balanced $\{M_t, M_c\}$, $\{F_t, F_c\}$
    2 imbalanced $\{M_t, F_c\}$, $\{F_t, M_c\}$
  - $\implies$ random pruning increases imbalance
- Continuous example
  - Dataset: $T \in \{0, 1\}$ randomly assigned; $X$ any fixed variable; with $n$ units
  - Measure of imbalance: squared difference in means $d^2$, where $d = \bar{X}_t - \bar{X}_c$
  - $E(d^2) = V(d) \propto 1/n$ (note: $E(d) = 0$)
  - Random pruning $\rightsquigarrow$ $n$ declines $\rightsquigarrow$ $E(d^2)$ increases
  - $\implies$ random pruning increases imbalance

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   - What if I match on a few important covariates and then use PSM? The low standards will be raised some, but the PSM Paradox will kick in earlier

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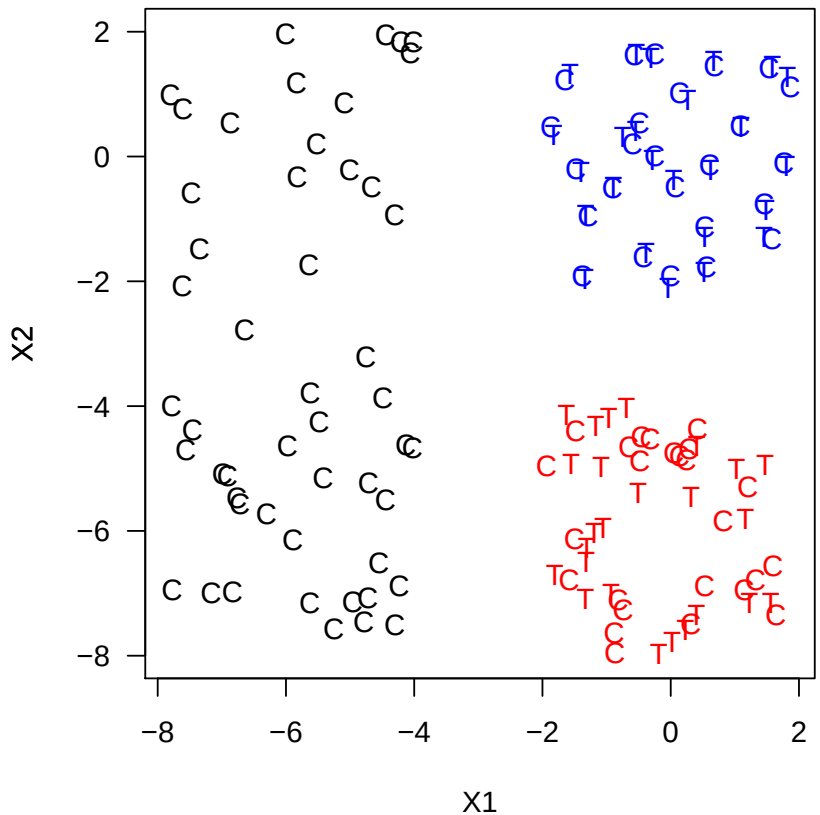

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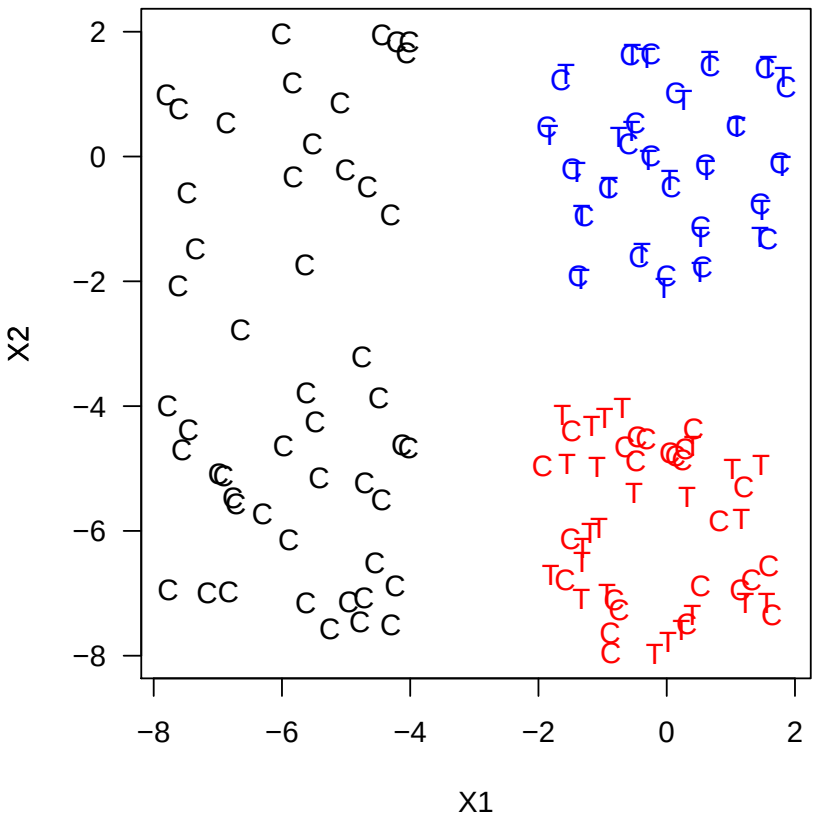
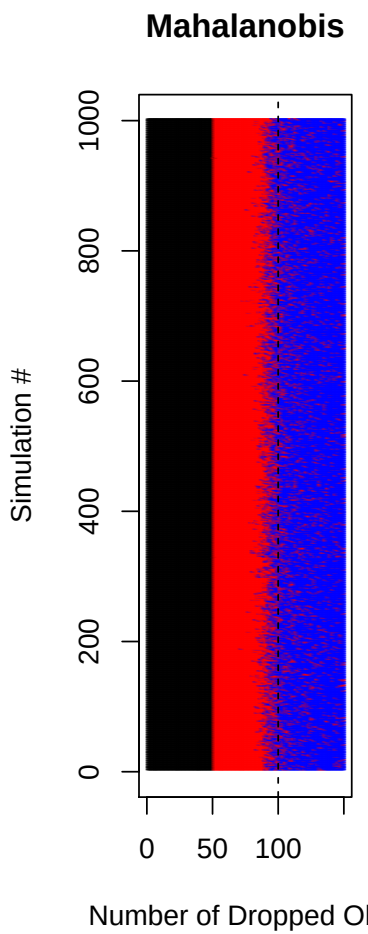
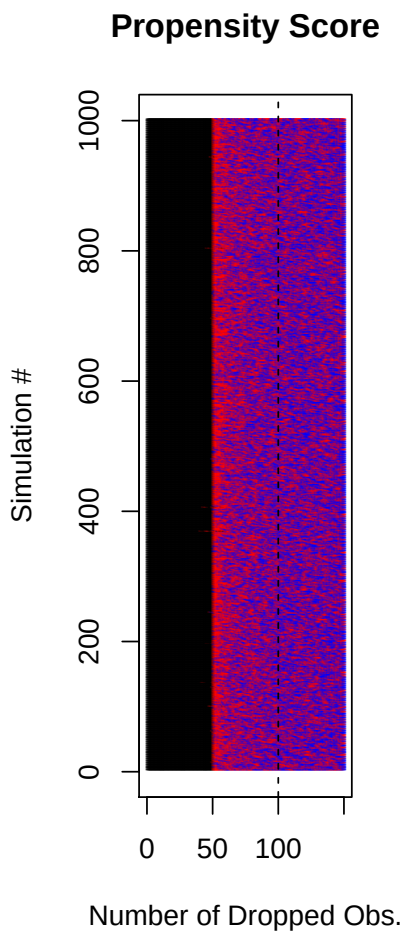
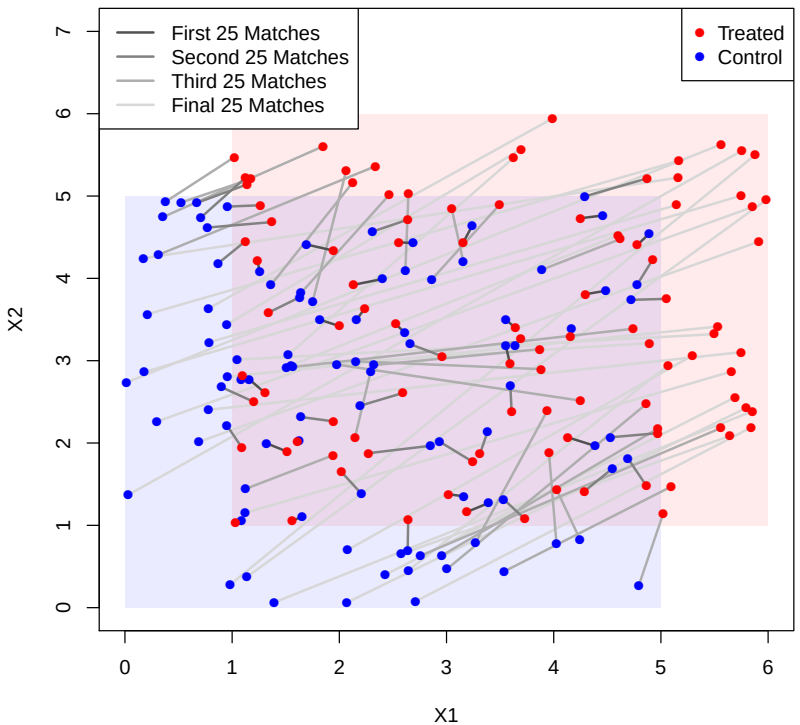


# What Does PSM Match?

## MDM Matches

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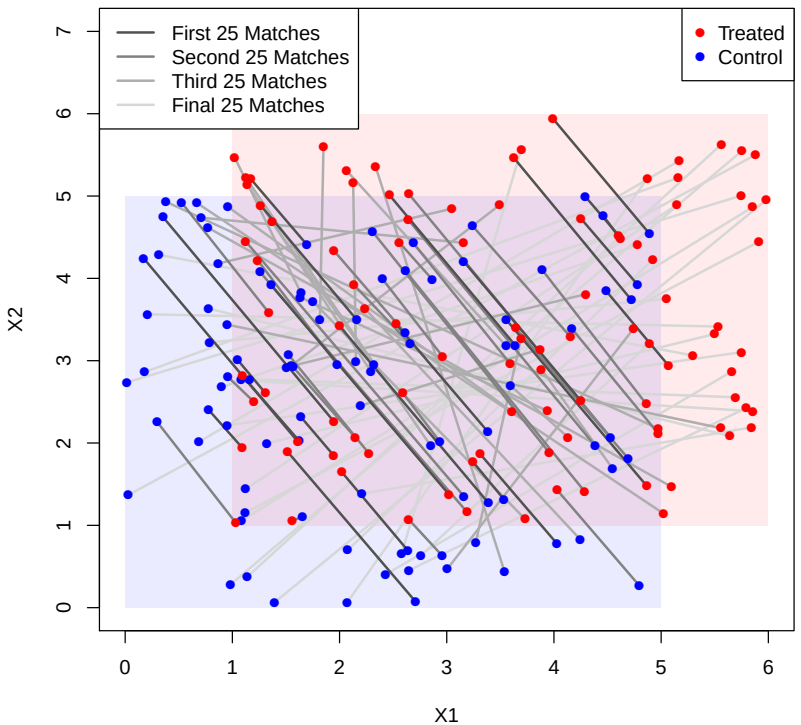
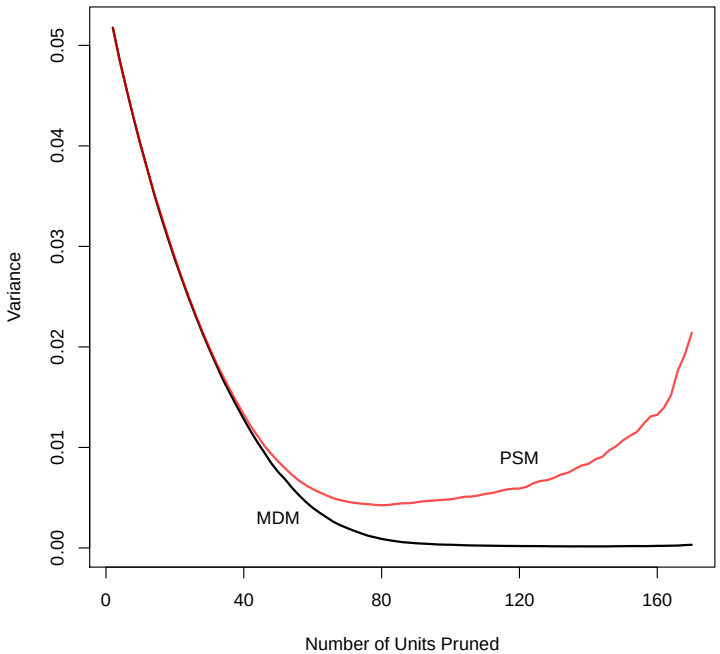



Controls: $X_1, X_2 \sim \text{Uniform}(0,5)$

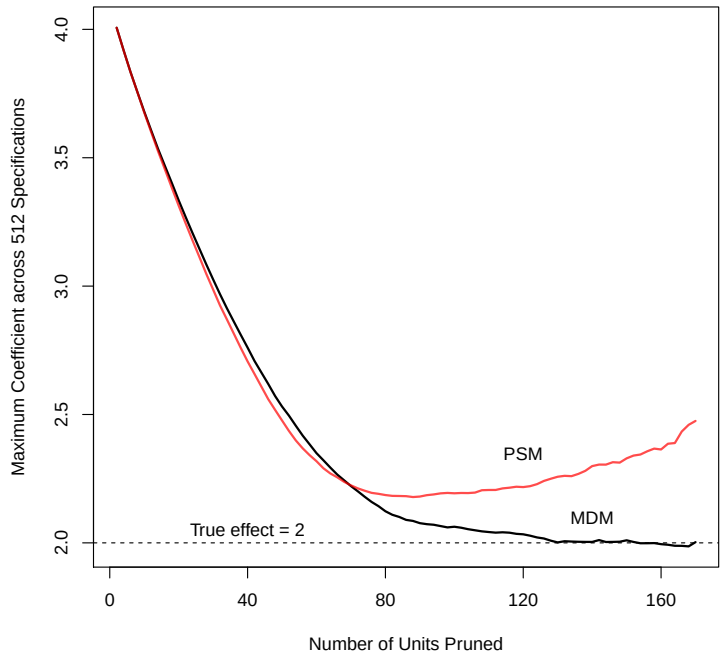
Treateds: $X_1, X_2 \sim \text{Uniform}(1,6)$

# PSM Increases Model Dependence & Bias

## Model Dependence



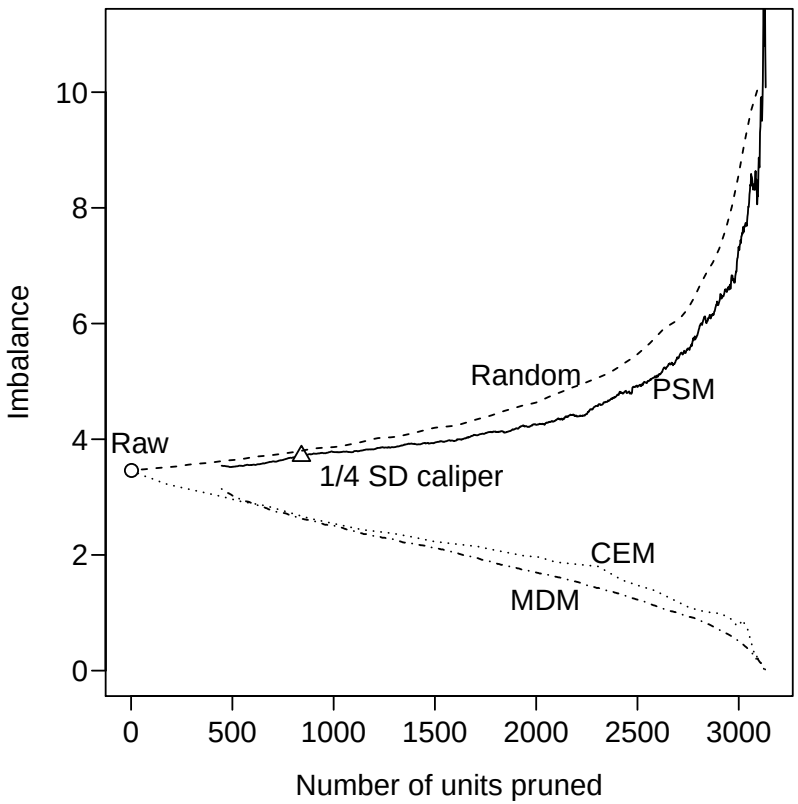

## Bias



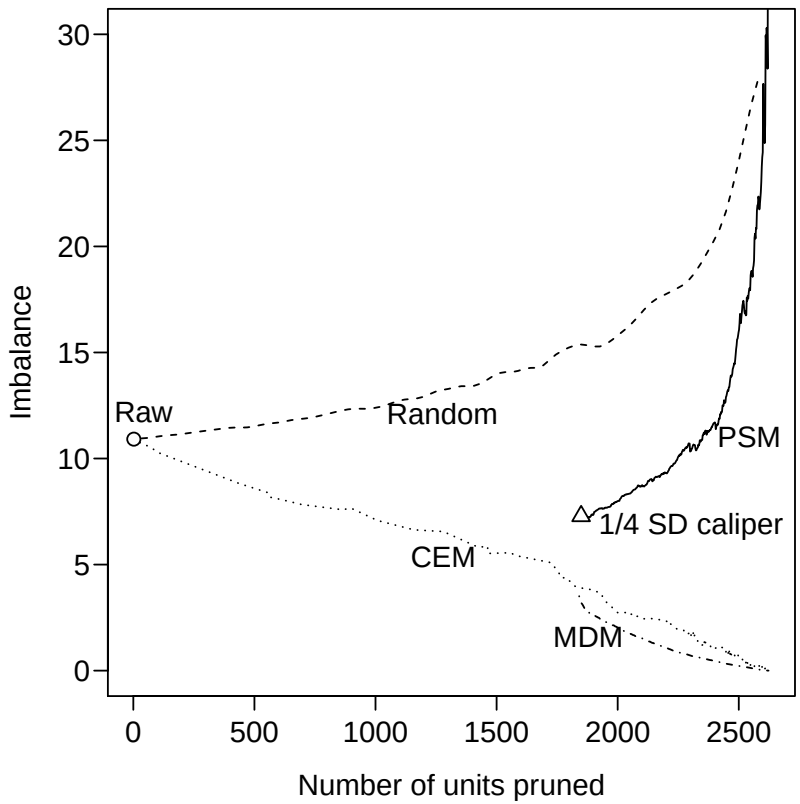

$$Y_i = 2T_i + X_{1i} + X_{2i} + \epsilon_i$$
$$\epsilon_i \sim N(0, 1)$$

# The Propensity Score Paradox in Real Data

Finkel et al. (JOP, 2012)




Nielsen et al. (AJPS, 2011)



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- Matching methods still highly recommended; choose one with higher standards

# For more information, papers, & software

GaryKing.org

www.mit.edu/∼rnielsen