Boosting

STAT 4710

November 7, 2023

Where we are

- ✓ **Unit 1:** R for data mining
- ✓ **Unit 2:** Prediction fundamentals
- ✓ **Unit 3:** Regression-based methods
- **Unit 4:** Tree-based methods
  - **Lecture 1:** Growing decision trees
  - **Lecture 2:** Tree pruning and bagging
  - **Lecture 3:** Random forests
  - **Lecture 4:** Boosting
  - **Lecture 5:** Unit review and quiz in class
- **Unit 5:** Deep learning

Looking back and looking ahead

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- Random forests: Grow deep decision trees in parallel
- Boosting: Grow shallow decision trees sequentially

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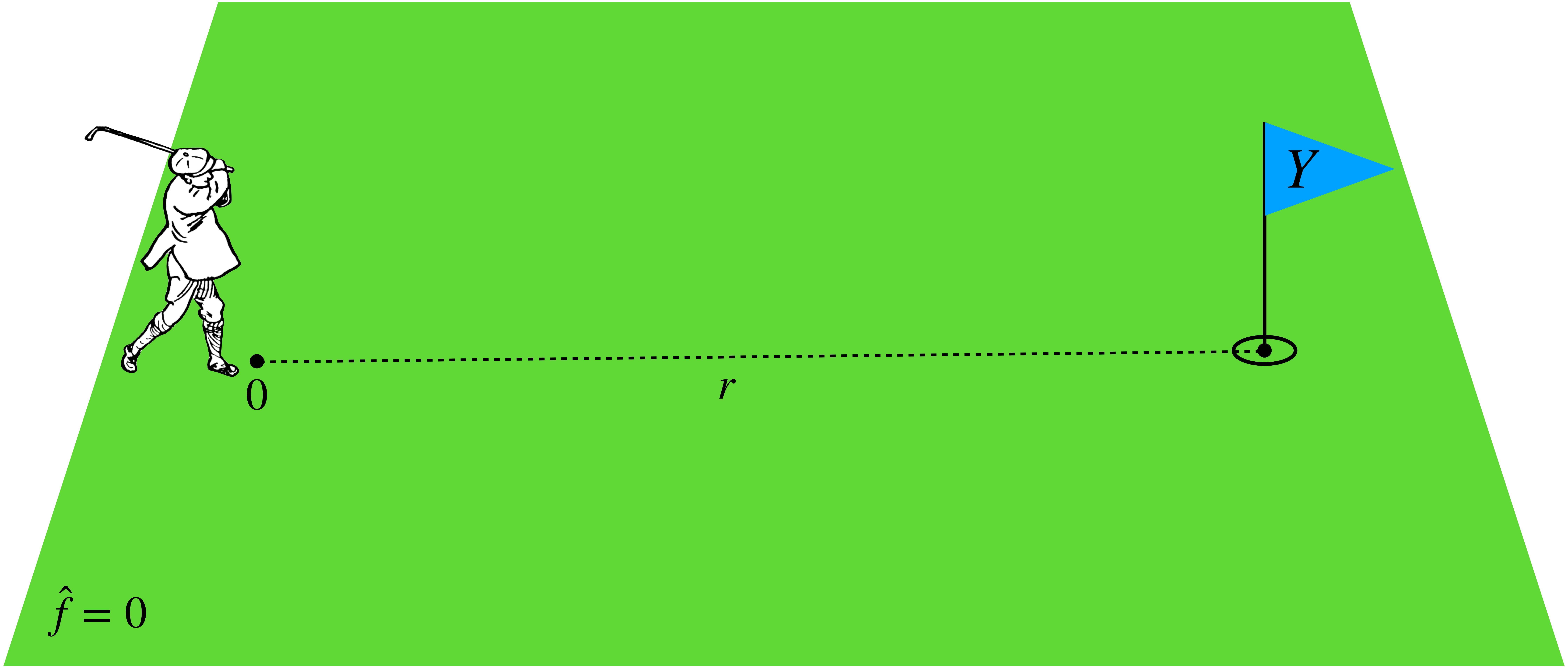
Each golf swing is not too accurate, but a sequence of them is.



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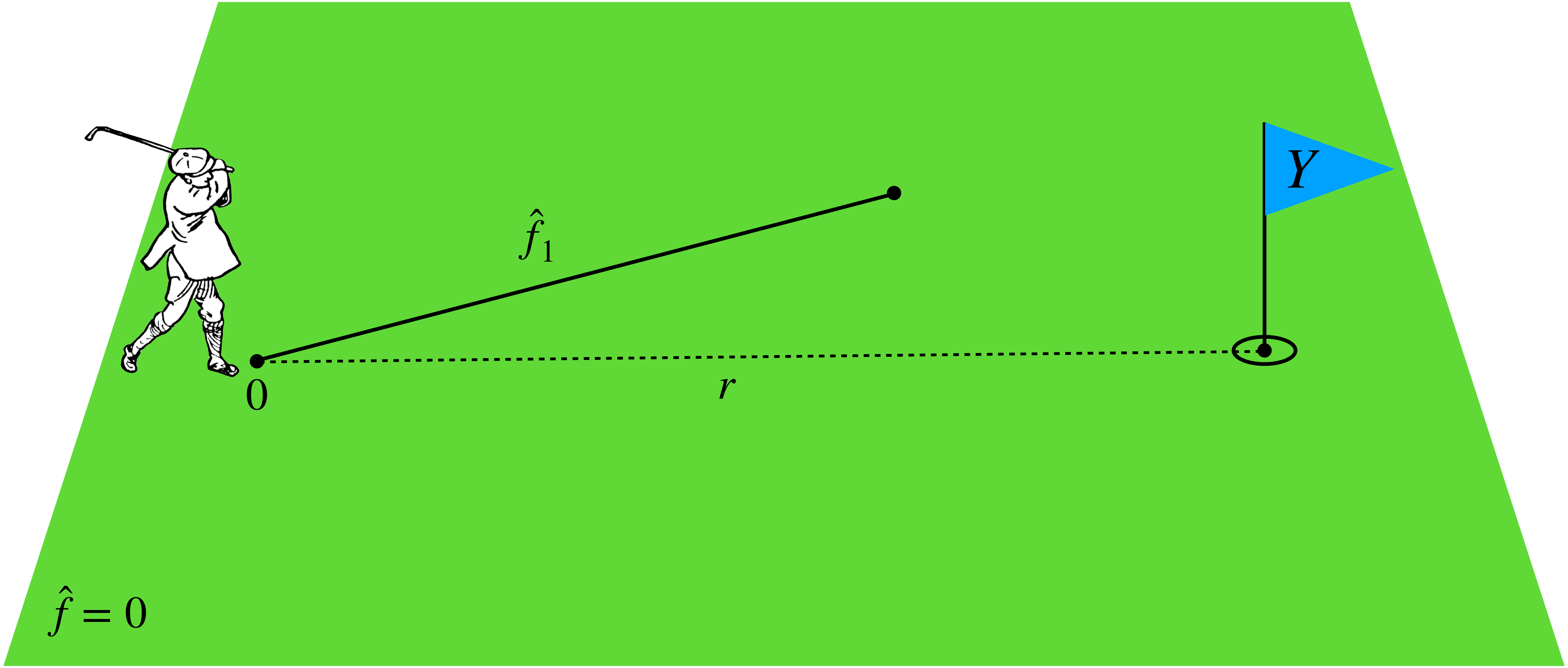

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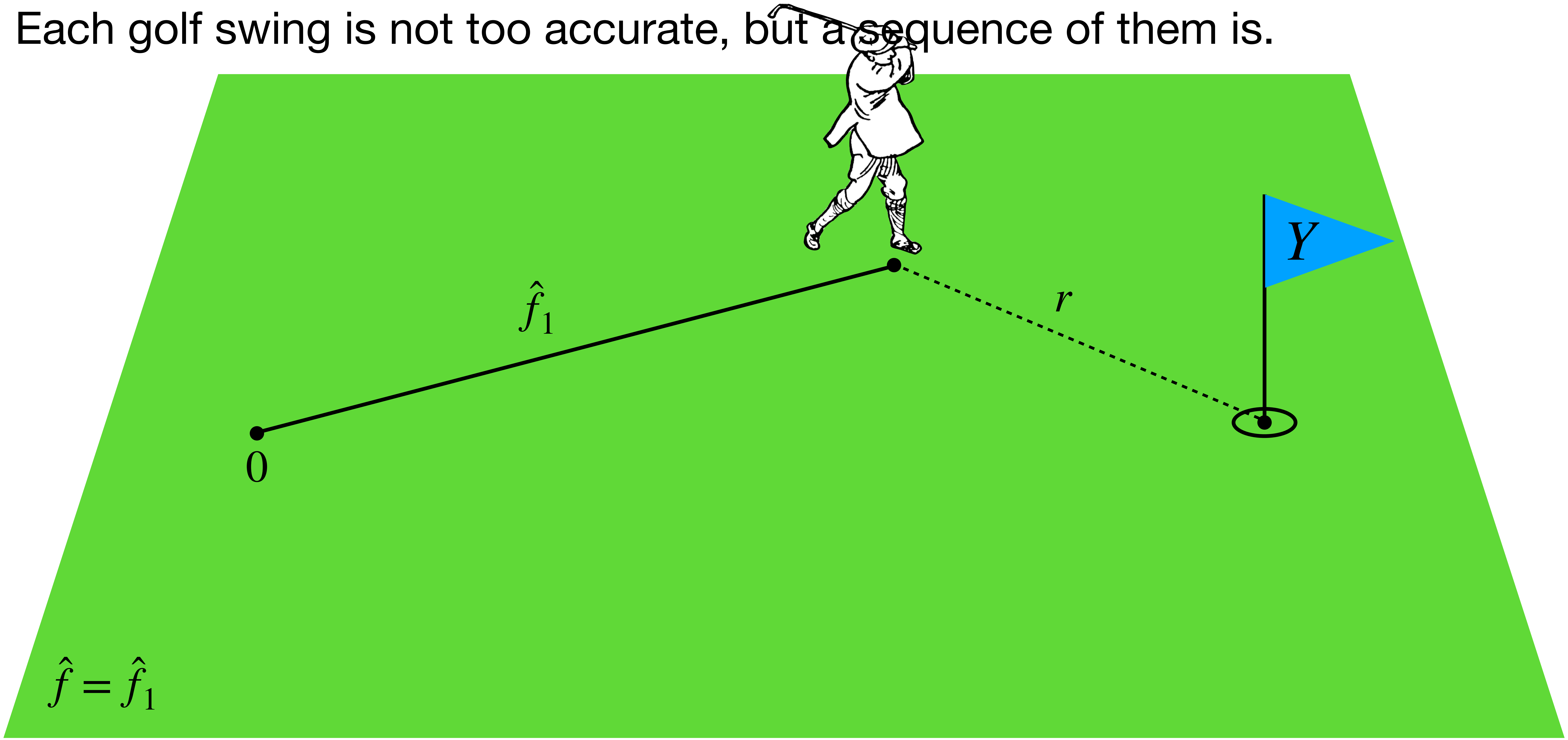

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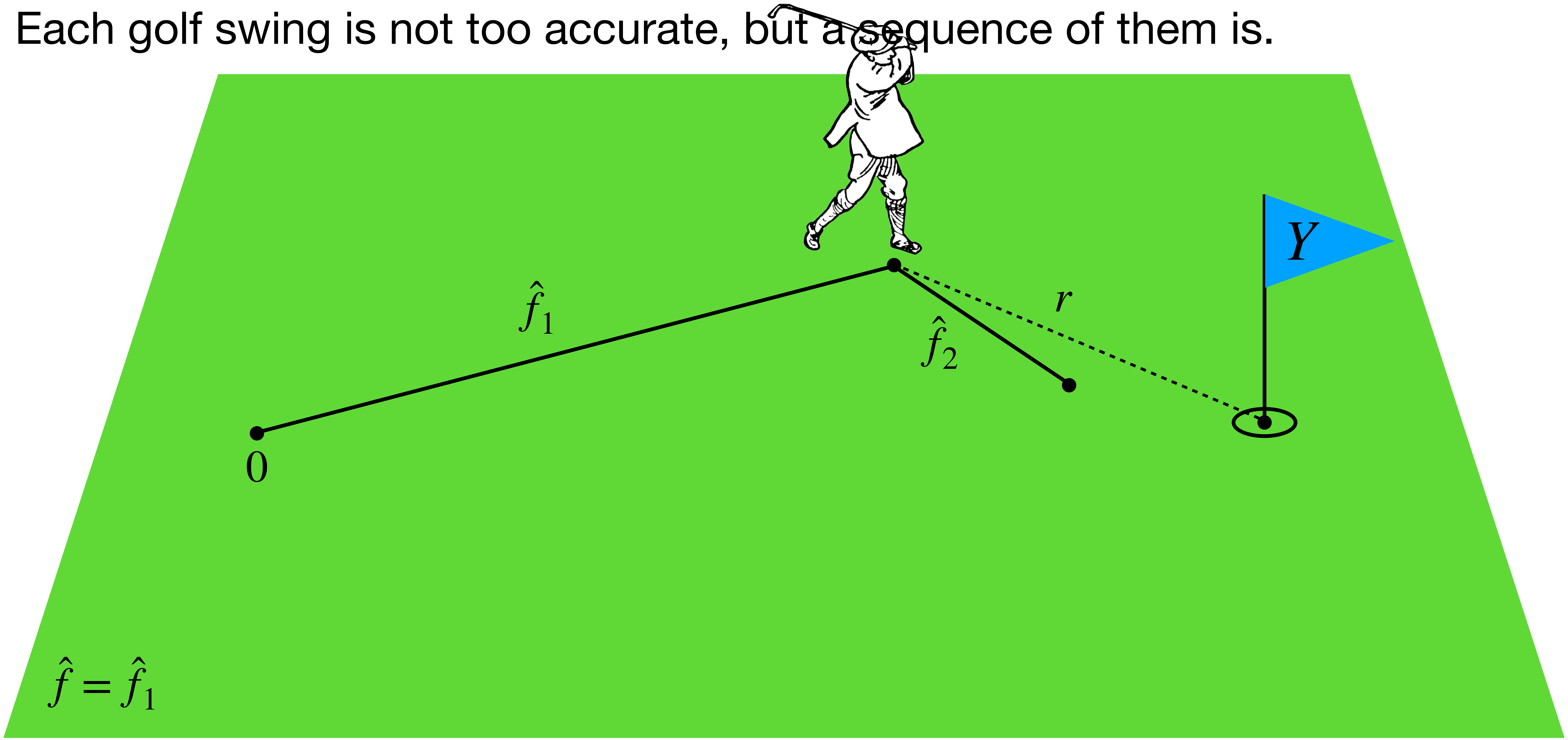

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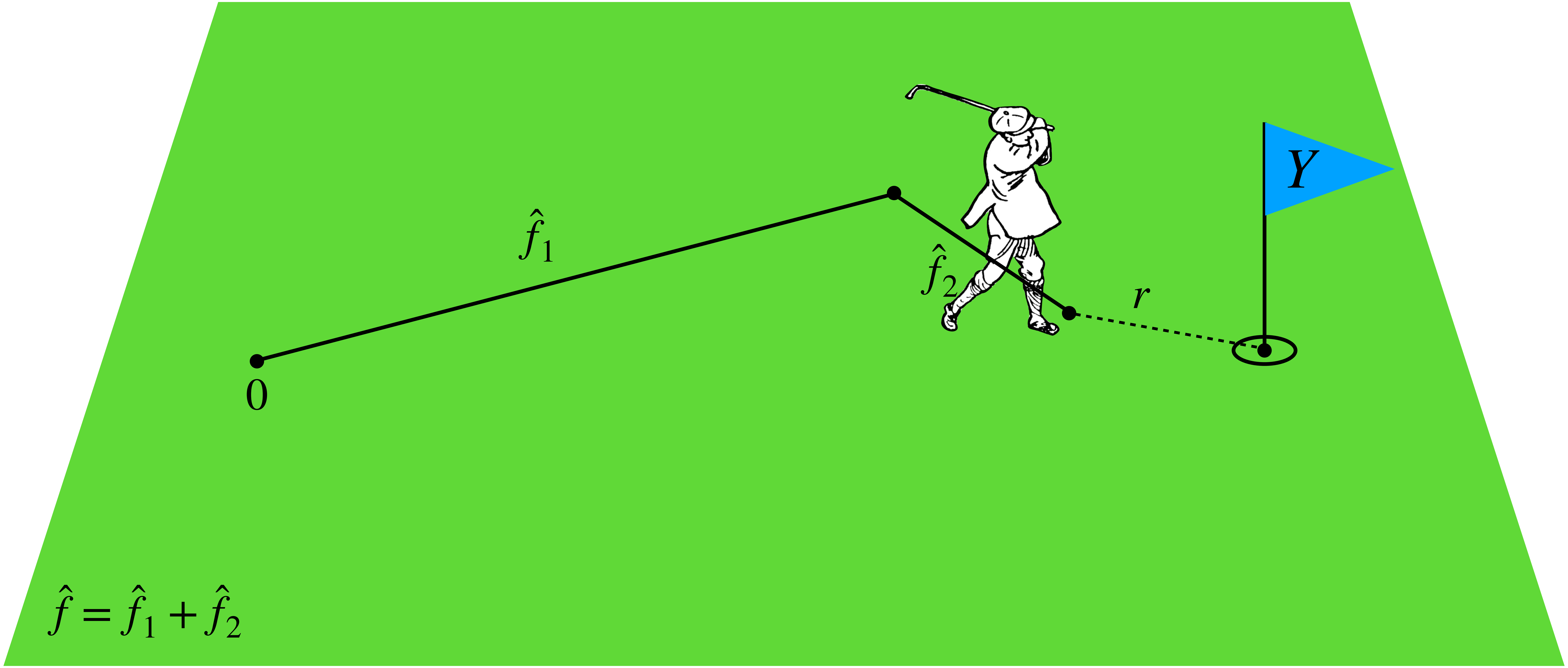

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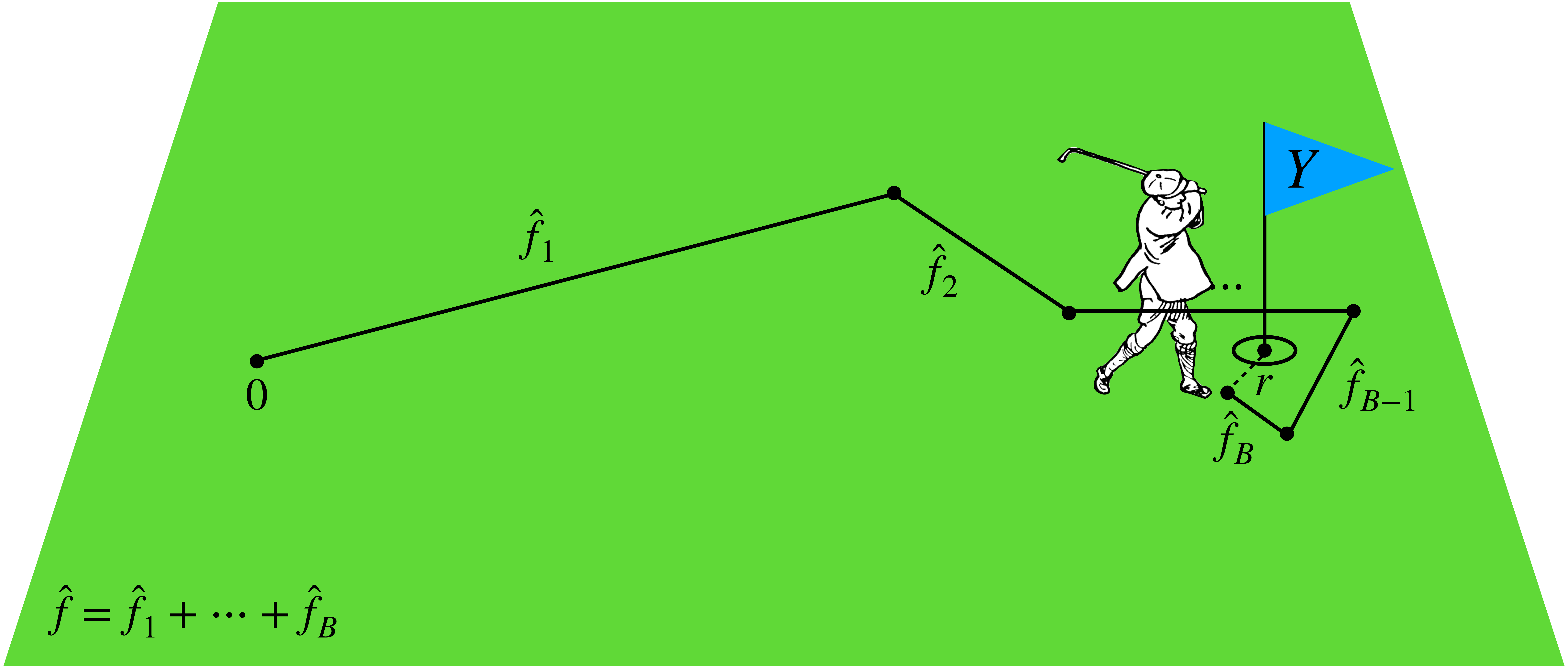

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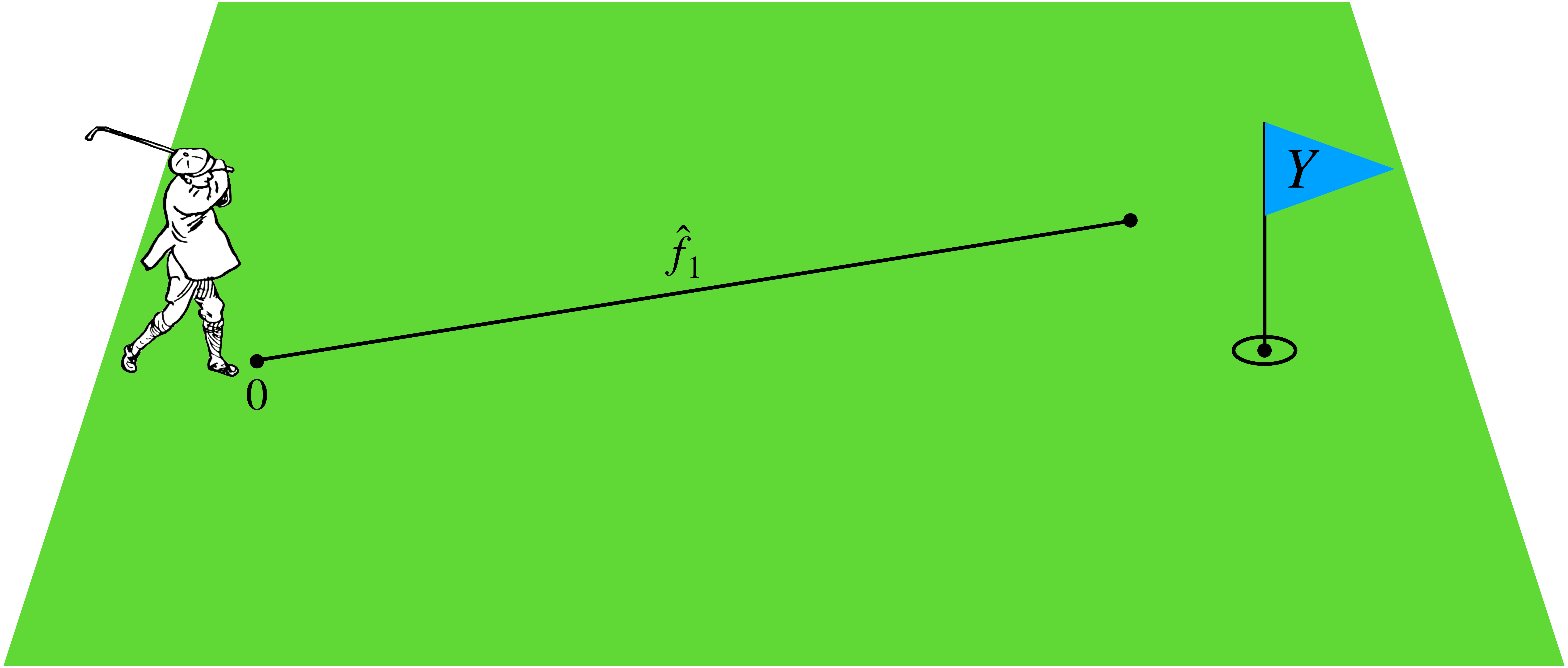

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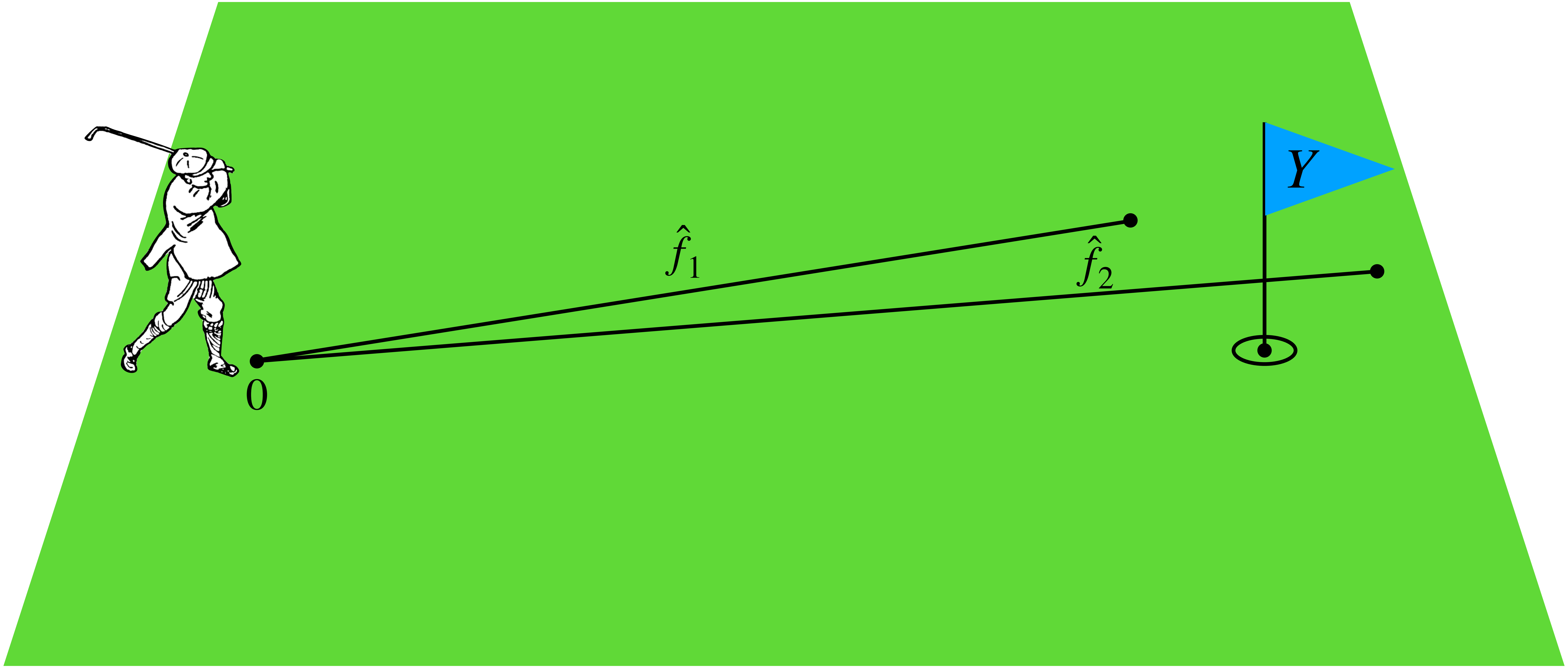

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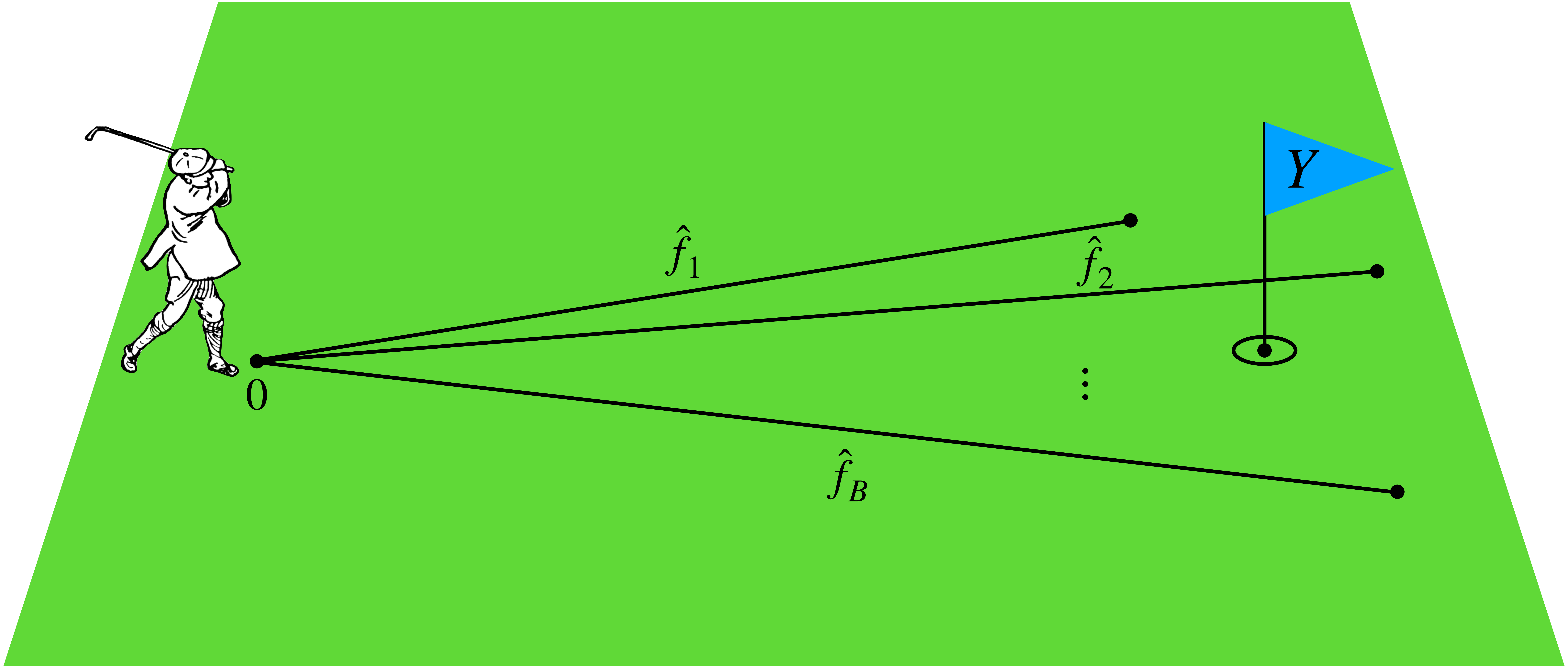

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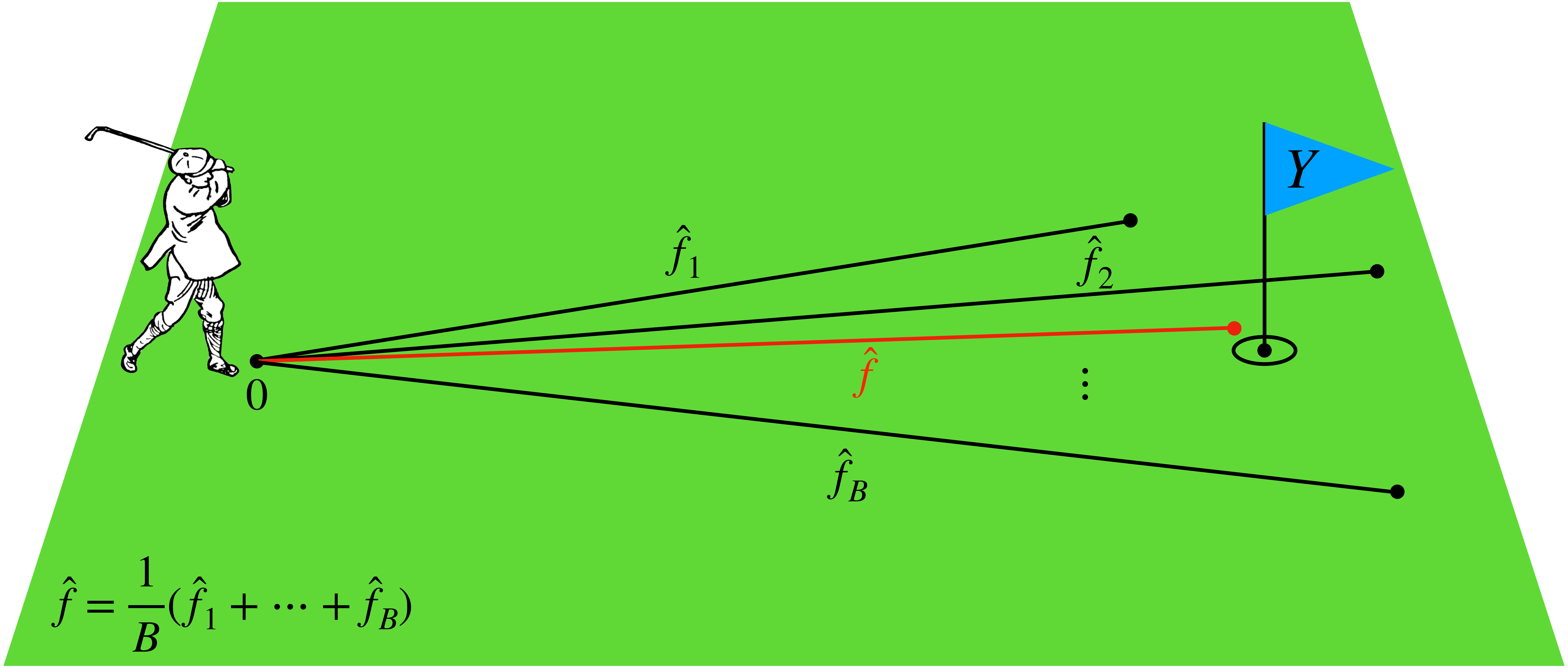

Boosting with shrinkage

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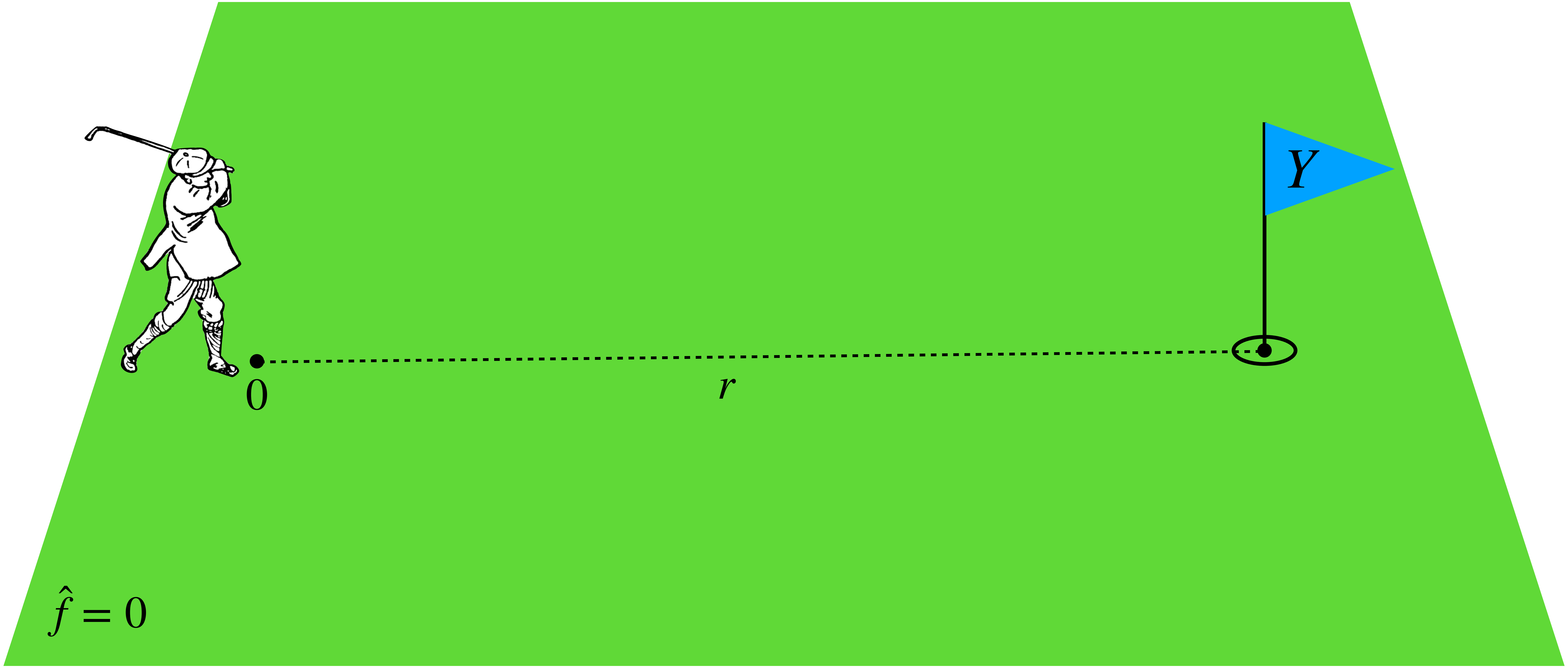

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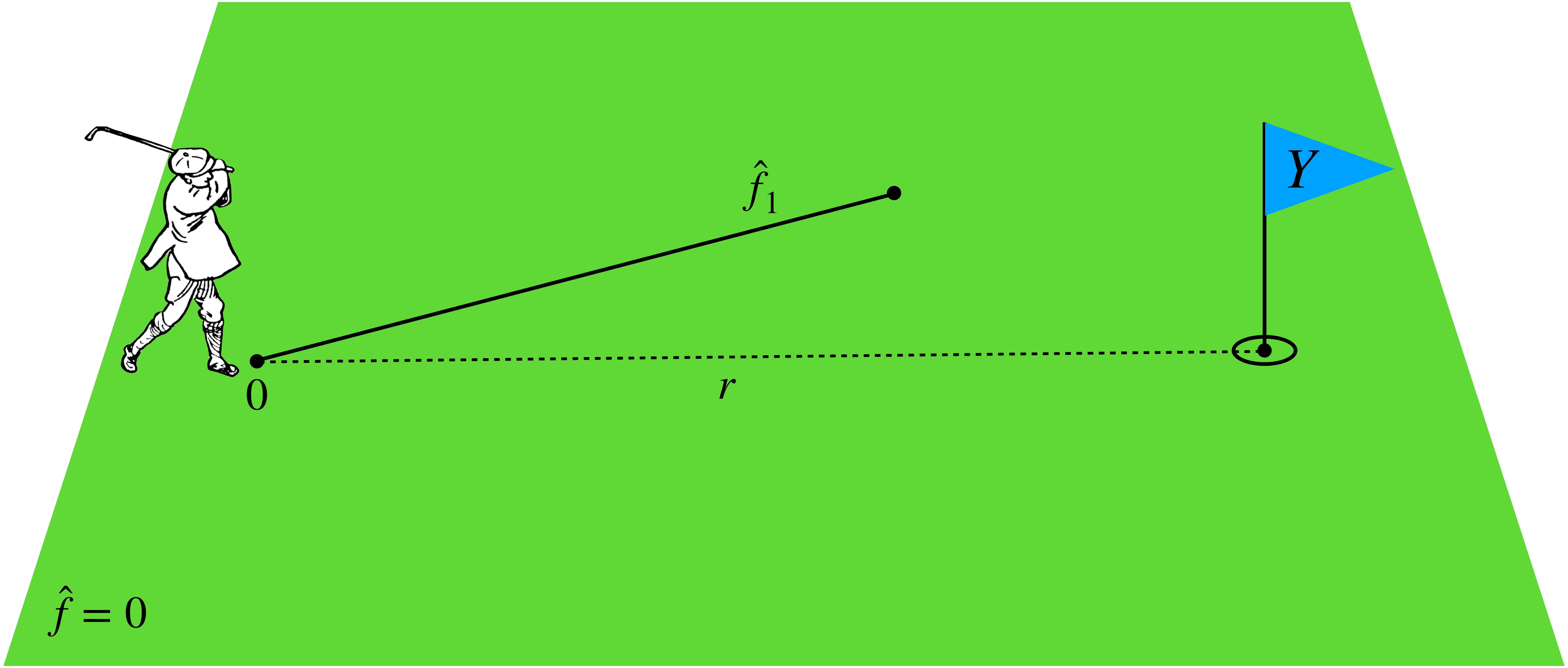

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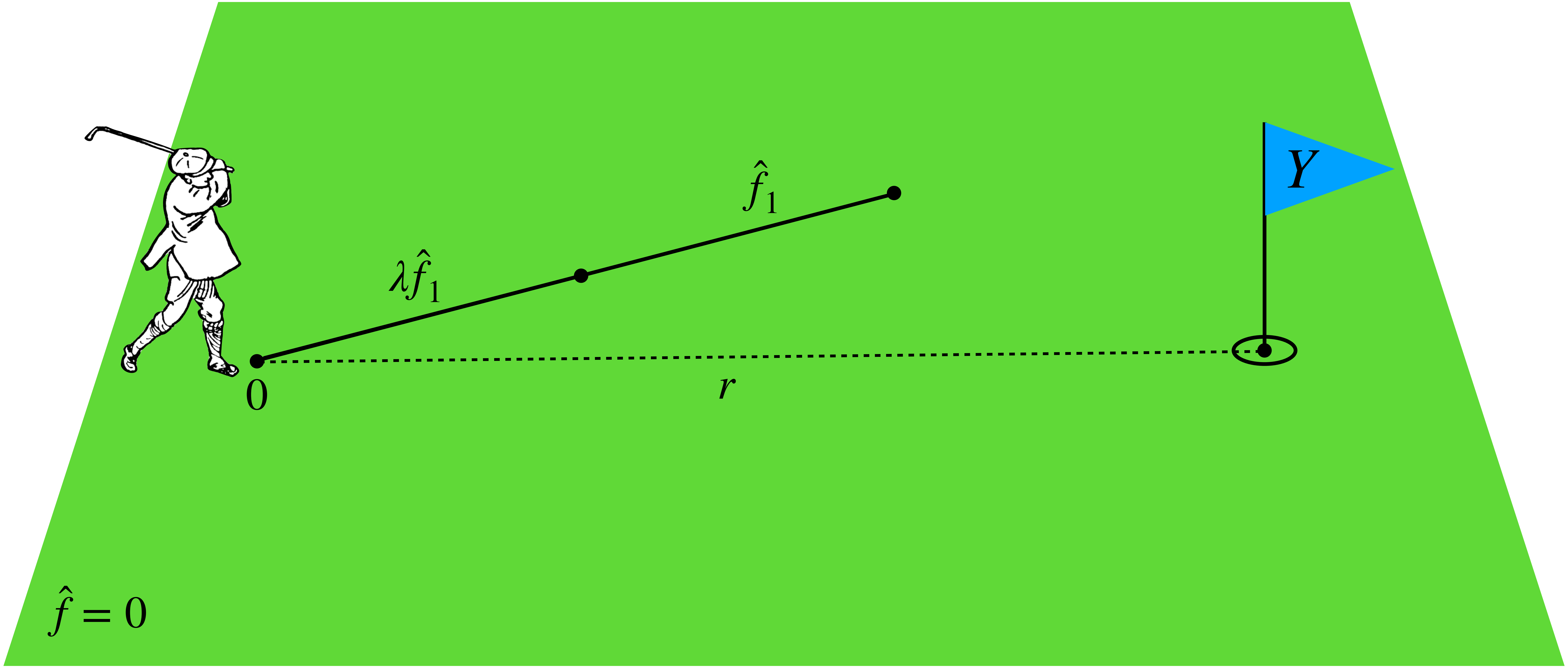

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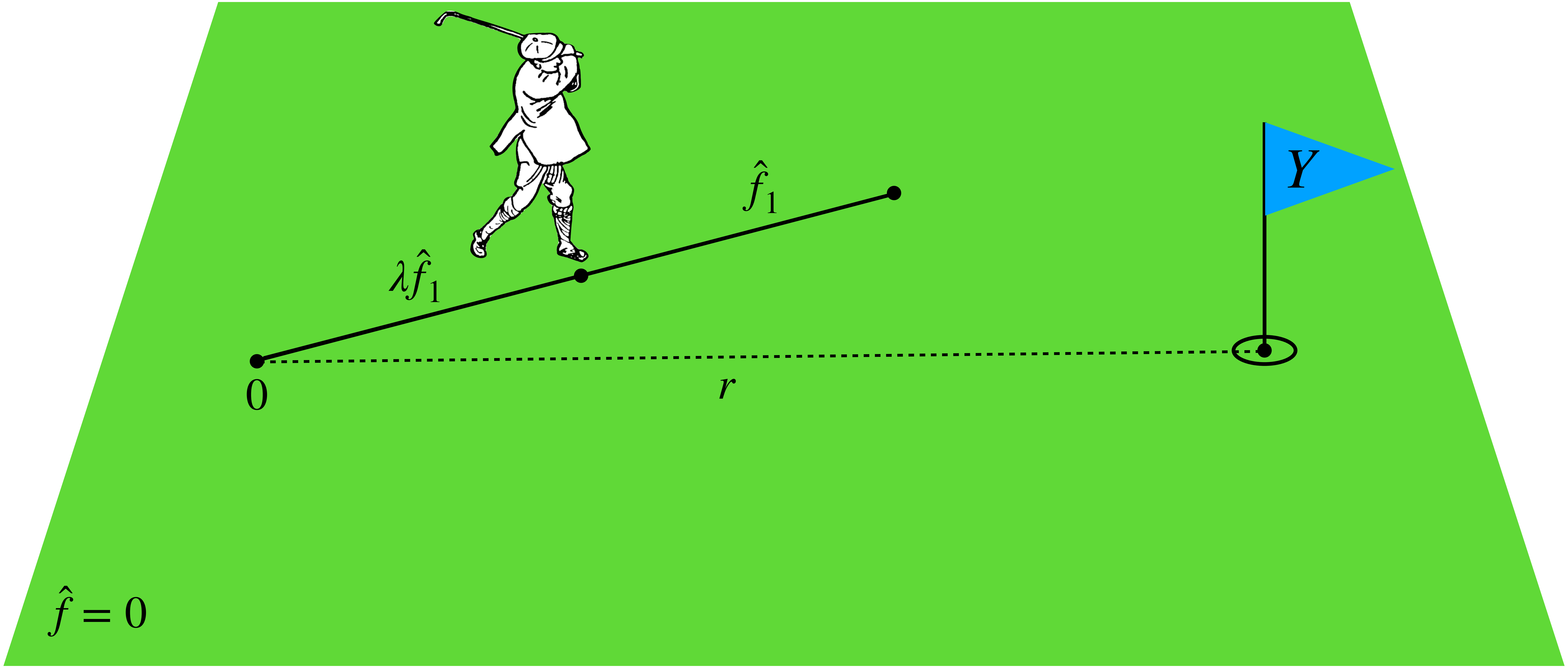

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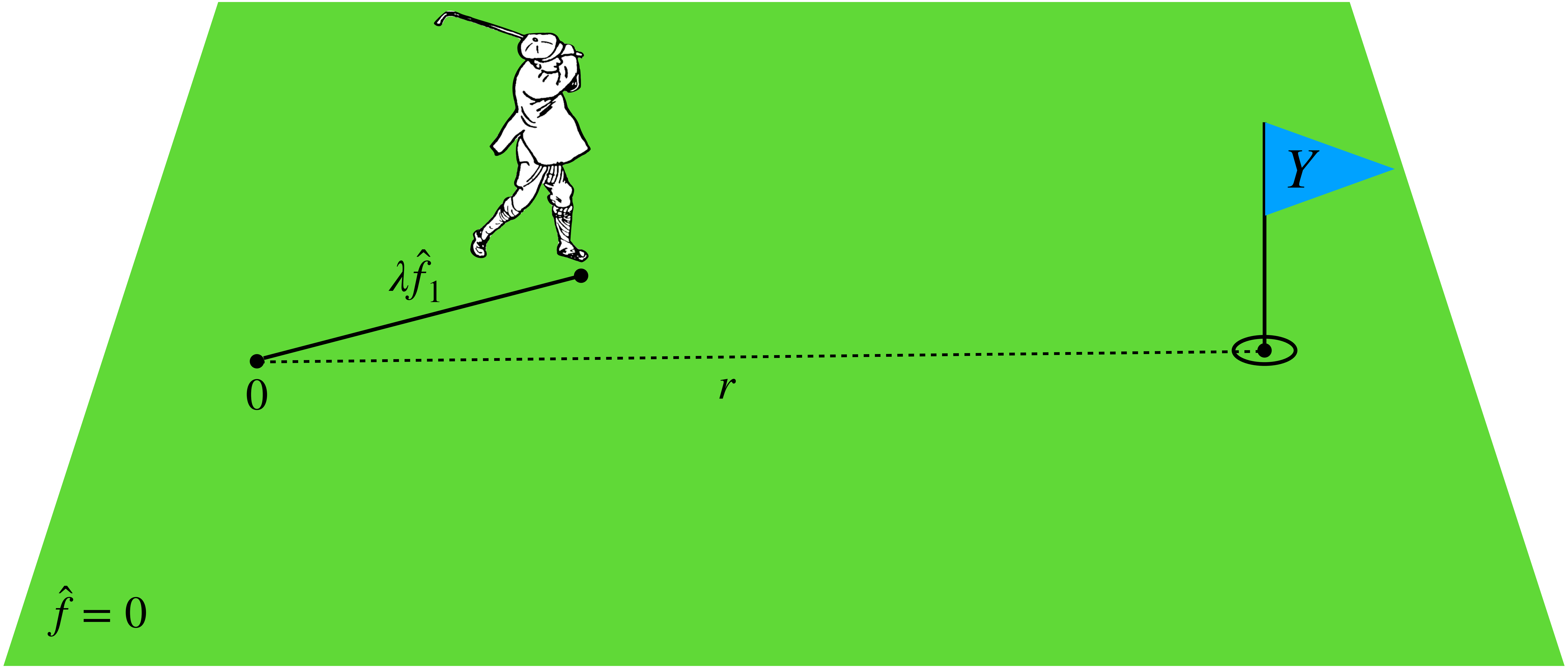

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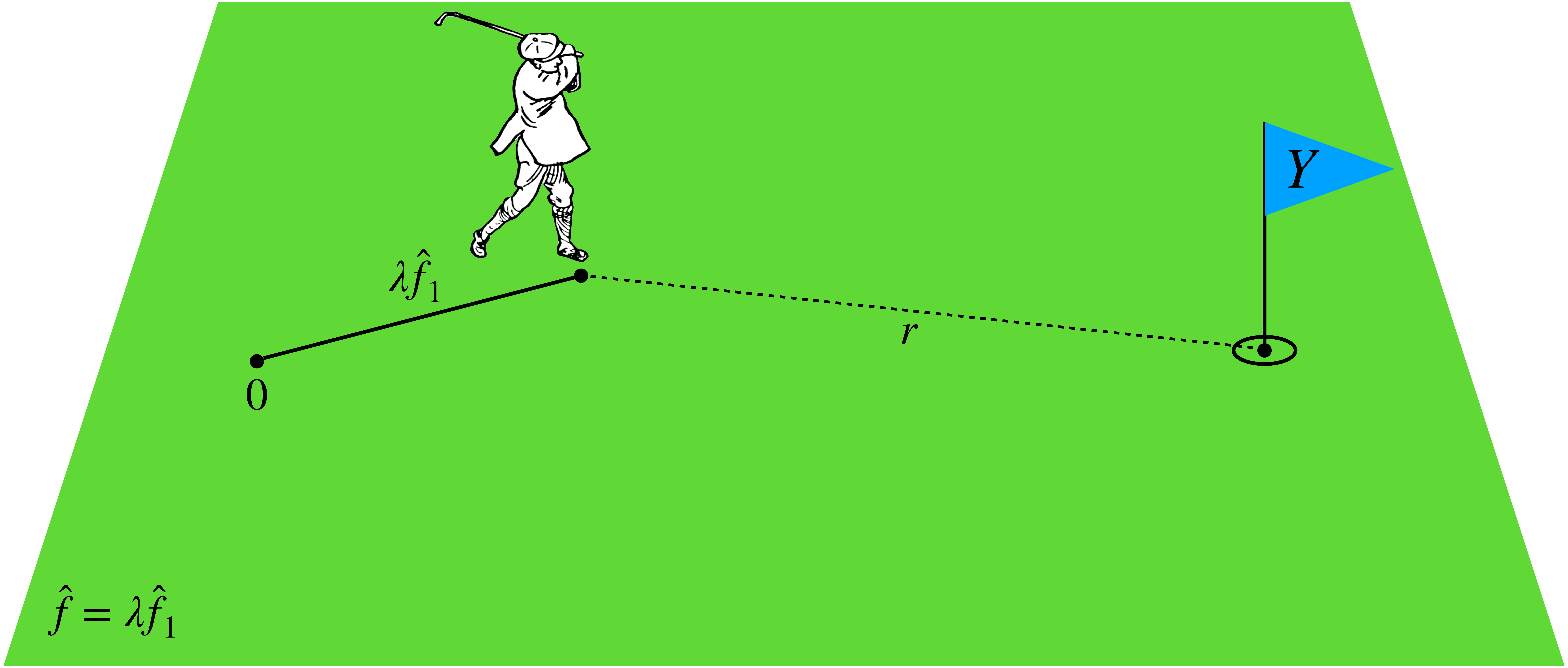

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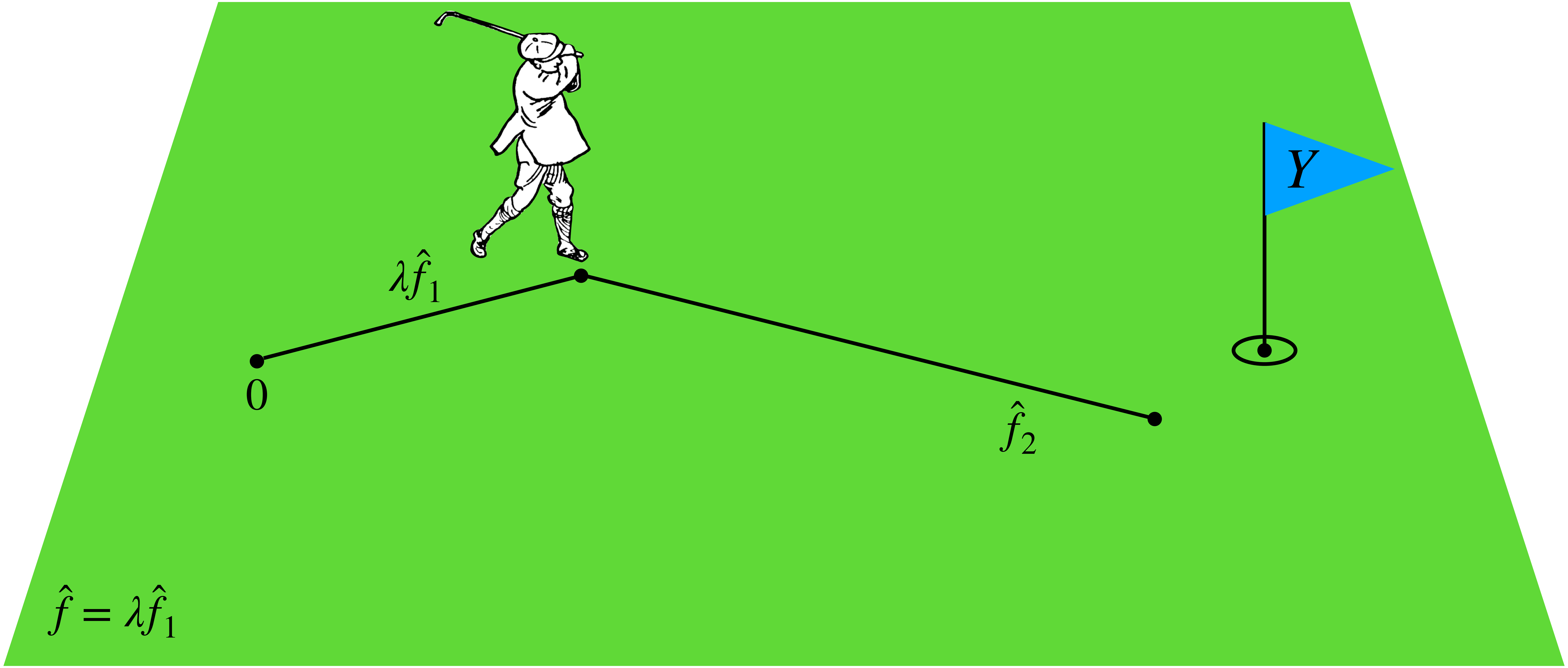

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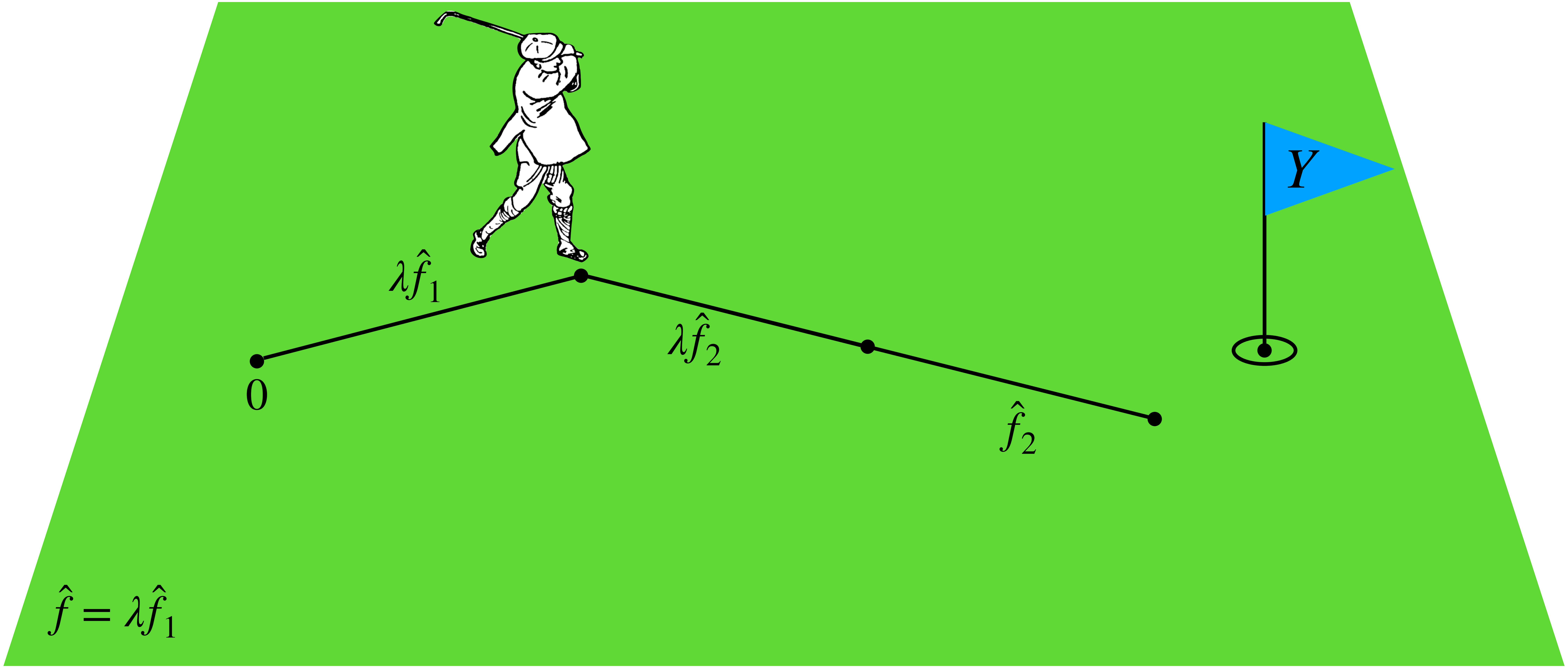

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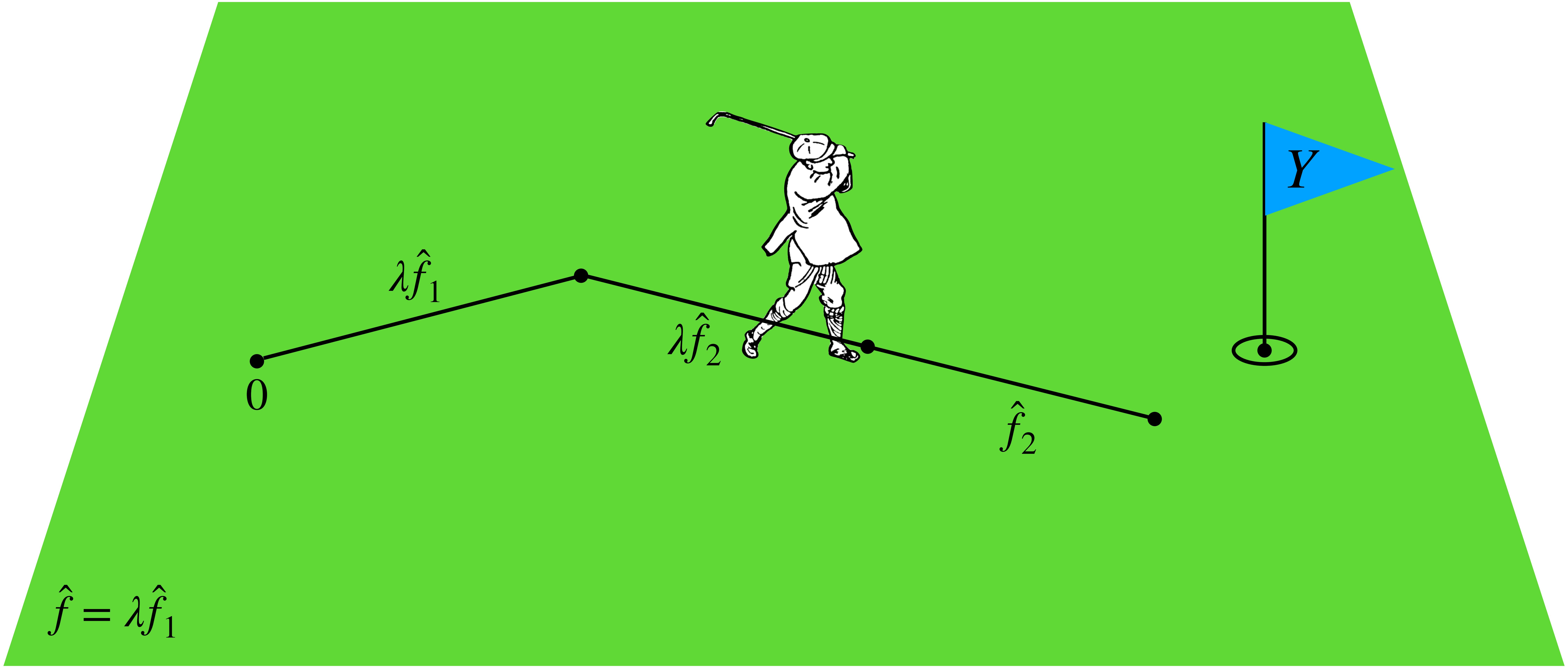

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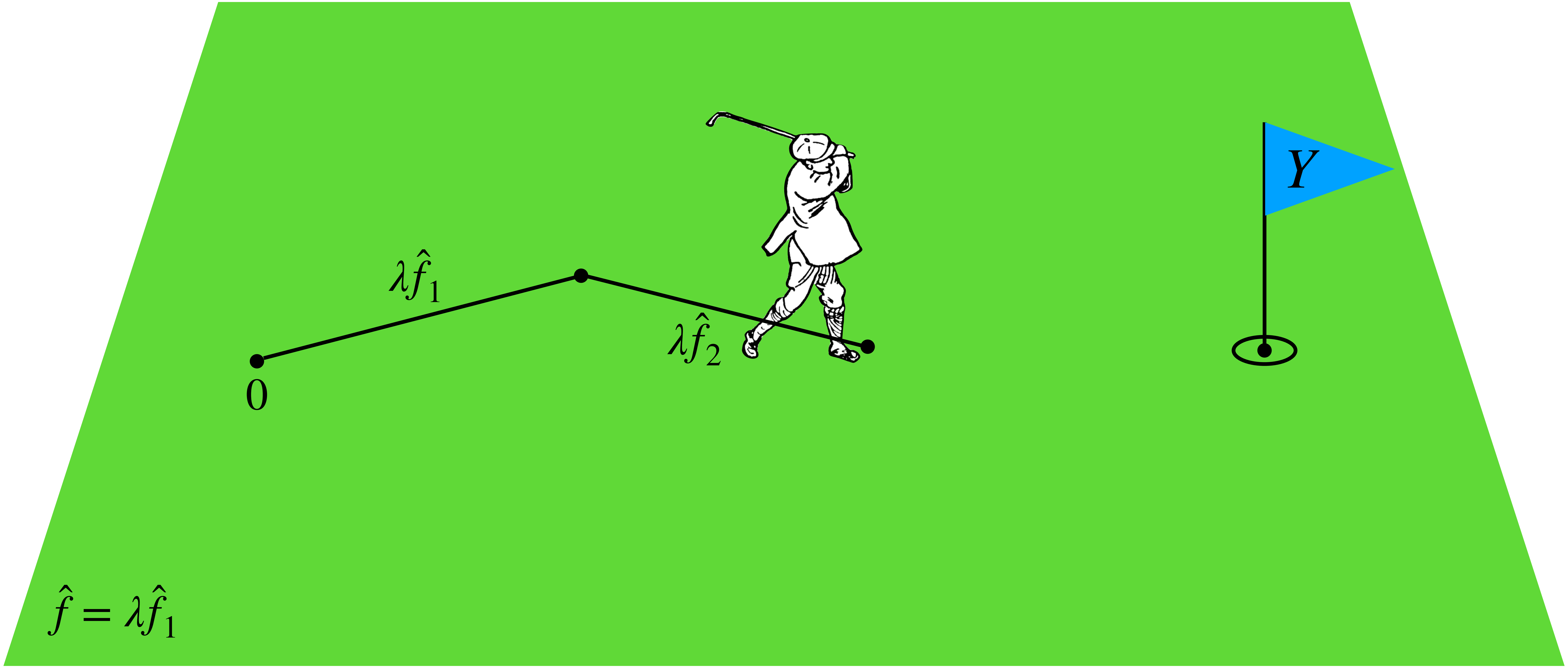

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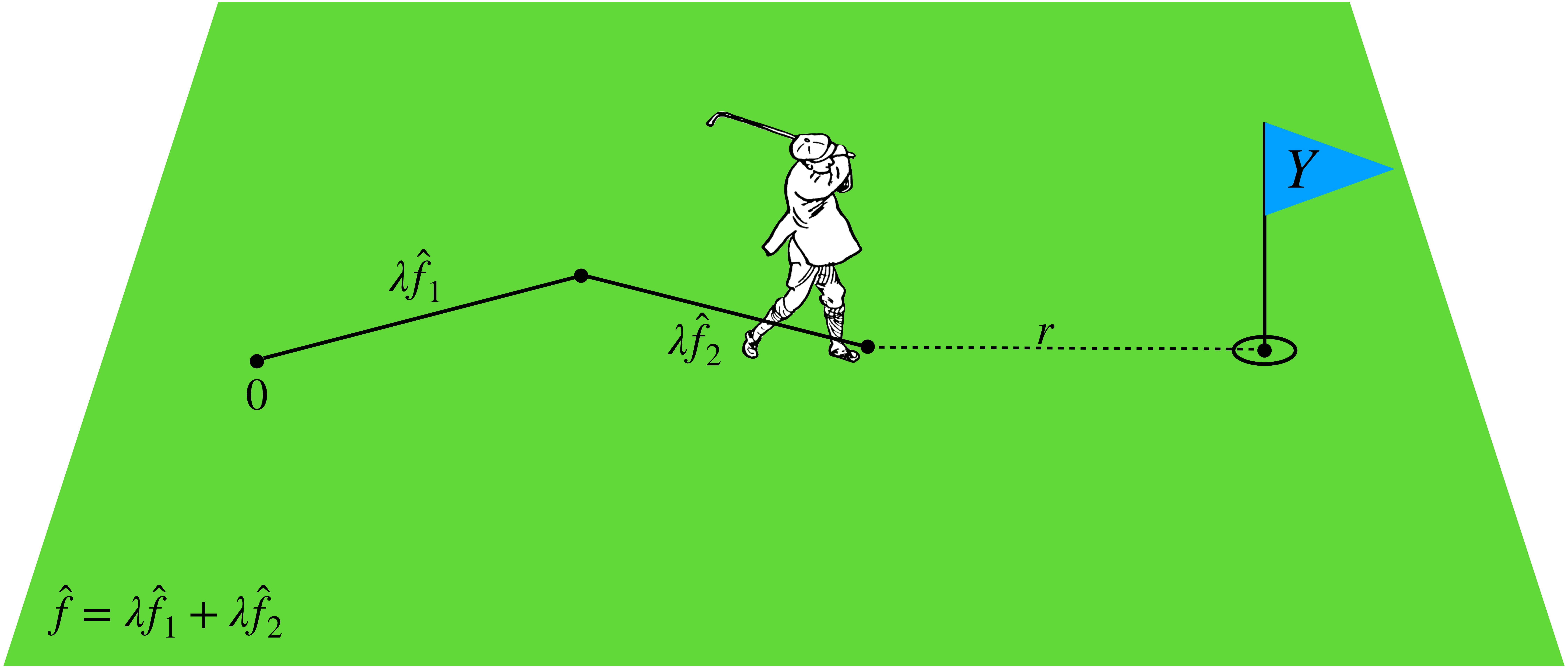

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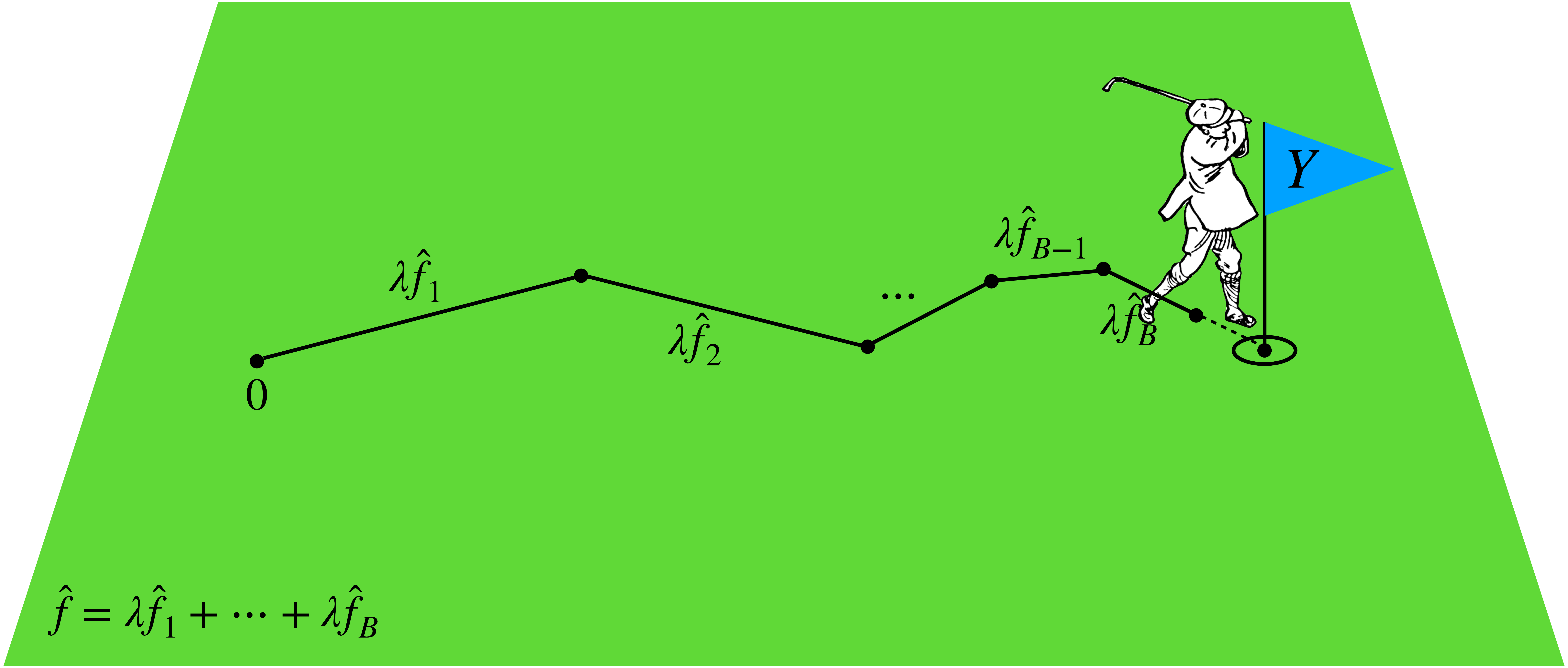

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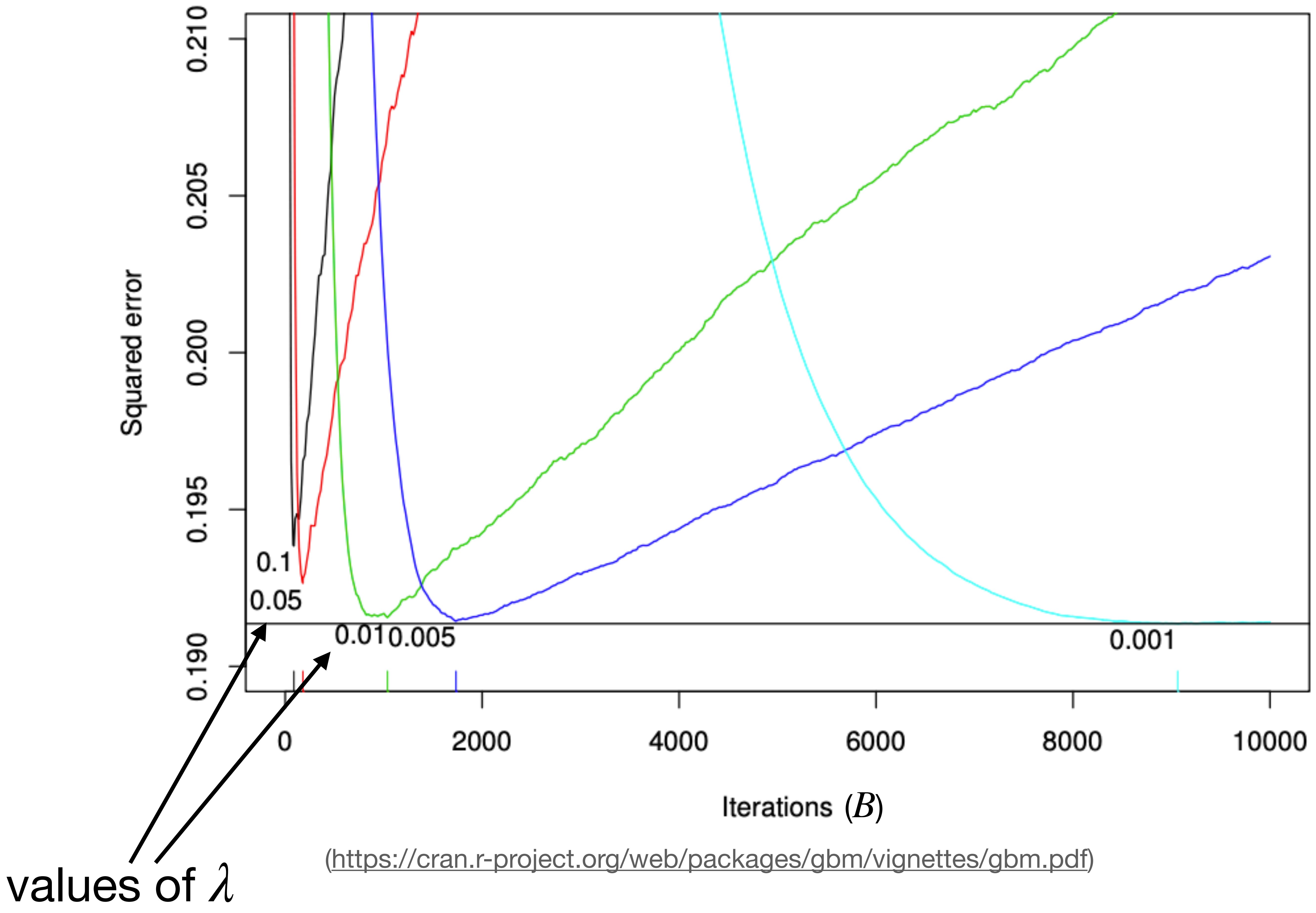

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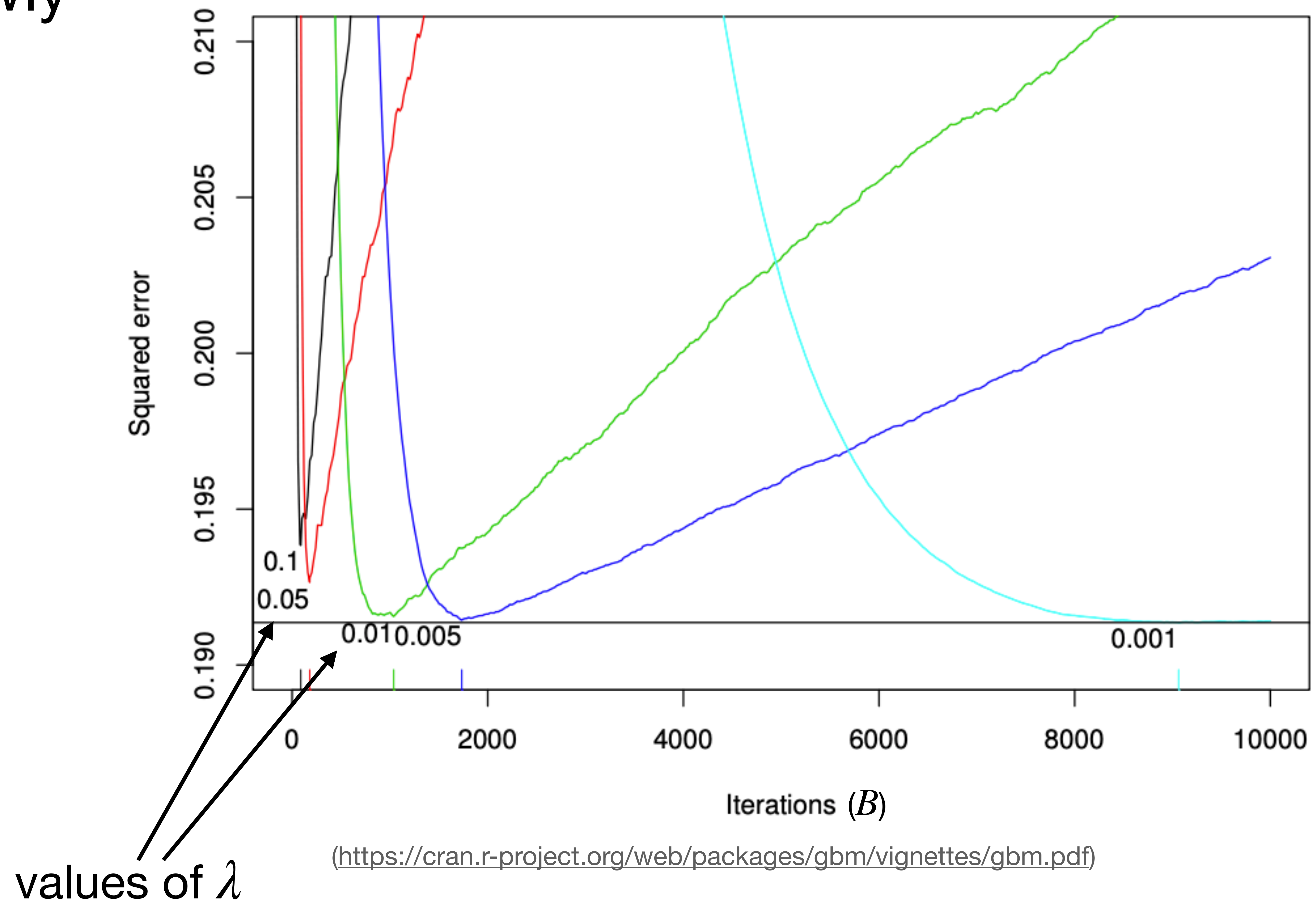

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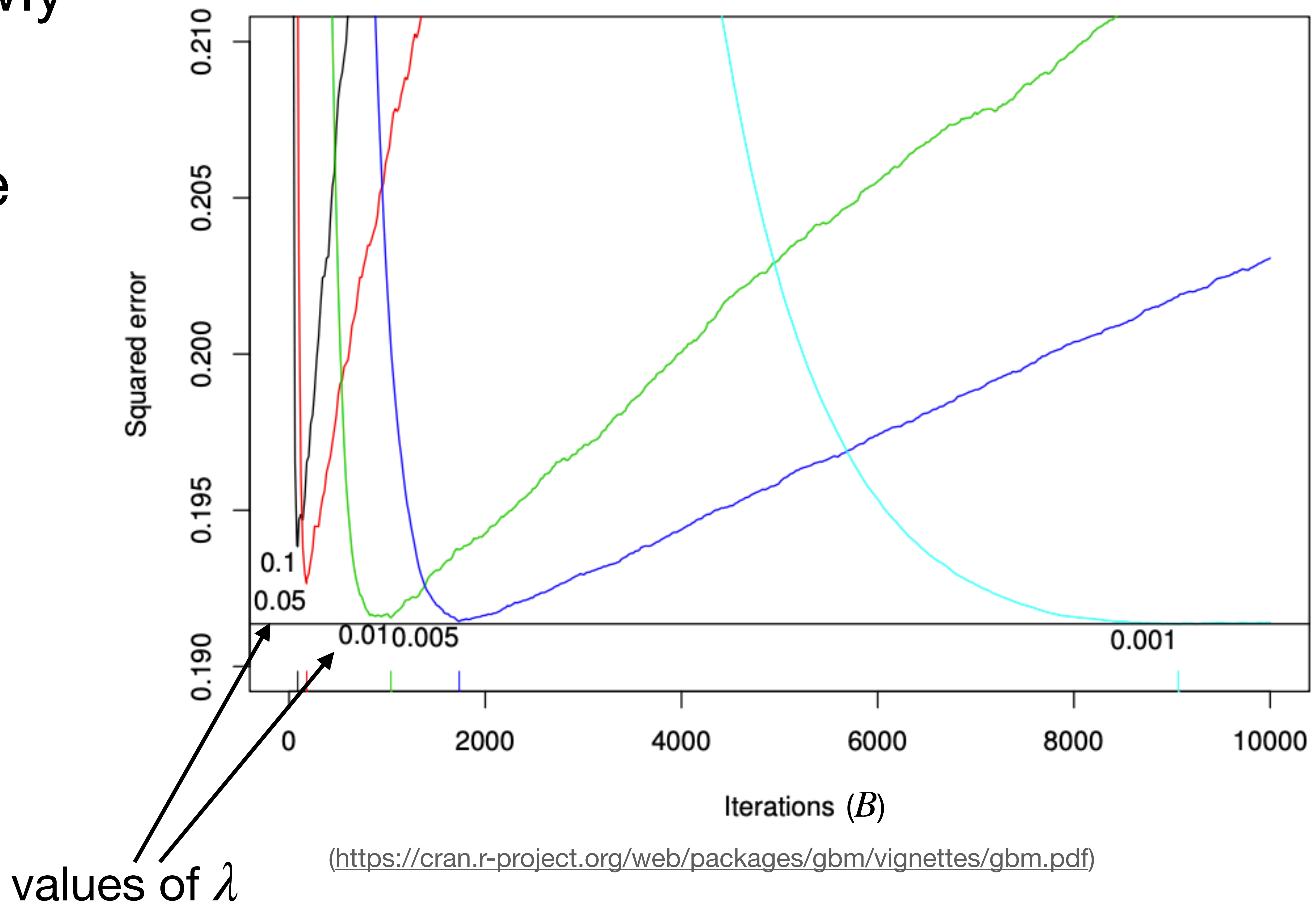

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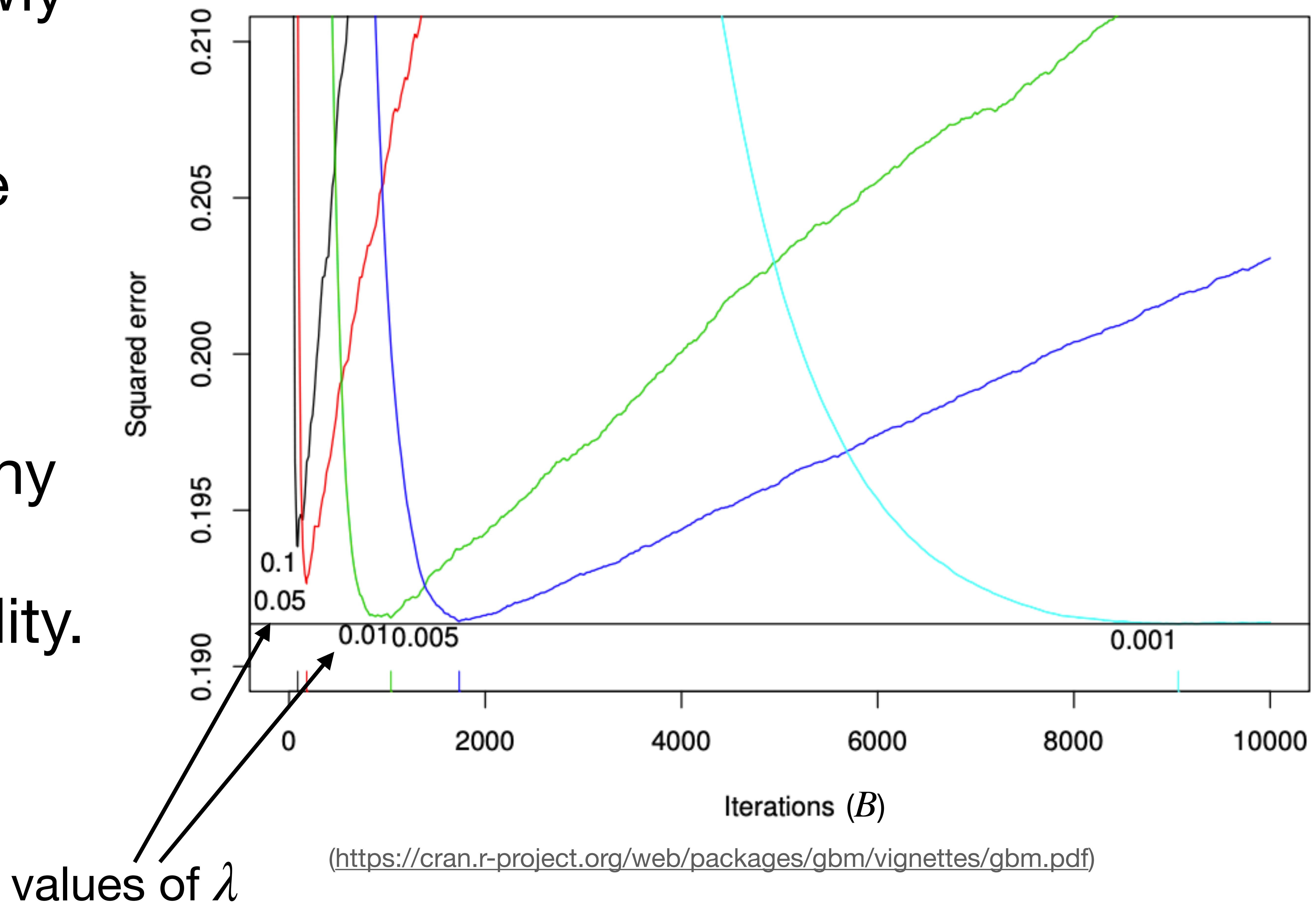

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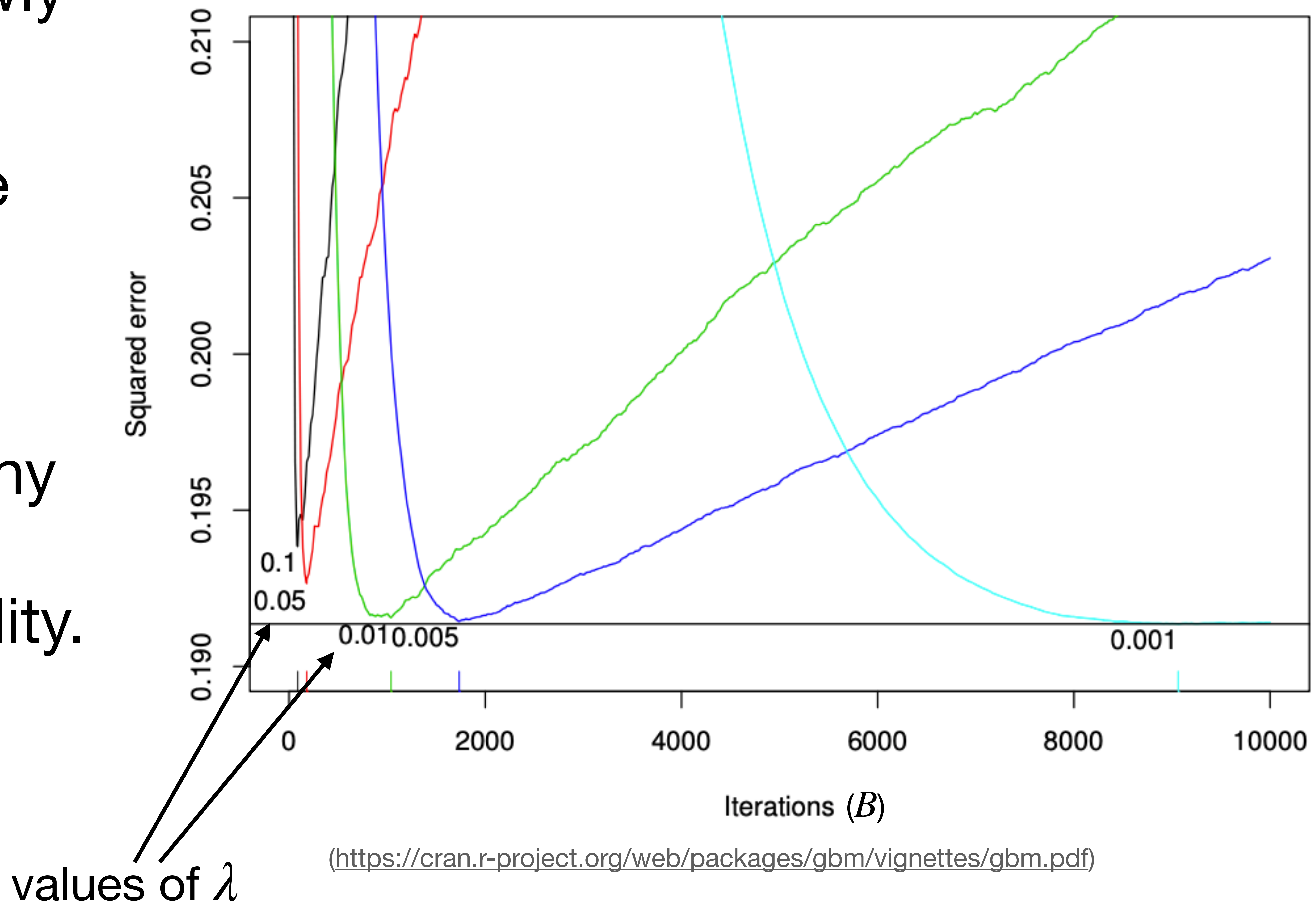
Large enough B can lead to overfitting, unlike random forests.



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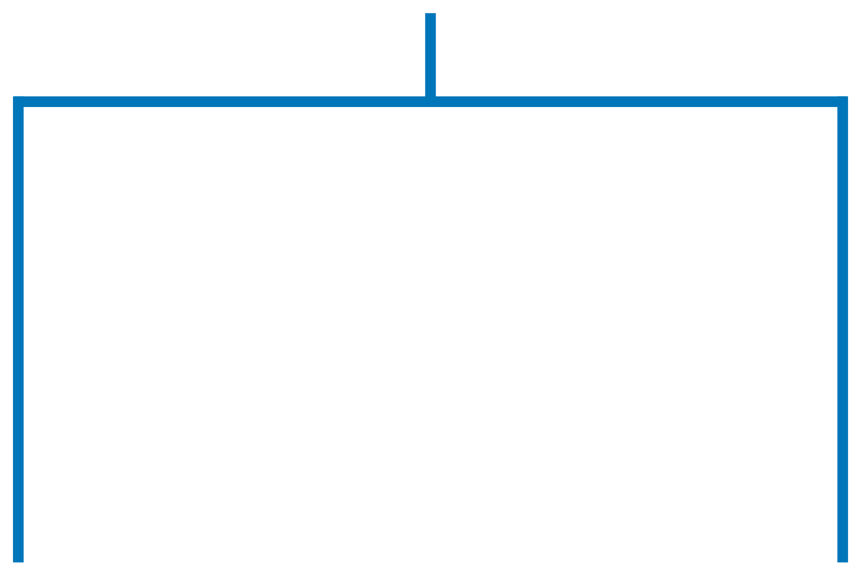

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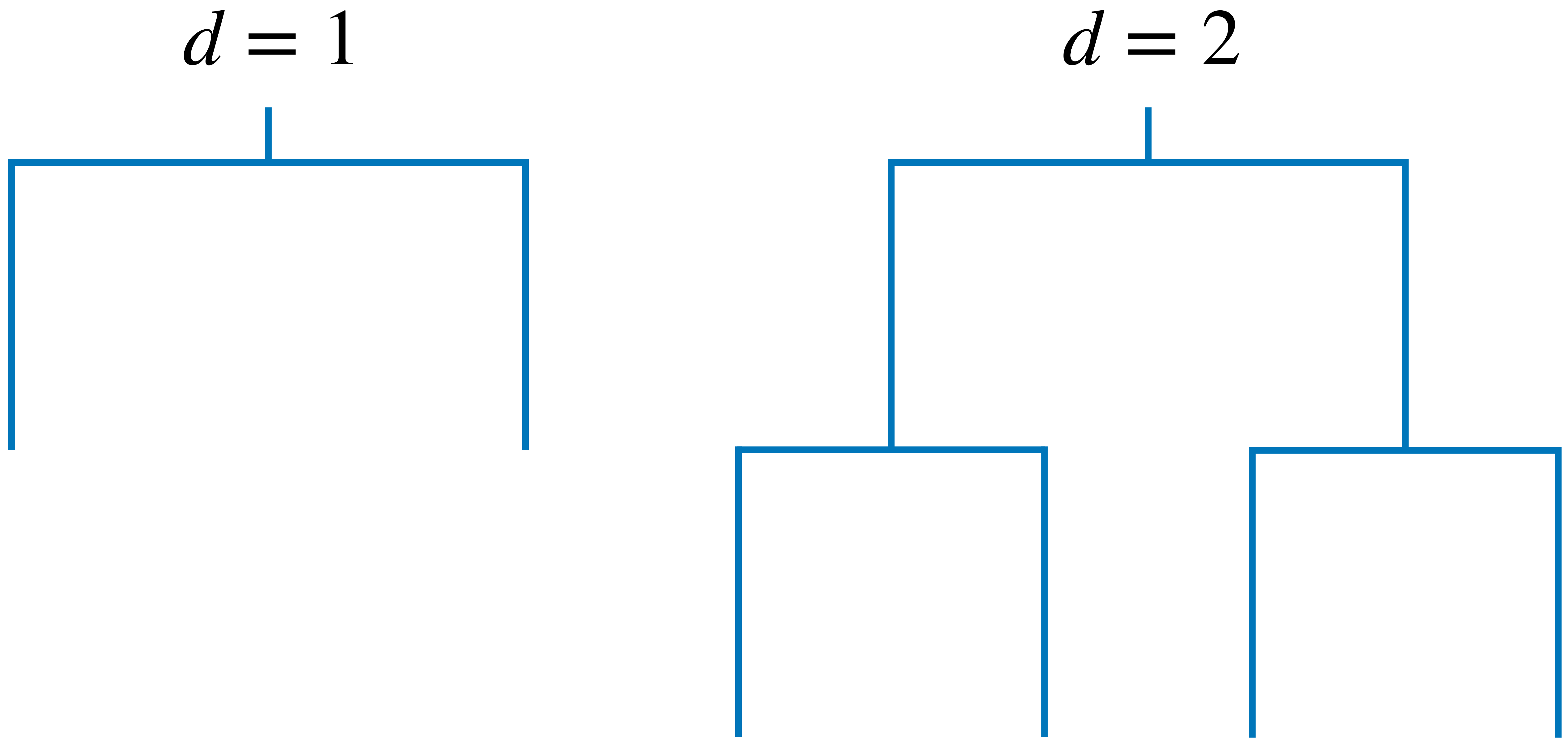

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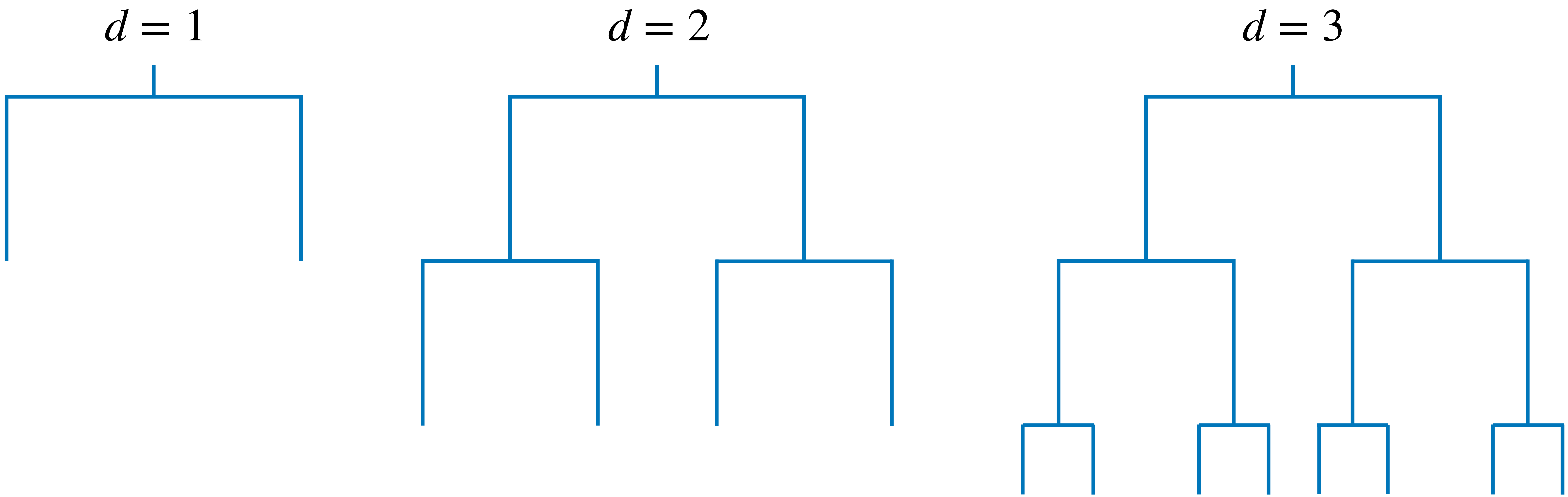

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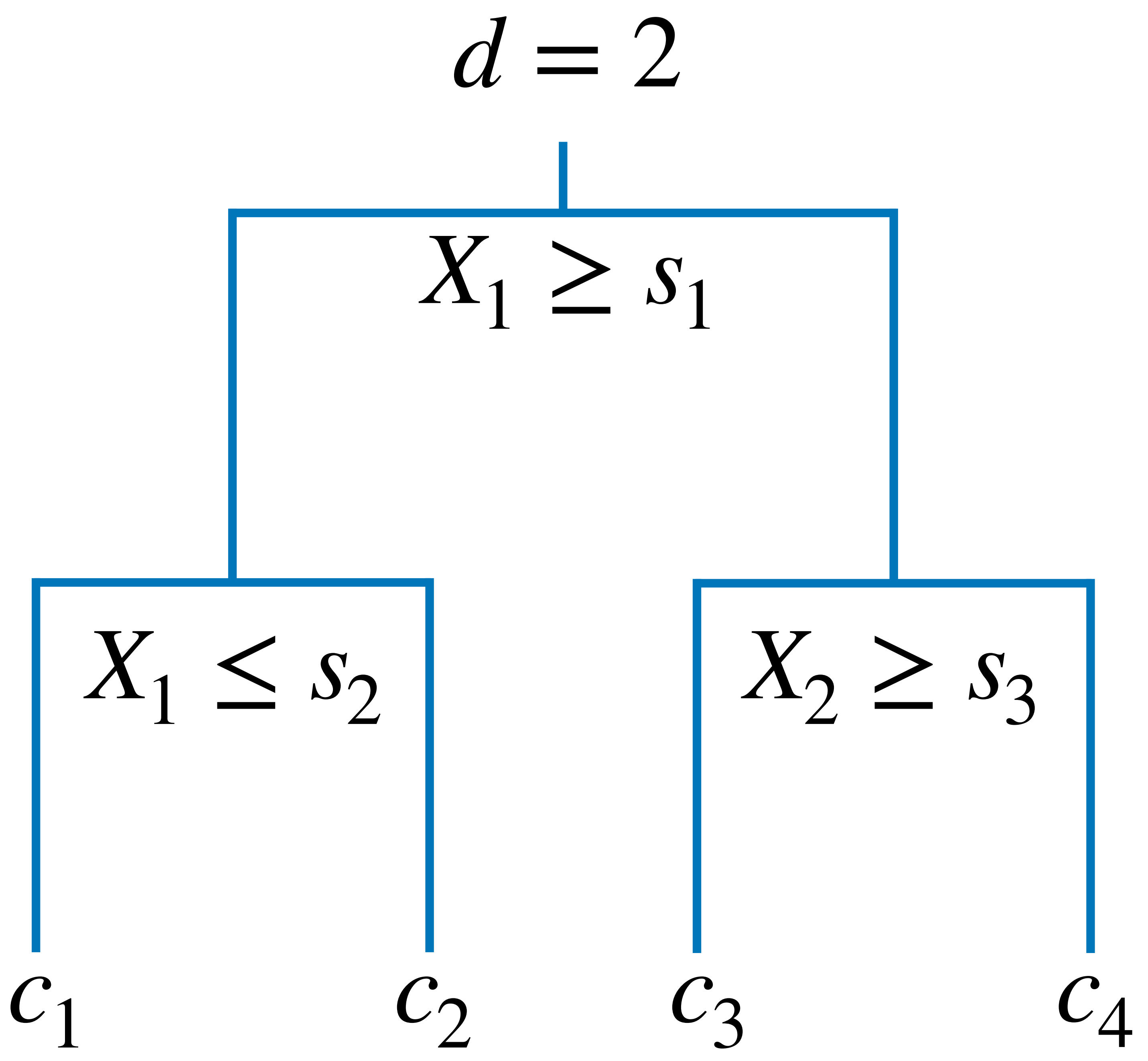

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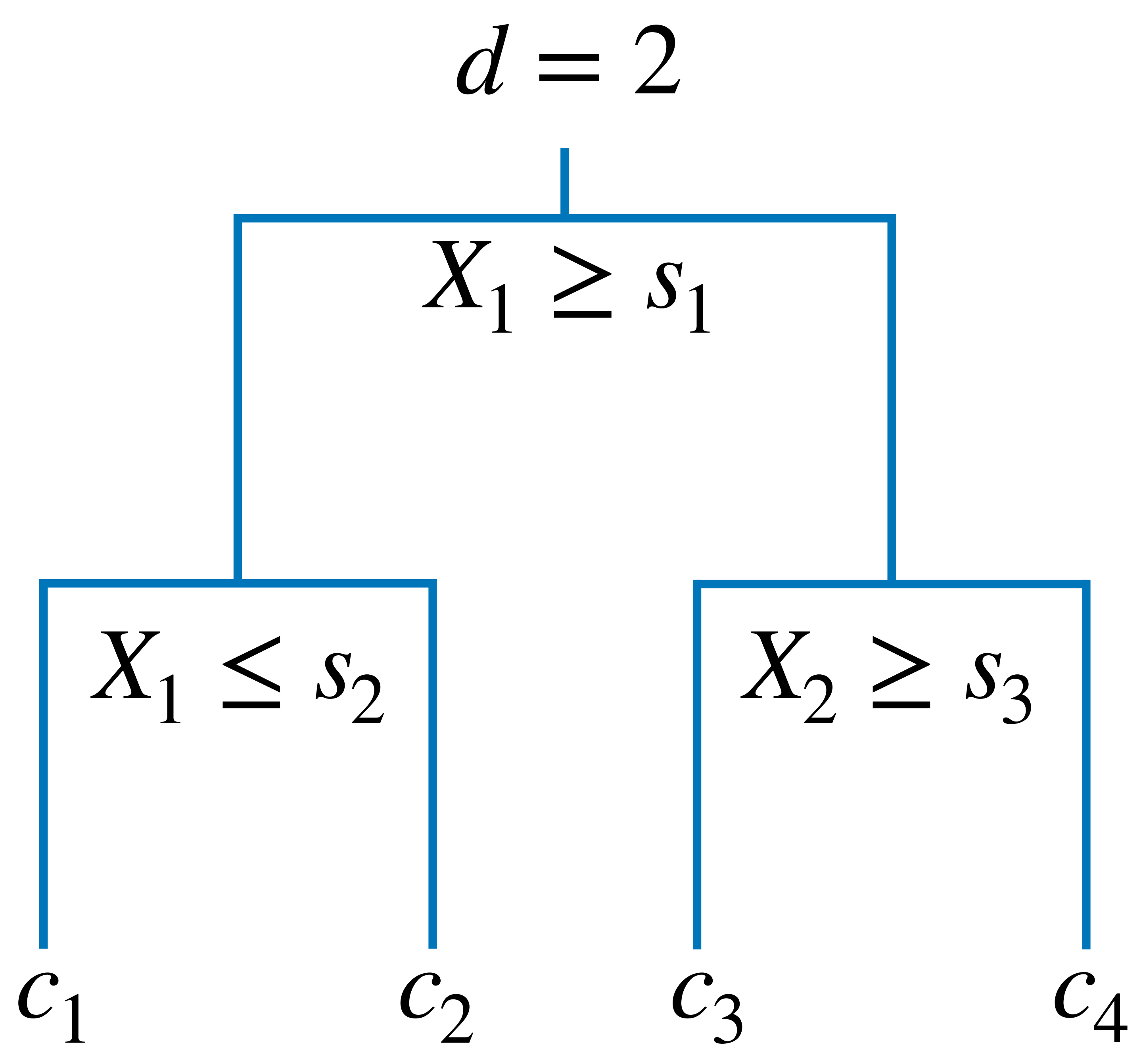

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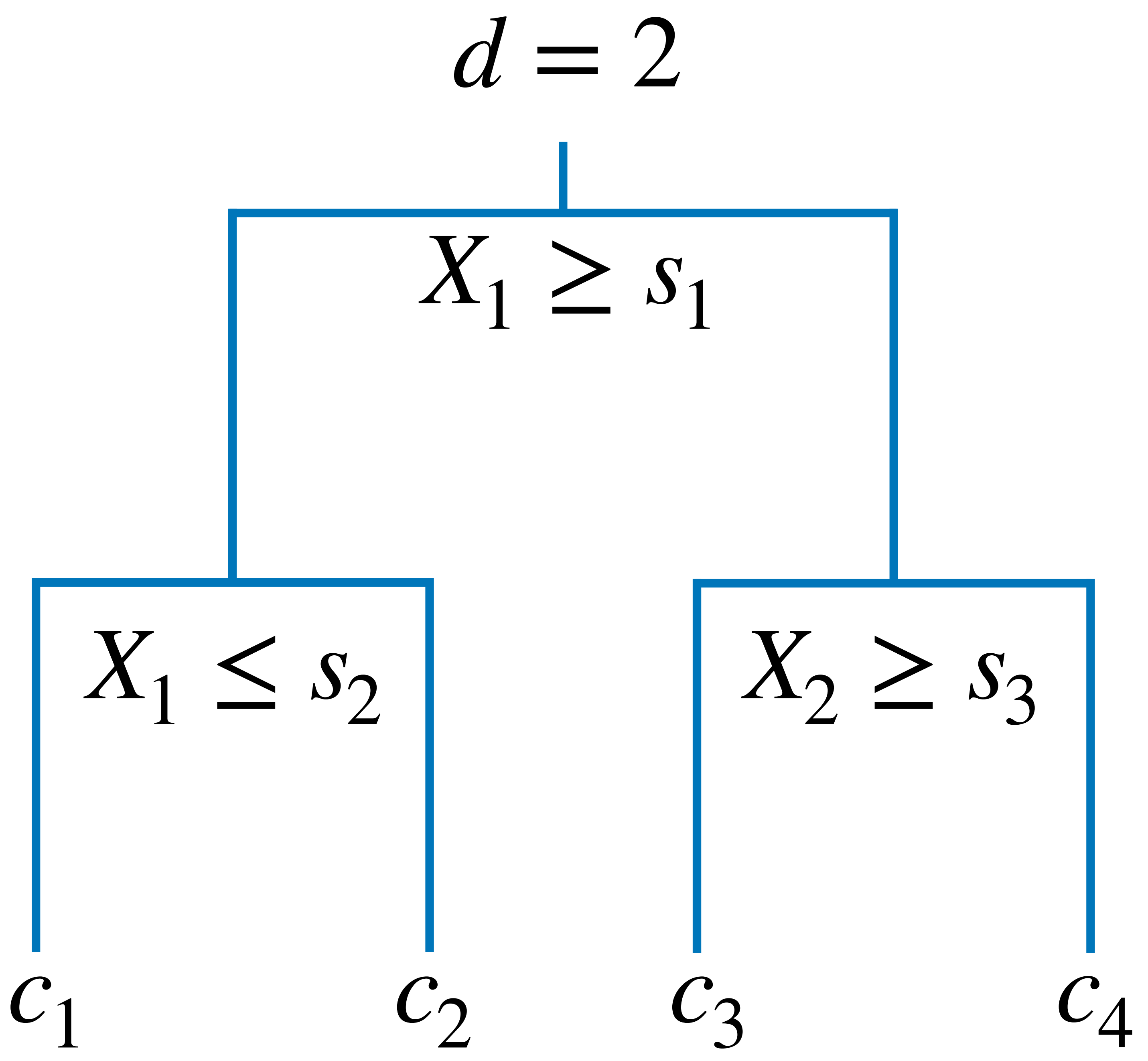

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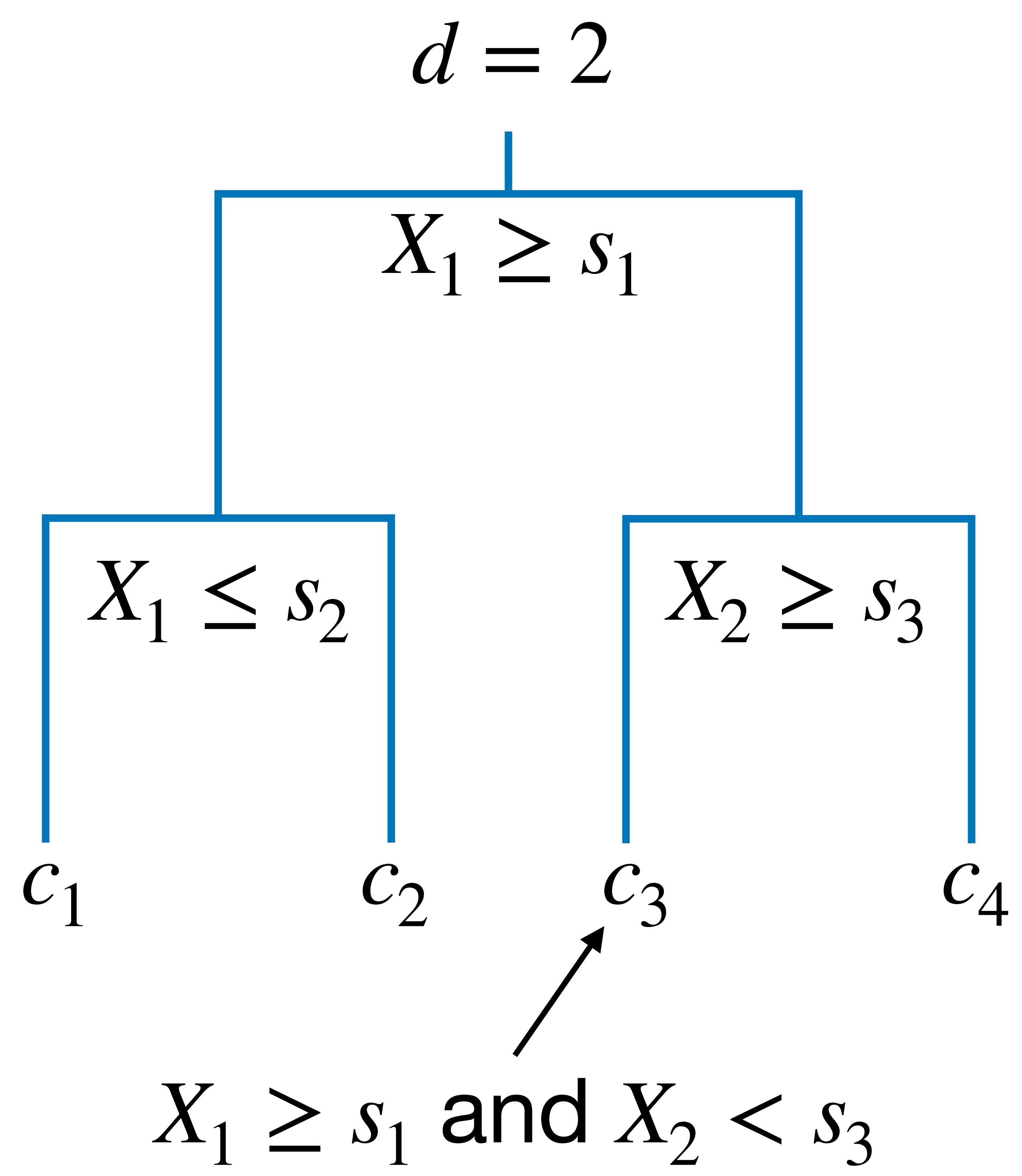

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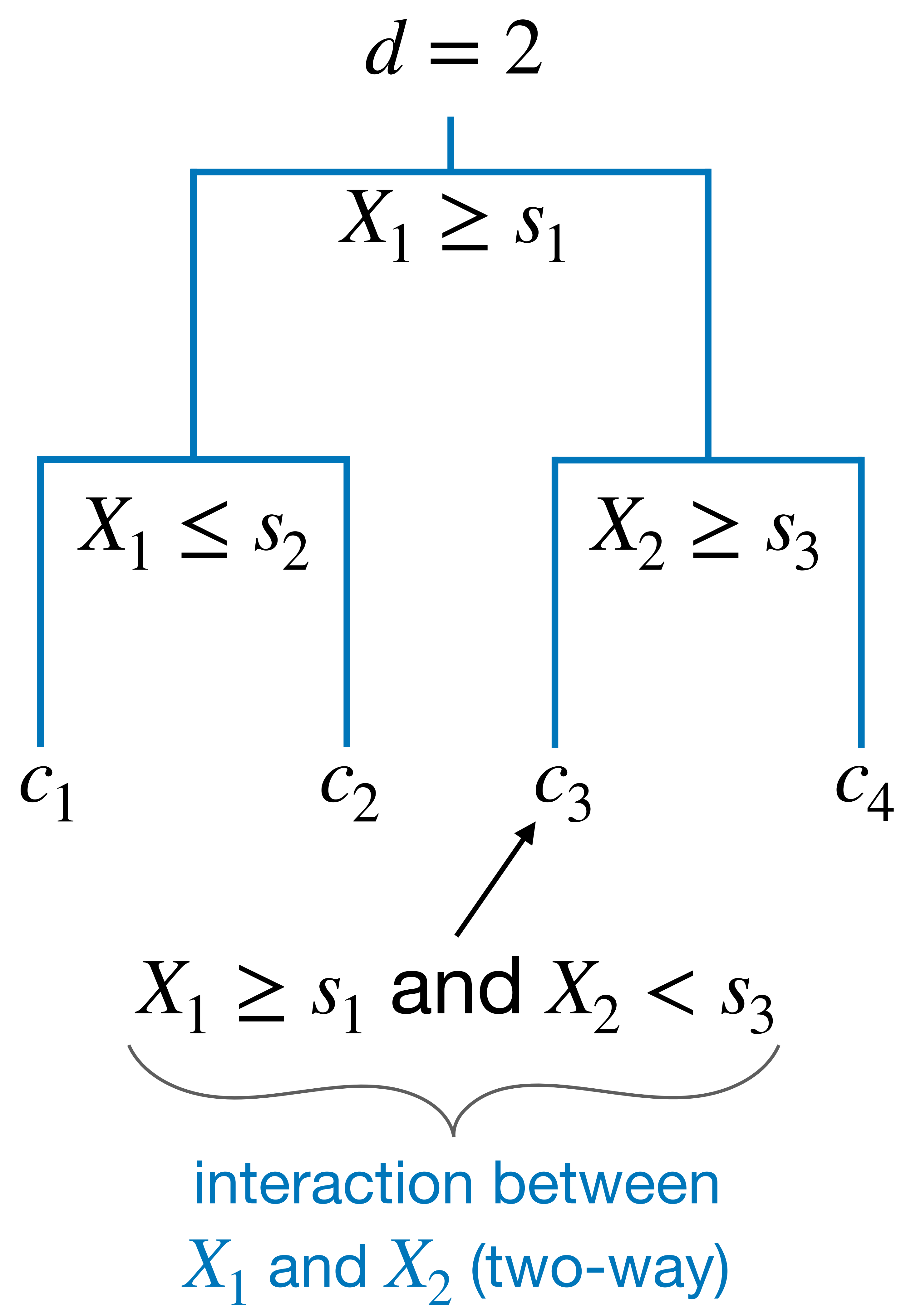

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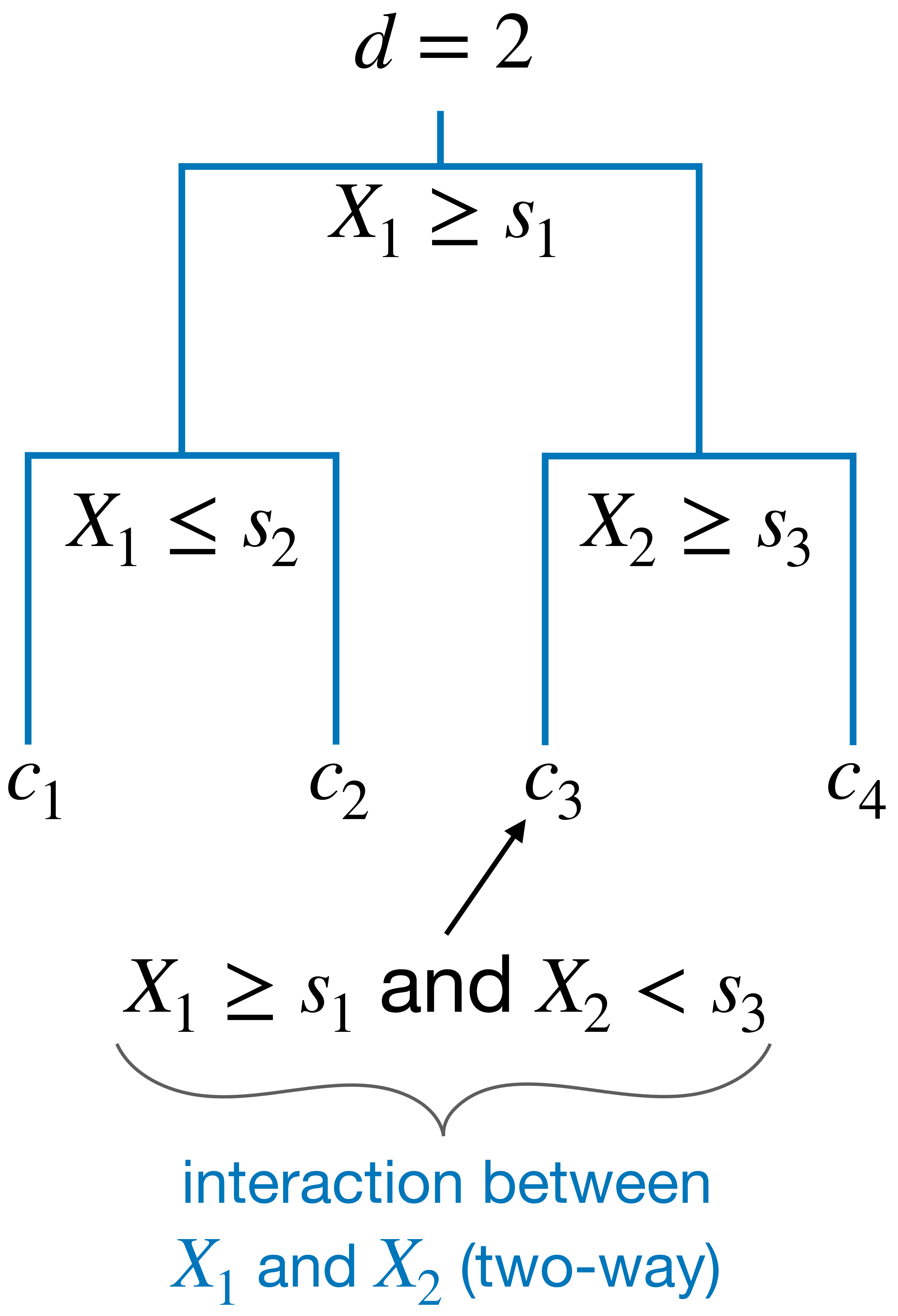

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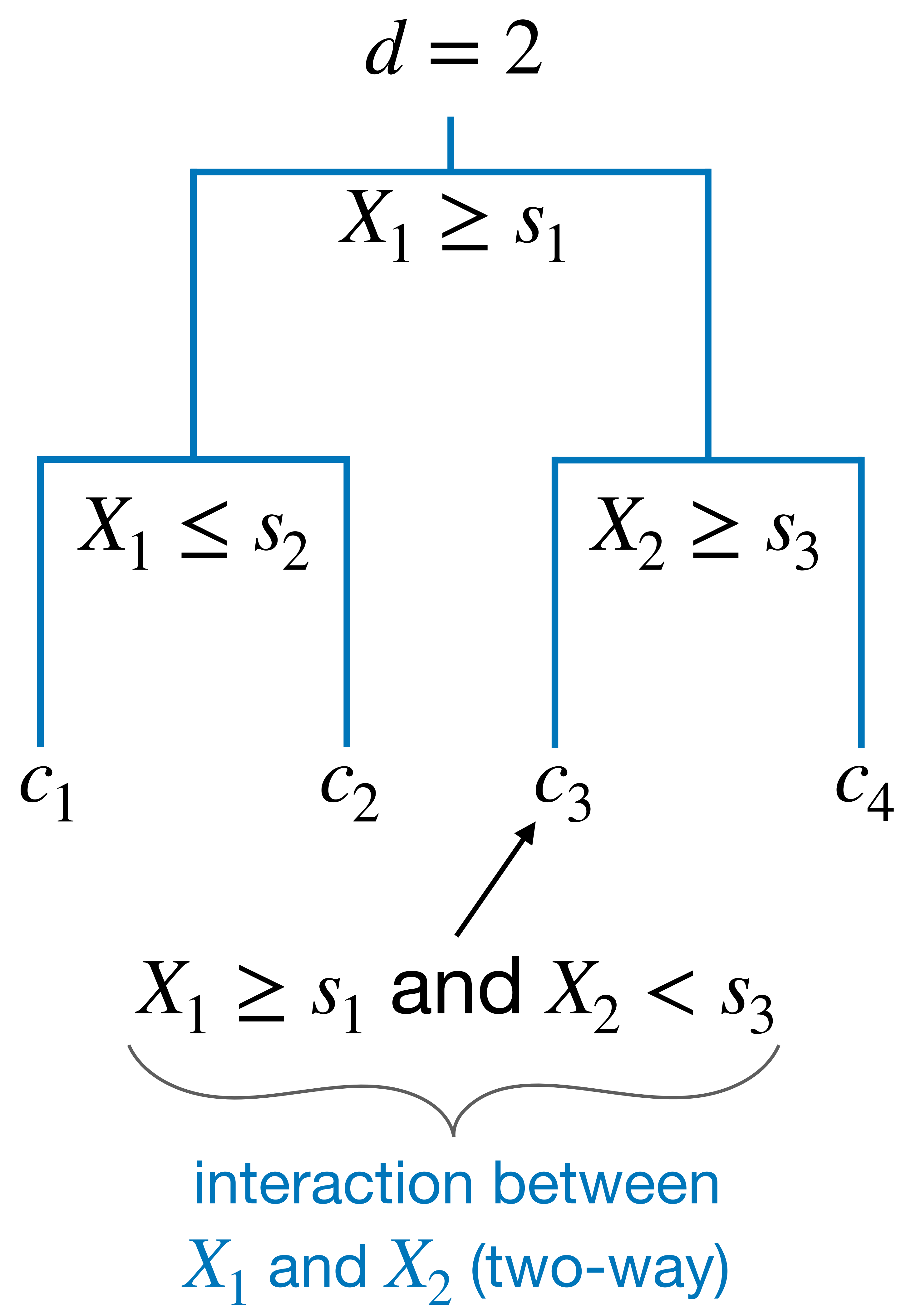

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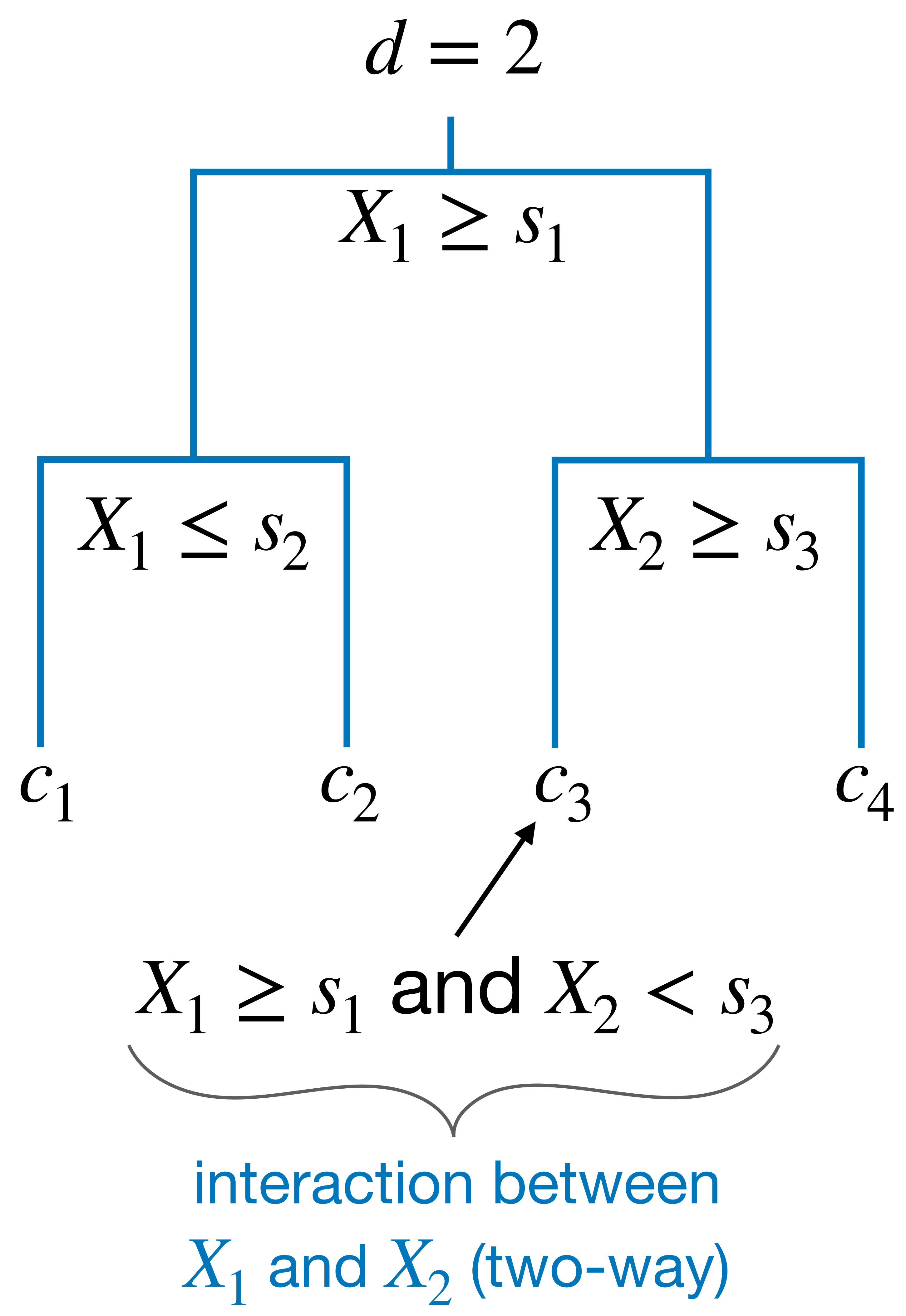
$$d = 1: \quad \hat{f}(X_1, X_2, X_3) = \hat{g}_1(X_1) + \hat{g}_2(X_2) + \hat{g}_3(X_3)$$



Interaction depth

Consider a single tree, for example with $d = 2$.

The prediction rule involves making decisions based on X_1 and X_2 together (two-way interactions).

For $d = 3$, we can get three-way interactions, etc.

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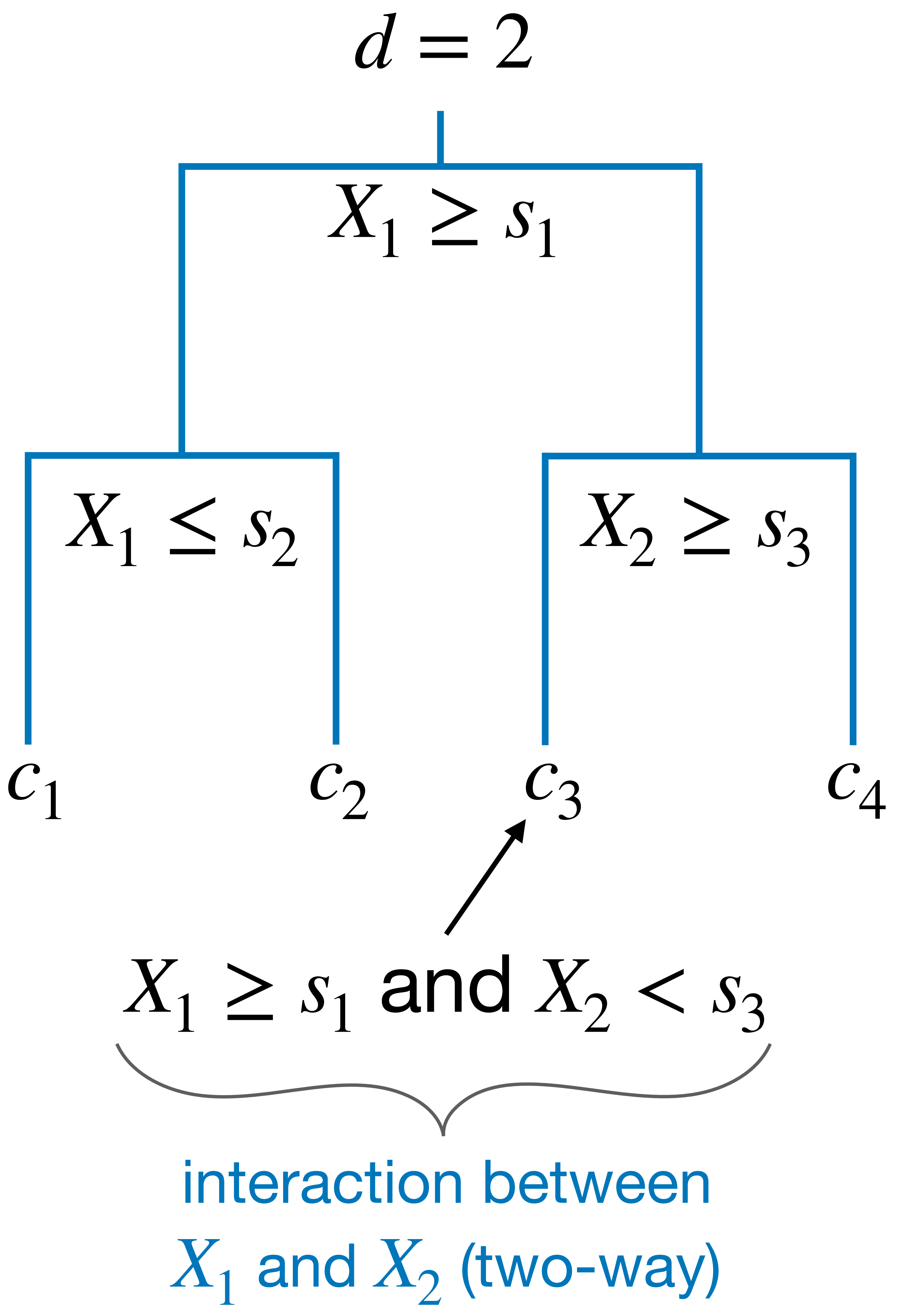

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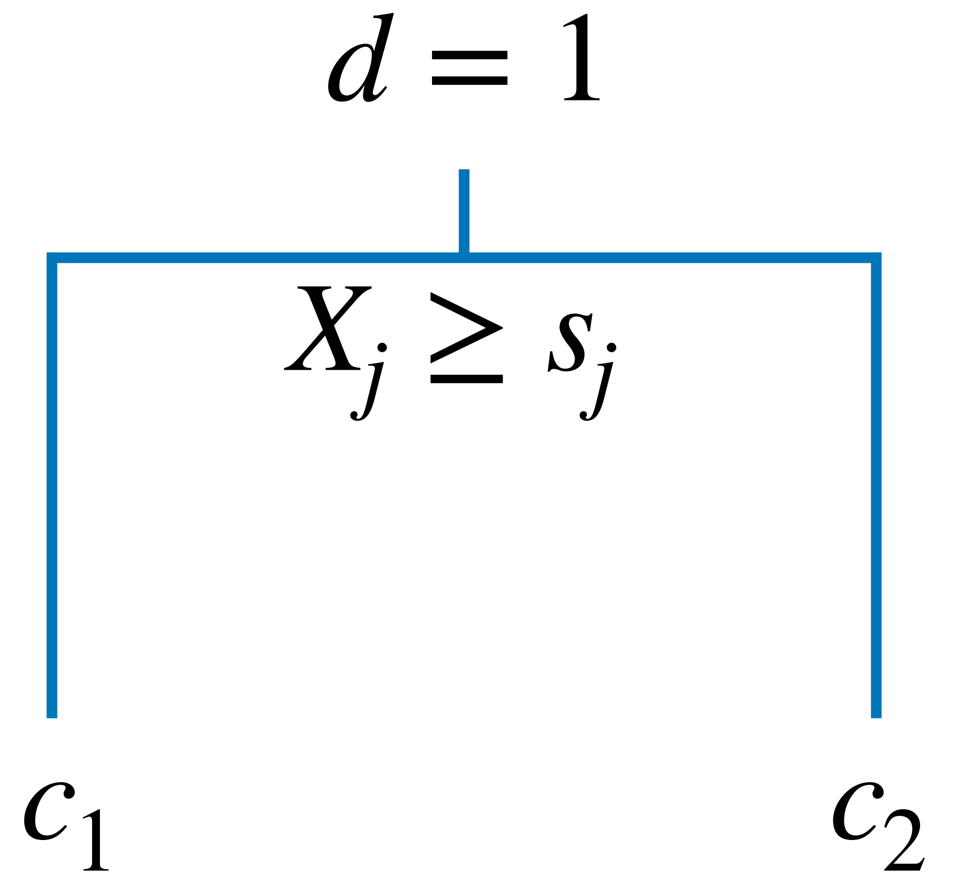

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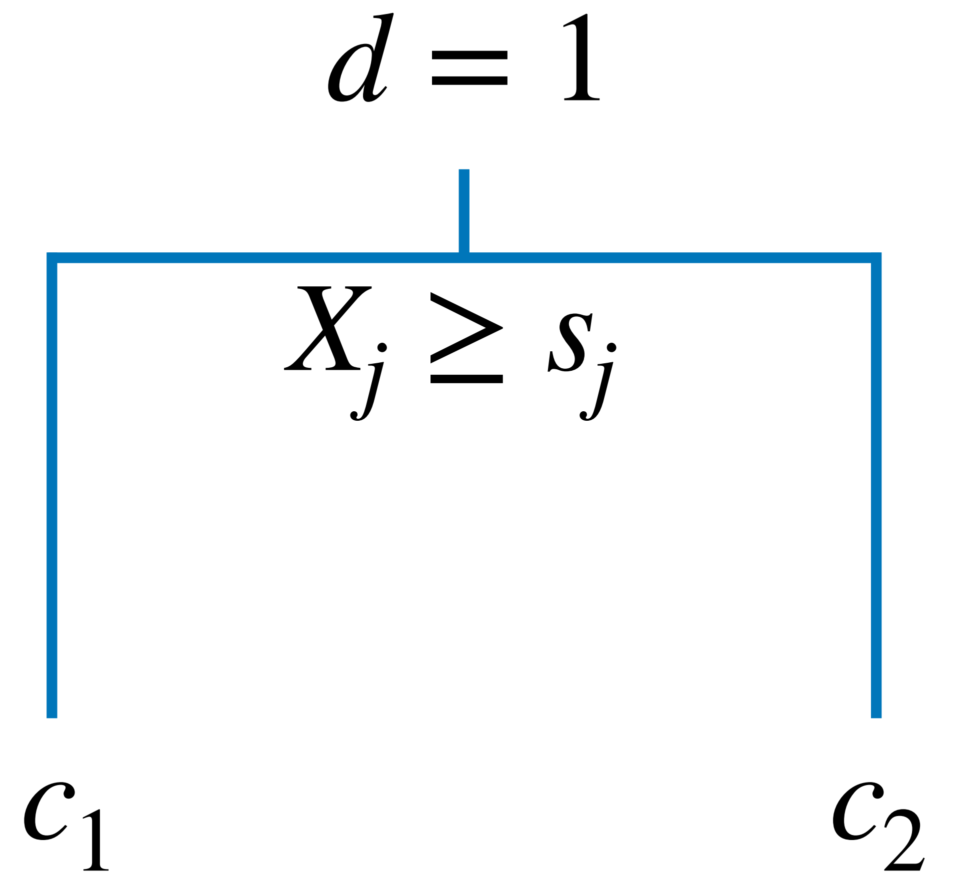

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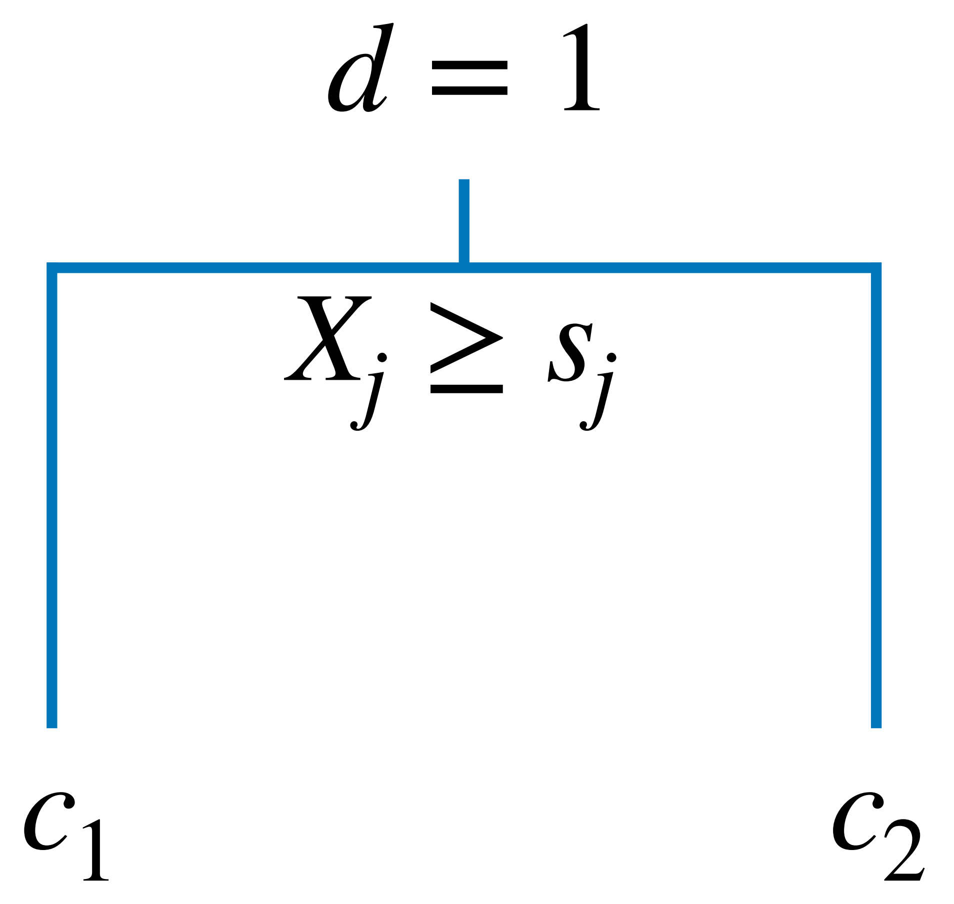
The coordinate functions can be easily plotted and interpreted.



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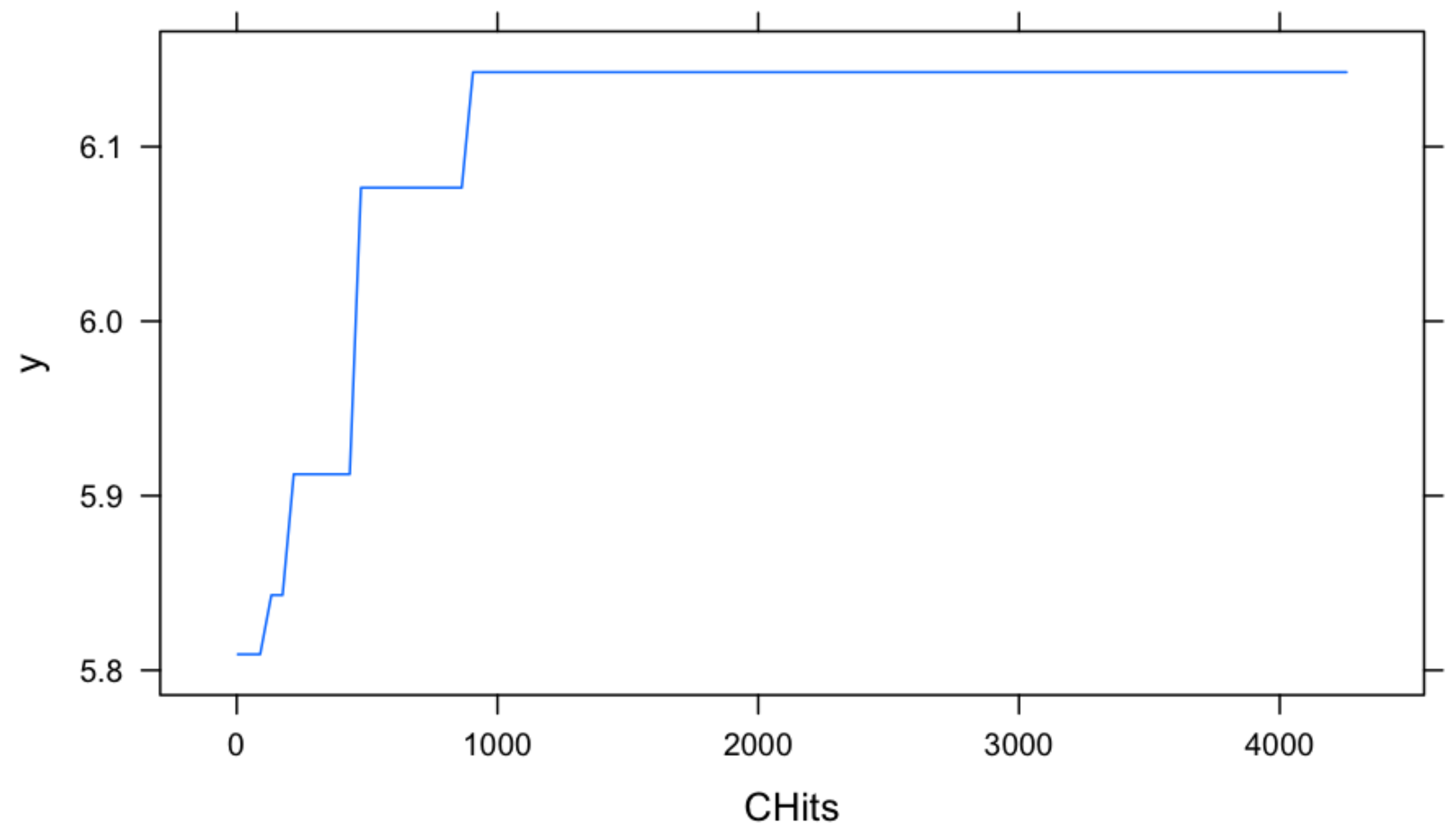

Derivation of coordinate functions

Get coordinate functions by grouping stumps splitting on the same variable:

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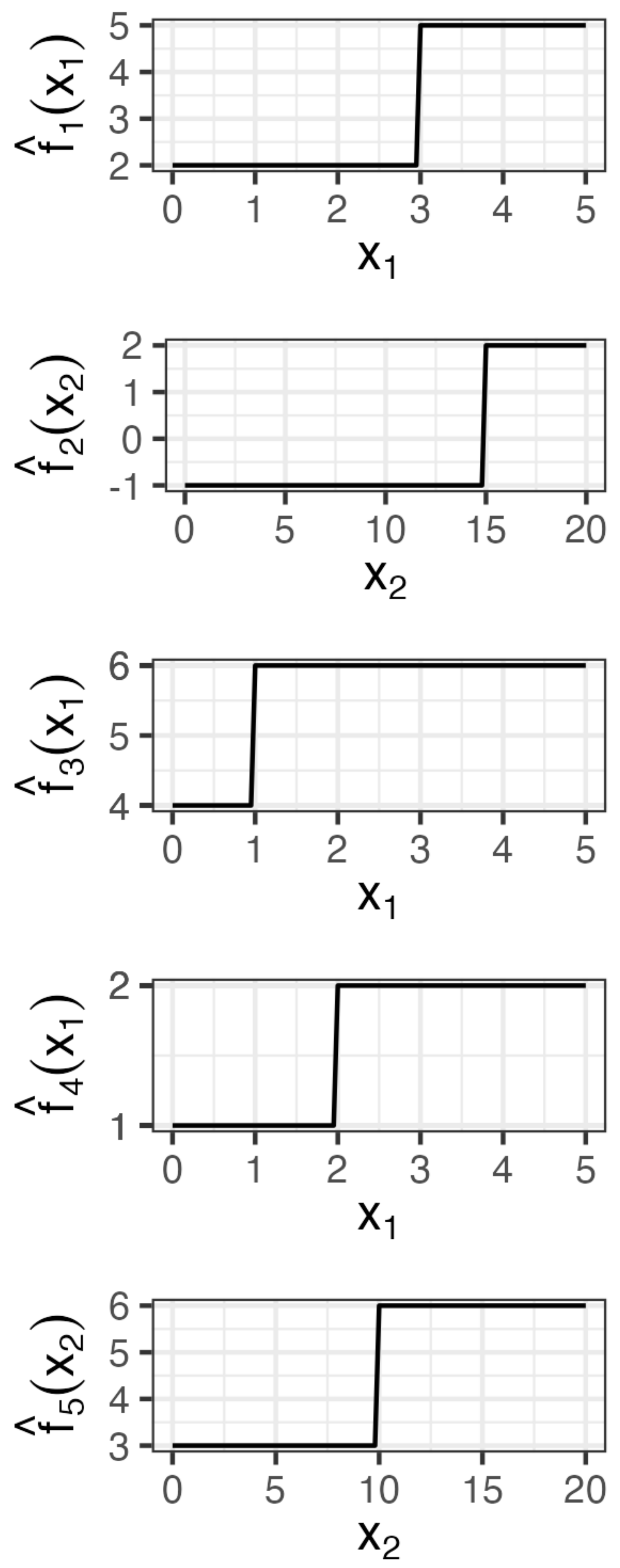

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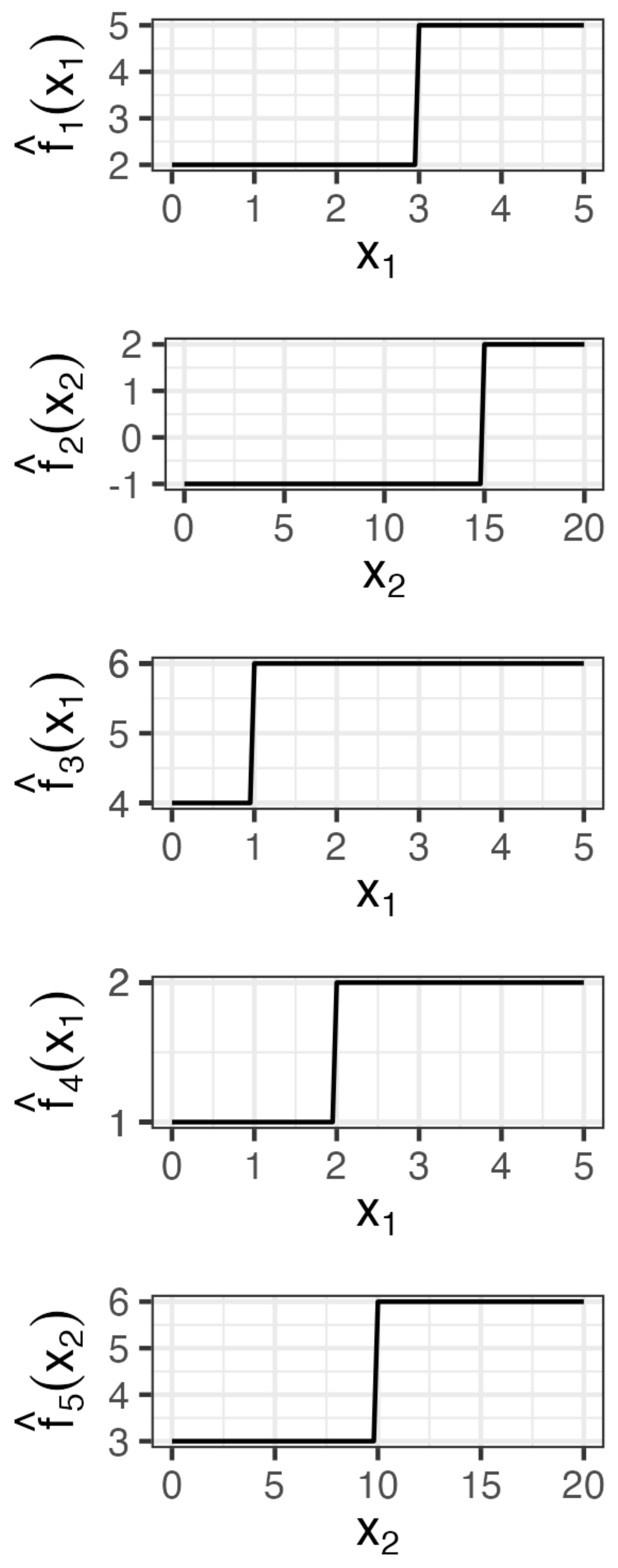

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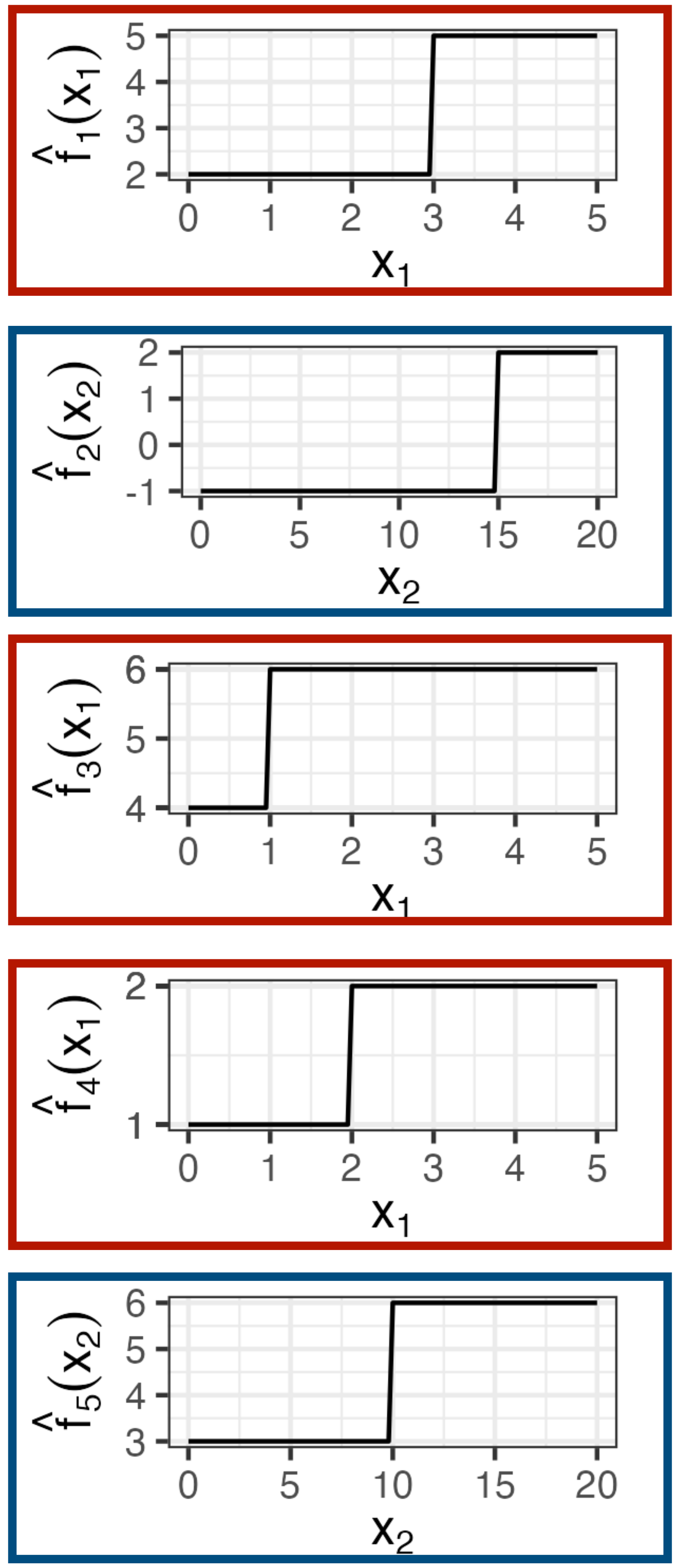

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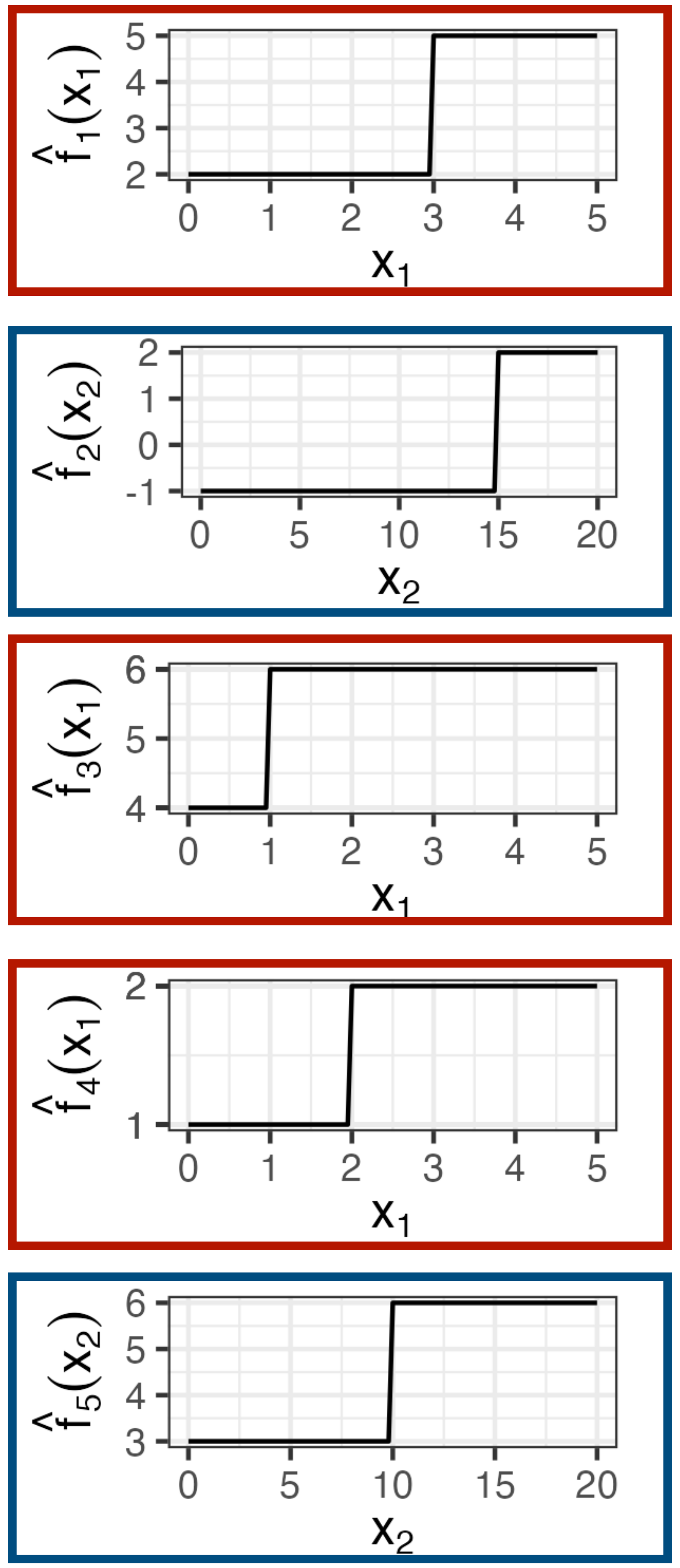

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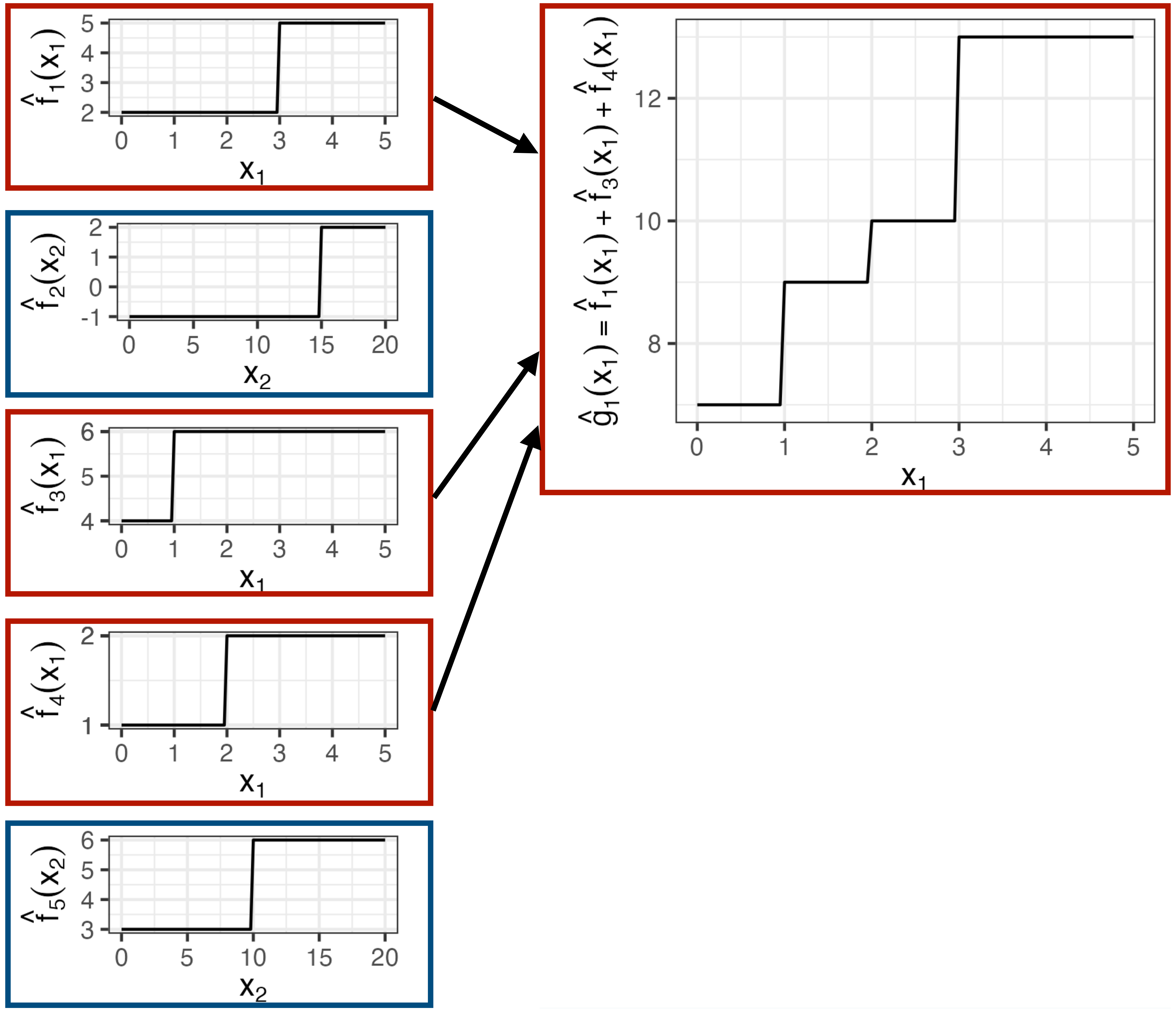

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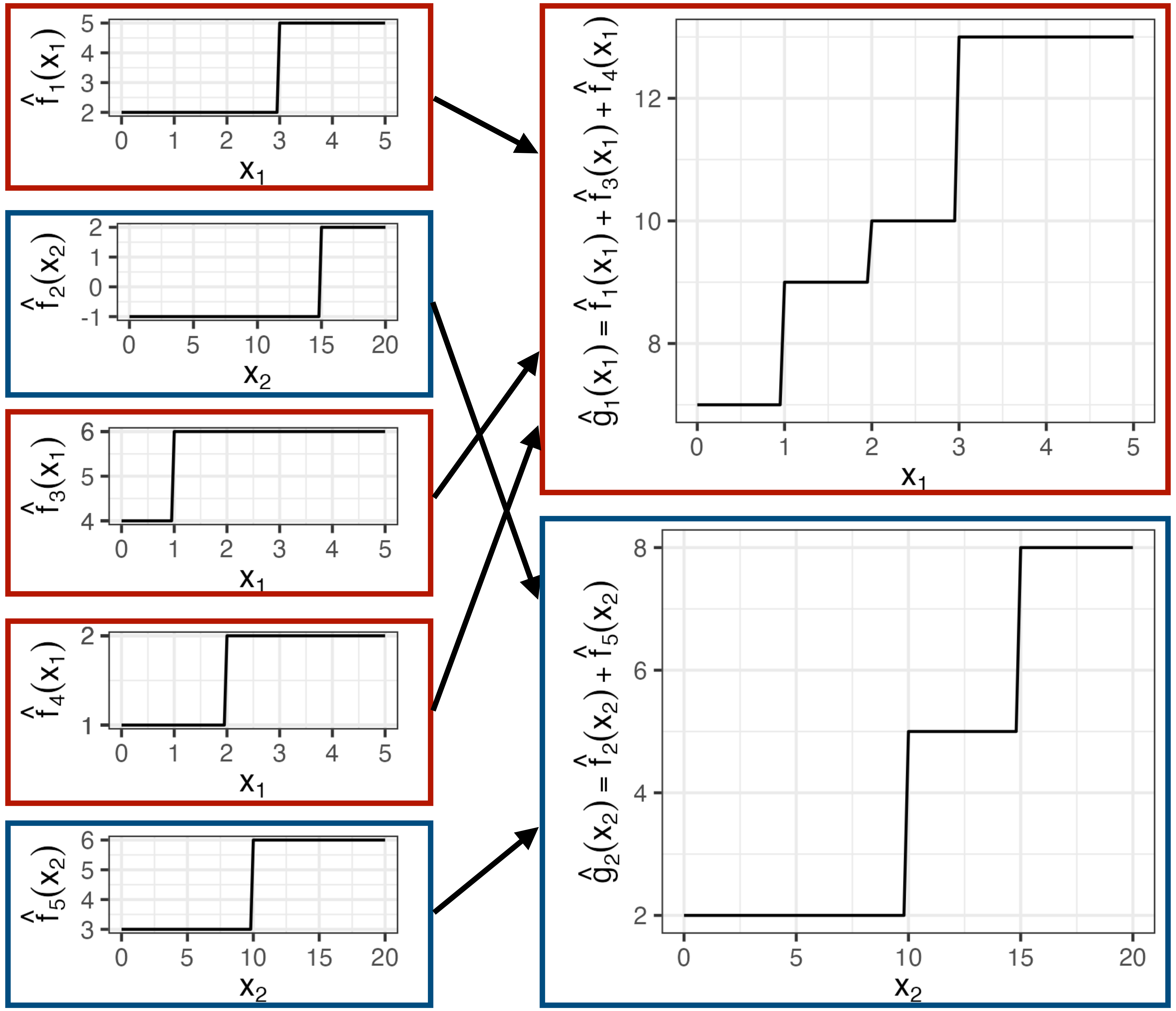

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A subsampling fraction of $\pi = 0.5$ tends to work well in most cases.

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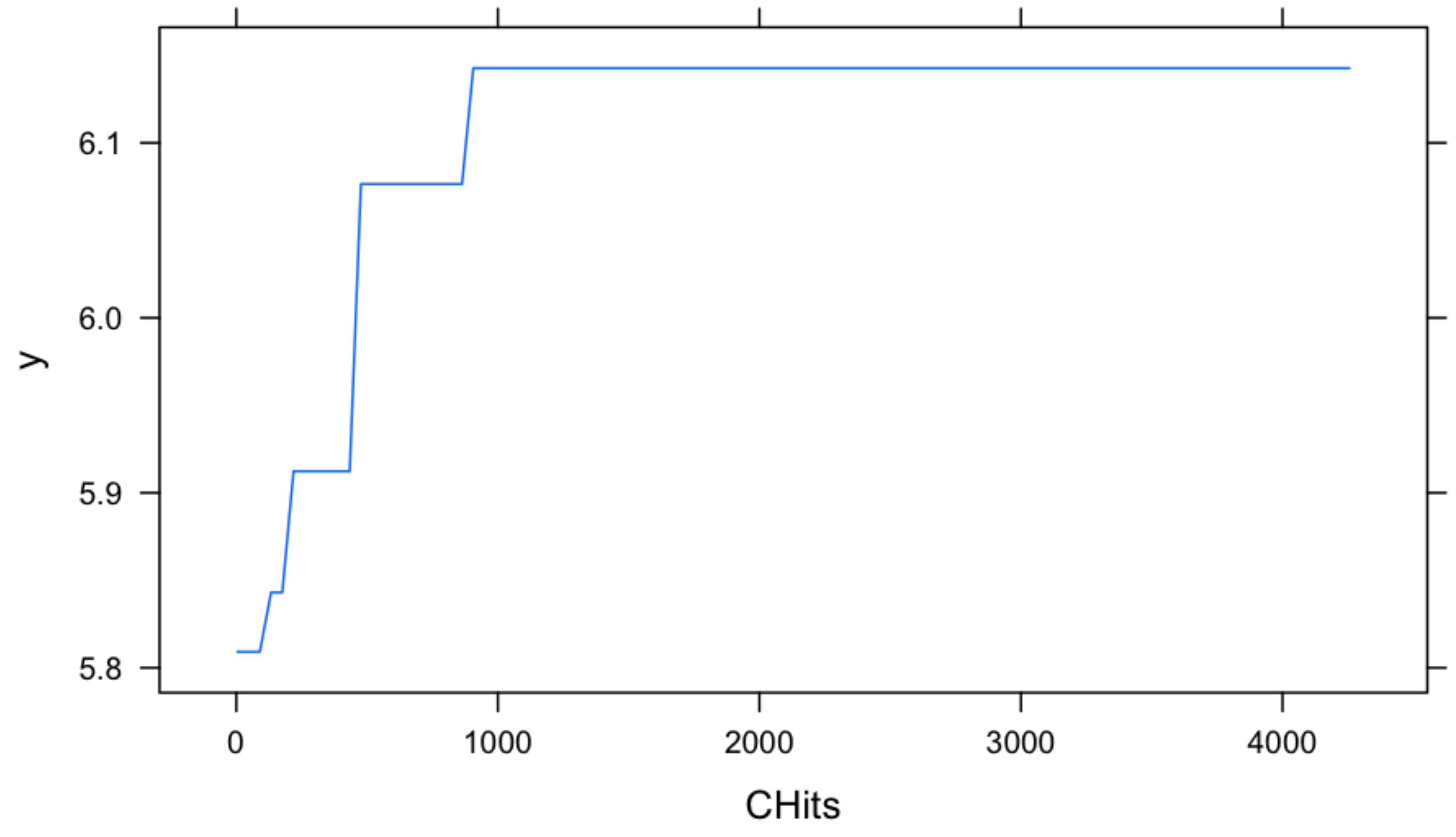

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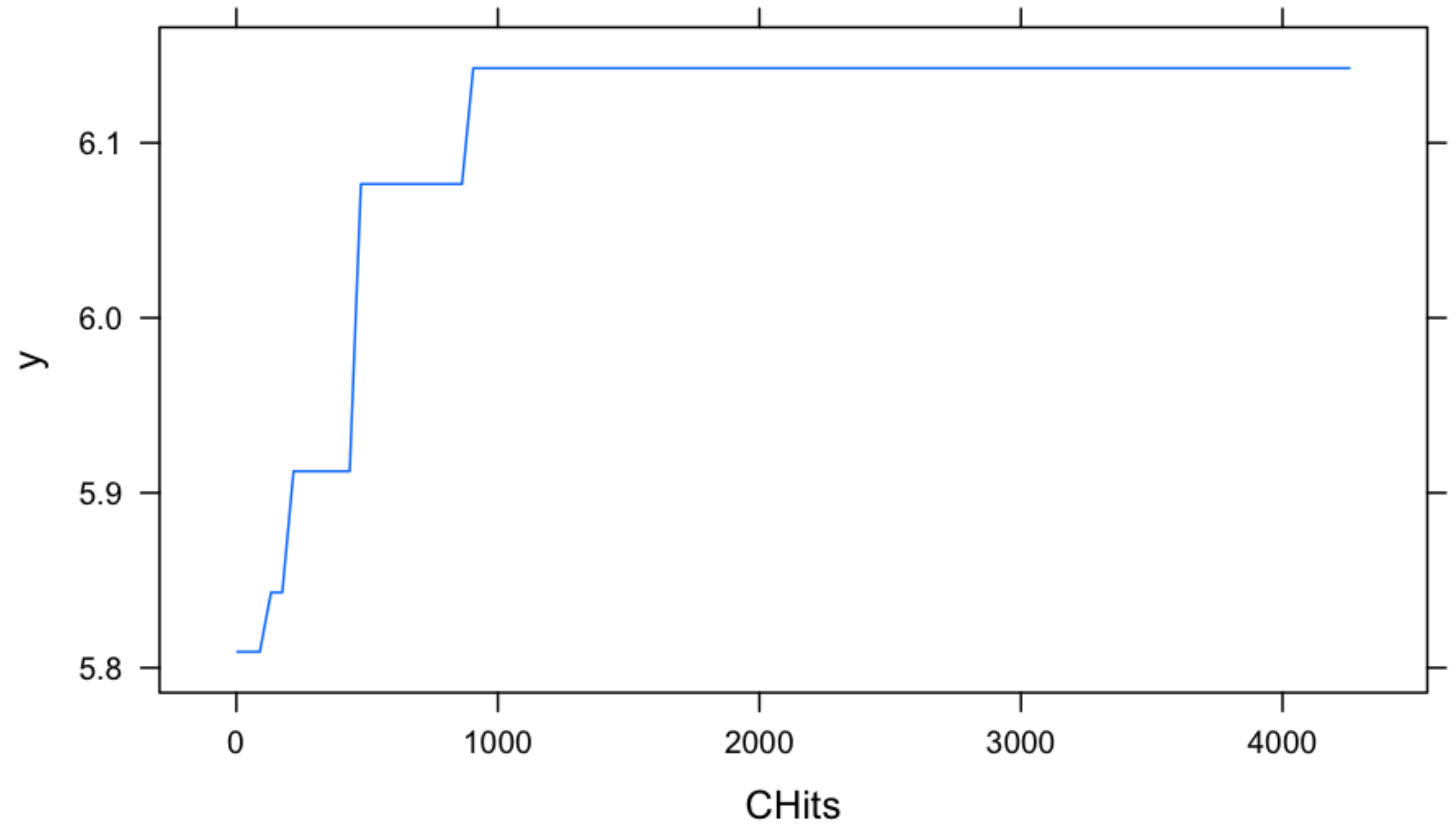

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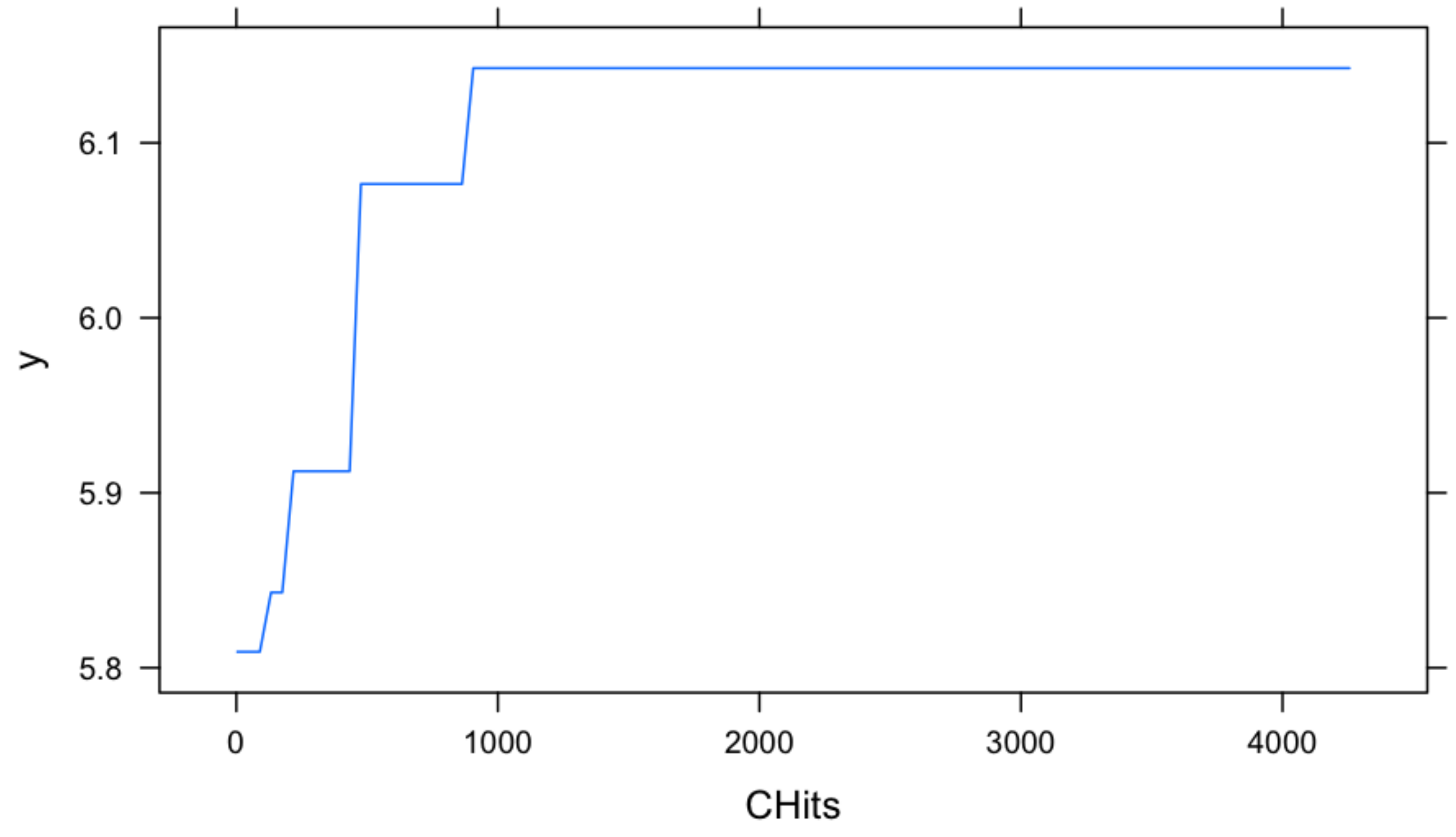
The larger d is, the worse the approximation.



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Implementation of boosting for classification is beyond the scope of the class, but the same intuitions from this lecture carry over to boosting for classification.

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- Unlike random forests, the number of trees B controls the complexity of the fit, and therefore must be tuned via cross-validation.
- Purity-based variable importance as well as partial dependence plots help interpret boosting models.