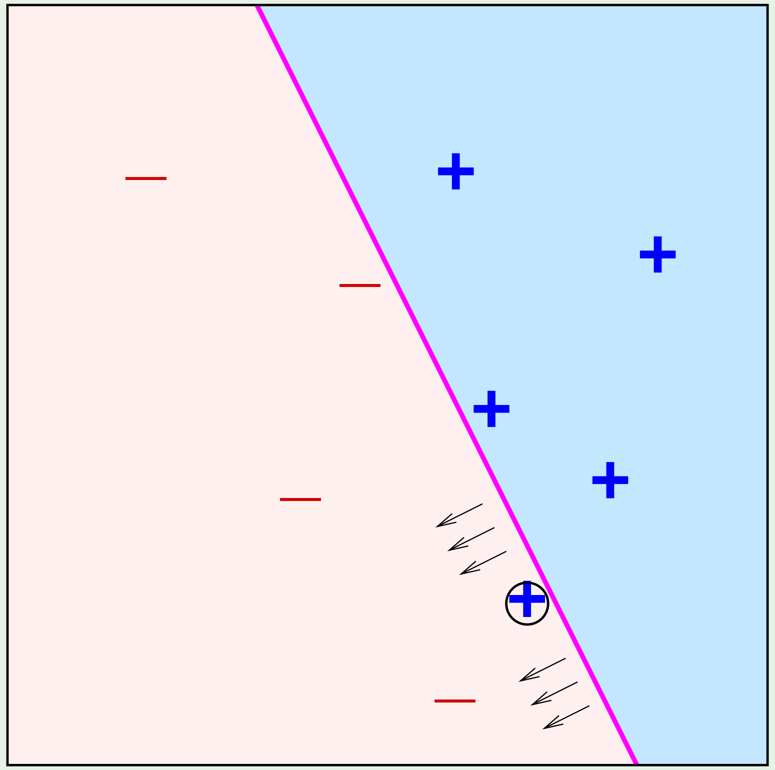
Review of Lecture 1

- **Learning is used when**
  - A pattern exists
  - We cannot pin it down mathematically
  - We have data on it

- **Focus on supervised learning**
  - Unknown target function $y = f(\mathbf{x})$
  - Data set $(\mathbf{x}_1, y_1), \cdots, (\mathbf{x}_N, y_N)$
  - Learning algorithm picks $g \approx f$ from a hypothesis set $\mathcal{H}$

Example: Perceptron Learning Algorithm



- **Learning an unknown function?**
  - Impossible ☹. The function can assume any value outside the data we have.
  - So what now?

Feasibility of learning - Outline

- Probability to the rescue
- Connection to learning
- Connection to *real* learning
- A dilemma and a solution

A related experiment

- Consider a 'bin' with red and green marbles.

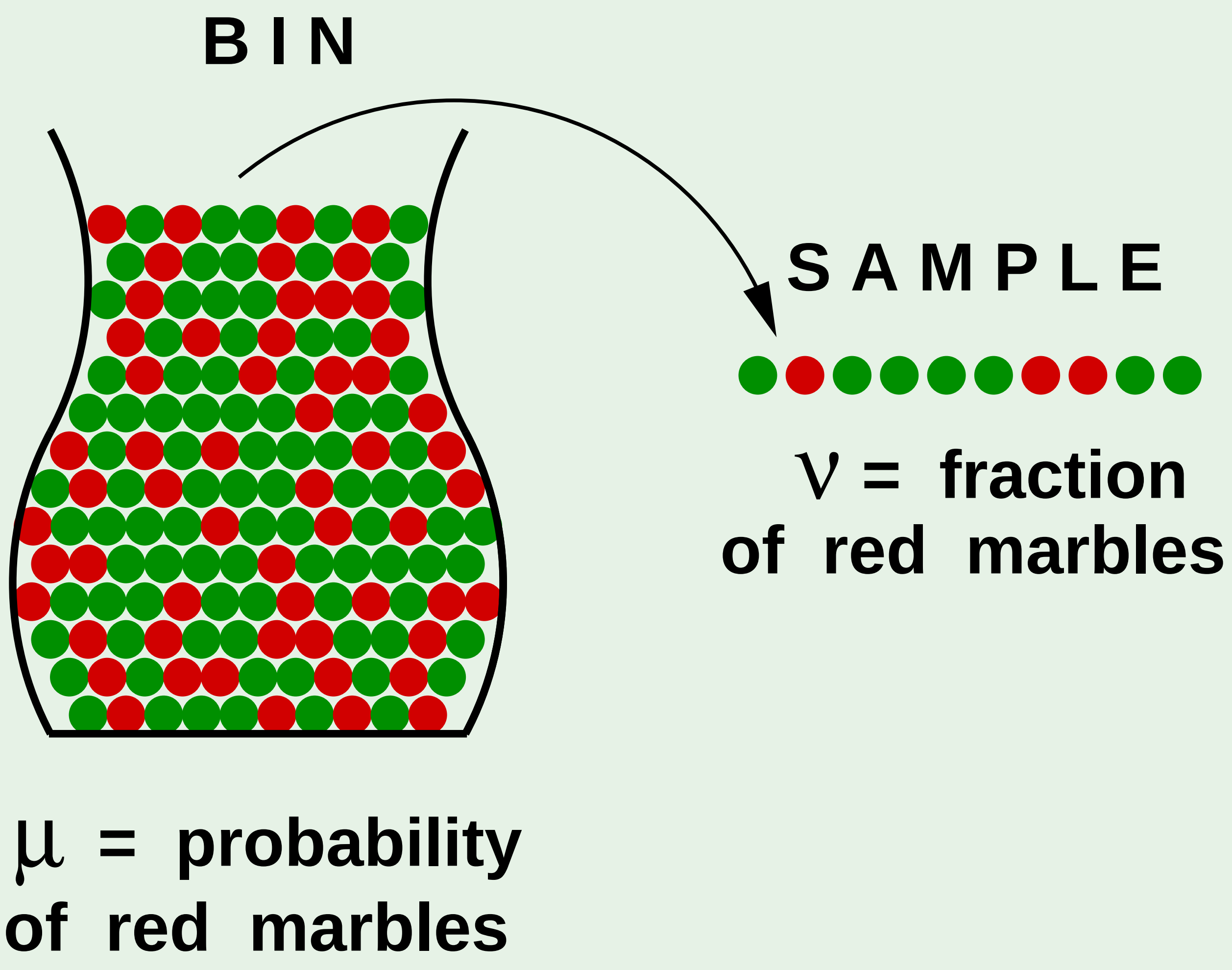
$$\mathbb{P}[\text{ picking a red marble }] = \mu$$

$$\mathbb{P}[\text{ picking a green marble }] = 1 - \mu$$

- The value of μ is unknown to us.

- We pick N marbles independently.

- The fraction of red marbles in sample $= \nu$



Does ν say anything about μ?

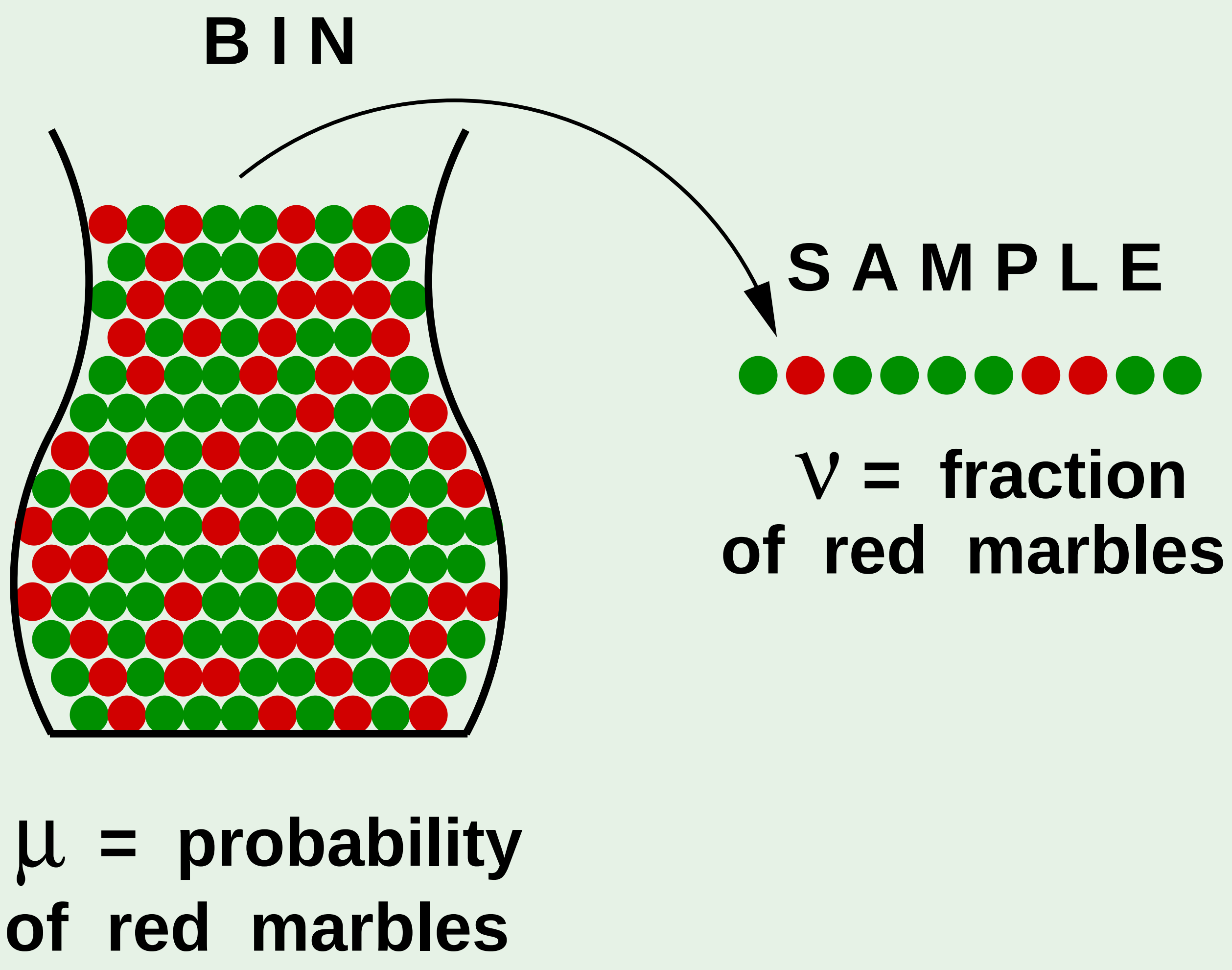
No!

Sample can be mostly green while bin is mostly red.

Yes!

Sample frequency ν is likely close to bin frequency μ.

possible versus probable



What does ν say about μ?

In a big sample (large N), ν is probably close to μ (within ϵ).

Formally,

$$\mathbb{P}\left[\,|\nu - \mu| > \epsilon\,\right] \leq 2e^{-2\epsilon^2 N}$$

This is called **Hoeffding's Inequality**.

In other words, the statement "$\mu = \nu$" is P.A.C.

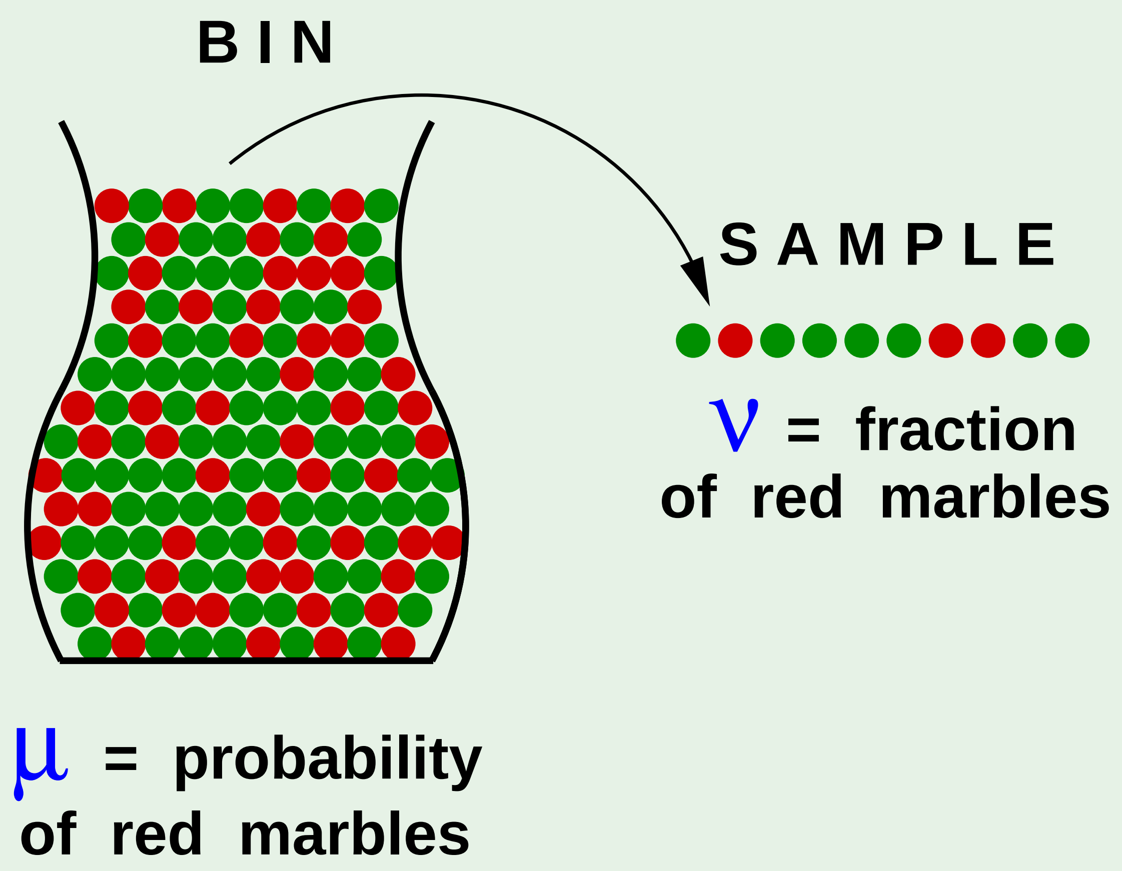
$$\mathbb{P}\left[\,|\nu - \mu| > \epsilon\,\right] \leq 2e^{-2\epsilon^2 N}$$

- Valid for all N and ϵ

- Bound does not depend on μ

- Tradeoff: N, ϵ, and the bound.

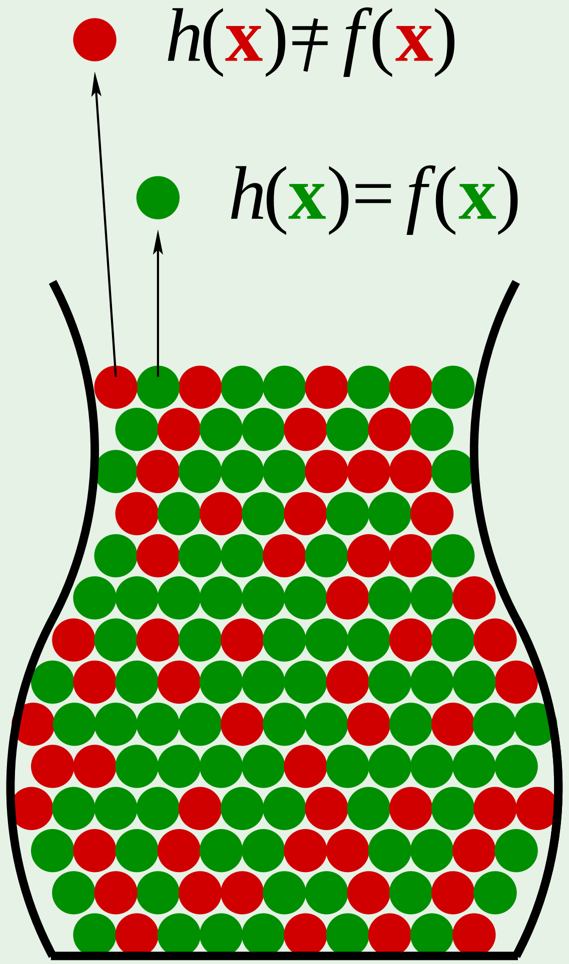
- $\nu \approx \mu \implies \mu \approx \nu$ ☺



Connection to learning

Bin: The unknown is a number μ

Learning: The unknown is a function $f : \mathcal{X} \to \mathcal{Y}$



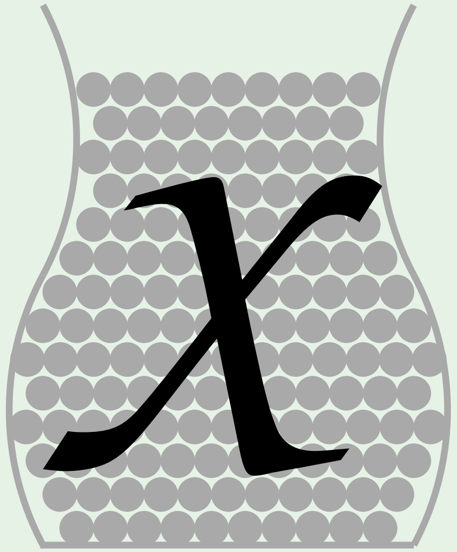
Each marble ● is a point $\mathbf{x} \in \mathcal{X}$

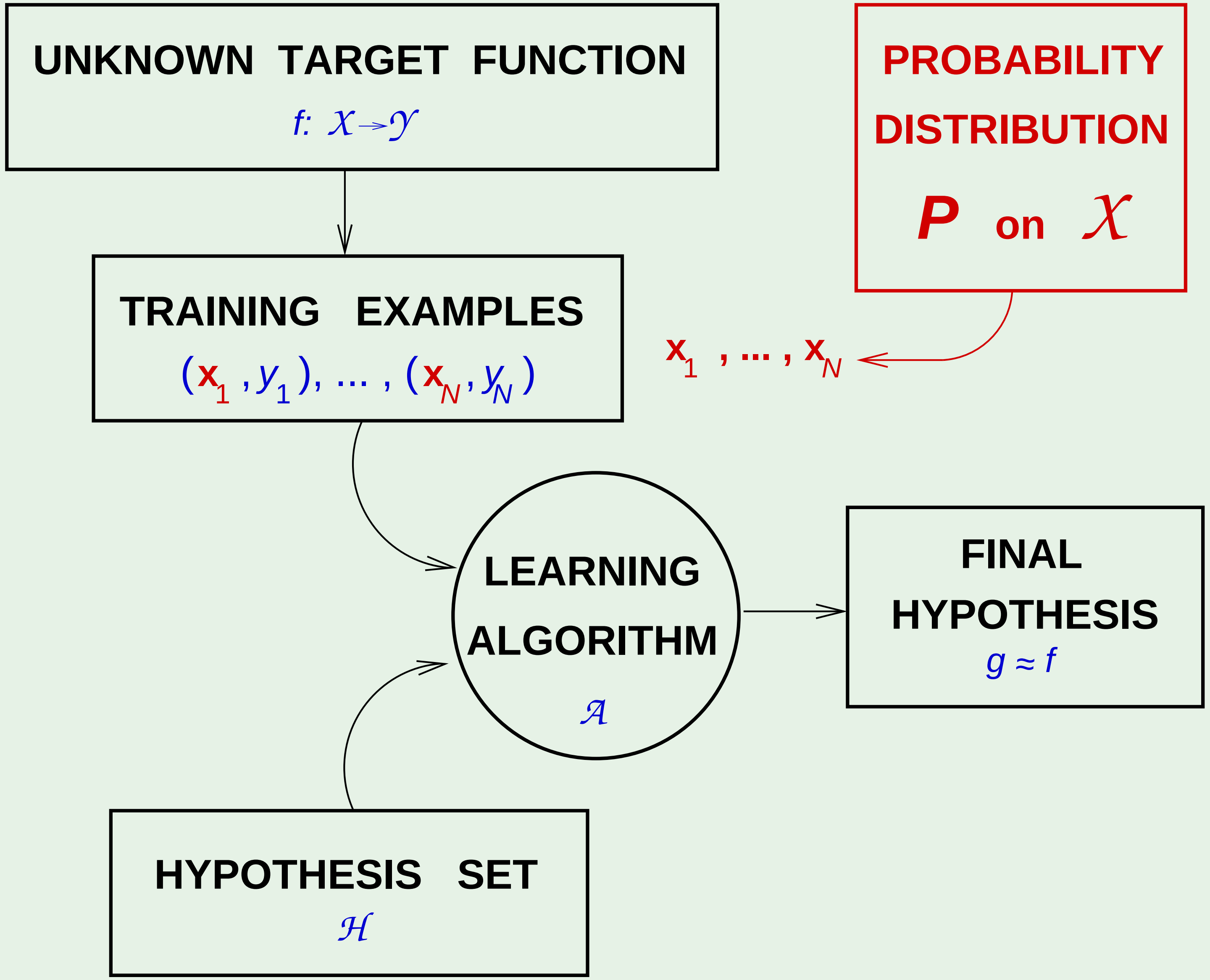
● : Hypothesis got it right $h(\mathbf{x}) = f(\mathbf{x})$

● : Hypothesis got it wrong $h(\mathbf{x}) \neq f(\mathbf{x})$

Back to the learning diagram

The bin analogy:





Are we done?

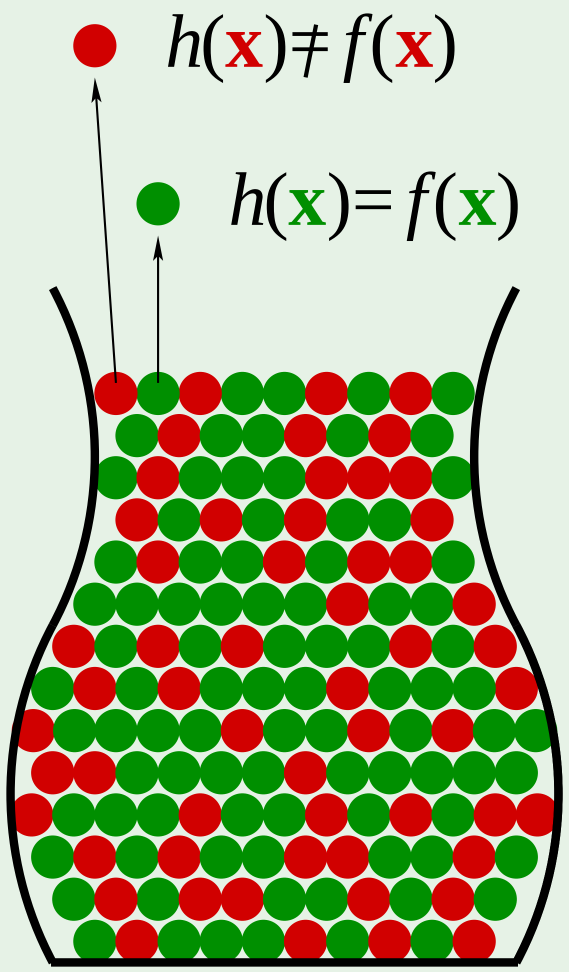
Not so fast! h is fixed.

For this h, ν generalizes to μ.

'**verification**' of h, not **learning**

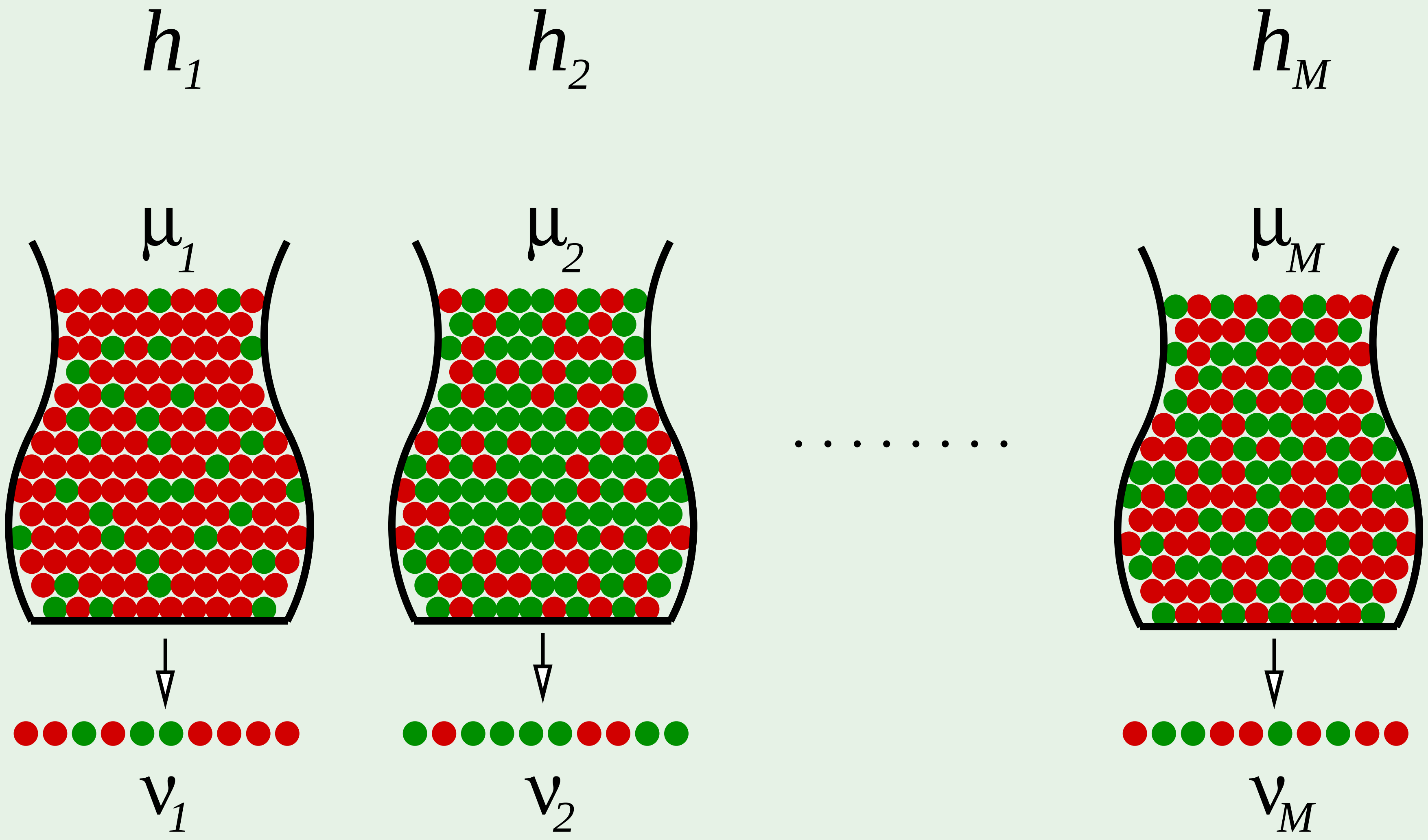
No guarantee ν will be small.

We need to **choose** from multiple h's.



Multiple bins

Generalizing the bin model to more than one hypothesis:



Notation for learning

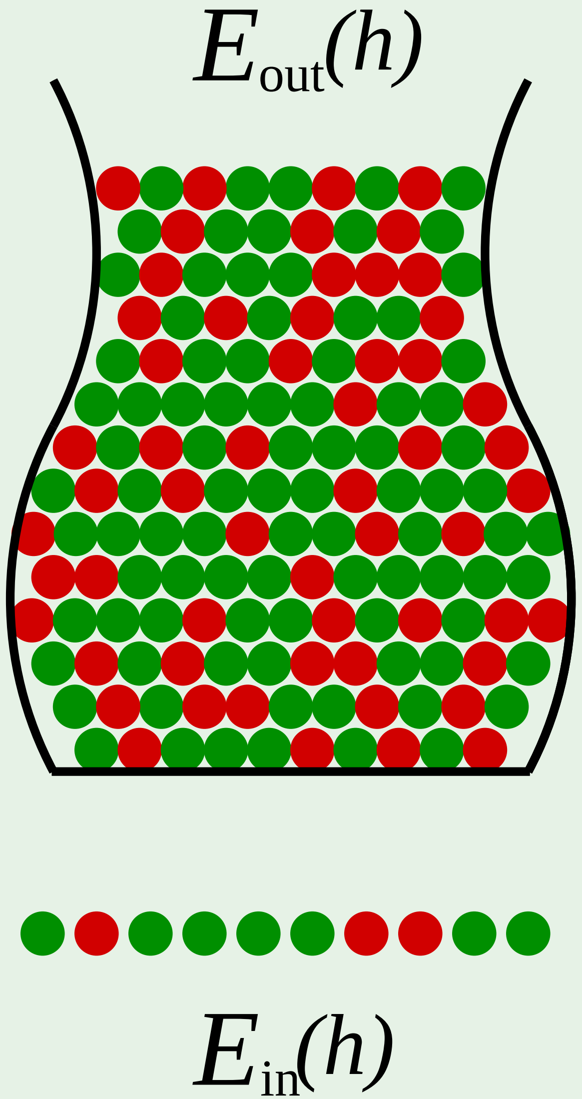
Both μ and ν depend on which hypothesis h

ν is '**in sample**' denoted by $E_{\text{in}}(h)$

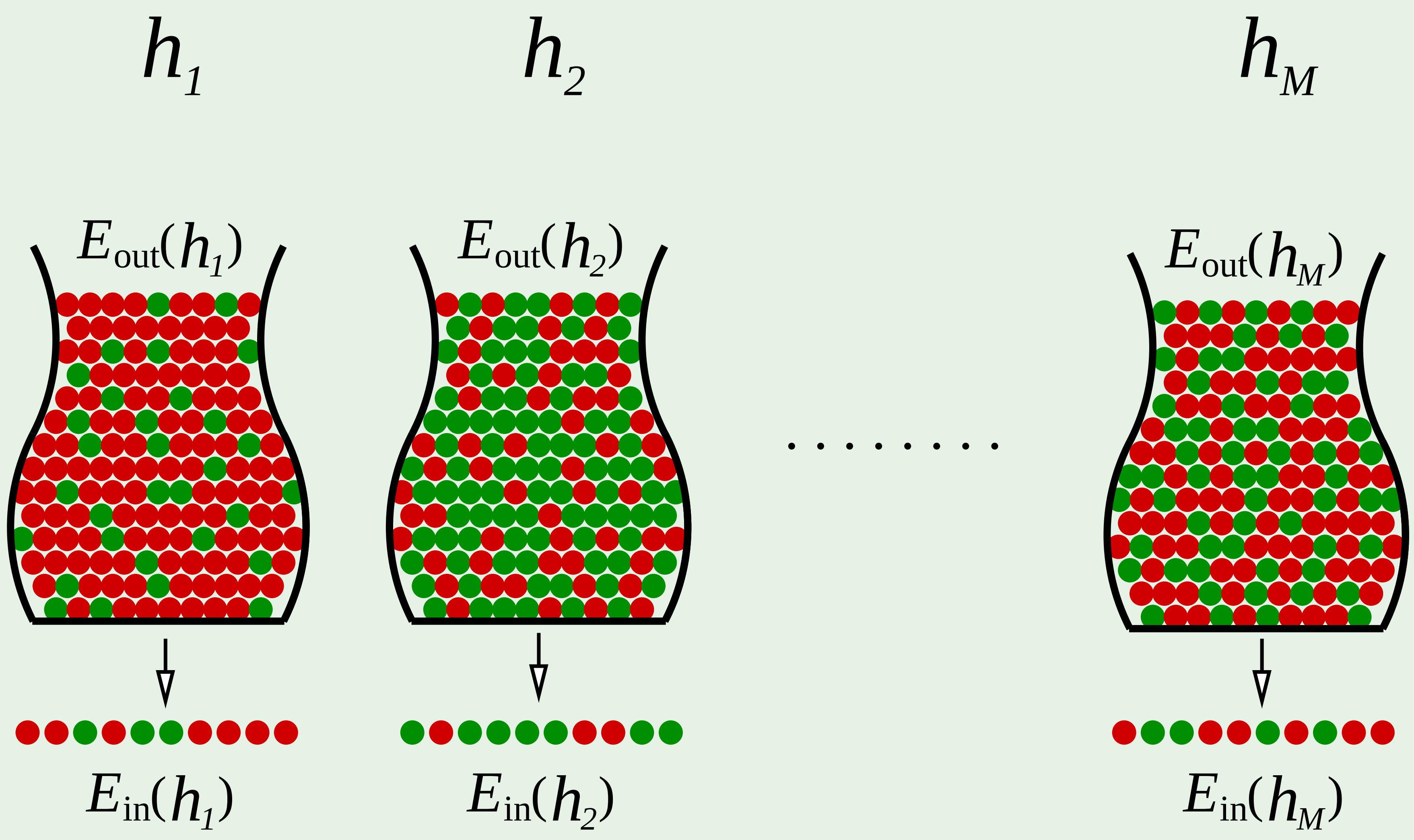
μ is '**out of sample**' denoted by $E_{\text{out}}(h)$

The Hoeffding inequality becomes:

$$\mathbb{P}\left[\ |E_{\text{in}}(h) - E_{\text{out}}(h)| > \epsilon\ \right] \ \leq\ 2e^{-2\epsilon^2 N}$$



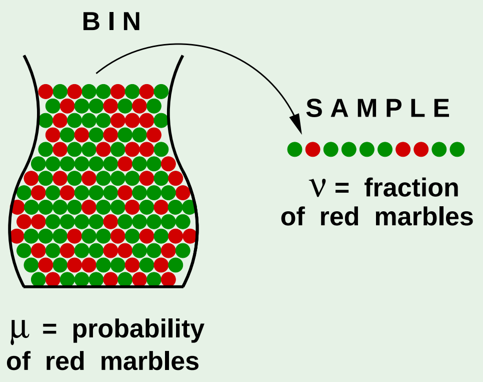
Notation with multiple bins



Are we done already? ☺

Not so fast!! Hoeffding doesn't apply to multiple bins.

What?



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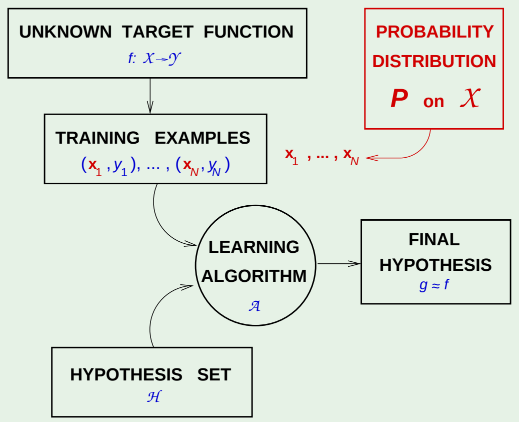
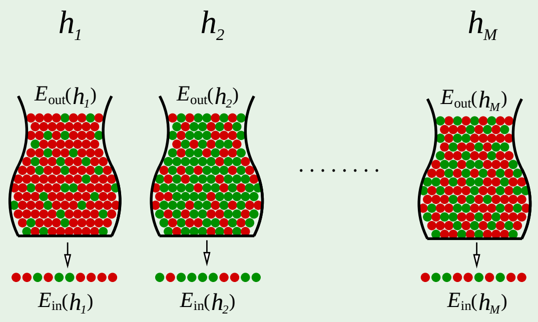


$\longrightarrow$



Coin analogy

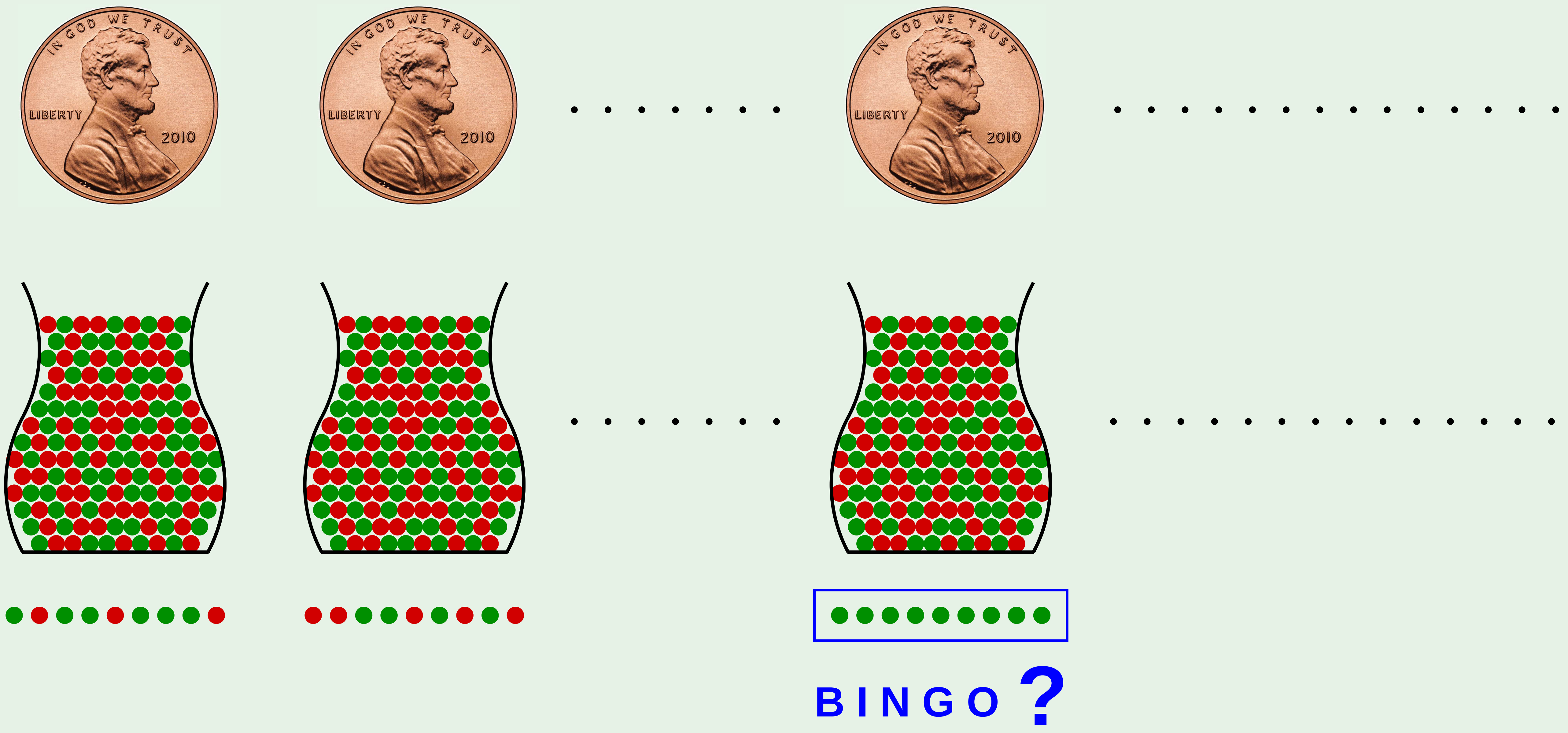
Question: If you toss a fair coin 10 times, what is the probability that you will get 10 heads?

Answer: $\approx 0.1\%$

Question: If you toss 1000 fair coins 10 times each, what is the probability that <u>some</u> coin will get 10 heads?

Answer: $\approx 63\%$

From coins to learning



A simple solution

$$
\begin{aligned}
\mathbb{P}[\ |E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon\ ] \ \leq\ \mathbb{P}[\quad & |E_{\text{in}}(h_1) - E_{\text{out}}(h_1)| > \epsilon \\
& \textbf{or } |E_{\text{in}}(h_2) - E_{\text{out}}(h_2)| > \epsilon \\
& \cdots \\
& \textbf{or } |E_{\text{in}}(h_M) - E_{\text{out}}(h_M)| > \epsilon\ ] \\
\leq\ \sum_{m=1}^{M} \mathbb{P}\left[|E_{\text{in}}(h_m) - E_{\text{out}}(h_m)| > \epsilon\right] &
\end{aligned}
$$

The final verdict

$$\mathbb{P}[\ |E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon\ ] \ \leq \ \sum_{m=1}^{M} \mathbb{P}\left[|E_{\text{in}}(h_m) - E_{\text{out}}(h_m)| > \epsilon\right]$$

$$\leq \ \sum_{m=1}^{M} 2e^{-2\epsilon^2 N}$$

$$\mathbb{P}[|E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon] \leq 2{\color{red}M}e^{-2\epsilon^2 N}$$

What we want

Instead of:

$$\mathbb{P}[\ |E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon\ ] \ \leq \ 2 \qquad M \qquad e^{-2\epsilon^2 N}$$

We want:

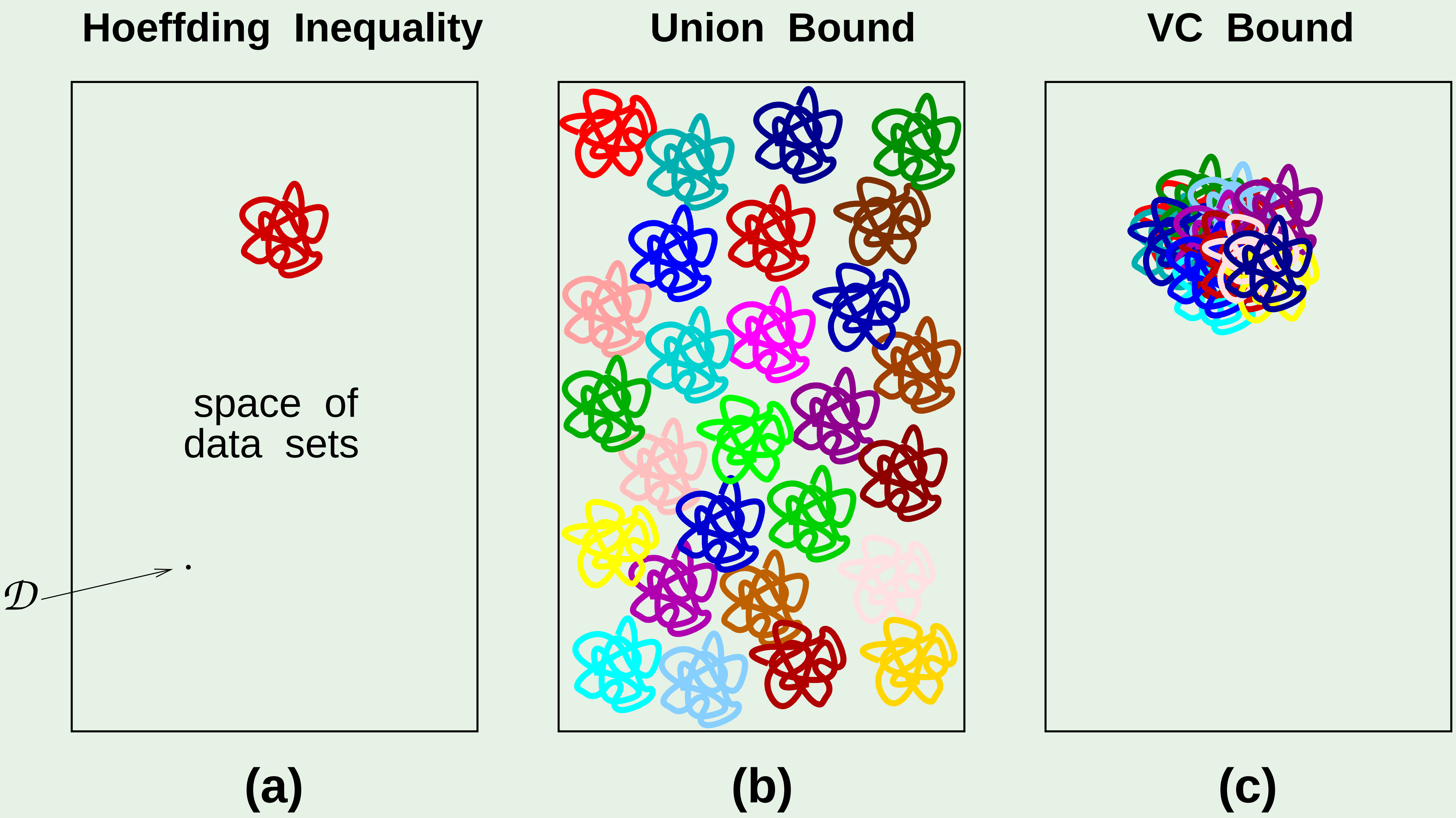
$$\mathbb{P}[\ |E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon\ ] \ \leq \ 2 \ \ m_{\mathcal{H}}(N) \ \ e^{-2\epsilon^2 N}$$

Pictorial proof ☺

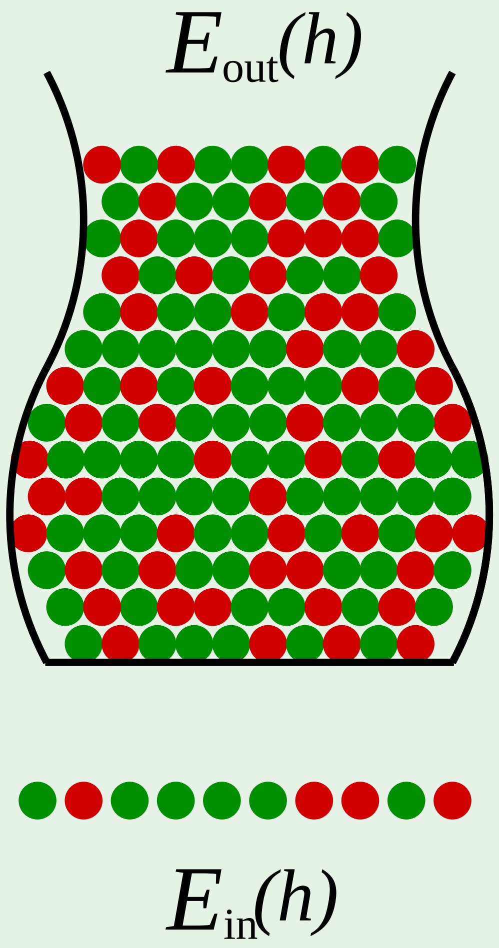
- How does $m_{\mathcal{H}}(N)$ relate to overlaps?

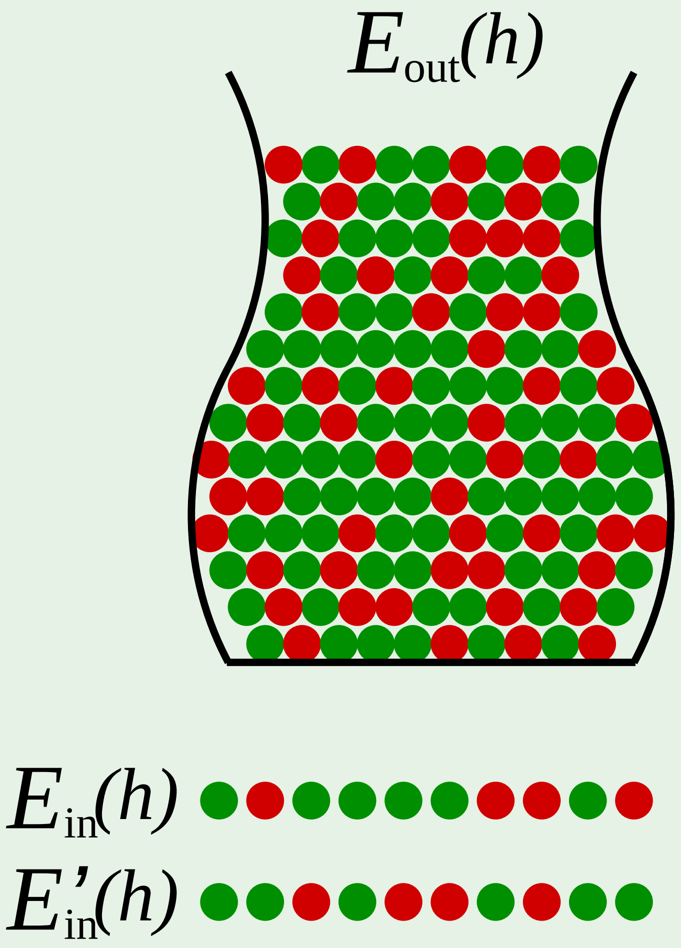
- What to do about E_{out}?

- Putting it together


Hoeffding Inequality
Union Bound
VC Bound
space of
data sets
$\mathcal{D}$
(a)
(b)
(c)

What to do about E_{out}





Putting it together

Not quite:

$$\mathbb{P}\left[\,|E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon\,\right] \;\leq\; 2\;\, m_{\mathcal{H}}(\,N\,)\;\, e^{-\,2\,\epsilon^2 N}$$

but rather:

$$\mathbb{P}\left[\,|E_{\text{in}}(g) - E_{\text{out}}(g)| > \epsilon\,\right] \;\leq\; 4\;\, m_{\mathcal{H}}(2N)\;\, e^{-\,\frac{1}{8}\,\epsilon^2 N}$$

The Vapnik-Chervonenkis Inequality