Fundamentals of Machine Learning

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Weekly Objectives

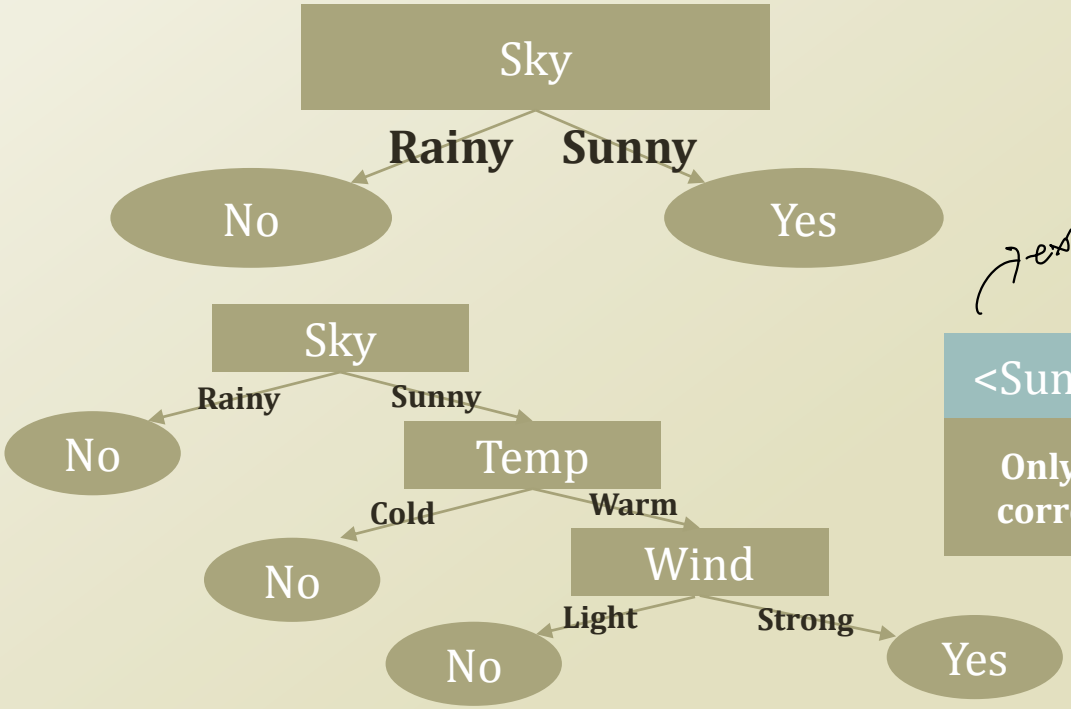
- Learn the most classical methods of machine learning
  - Rule based approach
  - Classical statistics approach
  - Information theory appraoch
- Rule based machine learning
  - How to find the specialized and the generalized rules
  - Why the rules are easily broken
- Decision Tree
  - How to create a decision tree given a training dataset
  - Why the tree becomes a weak learner with a new dataset
- Linear Regression
  - How to infer a parameter set from a training dataset
  - Why the feature engineering has its limit

DECISION TREE

Because we live with noises…

Sky	Temp	Humid	Wind	Water	Forecst	EnjoySpt
Sunny	Warm	Normal	Strong	Warm	Same	Yes
Sunny	Warm	High	Strong	Warm	Same	Yes
Rainy	Cold	High	Strong	Warm	Change	No
Sunny	Warm	High	Strong	Cool	Change	Yes

- We need a better learning method
  - We need to have more robust methods given the noises
  - We need to have more concise presentations of the hypotheses
- One alternative is a decision tree



<Sunny, ?,?,?,?,?>

ex) 기울기 inconsistency.

<Sunny, Warm, ?, Strong, ?, ?>

Only one potential decision tree corresponding to the hypothesis

Credit Approval Dataset

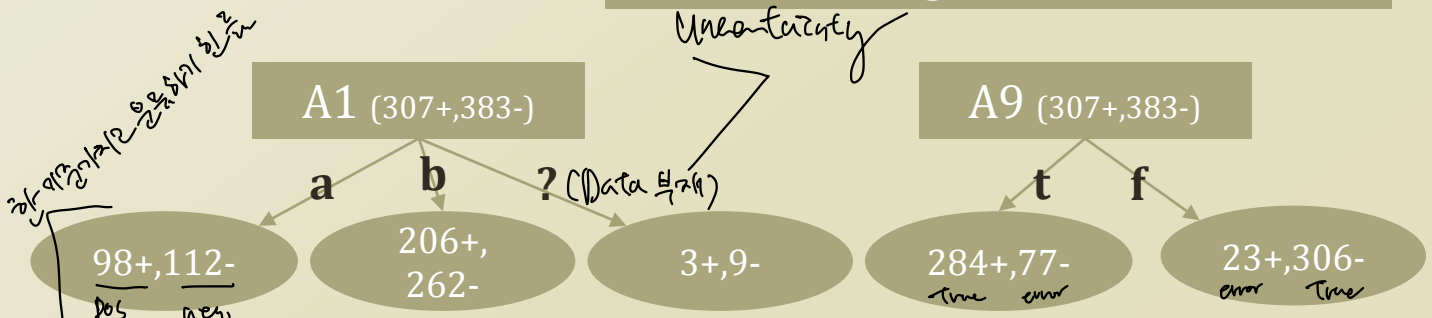
- http://archive.ics.uci.edu/ml/datasets/Credit+Approval
- To protect the confidential information, the dataset is anonymized
  - Feature names and values, as well

A1: b, a.
A2: continuous.
A3: continuous.
A4: u, y, l, t.
A5: g, p, gg.
A6: c, d, cc, i, j, k, m, r, q, w, x, e, aa, ff.
A7: v, h, bb, j, n, z, dd, ff, o.
A8: continuous.
A9: t, f.
A10: t, f.
A11: continuous.
A12: t, f.
A13: g, p, s.
A14: continuous.
A15: continuous.

C: +,- (class attribute)

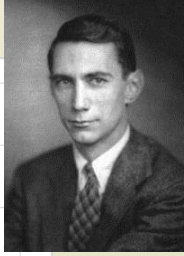
Some Counting Result

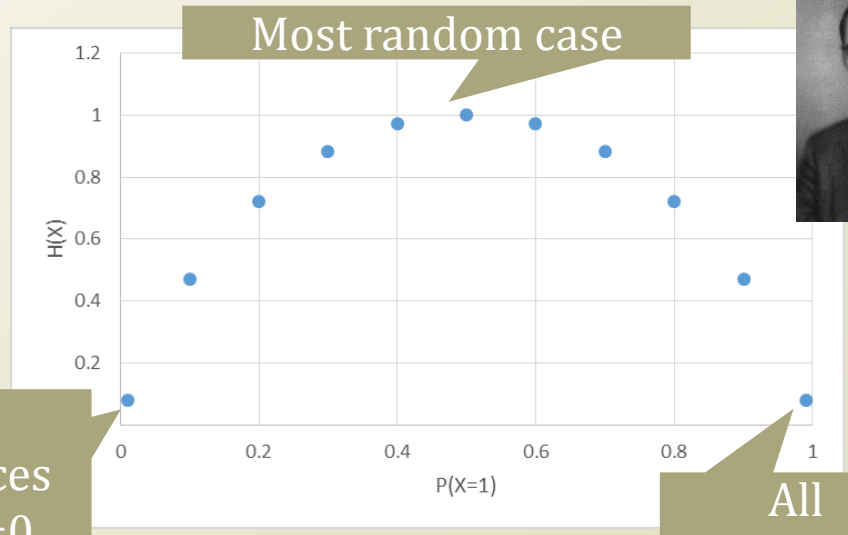
- 690 instances total
- 307 positive instances
- Considering A1
  - 98 positive when a
  - 112 negative when a
  - 206 positive when b
  - 262 negative when b
  - 3 positive when ?
  - 9 negative when ?
- Considering A9
  - 284 positive when t
  - 77 negative when t
  - 23 positive when f
  - 306 negative when f



Which is a better attribute to include in the feature set of the hypothesis?

Entropy



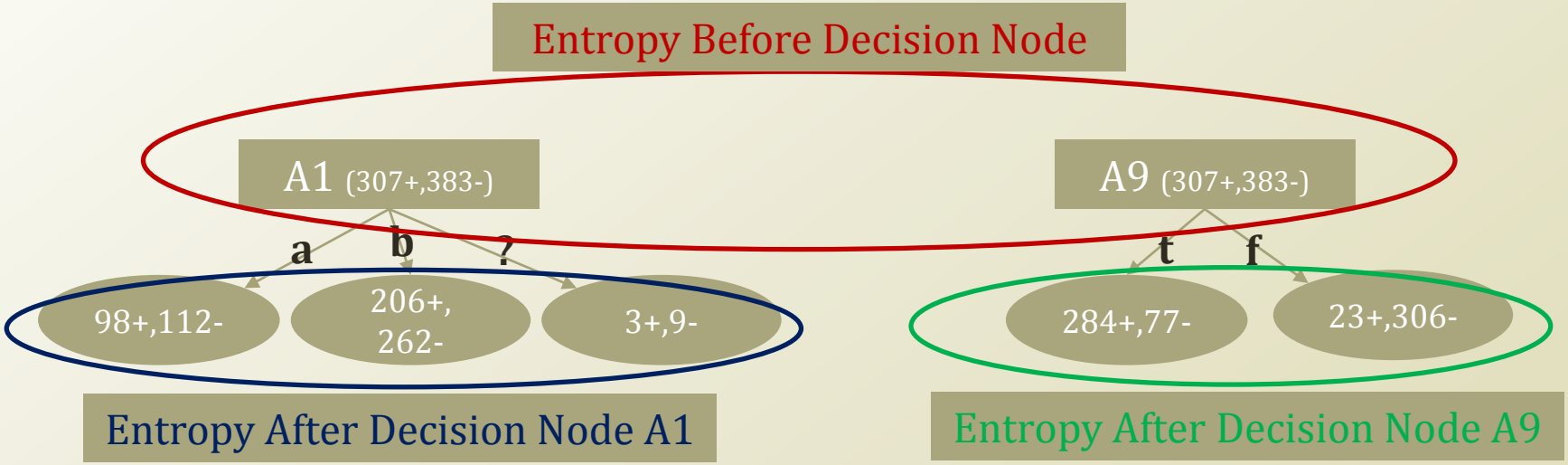


- Better attribute to check?
  - Reducing the most uncertainty
  - Then, how to measure the uncertainty of a feature variable
- Entropy of a random variable
  - Features are random variables
  - Higher entropy means more uncertainty
  - $H(X) = -\sum_X P(X = x) log_b P(X = x)$
- Conditional Entropy
  - We are interested in the entropy of the class given a feature variable
  - Need to introduce a given condition in the entropy
  - $H(Y|X) = \sum_X P(X = x) H(Y|X = x)$

$$= \sum_X P(X = x)\{-\sum_Y P(Y = y|X = x) log_b P(Y = y|X = x)\}$$

$-\left(\frac{4}{11}\log\frac{4}{11}+\frac{7}{11}\log\frac{7}{11}\right)$

Information Gain (measure of 불순도).



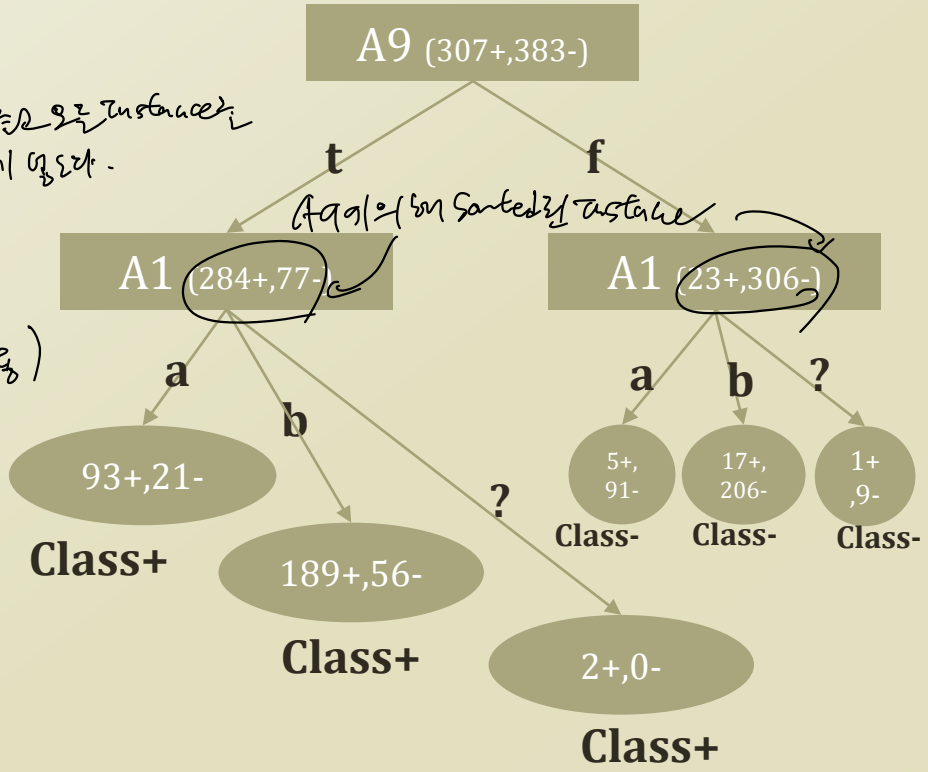
$P(Y=+)=\frac{307}{307+383}$ (MLE 방법)

- Let's calculate the entropy values
  - $H(Y)=-\sum_{Y\in\{+,-\}}P(Y=y)log_2P(Y=y)$
  - $H(Y|A1)=\sum_{X\in\{a,b,?\}}\sum_{Y\in\{+,-\}}P(A1=x,Y=y)log_2\frac{P(A1=x)}{P(A1=x,Y=y)}$ (A1이 Condition일 때 Y의 entropy)
  - $H(Y|A9)=\sum_{X\in\{t,f\}}\sum_{Y\in\{+,-\}}P(A9=x,Y=y)log_2\frac{P(A9=x)}{P(A9=x,Y=y)}$
- What's the difference before and after?
  - $IG(Y,A_i)=H(Y)-H(Y|A_i)$: entropy − Cond. = Inf. Gain.
- Who is the winner? : A9.

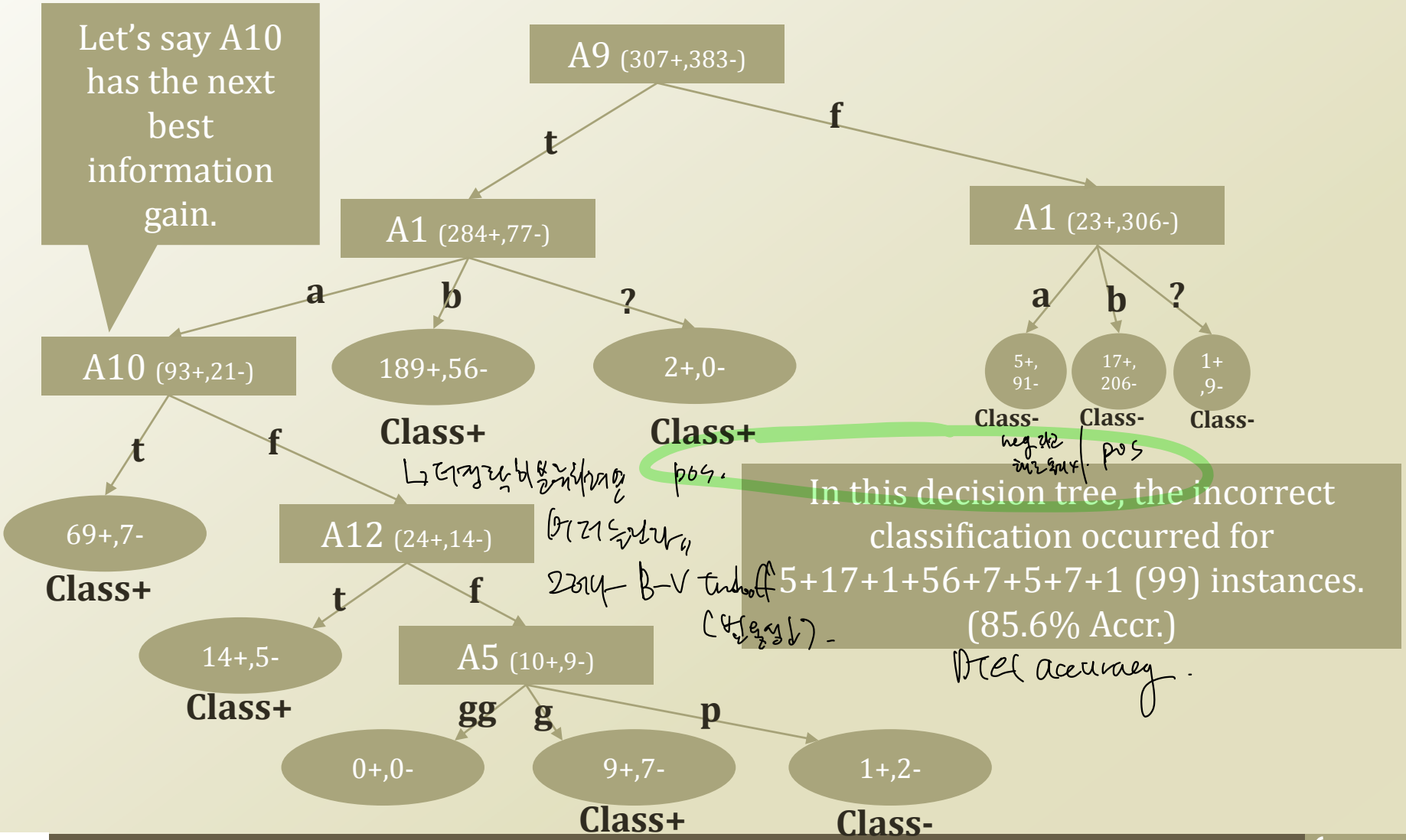
Top-Down Induction Algorithm

- Many, many variations in learning a decision tree
  - ID3, C4.5, CART….
- One example: ID3 algorithm
- ID3 algorithm
  - Create an initial open node
  - Put instances in the initial node
  - Repeat until no open node
    - Select an open node to split
    - Select a best variable to split
    - For values of the selected variable
      - Sort instances with the value of the selected variable
      - Put the sorted items under the branch of the value of the variable
      - If the sorted items are all in one class
        - Close the leaf node of the branch

Only using A1 and A9, we have 21+56+0+5+17+1 (100) instances classified inaccurately. (85.5% Accr.)



If you want more….

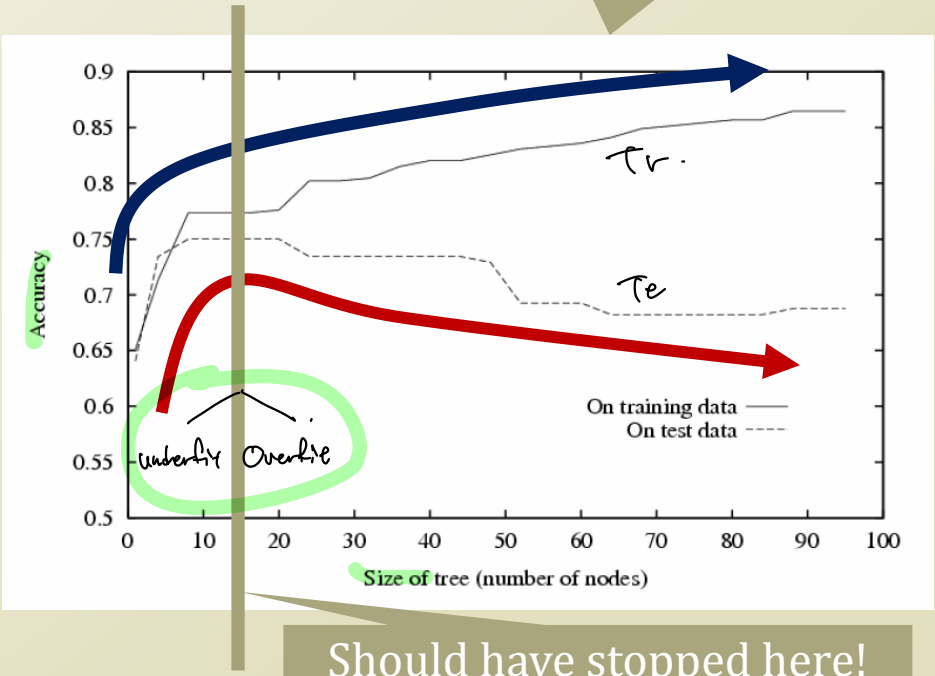


In this decision tree, the incorrect classification occurred for 5+17+1+56+7+5+7+1 (99) instances. (85.6% Accr.)

Problem of Decision Tree

- We did better in the given dataset!
  - Only in the given experience, a.k.a. Training dataset
- What if we deploy the created decision tree in the field?
  - World has so much noise and inconsistencies.
  - The training dataset will not be a perfect sample of the real world
    - Noise
    - Inconsistencies

Typical result of decision tree



Should have stopped here!

Knowing when to stop is a pretty difficult task. How to do it?

- Pruning by divided dataset?
- Path length penalty?

Why we are not interested in these?

- Rule based machine learning algorithms
  - Easy to implement
  - Easily interpretable
    - Particularly, decision tree
- Their weaknesses
  - Fragile
    - Assume the perfect world in the dataset
    - Any new observations, contradicting to the training, will cause problems
  - Convergence
    - Convergence only guaranteed in the perfect dataset
    - Once there is a noise, there is a possibility that the true hypothesis can be ruled out.
    - Also, very hard to tell when to stop in some cases
- Still used in many places
  - Easy → Wide audience and users → Many applications → Better result???
- Need a white knight as a savior
  - Should be able to handle noisy datasets
  - Robust to errors

Believe the small dataset?
(5/6→ Head with 83.3% prob?)