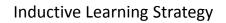


				Hypoth	esis	Spac
	correct (complete, partial, guessing)	color (yes, no)	original (yes, no)	presentation (clear, unclear)	binder (yes, no)	A+
1	complete	yes	yes	clear	no	yes
2	complete	no	yes	clear	no	yes
3	partial	yes	no	unclear	no	no
4	complete	yes	yes	clear	yes	yes
		attribut	es.	objects describ		
rge	t Function f	: Maps e	ach instanc	$e x \in X$ to targ	et label y	∈ Y (hid
/po	thesis h: Fu	nction th	at approxin	nates f.		
/po	thesis Space	e H: Set o	of functions	we consider f	or approx	kimating f



- Strategy and hope (for now, later theory): Any hypothesis h found to approximate the target function f well over a sufficiently large set of training examples S will also approximate the target function well over other unobserved examples.
- Can compute: – A hypothesis  $h \in H$  such that h(x)=f(x) for all  $x \in S$ .
- Ultimate Goal:
  - A hypothesis  $h\in H$  such that  $h(x){=}f(x)$  for all  $x\in X.$

				С	onsis	stend
				$h$ is consis $d$ only if $h(x,y) \in S:h$		for eac
	correct (complete,	color (yes, no)	original (yes, no)	presentation (clear, unclear)	binder (yes, no)	A+
1						A+ yes
1	(complete, partial, guessing)	(yes, no)	(yes, no)	(clear, unclear)	(yes, no)	
-	(complete, partial, guessing) complete	(yes, no) yes	(yes, no) yes	(clear, unclear) clear	(yes, no) NO	yes

## Version Space

**Definition:** The version space,  $VS_{H,S}$ , with respect to hypothesis space H and training examples S, is the subset of hypotheses from H consistent with all training examples in S.

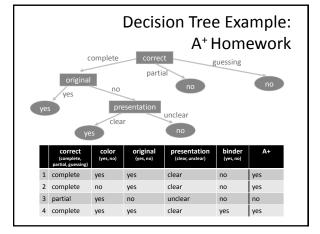
 $VS_{H,S} \equiv \{h \in H | Consistent(h, S)\}$ 

## List-Then-Eliminate Algorithm

• Init VS  $\leftarrow$  H

- For each training example (x, y) ∈ S

   remove from VS any hypothesis h for which h(x) ≠ y
- Output VS



## Top-Down Induction of DT (simplified)

Training Data:  $S = ((\vec{x}_1, y_1), \dots, (\vec{x}_n, y_n))$ 

## $\mathsf{TDIDT}(S, y_{def})$

- IF(all examples in S have same class y)
   Return leaf with class y (or class y<sub>dep</sub> if S is empty)
- ELSE
  - Pick A as the "best" decision attribute for next node
  - FOR each value  $v_i$  of A create a new descendent of node
    - $S_i = \{ (\vec{x}, y) \in S : \text{attribute } A \text{ of } \vec{x} \text{ has value } v_i) \}$
    - Subtree  $t_i$  for  $v_i$  is TDIDT( $S_{ij}y_{def}$ )
  - RETURN tree with A as root and  $t_i$  as subtrees

