

BIAS VARIANCE BOOTSTRAPPING AND BOOSTING

MOD1: INTUITIVE INTERPRETATION OF *H* FAMILY AND RISK

ERROR/RISK IN FUNCTIONAL SPACE

\mathcal{X}, \mathcal{Y}

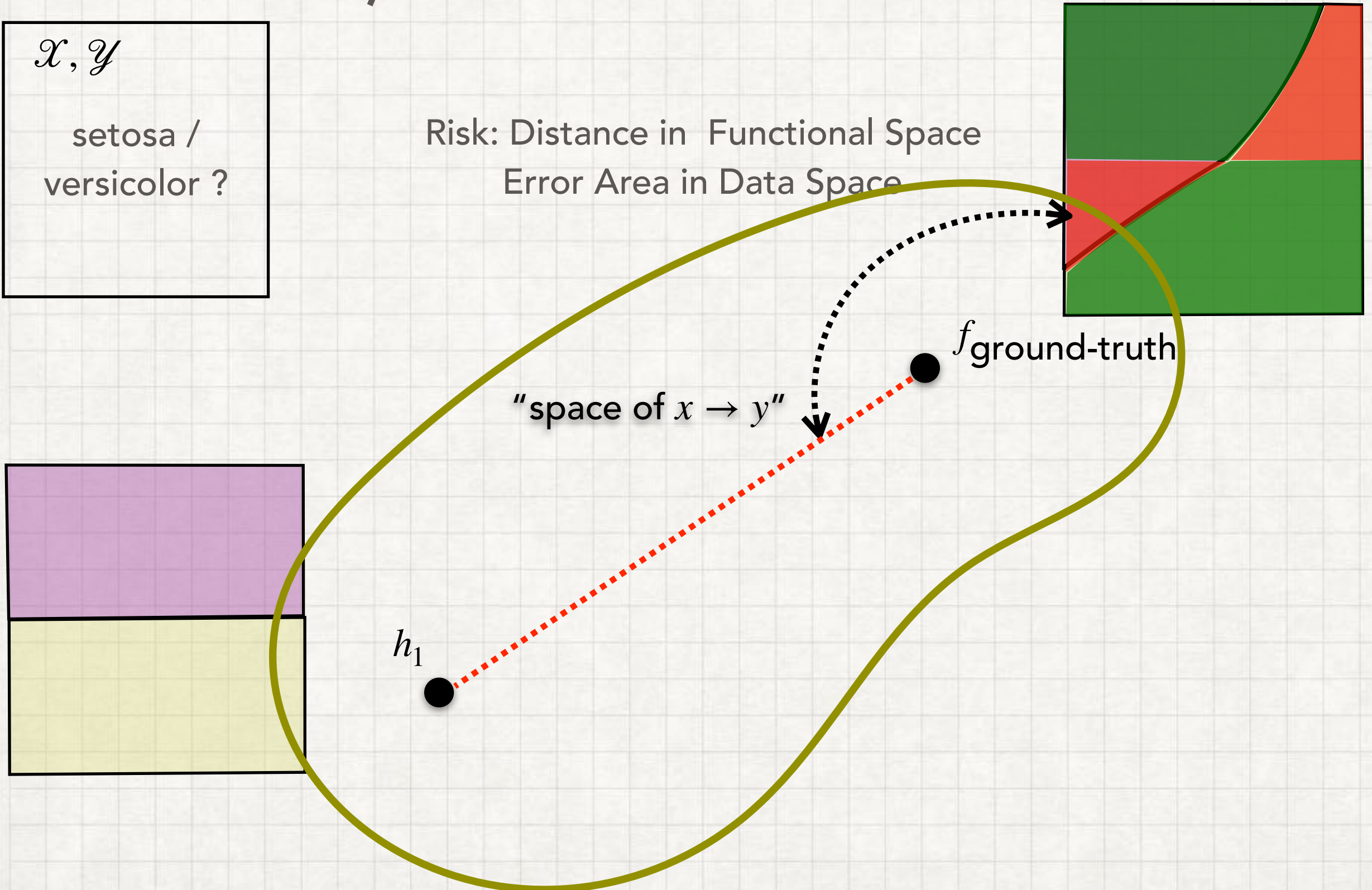
setosa /
versicolor ?

Risk: Distance in Functional Space
Error Area in Data Space

"space of $x \rightarrow y$ "

$f_{\text{ground-truth}}$

h_1



ERROR/RISKS OF TWO HYPOTHESES

\mathcal{X}, \mathcal{Y}

setosa /
versicolor ?

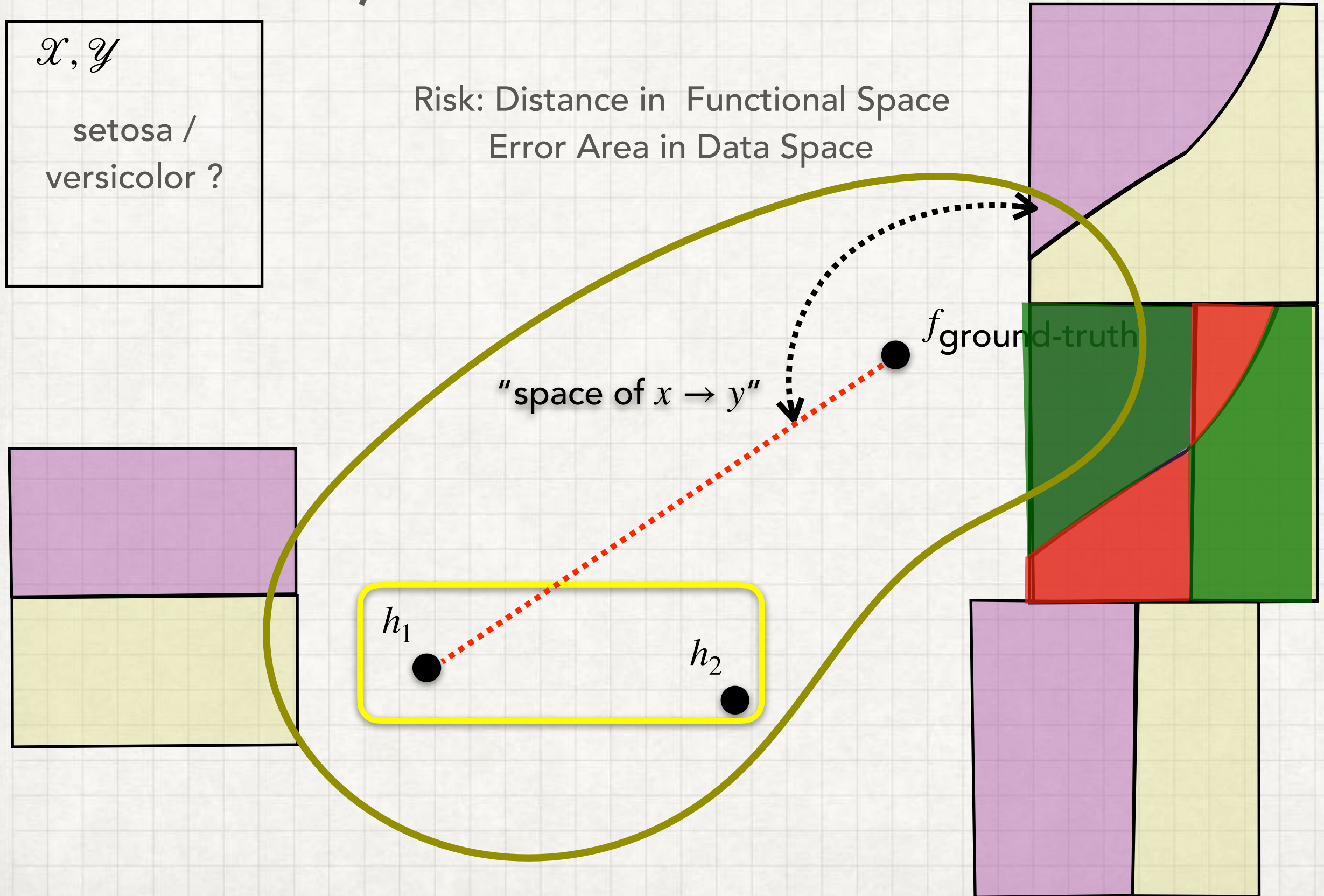
Risk: Distance in Functional Space
Error Area in Data Space

"space of $x \rightarrow y$ "

$f_{\text{ground-truth}}$

h_1

h_2

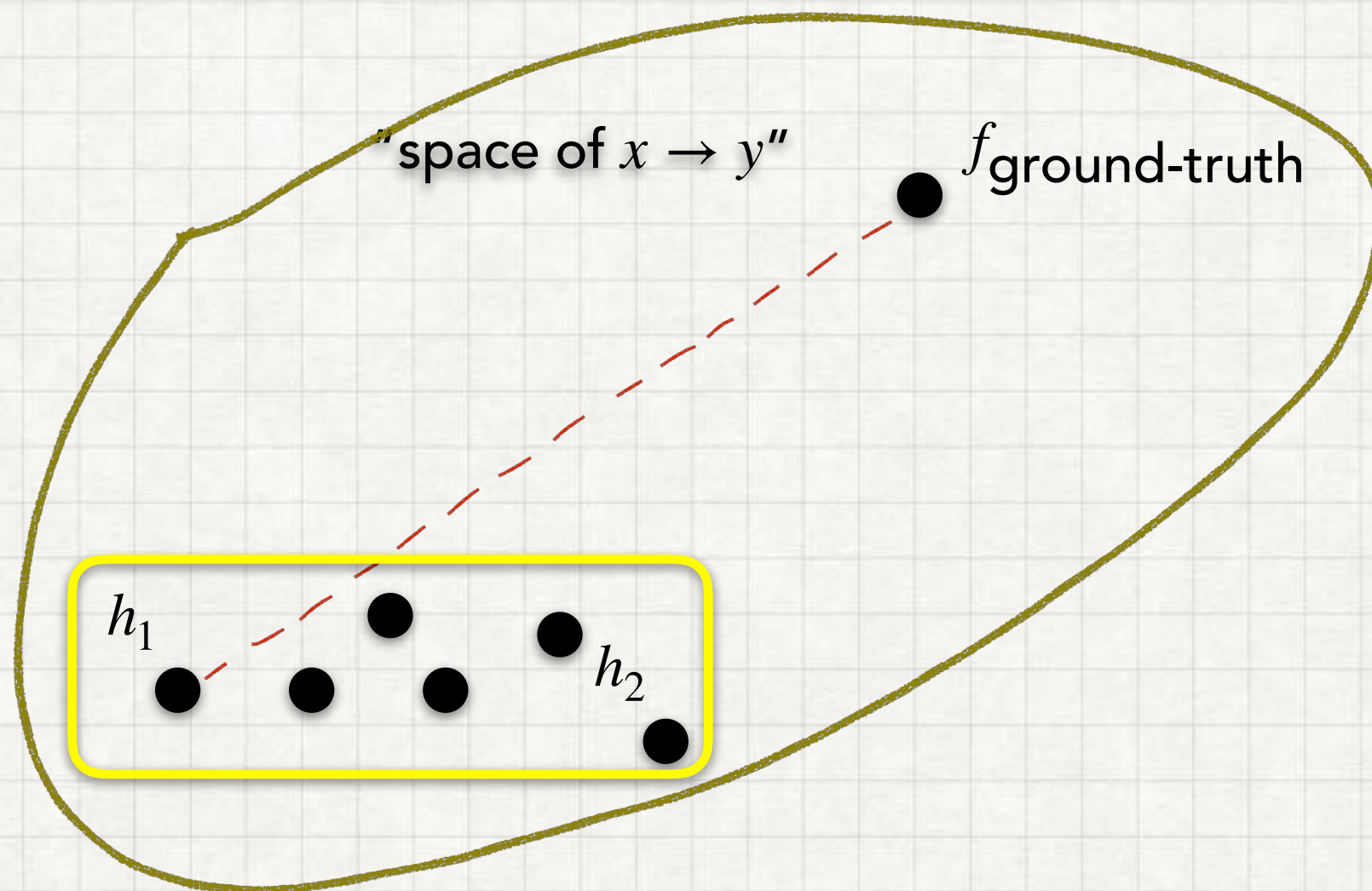


ERROR/RISKS OF MANY HYPOTHESES

x, y

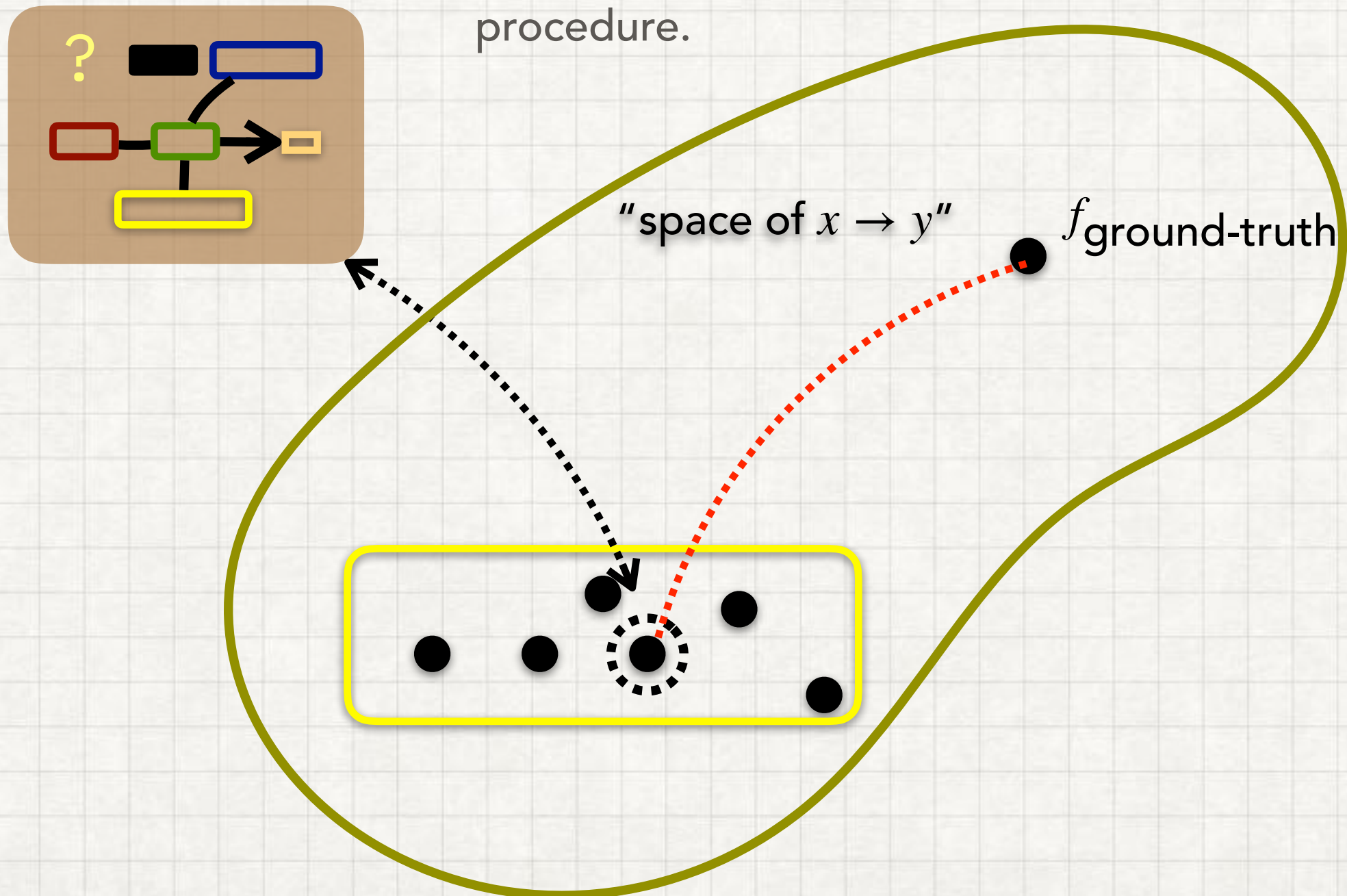
Risk: Distance in Functional Space

Error Area in Data Space

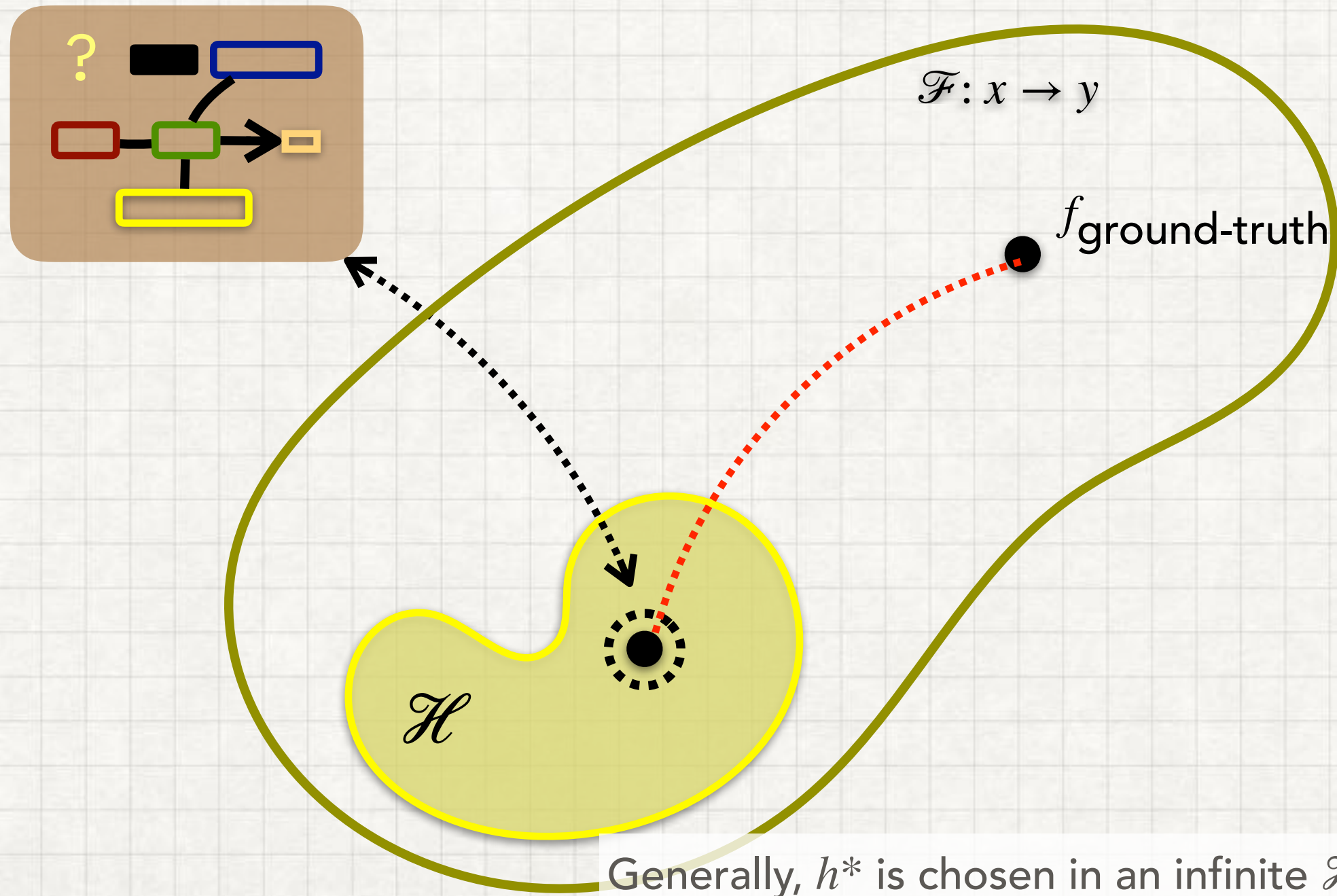


ERROR/RISKS OF **SELECTED** HYPOTHESES FROM MANY

The learning problem is concerned with the hypothesis selected by the learning procedure.

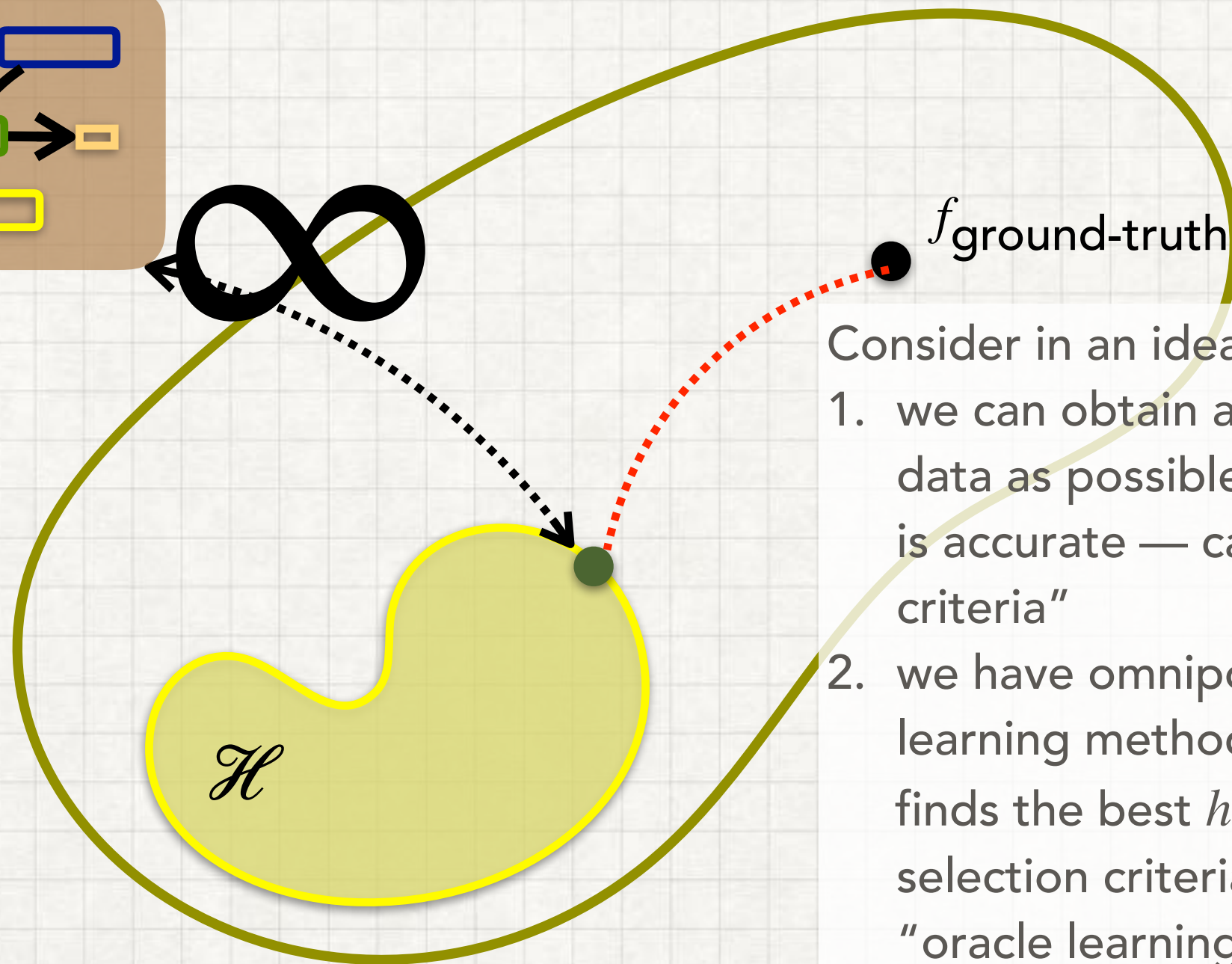
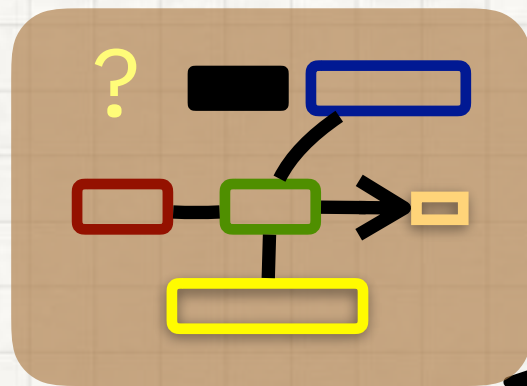


ERROR/RISKS OF SELECTED HYPOTHESIS FROM \mathcal{H}



MOD2: DISCRIMINATE TWO TYPES OF RISKS WHEN FACING RANDOM DATA BIAS AND VARIANCE

OPTIMUM WITHIN \mathcal{H}

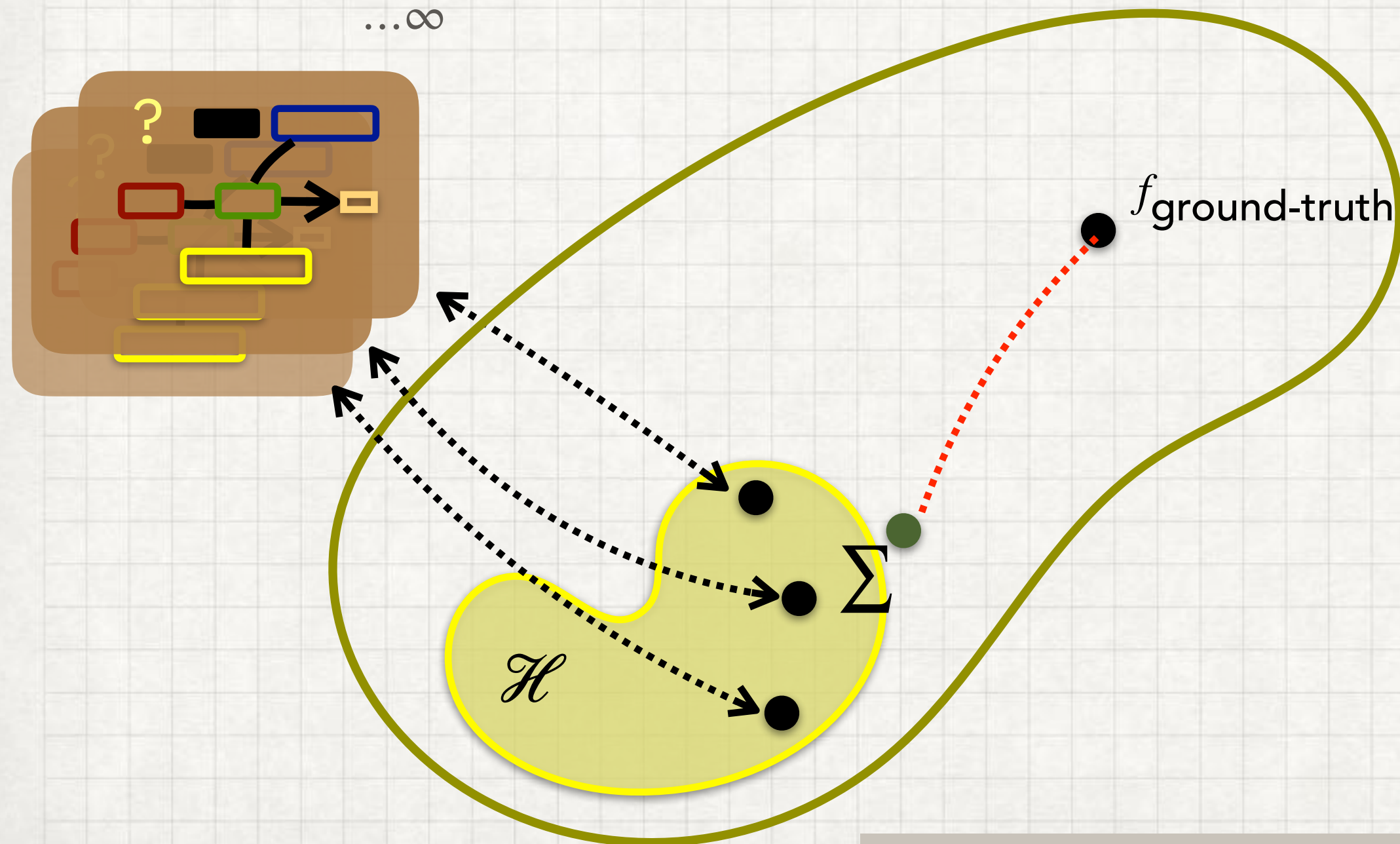


Consider in an ideal world,

1. we can obtain as many training data as possible — the evaluation is accurate — call this "oracle criteria"
2. we have omnipotently powerful learning method, which always finds the best $h^* \in \mathcal{H}$ for any selection criteria — call this "oracle learning algorithm"

Putting together, we then consider the minimal risk of an \mathcal{H} .

NOT INFINITE DATA, BUT INFINITE LEARNING EXPERIMENTS AND AVERAGING

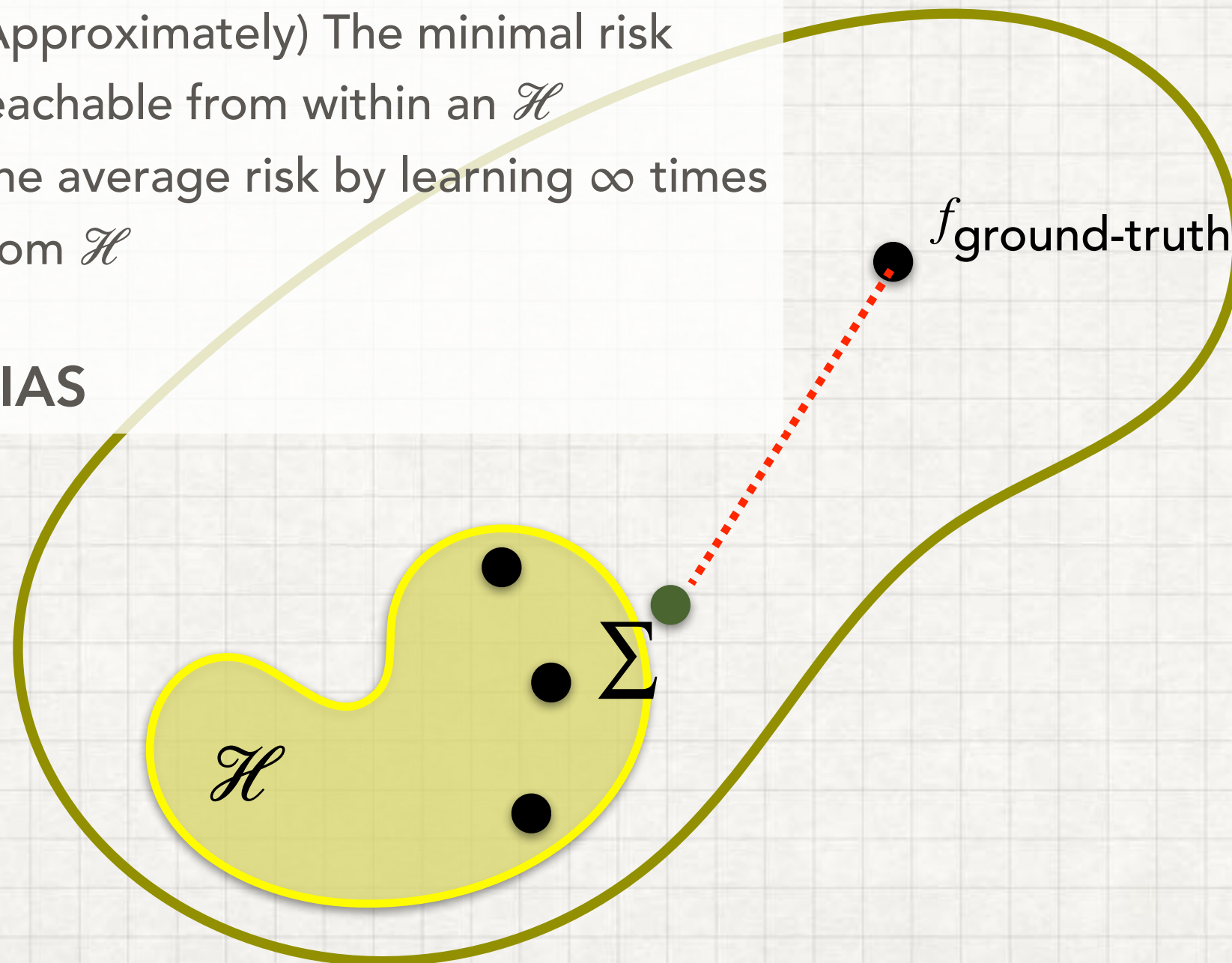


The average predictor is not always within the original \mathcal{H}

DEFINITION OF BIAS

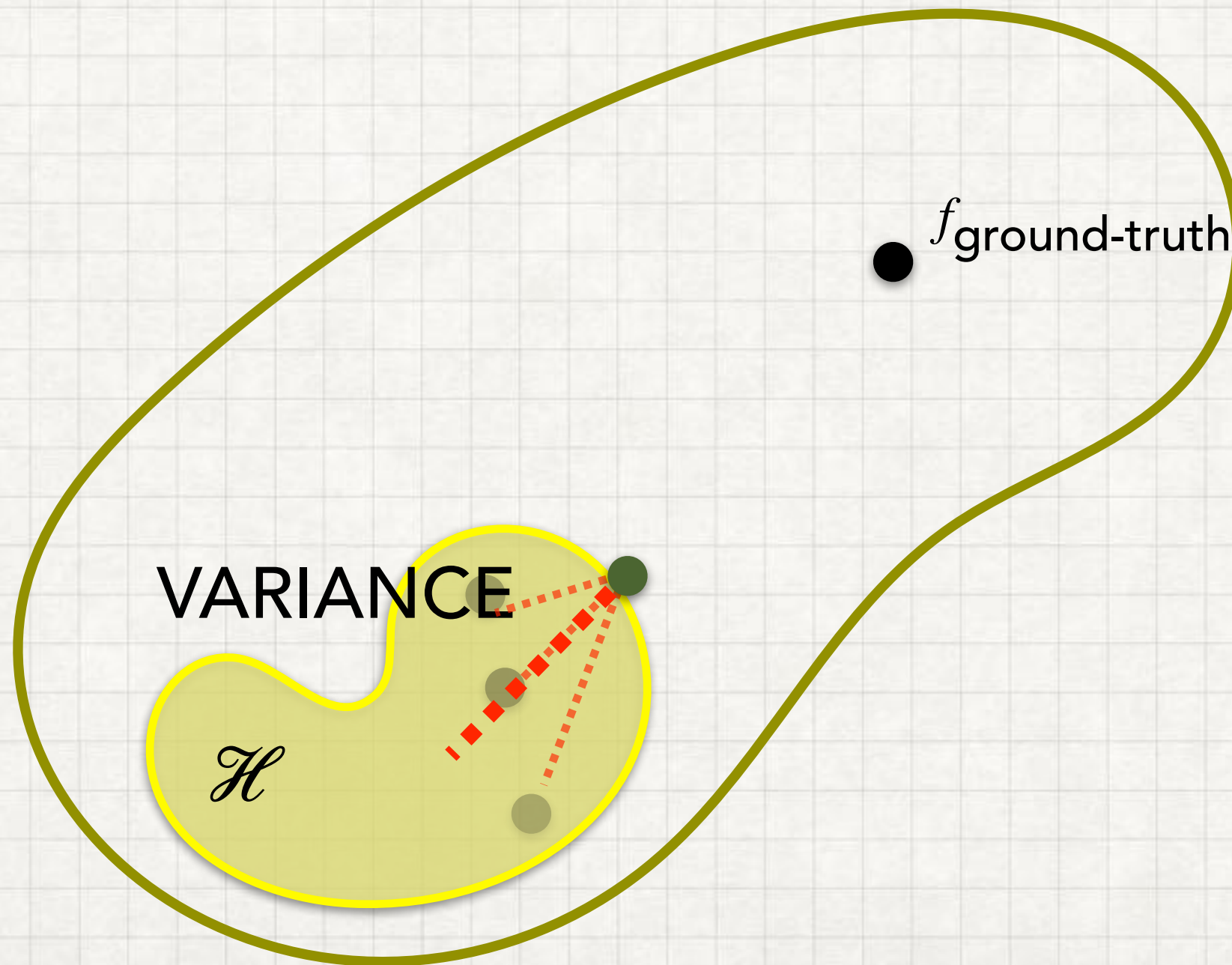
(Approximately) The minimal risk
reachable from within an \mathcal{H}
The average risk by learning ∞ times
from \mathcal{H}

∞ BIAS



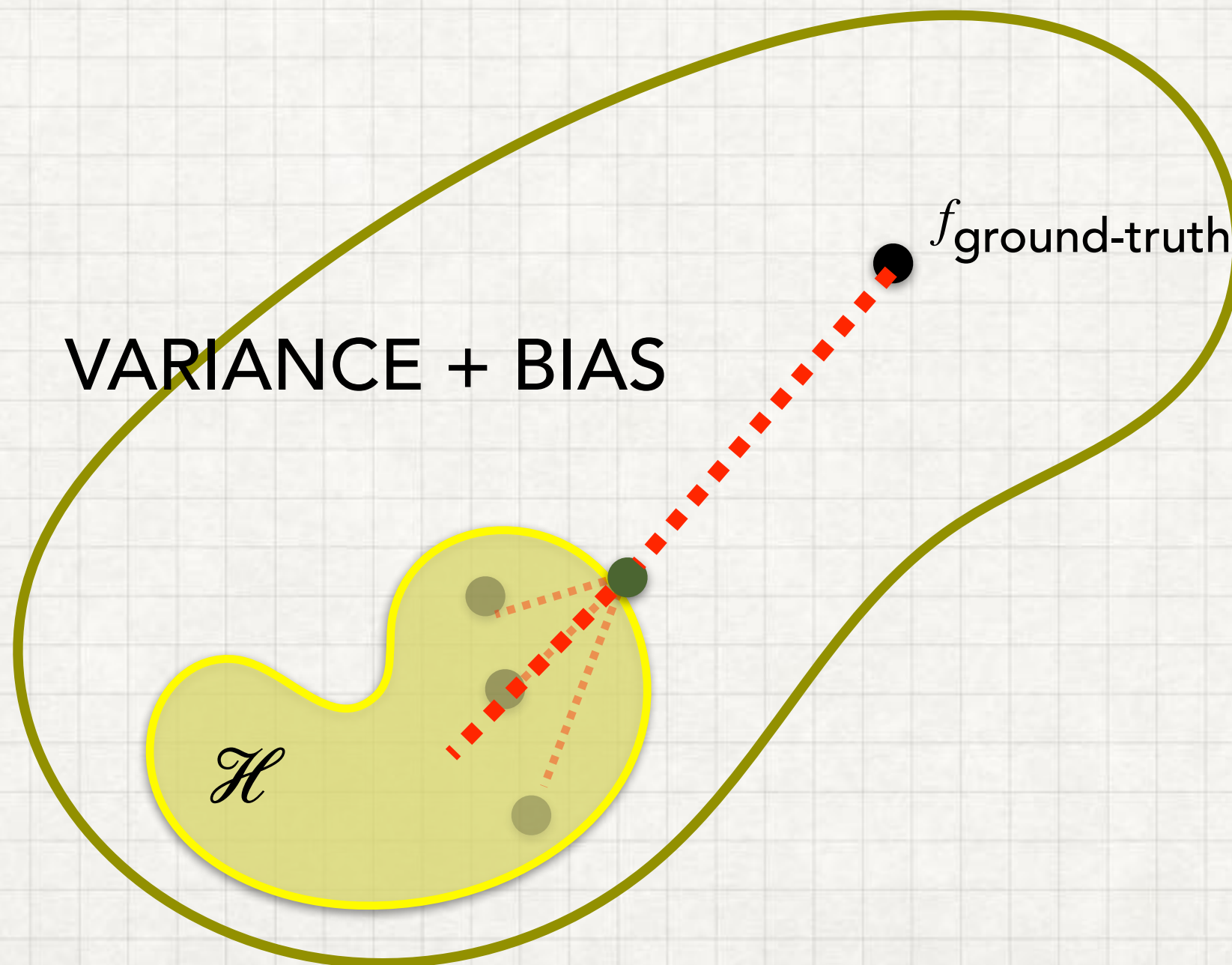
RISK OF TRAINING WITH ONE, RANDOM

D_{train}



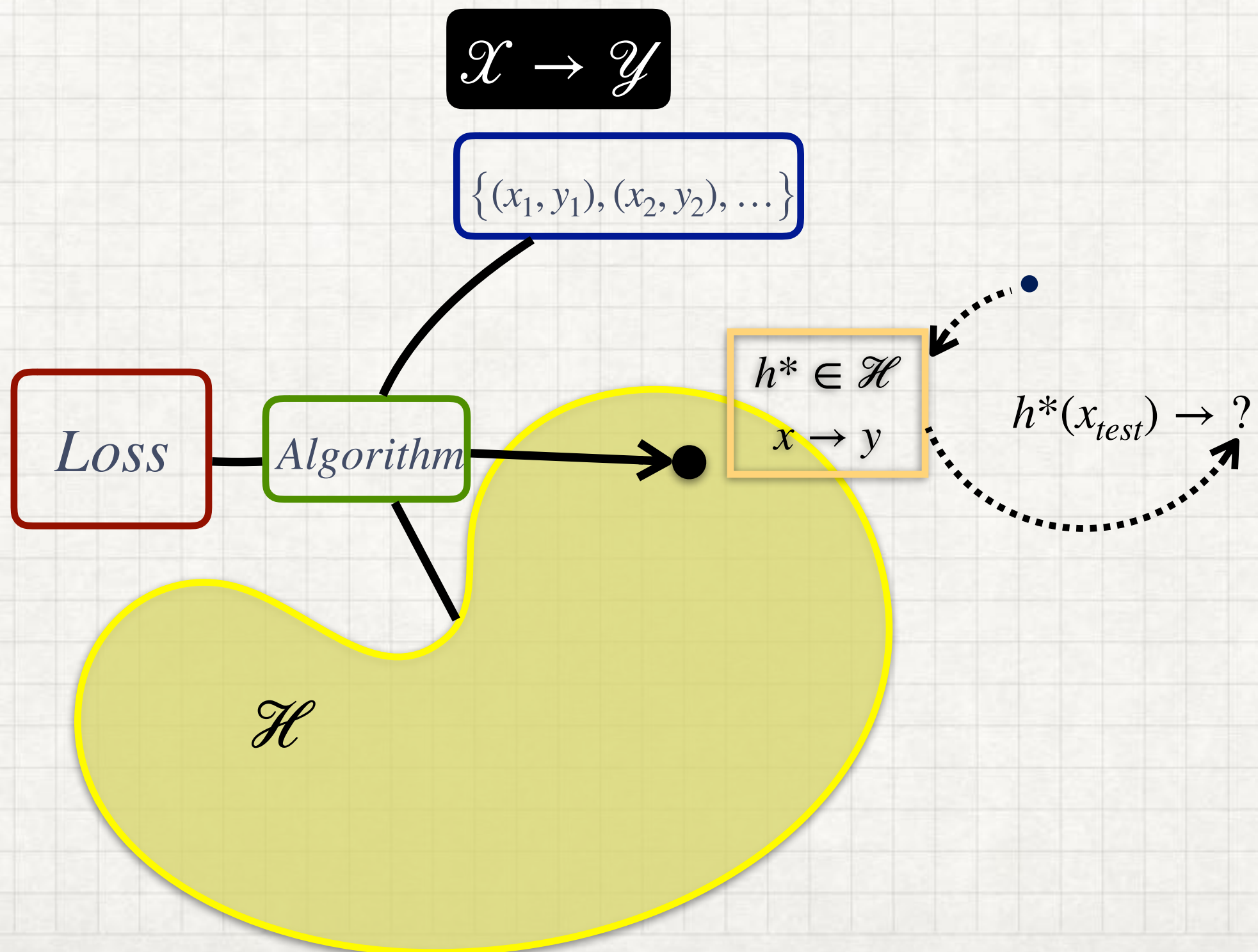
TOTAL RISK OF A TRAINING

- The expected risk of the hypothesis selected by the learning framework consists of the following two parts.



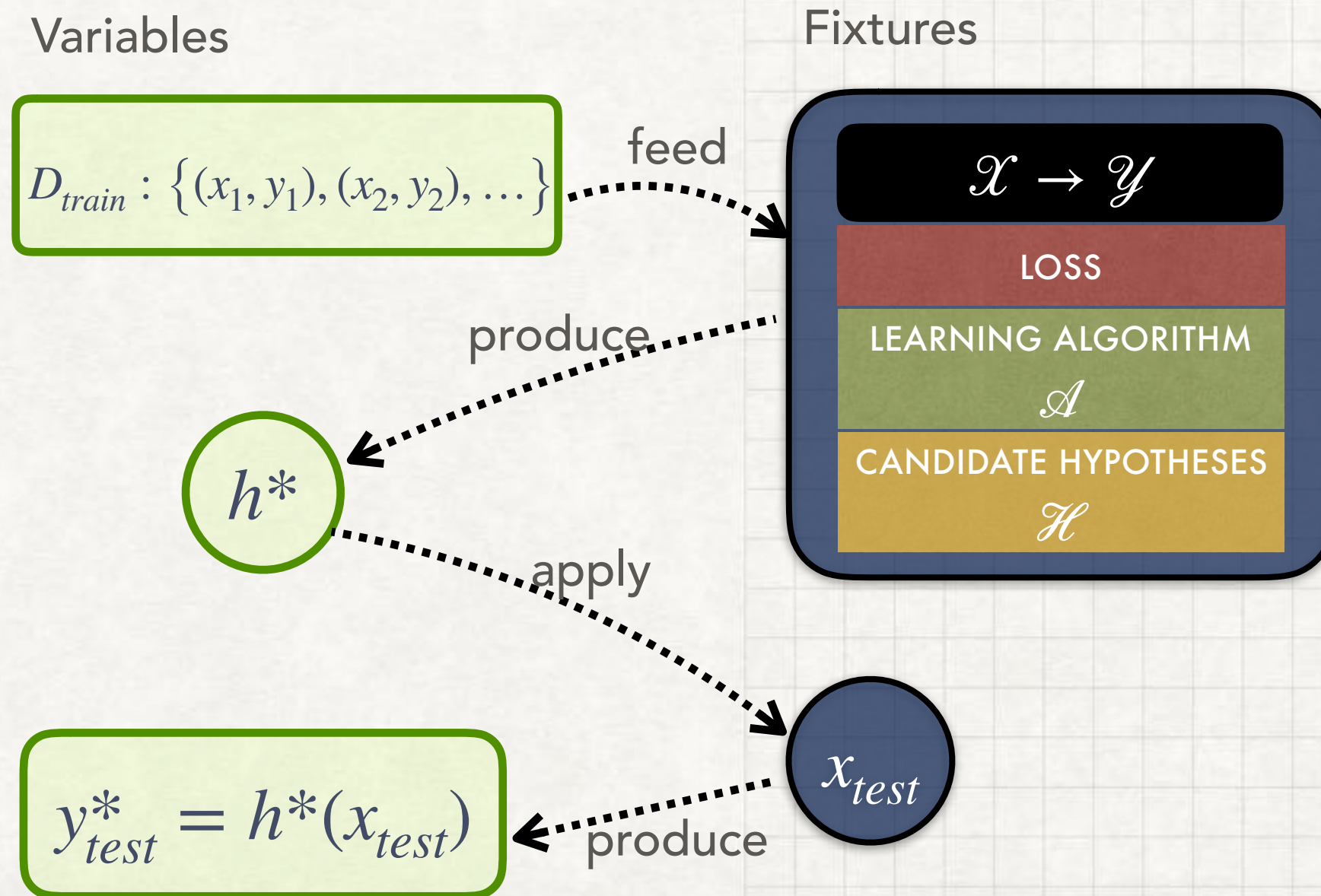
SUMMARISE: RANDOMISATION OF THE PREDICTION

- “Microscope of risk”, consider the generalisation error at one x_{test} .



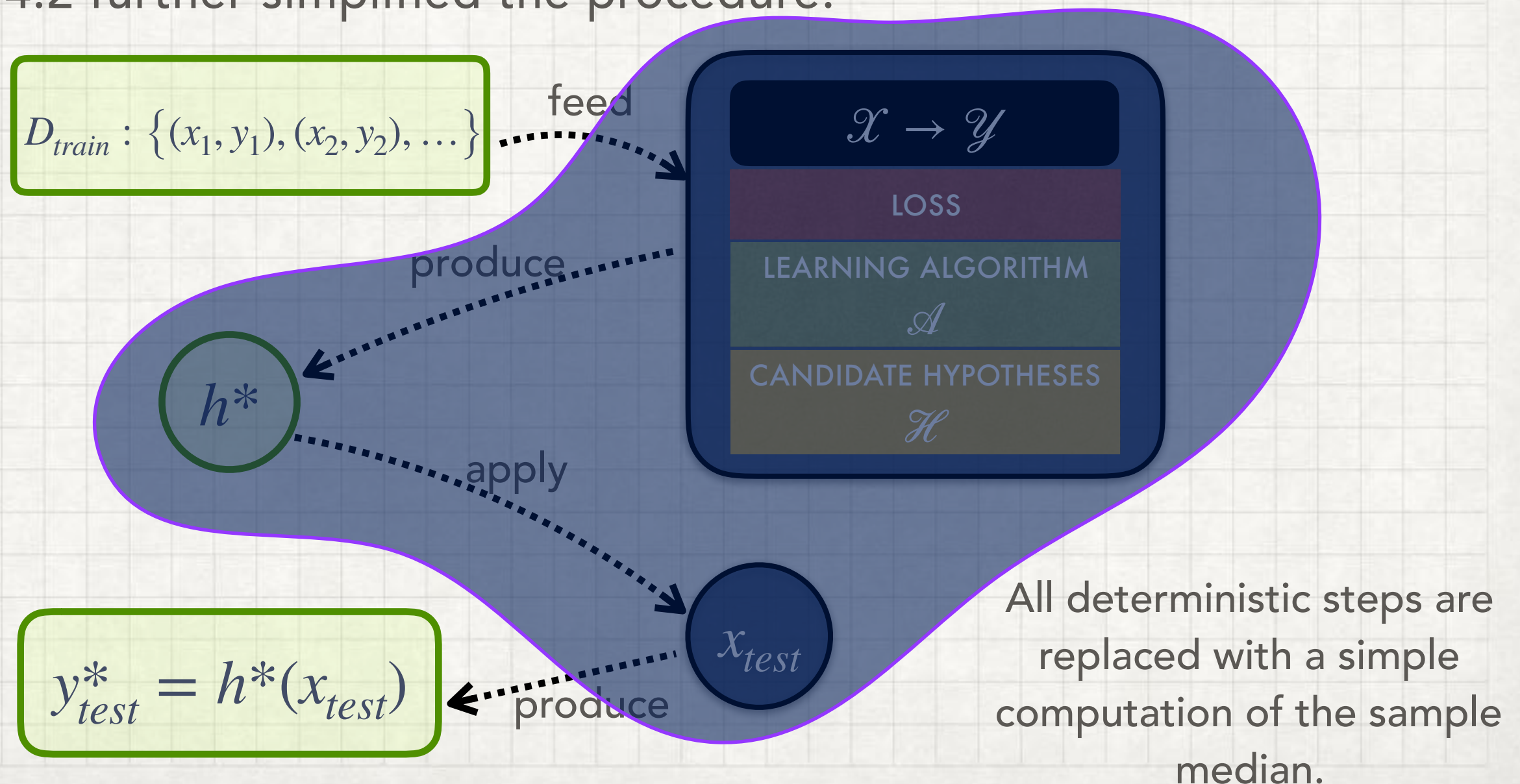
RANDOMISATION ANALYSIS

- The only factor that is inevitably random is the data sample D_{train} , so the final result of the following flow is random.



NOTEBOOK STUDY

- 4.2 and 4.3, Skip the “bootstrapping” parts (the notebook contains Python implementation, which must respect the structure of the contents, rather than the progress of ideas.)
- 4.2 further simplified the procedure:

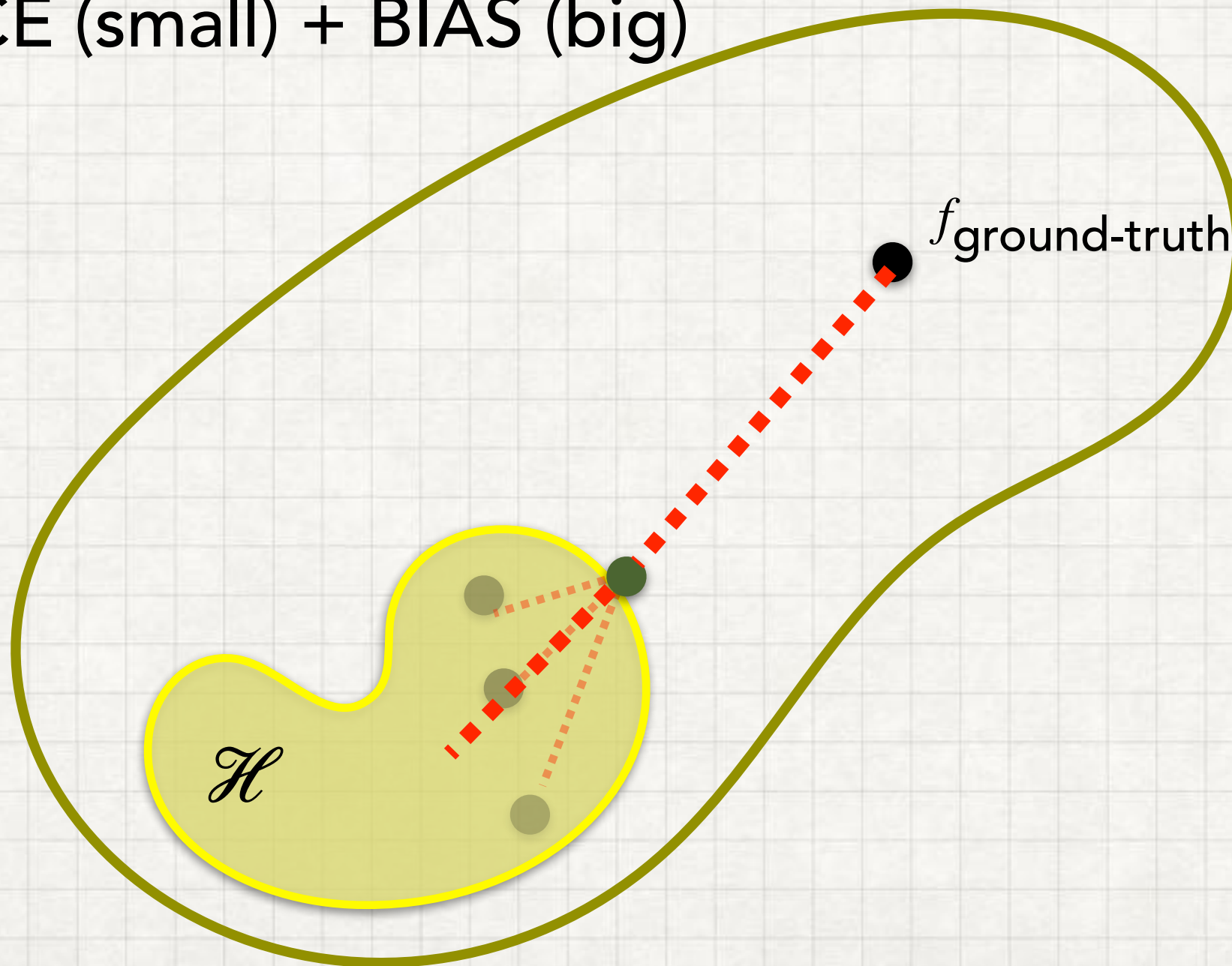


NOTEBOOK STUDY

- 4.2 and 4.3, Skip the “bootstrapping” parts (the notebook contains Python implementation, which must respect the structure of the contents, rather than the progress of ideas.)
 - 4.2 simplify -> median computation.
 - 4.3 Experiment with the first Exercise in “Bias and Variance Explained”.

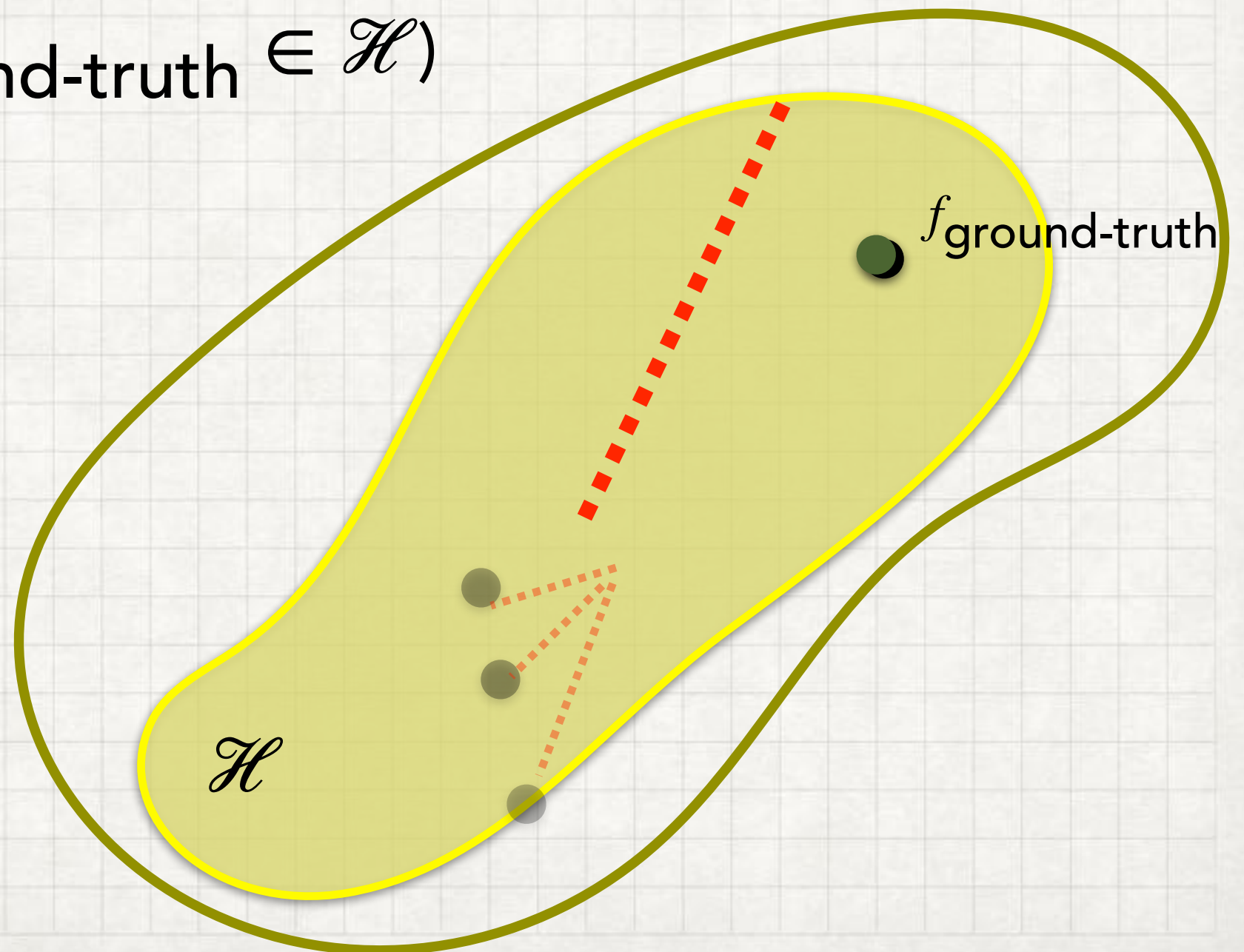
TOTAL RISK OF A TRAINING SMALL \mathcal{H}

VARIANCE (small) + BIAS (big)



TOTAL RISK OF A TRAINING BIG \mathcal{H}

VARIANCE (big) + BIAS (small/zero —
when $f_{\text{ground-truth}} \in \mathcal{H}$)



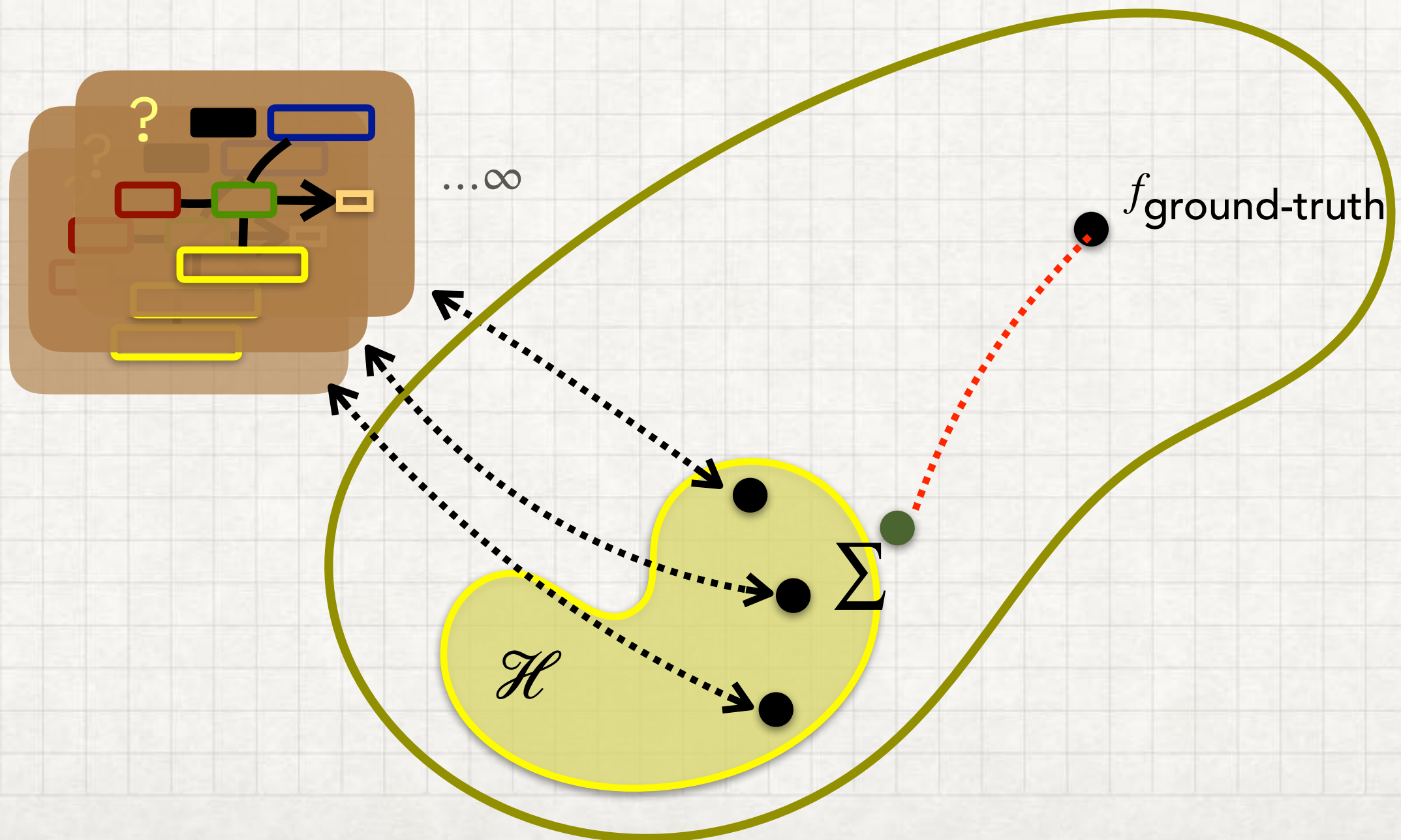
MOD3: ASSESSING AND
ADDRESSING VARIANCE
USING A SINGLE D_{train}

REVIEW: BOOTSTRAP / BAGGING

- IN: Data D_{train} , Model Family and Learning Method
- Repeat \$bootstrap-number times: do
 - Re-sample D_{train} with replacement, get $D_{bootstrap,i}$
 - Train model, get h_i^B
- Prediction: Aggregate $h_i^B(x_{test})$'s

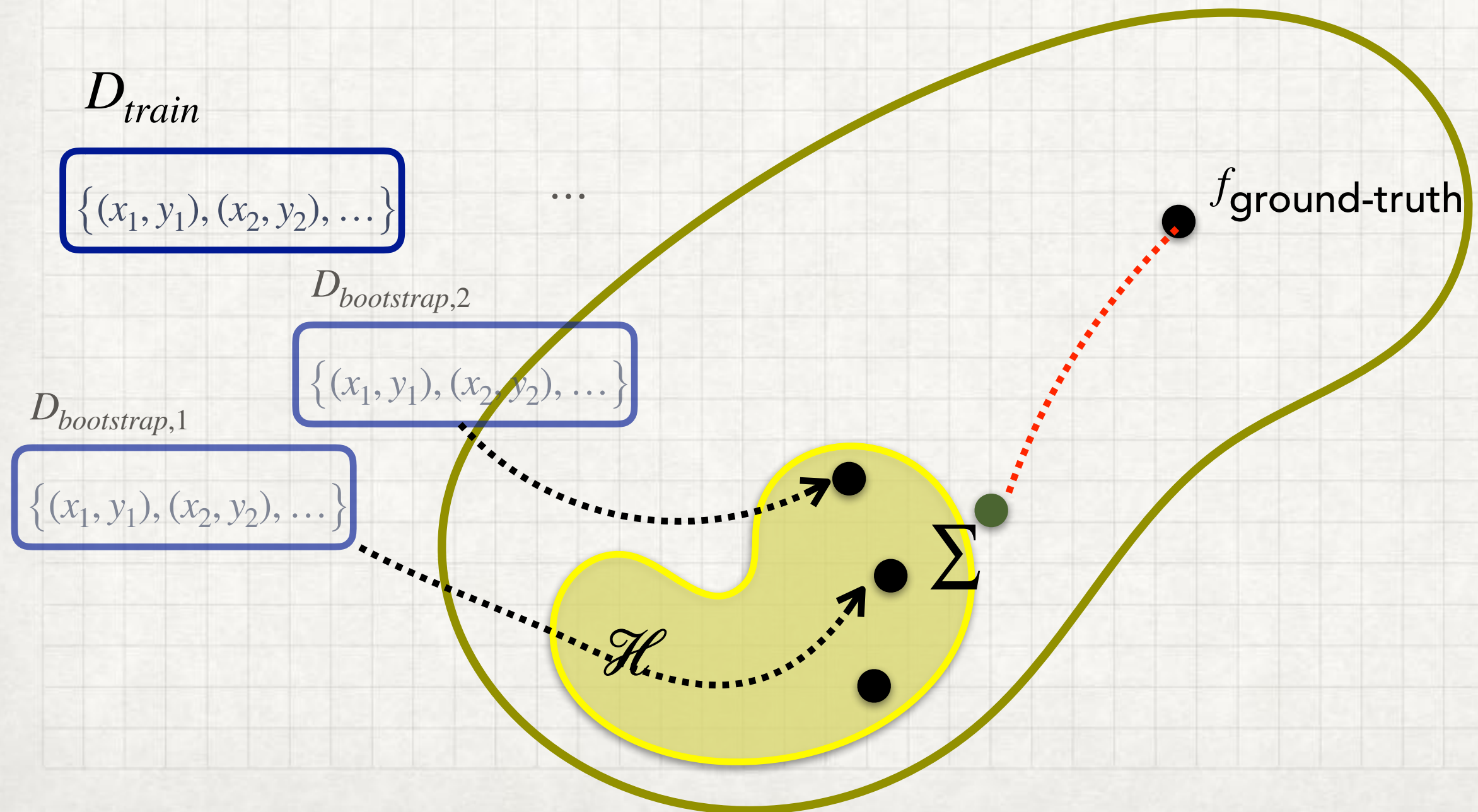
BAGGING IS AN **ATTEMPT** TO ACHIEVE "INFINITE" MODEL AVERAGING

- The bootstrap samples are used to assess statistical information and reduce the variance due to the randomisation of D_{train}



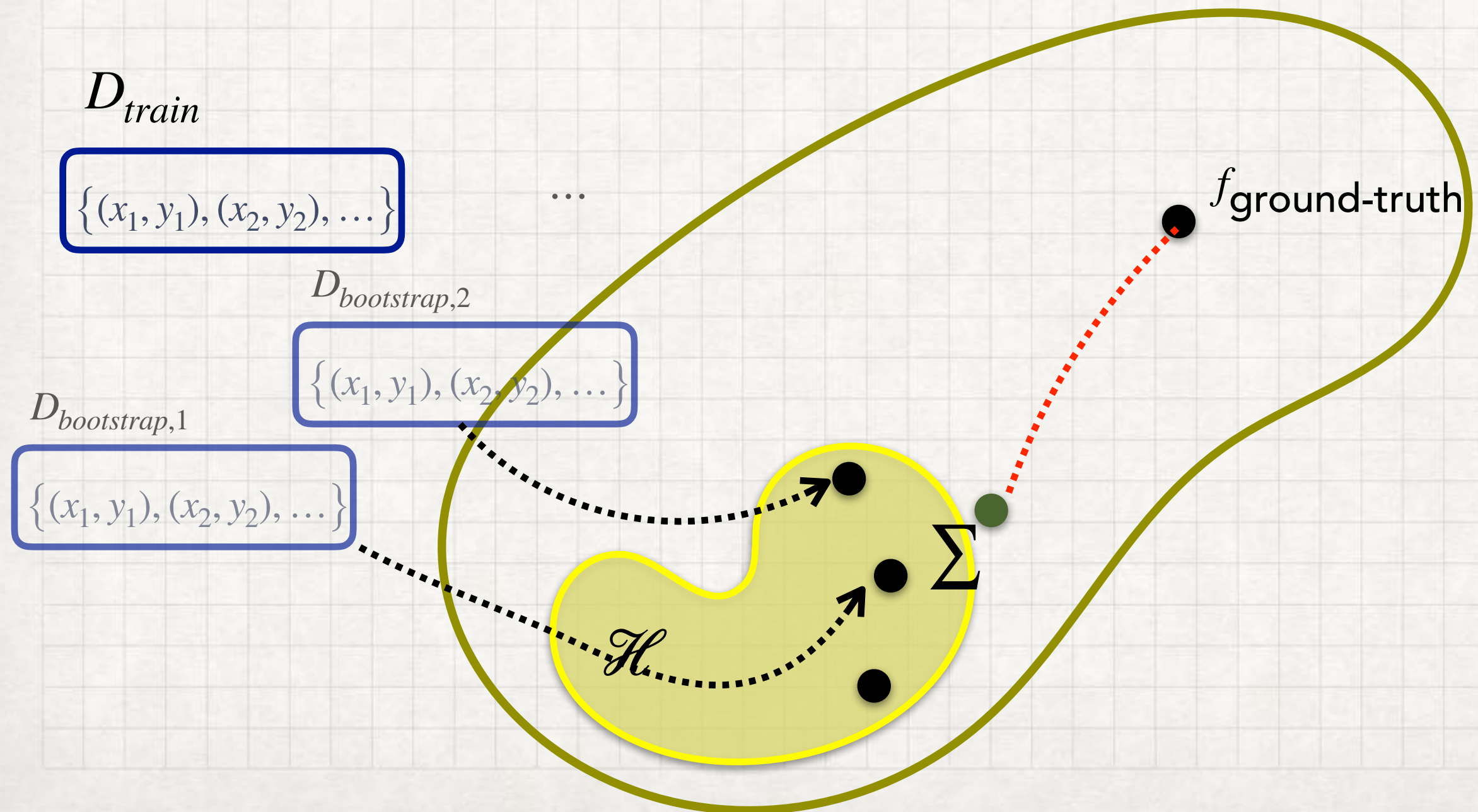
BOOTSTRAP SAMPLES

- The bootstrap samples are used to assess statistical information and reduce the variance due to the randomisation of D_{train}



BOOTSTRAP: FREE LUNCH?

- Bootstrap cannot change the bias. But it can reduce variance given right settings at the cost of computation.



NOTEBOOK STUDY

- 4.2 "bootstrap" parts
 - What is bootstrap samples.
 - Experiment and contemplate: For the estimation of median from samples, how bootstrap (resampling) helps reduce variance.
- 4.3 Observe Bias and Variance in sample model (if not done in the previous notebook study).
- 4.4 Bootstrap helps reduce variance in some settings.

THANKS