CS 4783/5783

Reusability of Holdout Set Using Differential Privacy

The Magic Broker Scam

Based on Aaron Roth's slide

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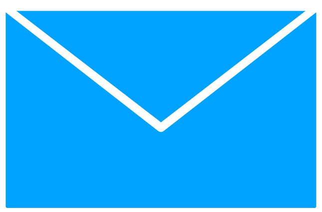
Day 1



Tomorrow Stock X

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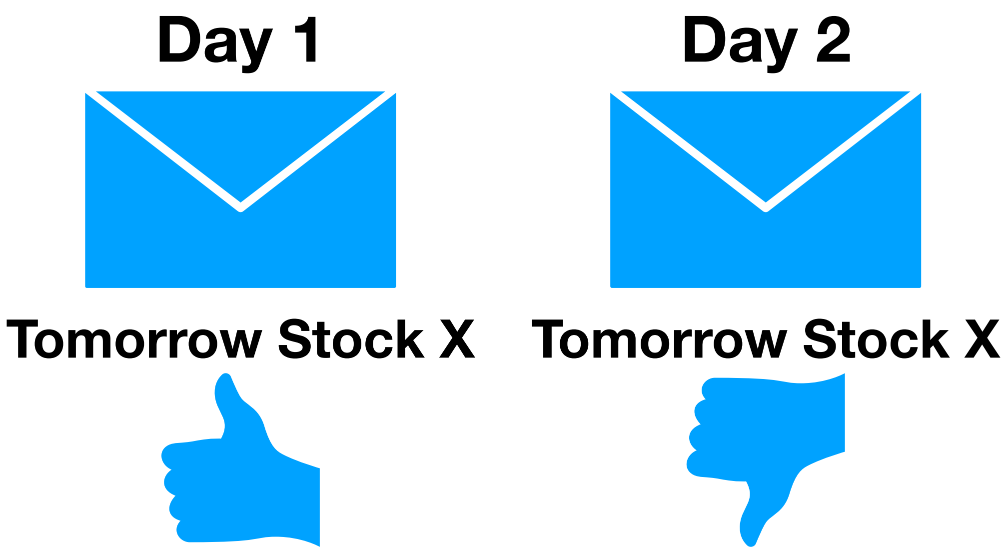

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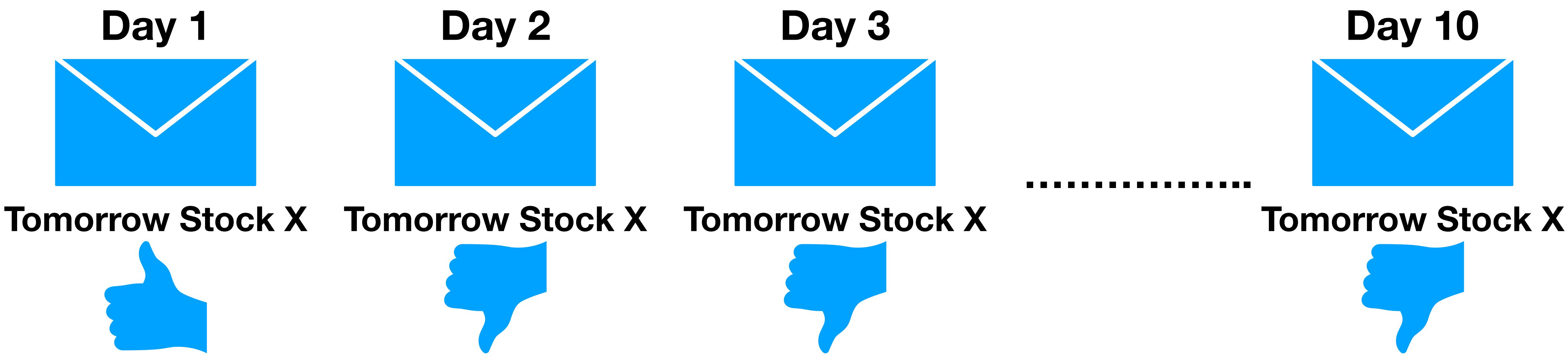

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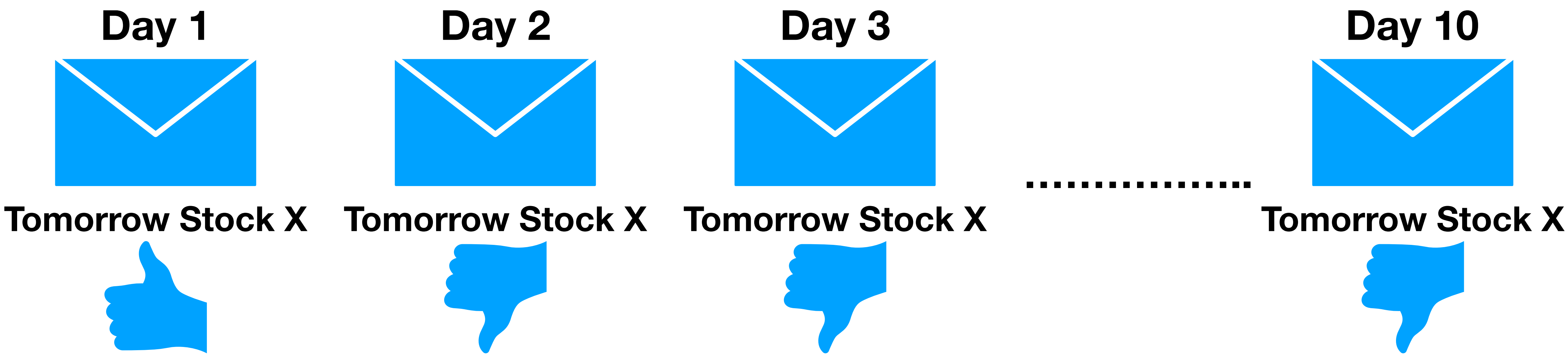

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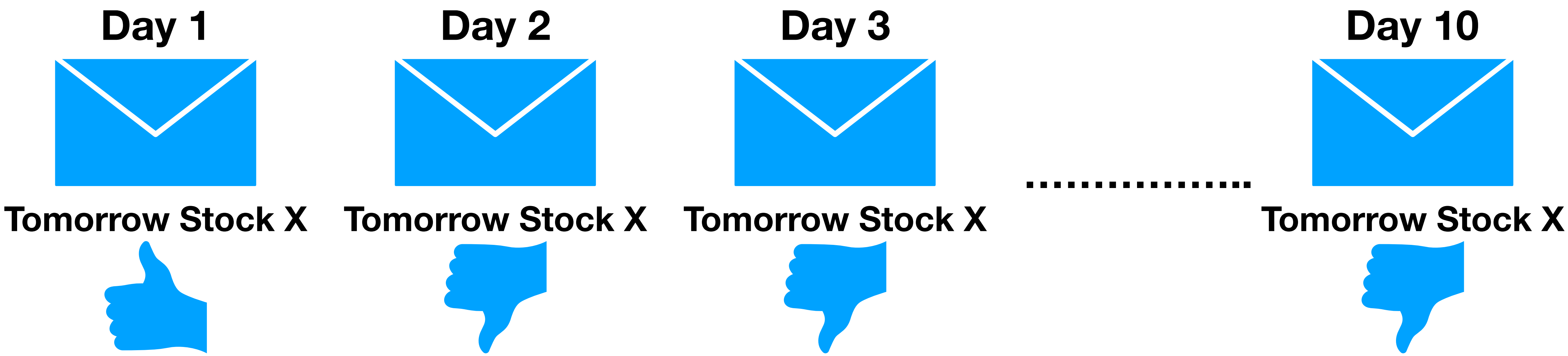

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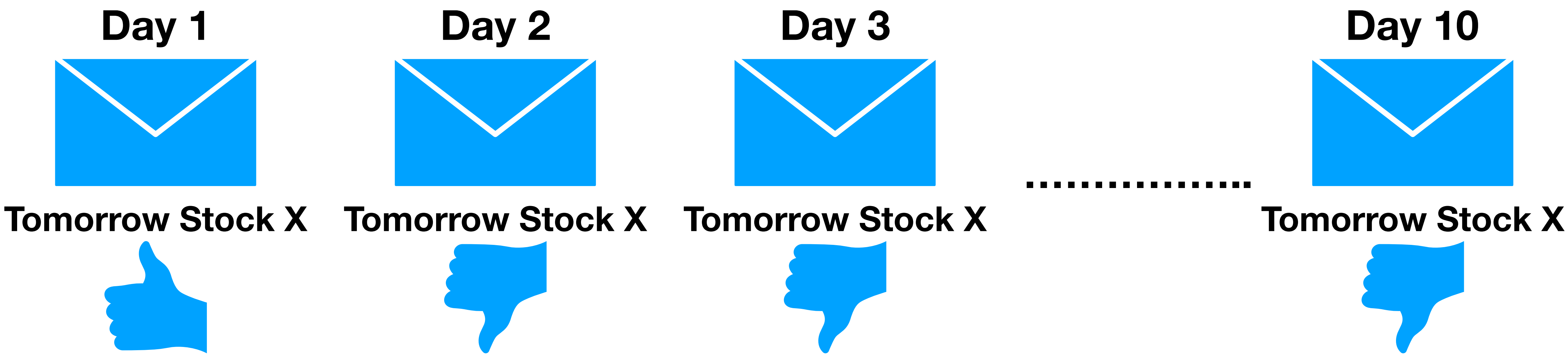

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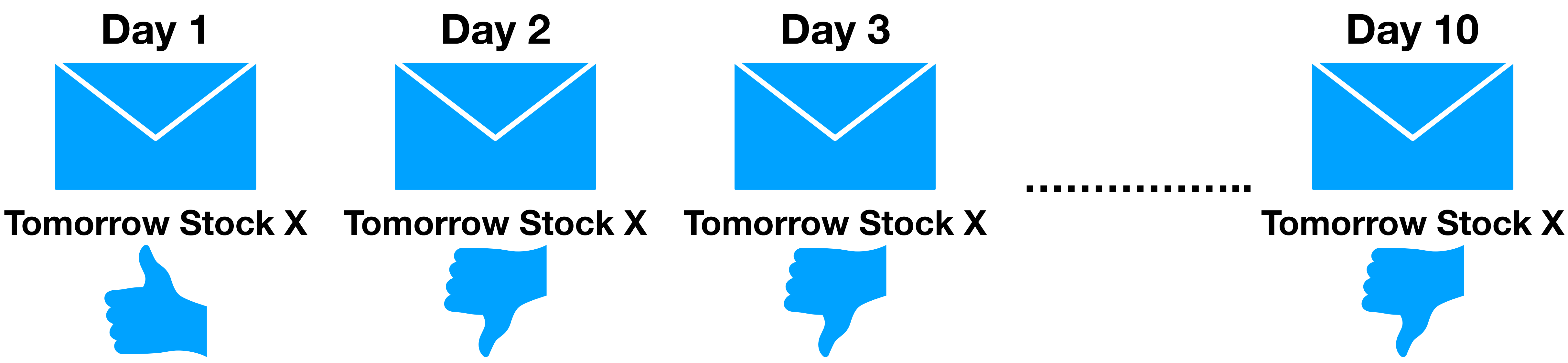

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  - 1 in 1024
- But the broker will always scam people, why?

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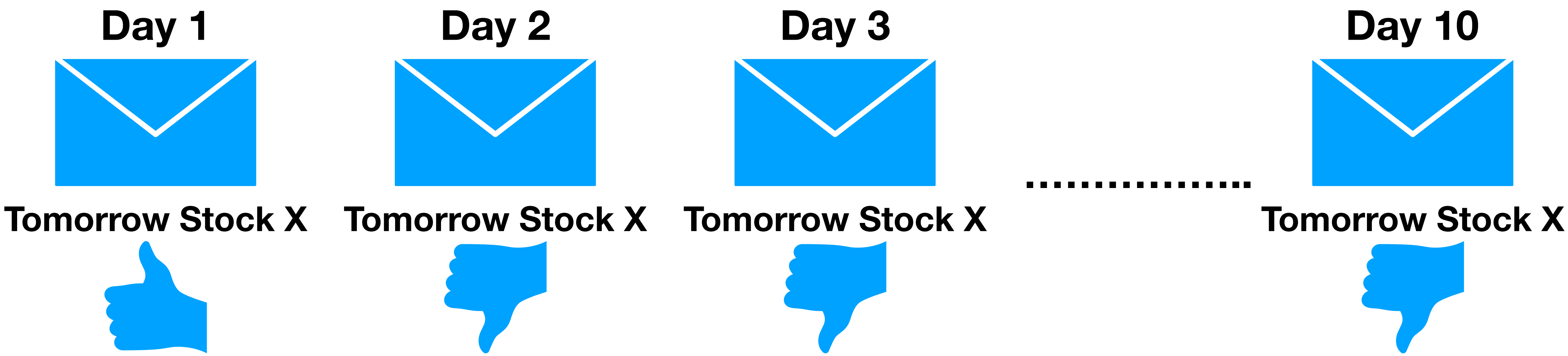

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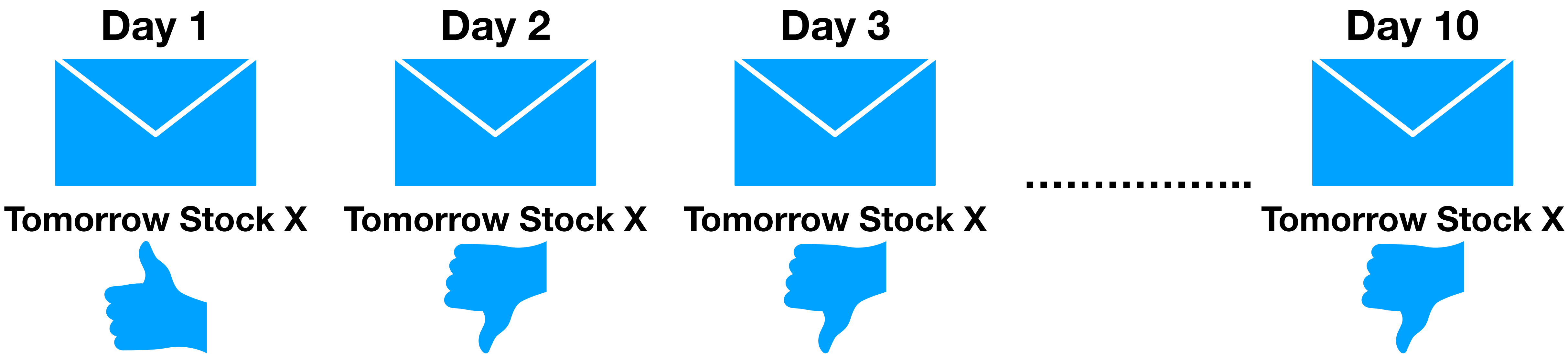

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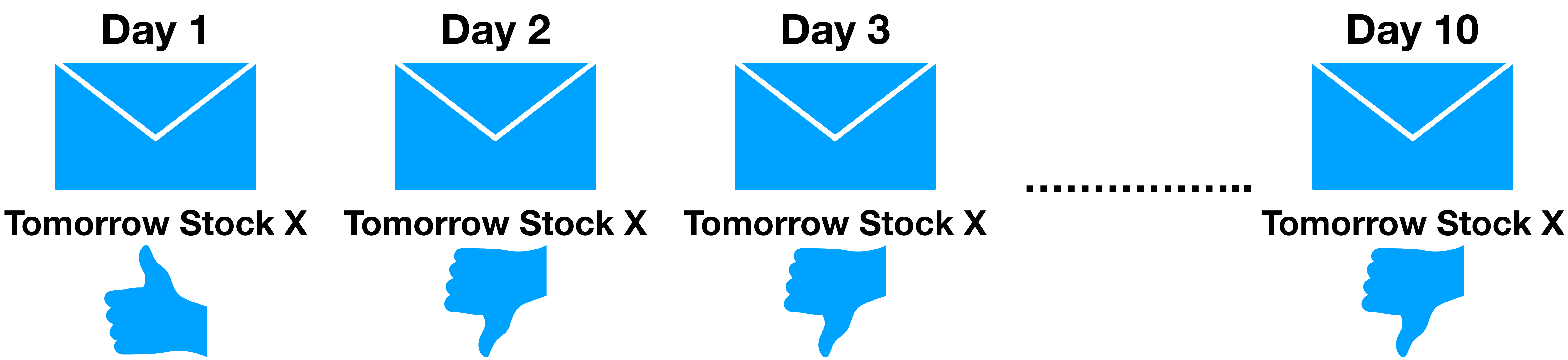

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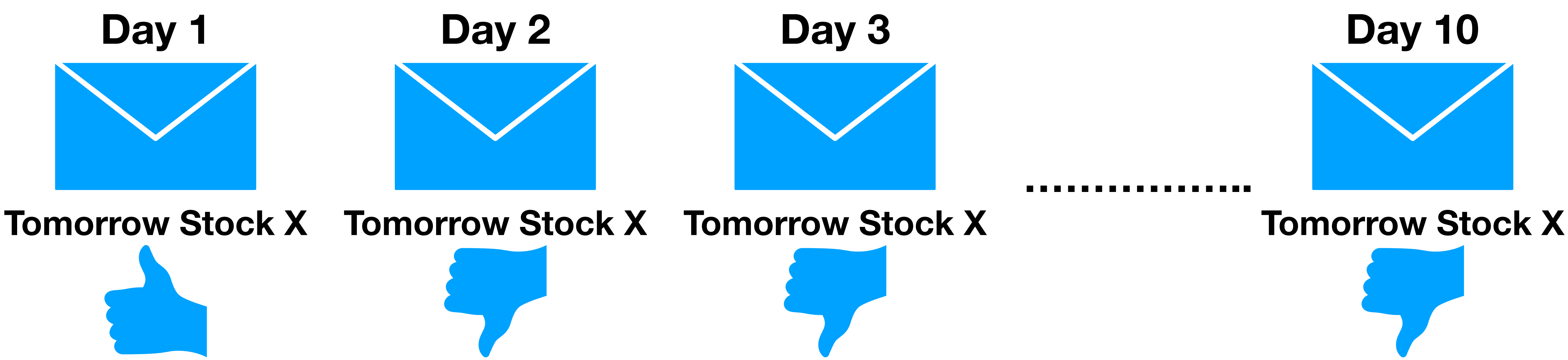

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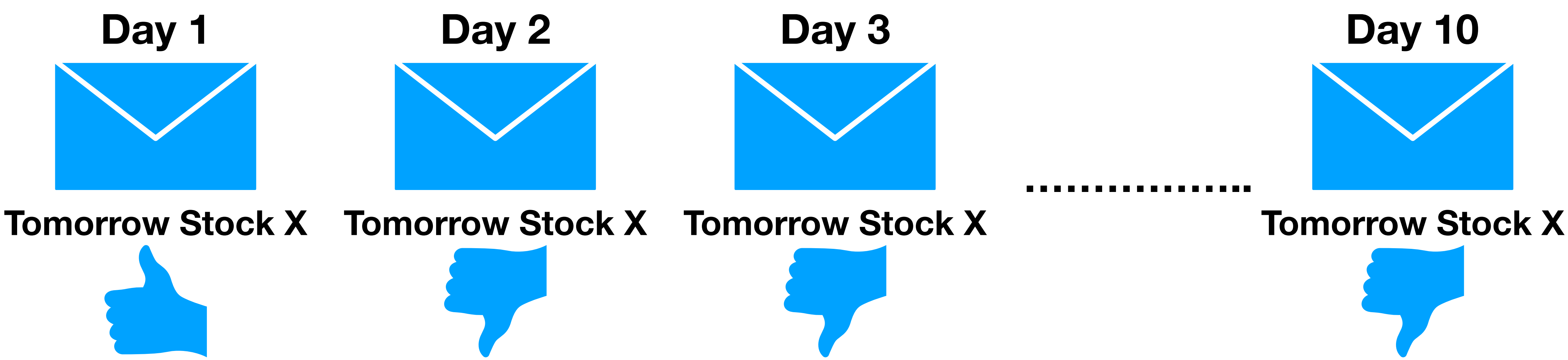

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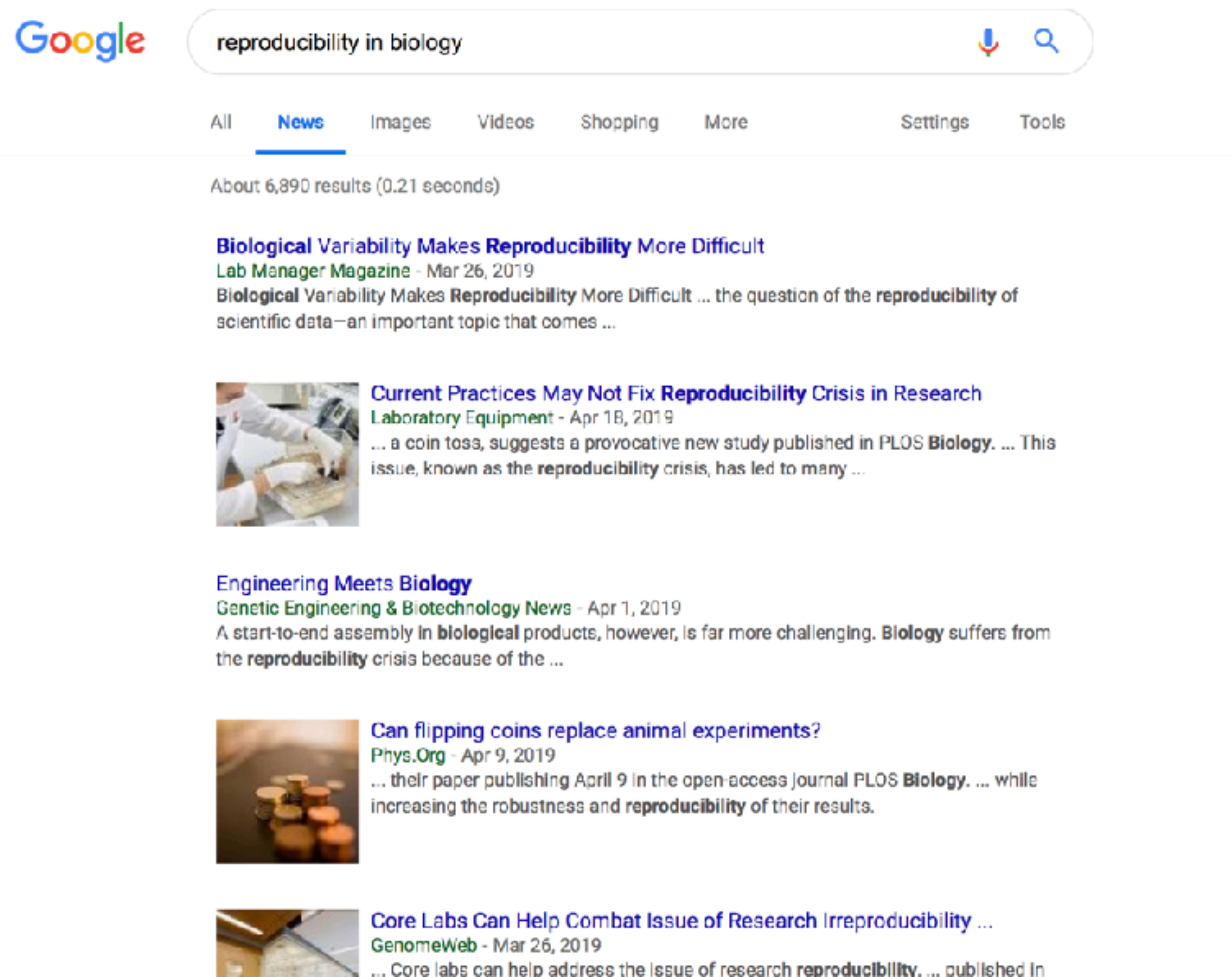
- …..
- Day 11: We are left with 1000000/1024 ~ 1000 people we can scam

Reproducibility problem



Ideal ML Experiment

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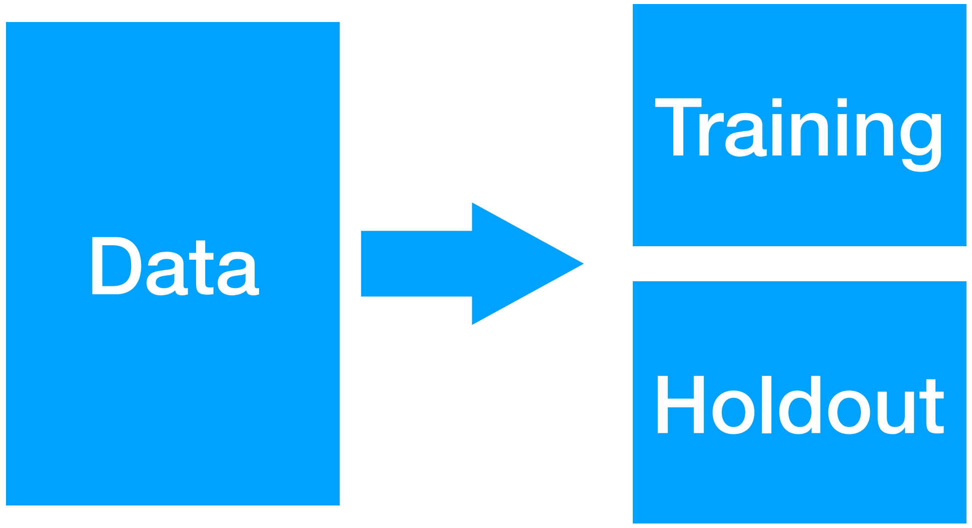

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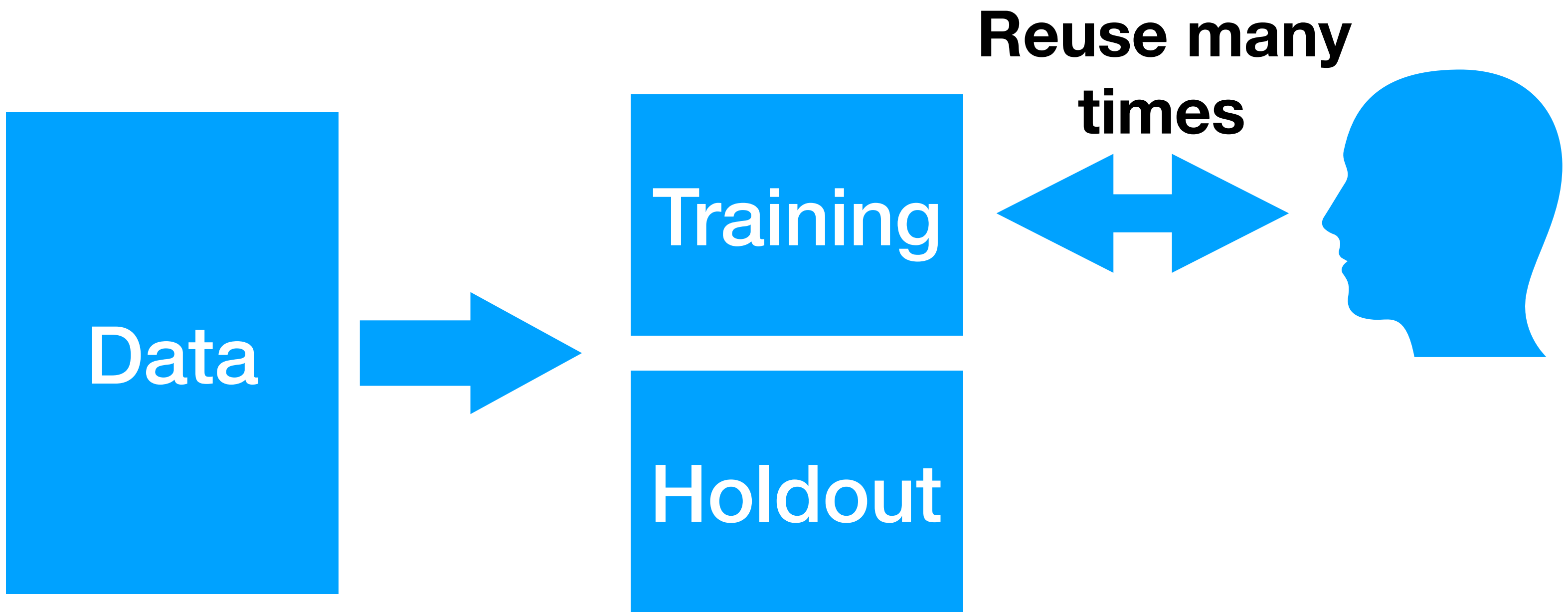

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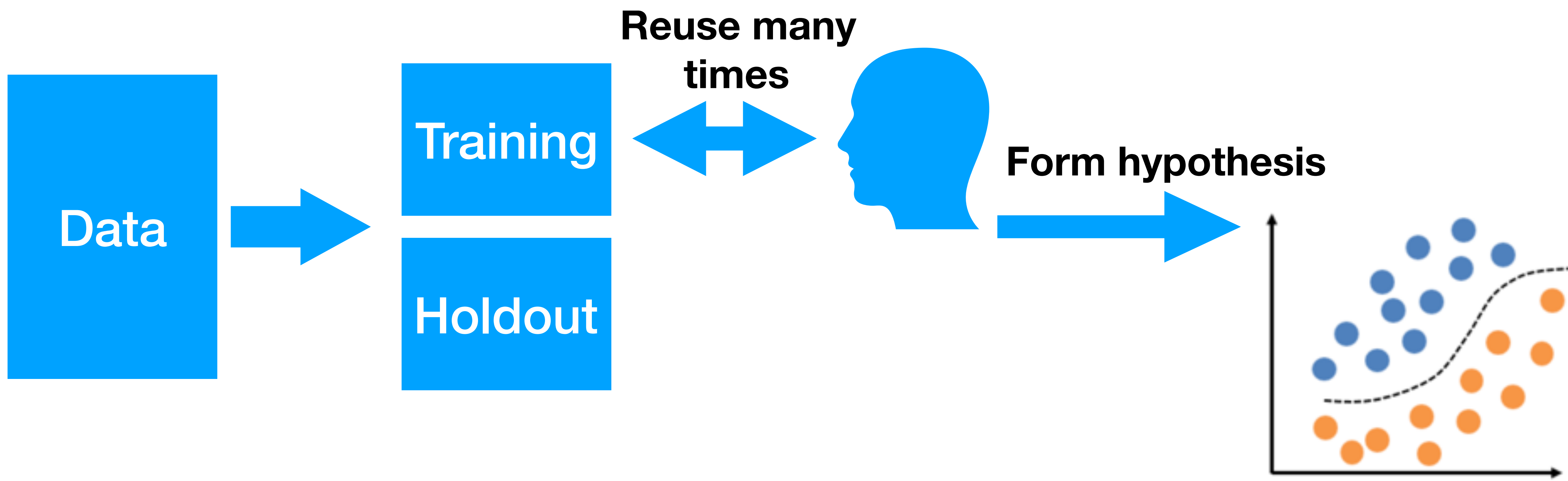

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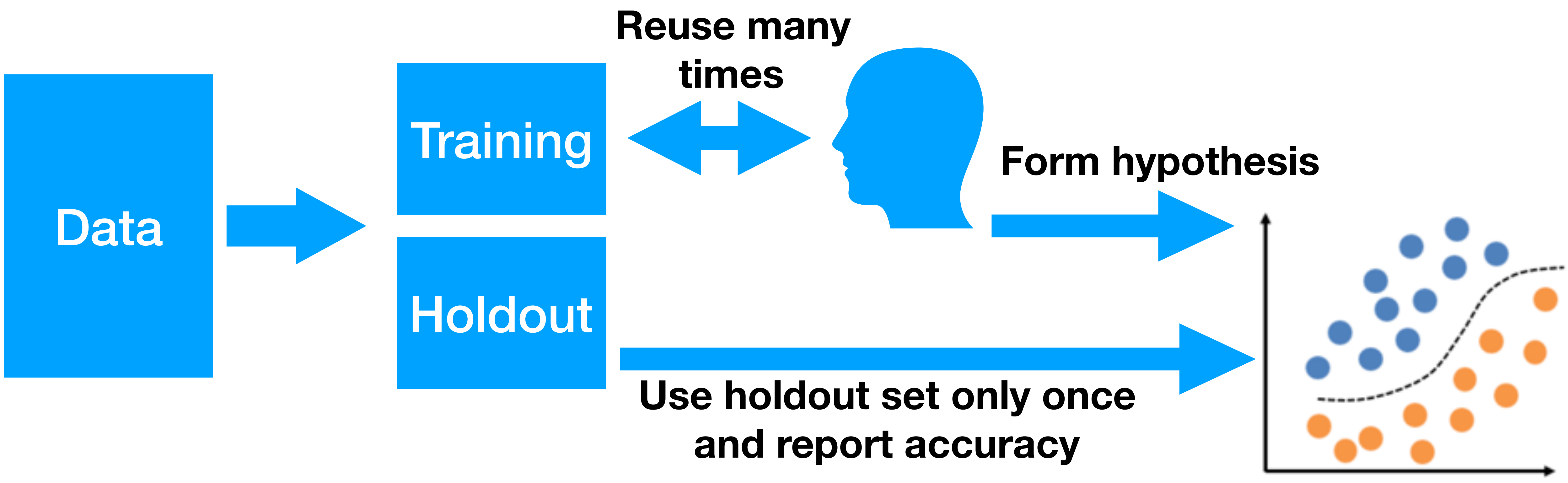

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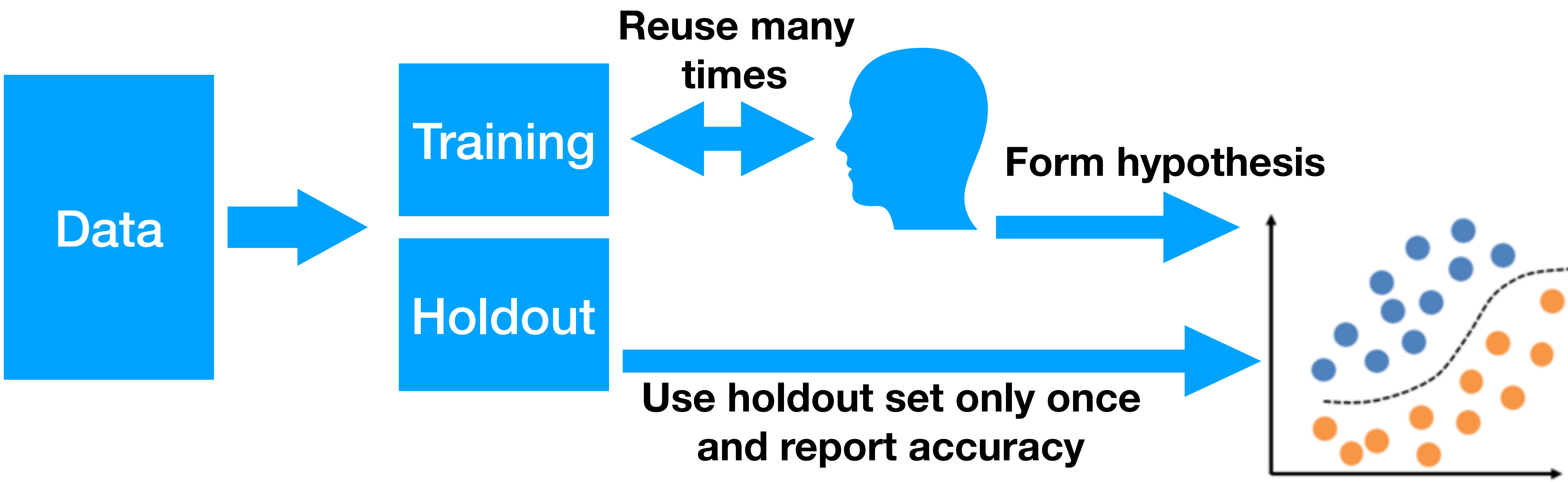

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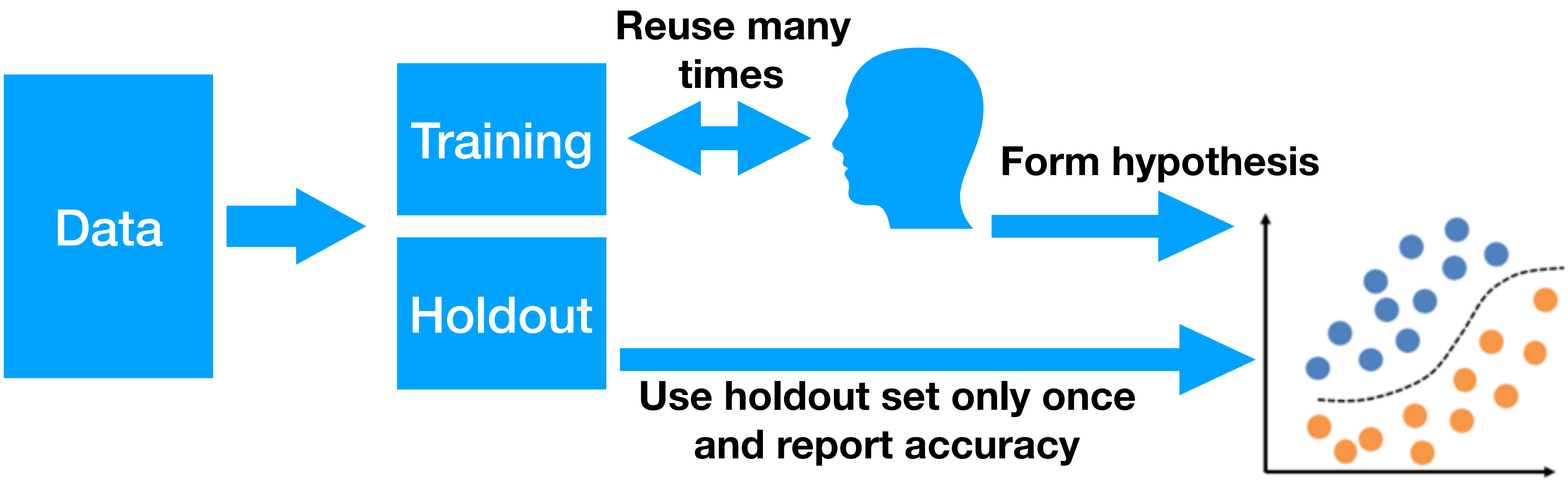

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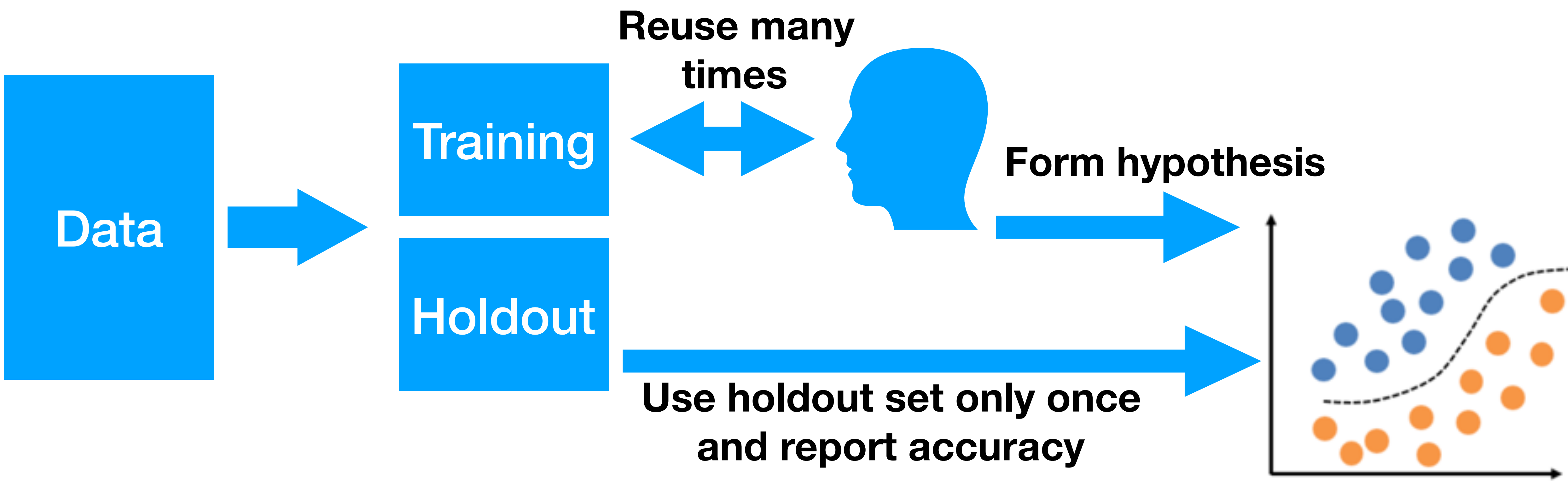

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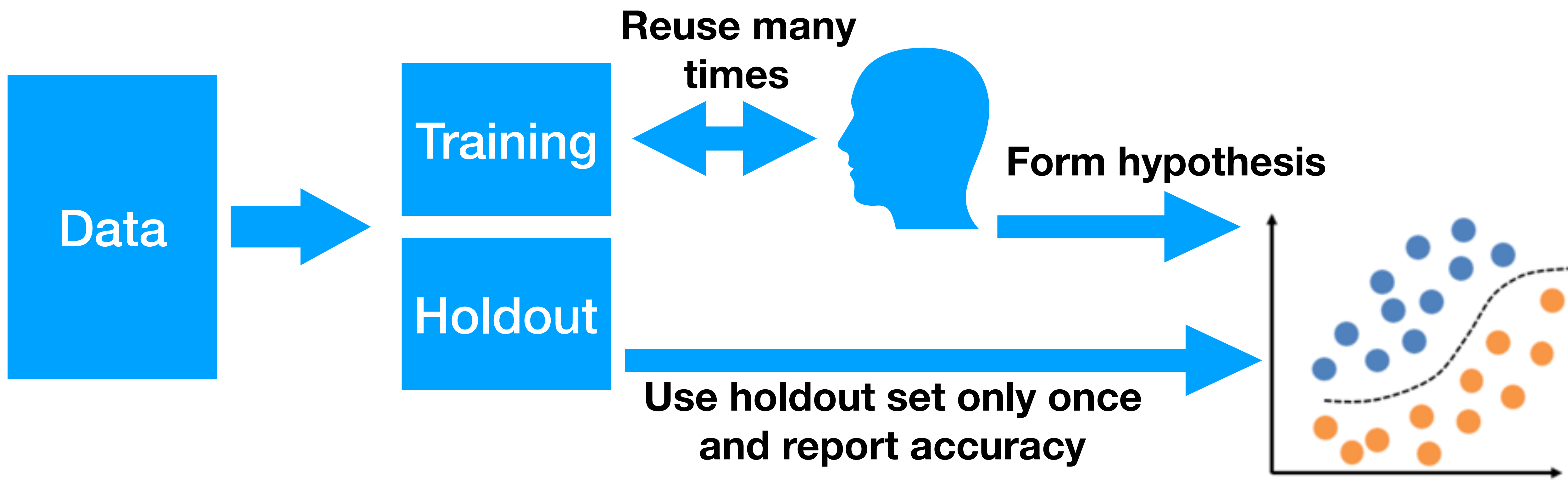

- We are not allowed to form hypothesis based on data we used to test: age old statistics
- But too tempting to form more informed opinion
- We do a train/validation/test set split
- But this means we can’y reuse datasets over time

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- Effort to collect public dataset to share….
- All great but we need to be careful!
    - Old fix: pre-register experiment, many many examples of people fudging this….

An Example

Code at:
https://github.com/isofer/thresholdout-experiments/blob/master/Thresholdout%20experiments.ipynb

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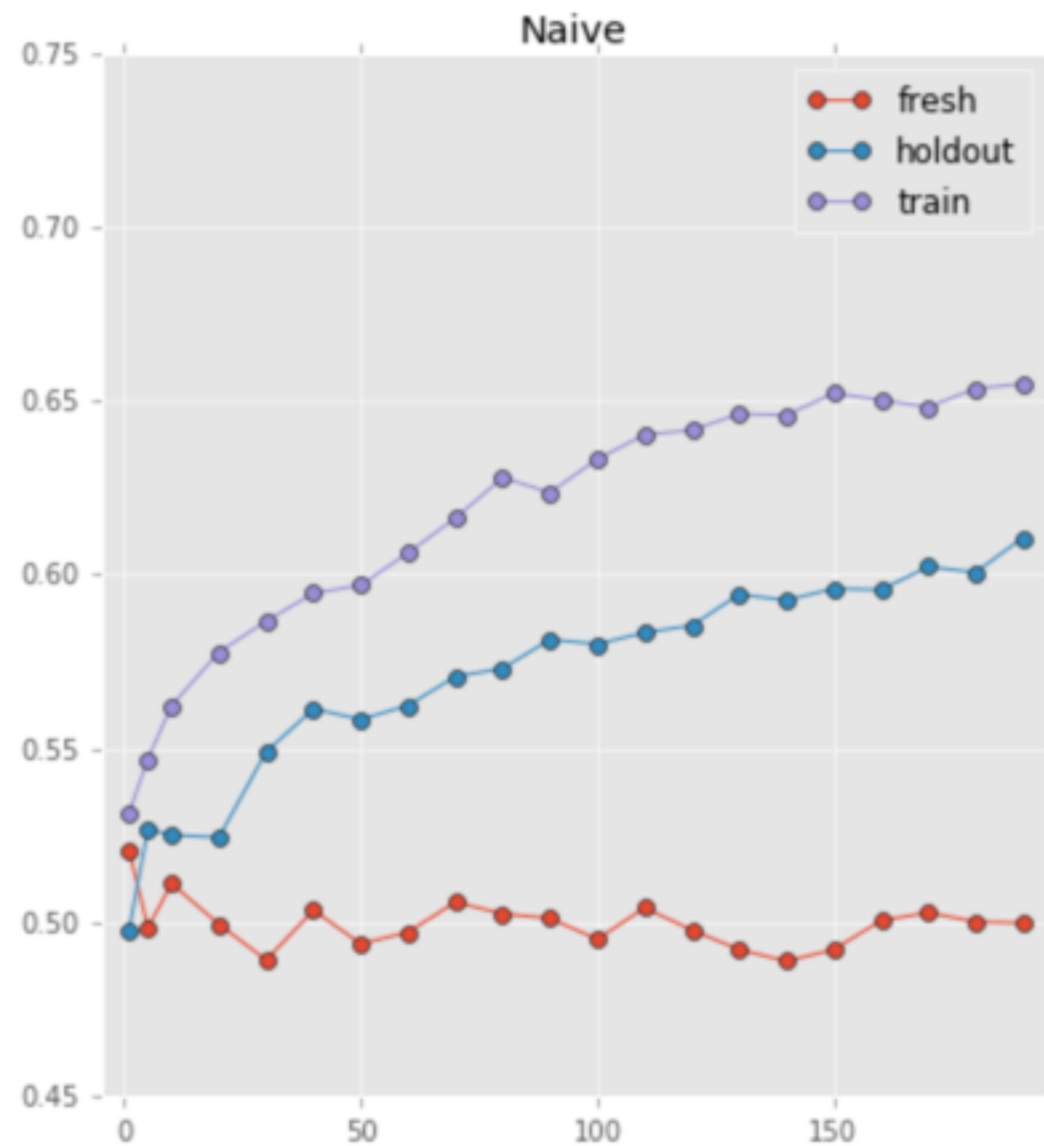

Number of features

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Can we reuse holdout set?

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- Eg. Report back accuracies on holdout set only when training and test accuracy are significantly different

Threshold-out Algorithm

Input:

Data S, holdout H, threshold $T > 0$, tolerance $\sigma > 0$

Given function q:

Sample η, η' from $N(0,\sigma^2)$

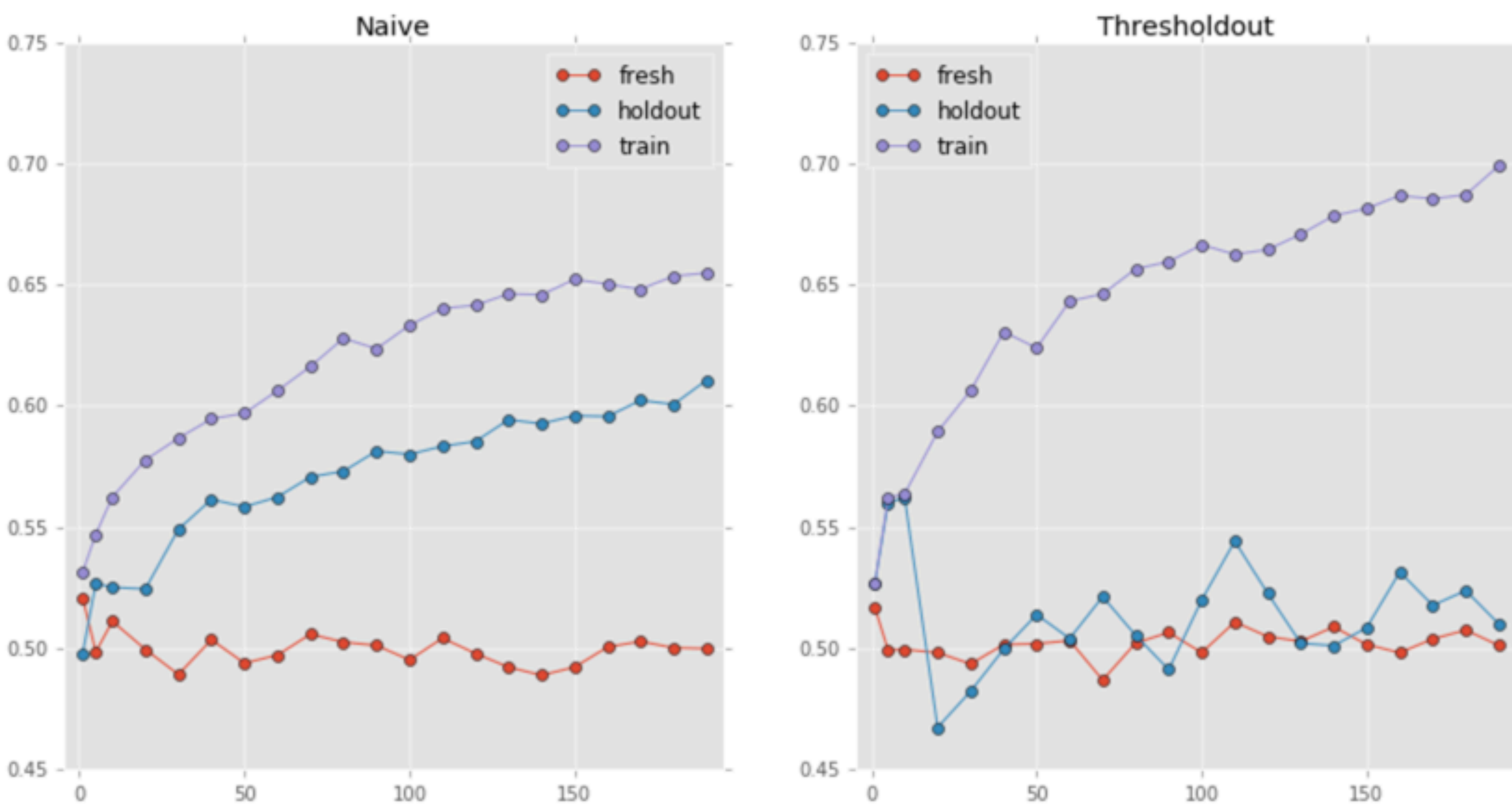
If $|\mathrm{avg}_H[q] - \mathrm{avg}_S[q]| > T + \eta$:

output $\mathrm{avg}_H[q] + \eta'$

Otherwise:

output $\mathrm{avg}_S[q]$

The Example



Naive
fresh
holdout
train
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0
50
100
150
Thresholdout
fresh
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0.55
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0.45
0
50
100
150

The Guarantee

- Say we have a holdout set of size n
- Rough statement: Thresholdout gives Δ-accurate estimates for any sequence of adaptively chosen queries until O(Δ^4 n^2) we report holdout accuracies

•

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Differential Privacy

- Post-processing: If A is a differentially private algorithm, and f is any mapping on the outcome space of A, then the algorithm that maps from sample S to f(A(S)) is also differentially private
- Composability: Algo(S) is given by following procedure
  - For i in 1 to k
    - If we choose any epsilon differentially private algorithm A_i based on outcomes $O_1,\ldots,O_{i-1}$
    - Set $O_i = A_i(S)$
  - Return $O_1,\ldots,O_n$
- The above algorithm is $O(\varepsilon \sqrt{k})$ differentially private

Differential Privacy

- Differential privacy implies generalization (via stability)
- Threshold-out is differentially private. Hence holdout set accuracy reported and population accuracy are close