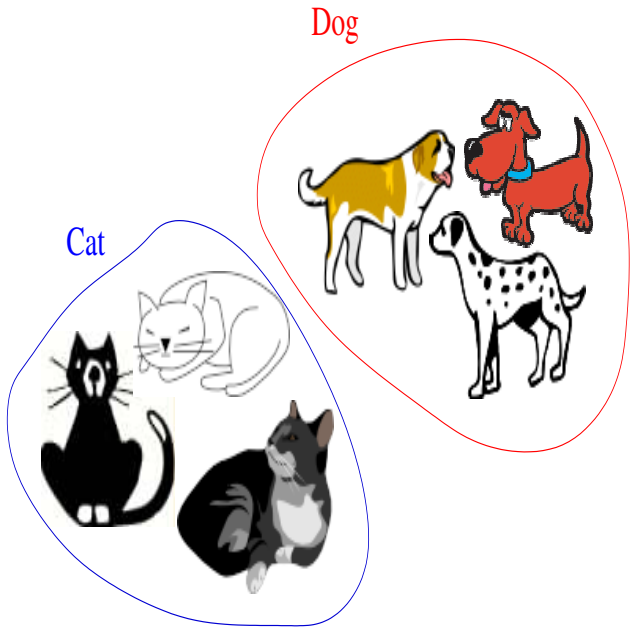
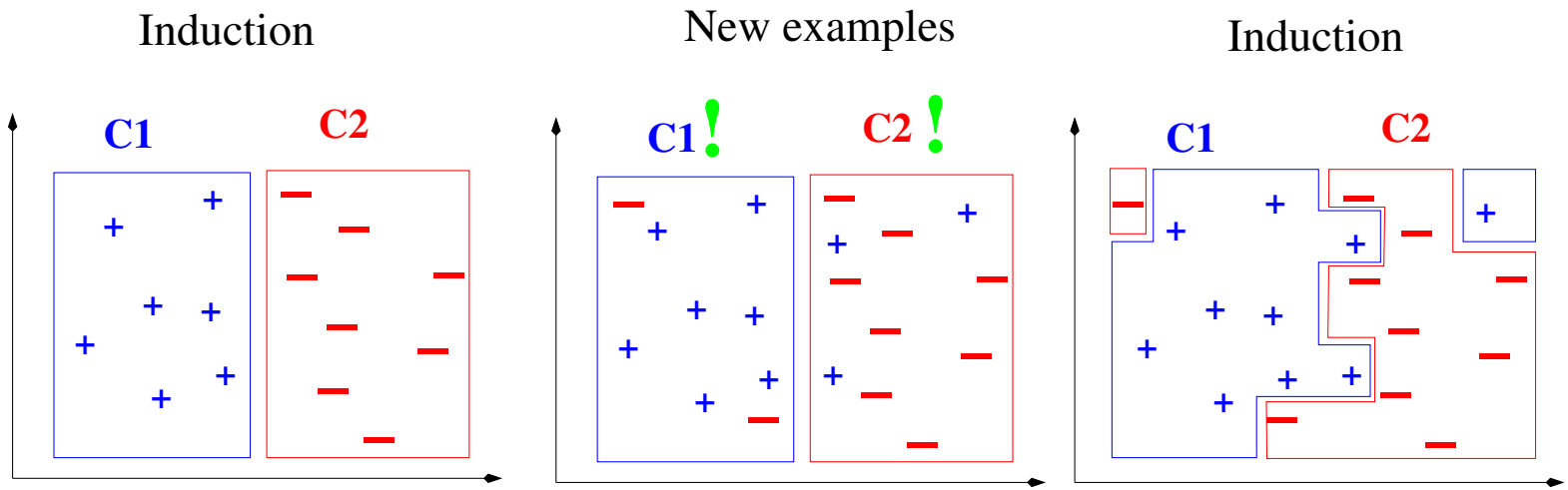
Inductive learning

- Is the area with the larger number of methods
- **Goal:** To discover general concepts from a limited set of examples (common patterns)
- It is based on the search of similar characteristics among examples
- All its methods are based on inductive reasoning



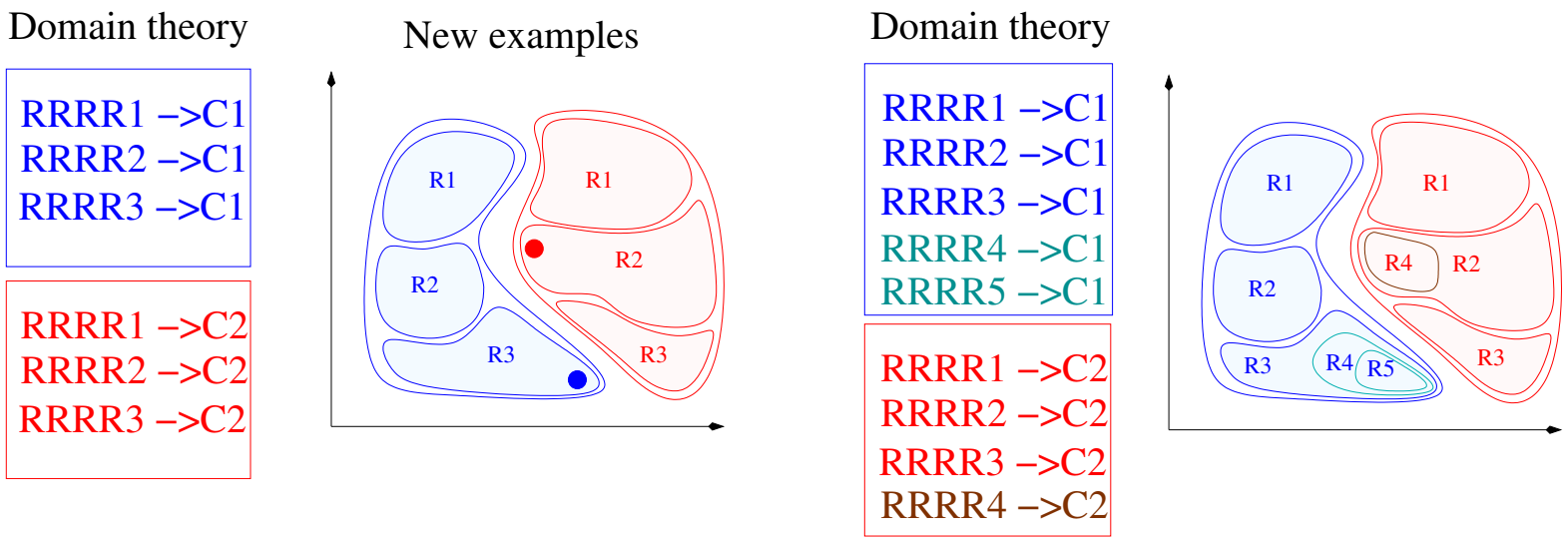
Inductive reasoning vs Deductive reasoning

- Inductive reasoning
  - It obtains general knowledge from specific information
  - The knowledge obtained is new
  - Its not truth preserving (new information can invalidate the knowledge obtained)
  - It has no well founded theory



Inductive reasoning vs Deductive reasoning

- Deductive reasoning
  - It obtains knowledge using well established methods (logic)
  - The knowledge is not new (it is implicit in the initial knowledge)
  - New knowledge can not invalidate the knowledge already obtained
  - Its basis is mathematical logic

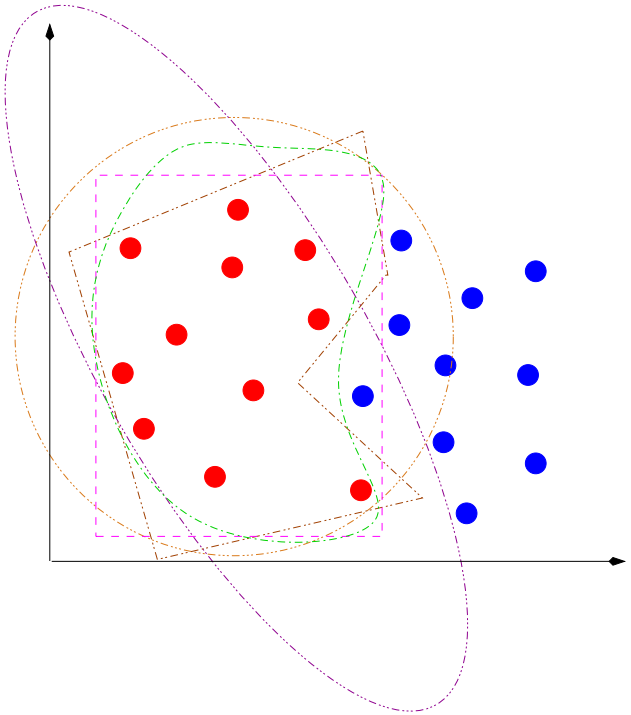


Inductive learning

- From a formal point of view its results are invalid
- We suppose that a limited number of examples represents the characteristics of the concept that we want to learn
- Just only one counterexample invalidates the result
- But, most of the human learning is inductive!

Learning as search (I)

- The usual way to view inductive learning is as a search problem
- The goal is to discover a function/representation that summarizes the characteristics of a set of examples
- The space of search is all the possible concepts that can be built
- There are different ways to do the search

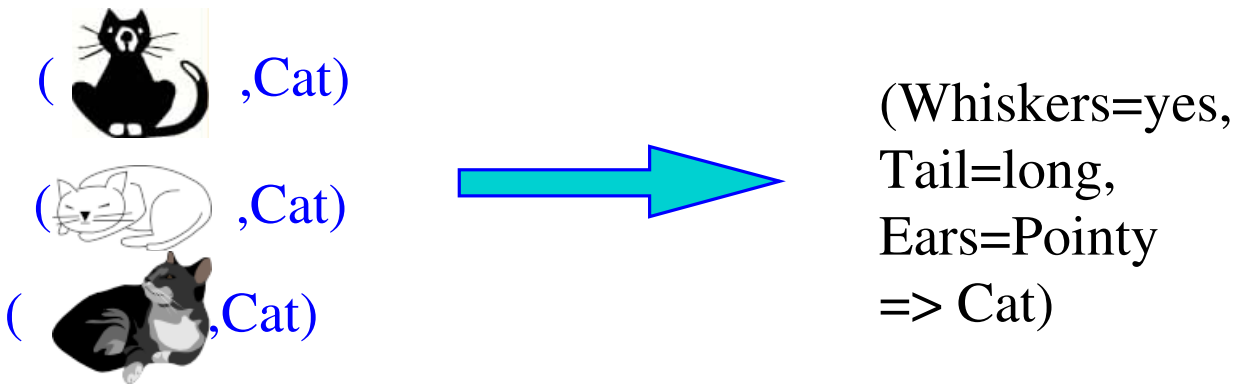


Learning as search (II)

- **Search space:** Language used to describe the concepts $\Longrightarrow$ Set of concepts that can be described
- **Search operators:** Heuristic operators that allow to explore the space of concepts
- **Heuristic function:** Preference function/criteria that guides the search (*Bias*)

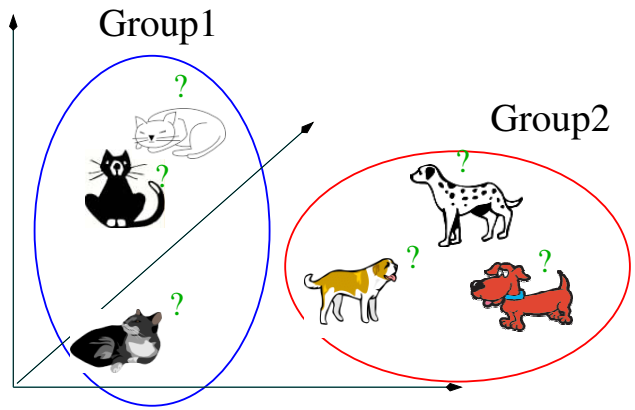
Types of inductive learning

- Supervised inductive learning
  - Each example is labeled with the concept it belongs to
  - Learning is performed by contrast among concepts
  - A set of heuristics allows to generate different hypotheses
  - A criteria of preference (*bias*) is used to choose the most *suitable* hypothesis for the examples
  - **Result:** The concept or concepts that describe better the examples



Types of inductive learning

- Unsupervised inductive learning
  - Examples are not labeled
  - We want to discover a suitable way to cluster the objects
  - Learning is based on the similarity/dissimilarity among examples
  - Heuristic preference criteria will guide the search
  - **Result:** A partition of the examples and a characterization of the partitions



Examples

The examples can have different levels of complexity, two scenarios:

- Unstructured examples: each example is an individual, concepts are the generalization of the individuals
  - Usually tables representing attribute–value pairs
- Structured examples: Examples are related, concepts include relations, substructures, subsequences, ...
  - Graphs, trees, sequences, ...

Attributes

Types of attributes

- Quantitative attributes (continuous or discrete): There is an order among the values of the attribute
- Qualitative attributes: There is not an order among the values of the attribute
- Hierarchical attributes: There is a generalization/specialization relationship among the values of the attribute
- Binary attributes, fuzzy attributes, ...

Name	Age	Height	Weight	Marital Status	Employed
Juan	17	1.85	75	Single	no
María	32	1.77	68	Married	yes
Pedro	58	1.72	83	Divorced	yes
...					

Concepts

Concept representation: The language used to describe the concepts defines the size of the search space and the kind of concepts that can be learn

- Pure conjunctive/disjunctive formulas (2^n)

$$(A \vee \neg B \vee C \vee \neg D \vee E)$$

- k-term-CNF/k-term-DNF (2^{kn})

$$(A \vee \neg B \vee D \vee \neg E) \wedge (A \vee B \vee \neg C) \wedge (A \vee \neg B \vee D \vee E) \wedge ...$$

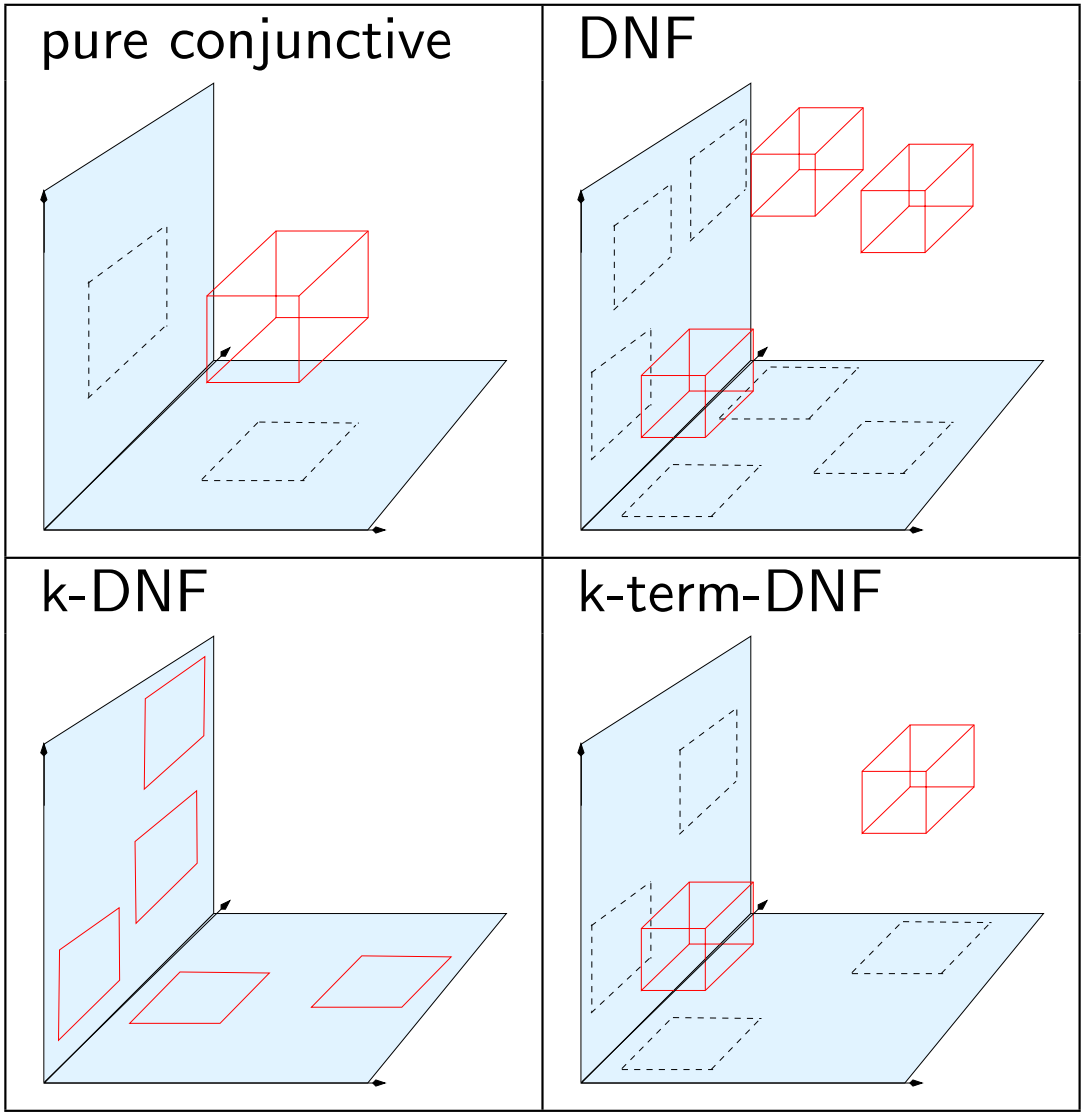
- k-CNF/k-DNF (2^{n^k})

$$(A \vee \neg B \vee C) \wedge (A \vee B \vee \neg D) \wedge (A \vee \neg B \vee E) \wedge ...$$

- CNF/DNF (2^{2^n})

$$(A \vee \neg B \vee D \vee \neg E) \wedge (A \vee B \vee \neg C) \wedge (A \vee \neg B \vee D \vee E)$$

Knowledge representation - Concepts



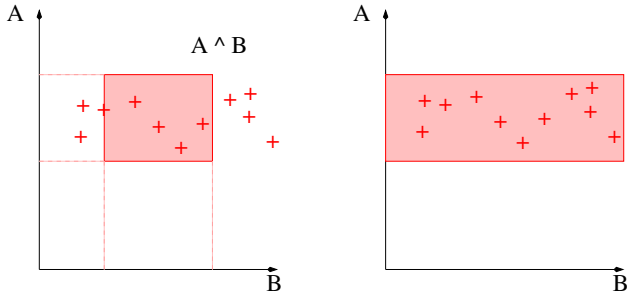
Inductive inference

- Basis of inductive learning
- Group of heuristic rules that allows to obtain general knowledge from specific knowledge
- Most of the methods of inductive learning use these rules implicitly or explicitly
- Elements:
  - A set of premises: Examples, previous generalizations, ...
  - Background knowledge: domain knowledge, constraints, biases, ...
- With the induction process we obtain concepts that are consistent with our background knowledge and premises

Rules of inductive inference (I)

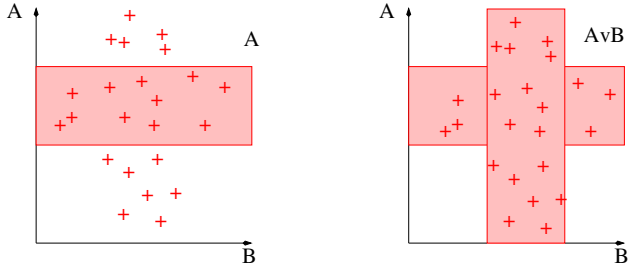
Condition elimination:

$$A \wedge B \wedge C \rightarrow K \Rightarrow A \wedge B \rightarrow K$$



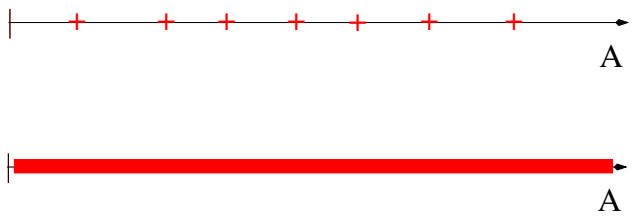
Option introduction:

$$A \rightarrow K \Rightarrow A \vee B \rightarrow K$$



Substituting constants by variables:

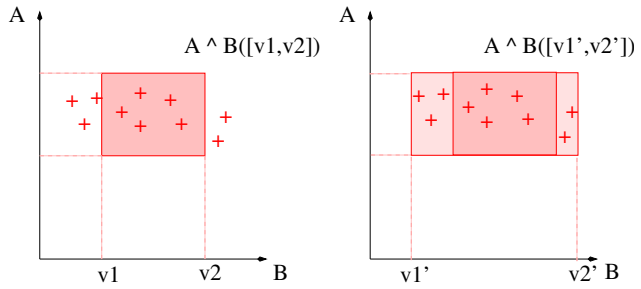
$$Aa \wedge Ab \wedge Ac \rightarrow K \Rightarrow \forall x(Ax \rightarrow K)$$



Rules of inductive inference (II)

Range extension:

$A \wedge (B \in [v_1, v_2]) \rightarrow K \Rightarrow A \wedge (B \in [v_1', v_2']) \rightarrow K$ con $[v_1, v_2] \subset [v_1', v_2']$



Interval closing:

$$\left.\begin{array}{l} A \wedge Ba \rightarrow K \\ A \wedge Bb \rightarrow K \end{array}\right\} \Rightarrow A \wedge (B \in (a, b)) \rightarrow K$$