

CSE 5693 Machine Learning HW2

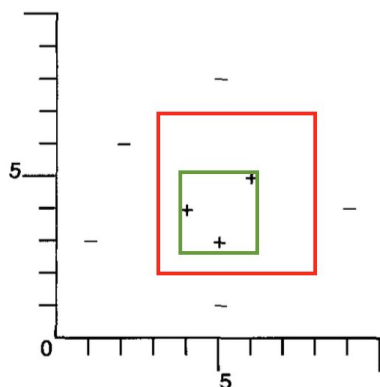
Due 7pm, Feb 22

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1.

a. G-Boundary: $h = (3 \leq x \leq 8), (2 \leq y \leq 7)$

b. S-Boundary: $h = (4 \leq x \leq 6), (3 \leq y \leq 5)$



c. Instance (6,5) will not improve G or S because that point is already known

Instance (7,6) will improve both because: $S(xMax) < 7 < G(xMax)$, $S(yMax) < 6 < G(yMax)$.

d. (3,2)+, (5,9)+, (2,1)-, (3,10)- : 4 Examples are need

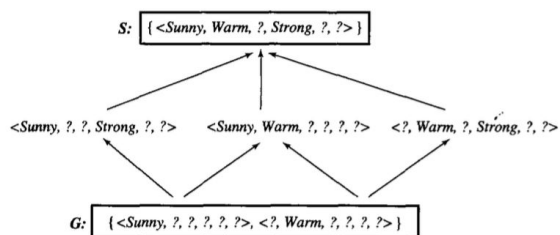
2.

$a < x < b$ This hypothesis cannot have a maximally specific consistent hypothesis because the precision of the allowed real values being represented can always be made more specific by adding decimals. For example if the hypothesis $4.5 < x < 6.1$ could be $4.49 < x < 6.09$...and so on.

To get around this issue, you could enforce a fixed precision for the representation, thus making it impossible to make the hypothesis more specific.

Example	Sky	AirTemp	Humidity	Wind	Water	Forecast	EnjoySport
1	Sunny	Warm	Normal	Strong	Warm	Same	Yes
2	Sunny	Warm	High	Strong	Warm	Same	Yes
3	Rainy	Cold	High	Strong	Warm	Change	No
4	Sunny	Warm	High	Strong	Cool	Change	Yes

3.



A. Root

```
|      Sky=Sunny : {true=3}
|      Sky=rainy : {false=1}
```

B. The tree above is equivalent to the <?,Warm,?,?,?> hypothesis from figure 2.3

C. Added example. Tree and log dump below

Root

```
|      Sky=sunny
|      |      Wind=strong : {true=3}
|      |      Wind=weak : {false=1}
|      Sky=rainy : {false=1}
```

=== Building Tree ===

Sky Gain: 0.3219280948873623

airtemp Gain: 0.3219280948873623

Humidity Gain: 0.01997309402197489

Wind Gain: 0.3219280948873623

water Gain: 0.17095059445466854

Gain: 0.01997309402197489

Created node Sky with Dist: {no=2, yes=3}

airtemp Gain: 0.0

Humidity Gain: 0.31127812445913283

Wind Gain: 0.8112781244591328

Feature: water Gain: 0.12255624891826566

Feature: forecast Gain: 0.12255624891826566

Created node Wind with Dist: {no=1, yes=3}

=== /Building Tree ===

D. Sunny warm normal strong warm same yes

== Example 1 == <Sunny warm normal strong warm same> yes

GRoot : yes

SRoot

```
|      Sky=sunny
|      |      Air-Temp=warm
|      |      |      Humidity=normal
|      |      |      |      Wind=strong
|      |      |      |      |      Water=warm
|      |      |      |      |      |      Forecast=same : {true:1}
```

== Example 2 == <Sunny warm **high** strong warm same> yes

GRoot : yes

SRoot

```
|      Sky=sunny
```

```

|      |      Air-Temp=warm
|      |      |      Humidity=normal
|      |      |      |      Wind=strong
|      |      |      |      |      Water=warm
|      |      |      |      |      |      Forecast=same : {true:1}
|      |      |      Humidity=high
|      |      |      |      Wind=strong
|      |      |      |      |      Water=warm
|      |      |      |      |      |      Forecast=same : {true:1}

```

The biggest problem in implementing Candidate-Elimination as a tree, would be the back tracking and rebuilding the tree for each new example. You would also need to build two trees at the same time which increases complexity. The STree would have individual paths for every example it comes across, until inconsistent examples are shown. This leads to a very large tree. The Overall inefficiencies and complexities of creating CE trees coupled with the (probable) miniscule performance delta make it poor choice.

4. Outlook[Sunny,Rainy,Cloudy] , Humidity[High] , PlayTennis[Yes,No]

i. Subsets(Cloud,Rainy,Sunny,High) * 2 = 8 Subsets..

ii. $H1 = \{h1(\text{Sunny} : \text{yes}), h2(\text{Sunny}:\text{No})...h_n(\text{Cloudy},\text{High}:\text{no})\} = 16$ unique hypothesis

iii. $H2 = \{ h1(\text{null},\text{null} : \text{yes}), h2(\text{null},\text{null} : \text{no}), h3(?,? : \text{yes}), h4(?,? : \text{no}) \dots \}$

8 possible, 4 unique

liii. $h = ((\text{Sunny or cloudy}) \text{ and High}): \text{yes})$ is a hypothesis that is found in $H1$ but not in $H2$