

Decision support systems remade: (machine) learning advisors



Filip Wójcik
Data Scientist
Wroclaw University Lecturer

Agenda

- What are decision support and expert systems?
- Brief history of expert systems
- Drawbacks of traditional expert systems
- Machine learning – modern decision support systems
- Association analysis
- Rule induction
- Decision trees
- Scalable solutions

What are expert systems? 1/4

Storing
experts
knowledge

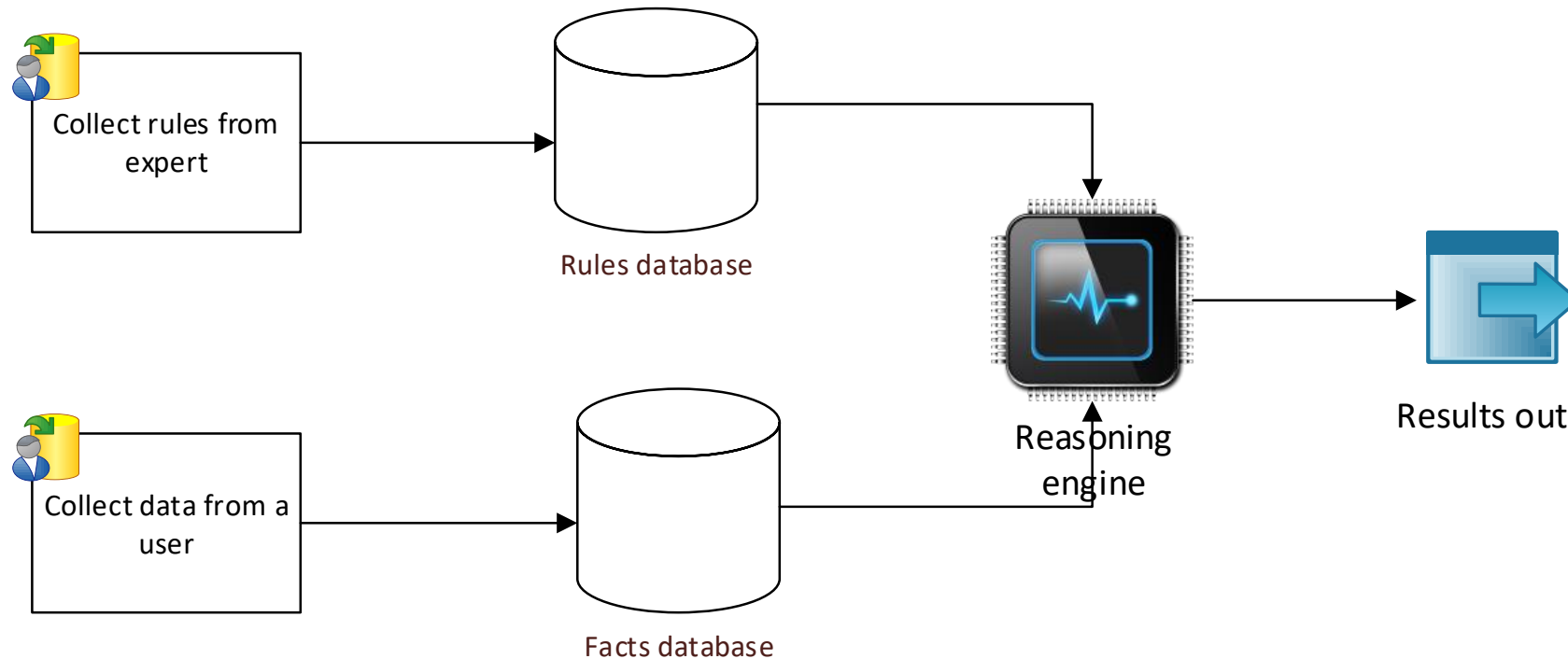
Reasoning
over certain
facts

Quick
reactions on
user queries

Transparency
of decisions

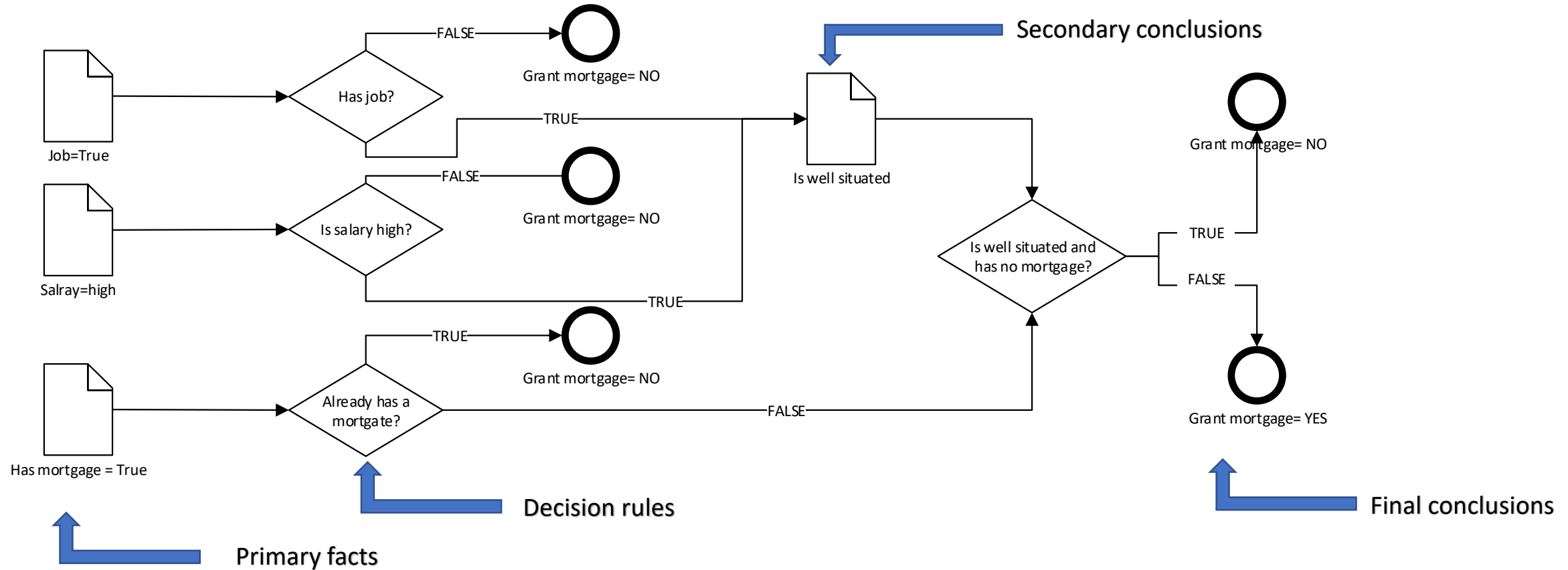
Explainability
of decisions

What are expert systems? 2/4

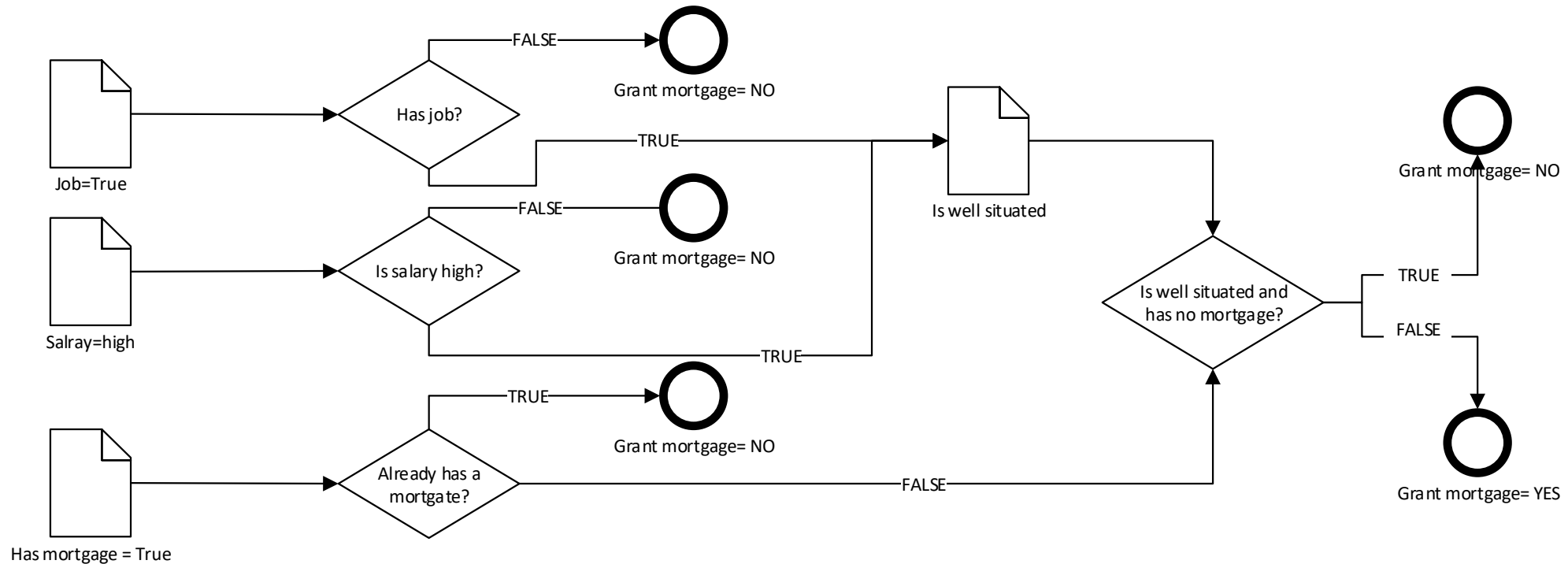


1. Collect rules from domain-experts
2. Collect facts from users
3. Perform reasoning over facts, using rules
4. Conclude facts
5. Present results of reasoning

What are expert systems? 3/4



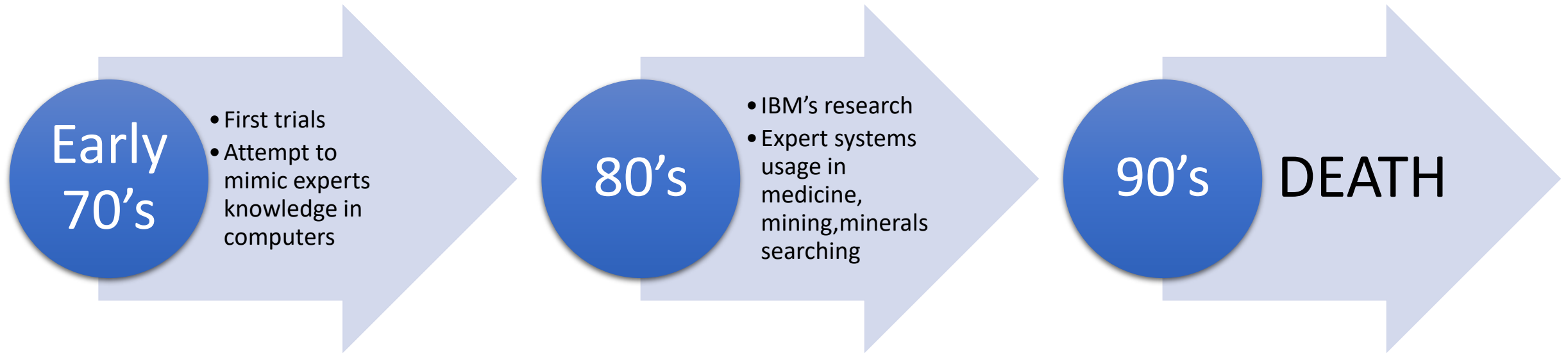
What are expert systems? 4/4



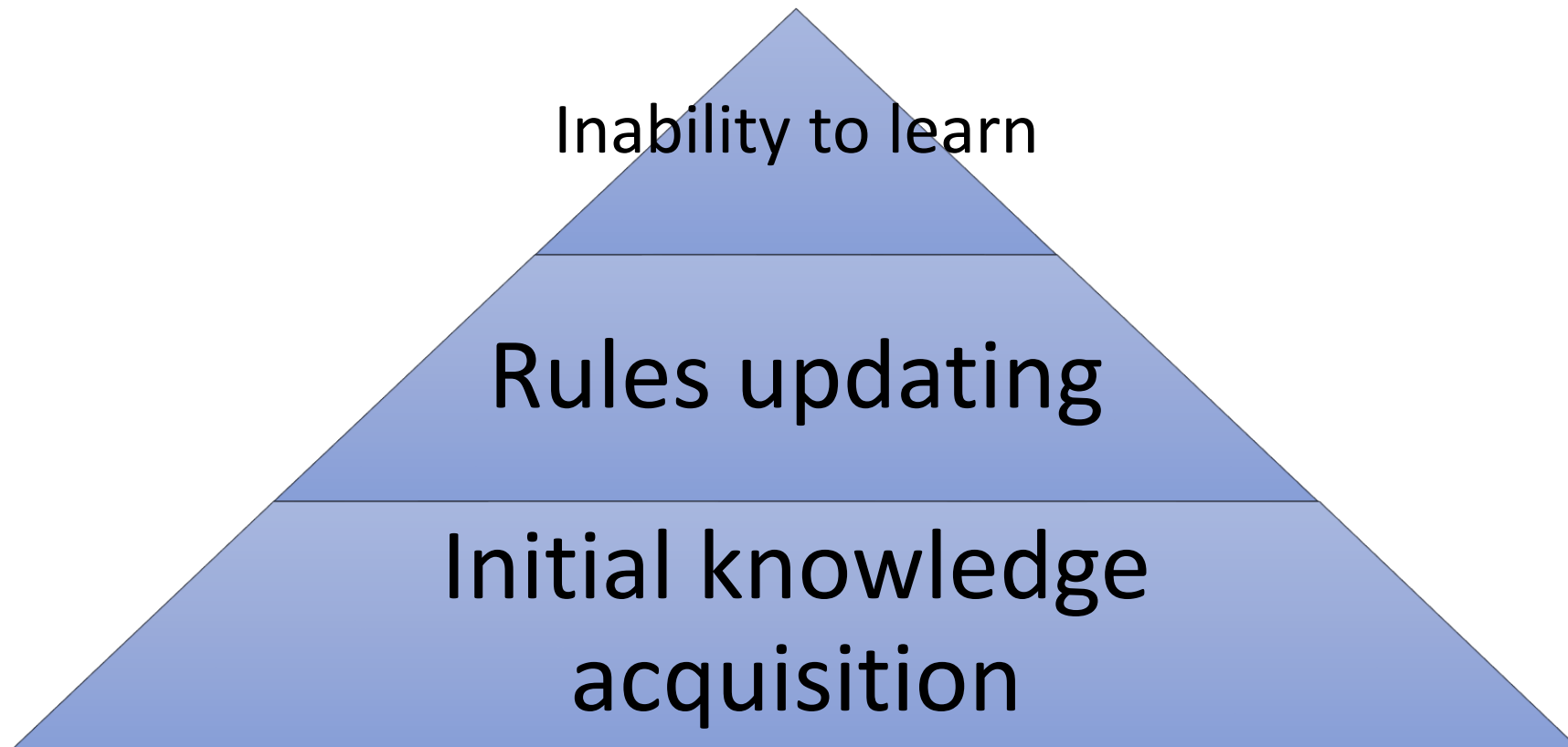
Reasoning FORWARD: from facts to conclusions

Reasoning BACKWARD: from conclusions to facts

Brief history of expert systems



What killed expert systems?



Machine learning – a modern decision support systems



Machine learning – a modern decision support systems

1/3

Ability to
automatically learn
from data

Usage of statistical
procedures to
validate knowledge

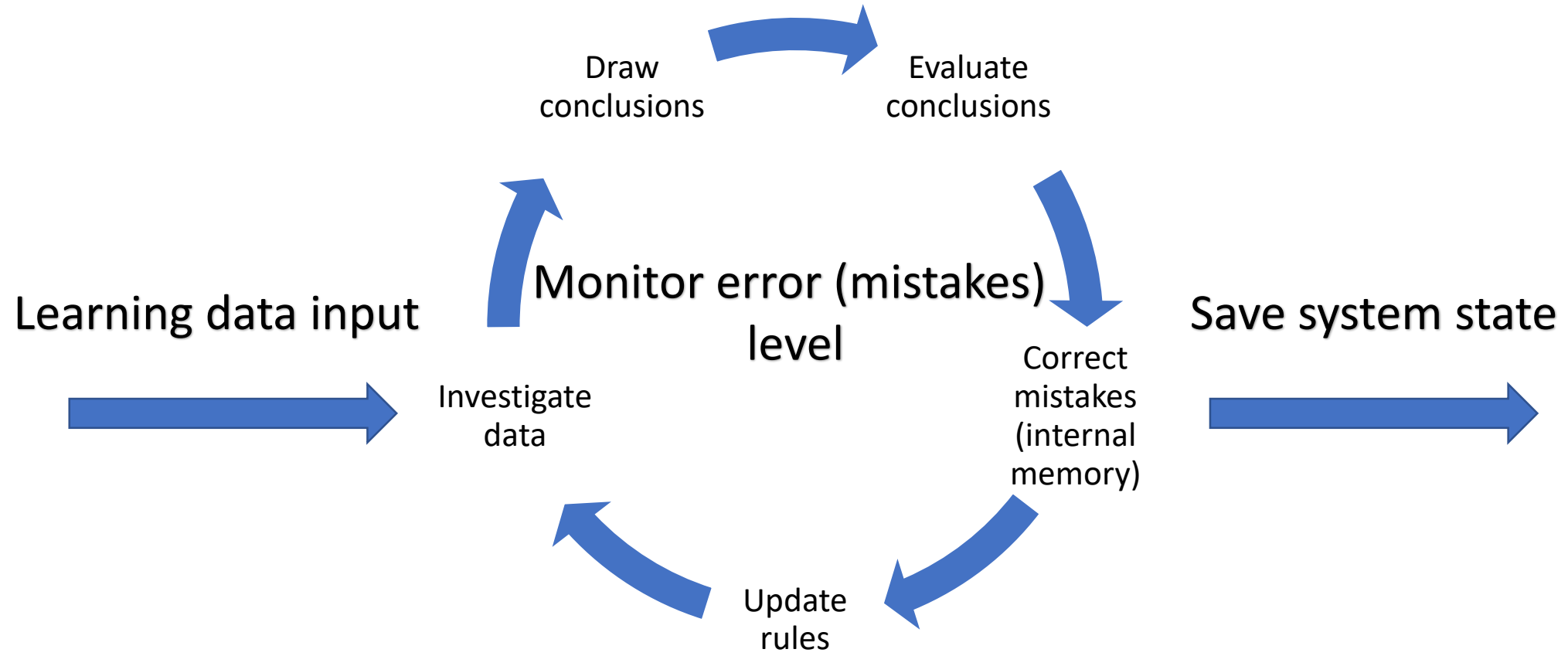
Variety of tasks

Explainability of
decisions
(sometimes)

Easy to
validate/score

Machine learning – a modern decision support systems

2/3



Machine learning – a modern decision support systems

3/3

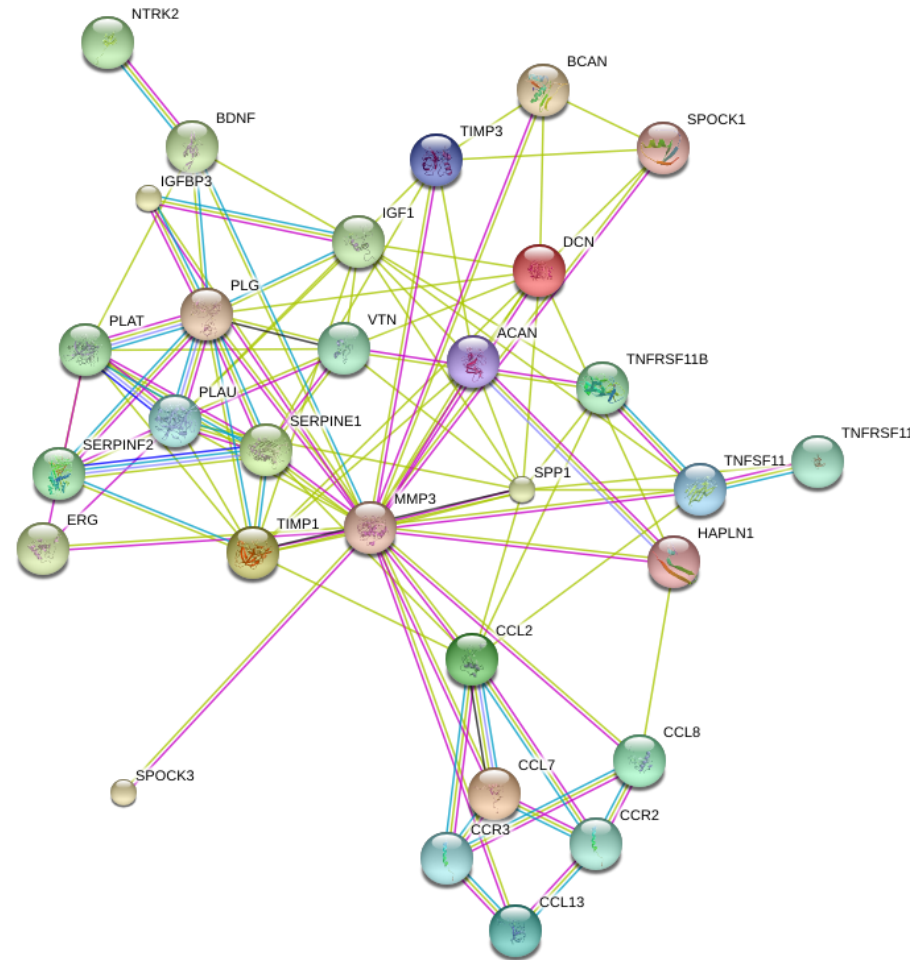
- Cannot be interpreted by humans
- Their internal structure is complicated and is hard to understand
- „Justifications” of predictions are purely mathematical

„Black box”
methods

- Easily interpretable
- Can be translated to human-friendly form
- Not so sophisticated mathematically

„White box”
methods

Association analysis systems



Association analysis systems 1/6

Key features



Easy to interpret



Wide range of use cases



Dual role: explaining data/making decisions



Scalable

Use cases



Market basket analysis



Social media graph structures analysis



Correlation finding



Consumer profiling

Association analysis systems 2/6

Transaction number	Products
1.	1. Soya milk 2. Salad
2.	1. Salad 2. Walnuts 3. Wine 4. Bread
3.	1. Soya milk 2. Walnuts 3. Wine 4. Juice
4.	1. Salad 2. Soya milk 3. Walnuts 4. Wine
5.	1. Salad 2. Soya milk 3. Walnuts 4. Juice

Normalized vs denormalized form

Order Id	Product category	city	state
1006414	BOOK	BURMINGHAM	AL
1006541	ARTWORK	MADISON	CT
1006542	OCCASION	OLD SAYBROOK	CT
1010154	BOOK	EASTCHESTER	NY
1009110	ARTWORK	LINCON PARL	NJ
1009110	BOOK	LINCON PARL	NJ
1008491	ARTWORK	TARRYTOWN	NY
1008492	ARTWORK	CARMEL	NY
1010189	BOOK	WHITE PLAINS	NY
1008493	BOOK	WHITE PLAINS	NY

Association analysis systems 3/6

Transaction number	Products
1.	1. Soya milk 2. Salad
2.	1. Salad 2. Walnuts 3. Wine 4. Bread IF
3.	1. Soya milk 2. Walnuts Antecedent 3. Wine 4. Juice
4.	1. Salad 2. Soya milk 3. Walnuts 4. Wine
5.	1. Salad 2. Soya milk 3. Walnuts 4. Juice

Frequent items	Rel. support
Soya, salad	0.6
Soya, salad, walnuts	0.4
Salad THEN	0.8



Implications	confidence
Soya => walnuts	0.75
Soya => salad	0.75
Soya, Walnuts, Wine => juice	0.4

Key features:

- Finding items that co-occur together
- Finding items that are correlated
- Form association rules, defining

relationships
Consequent

- Calculate probabilities and confidence values

Association analysis systems 4/6

Transaction number	Products
1.	1. Soya milk 2. Salad
2.	1. Salad 2. Walnuts 3. Wine 4. Bread
3.	1. Soya milk 2. Walnuts 3. Wine 4. Juice
4.	1. Salad 2. Soya milk 3. Walnuts 4. Wine
5.	1. Salad 2. Soya milk 3. Walnuts 4. Juice

Frequent items	Rel. support
Soya, salad	0.6
Soya, salad, walnuts	0.4
Salad	0.8

Implications	confidence
walnuts => soya	0.75
Soya => salad	0.75
Soya, Walnuts, Wine => juice	0.4

$$\text{support}(X) = \text{count}(X)$$

$$\text{relative support}(X \& Y) = \frac{\text{support}(X \& Y)}{N} = P(AB)$$

$$\text{confidence}(X \rightarrow Y) = \frac{\text{support}(X \& Y)}{\text{support}(X)} = P(A|B)$$

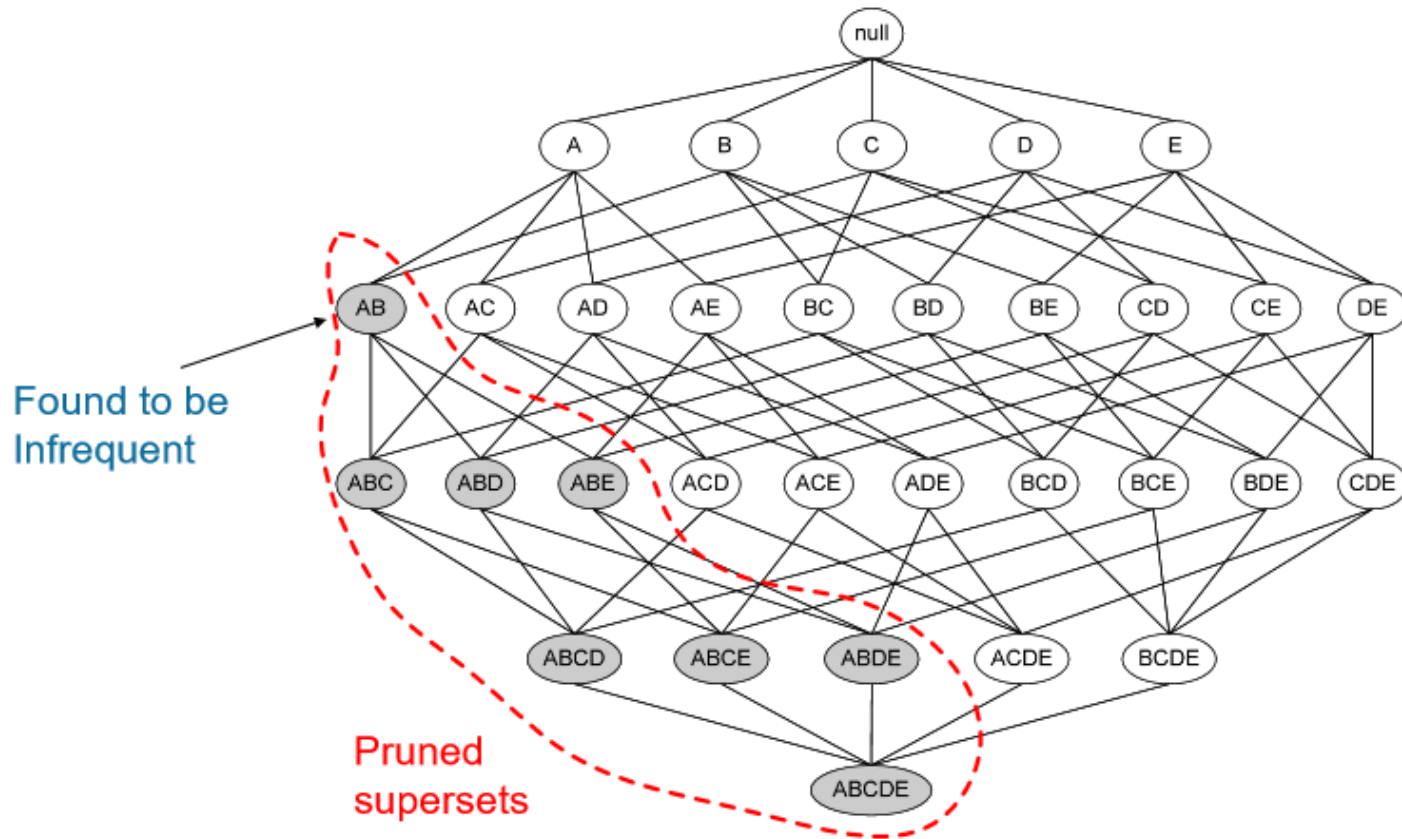
$$\text{relative support}(\text{soya} \& \text{salad}) = \frac{3}{5} = 0.6$$

$$\text{confidence}(\text{soya} \rightarrow \text{salad}) = \frac{3}{4} = 0.75$$

Association analysis systems 5/6

#	Measure	Formula
1	ϕ -coefficient	$\frac{P(A,B) - P(A)P(B)}{\sqrt{P(A)P(B)(1-P(A))(1-P(B))}}$
2	Goodman-Kruskal's (λ)	$\frac{\sum_j \max_k P(A_j, B_k) + \sum_k \max_j P(A_j, B_k) - \max_j P(A_j) - \max_k P(B_k)}{2 - \max_j P(A_j) - \max_k P(B_k)}$
3	Odds ratio (α)	$\frac{P(A,B)P(\bar{A},\bar{B})}{P(A,\bar{B})P(\bar{A},B)}$
4	Yule's Q	$\frac{P(A,B)P(\bar{A}\bar{B}) - P(A,\bar{B})P(\bar{A},B)}{P(A,B)P(\bar{A}\bar{B}) + P(A,\bar{B})P(\bar{A},B)} = \frac{\alpha - 1}{\alpha + 1}$
5	Yule's Y	$\frac{\sqrt{P(A,B)P(\bar{A}\bar{B})} - \sqrt{P(A,\bar{B})P(\bar{A},B)}}{\sqrt{P(A,B)P(\bar{A}\bar{B})} + \sqrt{P(A,\bar{B})P(\bar{A},B)}} = \frac{\sqrt{\alpha} - 1}{\sqrt{\alpha} + 1}$
6	Kappa (κ)	$\frac{P(A,B) + P(\bar{A},\bar{B}) - P(A)P(B) - P(\bar{A})P(\bar{B})}{1 - P(A)P(B) - P(\bar{A})P(\bar{B})}$
7	Mutual Information (M)	$\frac{\sum_i \sum_j P(A_i, B_j) \log \frac{P(A_i, B_j)}{P(A_i)P(B_j)}}{\min(-\sum_i P(A_i) \log P(A_i), -\sum_j P(B_j) \log P(B_j))}$
8	J-Measure (J)	$\max(P(A, B) \log(\frac{P(B A)}{P(B)}) + P(\bar{A}\bar{B}) \log(\frac{P(\bar{B} \bar{A})}{P(\bar{B})}),$ $P(A, \bar{B}) \log(\frac{P(\bar{B} A)}{P(\bar{B})}) + P(\bar{A}B) \log(\frac{P(B \bar{A})}{P(B)})$
9	Gini index (G)	$\max(P(A)[P(B A)^2 + P(\bar{B} A)^2] + P(\bar{A})[P(B \bar{A})^2 + P(\bar{B} \bar{A})^2]$ $- P(B)^2 - P(\bar{B})^2,$ $P(B)[P(A B)^2 + P(\bar{A} B)^2] + P(\bar{B})[P(A \bar{B})^2 + P(\bar{A} \bar{B})^2]$ $- P(A)^2 - P(\bar{A})^2)$
10	Support (s)	$P(A, B)$
11	Confidence (c)	$\max(P(B A), P(A B))$
12	Laplace (L)	$\max(\frac{NP(A,B)+1}{NP(A)+2}, \frac{NP(A,B)+1}{NP(B)+2})$
13	Conviction (V)	$\max(\frac{P(A)P(B)}{P(\bar{A}\bar{B})}, \frac{P(B)P(\bar{A})}{P(\bar{B}A)})$
14	Interest (I)	$\frac{P(A,B)}{P(A)P(B)}$
15	cosine (IS)	$\frac{P(A,B)}{\sqrt{P(A)P(B)}}$
16	Piatetsky-Shapiro's (PS)	$P(A, B) - P(A)P(B)$
17	Certainty factor (F)	$\max(\frac{P(B A) - P(B)}{1 - P(B)}, \frac{P(A B) - P(A)}{1 - P(A)})$
18	Added Value (AV)	$\max(P(B A) - P(B), P(A B) - P(A))$
19	Collective strength (S)	$\frac{P(A,B) + P(\bar{A}\bar{B})}{P(A)P(B) + P(\bar{A})P(\bar{B})} \times \frac{1 - P(A)P(B) - P(\bar{A})P(\bar{B})}{1 - P(A,B) - P(\bar{A}\bar{B})}$
20	Jaccard (ζ)	$\frac{P(A,B)}{P(A) + P(B) - P(A,B)}$
21	Kloggen (K)	$\sqrt{P(A, B)} \max(P(B A) - P(B), P(A B) - P(A))$

Association analysis systems 6/6



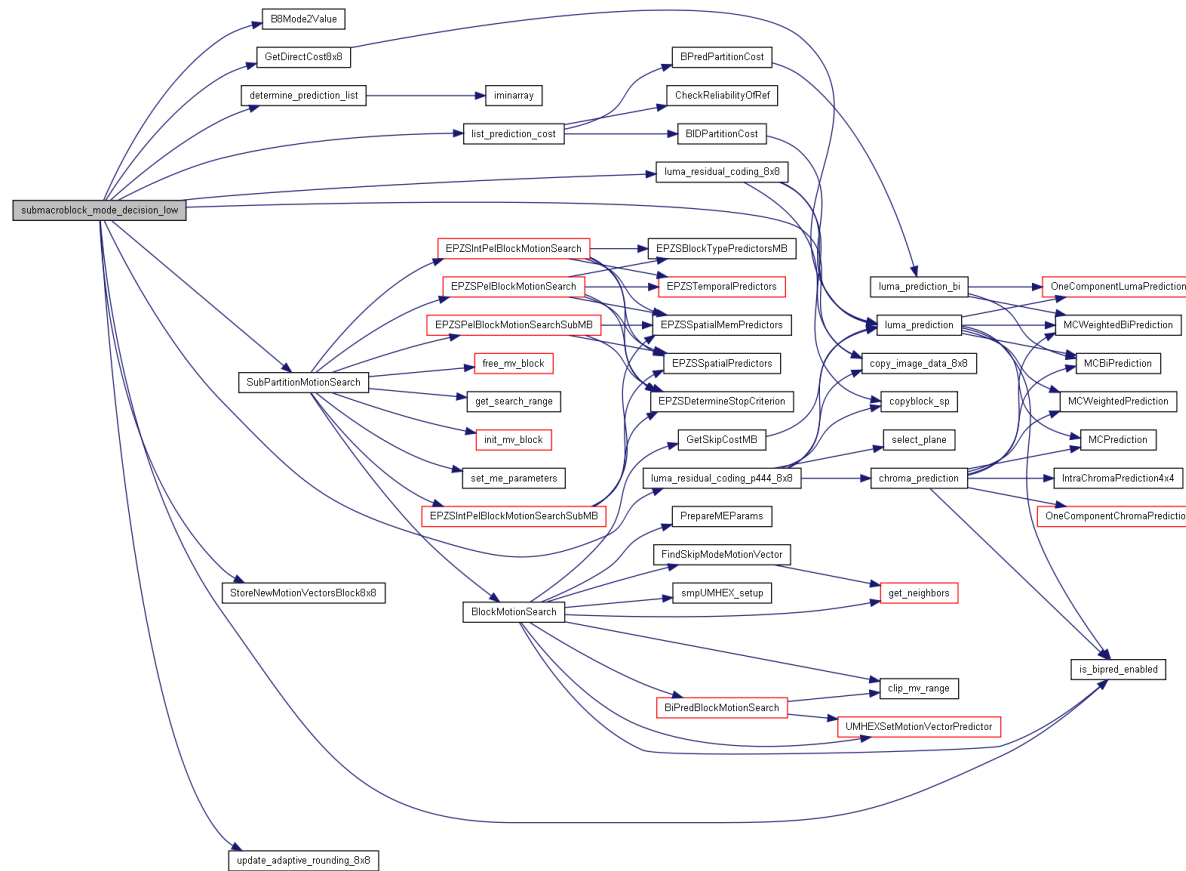
Apriori principle:

- Given user-defined frequency threshold T
- Given infrequent item **Itm** (**suport(Itm) < T**)
- No itemset containing **Itm** can be frequent

Result:

- Less combinatorial effort
- No need to check infrequent combinations

Rule induction systems



Rule induction systems 1/5

Key features



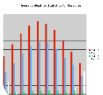
Full decision transparency



Full decision explainability



Automatic knowledge updating

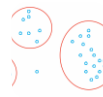


Based on statistical properties of data

Use cases



Classification systems



Pattern recognition



Intelligent advisors

Rule induction systems 2/5

client	hotel	addons	money_spent	offer
business	Hilton	trip	40,000	deluxe
business	Hilton	full board	38,000	deluxe
business	Hilton	trip	40,000	deluxe
middle class	Meta	none	800	basic
middle class	Meta	trip	900	basic
manager	Meta	trip	1,500	premium



Decisive attribute

Value	Count	%
Deluxe	3	0.5
Basic	2	0.333
Premium	1	0.16666

Rule induction systems 3/5

client	hotel	addons	money_spent	offer
business	Hilton	trip	40,000	deluxe
business	Hilton	full board	38,000	deluxe
business	Hilton	trip	40,000	deluxe
middle class	Meta	none	800	basic
middle class	Meta	trip	900	basic
manager	Meta	trip	1,500	premium

IF hotel == „Meta” THEN offer ==

Value	Count	Perc.
basic	2	66.6
premium	1	33.3

IF addons == „trip” THEN offer ==

Value	Count	Perc.
deluxe	2	50
basic	1	25
premium	1	25

Rule induction systems 4/5

client	hotel	addons	money_spent	offer
business	Hilton	trip	40,000	deluxe
business	Hilton	full board	38,000	deluxe
business	Hilton	trip	40,000	deluxe
middle class	Meta	none	800	basic
middle class	Meta	trip	900	basic
manager	Meta	trip	1,500	premium

IF

hotel == „Meta” AND
client == „middle class”

THEN

Value	Count	Perc.
basic	2	100

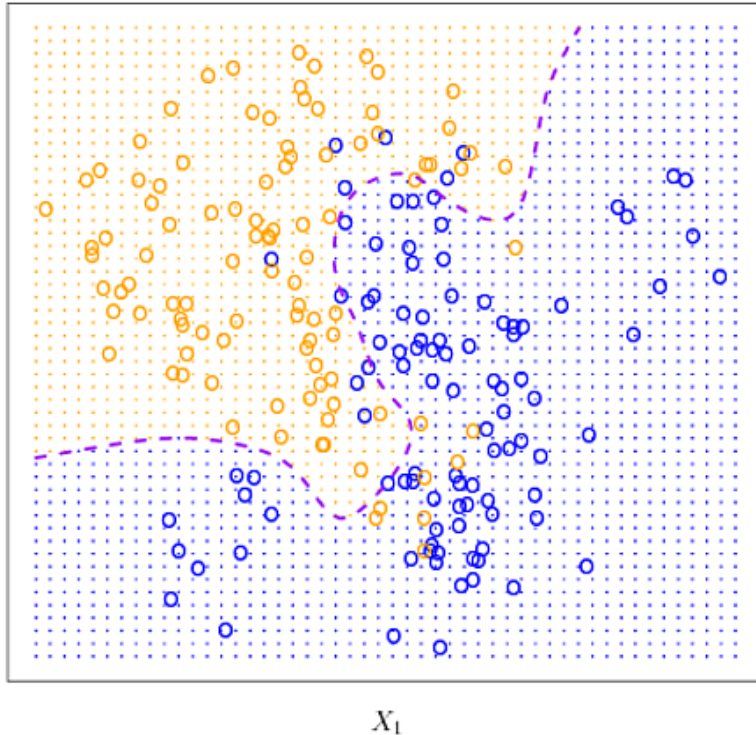
IF

hotel == „Meta” AND
client == „manager”

THEN

Value	Count	Perc.
premium	1	100

Rule induction systems 5/5



Key features:

- Incremental building of decision boundary – separating classes
- Adding conditions to rule antecedent to find a best separation between classes
- Several statistical measures:
 - Shannon entropy

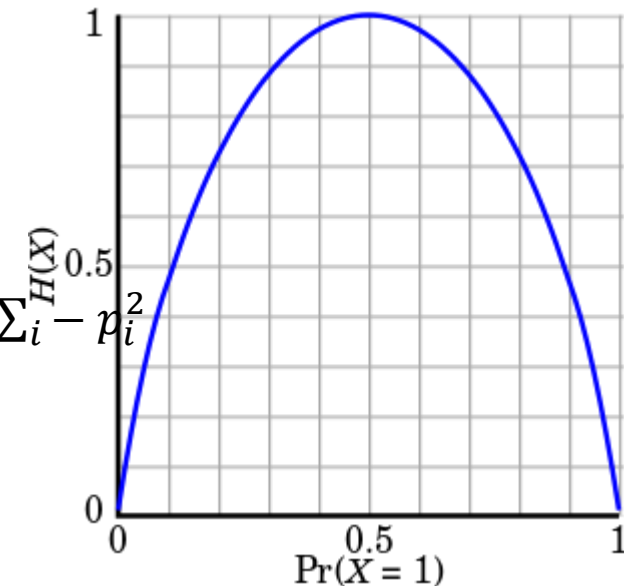
$$Entropy = \sum_i -p_i \ln p_i$$

- Gini impurity

$$Gini\ impurity = 1 - \sum_i p_i^2$$

- Rule accuracy

$$coverage = \frac{|records\ meeting\ antecedent\ \&\ consequent|}{|records\ meeting\ antecedent|}$$



Decision trees

Decision trees 1/5

Key features



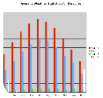
Full decision transparency



Full decision explainability



Compact data representation

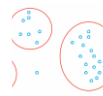


Based on statistical properties of data

Use cases



Classification systems



Pattern recognition

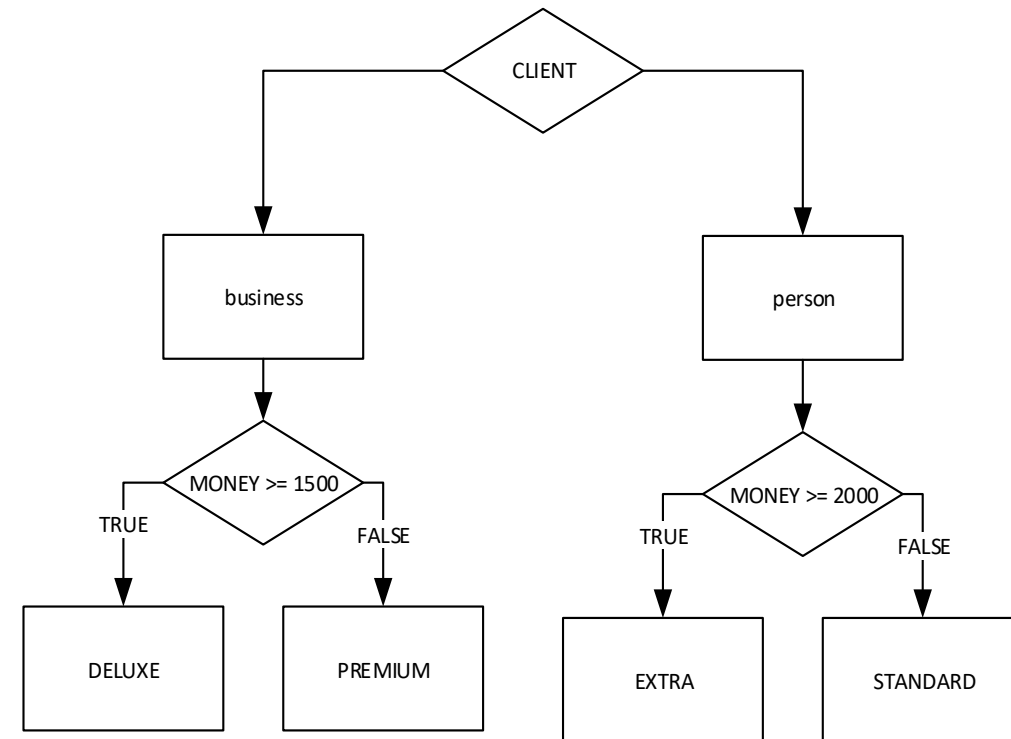
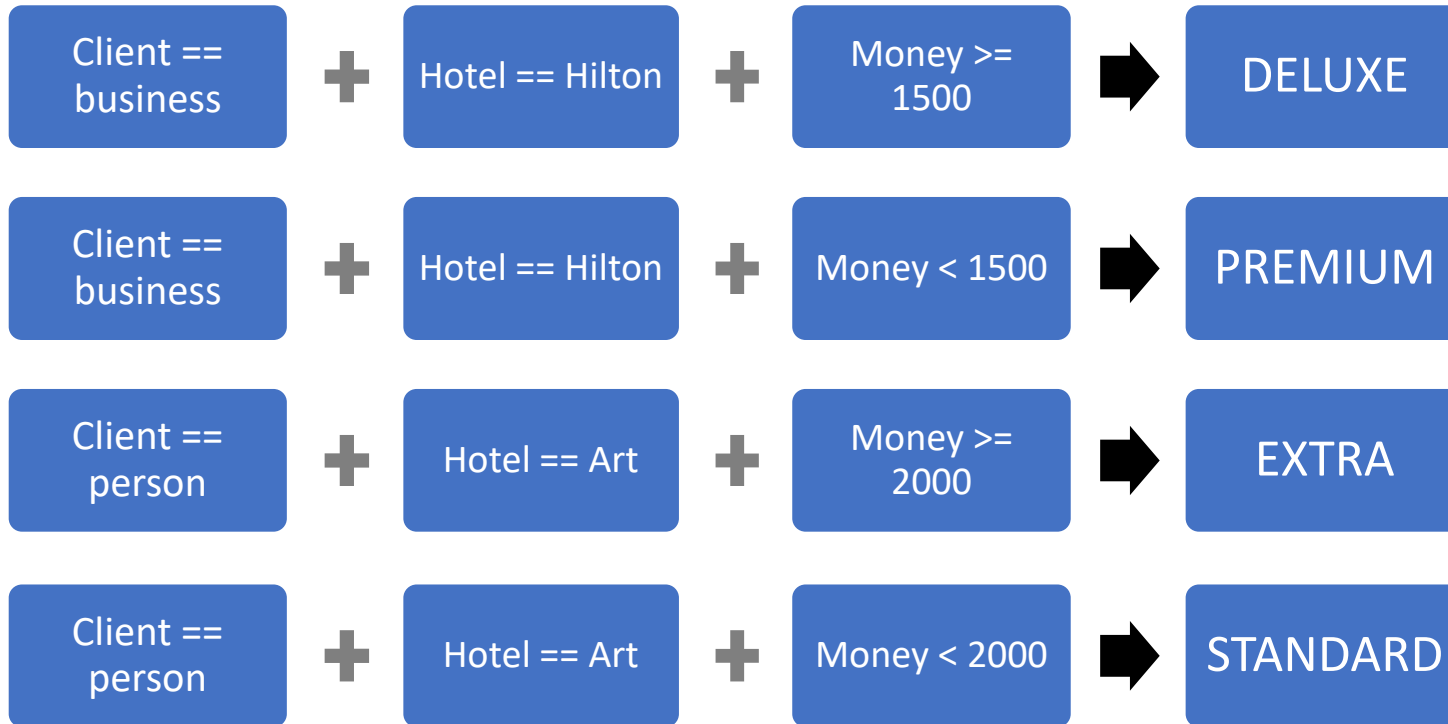


Intelligent advisors



Visualization capabilities

Decision trees 2/5



Decision trees 3/5

client	hotel	addons	money_spent	offer
business	Hilton	trip	40,000	deluxe
business	Hilton	full board	38,000	deluxe
business	Hilton	trip	40,000	deluxe
middle class	Meta	none	800	basic
middle class	Meta	meal	900	basic
manager	Meta	spa	1,500	premium



Client == business?

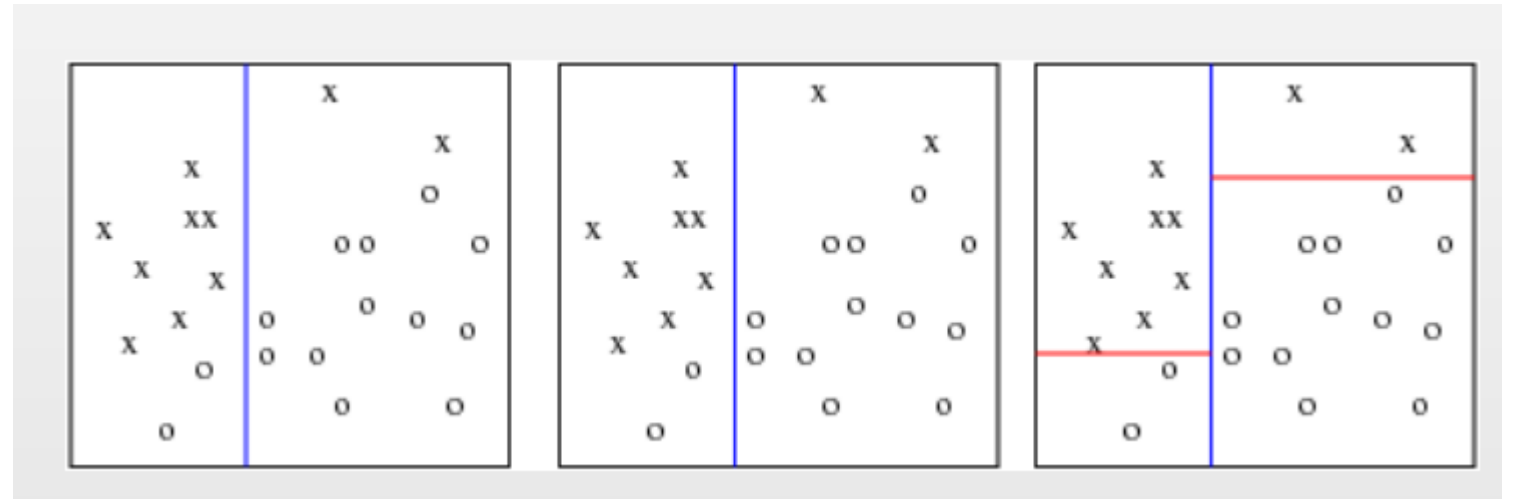
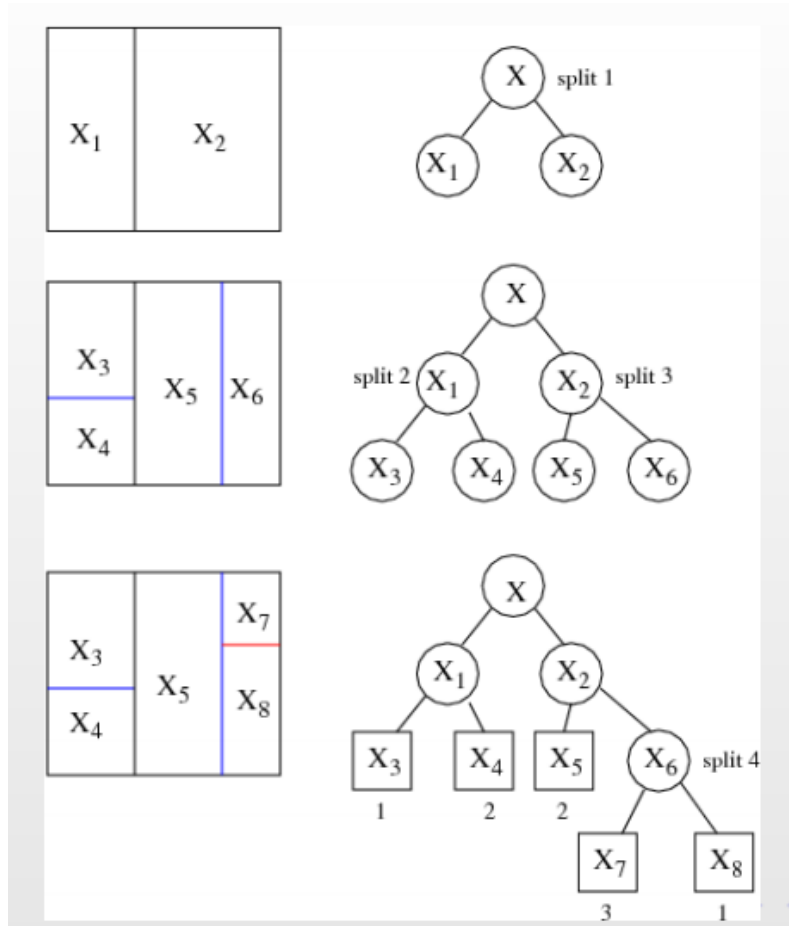
True

False

hotel	addons	money_spent	offer
Hilton	trip	40,000	deluxe
Hilton	full board	38,000	deluxe
Hilton	trip	40,000	deluxe

hotel	addons	money_spent	offer
Meta	none	800	basic
Meta	meal	900	basic
Meta	spa	1,500	premium

Decision trees 4/5



Decision trees 5/5

Recursive

- At each level performs the same operation
- Top – down approach
- Divide & conquer in construction
- $\log(N)$ in traversal

Greedy

- Tries to reduce „chaos” at each split
- $Entropy = \sum_i - p_i \ln p_i$
- Trying to impose ORDER on data

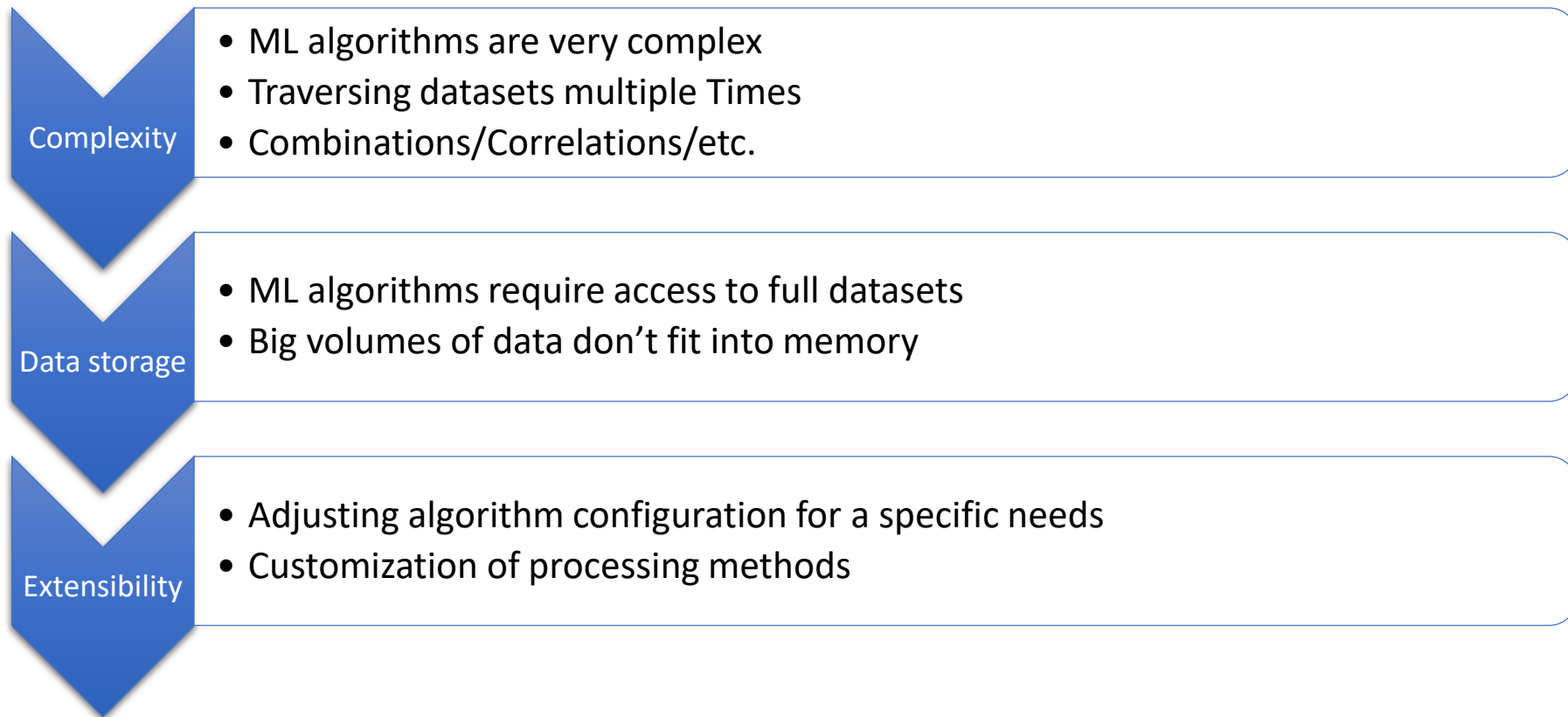
Two forms

- Binary
 - Yes/no splits
 - Single attribute value
- Multi-way
 - Split on every value
 - Multi-value splits

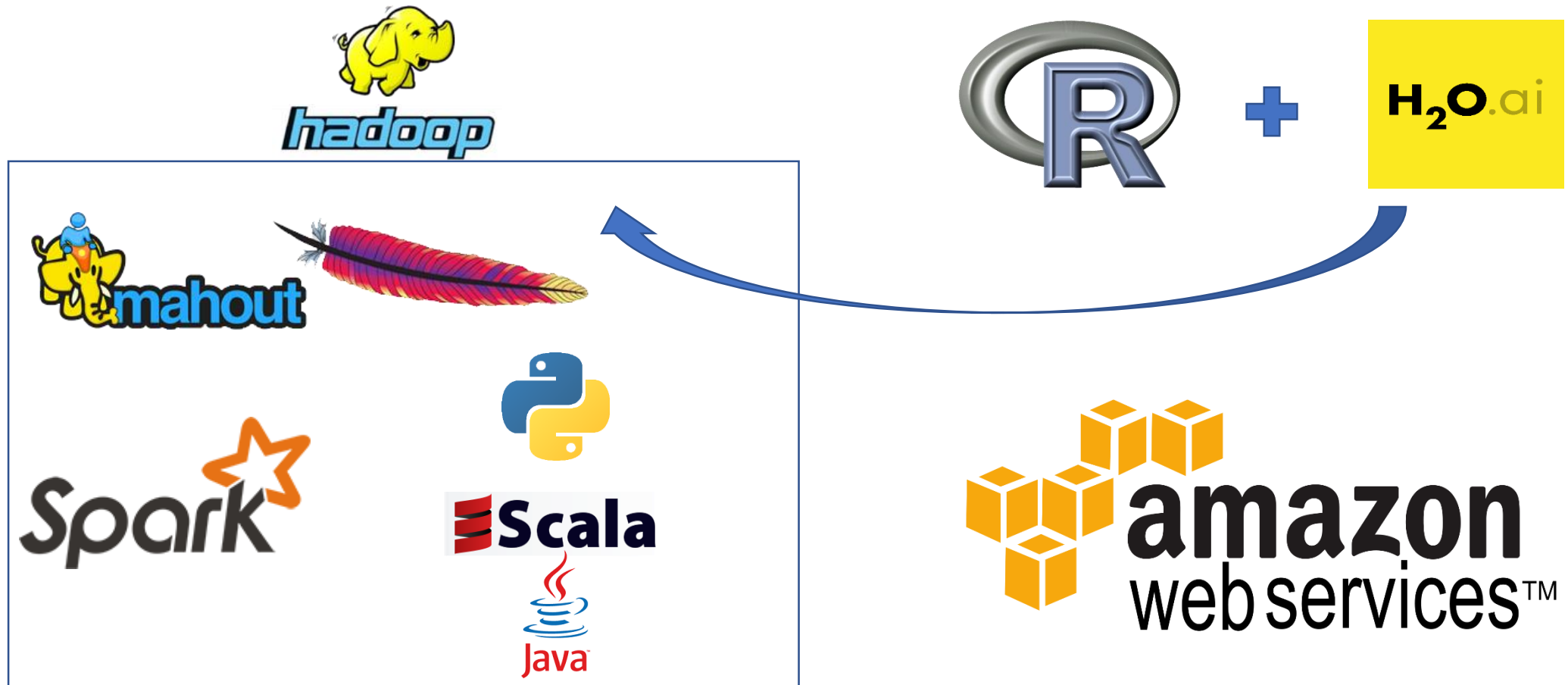
Scalable solutions



Scalable solutions 1/2



Scalable solutions 2/2



Thank you for attention!