



Birla Institute of Technology and Science Pilani, Hyderabad Campus
2nd Semester 2023-24

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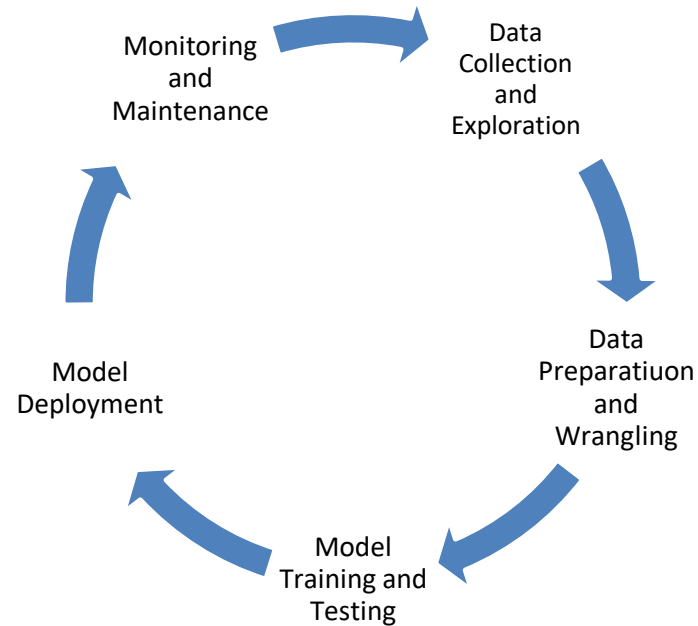
BITS F464: Machine Learning

SYMBOLIC ML: CONCEPT LEARNING

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Recap

- ML Frameworks
- Scikitlearn
- Pandas
- Matplotlib
- SciPy
- TensorFlow
- Keras
- PyTorch



(Machine Learning Life Cycle)

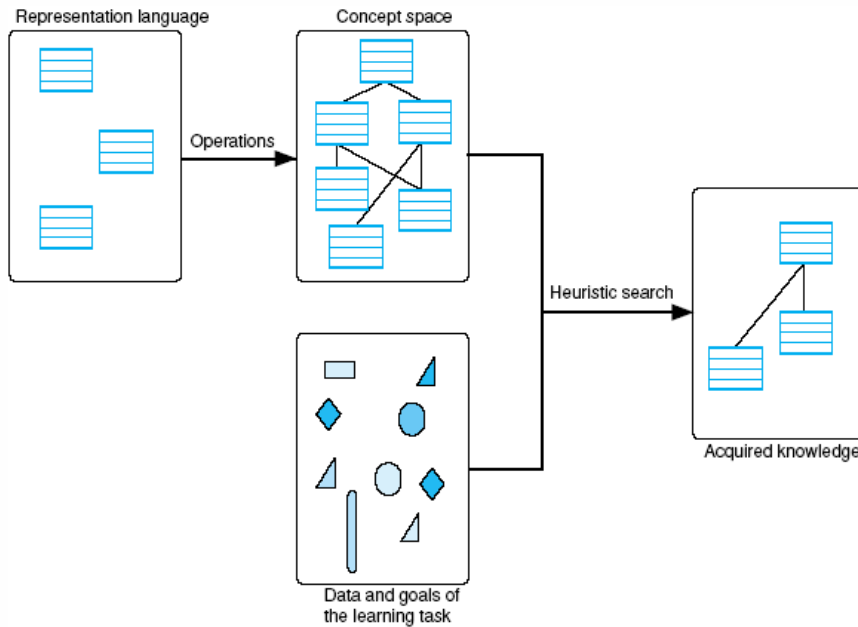
Approaches to Machine Learning

- Symbolic Learning
 - Knowledge Representation: Symbols and Rules
 - Learning Approach: Manipulation of Symbols
 - Interpretable and Transparent
 - Small Training data
- Connectionist Learning
 - Knowledge Representation: Distributed layers
 - Learning Approach: Weight adjustment
 - Highly non-linear relations
 - Large amounts of training data
- Probabilistic Learning
 - Ability to take into account uncertainty
- Evolutionary Learning

There are six mental faculties that we have, and how we use them sets the course for our life.

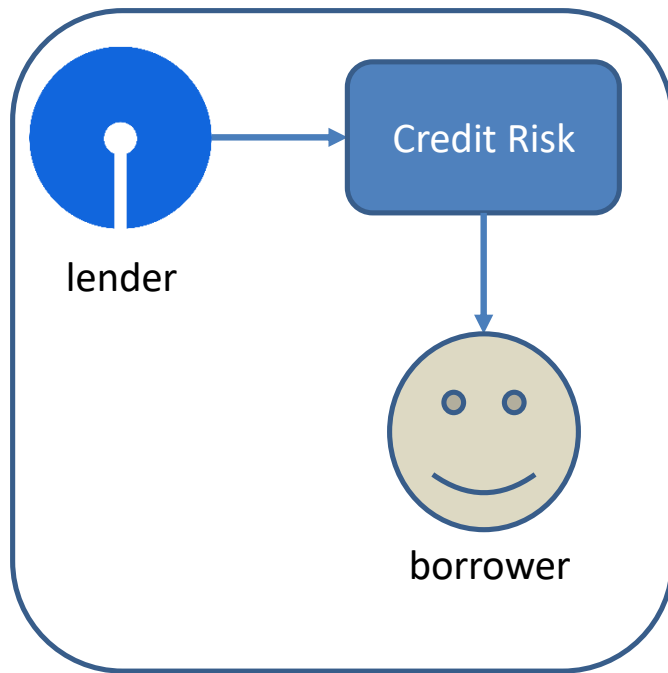
— Bob Proctor —

Concept Learning: A General Model



- Inferring a Boolean-valued function/hypothesis from labeled training examples. $c: X \rightarrow \{0, 1\}$
 - $h: X \rightarrow \{0, 1\}$, the goal is to find h such that $h(x) = c(x)$ for all x in X .
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How Concept Learning Infers a function?



(Credit Risk Assessment)

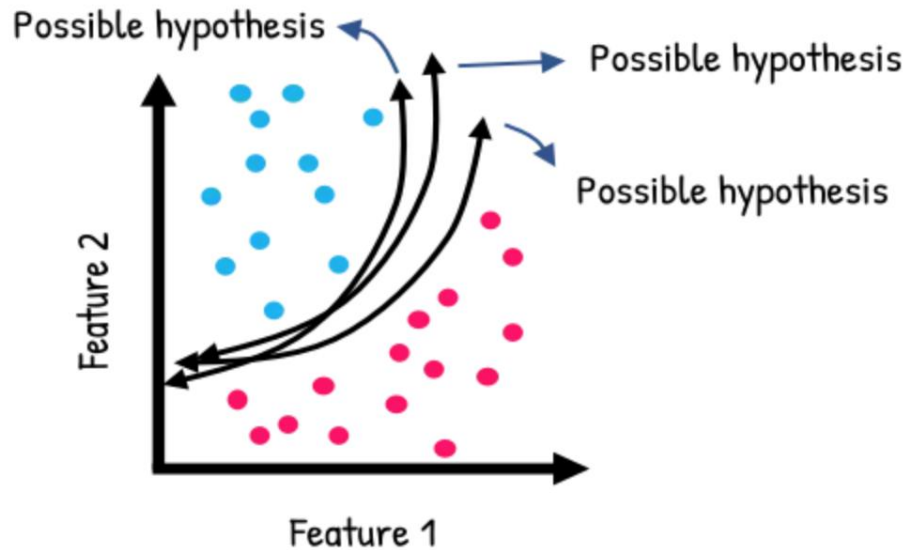
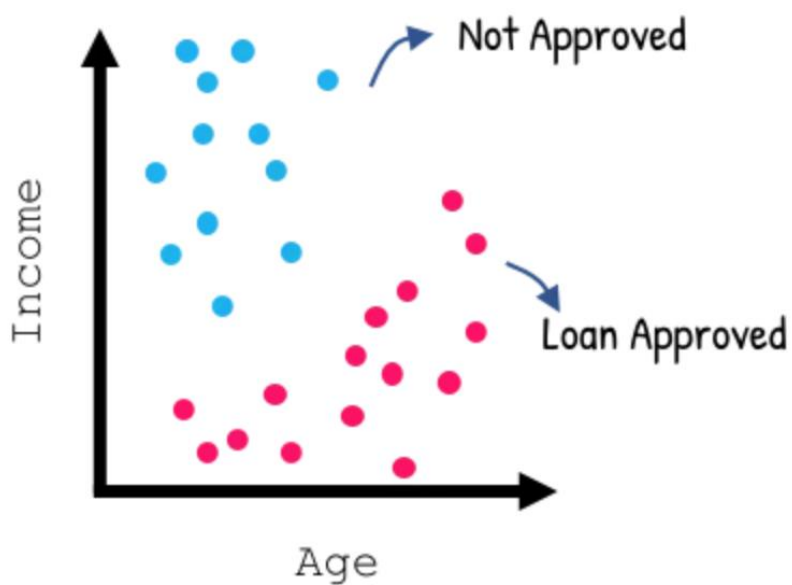
| Gender | Age Group | Income | Dependents | Loan Amount | Award Loan? |
|--------|-----------|--------|------------|-------------|-------------|
| Male | <18 | 3000 | 0 | 120 | No |
| Female | 35 - 50 | 2350 | 0 | 100 | No |
| Female | 35 - 50 | 4500 | 1 | 90 | Yes |
| Male | 18 - 25 | 6000 | 2 | 120 | Yes |

Negative Example

Positive Example

Img. Source: <https://www.analyticsvidhya.com/>

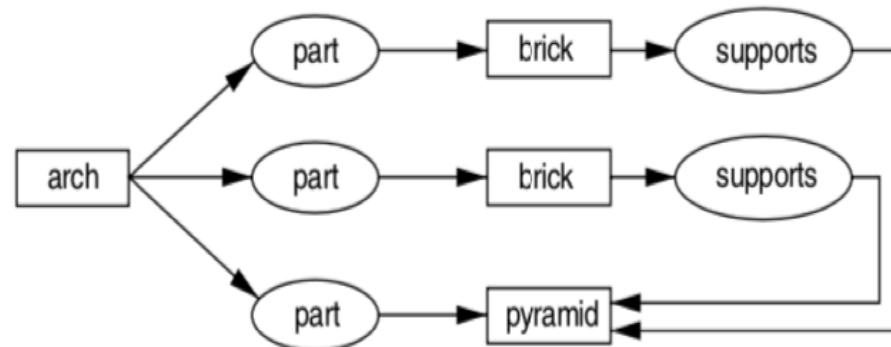
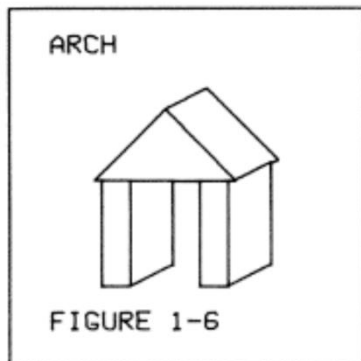
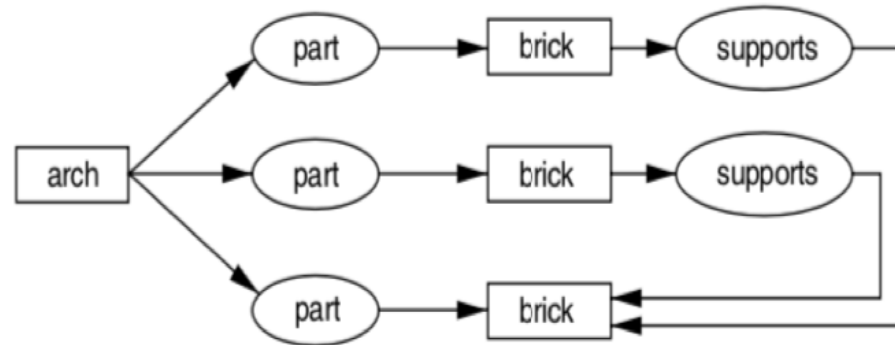
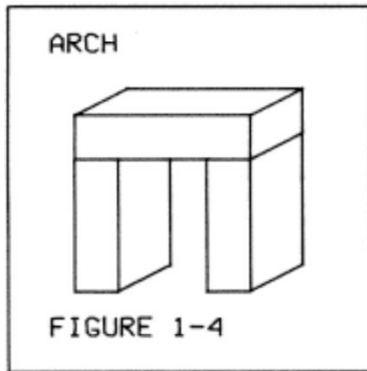
Credit Risk Assessment Continued...



Source: <https://www.analyticsvidhya.com/>

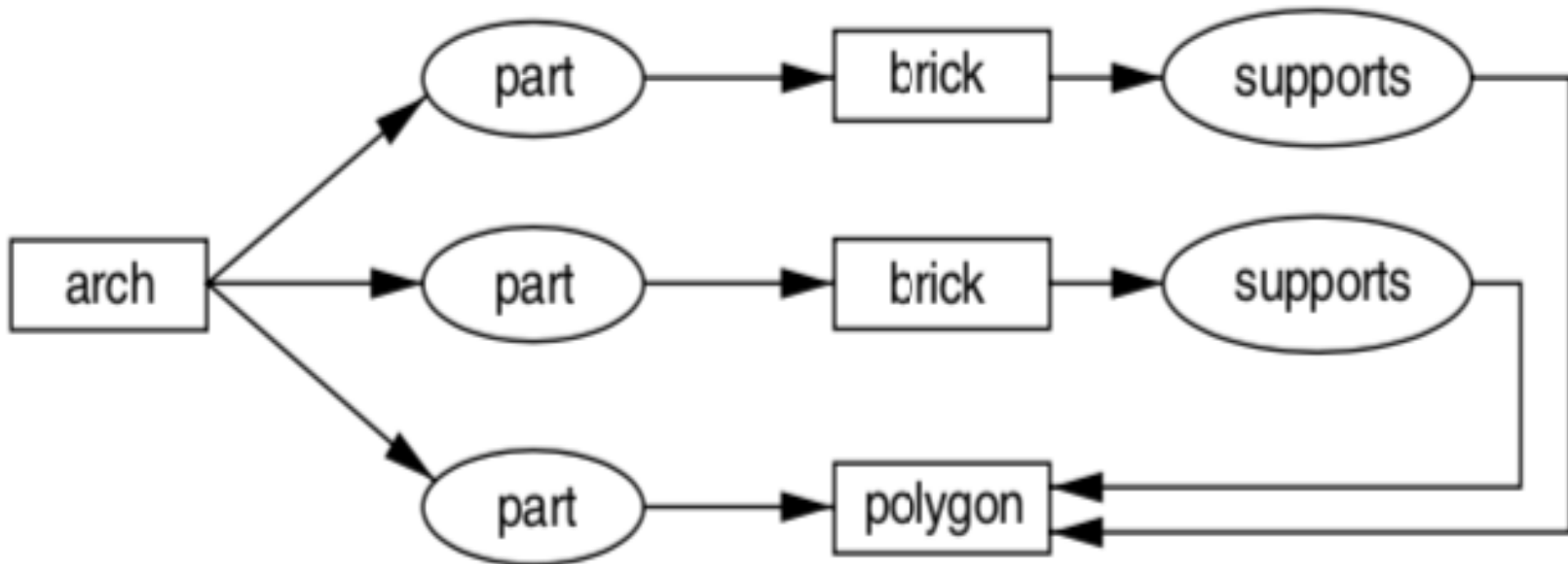
Winston's Program: Inductive Learning

(Learning Concept "Arch")

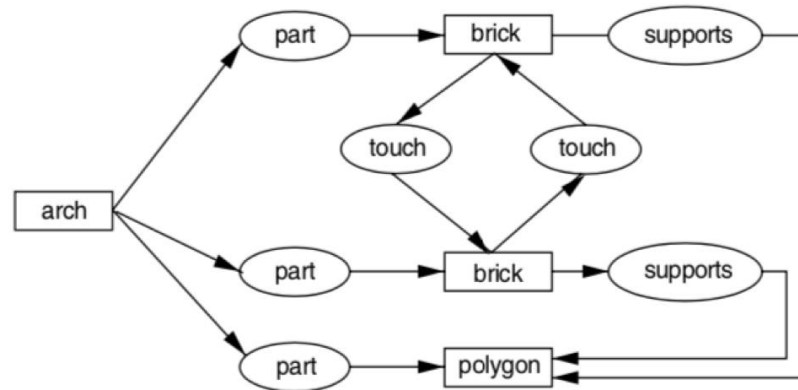
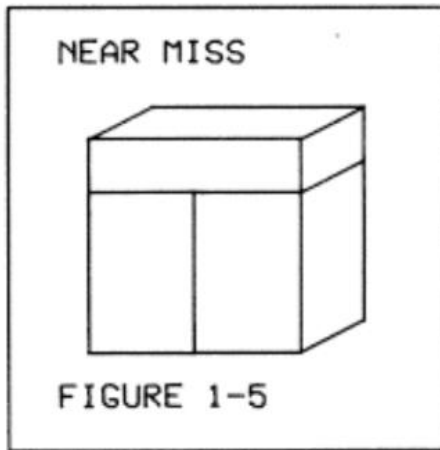


Generalization using background knowledge

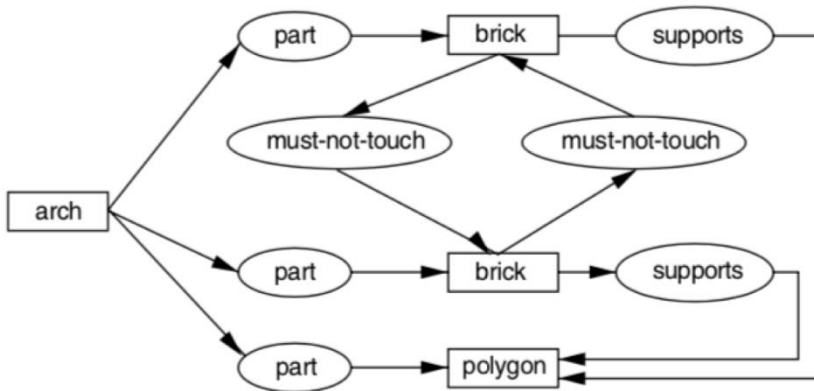
- What background knowledge learner can use here to generalize?



Description of a “near miss” & Specialization



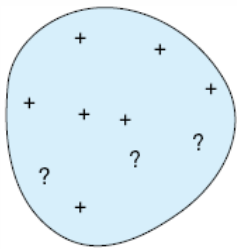
How important is order of examples ?



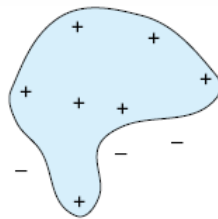
Hill Climbing

The Role of Negative Examples

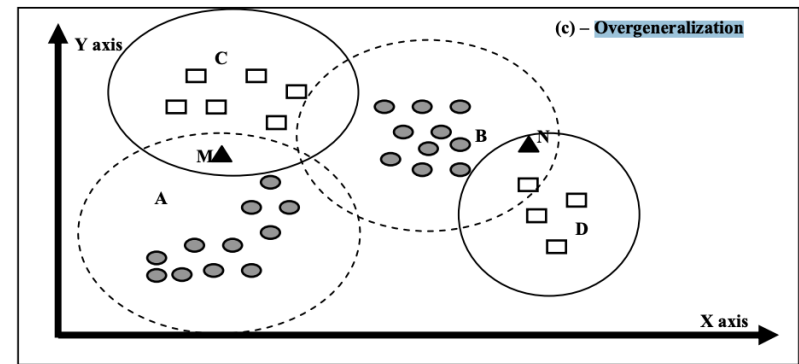
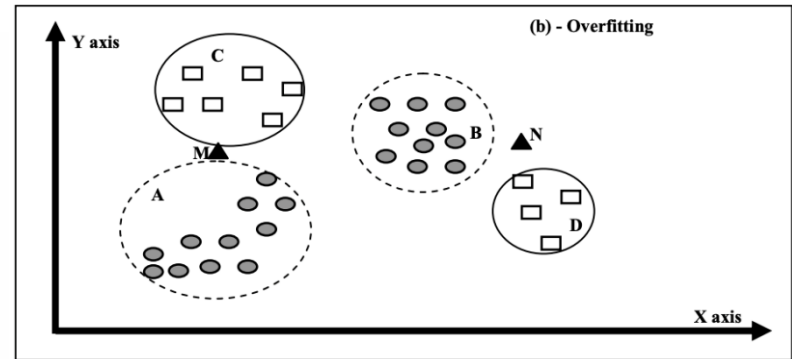
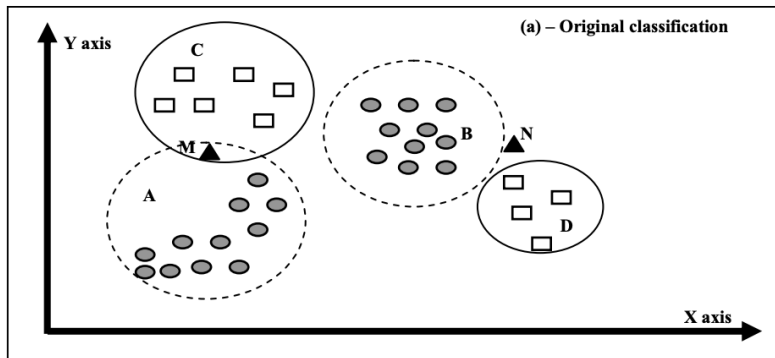
- Negative instances prevent **overgeneralization** by forcing the learner to specialize concepts in order to exclude negative instances.



Concept induced from positive examples only



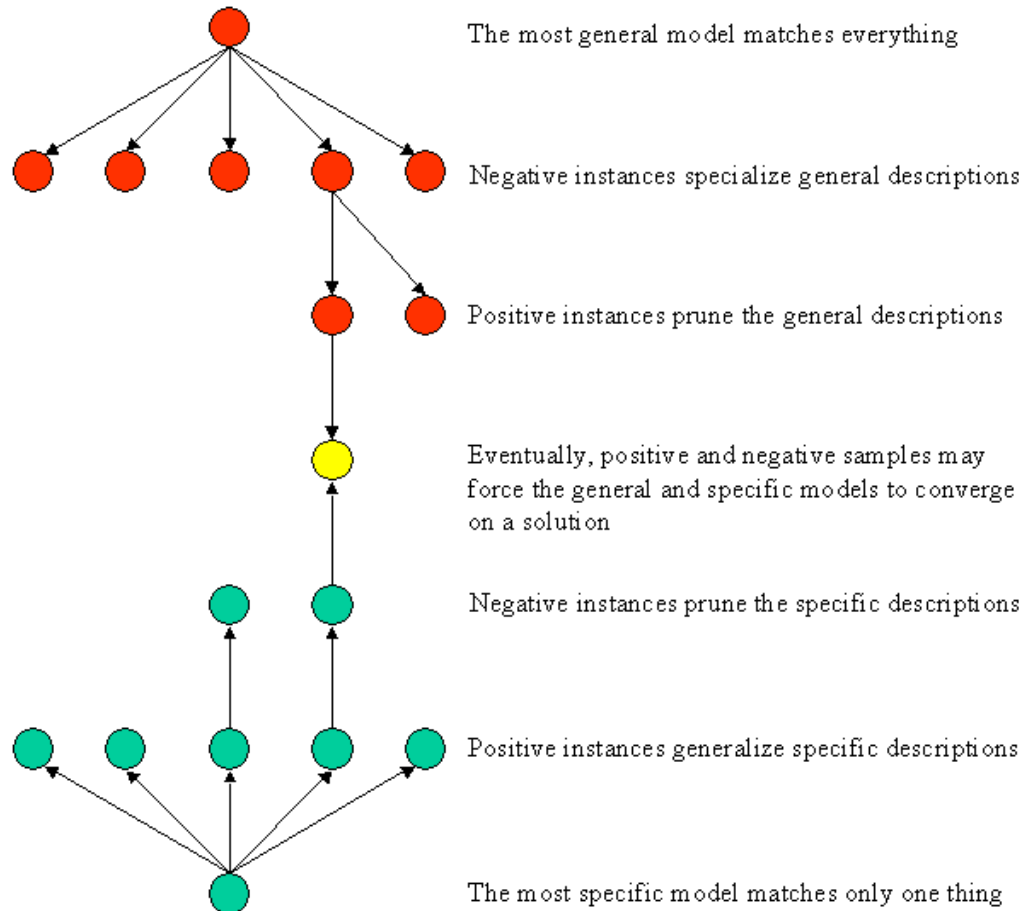
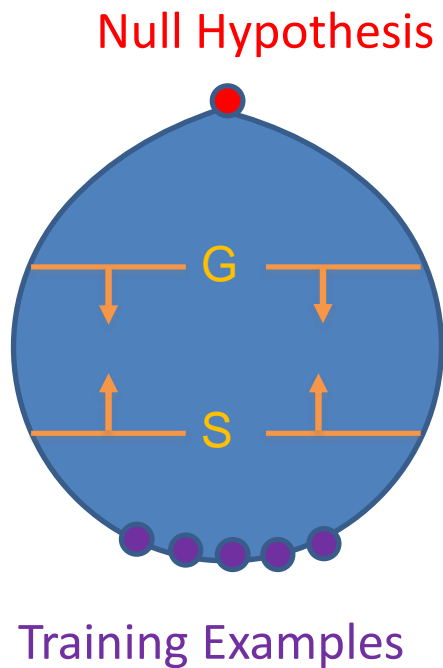
Concept induced from positive and negative examples



(Img. Source: Huy Nguyen)

Version Space as a Search

- Inductive learning as a Search through the Concept Space



Candidate Elimination (Mitchell, PhD, Stanford)

- Initialize G to contain one element: the most general description (all features are variables).
- Initialize S to empty.
- Accept a new training example.
- **Process Positive Examples:**
- Remove from G any hypothesis that do not cover the example.
- Generalize S as little as possible so that the new training example is covered.
- Remove from S all elements that cover negative examples.



(Tom Mitchell, CMU)

Algorithm continued...

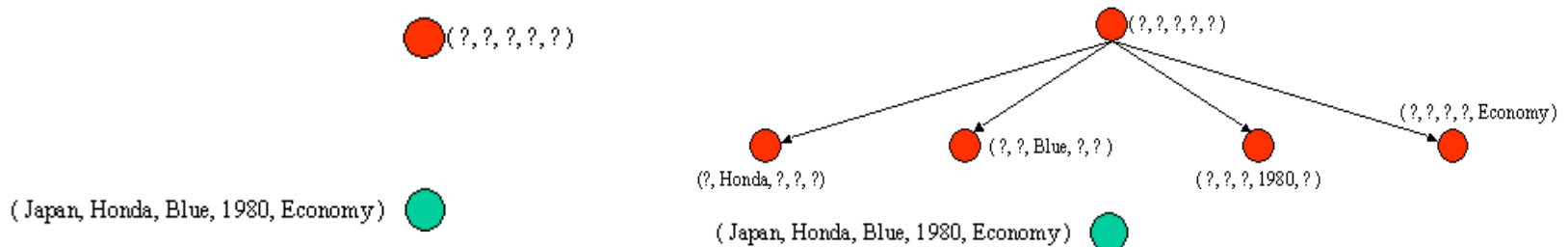
- **Process Negative Examples:**
 - Remove from S any descriptions that cover the negative example.
 - Specialize G as little as possible so that the negative example is not covered.
 - Remove from G all elements that do not cover the positive examples.
 - **Continue processing new training examples, until one of the following occurs:**
 - Either S or G become empty, there are no consistent hypotheses over the training space. Stop.
 - S and G are both singleton sets.
 - if they are **identical**, output their value and stop.
 - if they are **different**, the training cases were inconsistent. Output this result and stop.
 - No more training examples. G has several hypotheses.
-

Example

Learning the concept of "Japanese Economy Car"

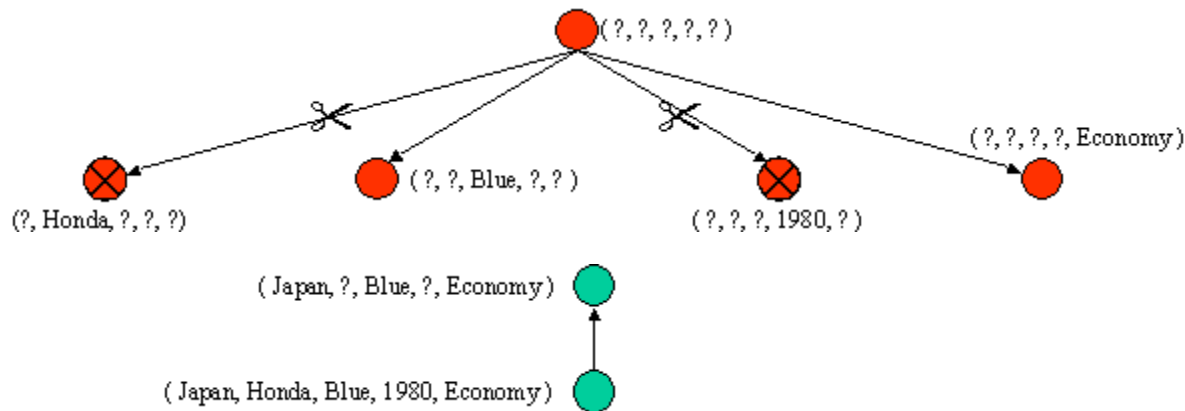
| Origin | Manufacturer | Color | Decade | Type | Example Type |
|--------|--------------|-------|--------|---------|--------------|
| Japan | Honda | Blue | 1980 | Economy | Positive |
| Japan | Toyota | Green | 1970 | Sports | Negative |
| Japan | Toyota | Blue | 1990 | Economy | Positive |
| USA |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

1. +ve:(Japan,Honda,Blue,1980,Economy) 2. -ve:(Japan,Toyota,Green,1970,Sports)

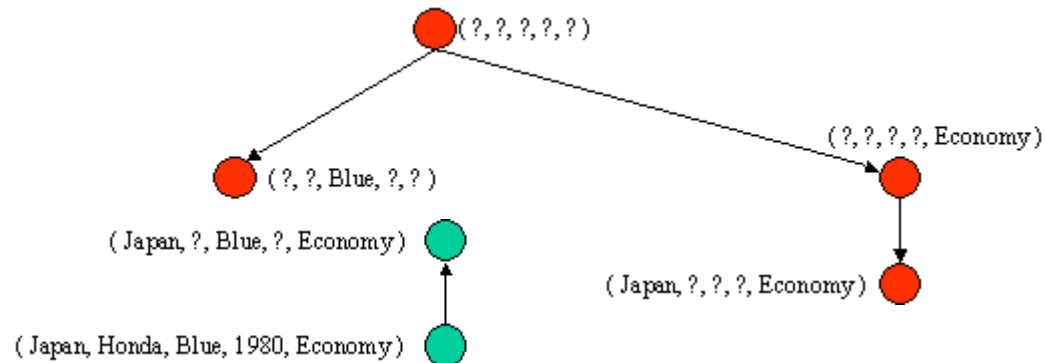


Example continued...

3. +ve : (Japan, Toyota, Blue, 1990, Economy)

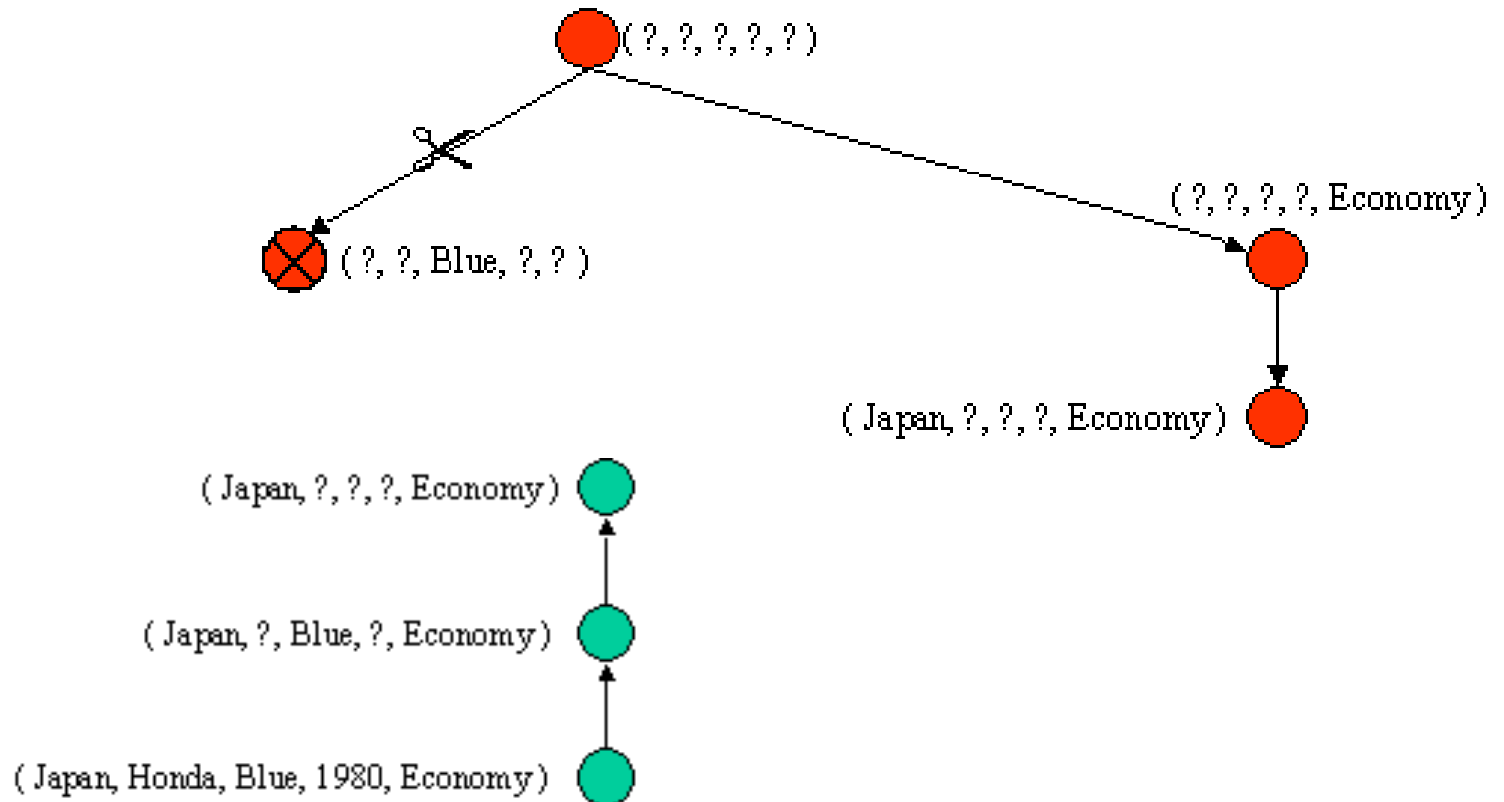


4. -ve : (USA, Chrysler, Red, 1980, Economy)



Example continued...

5. +ve : (Japan, Honda, White, 1980, Economy)



How important are training examples?

| <i>Origin</i> | <i>Manufacturer</i> | <i>Color</i> | <i>Decade</i> | <i>Type</i> | <i>Example Type</i> |
|---------------|---------------------|--------------|---------------|-------------|---------------------|
| 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 |

Consistent with version space, and hence $G: (\text{Japan}, ?, ?, ?, \text{Economy})$, and $S: (\text{Japan}, ?, ?, ?, \text{Economy})$ i.e. No change.

In-consistent with version space and hence, $G: \phi$, and $S: \phi$ (no concept)

Biased Hypothesis Space

- Candidate elimination will converge towards the target concept, provided:
 - Accurate training examples are available to the learner
 - Initial hypothesis space contains the target concept
- If target concept is not present, then it is **Biased**.

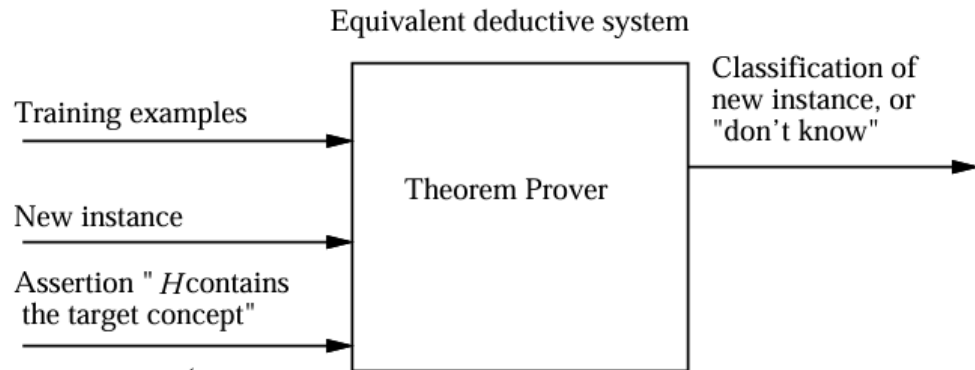
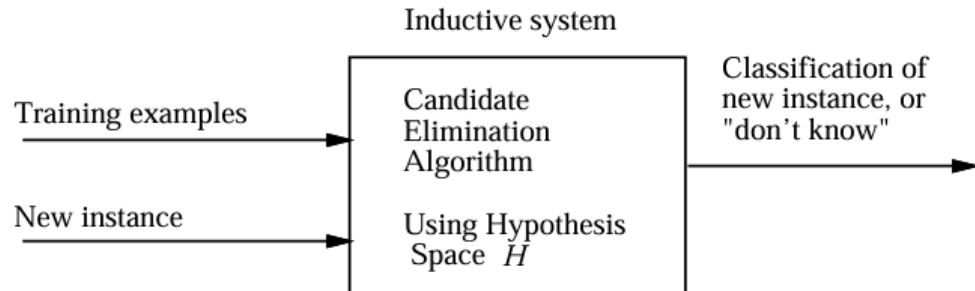
| Example | <i>Sky</i> | <i>AirTemp</i> | <i>Humidity</i> | <i>Wind</i> | <i>Water</i> | <i>Forecast</i> | <i>EnjoySport</i> |
|---------|------------|----------------|-----------------|-------------|--------------|-----------------|-------------------|
| 1 | Sunny | Warm | Normal | Strong | Cool | Change | Yes |
| 2 | Cloudy | Warm | Normal | Strong | Cool | Change | Yes |
| 3 | Rainy | Warm | Normal | Strong | Cool | Change | No |

ϕ
↑
S2 : (?, Warm, Normal, Strong, Cool, Change)
↑
S1 : (Sunny, Warm, Normal, Strong, Cool, Change)

The problem is that we have biased the learner to consider only conjunctive hypotheses.

Inductive Bias in Concept Learning

- **Idea:** Choose H that expresses every teachable concept (i.e. H is a powerset of X).
- Consider H' as disjunction, conjunction, and negation over previous H .



*Inductive bias
made explicit*

Quiz for you...

- Which of the following is **NOT** a knowledge representation scheme for Symbolic ML?
 - Propositional and Predicate Logic
 - Semantic Networks
 - Bayesian Networks ✓
 - Candidate elimination algorithm takes on training examples and searches **what** to find out a target concept?
 - Concept space
 - Version space ✓
 - Decision Tree
 - Which one **does not** contribute to Overgeneralization in ML?
 - Sufficient training data ✓
 - Imbalanced training data
 - Biased training data
 - Overfitting
-

Thank you!
