

# Outline

DM811  
Heuristics for Combinatorial Optimization

Lecture 14  
**Race: A Configuration Tool**

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1. Introduction
2. Inferential Statistics
  - Basics of Inferential Statistics
  - Experimental Designs
3. Race: Sequential Testing

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# A Motivating Example

- There is a competition and two stochastic algorithms  $\mathcal{A}_1$  and  $\mathcal{A}_2$  are submitted.
- We run both algorithms once on  $n$  instances.  
On each instance either  $\mathcal{A}_1$  wins (+) or  $\mathcal{A}_2$  wins (-) or they make a tie (=).

Questions:

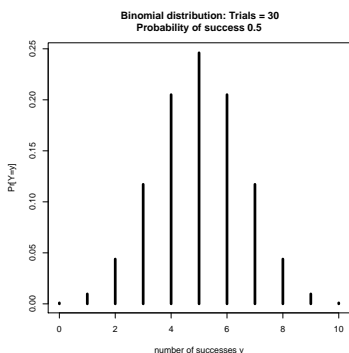
1. If we have only 10 instances and algorithm  $\mathcal{A}_1$  wins 7 times how confident are we in claiming that algorithm  $\mathcal{A}_1$  is the best?
2. How many instances and how many wins should we observe to gain a confidence of 95% that the algorithm  $\mathcal{A}_1$  is the best?

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- 1 If we have only 10 instances and algorithm  $\mathcal{A}_1$  wins 7 times how confident are we in claiming that algorithm  $\mathcal{A}_1$  is the best?

Under these conditions, we can check how unlikely the situation is if it were  $p(+)\leq p(-)$ .

If  $p = 0.5$  then the chance that algorithm  $\mathcal{A}_1$  wins 7 or more times out of 10 is 17.2%: quite high!



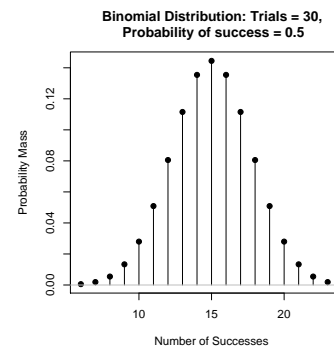
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# A Motivating Example

- $p$ : probability that  $\mathcal{A}_1$  wins on each instance (+)
- $n$ : number of runs without ties
- $Y$ : number of wins of algorithm  $\mathcal{A}_1$

If each run is independent and consistent:

$$Y \sim B(n, p) : \Pr[Y = y] = \binom{n}{y} p^y (1 - p)^{n-y}$$



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- 2 How many instances and how many wins should we observe to gain a confidence of 95% that the algorithm  $\mathcal{A}_1$  is the best?

To answer this question, we compute the 95% quantile, i.e.,  $y : \Pr[Y \geq y] < 0.05$  with  $p = 0.5$  at different values of  $n$ :

$n$	10	11	12	13	14	15	16	17	18	19	20
$y$	9	9	10	10	11	12	12	13	13	14	15

This is an application example of sign test, a special case of binomial test in which  $p = 0.5$

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General procedure:

- Assume that data are consistent with a **null hypothesis**  $H_0$  (e.g., sample data are drawn from distributions with the same mean value).
- Use a statistical test to compute how likely this is to be true, given the data collected. This “likely” is quantified as the **p-value**.
- Accept  $H_0$  as true if the **p-value** is larger than an user defined threshold called **level of significance**  $\alpha$ .
- Alternatively ( $\text{p-value} < \alpha$ ),  $H_0$  is rejected in favor of an **alternative hypothesis**,  $H_1$ , at a level of significance of  $\alpha$ .

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## Experimental Design

Algorithms  $\Rightarrow$  Treatment Factor;      Instances  $\Rightarrow$  Blocking Factor

Design A: One run on various instances (Unreplicated Factorial)

	Algorithm 1	Algorithm 2	...	Algorithm k
Instance 1	$X_{11}$	$X_{12}$		$X_{1k}$
⋮	⋮	⋮		⋮
Instance b	$X_{b1}$	$X_{b2}$		$X_{bk}$

Design B: Several runs on various instances (Replicated Factorial)

	Algorithm 1	Algorithm 2	...	Algorithm k
Instance 1	$X_{111}, \dots, X_{11r}$	$X_{121}, \dots, X_{12r}$		$X_{1k1}, \dots, X_{1kr}$
Instance 2	$X_{211}, \dots, X_{21r}$	$X_{221}, \dots, X_{22r}$		$X_{2k1}, \dots, X_{2kr}$
⋮	⋮	⋮		⋮
Instance b	$X_{b11}, \dots, X_{b1r}$	$X_{b21}, \dots, X_{b2r}$		$X_{bk1}, \dots, X_{bkr}$

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# Preparation of the Experiments

Variance reduction techniques

- Same pseudo random seed

Sample Sizes

- If the sample size is large enough (infinity) any difference in the means of the factors, no matter how small, will be significant
- Real vs Statistical significance  
Study factors until the improvement in the response variable is deemed small
- Desired statistical power + practical precision  $\Rightarrow$  sample size

Note: If resources available for  $N$  runs then the optimal design is **one run on  $N$  instances** [Birattari, 2004]

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**Procedure** Race [Birattari 2002]:

**repeat**

Randomly select an unseen instance and run all candidates on it

Perform *all-pairwise comparison* statistical tests

Drop all candidates that are significantly inferior to the best algorithm

**until** only one candidate left or no more unseen instances ;

- F-Race use Friedman test
- Holm adjustment method is typically the most powerful

```
stat.test=c('friedman','t.bonferroni','t.holm','t.none')
first.test=3
```

