

# Putting it all Together

Introduction to Automated Science

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- ▶ Single experiments do not leverage automation or high-throughput instruments.
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Planning **batch** or **parallel** experiments is challenging since most planning algorithms find the best treatment independent of other runs.

## Batched experiments (continued)

To avoid redundant information, batch planning combines two objectives:

1. Maximize a **planning metric** (response = exploitation, uncertainty = exploration) for every point in the batch.
2. Maximize the **diversity** of the points in the batch (e.g. the minimum distance between any treatments).

Batching reduces the information gained *per run*; however, batched experiments are less expensive and may increase the overall run budget.

Remember the goal is to maximize **total information**:

$$\text{total information} = (\text{information per run}) \times (\# \text{ of runs}).$$

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You need to push your automation team to increase flexibility **even at the expense of throughput**.

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  - ▶ QC strategy
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5. Automate!