Machine Learning - Idea

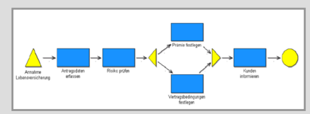
Knut Hinkelmann

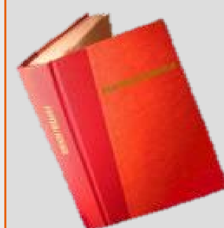
Knowledge Engineering

Knowledge

internal knowledge

documented knowledge



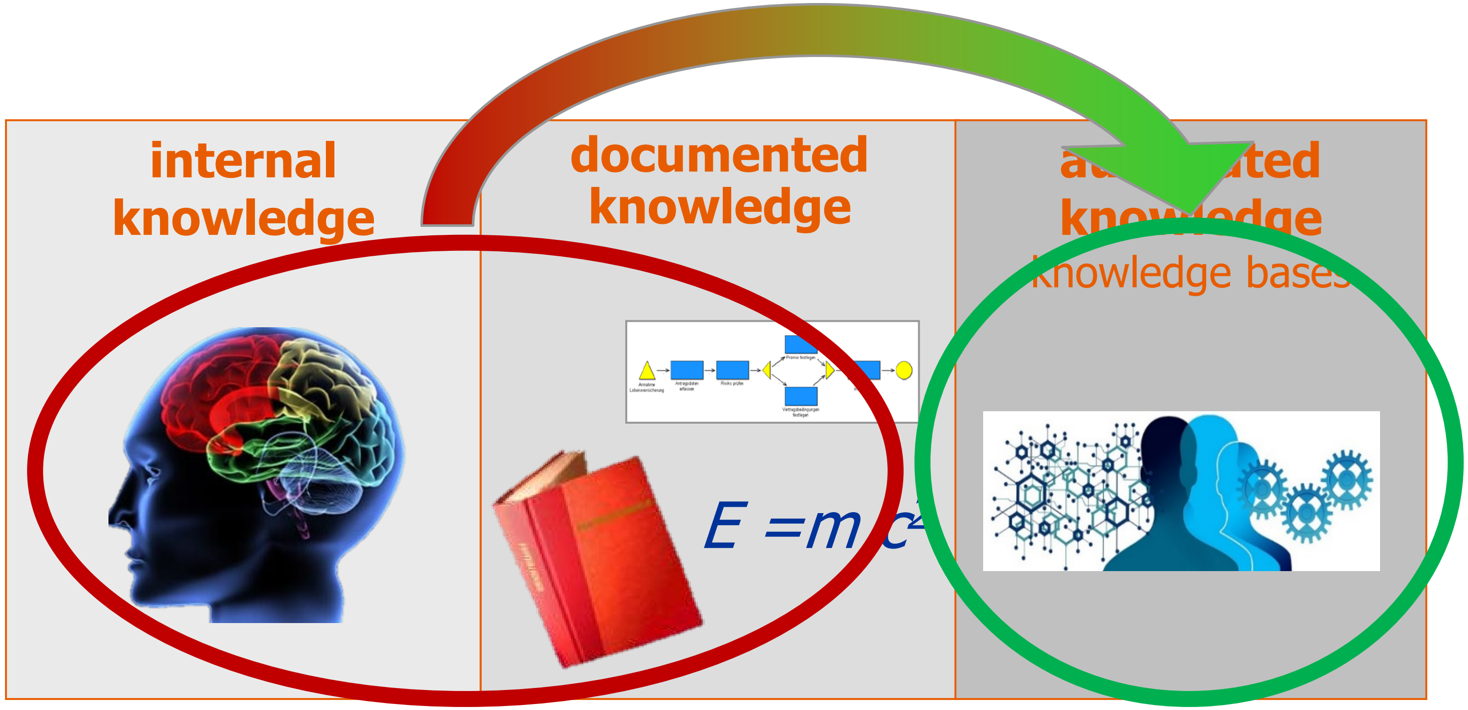


$E = m c^2$

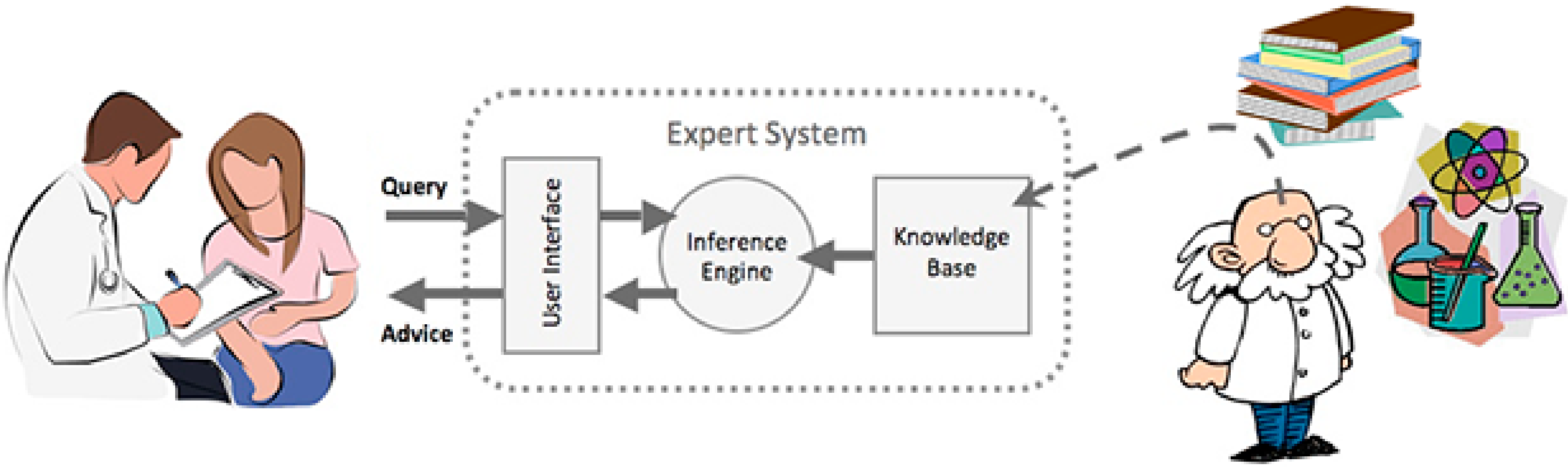
automated knowledge

knowledge bases

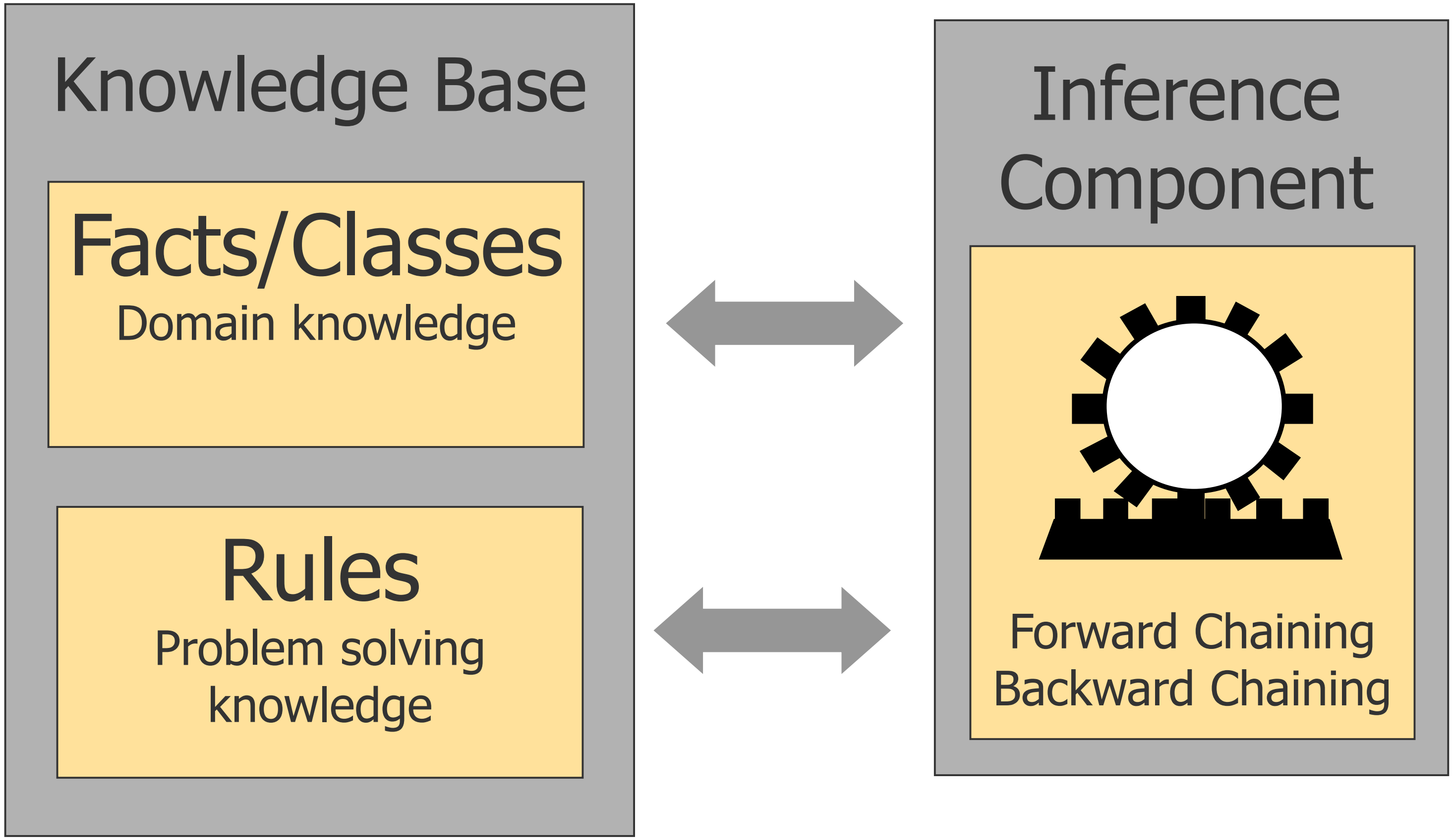
Knowledge Engineering: Human-Created Knowledge Base



Knowledge-Based Systems (Expert Systems)



Knowledge-Based Systems (Rules & Facts)



Decision Tables and Rule-Based Systems

Eligibility			
A	Degree valid	University Registered	eligible
	yes,no	*yes, no, unclear*	*yes,no*
1	yes	yes	yes
2	no	-	no
3	-	no	no
4	-	unclear	no

- Rule 1:
  - IF Temperature = *low*
    THEN heating power is *increased*
- Rule 2:
  - IF Temperature = *normal*
    AND humidity = *low*
    THEN heating power is *normal*

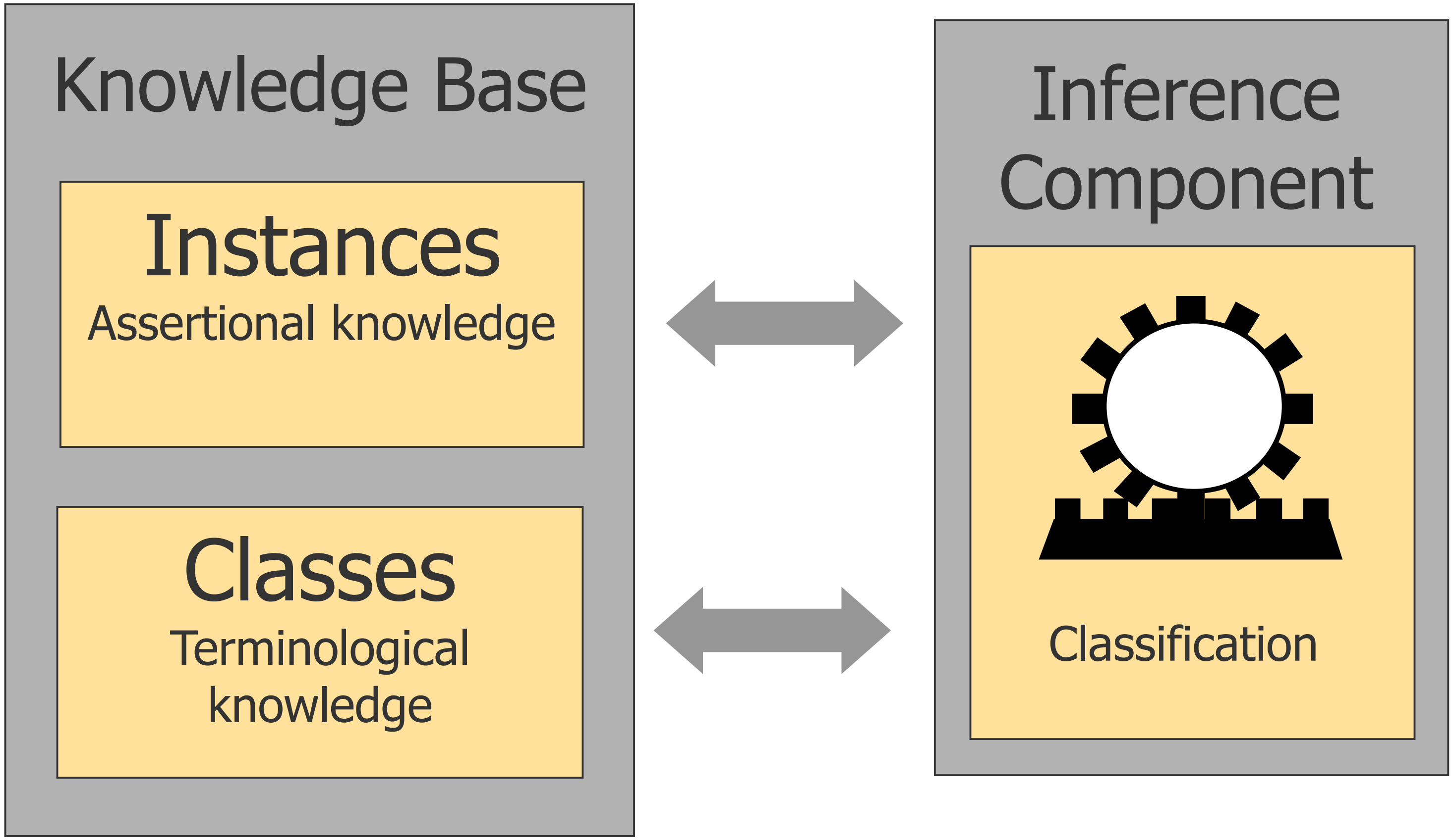
Facts:

father(peter,mary)
father(peter,john)
mother(mary,mark)
mother(jane,mary)

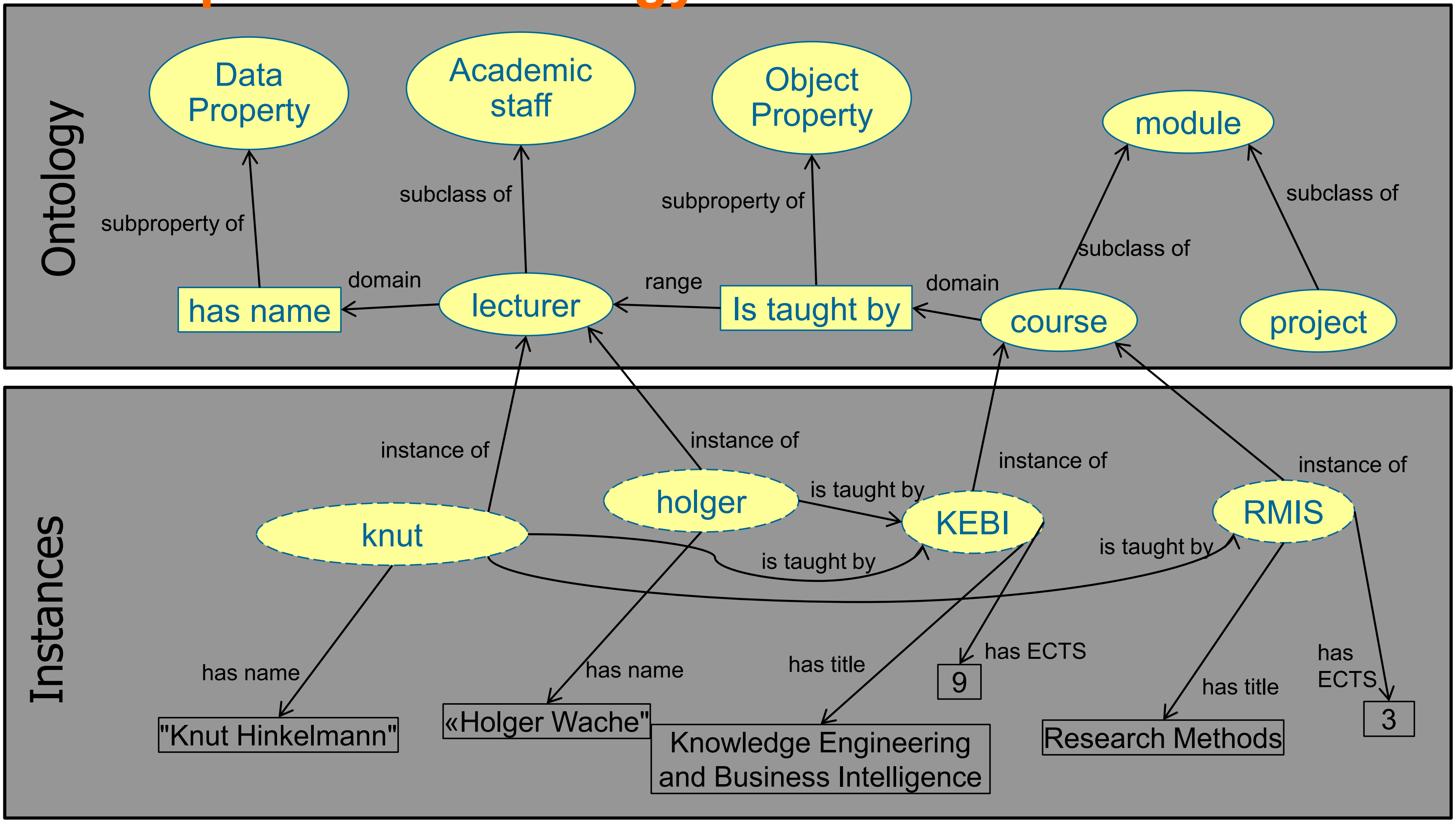
Rules:

father(X,Y) → parent(X,Y)
mother(X,Y) → parent(X,Y)
father(X,Y) AND parent(Y,Z) → grandfather(X,Z)
mother(X,Y) AND parent(Y,Z) → grandmother(X,Z)
parent(X,Y) AND parent(X,Z) → sibling(Y,Z)

Knowledge-Based Systems (Classes and Instances)

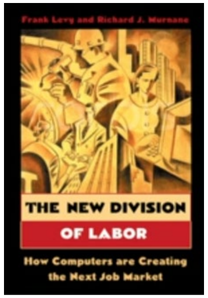


Example of an Ontology



Machine Learning

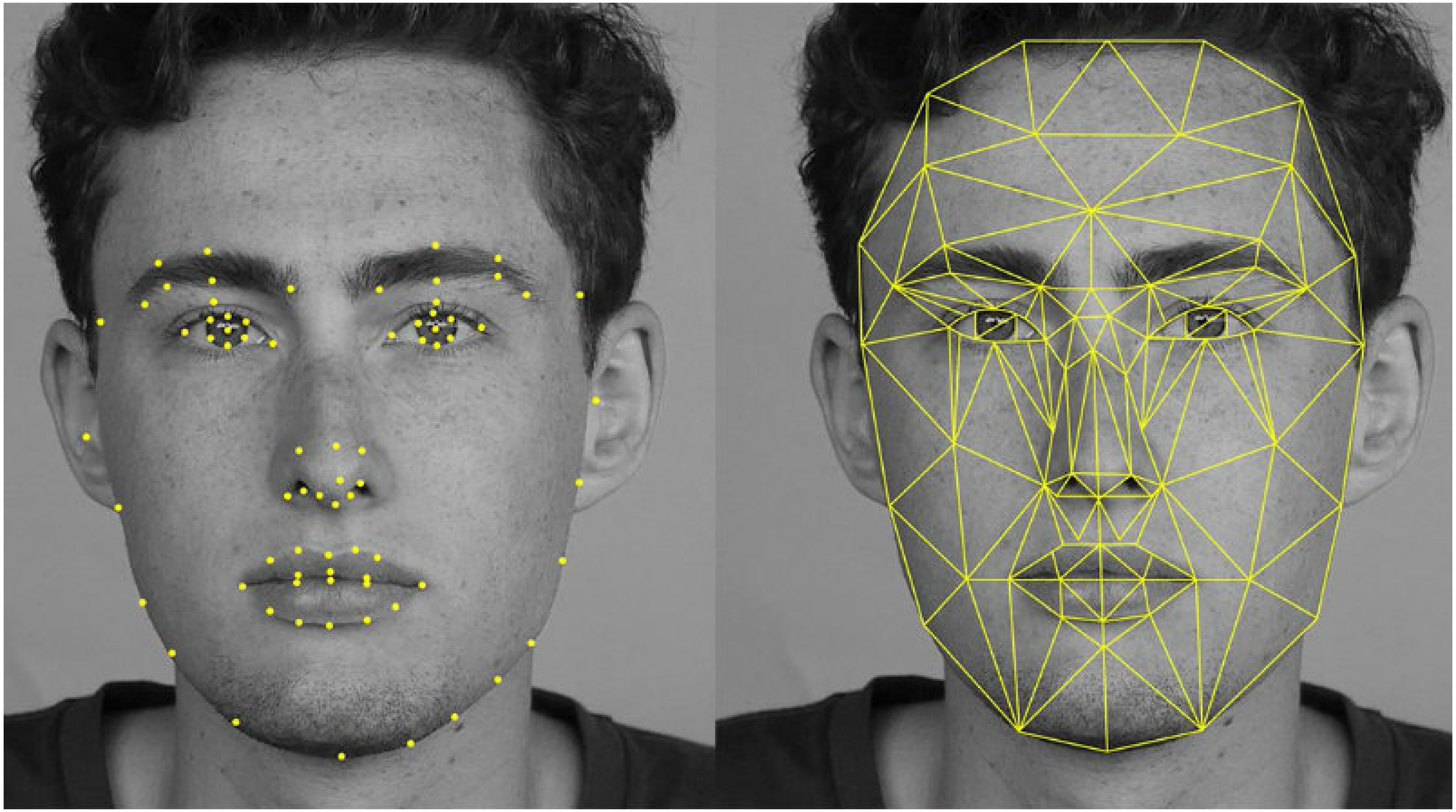
Self-driving Cars



"… it is hard to imagine discovering the set of rules that can replicate the driver's behavior."

(Levy & Murnane 2006)

Face Recognition



Recognizing Numbers

- It is very hard to specify what makes a «2»

Source: Geoffrey Hinton, https://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec1.pd

Spam Filter

"It's not the most sophisticated Spam blocker I've tried, but it's the only one that works!"

Translation

“The spirit was willing, but the flesh was weak”

…

“The vodka was good, but the meat was rotten”

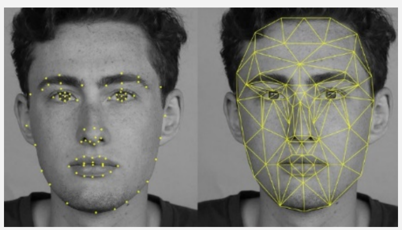
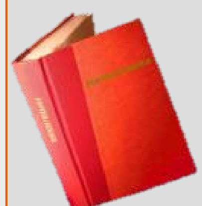
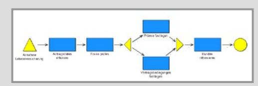
“Out of sight, out of mind.”

…

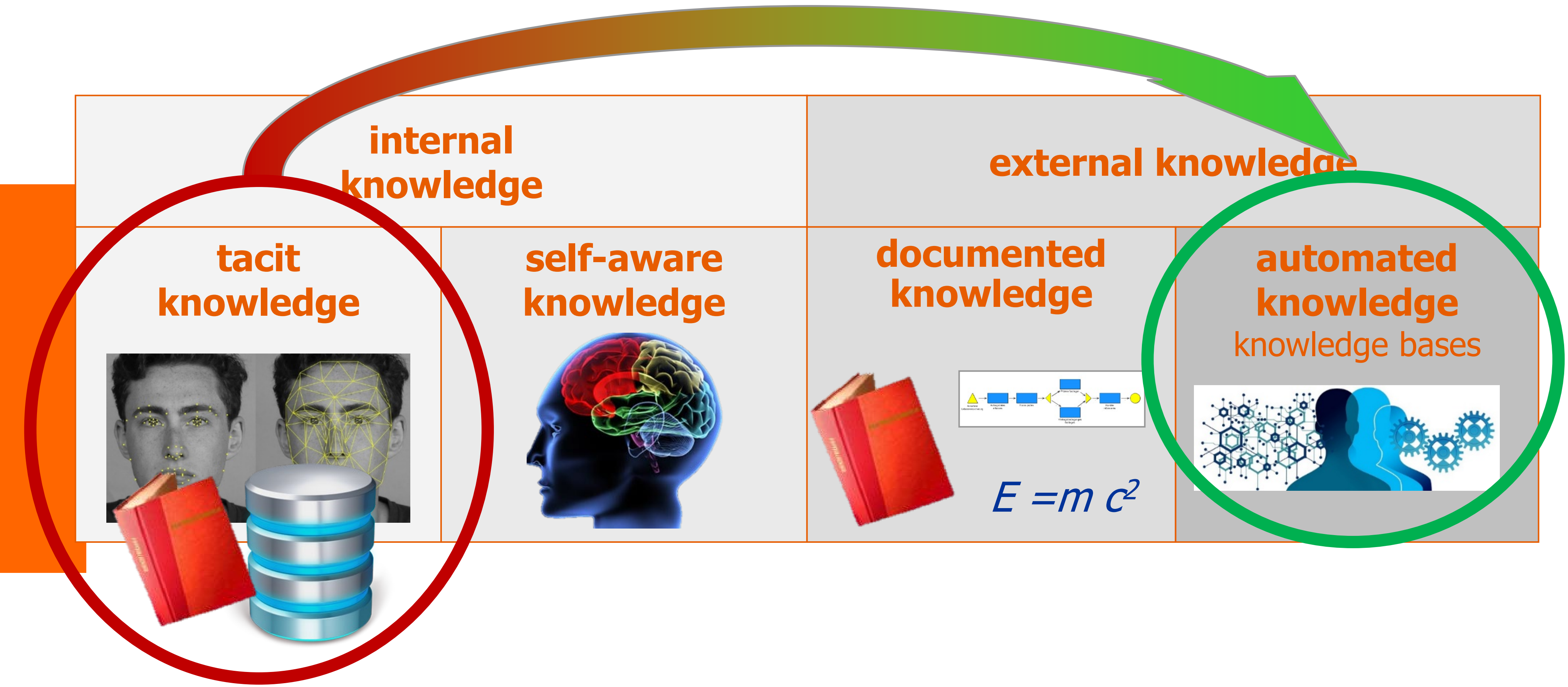
“Blind and insane.”

https://www.snopes.com/language/misxlate/machine.asp

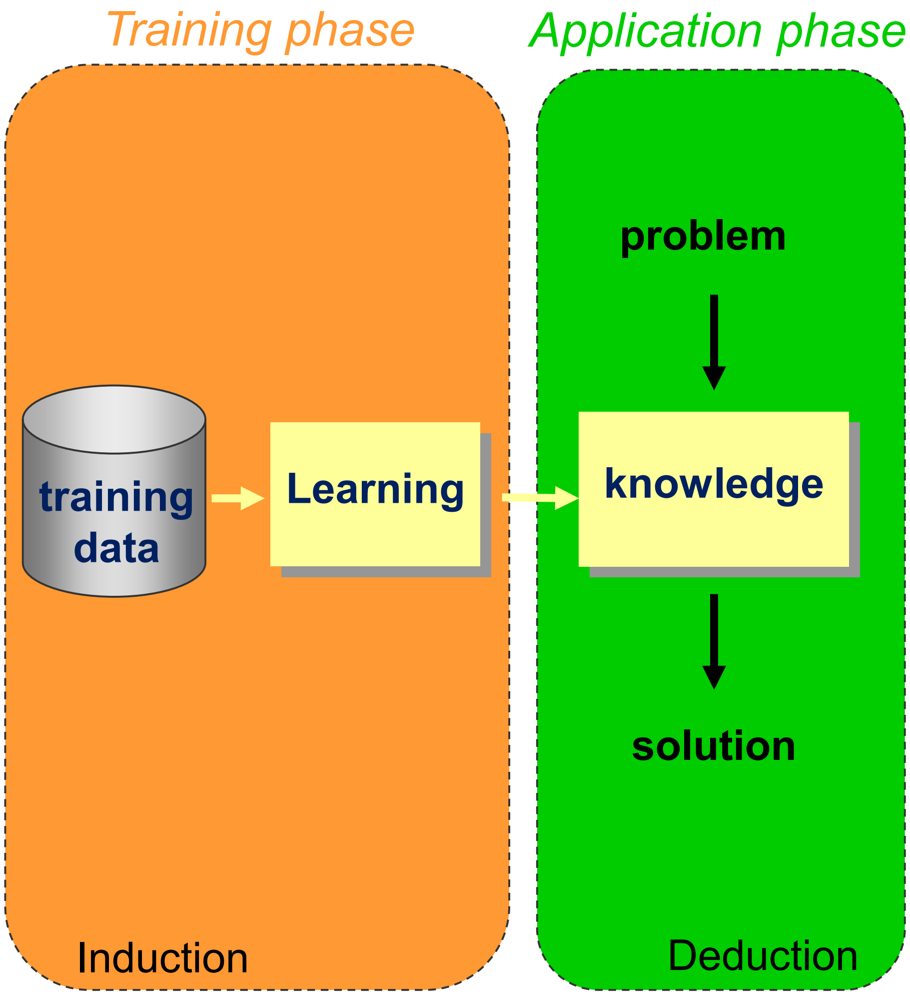
Knowledge

internal knowledge		external knowledge	
tacit knowledge 	**self-aware knowledge** 	**documented knowledge**   $E = m c^2$	**automated knowledge** knowledge bases 

Machine Learning: Learning (Tacit) Knowledge from Data



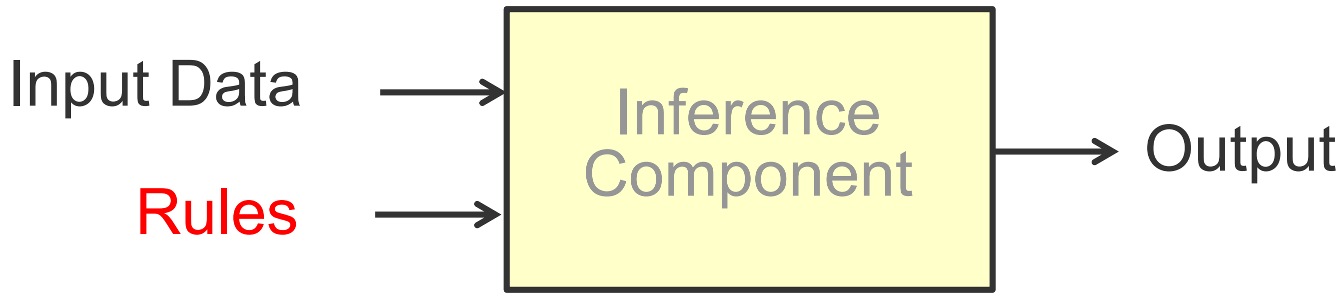
Machine Learning: General Idea



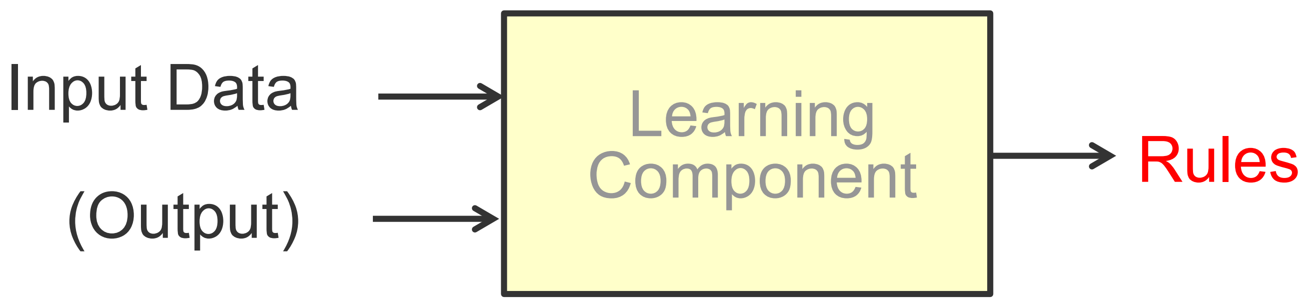
- **Training**
  - Collect data for the problem
  - Use the data to learn how to solve the type of problem
  - Result: Knowledge base
- **Application**
  - Use the learned knowledge for new problems

Machine Learning vs. Knowledge-based Systems

Knowledge-based System



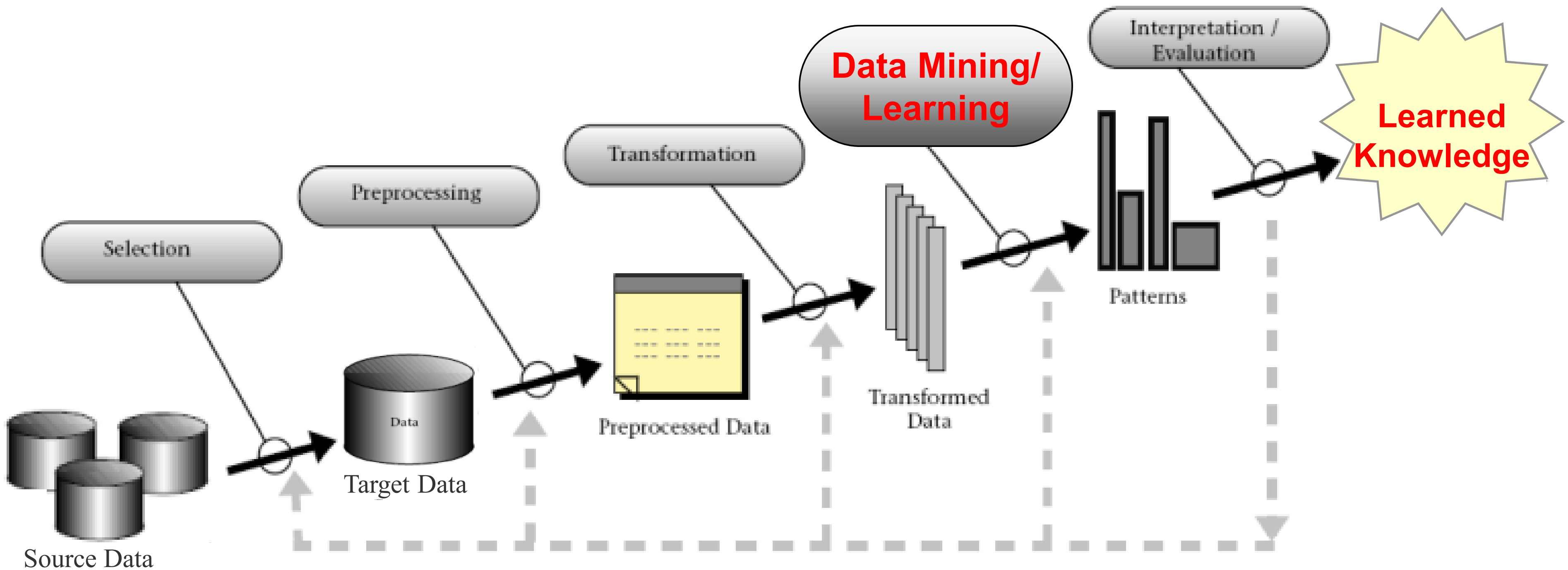
Machine Learning



Source: Vibhav Gogate, UT Dallas

Machine Learning in Context

- Machine Learning (Data Mining) is a step to discover knowledge in data



Knowledge is then used in processes and applications.

(Fayyad et al., 1996)

Types of Learning

- The learning method depends on the kind of data that we have at our disposal
  - The data contains sets of inputs and corresponding outputs: (i,o)
  - No prior knowledge: The data contains only the inputs i: output has to be determined
  - The data contains sets of inputs without corresponding «correct» output, but we can get some measure of the quality of an output o for input i.
    Rewards for good output quality.

Supervised Learning

Unsupervised Learning

Reinforcement Learning

(Lison, 2012)

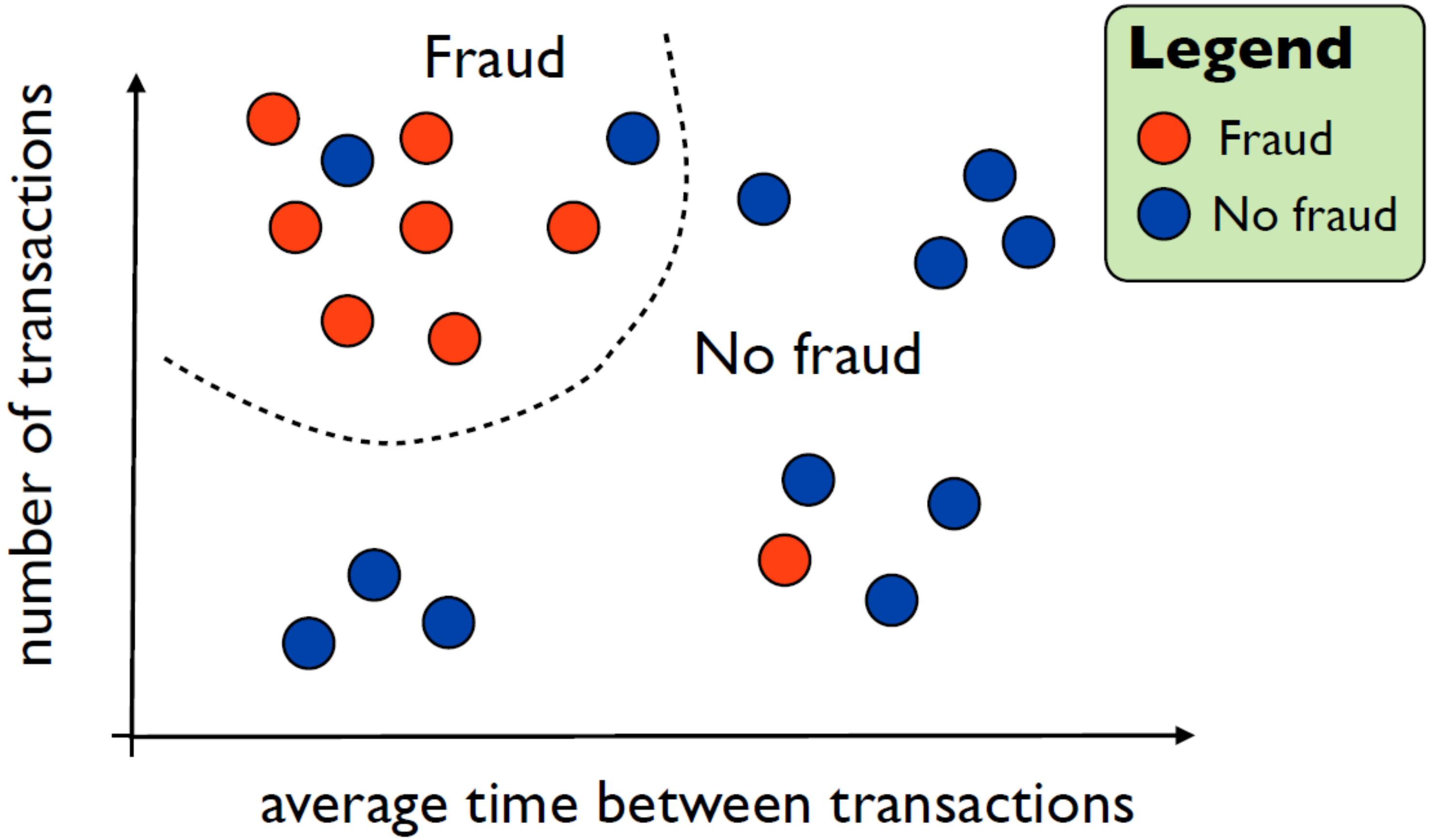
Supervised Learning: Application Examples

	Input ***i***	Output **o**
Spam filtering	An email	{spam, non-spam}
Face recognition	An image	Identified faces
Machine translation	A sentence in language A	A sentence in language B
Speech recognition	A speech signal	A (text) sentence
Fraud detection	A financial transaction	{fraud, non-fraud}
Robot motion	Sensory data	Motor control

(Lison, 2012)

Supervised Learning

Example: Classification

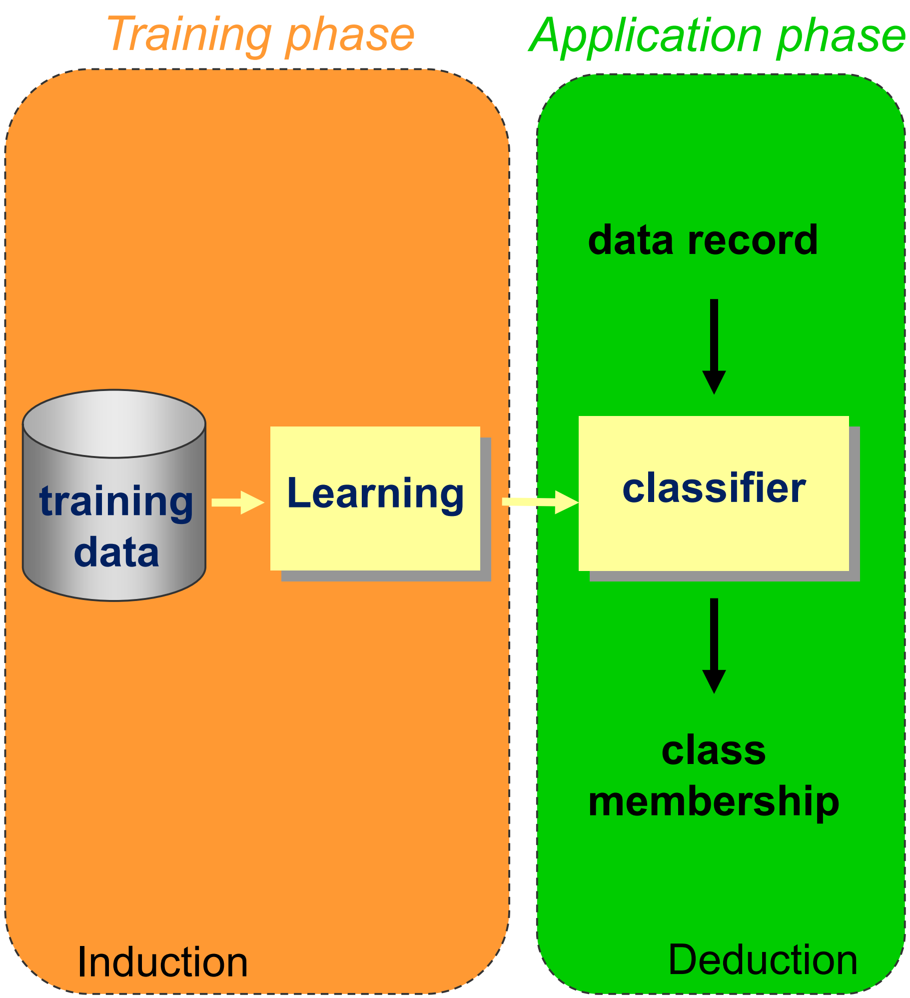


(Lison, 2012)

Classification

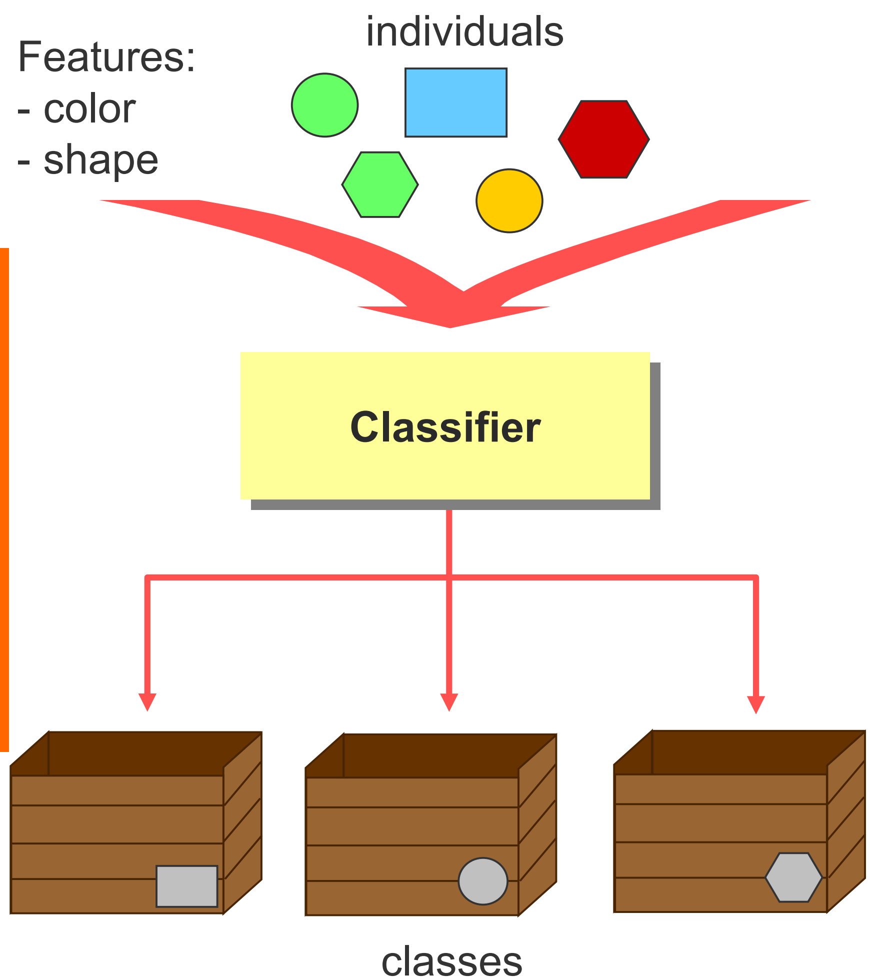
- Assign objects (input) to known classes (output)
- Examples:
  - credit assessment
    Input: customers of a bank
    Classes: credit worthy
    not credit worthy
  - Spam filtering
    Input: email
    Classes: spam
    non-spam
  - optical character recognition (OCR)
    Input: scanned pixel image
    Classes: ASCII characters

Training and Application Phase



- **Training:** Learning the classification criteria
  - Given: sample set of training data records
  - Result: Decision logic to determine class from values of input attributes (decision tree, rules, model)
- **Application:** Classification
  - Goal: assign a class to previously unseen records of input data as accurately as possible

Supervised Learning: Classification Criteria



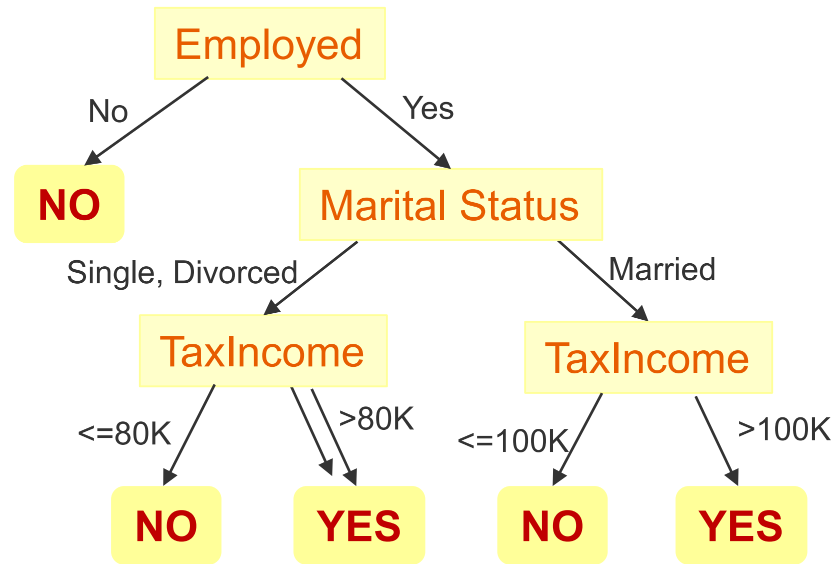
- The classifier decides, which individual belongs to which class
- Problem:
  - Input has different features
  - The criteria for the decision are not always obvious
- Supervised Learning:
  - Learn the classification criteria from known examples
  - Criteria = relevant features and their valures

Example for Supervised Learning

Problem: When to give credit

Tid	Employed	Marital Status	Taxable Income	accept
1	No	Single	125K	No
2	Yes	Married	160K	Yes
3	Yes	Single	70K	No
4	No	Married	120K	No
5	Yes	Divorced	95K	Yes
6	Yes	Married	60K	No
7	No	Divorced	220K	No
8	Yes	Single	85K	Yes
9	Yes	Married	95K	No
10	Yes	Single	90K	Yes

Training Data

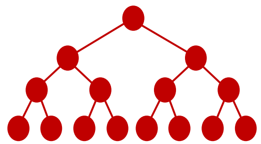


Credit Worthiness

	Employed	Marital Status	Taxable Income	Accept
	Yes, No	*Single, Divorced, Married*	*Integer*	*Yes, No*
1	No			No
2	Yes	Single	> 80K	Yes
3	Yes	Divorced	> 80K	Yes
4	Yes	Single	≤ 80K	No
5	Yes	Divorced	≤ 80K	No
6	Yes	Married	> 100K	Yes
7	Yes	Married	≤ 100K	No

Knowledge Base: Decision Tree , Decision Table

Classification Methods



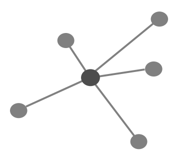
Decision Trees

criteria	*class*
… … …	…
… … …	…

Decision Table

IF …
THEN …

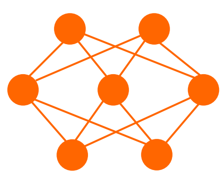
Rules



k-Nearest Neighbor

Genetic Algorithms

symbolic



Neuronale Netze

subsymbolic

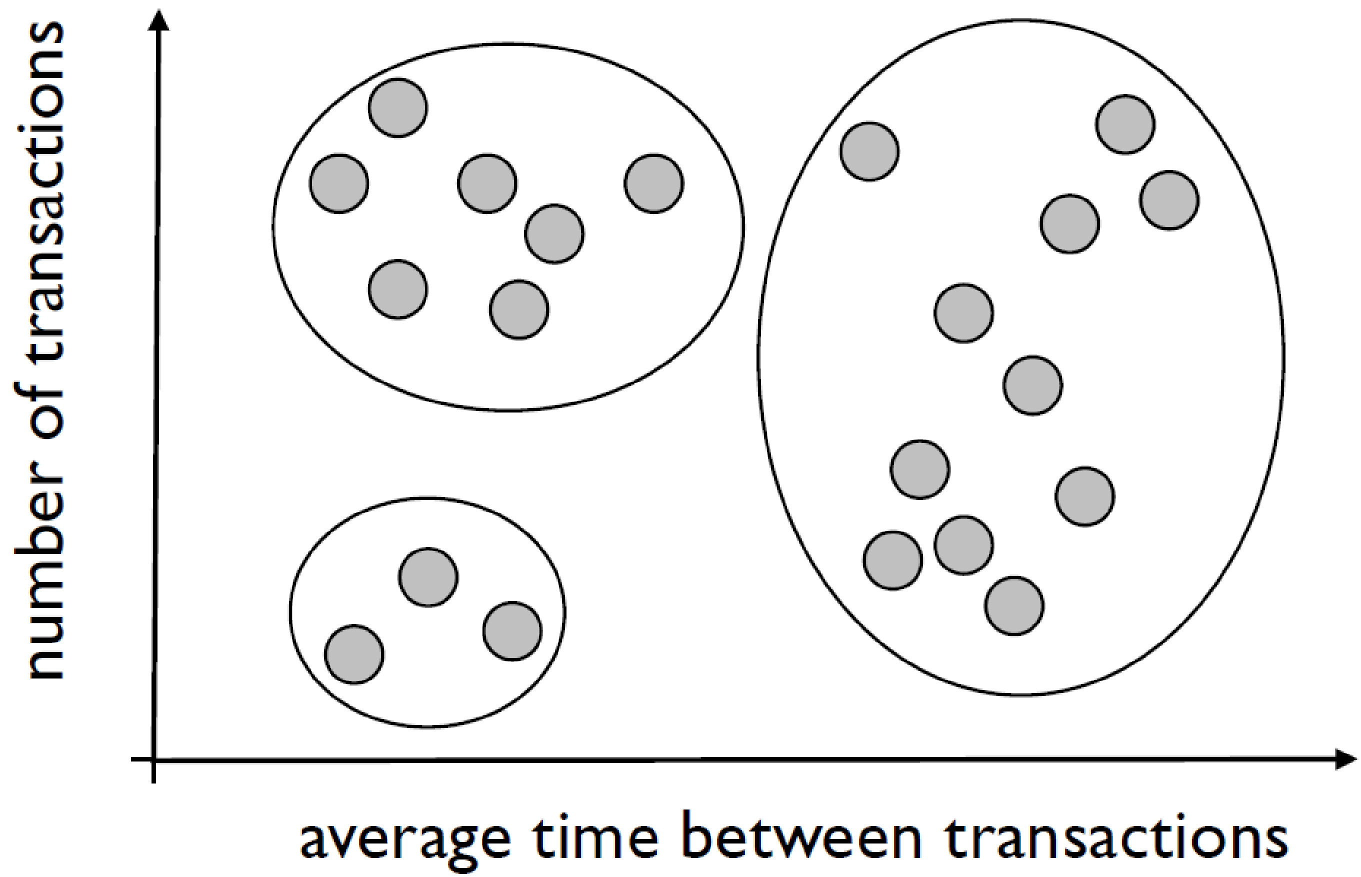
Unsupervised Learning

- Sometimes, we don't have access to any output value **o**, we simply have a collection of input examples **i**
- Input: data sets without corresponding output values.
- Objective: learn the underlying patterns of our data
  - Are there any *correlations* between features?
  - Can we *cluster* our data set in groups which behave similarly?

(Lison, 2012)

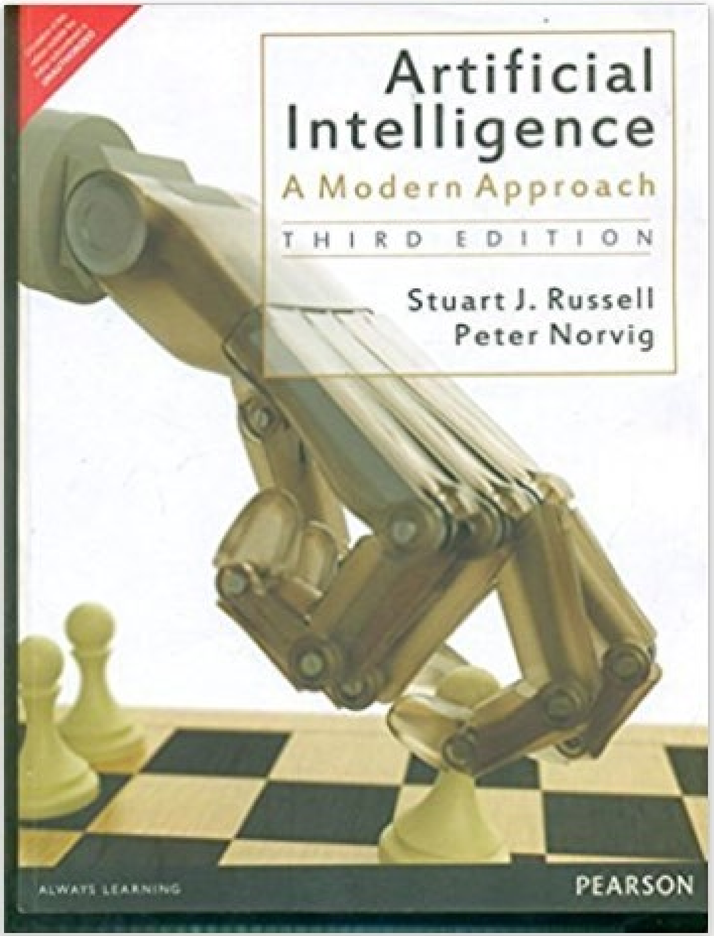
Unsupervised Learning

Example: Clustering (= identify new classes)

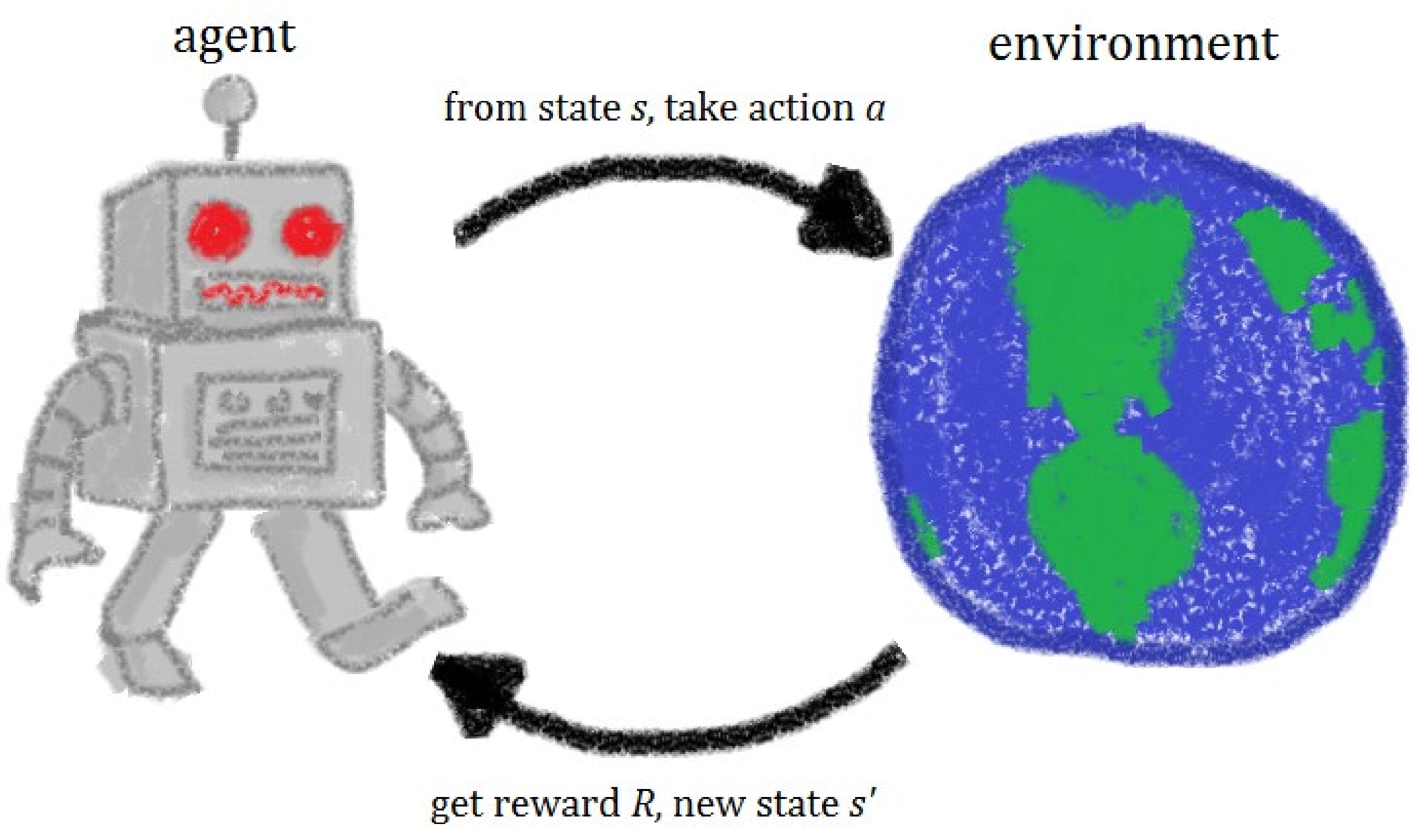


(Lison, 2012)

Example: Recommender Systems



Reinforcement Learning



Reinforcement Learning

- Sometimes we don’t have direct access to «the» correct output ***o*** for an input ***i***
- But we can get a measure of «how good/bad» an output is
  - Often called the *reward* (can be negative or positive)
- The goal of the agent is to learn the behaviour that maximises its expected cumulative reward over time
  - To learn how to flip pancakes, the reward could for instance be +3 if the pancake is flipped, -1 if the pancake stays in the pan, and -5 if it falls