CSC3022H: Machine Learning:

Concept Learning

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Examples of Machine Learning Types

Supervised Learning:

- Classification.
- Regression.

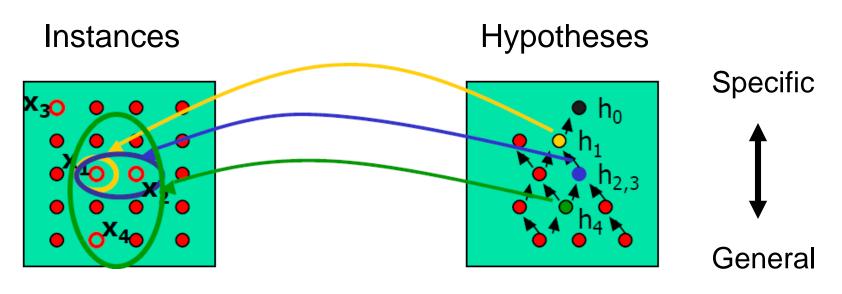
Unsupervised Learning:

- Clustering.
- Dimensionality reduction.

Reinforcement Learning:

- Value and policy iteration.
- Q Learning.

Recap: Hypothesis Space Search by Find-S



 $h0 = \langle \emptyset, \emptyset, \emptyset, \emptyset, \emptyset, \emptyset \rangle$

h4 = < Sunny, Warm, ?, Strong, ?, ? >

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x1 = < Sunny, Warm, Normal, Strong, Warm, Same >, +
h1 = < Sunny, Warm, Normal, Strong, Warm, Same >

x2 = <Sunny, Warm, High, Strong, Warm, Same>, +
h2 = < Sunny, Warm, ?, Strong, Warm, Same >

x3 = < Rainy, Cold, High, Strong, Warm, Change >, -
h3 = < Sunny, Warm, ?, Strong, Warm, Same >

x4 = < Sunny, Warm, High, Strong, Cool, Change >, +
```

Version Spaces

Hypothesis h:

Is <u>consistent</u> with a set of training examples D of target concept c if and only if h(x) = c(x) for each training example < x, c(x) > in D.

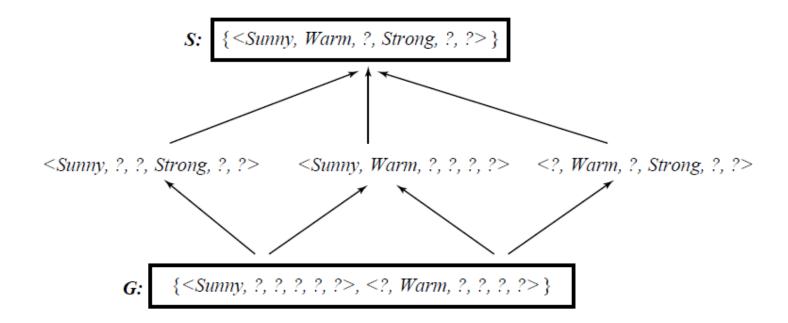
$$Consistent(h, D) \equiv (\forall \langle x, c(x) \rangle \in D) \ h(x) = c(x)$$

Version space VS_{H,D}:

With respect to hypothesis space H, and training set D,
 VS_{HD} is the subset of hypotheses from H that are consistent with all training examples (in D):

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

Example Version Space



List-Then Eliminate Algorithm

- VersionSpace → List containing every hypothesis in H
- For each training example < x, c(x) >
 - Remove from VersionSpace any hypothesis that is inconsistent with the training example h(x) ≠ c(x).
- Output the list of hypotheses in VersionSpace.
- Advantages? Disadvantages?

Representing Version Spaces

- General boundary G: Of version space VS_{H,D} is the set of maximally general members.
- Specific boundary S: Of version space VS_{H,D} is the set of maximally specific members.
- Every member of the version space lies between these boundaries:

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

Where: x ≥ y means x is more general or equal to y.

Candidate Elimination Algorithm

 $G \leftarrow$ Maximally general hypotheses in H

S ← Maximally specific hypotheses in H

FOR each training example *d*

IF *d* is a +ve example **THEN**

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 generalisations h of s such that:

h is consistent with d and a member of G is more general than h

Remove from S: Any hypothesis that is *more general than* another hypothesis in S

END FOR

END IF

END FOR

Candidate Elimination Algorithm

IF *d* is a -ve example **THEN**:

Remove from S any hypothesis that is 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:

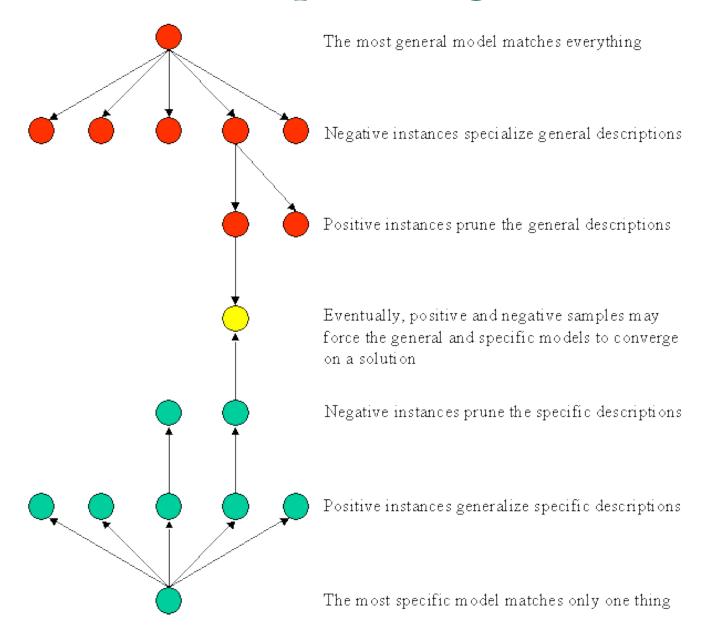
h is consistent with d and some member of S is more specific than h

Remove from *G* any hypothesis that is less general than another hypothesis in *G*

END FOR

END IF

Version Space Diagram



Features: (Country of Origin, Manufacturer, Color, Decade, Type)

Origin	Manufacturer	Colour	Decade	Туре	Example Type
Japan	Honda	Blue	1980	Economy	Positive
Japan	Toyota	Green	1970	Sports	Negative
Japan	Toyota	Blue	1990	Economy	Positive
USA	Chrysler	Red	1980	Economy	Negative
Japan	Honda	White	1980	Economy	Positive
Japan	Toyota	Green	1980	Economy	Positive
Japan	Honda	Red	1990	Economy	Negative

1. Positive Example: (Japan, Honda, Blue, 1980, Economy):

Initialise G to a singleton set that includes everything.

Initialise S to a singleton set that includes the first positive example.

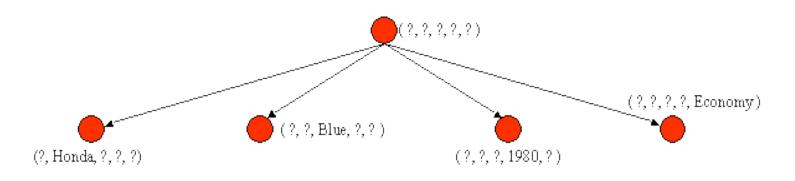
$$G = \{ (?, ?, ?, ?, ?) \}$$

(?, ?, ?, ?, ?)

(Japan, Honda, Blue, 1980, Economy)



2. Negative Example: (Japan, Toyota, Green, 1970, Sports): Specialise G to exclude the -ve example.



(Japan, Honda, Blue, 1980, Economy)

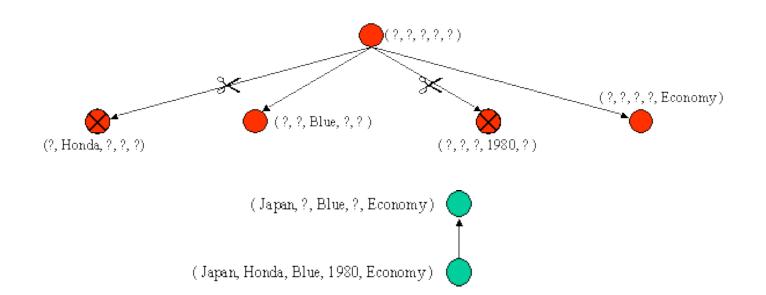


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Japan	Toyota	Green	1980	Economy	Positive
Japan	Honda	Red	1990	Economy	Negative

- 3. Positive Example: (Japan, Toyota, Blue, 1990, Economy):
 - Prune G to exclude descriptions inconsistent with +ve example.
 - Generalise S to include the positive example.

G =	{ (?, ?, Blue, ?, ?), (?, ?, ?, Economy) }
S =	{ (Japan, ?, Blue, ?, Economy) }

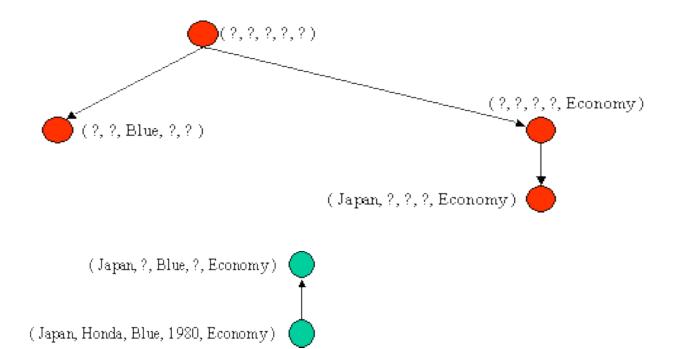


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Japan	Honda	White	1980	Economy	Positive
Japan	Toyota	Green	1980	Economy	Positive
Japan	Honda	Red	1990	Economy	Negative

- 4. Negative Example: (USA, Chrysler, Red, 1980, Economy):
- \square Specialise G to exclude -ve example (but stay consistent with S).

G =	{ (?, ?, Blue, ?, ?), (Japan, ?, ?, ?, Economy) }	
S =	{ (Japan, ?, Blue, ?, Economy) }	

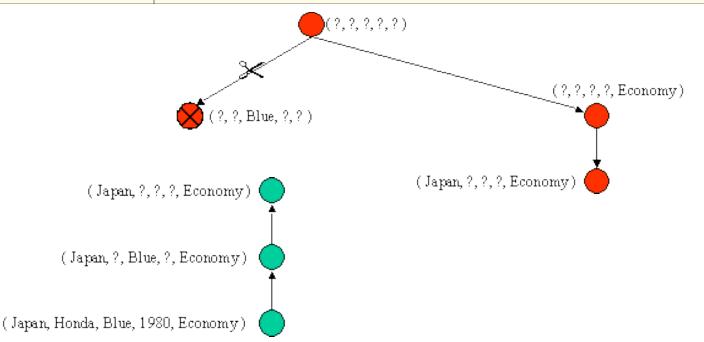


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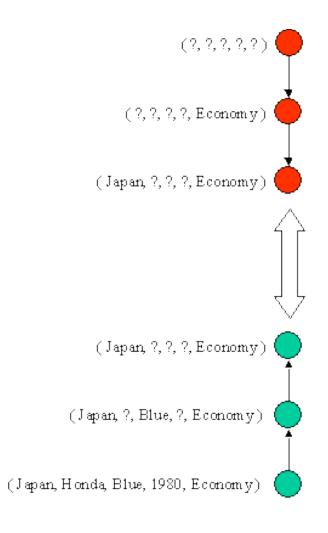
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Japan	Honda	White	1980	Economy	Positive
Japan	Toyota	Green	1980	Economy	Positive
Japan	Honda	Red	1990	Economy	Negative

- 5. Positive Example: (Japan, Honda, White, 1980, Economy):
 - \square Prune G to exclude descriptions inconsistent with +ve example.
 - Generalise S to include positive example.

G =	(Japan, ?, ?, ?, Economy) }
S =	{ (Japan, ?, ?, ?, Economy) }

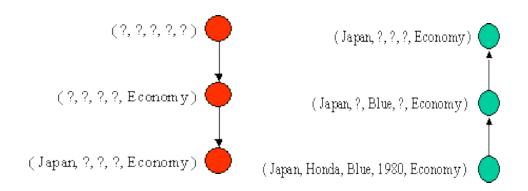


• G and S are singleton sets and S = G.

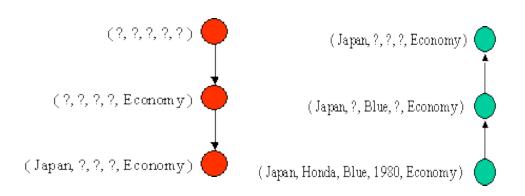


6. Positive Example: (Japan, Toyota, Green, 1980, Economy):

New example is consistent with version-space, so no change is made.



7. Negative Example: (Japan, Honda, Red, 1990, Economy):

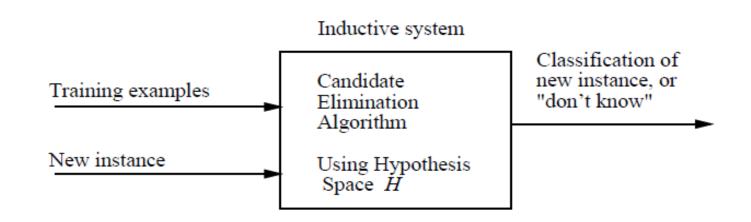


7. Negative Example: (Japan, Honda, Red, 1990, Economy):

Example is inconsistent with the version-space.

G cannot be specialised. S cannot be generalised.

Problems with Candidate Elimination Algorithm?



CEA Learner Properties

- If there is a consistent hypothesis then the algorithm will converge to $S = G = \{h\}$ when enough examples are provided.
- "Noisy" examples may cause the removal of the correct h.
- If too many examples are inconsistent, S and G become empty.
- This can also happen, when concept to be learned is not in *H*.

Assumes:

- There are no errors in the training examples.
- There is some h in H that correctly describes the target concept.

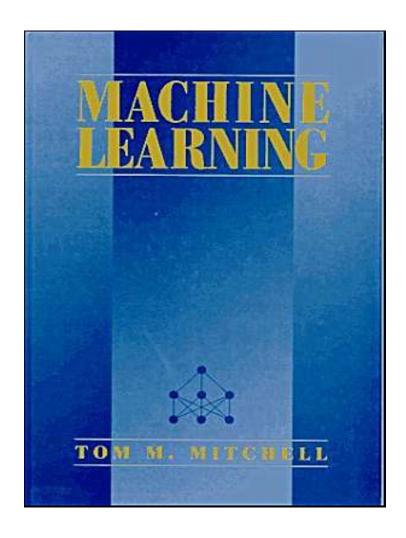
Inductive Bias

- Concept learners classify unseen examples because of implicit inductive bias.
- Bias is that the target concept can be found in the hypothesis space ($c \in H$).
- More bias implies more generality in classifying unseen examples.
- If there is a hypothesis corresponding to every possible instance, this removes inductive bias from Candidate-Elimination.
- This also removes the ability to classify any instance beyond the observed training examples.
- Unbiased learner cannot classify unseen examples (no induction!).

Concept Learners → Bias!

- Inductive bias of:
 - Rote learner: Store examples, Classify x iff it matches previously observed example.
 - No inductive bias (→ no generalisation!)
 - Candidate Elimination Algorithm:
 - \mathbf{c} is in H.
 - Find-S:
 - c is in H.
- Inductive leaps possible only if learner is biased.

ML: Reading



Chapter 2: Concept Learning