

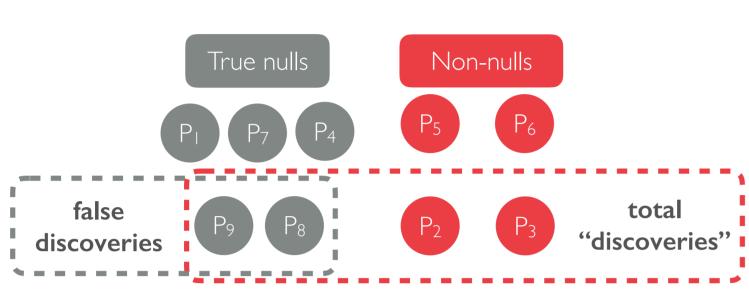
# Online control of the false discovery rate with decaying memory

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#### What we solve

Simple motivational problem: **Multiple** A/B tests arrive sequentially over time, we make rejections using *p*-values vs. // Some null hypotheses are true, others false:



Our goal: Control false discovery rate (FDR) at every time T

$$\mathsf{FDR}(T) = \mathbb{E} \, rac{\# \, \mathsf{false \, discoveries}}{\# \, \mathsf{total \, discoveries}} = \mathbb{E} \, rac{V(T)}{R(T)}$$

Our framework, more flexible than existing ones, incorporates

- finite or decaying memory
- ▶ importance of each test
- prior knowledge about possible non-null locations,

is more powerful and guarantees anytime FDR control.

# **Generalized Alpha-investing(++)**

Given  $\alpha$ , and valid independent p-values  $P_t$ , online FDR procedure outputs significance levels  $\alpha_t$ , and makes the decision  $R_t := \mathbf{1}\{P_t \leq \alpha_t\}$ , where  $\alpha_t$  is designed to be a monotone function of past rejections  $R_{t-1}, \ldots, R_1$ .

Generalized alpha-investing rules (GAI) update

- ▶ the wealth (with  $W_0 \leq \alpha$ )  $W(t) := W(t-1) \phi_t + R_t \psi_t$
- the test penalty  $\phi_t \leq W(t-1)$
- ▶ the test reward  $\psi_t \leq \min\{\phi_t + b_t, \frac{\phi_t}{\alpha_t} + b_t 1\}$ with  $b_t = B_0 = \alpha - W_0$ .

Procedure	$\alpha_t$	$ \phi_t $	$ \psi_{t} $	Condition
[FS'08] AI	$\frac{\phi_t}{1+\phi_t}$	$\leq W(t-1)$	$\phi_t + B_0$	
[AR'14] ASR	$\kappa\phi_{t}$	cW(t-1)	satisfy (1)	$c \leq 1$
[JM'17] LORD	$\phi_{t}$	$\gamma_t W_0 + B_0 \sum_{\tau_j} \gamma_{t-\tau_j}$	$B_0$	$\sum_{i=1}^{\infty} \gamma_i = 1$
		$j:\tau_j < t$		

We propose an enhanced procedure (GAI++) with

$$b_t = \begin{cases} lpha - W_0 & ext{when} \quad R(t-1) = 0 \\ lpha & ext{otherwise} \end{cases} \in \mathcal{F}^{t-1}.$$

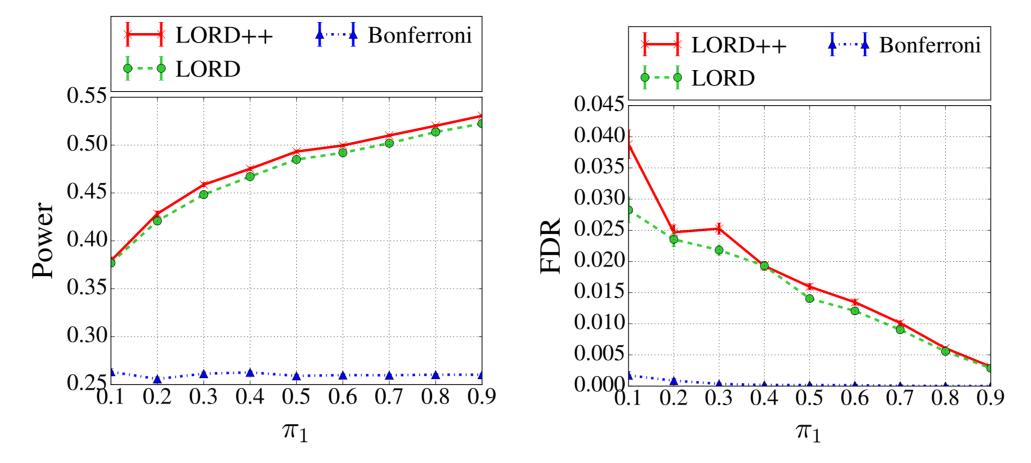
**Theorem:** Any monotone GAI++ rule has FDR(T)  $\leq \alpha$  at all times T, and is **more powerful** than corresponding GAI rule.

### Simulations: more power with GAI++

With  $\pi_1$  proportion of non-nulls

Color

Orientation



 $\implies$  GAI++ consistently more powerful!

#### Possible practical scenario

- Some tests are more important than others ⇒ weighted FDR and weighted procedure
- $\triangleright$  Know from previous experiments that for certain tests,  $H_0$  is likely true  $\implies$  can make it easier to reject

## **Incorporating prior and penalty weights**

[Benjamini and Hochberg '97], [Genovese et al. '06] introduced penalty and prior weights for the batch setting. How about the online case?

We use **penalty weights**  $u_t > 0$ , **prior weights**  $w_t > 0$  and reject according to

$$R_t := \mathbf{1} \{ P_t \le \alpha_t w_t u_t \}.$$

**Note:**  $u_t$ ,  $w_t$  may depend on  $R_1, \ldots, R_{t-1}$ 

What if I'm interested only in the FDR in the recent past? The global FDR at any time is controlled, how about locally?

# Doubly-weighted decaying memory FDR

Adding penalty weights  $u_t$  and memory factor  $\delta$  to FDR

$$\operatorname{mem-FDR}_u(T) := \mathbb{E} \, \frac{V_u^\delta(T)}{R_u^\delta(T)}$$
 with weighted and decaying discoveries

$$V_u^{\delta}(T) := \delta V_u^{\delta}(T-1) + u_T R_T \mathbf{1} \{ T \in \mathcal{H}^0 \}$$
  
 $R_u^{\delta}(T) := \delta R_u^{\delta}(T-1) + u_t R_t$ 

**Note:** Setting  $\delta = 1$ ,  $u_t = 1$  reduces to FDR(T). Let's define the (random) time of the k-th rejection as

$$\tau_k = \min_{s \in \mathbb{N}} \mathbf{1} \left\{ \sum_{t=1}^s R_t = k \right\},\,$$

# Doubly-weighted mem-FDR control using mem-GAI++

The doubly-weighted mem-GAI++ rules update

the adjusted wealth

$$egin{aligned} W(t) := \delta W(t-1) + (1-\delta) W_0 \mathbf{1} ig\{ au_1 > t-1 ig\} - \phi_t + R_t \psi_t \ = W_0 \delta^{T-\min\{ au_1,T\}} + \sum_{t=1}^T \delta^{T-t} (-\phi_t + R_t \psi_t). \end{aligned}$$

the adjusted penalty

$$\phi_t \leq \delta W(t-1) + (1-\delta) W_0 \mathbf{1} \{ \tau_1 > t-1 \},$$

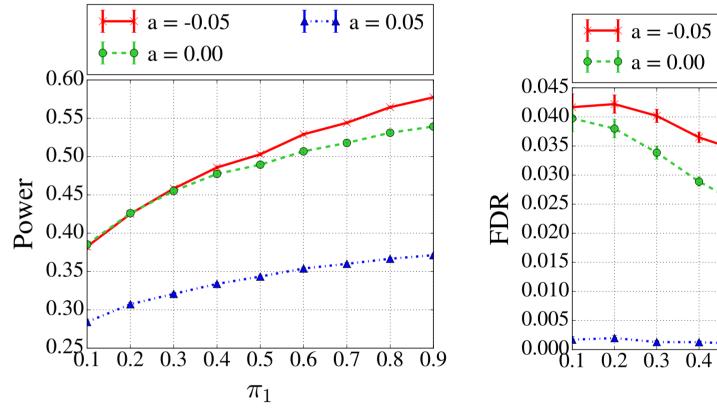
► the adjusted reward

$$0 \leq \psi_t \leq \min\left\{\phi_t + u_t b_t, rac{\phi_t}{w_t \alpha_t u_t} + u_t b_t - u_t
ight\}, \quad ext{where}$$
  $b_t := lpha - rac{W_0}{u_t} \mathbf{1}\{ au_t > t - 1\} \in \mathcal{F}_{t-1}.$ 

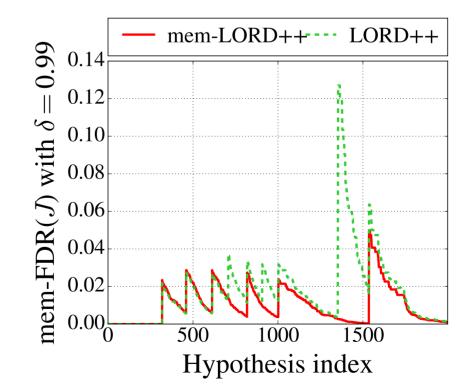
**Theorem:** All monotone double-weighted mem-GAI++ rules have mem-FDR<sub>u</sub>(T)  $\leq \alpha$  at all times T.

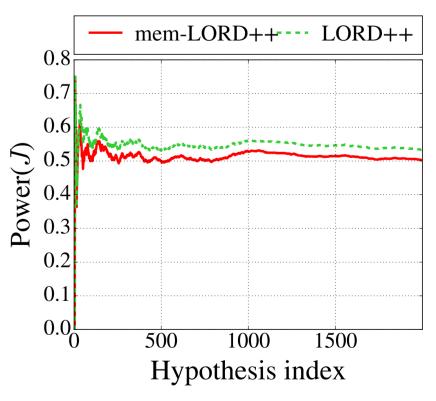
### Simulations: with weights and decaying memory

LORD++ ( $\delta=0$ ) with prior weights  $1\pm a$  on non-nulls/nulls









a = 0.05

 $\implies$  mem-LORD++ prevents peaks of the local mem-FDR!

#### References

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