Interactive configuration with constraints consistency and recommendation

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Complex products

Complex, highly customizable products (combinatorial domains)
$\rightarrow$ **cars**, computers, travels, kitchens. . .
$\rightarrow$ number of possibilities exponential in the number of configuration variables
$\rightarrow$ all products aren't feasible (like a convertible car with a sunroof)

Presence of hard constraints

The constraints are hard : some products are infeasible

They come from :

- technical limitations (no sunroof on a convertible car)
- commercial considerations (no leather wheel on a lower-end car)
- stock variability (out-of-stock item)
- etc.

Renault Master : 10^{21} cars, 10^{16} feasible cars

Product construction: the interactive configuration process

- the user chooses a configuration variable
- the configurator proposes possible values
- the user chooses a value for this variable

This process continues until the product is fully defined

Every proposed value must lead to a possible vehicle, but it's an NP-hard problem ! Two techniques :

- constraints propagation [Wal72]
- compilation [AFM02]

Recommendation

At each step of the interactive configuration, there is a partial, ongoing configuration

Recommendation = recommend, given a **partial configuration** u, a **value** for a **variable** Next

A good recommendation is:

- accurate

  $\rightarrow$ the user is willing to accept
- quick

  $\rightarrow$ on-line application

Context

- We have a sales history from Renault, no other information
  $\rightarrow$ no information about the user
- The user chooses the variables one by one
  $\rightarrow$ the order of the variables is unknown
- There are constraints on allowed configurations
  $\rightarrow$ we use the *SaLaDD* compiler [Sch15]
- The sales history products may or may not satisfy the constraints

Recommendation in interactive configuration not very studied

Two categories of tools:

- *k*-nearest neighbours [CGO+02]
- Bayesian network

Goal: experiment and compare these methods

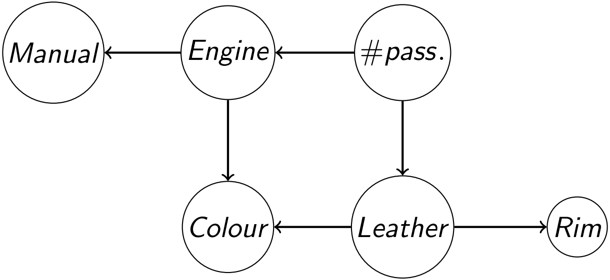
Outline

1. Context and issue
2. Algorithms
   1. based on Bayesian networks
   2. based on *k*-nearest neighbours
3. Experiments
4. Conclusion

Bayesian network

Bayesian networks represent a probability distribution on the configurations by means of a direct acyclic graph (DAG) and probability tables

- Each node is a variable
- An edge between A and B means that the probability of A depends on the value of B (and vice-versa)



How to recommend with a Bayesian network ?

Probability $p(o)$ that a car o will be bought

Our recommendation is based on:

$$\operatorname*{argmax}_{x \in \underline{\mathrm{Next}}} p(\mathrm{Next} = x \mid \mathrm{Assigned} = u)$$

Next is the configuration variable chosen by the user, u the partial configuration

We assume the sales history are a representative sample of future user choices

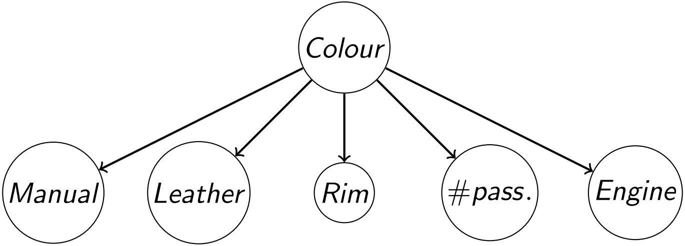
Two phases:

- Learn a Bayesian network from the sales history off-line
  $\rightarrow$ constraints aren't taken into account during the learning
- Recommend a value of the conf. variable on-line
  $\rightarrow$ the learning isn't critical, the inference is

Naive Bayesian network: special case of Bayesian network with strong assumptions of independence

+ inference is quick

— roughly approximates the real probability distribution (less accurate)



Neighbourhood-based algorithms

3 algorithms based on k-nearest neighbours

Instead of using the whole sample, they use previous sales similar to the current one

The 3 algorithms process these neighbours in a different way

Three algorithms

Among the k-nearest neighbours of the current partial configuration

Weighted Majority Voter: each neighbours votes with a weight proportional to its similarity with the current configuration

Naive Bayes voter: uses the neighbours to learn a naive Bayesian network. No learning is possible off-line

Most popular choice: computes the most probable completion of the current configuration and recommend the value of Next in it

Experimental protocol

10 folds cross-validation : history sales split into a training set and a test set

- Training set: Bayesian networks learning / neighbours searching
- Test set: for each item we simulate a configuration session
  For each recommendation for Next, we compare the recommended value with the value really chosen
  $\rightarrow$ Only one possible value: no evaluation
  $\rightarrow$ Recommanded $=$ chosen: success, else: failure

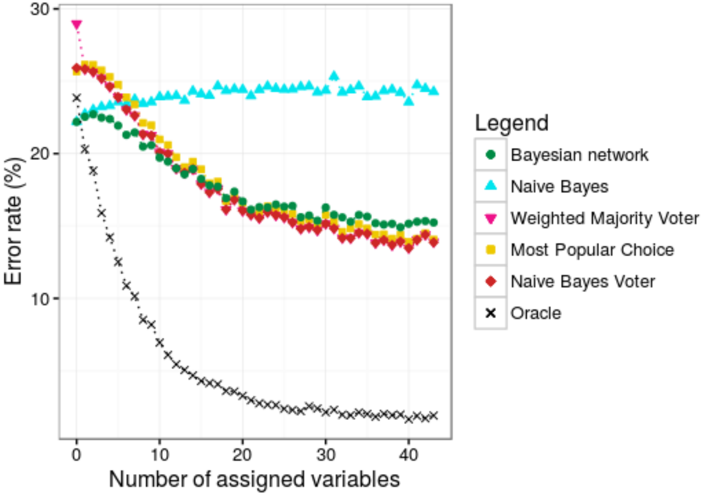
We measure the success rate and the recommendation time w.r.t. the number of assigned variables

Datasets from Renault

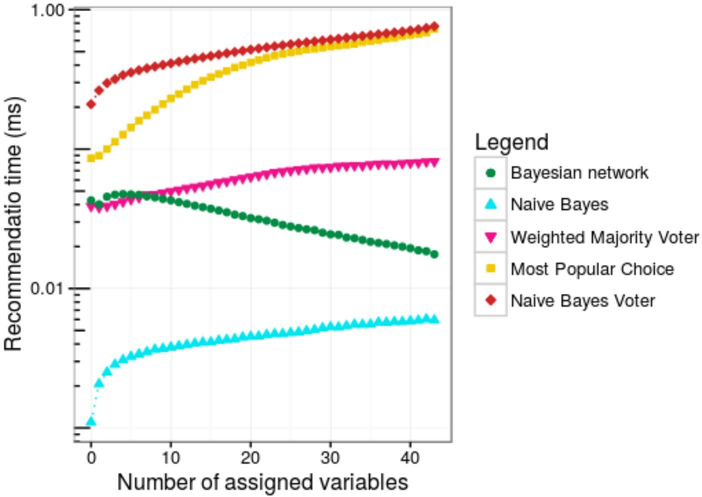
Experiments made on i5 processor at 3.4GHz, using one core
All algorithms are written in Java

- dataset "*Renault-44*"
  - 44 variables
  - 14786 examples, 8252 examples consistent with the constraints
  - 70.80% recommendations are trivial
- dataset "*Renault-48*"
  - 48 variables
  - 27088 examples, 710 examples consistent with the constraints
  - 71.73% recommendations are trivial
- dataset "*Renault-87*"
  - 87 variables
  - 17715 examples, 8335 examples consistent with the constraints
  - 46.89% recommendations are trivial

Error rate w.r.t. the number of assigned variables

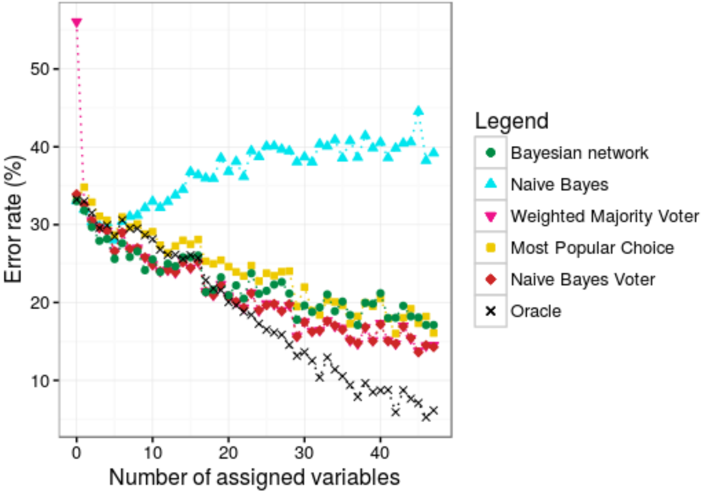


Experiment on *Renault-44* : 44 variables, 14786 examples including 8252 examples consistent with the constraints



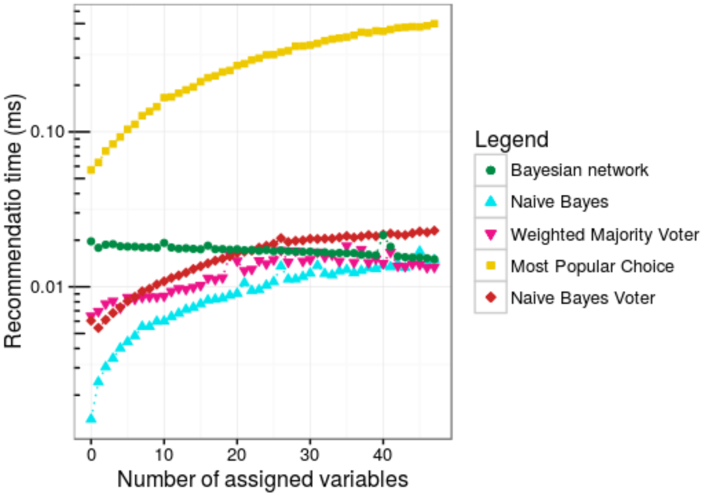
Experiment on *Renault-44* : 44 variables, 14786 examples including 8252 examples consistent with the constraints

Error rate w.r.t. the number of assigned variables



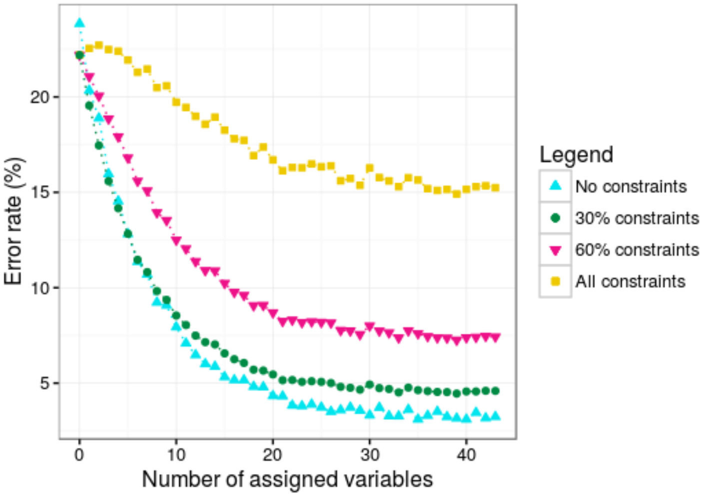
Experiment on *Renault-48* : 48 variables, 27088 examples including 710 examples consistent with the constraints

Recom. time w.r.t. the number of assigned variables



Experiment on *Renault-48* : 48 variables, 27088 examples including 710 examples consistent with the constraints

Error rate w.r.t. the amount of constraints



Experiment on *Renault-44* : 44 variables, 14786 examples including 8252 examples consistent with the constraints

Summary

- Constraint compilation is usable on-line

- *k*-nearest neighbours and Bayesian networks are accurate and fast enough
- Naive Bayesian network is adapted when execution time is more critical than accuracy

- The presence of constraints reduces the accuracy

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