



Machine learning using TIL

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Outline

- Supervised machine learning
- Refining the hypothesis space
- Algorithm framework
- Semantic network
- Algorithm specification
- Learning example

Supervised machine learning

- Examples described by attributes(input/output) provided by a teacher
- Hypothesis
- Prediction of output attributes values from input attributes
- Training/test examples
- Classification/regression

Refining the hypothesis space

- Learning is finding hypotheses that are consistent with the training data[Poole, 2010]
 - There is only one output(Boolean) attribute Y
 - Hypotheses determine output attribute value
 - There is no noise in data
- Hypothesis is written as a proposition
- Refining of hypothesis(in form of proposition) by induction learning

Algorithm framework

- Machine learning algorithm can be described by[Luger, 2009]:
 - Task goal
 - Training data
 - Data representation
 - Knowledge modifying operations

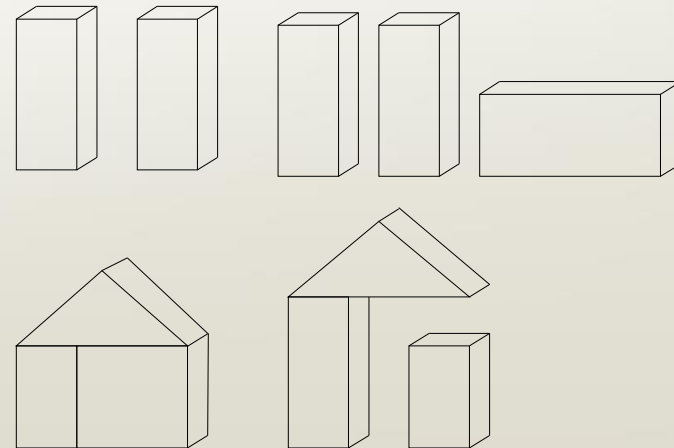
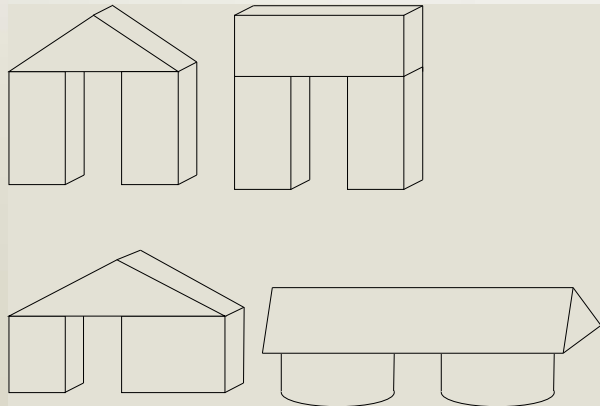


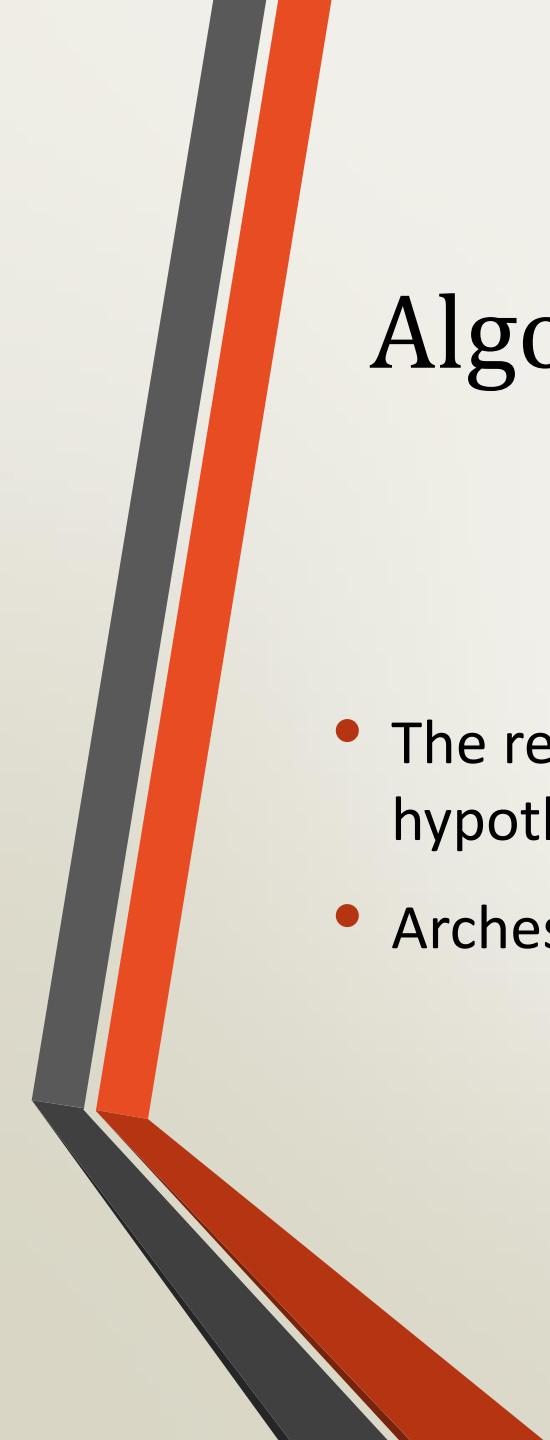
Algorithm framework – task goal

- The goal is to find a general concept describing the class of arches.

Algorithm framework – training data

- The learner is working with a set of (positive) examples of arches and a set of “almost” arches
- Teacher’s responsibilities





Algorithm framework – data representation

- The representation must be so fine that the agent is able to find the hypothesis
- Arches in our example are defined by means of TIL constructions

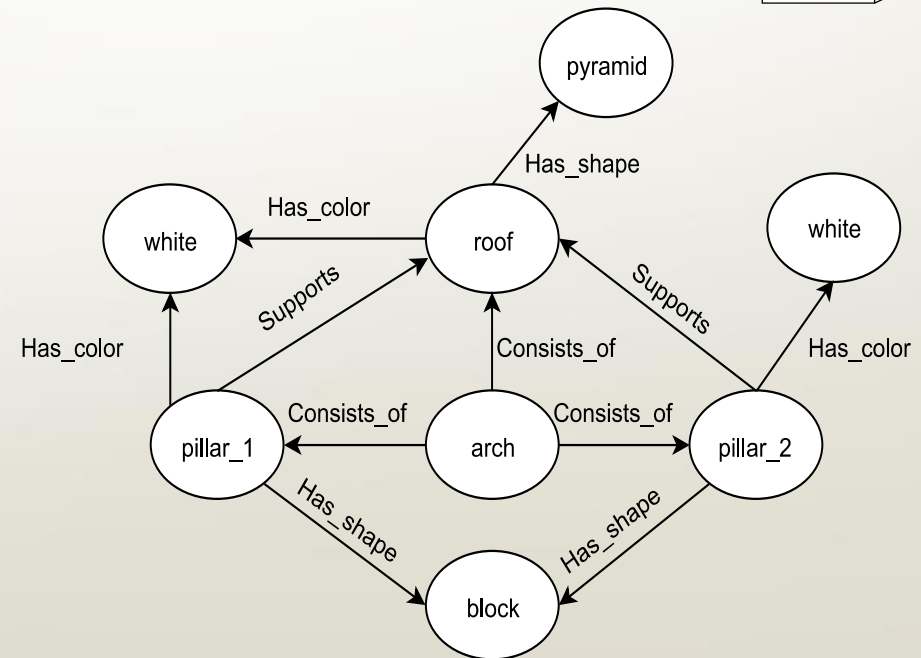
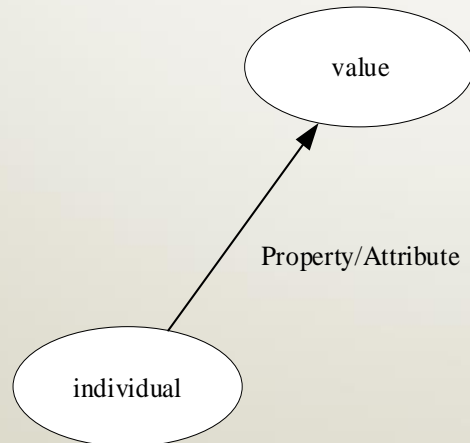
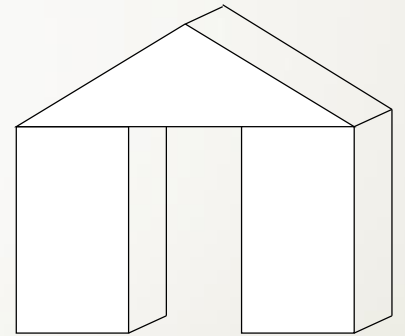


Algorithm framework - operations

- Patrick Winston algorithm [Winston, 1992]
- Generalization – makes hypothesis more permissive
- Specialization – makes hypothesis more restrictive

Semantic network

- Relation link (Individual, Property/Attribute, Value)





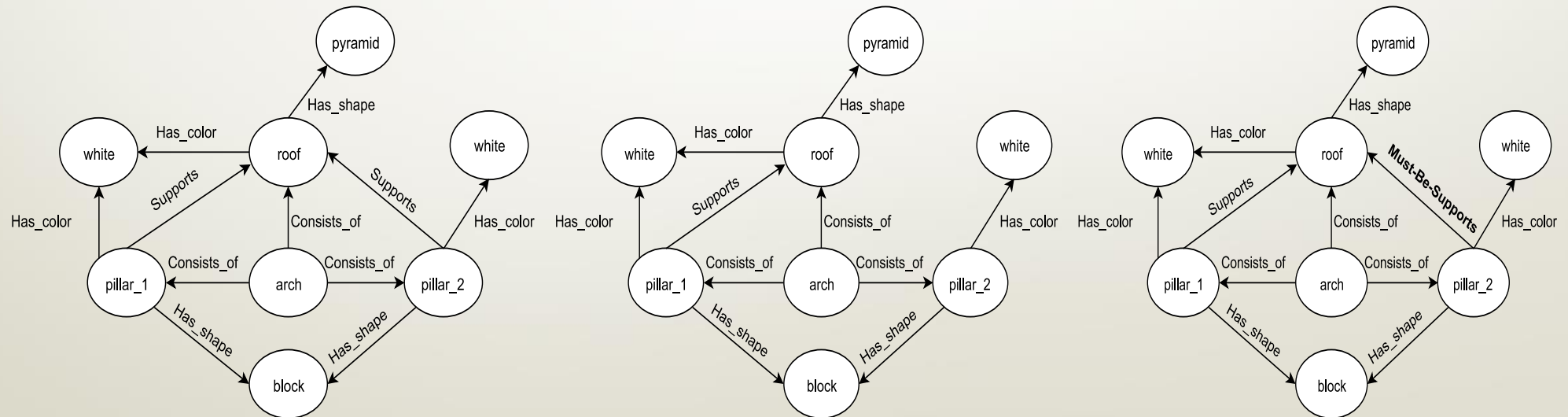
Algorithm

Specialization

- Specialization is used to refine the hypothesis by a near-miss example.
 1. Compare the model hypothesis (to be refined) and the near-miss example to find a significant difference
 2. If there is a significant difference between model and near-miss example, then
 - a) if the model has a link relation while the near-miss example does not, use **require-link**

Require-link

- Heuristic is applied in case that the model has while the near-miss example does not have a *link relation*.
- In the model the *link relation* is marked as MUST-BE.

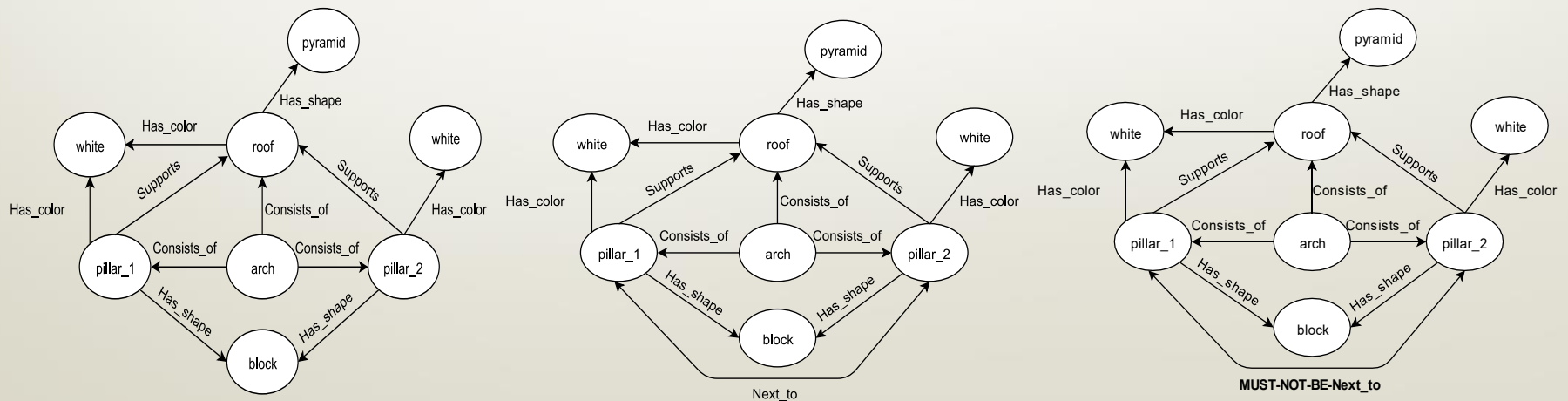


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 - b) if the near-miss example has a link relation that the model does not have, use **forbid-link**

Forbid-link

- There is a link relation in the near-miss example which is missing in the model.
- Model is enriched with this *link relation* marked by 'MUST-NOT-BE'.



Specialization

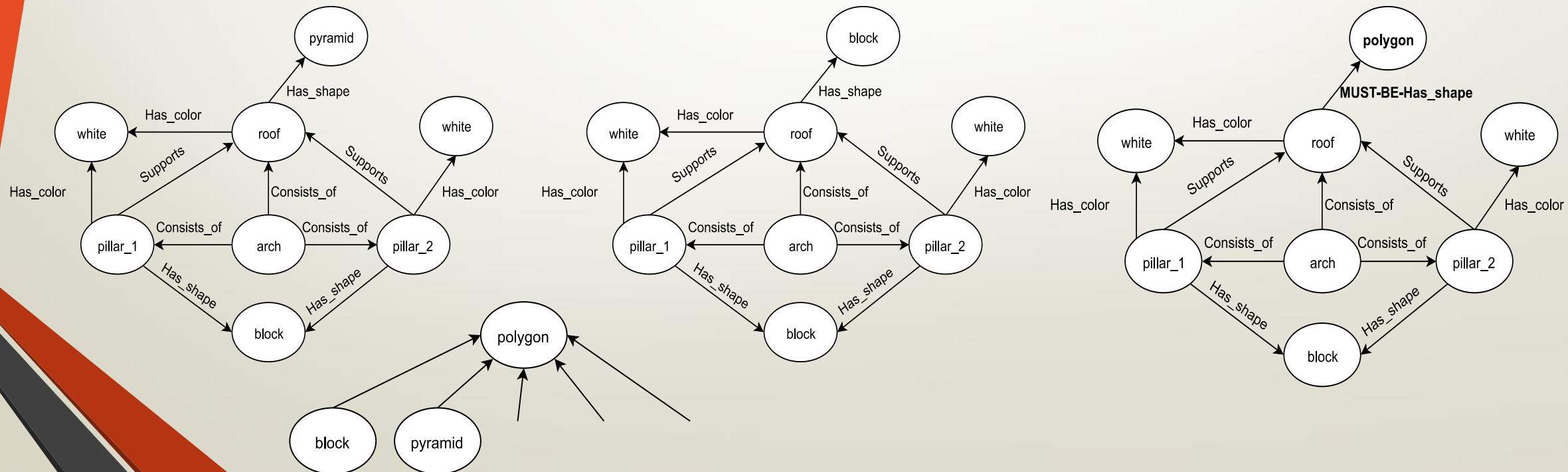
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 - c) else ignore example

Generalization

- Generalization is used to refine hypothesis by a positive example
 1. Compare the model hypothesis and the positive example to determine a difference
 2. For each difference do
 - a) if a link relation in the model points at a value that differs from the value in the example, then
 - i. if the values in which the model and example differ have the most specific general class, use the **climb-tree**

Climb-tree

- This heuristic is applied in case we need to generalize the concepts to avoid problems with too specialized models.

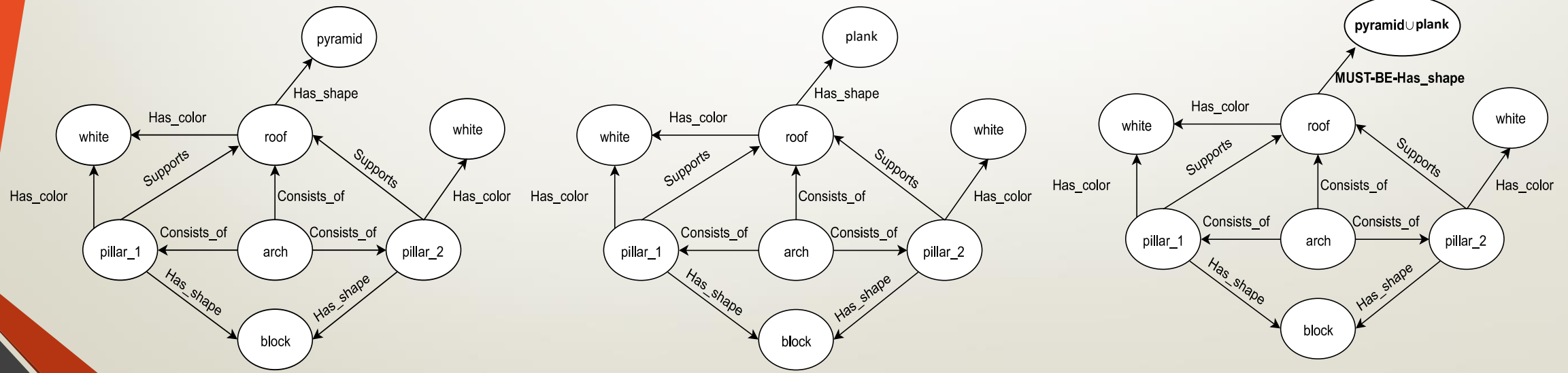


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 - ii. else if the values in which the model and example differ don't have the most specific general class, use the **enlarge-set**

Enlarge-set

- This heuristic is applied in case we need to generalize concepts of classes but there is no common most specific general class at our disposal.
- Generalization is achieved by unifying these classes.



Generalization

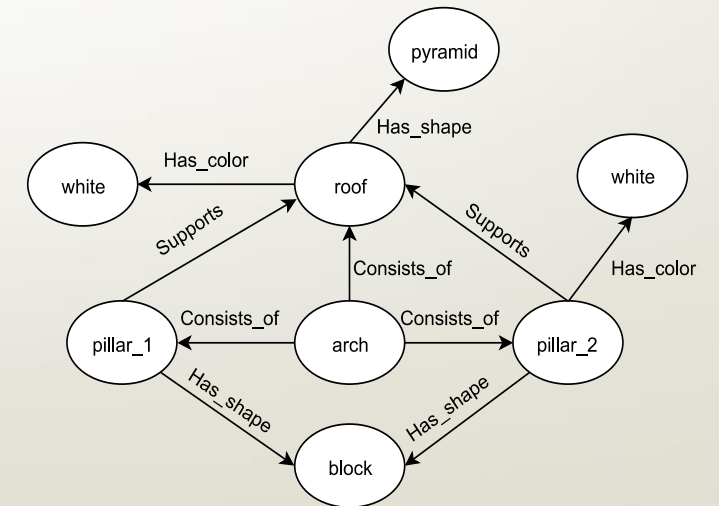
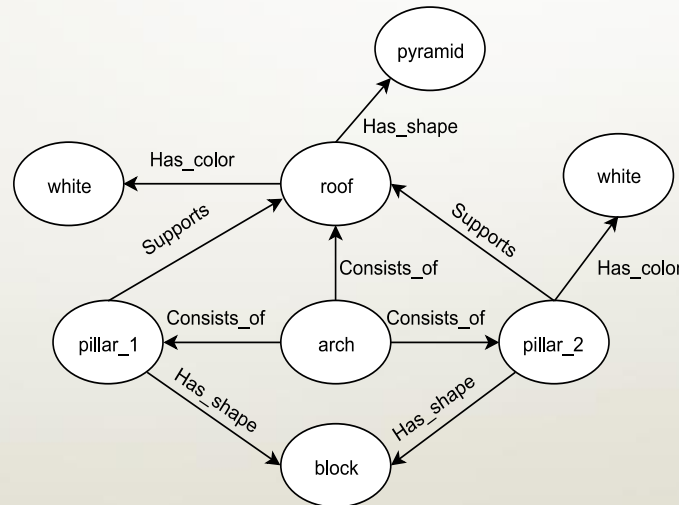
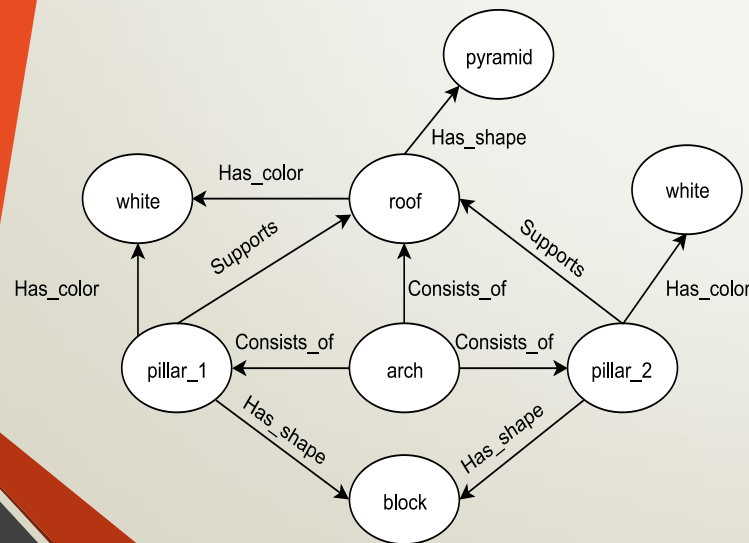
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 - iii. else if these classes are excluding each other use **drop-link**

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 - ii. else use **enlarge-set**
 - iii. if these classes are excluding each other use **drop-link**
 - b) if there is a link in the model that is missing in the example, use **drop-link**

Drop-link

- If the model contains link that is missing in the positive example or the values related to the link excluding each other

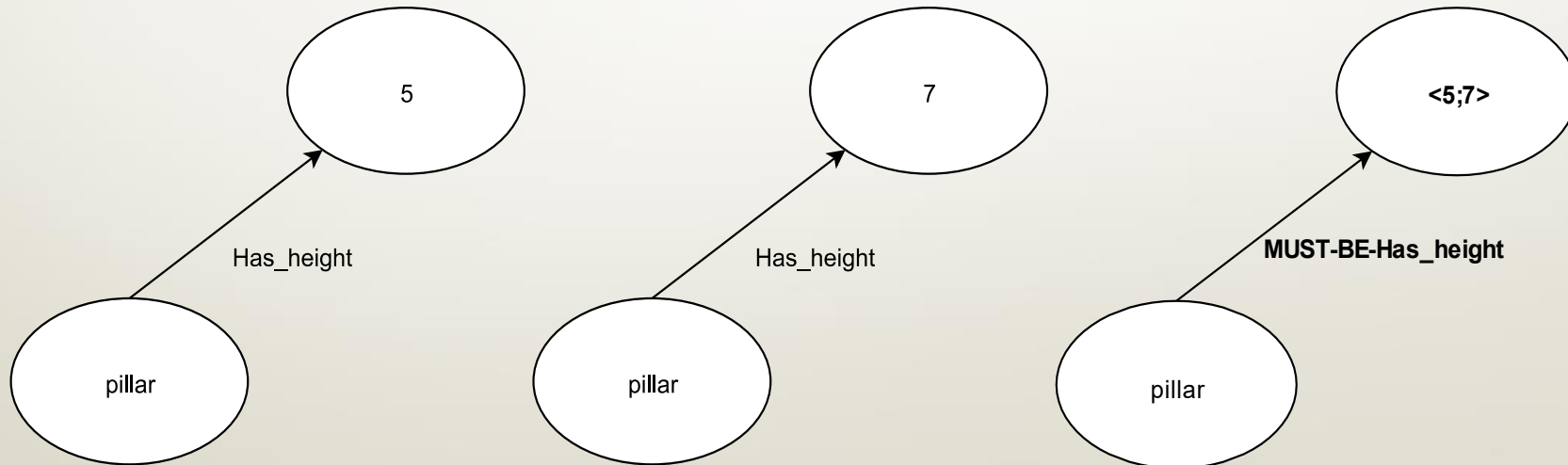


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 - ii. else use **enlarge-set**
 - iii. if these classes are excluding each other use **drop-link**
 - b) if there is a link in the model that is missing in the example, use **drop-link**
 - c) if the model and example differ at an numerical attribute value , use **close-interval**

Close-interval

- This heuristic is used if there are links in model and example with numerical value or interval



Generalization

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 - ii. if these classes are excluding each other use **drop-link**
 - iii. else use **enlarge-set**
 - b) if there is a link in the model that is missing in the example, use **drop-link**
 - c) if the model and example differ at an attribute value , use **close-interval**
 - d) else ignore example

Example of learning - types

- $x \rightarrow l$;
- *Pillar, White, Standing, Block, Tall, Short* / $(ol)_{\tau\omega}$;
- *True* / $(oo_{\tau\omega})_{\tau\omega}$
- *Colour, Shape, Size, Position* / $((ol)_{\tau\omega}l)_{\tau\omega}$: attributes, i.e. empirical functions that associate an individual with a property the individual has;
- $= / (o(ol)_{\tau\omega} (ol)_{\tau\omega})$: identity of properties.

Example of learning – positive examples

- Tall white standing object with a shape of block

$$\begin{aligned} & \lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Colour_{wt} x \right] {}^0 White \right] \right. \right. \\ & \wedge \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \wedge \left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \\ & \left. \left. \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right] \end{aligned}$$

- Tall standing object with a shape of block

$$\begin{aligned} & \lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \right. \right. \\ & \left. \left. \wedge \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right] \end{aligned}$$

Example of learning – near-miss examples

- Tall white object with a shape of a block.

$$\lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Colour_{wt} x \right] {}^0 White \right] \right. \right. \\ \left. \left. \wedge \left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right]$$

- Short standing object with a shape of a block.

$$\lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Short \right] \right. \right. \\ \left. \left. \wedge \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right]$$

Example of learning

- Initial hypothesis:

$$\lambda w \lambda t \left[\begin{array}{l} {}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Colour_{wt} x \right] {}^0 White \right] \right. \\ \wedge \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \wedge \left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \\ \left. \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \end{array} \right]$$

Example of learning - Specialization

- Near miss example: difference is in position -

$$\lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Colour_{wt} x \right] {}^0 White \right] \wedge \left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \right. \right. \\ \left. \left. \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right]$$

- Require-link -> new hypothesis:

$$\lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Colour_{wt} x \right] {}^0 White \right] \wedge \left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \right. \right. \\ \left. \left. \wedge \left[{}^0 \mathbf{True}_{wt} \lambda w \lambda t \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \right] \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right]$$

Example of learning - Generalization

- Positive example: difference is in color-

$$\lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \wedge \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right]$$

- Drop-link -> new hypothesis:

$$\lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \wedge \left[{}^0 \mathbf{True}_{wt} \lambda w \lambda t \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right] \right]$$

Example of learning - specialization

- Near-miss example:

$$\lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Short \right] \wedge \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \right. \right. \\ \left. \left. \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right]$$

- Conditions are not satisfied -> model is not modified:

$$\lambda w \lambda t \left[{}^0 = {}^0 Pillar \lambda w \lambda t \lambda x \left[\left[{}^0 = \left[{}^0 Size_{wt} x \right] {}^0 Tall \right] \right. \right. \\ \left. \left. \wedge \left[{}^0 \mathbf{True}_{wt} \lambda w \lambda t \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \right] \wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \right] \right]$$

Definition of an arch

$o, x, y, z \rightarrow \iota$;
 $Arch, Pillar, Roof / (oi)_{\tau\omega}$;
 $Composed_of / (ouu)_{\tau\omega}$;
 $Supports / (ou)_{\tau\omega}$;
 $Block, Polygon / (oi)_{\tau\omega}$;
 $Shape, Position, Size /$
 $((oi)_{\tau\omega} \iota)_{\tau\omega}$;
 $Standing, Tall / (oi)_{\tau\omega}$;
 $=_{\iota} / (ou)$;
 $= / (o(oi)_{\tau\omega} (oi)_{\tau\omega})$;
 $\neg / (oo)$;

$\lambda w \lambda t \left[\begin{aligned} &{}^0 = {}^0 Arch \lambda o \exists x \exists y \exists z \left[\left[{}^0 Composed_of_{wt} o x y z \right] \right. \\ &\wedge \left[{}^0 Pillar_{wt} x \right] \wedge \left[{}^0 Pillar_{wt} y \right] \wedge \left[{}^0 Roof_{wt} z \right] \wedge \left[{}^0 \neg \left[{}^0 =_{\iota} x y \right] \right] \\ &\wedge \left[{}^0 Supports_{wt} x z \right] \wedge \left[{}^0 Supports_{wt} y z \right] \\ &\wedge \left[{}^0 True_{wt} \lambda w \lambda t \left[{}^0 = \left[{}^0 Position_{wt} x \right] {}^0 Standing \right] \right] \\ &\wedge \left[{}^0 True_{wt} \lambda w \lambda t \left[{}^0 = \left[{}^0 Position_{wt} y \right] {}^0 Standing \right] \right] \\ &\wedge \left[{}^0 = \left[{}^0 Shape_{wt} x \right] {}^0 Block \right] \wedge \left[{}^0 = \left[{}^0 Shape_{wt} y \right] {}^0 Block \right] \\ &\wedge \left[{}^0 = \left[{}^0 Shape_{wt} z \right] {}^0 Polygon \right] \left. \right] \end{aligned} \right]$

Sources

- Luger G. F.(2009): *Artificial intelligence: structures and strategies for complex problem solving*. 6th ed. Boston: Pearson Addison-Wesley, 2009. ISBN 978-0-321-54589-3.
- Poole D. L., Mackworth A. K.(2010). *Artificial intelligence: foundations of computational agents*. 2nd pub. Cambridge: Cambridge University Press, 2010. ISBN 978-0-521-51900-7.
- Winston P. H.(1992): *Artificial intelligence*. 3rd ed. Reading, Mass.: Addison-Wesley Pub. Co., 1992. ISBN 02-015-3377-4.



Thank you for your attention