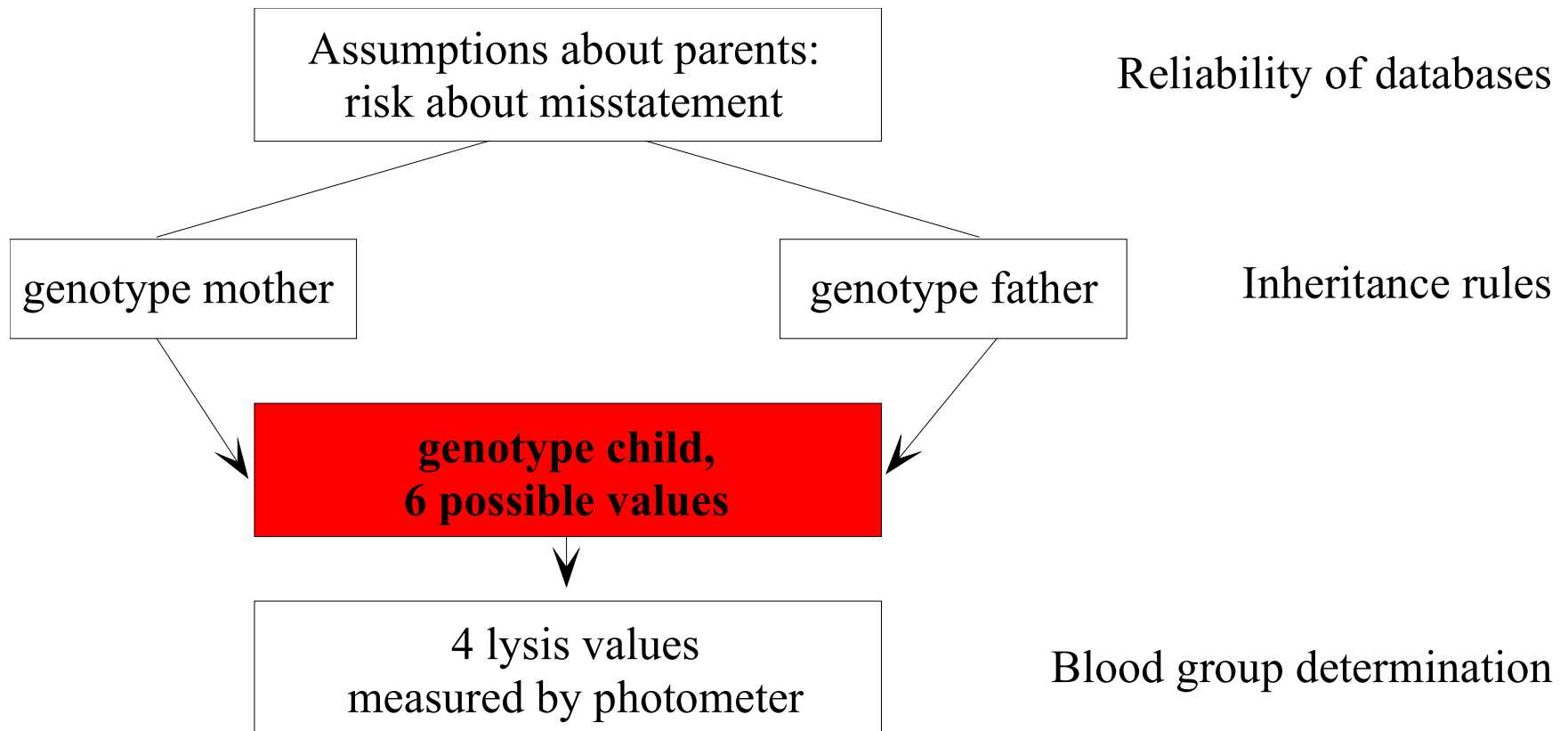
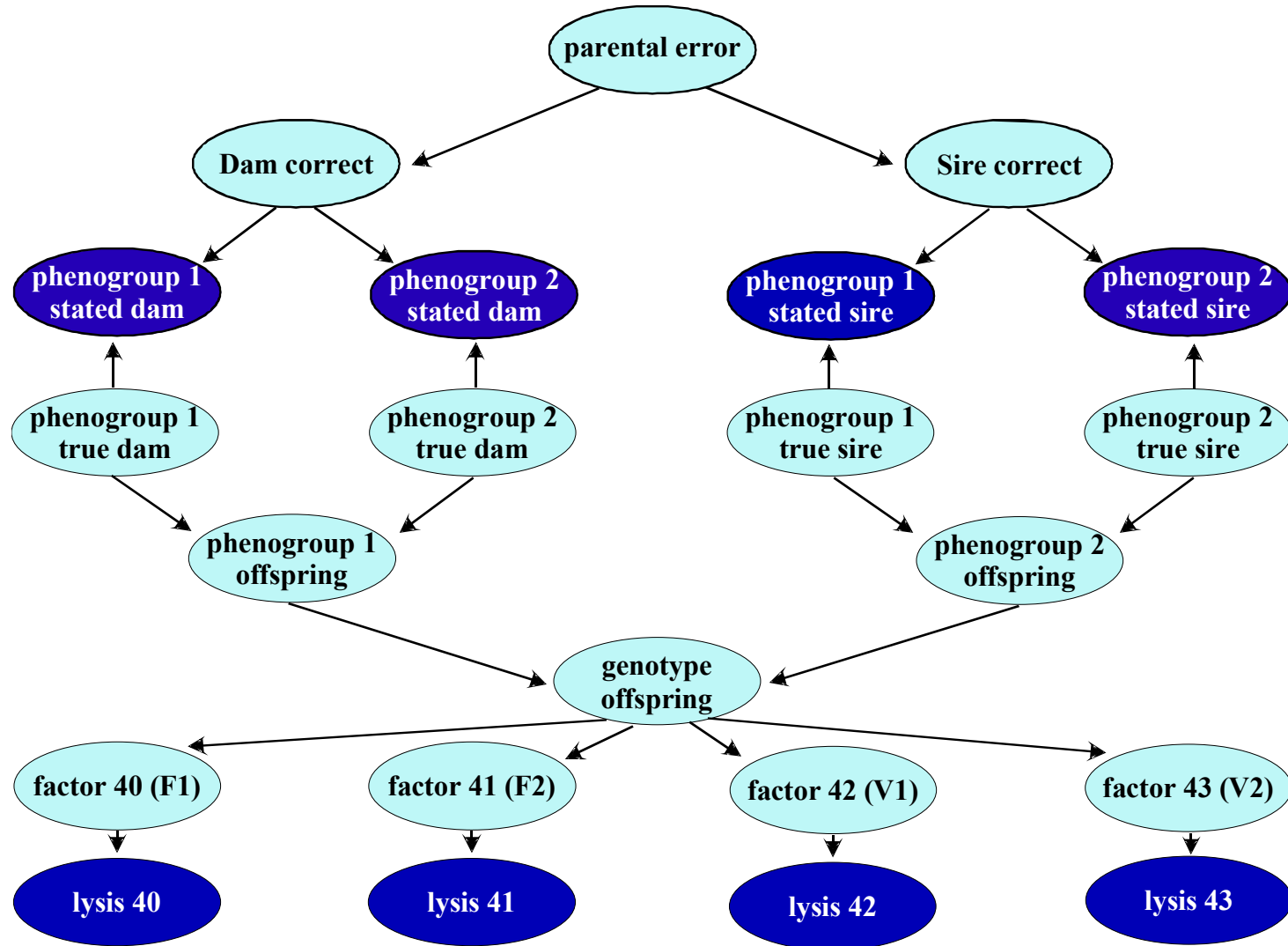


Genotype Determination of Danish Jersey Cattle

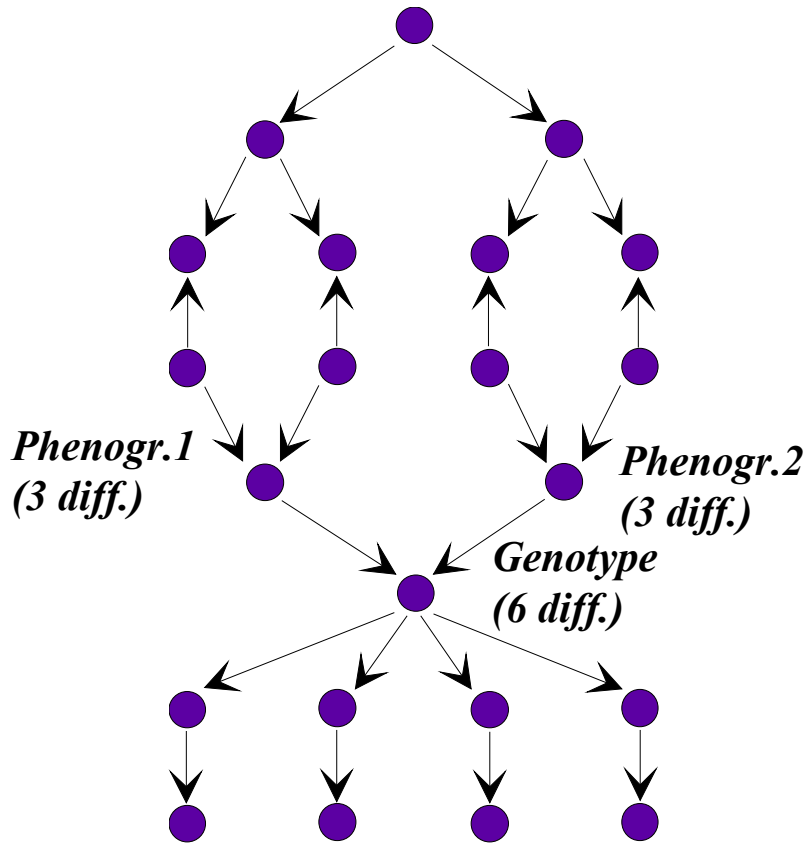


Qualitative Knowledge



Example: Genotype Determination of Jersey Cattle

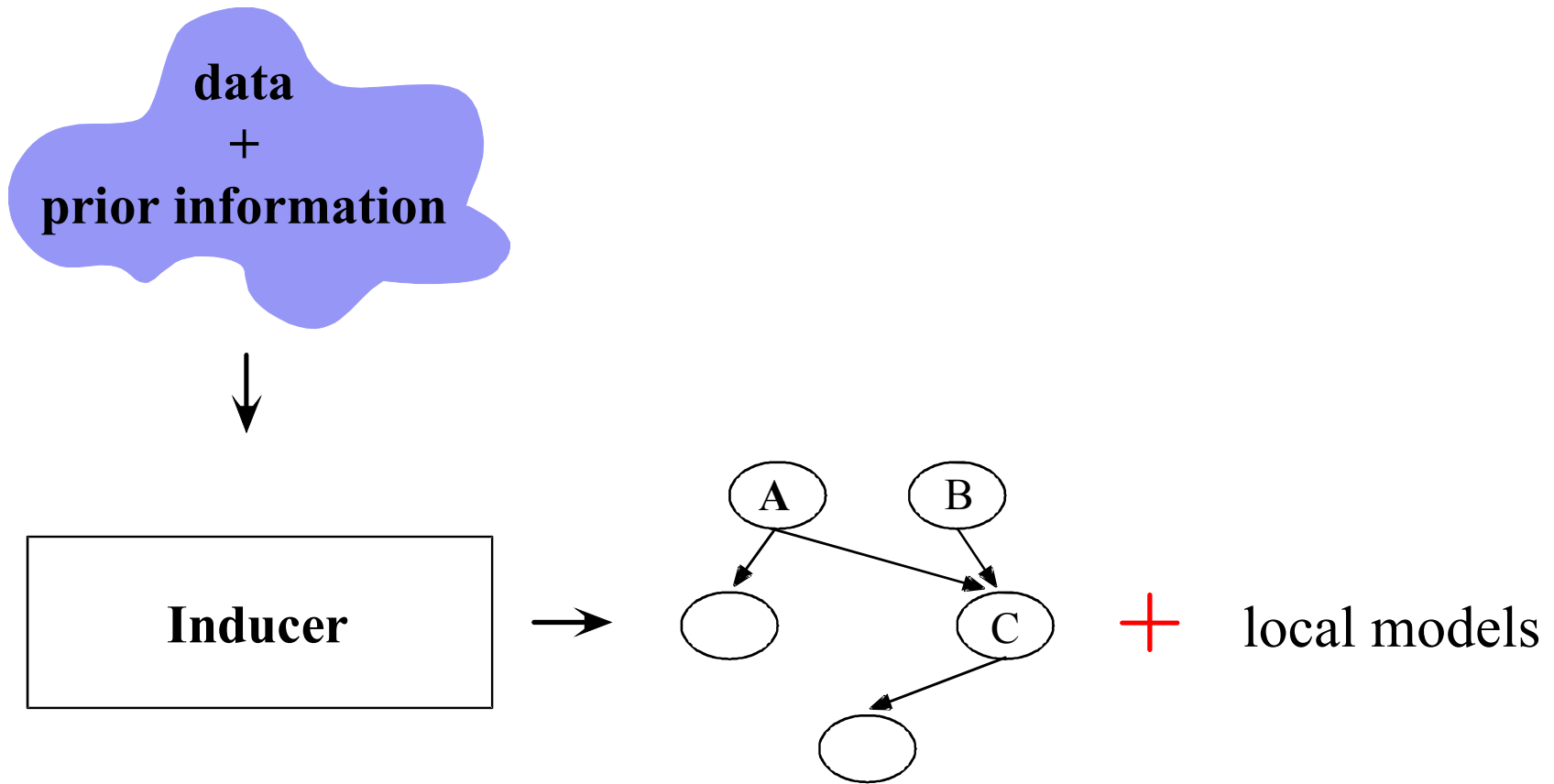
variables: 22, state space $6 \cdot 10^{13}$, parameters: 324



Graphical Model

- node
→ random variable
- edges
→ conditional dependencies
- decomposition
→ $P(X_1, \dots, X_{22}) = \prod_{i=1}^{22} P(X_i | \text{parents}(X_i))$
- diagnosis
→ $P(\cdot | \text{knowledge})$

Learning Graphical Models

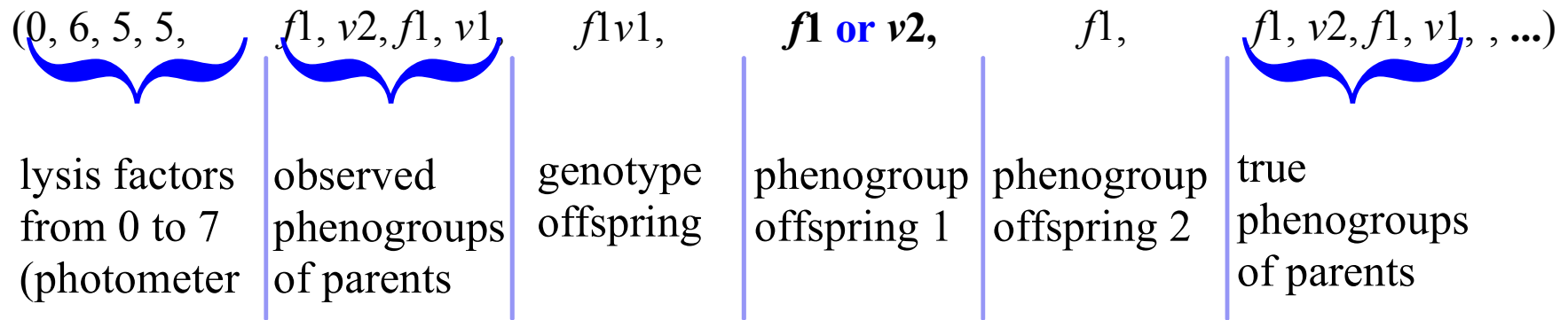


Genotype Determination of Danish Jersey Cattle: Database of Cases

747 cases

22 entries per case

Case 657:



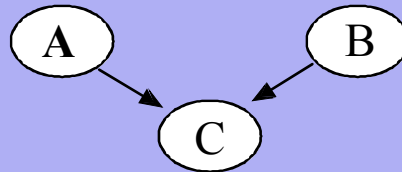
■ ESPRIT Project DRUMS 2, BR 6156

■ Problems:

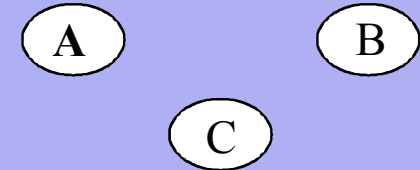
- How to reduce complexity problems?
- How to handle imprecise (fuzzy, vague, ...) data?

The Learning Problem

known structure



unknown structure



complete data

A	B	C
$\langle a_4, \dots \rangle$	$\langle b_3, \dots \rangle$	$\langle c_1, \dots \rangle$
$\langle a_3, \dots \rangle$	$\langle b_2, \dots \rangle$	$\langle c_4, \dots \rangle$

Statistical Parametric

Estimation (closed form eq.):

- statistical parameter fitting,
- ML Estimation,
- Bayesian Inference, ...

Discrete Optimization over Structures (discrete search):

- likelihood scores,
- MDL

Problem:

search complexity \rightarrow heuristics

incomplete data

(missing values,
hidden variables,...)

A	B	C
$\langle a_4, \dots \rangle$	$\langle ?, \dots \rangle$	$\langle c_1, \dots \rangle$
$\langle a_3, \dots \rangle$	$\langle b_2, \dots \rangle$	$\langle ?, \dots \rangle$

Parametric Optimization:

- EM,
- gradient descent, ...

Combined Methods:

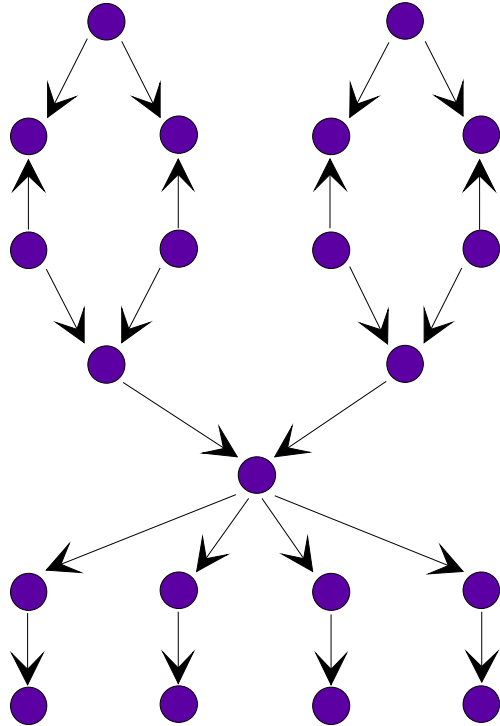
- structured EM
- only few approaches

Problems:

- criterion for fit?
- new variables?
- local maxima?
- fuzzy values?

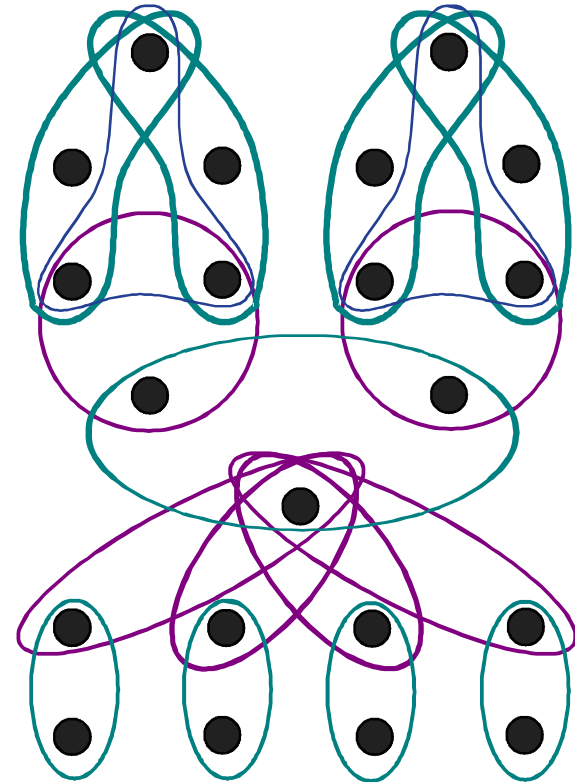
Genotype Determination

Directed dependency network



Rule \rightarrow conditional dependency

Hypergraph representation



Rule \rightarrow constraint

Daimler-Chrysler Research and Technology Ulm, „Data Mining“ Project

Fields of Application

- Improvement of Product Quality by Finding Weaknesses
 - Learn dependency network for vehicle properties and faults
 - Look for unusual conditional fault frequencies
 - Find causes for these unusual frequencies
 - Improve construction of vehicle

- Improvement of Error Diagnosis in Garages
 - Learn dependency network for vehicle properties and faults
 - Record properties of new faulty vehicle
 - Test for the most probable faults

Analysis of Daimler/Chrysler Database

- Database: ~ 18.500 passenger cars
> 100 attributes per car
- Analysis of dependencies between **special equipment** and **faults**.
- Results used as a starting point for technical experts looking for causes.

- Use a criterion to measure the degree to which a network structure fits the data and the prior knowledge
(model selection, goodness of hypergraph)

- Use a search algorithm to find a model that receives a high score by the criterion
(optimal spanning tree, K2: greedy selection of parents, ...)

Measuring the Deviation from an Independent Distribution

Probability- and Information-based Measures

- information gain *
- identical with mutual information
- information gain ratio *
- g -function (Cooper and Herskovits)
- minimum description length
- gini index *

Possibilistic Measures

- expected nonspecificity
- specificity gain
- specificity gain ratio

(Measures marked with * originated from decision tree learning)

Data Mining Tool Clementine

Clementine Data Mining System Version 4.0 - (c) ISL 1994-1997 - (None)*

System Diagram Displays SuperNode Help

```
graph LR; BasketsIn((BasketsIn)) --> table[table]; BasketsIn --> type{{type}}; type --> Apriori{{Apriori}}
```

0.13M USED, 23.87M FREE

Generated Models

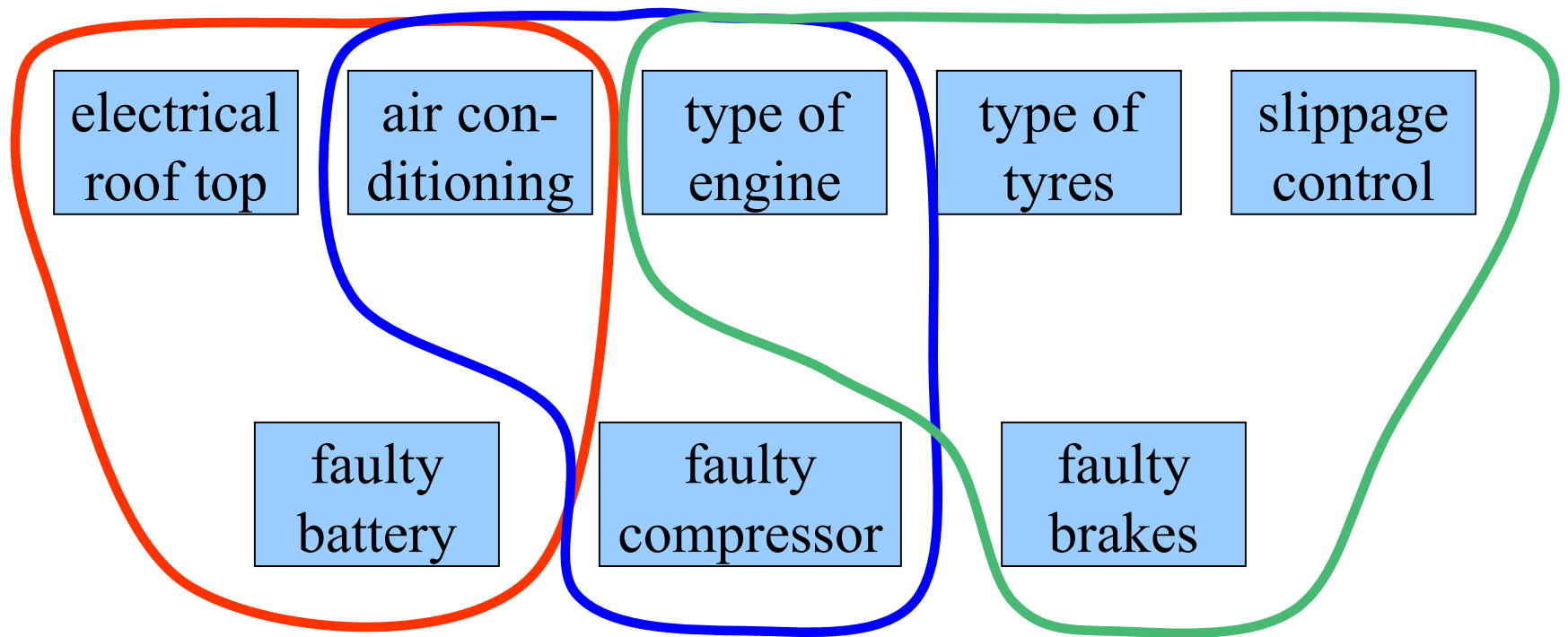
apriori

EXECUTE

Editing diagram

Sources	Record Ops	Field Ops	Graphs	Modelling	Output					
Var. File	Select	Merge	Filter	Derive	Plot	Histogram	Regression	Apriori	Table	Analysis
ODBC	Sample	Balance	Type	Filler	Distribution	Web	GRI	Matrix	Statistics	

Analysis of Daimler/Chrysler Database



Fictitious example:

There are significantly more **faulty batteries**, if both **air conditioning** and **electrical roof top** are built into the car.

Example Subnet

Influence of special equipment on battery faults:

(fictitious) frequency of battery faults		air conditioning	
		with	without
electrical sliding roof	with	8%	3%
	without	3%	2%

- significant deviation from independent distribution
- hints to possible causes and improvements
- here: larger battery may be required, if an air conditioning system *and* an electrical sliding roof are built in

(The dependencies and frequencies of this example are fictitious, true numbers are confidential.)

Data Mining Tool “Information Miner

