



A Discussion of Modeling Techniques for Personal Lines Pricing

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A New Millennium. New Challenge for Actuarie



Agenda

0 verview of the insurance market

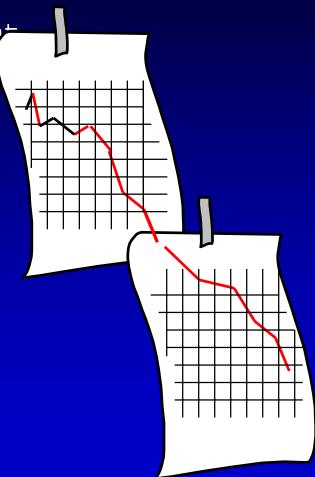
Pricing approach

- Overview of the methodobgies:GLM, Decision Trees and NN
- Comparison among the three techniques

Conclusions

An overview of the insurance market

- Presence of inadequate tools for a complete and effective analysis of the clien
- Poorknow ledge of clients
- Som e lines of business are running ata bss in mostof the countries (i.e.motor business)
- Low evelofsophistication
 - Cross-subsidies am ong clients

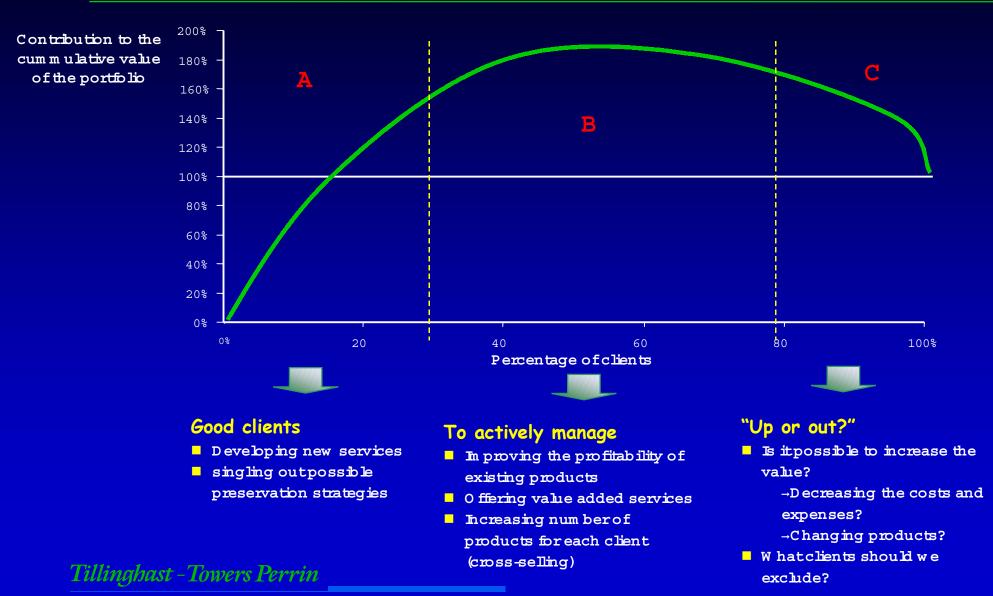


Criticalareas

The risk increases with:

- high exposure on insurance business;
- ultim ate costnot com pletely recognized ;
- inadequate selection of underwritten risks;
- noteffective claim m anagem ent;
- bw cross-selling level;
- notenough em phasis on client.
- The necessary elements for reaching the objective "client" are:
 - econom ic costestim ation;
 - lapse probability of the insured and his elasticity of dem and.
 - Competitive MarketAnalysis

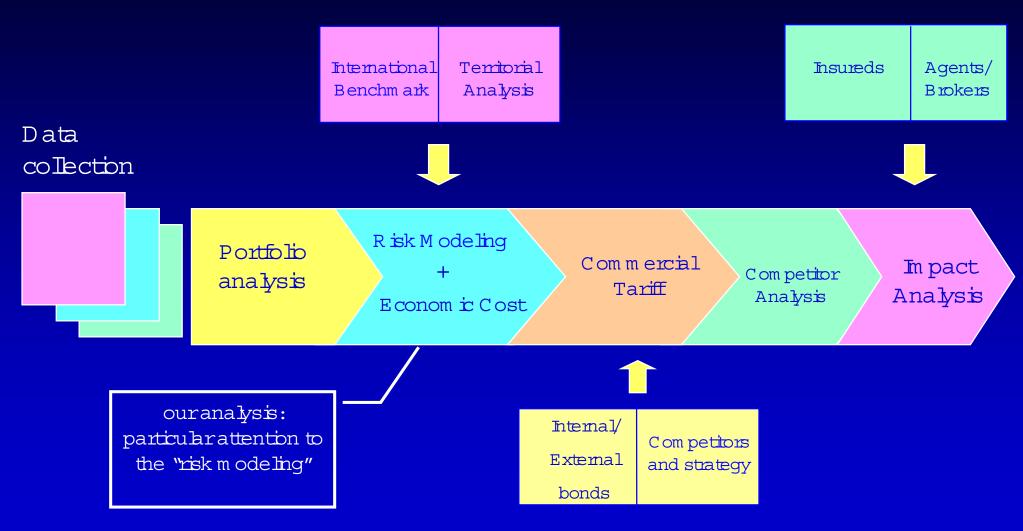
The profitability varies with the risk profile



Now adays, too much attention is paid to the cance lation of 'bad" risk

- ... it could be better to find the right strategies so that:
 - the premium be correctly calibrated on the risk;
 - the economic cost of the client be projected;
 - new "ad hoc" products be created;
 - the portfolio be segmented in order to define the market niches, which destroy value.

Pricing Strategy



Risk Modelling: Overview of Methodobgies

New multivariate techniques available which are replacing olderm ethodologies;

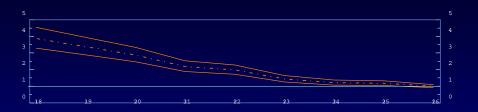
- These techniques represent advances in:
 - quantifying the TRUE economic costofwriting each policy;
 - m easuring the econom ic in pactof adopting any rate plan other than the actuarialm odel;
 - understanding lapse and renew alexperience;
- marketpricing behaviour;
- in short, m anaging the business.

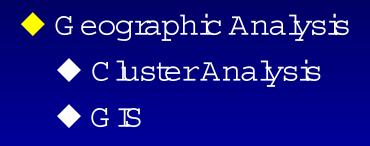
Mostrating variables are correlated;

- Different variables m ay be showing the same underlying effect;
- Repeated use of univariate techniques leads to doublecounting of the sam e effects;
- They can capture interactions;
- They provide more than a pointestim ate and standard errors.

... boking form one suitable techniques

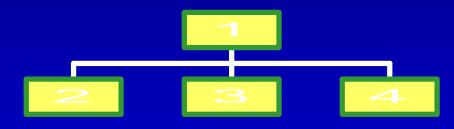
♦ GLM :Generalized Linear Models

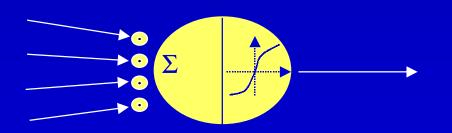












W hat is GLM?

It is a statistical procedure form easuring the effect of one orm one independent variables upon a dependent variable;

Dependent variable for ratem aking are:

- frequency
- severity
- pure prem ium

GLM albws extrem e flexibility in modeldesign:

multiplicative, additive orm ixed plans

differenterrordistributions (i.e. Normal, Gamma, etc.)

variable interactions (i.e. sex & age)

An example of Generalised Linear Model

This statistical approach allows us to determ ine the cross-subsides among the clients and to create a theoretical rating structure, which penalizes bad clients and favors good clients



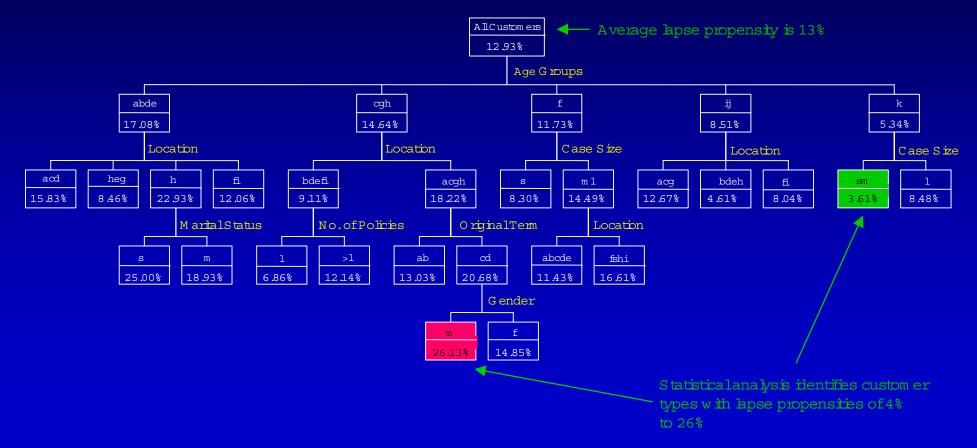
W hatare decision trees?

Procedures for successively subdividing data into hom ogeneous groups;

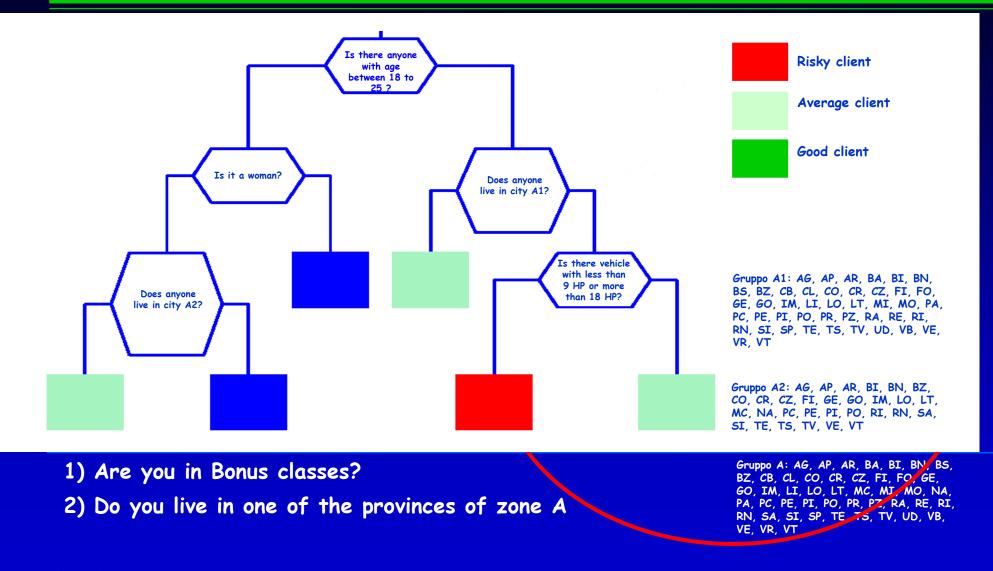
- Like GLM s, they use a dependent variable and one orm ore independent ones;
- Results are not necessarily symmetric;
- In plicitly capture the natural interactions between factors;
- Produces hom ogeneous groups (i.e., a tree structure), but no rating plan or relativities;
- Possible m ethodobgies, m ost fam ous:
 - CHAD: Chi-Square Autom ated Inform ation Detection
 - CART:Classification and Regression Tree

Decision Trees: 'Divide et in pera"

A decision tree is given by a set of decisional rules for predicting a fixed dependent variable (for example, claim severity, frequency or lapse rate)



Decision tree: an example



W hatare NeuralNetworks?

Neuralnetworks: are non-linearpredictive models that learn how to detect a pattern in order to match a particular profile through a training process;

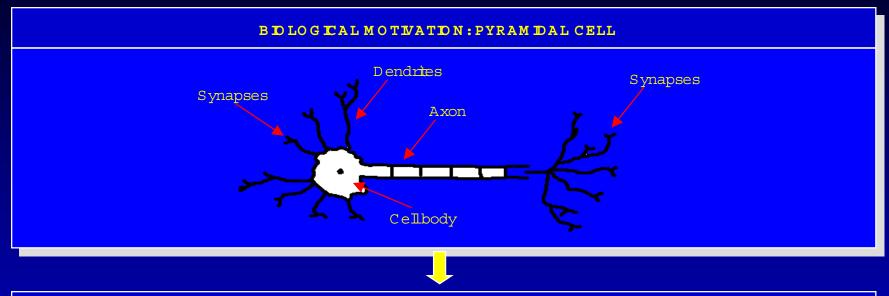
It's not necessary to split the pure premium into its components:

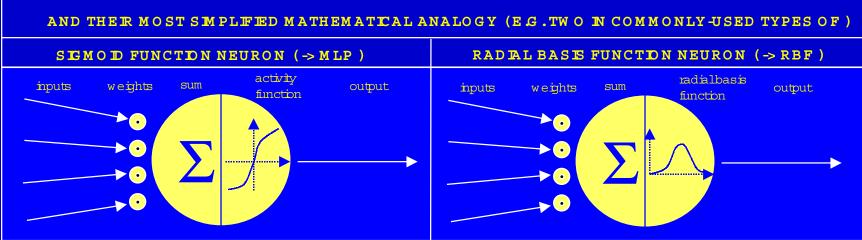
- frequency and
- severity;
- Advantages and disadvantages:

+ U sable even when relationships am ong variables are unknown

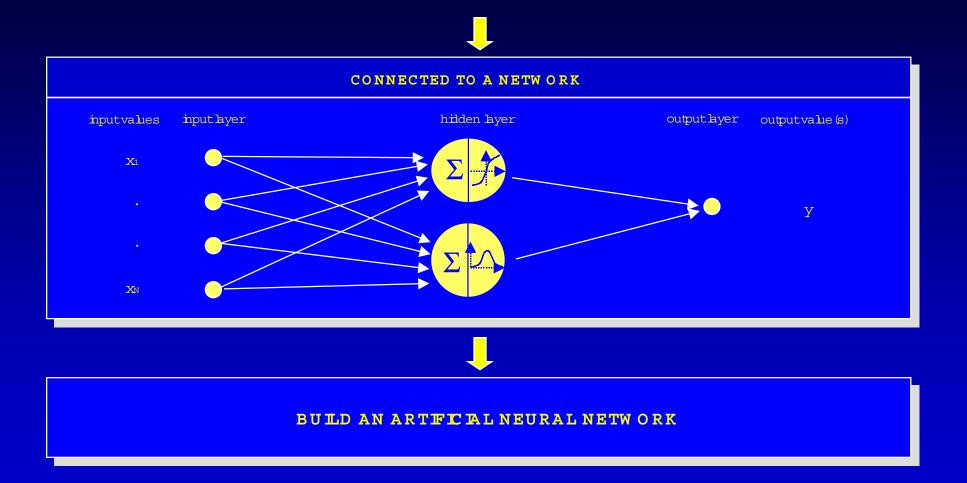
- + W illm odelnon-linearity and interaction well
- The solutions can not be interpreted ('Black box"?)
- Can take trem endous com puting powerand stillnot converge to a solution

NeuralNetworks are motivated by a simplified modelofbibbgical neurones in the brain



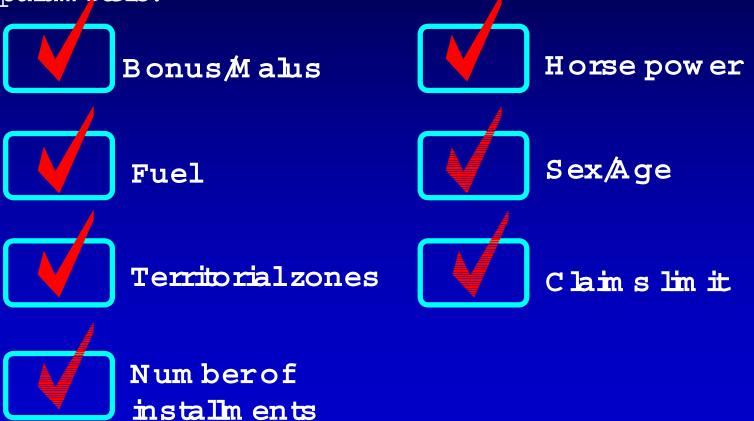


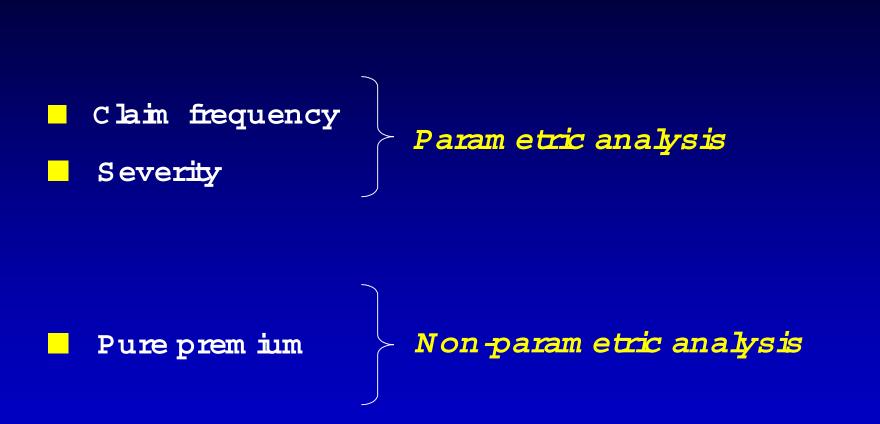
NeuralNetworks (contd.)



Ouranalysis...

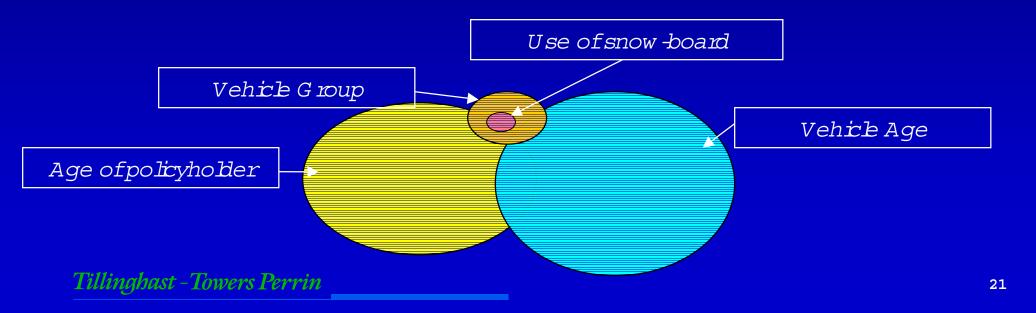
A sinulated portfolio was created using the distributions of the Italian market (public data - 1999) relative to the main rating parameters:





Choosing the rating parameters

- The selection of inappropriate variables can spoil the final result;
- Including a variable, which does not contribute in any way to the final result, could have the effect of dim inishing the model perform ance;
- This danger is very high in NN, moderate in GLM, totally indifferent in CART/CHAD.



'O ver-fitting" or 'over-param eterization" danger

- The 'over-fitting" (or 'over-param eterisation") concept is always there, whatever the statisticalm ethod used;
- Using a too m any variables in the estim ation process, m ay lead to:
 - memorising also the dibsyncrasy of the training set (in the language of neural nets),
 - incomplete separation of the stochastic part from the determ inistic one (in the parametric language);
- In GLM there are specific statistics that report the 'overparam eterisation" phenom enon;
- In decision trees analysis, it is necessary to reach maximum depth (challenging the 'over-fitting" danger), in order to proceed to the pruning step until the best tree is defined.

Managing m issing values

There are differentm ethods for the missing values management:

- dropping the record with a missing value -GLM,
- substituting the m issing value with characteristic or typical values (average, quantiles, cbsestneighbor,...) - CART, NN,
- estimating the missing value, after having assigned a fixed level (Emors', 9999) - manipulating the data,
- building separate models for each set of m issing values m anipulating the data,
- using the non-coded values in the learning phase of the network -NN;
- CART and NN are very robustm ethods in m anaging the m issing values. The correctway to proceed is not clear..

Managing anom abus values or outliers

- In order to identify every anom a bus value, it is a good idea to start with a `datamining" phase using the following:
 - residuals pbts,
 - over-dispension analysis,
 - Cook and Leverage statistics;
- Once the outliers have been identified, it is possible:
 - to assign a bw marginal probability,
 - to drop the observation from the data set,
 - to confine them in a separate class and to make an estimate in a successive phase;
- Non-param etric techniques are more robust then the param etric ones in managing the anom abus values and outliers.

Is a NeuralNet a 'Black box"?

- If such a term refers to a presentationalor a synthesis of the results problem s, the answer is YES;
- if it refers to the arithmetic of the algorithm, the answer is NO or, at least, not more then other statistical techniques, including GLM and Decision trees;
- In fact, working with a NeuralNet:
 - it is difficult to know which are the important variables to be included in the model and how they interact among them selves; and,
 - there is no structure of coefficients (relativities), as it is for the parametric regression and there is not a final model;

B hck box = bw synthesis, bw presentational power

Computing time

- A few years ago, neural networks were used alm ost exclusively for "pattern recognition" problem s, mainly due to the bng computing time required;
- A similar problem was true also for decision trees methods. CHAD, in particular, based on a contingency table where a CHI-squared is performed on each cell, could be very heavy from a computing point of view;
- With the adventofnew and more powerfulcom puters, even these techniques can be used in the solution of 'everyday" problems.

Reading and interpreting the results

GLM

The results are directly comparable with the rating coefficients applied by the insurance companies. The reading is easy for specialists;

CART/CHAD

It is a method that communicates through in ages. The results are always in the form of an upside down tree. The reading is very easy also for by people;

NN

It gives an estimate close to the real observation of the data base in the training and testing set. Once the training set has been memorized, the network can be used in another sam ple where the observation is missing. The reading is not very easy even by specialists.

GLM

Fastand easy. The coefficient structure reproduces the rating structure of the company and it is directly comparable and easy to implement;

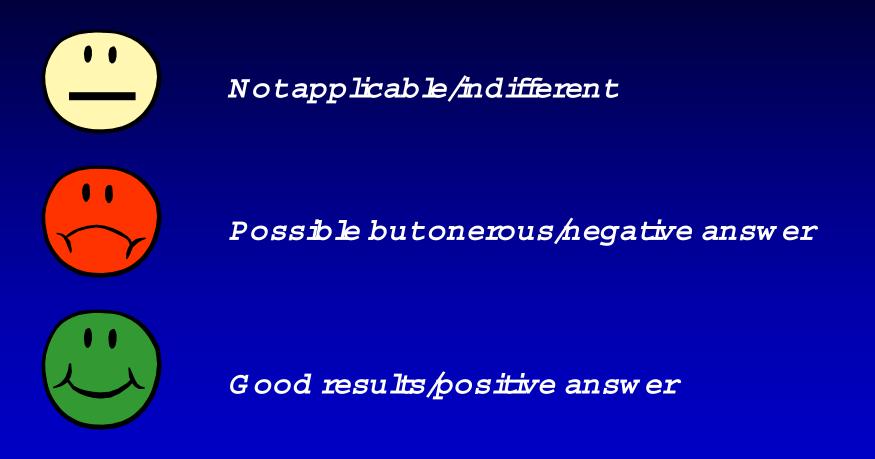
CART/CHAD

The result is very easy and readable. It is composed by a limited num berofnodes and to each of them an average premium is associated. The question is, is tracceptable to have a rating structure consisting of 49-50 profiles?

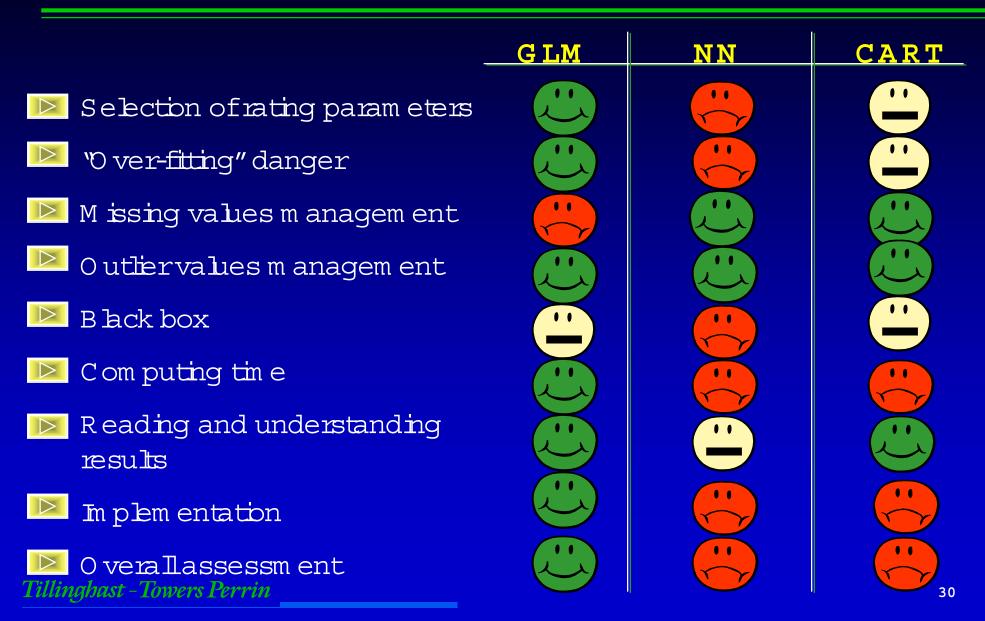
NN

It is very usefulas discrim inate analysis, but it needs a great dealofm odification in order to be implemented.

A comparison among the three techniques: a final report card



A comparison among the three techniques: a final report card



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Pearls of wisdom ...

- It's in portant to understand the ideas behind the various techniques, in order to know how and when to use them ;
- It's in portant to accurately assess the perform ance of a m ethod, to know how wellit can be expected to work (... simplerm ethods often perform as wellas complex ones!);
- in data mining, understanding the system used is notalways a crucialproblem. A neuralnetwork that produces optim alestim ates can be preferable to easierbut less efficientm odels;
 - This is an exciting research area, that has applications in science, industry, finance, etc.