

# Data mining, machine learning, and uncertainty reasoning

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## Search through the space of generalization

- A **representation language** has been selected by learners to learn a concept from a set of positive and negative examples (space of generalization)
- If the descriptions are based on attribute-value logic, the space of all concepts is large → **Ten attributes with five possible values** for each of them amount to  $5^{10}=9765625$  possible vectors

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## Search through the space of generalization

- Any subset of such vectors can correspond to a concept, which means  $2^{9765625}$  concepts can be defined over these attributes
- Background knowledge can **limit the size** of the representation space
- To cope with the problem of **computational tractability**, the learner combines two powerful techniques: **induction and heuristic search**

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## Inductive Essence of learning

- An ET has some preliminary linguistic knowledge and asks **“what is a bird?”**
- A blackbird is a **positive example** of the concept. However, it is a hard job to teach it. (S)
- To memorizing all **features** of blackbirds is hardly sufficient to recognize other birds as instances of the **same category** → A **generalization** of this example is needed.

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## Inductive Essence of learning

- A **negative example** is what is not a bird? → (G) a dog is not a bird because it **do not possess wings**
- All creatures **with wings** are birds → **too general**
- A fly is this category but not a bird. A **specialization** is necessary.
- A noticeable features of the blackbird → absent in dogs and flies is that **Birds have beaks**
- Finally, ET concludes **birds are winged creature with beaks**

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## Inductive Essence of learning

- The set of the most **specific descriptions**, denoted by **S**
- The most **general descriptions** denoted by **G**
- The **G** has to be **specialized**
- The next positive examples should **enriches** the set **S** with another most **specific description**
- **Generalization** is applied to the set **S** whenever a new **positive example** arrives
- A **negative example** can necessitate the **specialization** of the set **G** → **version space algorithm**

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## Inductive Essence of learning

- **Version space algorithm** built on the idea of **gradual reduction of the space of current versions of the concept description**
- **Concept learning** can be viewed as a series of **generalization** and **specialization** of a single hypothesis
- **Concept learning** can also be conceived as a **search** through the **space of descriptions**, the essential search operators are **generalization** and **specialization**

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## Inductive Essence of learning

- Horn clauses can be **generalized** by **turning a constant into a variable** or by **dropping a condition**  
$$P(x, y) :- q(x, 2), r(y, 2) \rightarrow_G P(x, y) :- q(x, z), r(y, z)$$
$$\rightarrow_G P(x, y) :- q(x, 2)$$
- A Horn clause can be **specialized** by **turning a variable into a constant**, or by **adding a literal to the clause**
- Proper selection of the **search operators** is the critical task of the designer of a **learning program**

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## Search process

- A widespread **framework** for **concept learning** is **search** through the **space of descriptions** permitted by the learner's representation language
- **Search** techniques have been widely investigated

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## Search process

A search process explores states in a search space according to the following steps:

1. **Initial state**: the starting position of the search (the most specific concept description → positive example)
2. **Termination criterion**: the objective to be arrived at. States that satisfy the termination criterion are referred as **final states** (covers all positive and no negative examples)

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## Search process

3. **Search operators** advance the search from one state to another ( **operators** are **generalizations and/or specialization** of concept descriptions)
4. **Search strategy** determines under what conditions and to which **state** an operator is to be applied
  - There are two fundamental systematic searches such as **depth-first and breadth-first search**
  - Visualize the space of all possible **states** as an **oriented graph** whose **nodes** represent **individual states** and the **edges** are the **search operator**

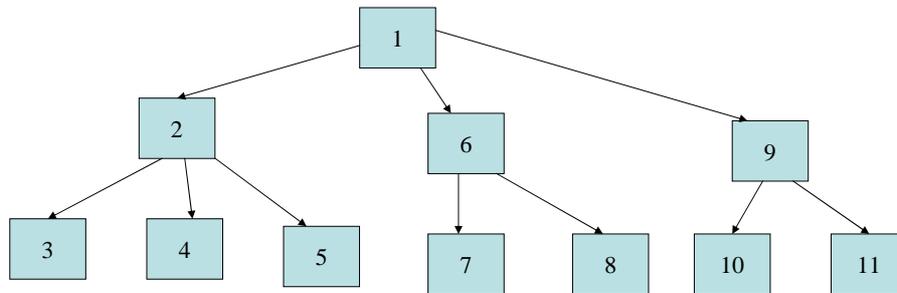
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## Depth-first search

- An **operator** is applied to the **initial state  $S_1$** , arriving at a new state  **$S_2$** . If  **$S_2$**  is not the final states, then, again, an **operator** is applied to  **$S_2$**  arriving at a new state  **$S_3$**
- If **no new state** can be reached in this way and the **final state** has not been found, the system **backtracks to the previous state** and applies some **other operator**
- If this is not possible, the system backtracks until **a state is found** that allows the application of some of the operators.
- If no such state, the search **terminates**

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## Depth-first search



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## Breadth-first search

- The numbers in the rectangles indicate the **order** in which the states are visited
- All **operators** are applied, one by one, to the **initial state  $S_1$** , the result states are tested. If some of them are the **final states**, the search algorithm stops
- Otherwise, the **operators** are applied to all **subsequence states**, then again to the **subsequence states**, and so on, until the **termination criterion** is satisfied

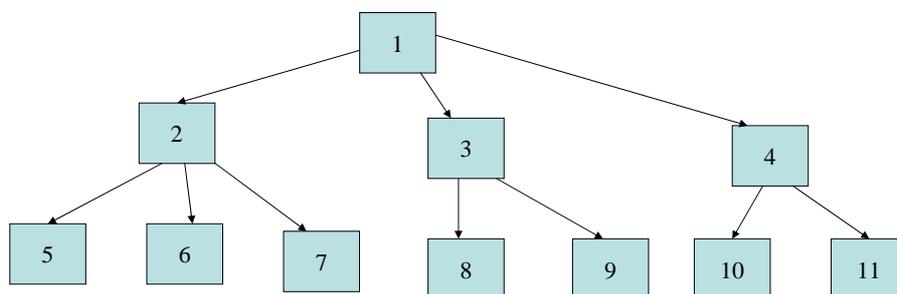
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## Breadth-first search

- BFS assumes **no backtracking**, which is a slight simplification of the task than DFS
- However, the searcher must store **many intermediate states**
- **Time V.S. Space** waste!!! → trade-off

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## Breadth-first search



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## Heuristic Search

- Decide which of the **available operator** will lead to the closest proximity of the final state
- This requires an **evaluation function** to assess the value of each of the states reached → assume the **evaluation function** is given
- Two search algorithms are of this types such as **BEST-FIRST**, **BEAM search** algorithm

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## BEST-FIRST search algorithm

1. Let the **initial state** be referred to as the **best state**, the **set of current states** consist of this single state
2. If the **best state** satisfies the given **termination criterion**, then stop → the best state is the **solution** of the search
3. Apply all applicable **operators** to the best state, thus creating a set of **new states** that are added to the **set of current states**

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## BEST-FIRST search algorithm

4. Evaluate all **current states**. Decide which is the best state and go to step 2.
- Differs from the BFS in that it always extends only **the most promising state**, thus **speeding up the search**
  - The price is the danger of falling to a **local maximum** of the evaluation function

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## BEST-FIRST Search process

- $\oplus$  stands for positive example and  $\otimes$  stands for negative example
- 2 operators for the example to demonstrate the search process :
  - **specialize** the current description by adding a **conjunction**
  - **generalize** the current description by adding a **disjunction**

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## BEST-FIRST Search process

- Initial state is **any description**. The application of the **specialization operator** will produce the descriptions:  $at1=a$ ,  $at1=b$ ,  $at2=x$ ,  $at2=y$ ,  $at2=z$ ,  $at3=m$ , and  $at3=n$
- **$At2=x$  and  $at3=m$**  do not cover any  $\otimes$  and will probably achieve the **highest value** of a reasonable evaluation (the row in **red**)

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## BEST-FIRST Search process

- For some reason,  **$at2=x$**  is preferred and will become the best description
- Some  $\oplus$ 's in the table are now **not covered**, the learner will try to **apply the search operator** to the best description
- Applying the generalize operator  $\rightarrow$   **$at2=x \vee at2=y$** , the number of  $\oplus$ s covered increased and the evaluation function confirms this description is better than  **$at2=x$**

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## BEST-FIRST Search process

- The new description covers **all  $\oplus$ s** but it also covers **2  $\otimes$ s**.
- The description is **specialized** into  **$at2=x \vee [(at2=y) \wedge X]$** , where X stands for any of the following conjuncts :  **$at1=\{a, b\} \wedge at3=\{m\}$**  and  **$at3=\{n\}$** 
  - Among the new states ,the best one is  **$at2=x \vee [(at2=y) \wedge (at3=m)]$**  . As it covers all  $\oplus$ s but no  $\otimes$ s, the search terminates
  - The best-first search requires **excessive memory** because it stores **all generated states**

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## Car can attract analysis?

Object	Make	Size	Price	Classification
Car1	European	Big	Affordable	$\oplus$ (positive)
Car2	Japanese	Big	Affordable	$\oplus$
Car3	European	Medium	Affordable	$\otimes$ (negative)
Car4	European	Small	Affordable	$\otimes$
Car5	European	Medium	Expensive	$\oplus$
Car6	Japanese	Medium	Affordable	$\otimes$
Car7	Japanese	Medium	Expensive	$\oplus$
Car8	European	Big	Expensive	$\oplus$

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## Positive and negative examples for concept learning

example	at1	at2	at3	Classification
e1	a	x	n	$\oplus$ (positive)
e2	b	x	n	$\oplus$
e3	a	y	n	$\otimes$ (negative)
e4	a	z	n	$\otimes$
e5	a	y	m	$\oplus$
e6	b	y	n	$\otimes$
e7	b	y	m	$\oplus$
e8	a	x	m	$\oplus$



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## Beam Search Algorithm

- A more economic approach is the beam search that only contains **N best states** at any time

Algorithm of Beam search Algorithm :

1. Let the **initial state** be the **best state**
2. If the best state satisfies some **termination criterion**, then **stop**  $\rightarrow$  the best state is the solution of the search
3. If the number of current states is **larger than N**, keep only the **N best states and delete all others**

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## Beam Search Algorithm

4. Apply the search operators to the **best state**, and add the **newly created states** to the set of current states
  5. **Evaluate all states** and go to step 2
- ⌘ A popular instantiation of the beam-search algorithm is defined **N=1** is sometimes called **hill-climbing** algorithm.
- ⌘ Hill climbers striving to find the **shortest trajectory to the peak** always pick the **steepest path**

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## Classic methods of learning

2 essential learning principles

- **Divide-and-Conquer**
  - The entire set of examples is **split into subsets** that are more easy to handle (**TDIDT algorithm**)
- **AQ-philosophy**
  - Based on the idea of **progressive coverage** of the training data by **consecutively generated decision rules**

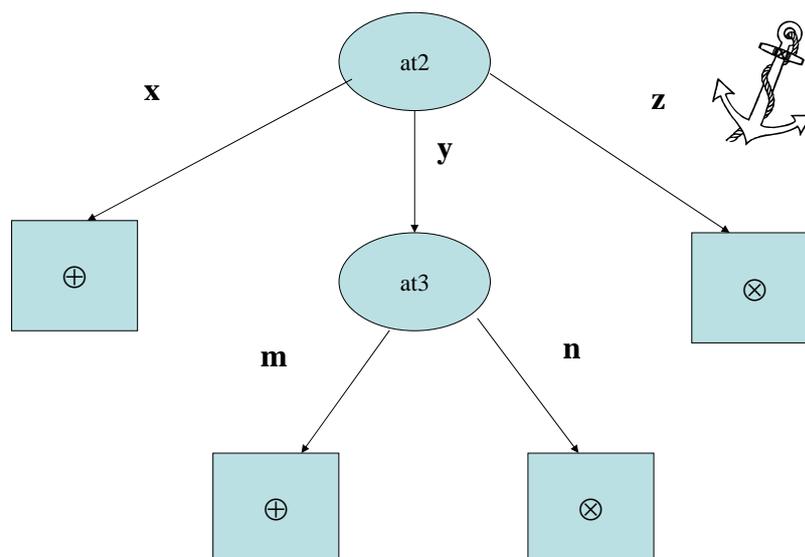
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## Divide-and-Conquer Learning

- In attributional logic, the partitioning is carrying out along **attribute values** so that all examples in a subset **share the same value of given attribute**
- Table is analyzed to classify as  $at1=\{a, b\}$  ,  $at2=\{x, y, z\}$  ,  $at3=\{m, n\}$  ( solutions is  $at2=x \vee [(at2=y) \wedge (at3=m)]$  )
- **Induction of decision trees** is known under the acronym **TDIDT** (Top-Down Induction of Decision Tree) or **ID3**.

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## Decision tree of example table



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## Decision tree explanation

- e1 has  $at2=x$  which sends it **downward** along the **leftmost branch**, only to end up in the box labeled with  $\oplus$
- e3 has  $at2=y$  and  $at3=n$ , which is end up in the box labeled with  $\otimes$

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## Decision tree explanation

These tree can be rewritten as following logical expressions:

- $(\text{class} = \oplus) \leftarrow (at2=x) \vee \mathbf{[(at2=y) \wedge (at3=m)]}$
- ( match solutions :  $at2=x \vee \mathbf{[(at2=y) \wedge (at3=m)]}$  )
- $(\text{class} = \otimes) \leftarrow (at2=z) \vee \mathbf{[(at2=y) \wedge (at3=n)]}$
- The classification of examples that do not satisfy either of these rules can be based on the **distance between the example description and the rules** or an “I-don’t-know” answer can be issued

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## Homework

- Describe the table in P27 in the conjunction rules
- Draw the possible decision tree of this example!!

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