# AdaPT: Interactive Multiple Testing with Side Information

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#### Side Information

Setting: hypotheses  $H_1, \ldots, H_n$  with p-values  $p_1, \ldots, p_n$ 

Observe side information  $x_i \in \mathcal{X}$  for each  $H_i$ 

#### Examples:

- Identifying differentially expressed genes with "prioritization scores" (priors, auxiliary information, etc.)
- Spatiotemporal testing;
- Clinical meta-analysis;

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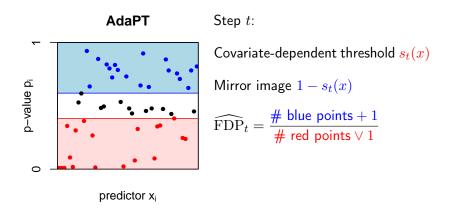
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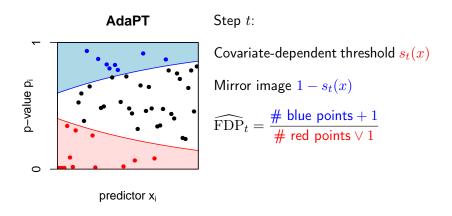
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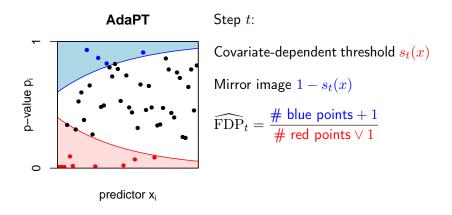
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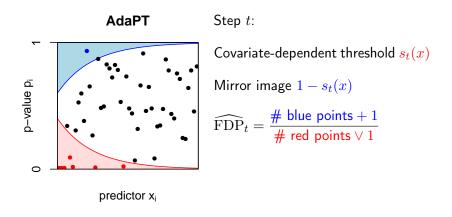
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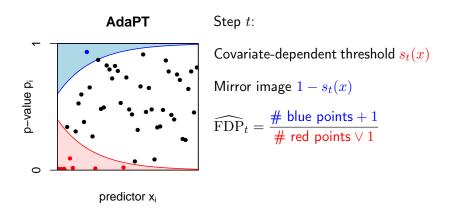
Goal: produce hypothesis-specific p-value thresholds  $s_i$ 's and control False Discovery Rate (FDR).









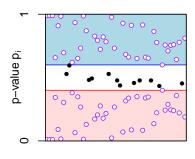


Stop when  $\widehat{\mathrm{FDP}}_t \leq \alpha$ , and reject all red points

#### Define partially masked p-values:

$$\tilde{p}_{t,i} = \begin{cases} p_i & s_t(x_i) < p_i < 1 - s_t(x_i) \\ \{p_i, \ 1 - p_i\} & \text{otherwise}. \end{cases}$$

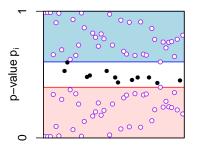
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p-value p<sub>i</sub> predictor xi

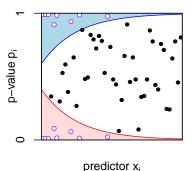
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Don't worry. Use your favorite model to guide the update!

## THANKS!