# Treatment Interaction Trees (TINT)

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# **Aim**

- Insight: For which problems can we use TINT?
- Knowledge: How does TINT work?
- Inspiration: New ways to evaluate clinical trials

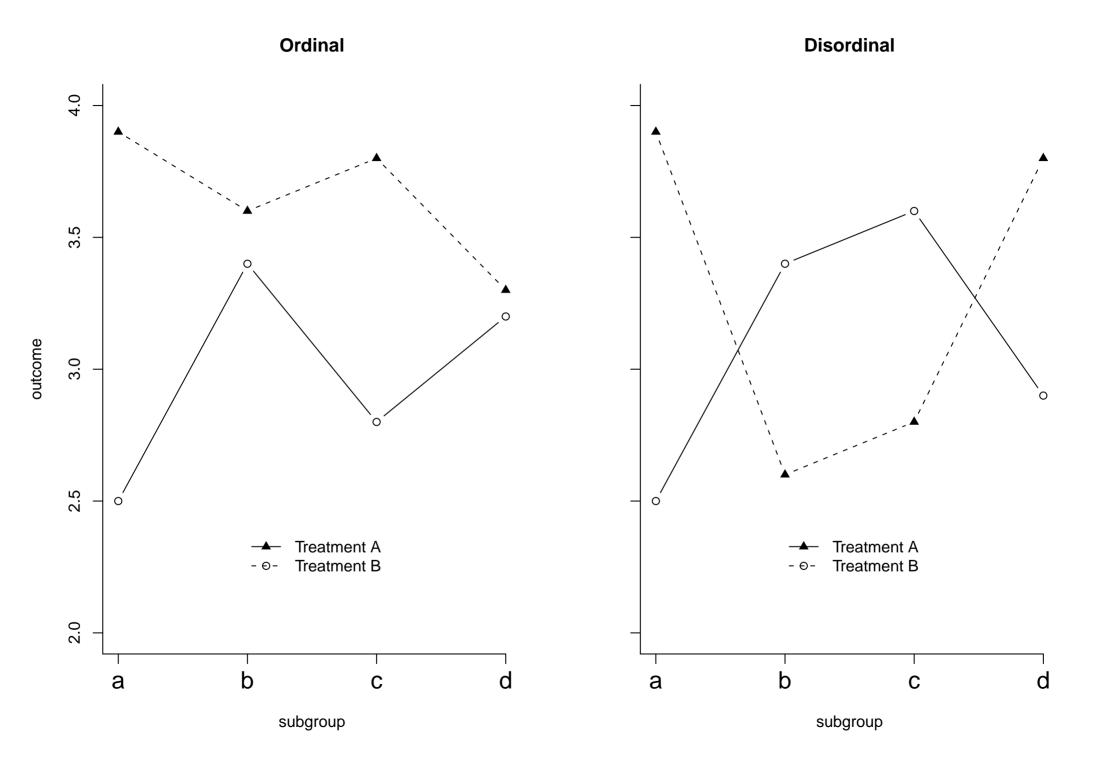


# **Problem**

Two treatments – **A** and **B** – are available for patients. [surgery and radiotherapy for patients with prostate carcinoma]

- 1. Which of the two treatments is most effective? [not our focus]
- 2. For whom is A better than B and for whom is B better than A (and for whom it does not make a difference)? ⇒ different subgroups of patients
- ⇒ Disordinal treatment-subgroup interaction





# Disordinal treatment-subgroup interaction

- Relevance for policy-makers: patient-tailored treatment assignment
- Moderators or effect modifiers: patient characteristics identifying the subgroups
- Goal of statistical method: identifying the patient characteristics that maximize the disordinal treatment-subgroup interaction
- Available methods: Moderator analysis (Baron & Kenny, 1986),
   Interaction Trees (Su et al, 2008), STIMA (Dusseldorp et al, 2010)



# **New method: TINT**

 Appropriate for complex situations: The subgroups may comprise several types of patients defined by different (possibly nonlinear) combinations of patient characteristics

Three main subgroups / partition classes:

 $\mathfrak{S}_1$ : those for whom A is better than B

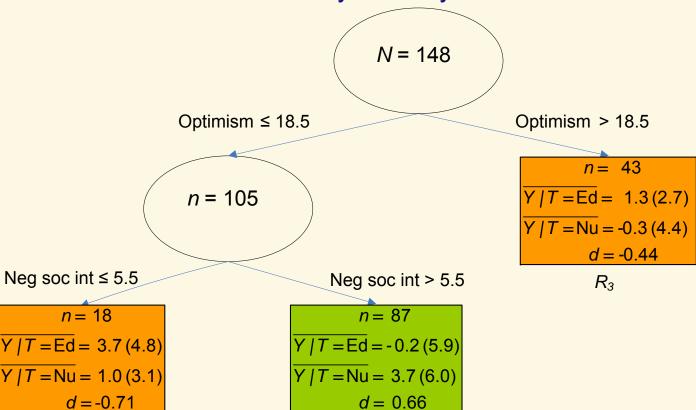
2 : those for whom B is better than A

 $\wp_3$ : those for whom it does not make any difference



# Treatment INteraction Trees (TINT)

Tree-based method: partitions on the basis of the patient characteristics are obtained by a binary tree



 $R_2$ 



 $R_1$ 

# **Ingredients Partitioning criterion**

## Difference in treatment outcome component:

 $\Delta_1$ : the weighted average difference in mean outcome between the treatments across the leafs assigned to  $\wp_1$  and

 $\Delta_2$ : the weighted average difference in mean outcome between the treatments across the leafs assigned to  $\wp_2$ 

## **Cardinality component:**

 $\Sigma_1$ : the total number of patients in the leafs assigned to  $\wp_1$  and

 $\Sigma_2$ : the total number of patients in the leafs assigned to  $\wp_2$ 

$$C \approx \Delta_1 * \Delta_2 * \Sigma_1 * \Sigma_2$$



## Real data: Breast Cancer Recovery Project (BCRP)

Scheier MF, Helgeson VS, et al. (JCO, 2007)

#### Patients:

Young women with early-stage breast cancer

## Two different types of treatments:

A) Nutrition information: how to adopt a low-fat diet (n = 78; T = 1)

B) Education: provision of coping skills (n = 70; T = 0)

## Design:

Pretest-posttest design with random assignment to the treatments

## Outcome (Y):

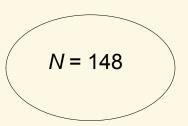
Improvement in depression from pre-test to post-test (change score)

## Possible moderators $(X_i)$ :

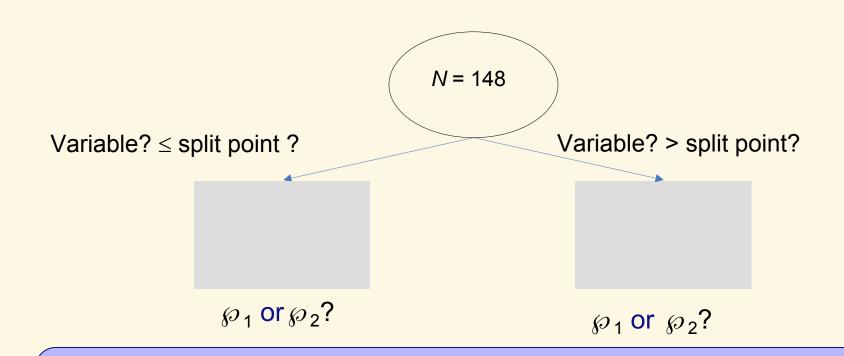
Nationality, Marital status, Age, Weight-change, Treatment extensiveness, Comorbidity, Dispositional optimism, Unmitigated communion, Negative social interaction



# How do we grow a Treatment Interaction tree?



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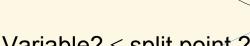


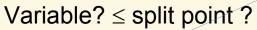
Step 1: Determine the optimal triplet  $(X_j, \text{ split point, assignment})$ :

 $\Rightarrow$  Select  $X_j$  (with associated optimal split point and assignment) that induces the highest C











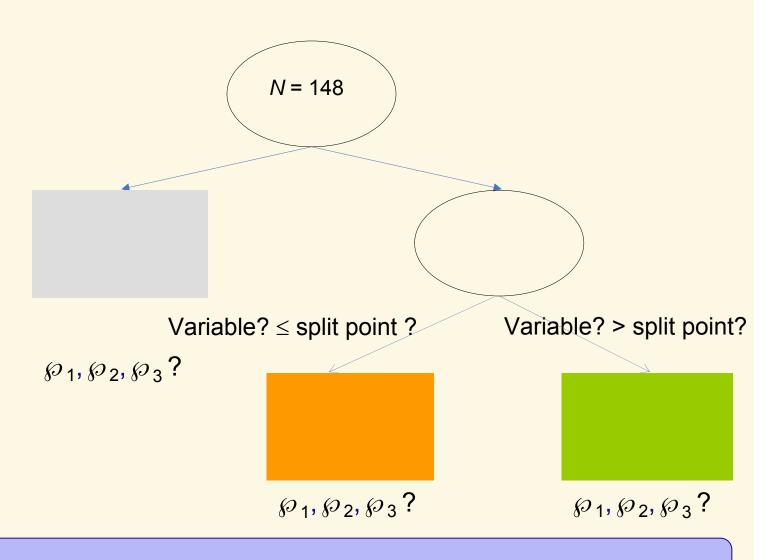
$$\wp_1, \wp_2, \wp_3$$
?

Variable? > split point?



$$\wp_1, \wp_2, \wp_3$$
?

 $\wp_1, \wp_2, \wp_3$ ?



**Step 2**: Accross all parent nodes: Select the one with the optimal triplet that implies the highest *C* 

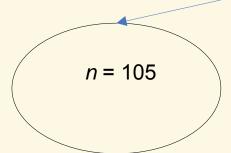


# **Treatment Interaction Tree for** Improvement in Depression

$$N = 148$$

Optimism ≤ 18.5

Optimism > 18.5



$$n = 43$$
 $\overline{Y/T} = Ed = 1.3 (2.7)$ 
 $\overline{Y/T} = Nu = -0.3 (4.4)$ 
 $d = -0.44$ 

 $R_3$ 

Neg soc int ≤ 5.5

$$n = 18$$
 $\overline{Y/T = Ed} = 3.7 (4.8)$ 
 $\overline{Y/T = Nu} = 1.0 (3.1)$ 
 $d = -0.71$ 

 $R_1$ 

14

$$n = 87$$
 $\overline{Y/T} = Ed = -0.2 (5.9)$ 
 $\overline{Y/T} = Nu = 3.7 (6.0)$ 
 $d = 0.66$ 

 $R_2$ 

Neg soc int > 5.5

801 802



## Conclusion

- Results of TINT application to BCRP were promising
  - Large reduction of number of required analysis
  - ➤ Insightful picture of overall pattern of moderation
- Future:
  - Large-scale test with artificial data
  - Generalization to categorical outcome and patient characteristics
  - ➤ Integration of costs of the treatments
  - Optimal assignment to 1 treatment: Only Partition class 1 and 3

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