# Chapter 1:
# Concept Learning

Adopted from Machine Learning, Mitchell

# Logistics

- Course Instructor: Tanmoy Chakraborty (NLP)
  https://tanmoychak.com/
- Guest Lecture: TBD (possibly from the industry)
- TAs: Sahil, Aswini, Palash, Prottoy, Vaibhav, Soumyodeep, Anand
- Course page: https://lcs2-iitd.github.io/ELL409-2401/
- Discussion forum: Piazza (https://piazza.com/iitd.ac.in/fall2024/ell409)
  Access Code: *ell409mli*
- For assignment submission: Moodle
- Group Email: 2401-ELL409@courses.iitd.ac.in

# Course Directives

- **Class Time:** Mon and Thu, 8:00 AM - 9:20 AM
- **Office Hour:** as per requirement (email me to schedule an appointment)
- **TA Hour:** (Please email at least an hour before to confirm the meeting location)
  - **Monday** 4 PM to 5 PM: Vaibhav (mt1210236@iitd.ac.in)
  - **Tuesday** 4 PM to 5 PM: Soumyodeep (aiy237526@scai.iitd.ac.in)
  - **Wednesday** 4 PM to 5 PM: Sahil (eez238354@ee.iitd.ac.in)
  - **Wednesday** 3 PM to 4 PM: Aswini (eez238359@iitd.ac.in)
  - **Thursday** 4 PM to 5 PM: Palash (sondhanil1@gmail.com)
  - **Friday** 3 PM to 4 PM: Anant (aib232068@scai.iitd.ac.in)
- **Room:** LH114

# Timeline

- **Project Finalization:** 10/08/2024
- **Quiz 1:** 12/08/2024
- **Assignment 1:** 13/08/2024
- **Quiz 2:** 05/09/2024
- **Mid-Term:** 12/09/2024 - 18/09/2024
- **Assignment 2:** 20/09/2024
- **Assignment 3:** 17/10/2024
- **Quiz 3:** 21/10/2024
- **Quiz 4:** 11/11/2024
- **Major:** 16/11/2024 - 23/11/2024
- **Project assessment:** Before endsem

# Some announcements

- Coding practice twice a month (led by the TA) – outside the regular lecture hours

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- Quiz every class - 8:00 AM to 8:05 AM

# Outline

- Learning from examples
- General-to-specific ordering over hypotheses
- Version spaces and candidate elimination algorithm
- Picking new examples
- The need for inductive bias

# Training Examples for *EnjoySport*

| 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 |

What is the general concept?

# Concept Learning

Inferring a Boolean-valued function from training examples of its input and output

# Representing Hypotheses

Many possible representations

Here, $h$ is conjunction of constraints on attributes

Each constraint can be

- a specfic value (e.g., $Water = Warm$)
- don't care (e.g., "$Water =?$")
- no value allowed (e.g.,"Water=$\emptyset$")

For example,

| Sky | AirTemp | Humid | Wind | Water | Forecst |
|---|---|---|---|---|---|
| $\langle Sunny$ | ? | ? | $Strong$ | ? | $Same \rangle$ |

# Notations

- Instances: The set of items over which the concept is defined
- Target concept (c): The concept to be learned
- Hypothesis (h): A supposition or proposed explanation made on the basis of limited evidence (training set)
- Hypotheses Space (H): The set of all possible hypotheses

# Prototypical concept learning task

- **Given:**
  - Instances $X$: Possible days, each described by the attributes *Sky, AirTemp, Humidity, Wind, Water, Forecast*
  - Target function $c$: $EnjoySport : X \rightarrow \{0, 1\}$
  - Hypotheses $H$: Conjunctions of literals. E.g.

$$\langle ?, Cold, High, ?, ?, ? \rangle.$$

  - Training examples $D$: Positive and negative examples of the target function

$$\langle x_1, c(x_1) \rangle, \ldots \langle x_m, c(x_m) \rangle$$

- **Determine:** A hypothesis $h$ in $H$ such that $h(x) = c(x)$ for all $x$ in $D$.

**The inductive learning hypothesis:** Any hypothesis found to approximate the target function well over a sufficiently large set of training examples will also approximate the target function well over other unobserved examples.

# Concept Learning as a search

- The task of searching through a large space of hypotheses
- Goal: Find the hypothesis that best fits the training example
- *How many distinct instances are possible?*

| Sky | Temp | Humid | Wind | Water | Forecst | EnjoySpt |
|---|---|---|---|---|---|---|
| Sunny | Warm | Normal | Strong | Warm | Same | Yes |
| Sunny | Warm | High | Strong | Warm | Same | Yes |
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| Sunny | Warm | High | Strong | Cool | Change | Yes |

- *How many systematically distinct hypotheses are possible?*
- *How many **semantically** distinct hypotheses are possible?*

# General-to-specific ordering of hypotheses

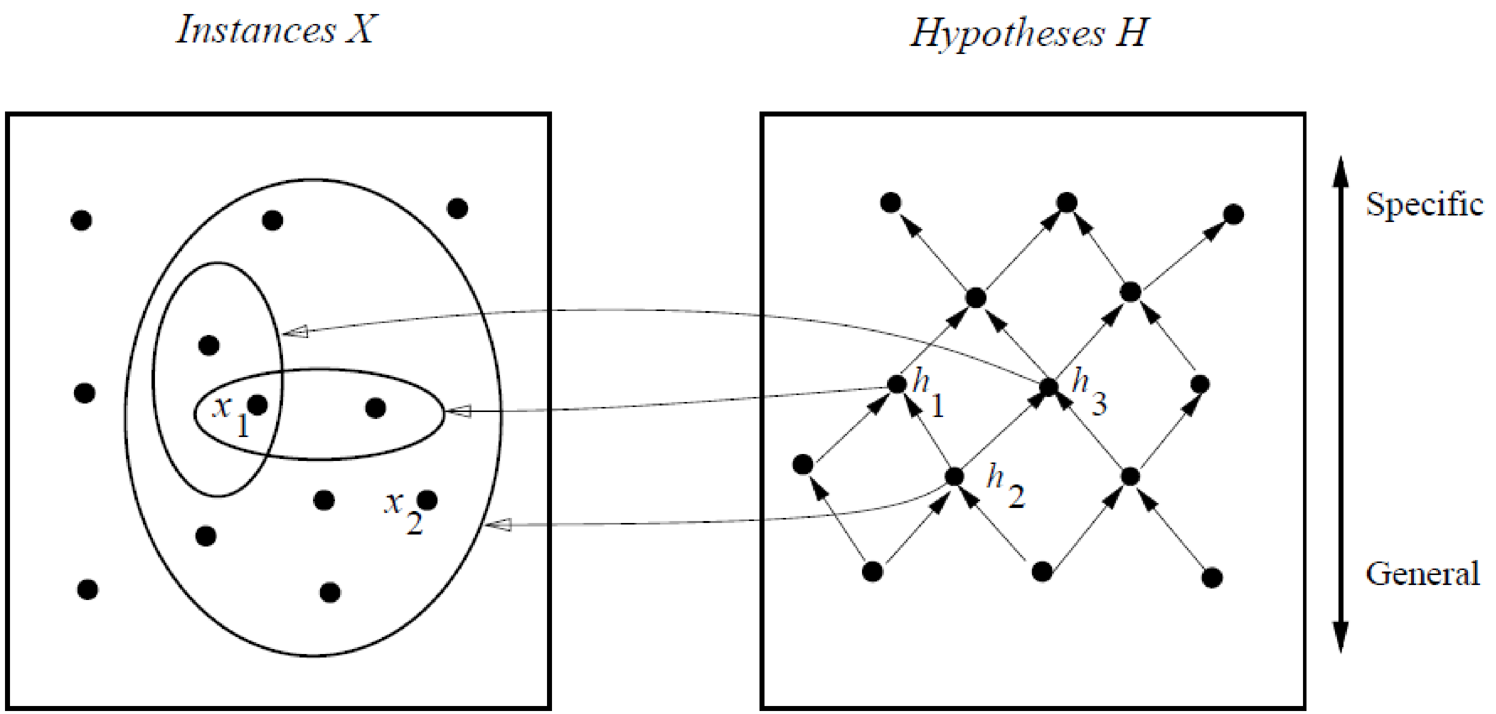
- h1= <Sunny, ?, ?, Strong, ?, ?>
- h2= <Sunny, ?, ?, ?, ?, ?>

- For any instance *x* in *X* and hypothesis *h* in *H*, we say that x ***satisfies*** h if and only if h(x) = 1.

***Definition***: Let $h_j$ and $h_k$ be boolean-valued functions defined over $X$. Then $h_j$ is **more_general_than_or_equal_to** $h_k$ (written $h_j \geq_g h_k$) if and only if

$$(\forall x \in X)[(h_k(x) = 1) \rightarrow (h_j(x) = 1)]$$

# Hasse diagram




$x_1$ = <*Sunny, Warm, High, Strong, Cool, Same*>
$x_2$ = <*Sunny, Warm, High, Light, Warm, Same*>

$h_1$ = <*Sunny, ?, ?, Strong, ?, ?*>
$h_2$ = <*Sunny, ?, ?, ?, ?, ?*>
$h_3$ = <*Sunny, ?, ?, ?, Cool, ?*>

# Find-S Algorithm

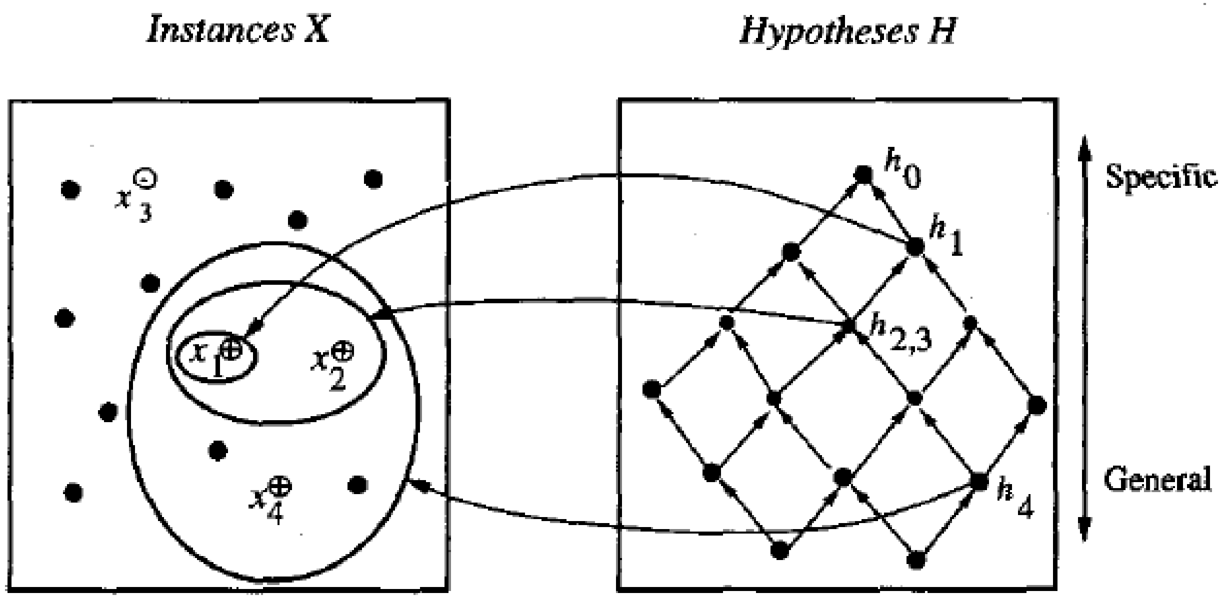
1. Initialize $h$ to the most specific hypothesis in $H$
2. For each positive training instance $x$
   - For each attribute constraint $a_i$ in $h$

     If the constraint $a_i$ in $h$ is satisfied by $x$

     Then do nothing

     Else replace $a_i$ in $h$ by the next more general constraint that is satisfied by $x$
3. Output hypothesis $h$

# Find-S Algorithm




$h_0 = <\varnothing, \varnothing, \varnothing, \varnothing, \varnothing, \varnothing>$

$x_1$ = <*Sunny Warm Normal Strong Warm Same*>, +

$x_2$ = <*Sunny Warm High Strong Warm Same*>, +

$x_3$ = <*Rainy Cold High Strong Warm Change*>, -

$x_4$ = <*Sunny Warm High Strong Cool Change*>, +

$h_1$ = <*Sunny Warm Normal Strong Warm Same*>

$h_2$ = <*Sunny Warm ? Strong Warm Same*>

$h_3$ = <*Sunny Warm ? Strong Warm Same*>

$h_4$ = <*Sunny Warm ? Strong ? ?* >

At each step, h is the most/least specific/general hypothesis consistent with the training examples observed to this step

# Find-S Algorithm – ignore negative instances

- Ignores every -ve training instances!
- However, the current hypothesis is already consistent with the -ve example
- As long as we assume that H contains a hypothesis that describes target concept and the training data is correct, it never requires to consider –ve examples

- *Why?*

# Complaints about Find-S

- **Has the learner converged to the current target concept?**
  - No way to determine if it has found the *only hypothesis* that is consistent with the target concept
  - *Or* there are many other consistent hypotheses as well
- **Why prefer the most specific hypothesis?**
  - In case of multiple hypotheses consistent with the target concept, why to consider the most specific one?
- **Are the training example consistent?**
  - What if a few training instances are corrupted?
- **What if there are several maximally specific consistent hypotheses?**
  - Find-S should be backtracked to generalize the hypothesis

# Version Space and CANDIDATE- ELIMINATION

- Outputs a description of the set of all hypotheses consistent with the training set
- It uses ***more_general_than*** partial order

A hypothesis $h$ is **consistent** with a set of training examples $D$ of target concept $c$ if and only if $h(x) = c(x)$ for each training example $\langle x, c(x)\rangle$ in $D$.

$$Consistent(h, D) \equiv (\forall \langle x, c(x)\rangle \in D)\ h(x) = c(x)$$

# Version Space and CANDIDATE- ELIMINATION

- An example x is said to ***satisfy*** hypothesis h when h(x) = 1, regardless of whether x is a positive or negative example of the target concept.

- However, whether such an example is ***consistent*** with h depends on the target concept, and in particular, whether $h(x) = c(x)$.

# Version Space and CANDIDATE- ELIMINATION

- CANDIDATE-ELIMINATION generates set of all hypotheses consistent with the observation
- This set is called **version space**

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

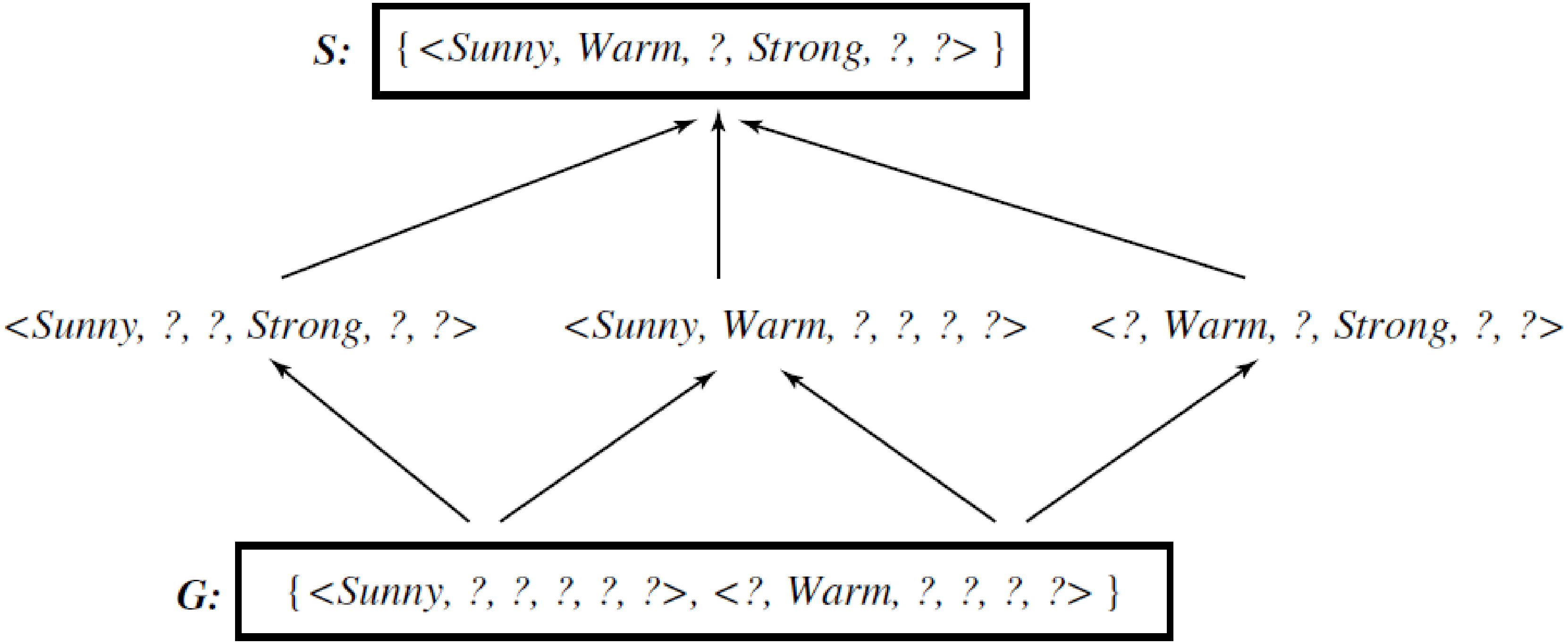
$$VS_{H,D} \equiv \{h \in H | Consistent(h, D)\}$$

# LIST-THEN-ELIMINATION Algorithm

1. $VersionSpace \leftarrow$ a list containing every hypothesis in $H$
2. For each training example, $\langle x, c(x) \rangle$

   remove from $VersionSpace$ any hypothesis $h$ for which $h(x) \neq c(x)$
3. Output the list of hypotheses in $VersionSpace$

# Compact Representation of Version Space




Find-S only generates <Sunny, Warm, ?, Strong, ?, ?>
But all six hypotheses shown above are consistent

| 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 |

# Representing Version Space

The **General boundary**, G, of version space $VS_{H,D}$ is the set of its maximally general members

The **Specific boundary**, S, of version space $VS_{H,D}$ is the set of its maximally specific members

Every member of the version space lies between these boundaries

$$VS_{H,D} = \{h \in H | (\exists s \in S)(\exists g \in G)(g \geq h \geq s)\}$$

where $x \geq y$ means $x$ is more general or equal to $y$

# CANDIDATE- ELIMINATION Algorithm

$G \leftarrow$ maximally general hypotheses in $H$
$S \leftarrow$ maximally specific hypotheses in $H$
For each training example $d$, do

- If $d$ is a positive example
  - Remove from $G$ any hypothesis inconsistent with $d$
  - For each hypothesis $s$ in $S$ that is not consistent with $d$
    - Remove $s$ from $S$
    - Add to $S$ all minimal generalizations $h$ of $s$ such that
      1. $h$ is consistent with $d$, and
      2. some member of $G$ is more general than $h$
    - Remove from $S$ any hypothesis that is more general than another hypothesis in $S$

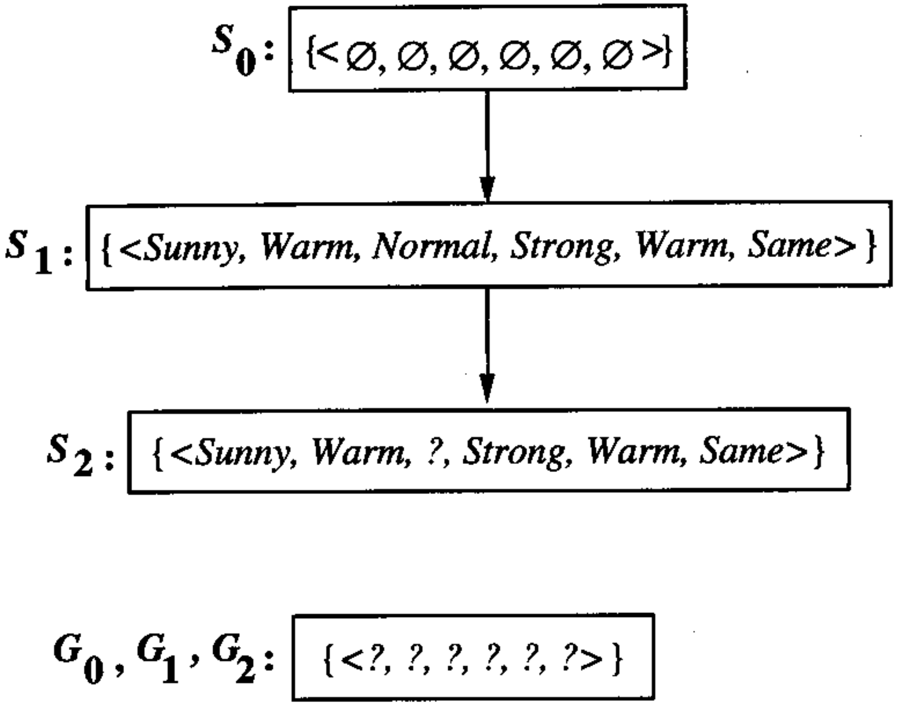
- If $d$ is a negative example
  - Remove from $S$ any hypothesis inconsistent with $d$
  - For each hypothesis $g$ in $G$ that is not consistent with $d$
    - Remove $g$ from $G$
    - Add to $G$ all minimal specializations $h$ of $g$ such that
      1. $h$ is consistent with $d$, and
      2. some member of $S$ is more specific than $h$
    - Remove from $G$ any hypothesis that is less general than another hypothesis in $G$

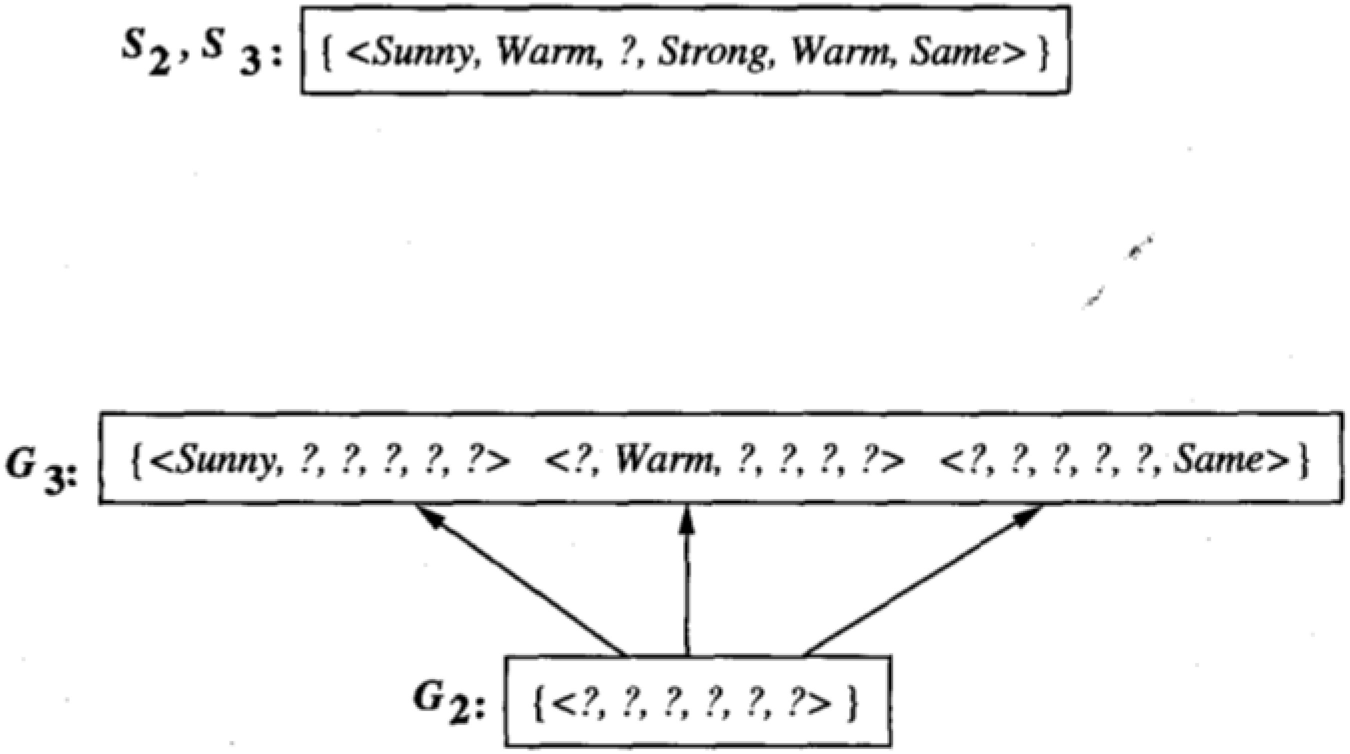
# Example

$S_0$: $\{\langle \varnothing, \varnothing, \varnothing, \varnothing, \varnothing, \varnothing \rangle\}$

$G_0$: $\{\langle ?, ?, ?, ?, ?, ? \rangle\}$

# Example



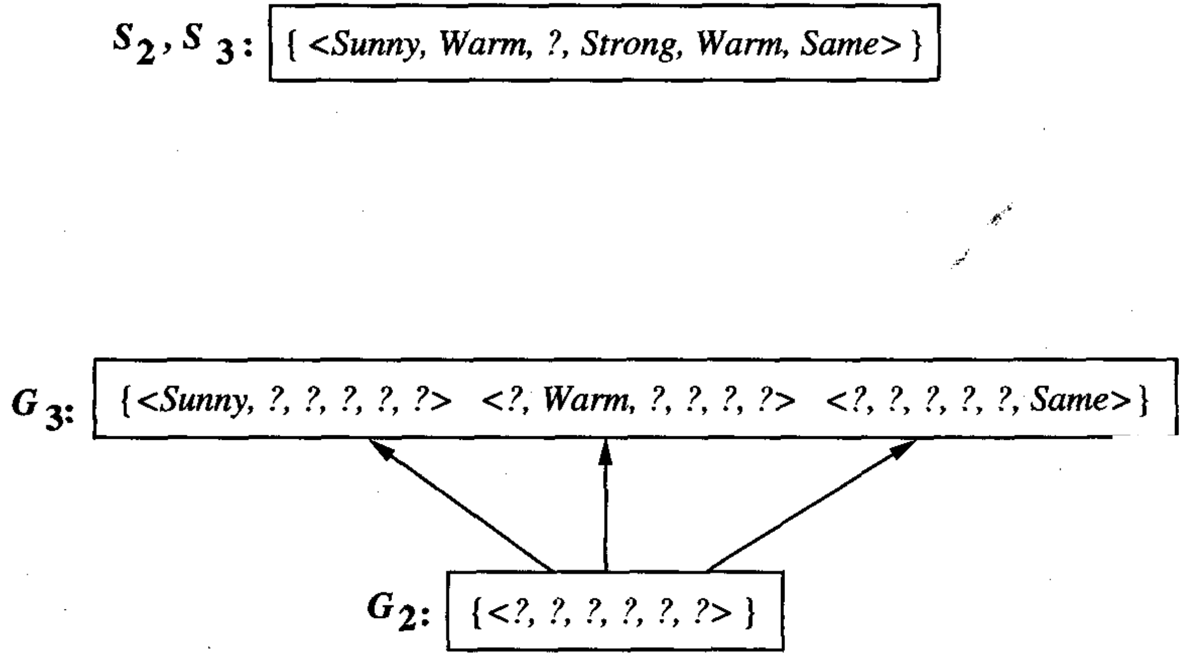




Training examples:

1. *<Sunny, Warm, Normal, Strong, Warm, Same>, Enjoy Sport = Yes*
2. *<Sunny, Warm, High, Strong, Warm, Same>, Enjoy Sport = Yes*

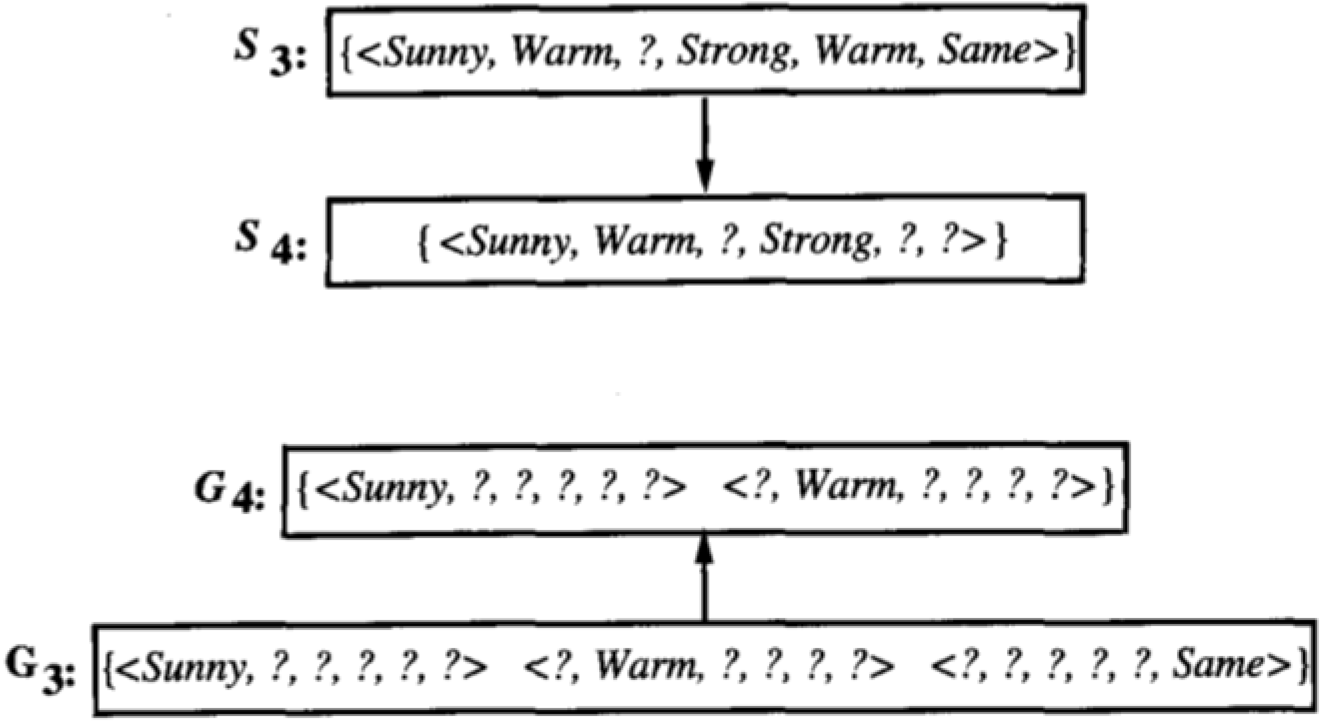
Training Example:

3. *<Rainy, Cold, High, Strong, Warm, Change>, EnjoySport=No*




Training Example:

3. *<Rainy, Cold, High, Strong, Warm, Change>, EnjoySport=No*




Training Example:

4. *<Sunny, Warm, High, Strong, Cool, Change>, EnjoySport = Yes*

# Example

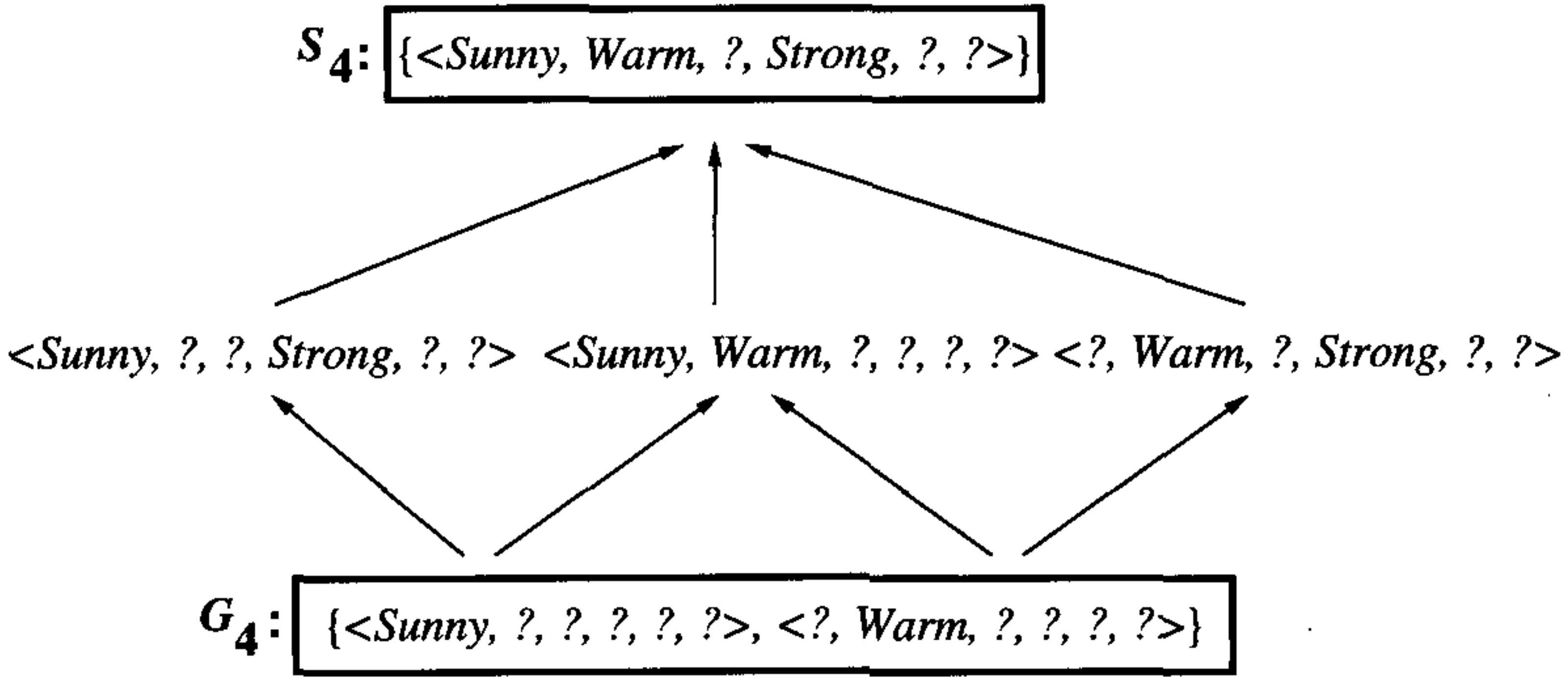



**FIGURE 2.7**
The final version space for the *EnjoySport* concept learning problem and training examples described earlier.

# Remarks on CANDIDATE-ELIMINATION

- Will the CANDIDATE-ELIMINA algorithm Converge to the Correct Hypothesis?

- What Training Example Should the Learner Request Next?

- How Can Partially Learned Concepts Be Used?

| Instance | *Sky* | *AirTemp* | *Humidity* | *Wind* | *Water* | *Forecast* | *EnjoySport* |
|---|---|---|---|---|---|---|---|
| A | Sunny | Warm | Normal | Strong | Cool | Change | ? |
| B | Rainy | Cold | Normal | Light | Warm | Same | ? |
| C | Sunny | Warm | Normal | Light | Warm | Same | ? |
| D | Sunny | Cold | Normal | Strong | Warm | Same | ? |