ARMURS – Automatic Recognition for Map Update by Remote Sensing

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ARMURS – The team

- IGEAT Institut de Gestion de l'Environnement et de l'Aménagement du Territoire – Geospatial analysis(ULB)
  - Pr. Eléonore Wolff, Dr. Christine Leignel and Ms. Emilie Hanson
- LISA Laboratory of Image Synthesis and Analysis (ULB)
  - Pr. Olivier Debeir, Pr. Nadine Warzée and Dr. Thierry Leloup
- Signal & Image Centre, Royal Military Academy
  - Pr. Charles Beumier and Dr. Christophe Simler
- MLG Machine Learning Group (ULB)
  - Pr. Gianluca Bontempi and Dr. Olivier Caelen

ARMURS – A concise description of the Project

- Topographical data producers are currently confronted by the need for a faster updating method.
- The aim of the project is to build a demonstrator to assist data producers in planning the update of their topographic database more efficiently.
- We use remote sensing images and socio-economic data.
- Official project start : 1st October 2007

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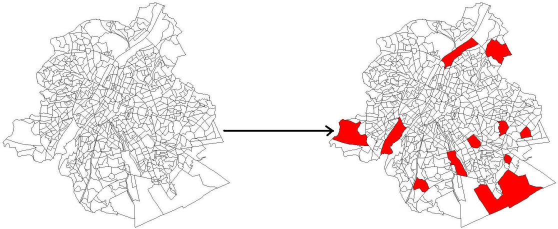
Prediction at a regional scale

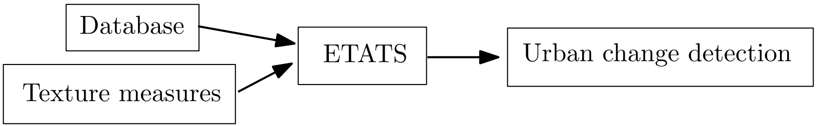
At a regional scale, the objective is to highlight areas of change in man-made structures and to predict their localisation.



To reach this objective, the results from the ETATS module are merged with statistical analysis.

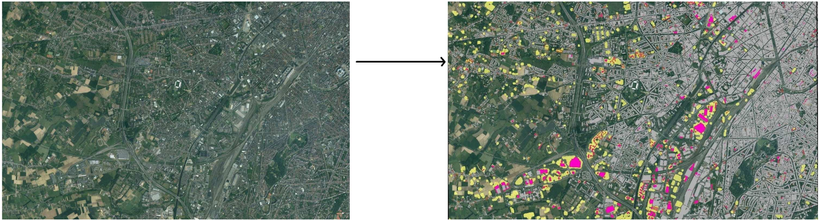
Prediction at a regional scale – the ETATS module

- In the ETATS module [Lacroix2006], texture measures extracted from *High Resolution* (HR) images are used to distinguish man-made structures' pixels from the rest.
- Those pixels are then compared to a database to drive a map with two classes:
  - *no urban change* (gray),
  - *new urban area* (yellow),



Prediction at a regional scale – the ETATS module

- An example where the ETATS module was applied to a western zone of the Brussels Region and neighbourhood (8×5 km).
- Note that ETATS is designed to run on SPOT 5P (2.5 m) images.
- Image: An arial photography degraded to a HR resolution (2.5m).



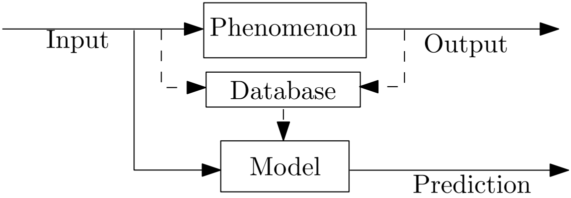
- Concentrating on large buildings or large built-up areas (min. $3000m^2$), the success rate for detecting new built-up areas achieved 77%.
- Wrong detection of roads mainly concerned those ones accluded by trees.

Prediction at a regional scale – the statistical module

- We also propose a change detection approach based on statistical learning analysis of socio-demographic data.

Socio-demographic data → Building the predictive model → Making prediction on new data

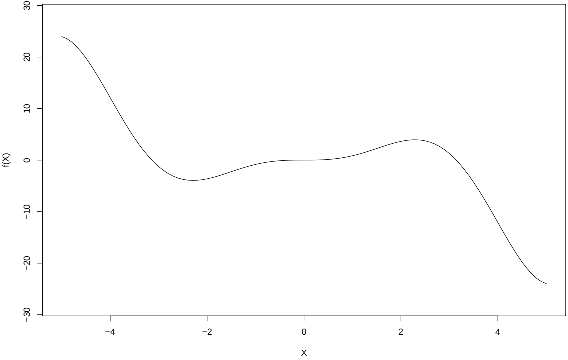
What is a statistical predictive model?



Input/output of real world data are stored in a database and used to parameterise a predictive model such that it will return a good prediction for new inputs.

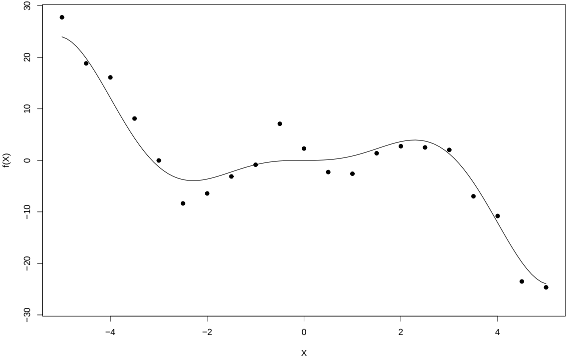
Building a predictive model – Exemple

Let's suppose we have an unknown input/output function (the phenomenon).



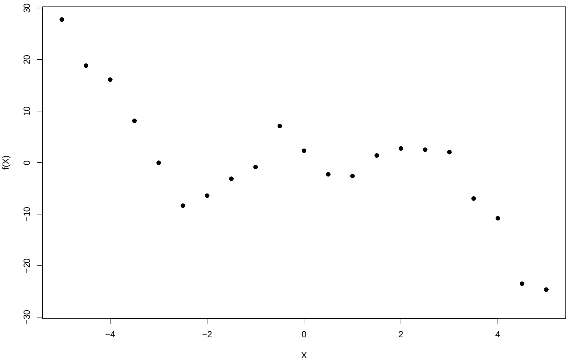
Building a predictive model – Exemple

Samples with noise are collected from the phenomenon and stored in a database.



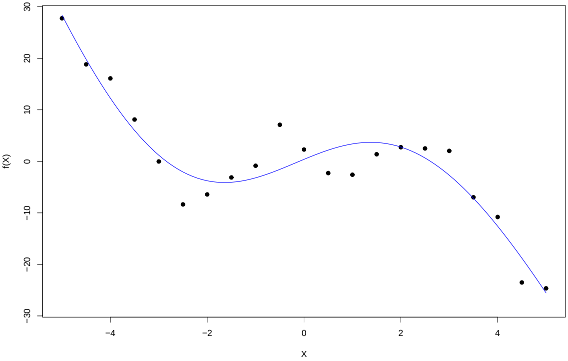
Building a predictive model – Exemple

The curve of the fonction is unknown, thus we only have the samples to build a predictive model.



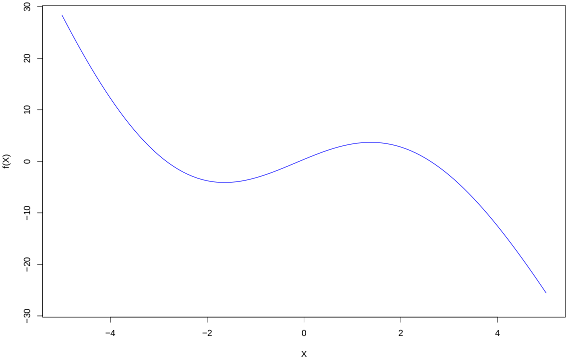
Building a predictive model – Exemple

Using the information contained in the database, a predictive model is built.



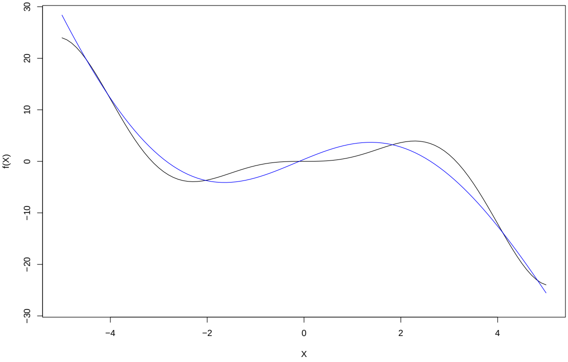
Building a predictive model – Exemple

The predictive model can be used to predict the outputs of new inputs that are not in the database.

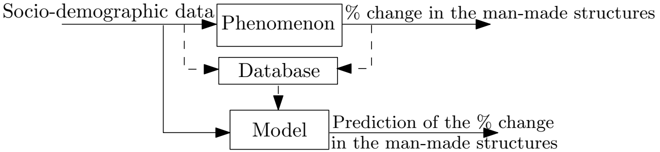


Building a predictive model – Exemple

Note that the predictive model (in blue) is an approximation of the real unknown phenomenon (in black).



Building a predictive model



In our case, the input are *socio-demographic data* and the output is the % of change in the man-made structures.

Fusion of ETATS and the statistical module

- Both ETATS and the statistical module return prediction of change but at different levels :
  - The ETATS module returns a prediction at the pixel level.
  - The statistical module makes predictions at regional level.
- A solution to merge these predictions :
  - Aggregate the prediction of ETATS for each region.
- The final prediction will be obtained by weighted averaging of these predictions.

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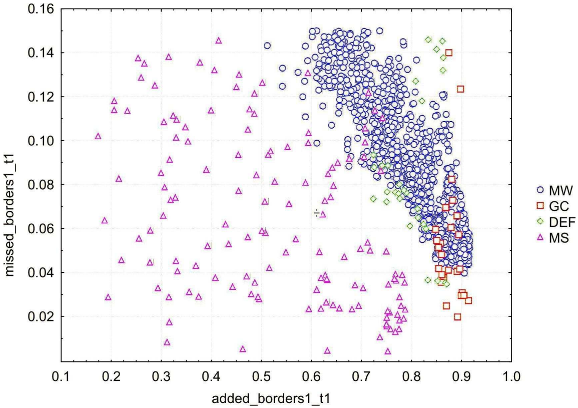
Prediction at a local scale

- For regions with a high predicted change, a local scale change detection can be applyed.
- In this case, an older database is compared with a recent *Very High Resolution* (VHR) images in order to detect man-made structure changes.
- Four steps :
  - segmentation
  - feature selection
  - classification
  - comparison with an older database (change detection)

Segmentation

- Three segmentation algorithms are compared to the one included in the Definiens software :
  - Mean-Shift [Comaniciu2002],
  - Graph-Cut [Boykov2001],
  - Multi-Watershed Assembly [Beucher1979].
- Most methods were adapted to include the old database as *priori* knowledge → this knowledge allows constraint segmentation.

Segmentation – Results



Feature selection

- After the segmentation procedure, the regions may be characterised according to their spectral characteristics, but also to their shape, size, texture, pattern, context, association.
- Therefore, when considering the high number of parameters in the classification process, a step of variables selection is necessary to avoid overfitting.
- In this study, feature selection is guided by
  - a visual interpretation formalised into an interpretation key
  - a quantitative approach according to :
    - the Jeffries-Matusita distance [Richards1999].
    - the mRMR criteria [Peng2005].

Feature selection – MRMR

The MRMR criterion [Peng2005] consists in

- selecting the variable that maximizes u_i, the relevance to the output Y,

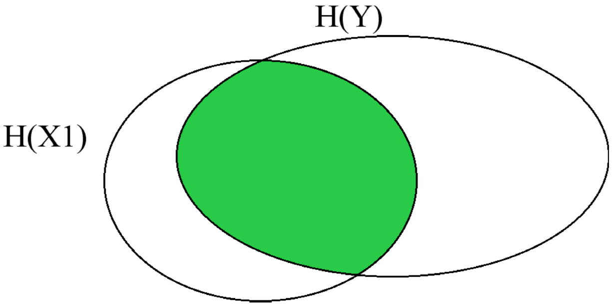
$$u_i = I\left(X_i; Y\right)$$

- and that minimizes the mean redundancy z_i with the already selected variable,

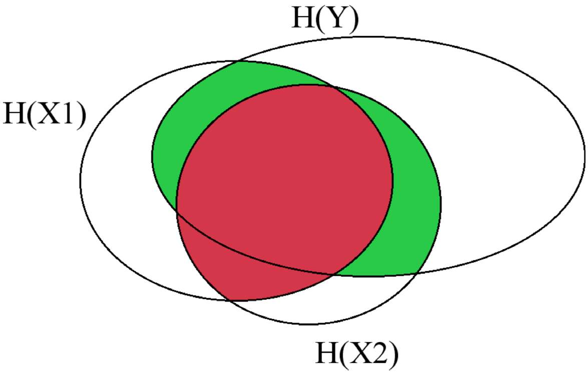
$$z_i = \frac{1}{d} \sum_{X_j \in X_S} I\left(X_i; X_j\right)$$

$$X_{MRMR} = \arg \max_{X_i \in X_{-S}} \left\{u_i - z_i\right\}$$

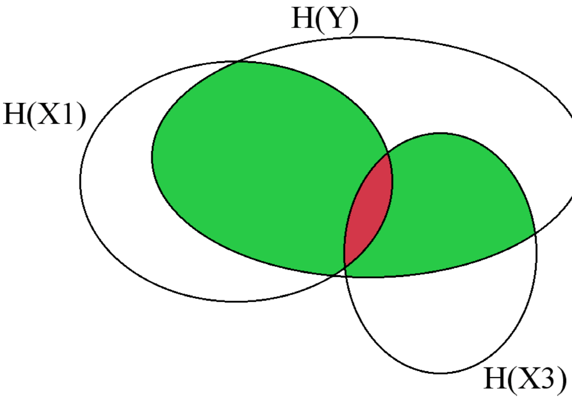
Feature selection – MRMR Example



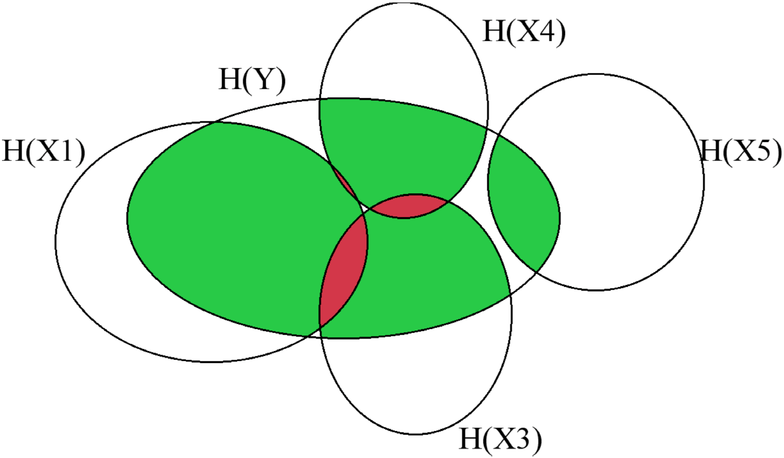
Feature selection – MRMR Example



Feature selection – MRMR Example



Feature selection – MRMR Example



Feature selection – JM distance (based on the Bhattacharyya distance)

The JM distance between a pair of probability distribution is defined as

$$J_{ij} = \int_{\mathbf{x}} \left\{ \sqrt{p(\mathbf{x}|\omega_i)} - \sqrt{p(\mathbf{x}|\omega_j)} \right\}^2$$

which is seen to be a measure of avergage distance between the two density functions.
For normally distribution, this becomes

$$J_{ij} = 2\left(1 - e^{-B}\right)$$

where

$$B = 1/8\left(\mathbf{m}_i - \mathbf{m}_j\right)^t \left\{\frac{\Sigma_i + \Sigma_j}{2}\right\}^{-1} \left(\mathbf{m}_i - \mathbf{m}_j\right) + 1/2 \ln \left\{ \frac{\left|\left(\Sigma_i + \Sigma_j\right)/2\right|}{\left|\Sigma_i\right|^{1/2} \left|\Sigma_j\right|^{1/2}} \right\}$$

which is referred to as the Bhattacharyya distance.
The pairwise JM distance is defined as

$$d_{ave} = \sum_{i=1}^{M} \sum_{j=1}^{M} p(\omega_i) p(\omega_j) J_{ij}$$

where M is the number of classes and $p(\omega_i)$, $p(\omega_j)$ are the prior probabilities.

Feature selection – Results

- With the mRMR method, more textural features are selected, whereas in the JM distance method, spectral features are highlighted.
- For both feature selection algorithms, the variables *Length/Width*, *NDVI*, and *GLCM Entropy* were selected in the first stages of the quantitative approach, and thus seem to be good variables for prediction.
- Among the variables selected from the visual interpretation key, three of them have been selected by the feature selection process.

Classification

- The classification consists in finding the type of a segment :
  - water,
  - road,
  - bare ground,
  - building,
  - vegetation.
- The set of segments is first split into two parts : a test set and a training set.
- All the learning process is done on the training set and we use the test set to compute :
  - the overall accuracy [Congalton1991],
  - the KAPPA statistic [Congalton1991],
  - the balanced accuracy [Melvin2007].

Classification – accuracy

Confusion matrix (Random Forest using 40 variables selected by mRMR) :

	water	road	bare	building	vegetation	
Pred water	778	55	22	33	433	1321
Pred road	49	969	71	73	1012	2174
Pred bare	6	124	196	107	650	1083
Pred building	20	167	127	945	1111	2370
Pred vegetation	59	61	87	35	12797	13039
	912	1376	503	1193	16003	19987

Overall accuracy :

$$\frac{\sum_{i=1}^{M} x_{ii}}{N} = \frac{778 + 969 + 196 + 945 + 12797}{19987} = \frac{15685}{19987} = 0.784$$

Khat statistic :

$$\frac{N \sum_{i=1}^{M} x_{ii} - \sum_{i=1}^{M} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{M} (x_{i+} * x_{+i})} = \frac{19987 * 15685 - 216231452}{19987^2 - 216231452} = 0.530$$

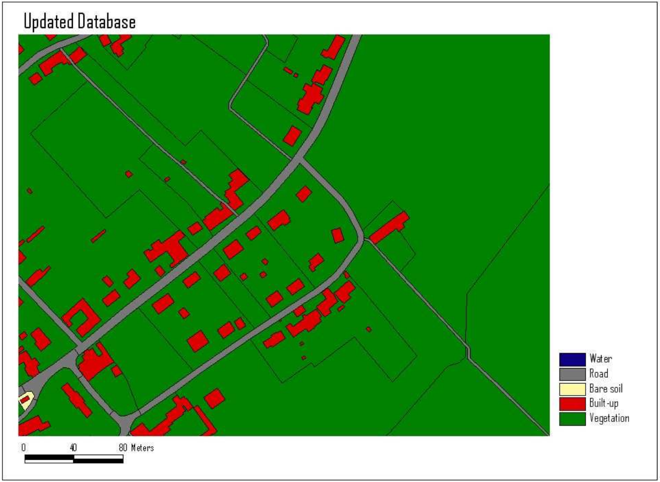
Balanced accuracy :

$$\frac{\sum_{i=1}^{M} \frac{x_{ii}}{x_{+i}}}{M} = \frac{\frac{778}{912} + \frac{969}{1376} + \frac{196}{503} + \frac{945}{1193} + \frac{12797}{16003}}{5} = 0.707$$

Classification – Definiens

- To evaluate our proposed classification algorithms, a comparison with the results obtained with the commercial software Definiens was used.
- In Definiens, Nearest Neighbour classification (with rules) has been used with features selected by the visual interpretation.

Classification – Definiens results

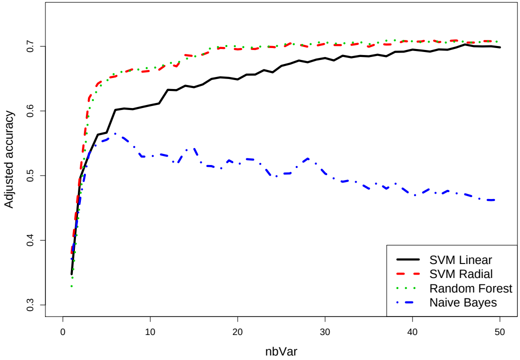


Classification – Definiens results

Classification – Others classification methods

- The results of Definiens where compared with the results of three proposed classification algorithms.
- In our learning set, the output of the samples is highly unbalanced (i.e., 80% of the samples is vegetation) and this makes prediction difficult.
- We use a boosting process in which fifteen models are built with balanced re-sampled learning sets and a prediction is made after a majority voting process.
- We apply this boosting process with four types of models :
  - a Random Forest,
  - a Naive Bayes Classifier,
  - a SVM with a linear and a radial kernel.

Classification – Results



- The evolution of the balanced accuracy in case of mRMR.
- Note that the best predictions - according the balanced accuracy - were done by a Random Forest using 40 variables selected by mRMR.

Classification – Results

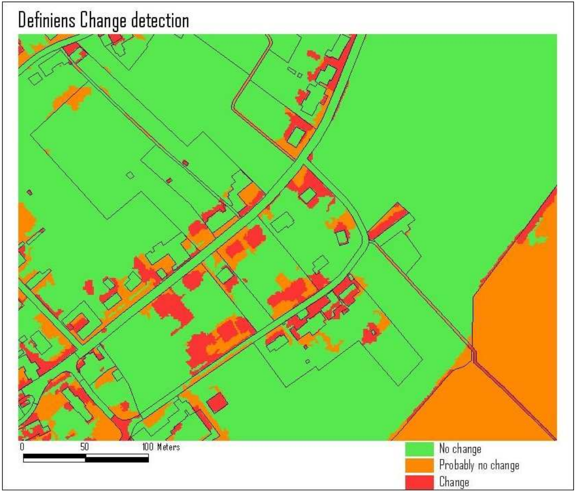
	Definiens	Random Forest + mRMR
Kappa	0.41	0.53
Overall accuracy	0.71	0.78
Balanced accuracy	0.51	0.71

Change Detection

A map has been established with the changes between the updated database and the results given by the Definiens classifier based on Nearest Neighbors.

Change Detection

Change Detection – Definiens



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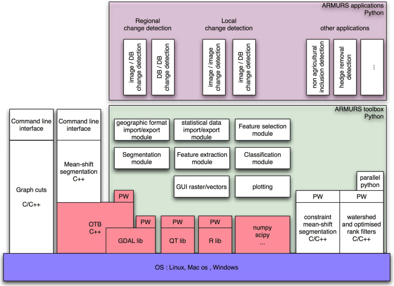
Demonstrator

The different developed algorithms are integrated in a same software environment, based on existing open source libraries (OTB, GDAL, QT, R, Python. . .).
This environment is divided into two layers:

Toolbox layer: consists in a coherent set of classes and methods using the features of the existing libraries and linking them together.

Application layer: groups different applications based on the toolbox layer with user-friendly graphic user interfaces (GUI).



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Conclusion

- We presented an approach for automatic change detection of man made structures in order to help database producers to updata there topographical databases.
- The regional change detection aims at finding changes at a high level from HR image and statistical data.
- The local approach, solely based on a VHR image, intends to detect changes between the old database and a recent image thanks to the classification of regions obtained by segmentation of this image.
- All the developments are progressively integrated into a prototype.

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Thank you for your attention !