Selection and evaluation of air traffic complexity metrics

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Air traffic complexity

A growing need of complexity measures, and a multitude of metrics...
...used for various purposes :

- assessment of ATC/ATFM performances,
- benchmarking new airspace structures,
- design of new tools...

There is no single universal complexity measure.

All we may expect is a set of complexity metrics, useful in a particular context, for a particular purpose.

$\Rightarrow$ we must assess the relevance of the complexity measures to the final goal !

Context and motivation of our study

Context

- Air traffic complexity in relation with the controller's workload.
- Geographic area : a set of control sectors.
- Time scale : one measure every minute.

What for ?

- Purpose : find a criterion to evaluate the controller's workload.
- Application : optimal sector configurations (pre-tactical level).
  $\longrightarrow$ use relevant complexity metrics
  instead of incoming flows / sector capacities.

Other works

Several studies tried to find a relationship between the complexity metrics and the controller's workload, using :

- linear or logistic regression,
- cross-sectional time series analysis,
- neural networks...

Existing evaluations of the controller's workload :

- interactions with the computer,
- physiological activity,
- subjective ratings...

The data

- may be noisy or biased.
- is difficult to collect (heavy experimental setup),
- and is not available in large quantities.

Our proposal

The sector status (*merged*, *armed*, or *split*) is representative of the controller's workload.

The aim :

Select a subset of relevant metrics,
allowing to predict the sector status.

The data (radar tracks, sector configuration records)

- may still be noisy or biased :
  merging of splitting a sector may have various causes, other than the traffic load,
- is noticeably cheap to collect (ATCC databases),
- and available in large quantities.
- It reflects an objective operational reality.

Metrics evaluation method

Principal Component Analysis

- Identify the correlations among the metrics,
- Reduce the dimensionality of the problem.

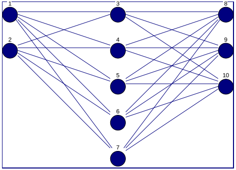
Select the most relevant components

- Apply neural networks :
  - input : main Components (eigenvalue > 1)
  - output : prediction of the sector status
- Select model with best fit : predicted *vs.* recorded status.

Evaluate the individual metrics

- Consider the metrics related to each relevant component
- Select the most relevant subset in each component

Neural networks with one hidden layer



Input vector $x = (x_1, ..., x_i, ..., x_p)^T$
Output vector $y = (y_1, ..., y_k, ..., y_q)^T$

$$y_k = \Psi(\sum_{j=1}^{q} w_{jk} \Phi(\sum_{i=1}^{p} w_{ij} x_i + w_{0j}) + w_{0k}) \quad (1)$$

$$\Phi(z) = \frac{1}{1 + e^{-z}} \qquad \Psi(z_k) = \frac{e^{z_k}}{\sum_{m=1}^{C} e^{z_m}}$$

Neural network's training

Classification problem –> assign each input vector x to a class *merged*, *armed*, or *split*

Training

- Choose the weights and biases so as to minimize the cross-entropy :

$$E(w) = -\sum_{n=1}^{N}\sum_{k=1}^{C} t_k^{(n)} ln(y_k^{(n)})$$

- considering N data samples (*train* set), and $C = 3$ classes,
- where t is the target vector (known class vector)
  - *merged* class : $t = (1, 0, 0)^T$
  - *armed* class : $t = (0, 1, 0)^T$
  - *split* class : $t = (0, 0, 1)^T$

Software and input data

Software

- package `nnet` (written by Pr Ripley) of the `R` environment,
- training : quasi-Newton minimization method (BFGS).

Data

- recorded radar tracks and sector configurations of the 5 french ATCCs. One day of traffic (1st june, 2003),
- 103 different sectors (elementary or group) were armed,
- metrics computed every round minute of the day.

	Total	Merged	Armed	Split
Train	71270	46.6%	27.0%	26.4%
Test	47513	46.4%	27.0%	26.6%

Building a set of complexity metrics

27 metrics from various sources
(whenever a clear definition was found) :

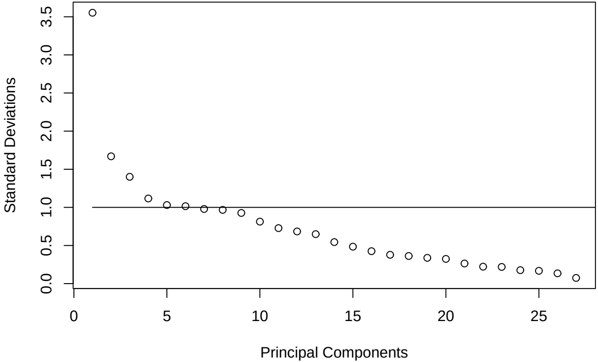
- [Kopardekar & Magyarits (2003)]
- [Chatterji & Sridhar 2001]
- [Delahaye & Puechmorel 2000]
- Performance Review Unit
- P. Averty (CREED)
- Incoming flows (time horizon 5 to 60 minutes)

+ Sector volume V

- Individual indicators typically focus on a single aspect of traffic complexity $\Rightarrow$ need to use complementary indicators.
- Many redundancies $\Rightarrow$ need to reduce dimensionality.

The principal component analysis

The standard deviations are :



$\Rightarrow$ 6 components carry a variance greater than one.

The principal component analysis

The first component is a "size factor" $\simeq$ *number of aircraft*.
It explains 46.7% of the variance of the sample.

Indicator	*Other components*				
	Speed var. & alt. changes	*Incoming flows*	*Structure & Convergence*	*Divergence*	*Vertical separation*
avg_vs $\sigma_{gs}/\bar{gs}$ σ^2_{gs}	0.70 0.69 0.68				
Inc. flows		0.60 to 0.67			
Nb *inter_hori* Nb^2 *incen_c*			0.47 0.44 0.39 0.32		
insen_d *div_p*				0.48 0.37	
vprox_2 *vprox_1*					0.70 0.51
% Variance Explained	10.3	7.3	4.6	3.9	3.8

Neural networks applied to the components

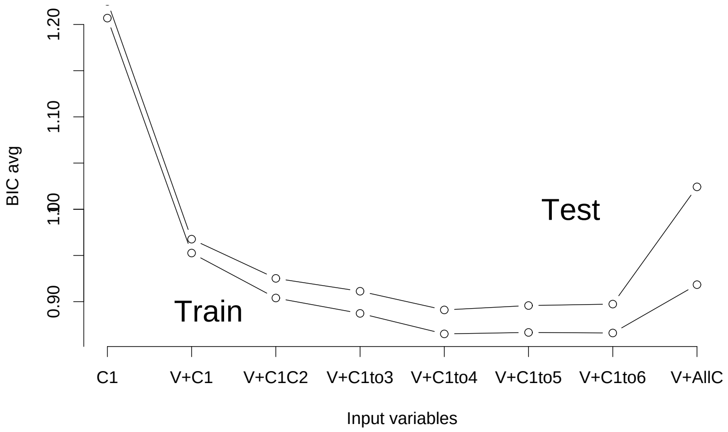
Iterative approach :

- We first use component C_1 as sole input,
- then add the sector volume V,
- then component C_2 to C_6, successively.
- At last, we use the 27 components and the volume as input.

Schwartz Information Criterion : $(BIC = 2\lambda.ln(N) - 2ln(L))$

- λ is the number of unadjusted parameters of the model −> weights and biases,
- N is the size of the data set,
- $ln(L)$ is the log-likelihood −> cross-entropy in our case.

Evolution of the BIC for the components



Why use the BIC ?

The network's results (classification rates, cross-entropy) evolve with :

- the relevant/non-relevant variables added to the model,
- but also the *number of model's parameters* (weights, biases).

$==>$ The BIC is more reliable. Best model : $\{V; C_1; ..; C_4\}$

Set	Hidden units	Nb params.	Classification rate
$\{V; C_1; ..; C_{27}\}_{test}$	15	483	82.67%
$\{V; C_1; ..; C_4\}_{test}$	15	138	81.82%%
$\{V; C_1; ..; C_4\}_{test}$	53	480	83.84%

Results on the components

Selection process : 27 metrics –> 4 relevant components

Best components model among the candidate models :

- C_1 : size factor, number of aircraft,
- V : sector volume,
- C_2 : speed variance, altitude changes,
- C_3 : incoming flows,
- C_4 : flows convergence, anticipation of conflicts.

Functional relationship :

- metrics –> components
- relevant components –> sector status.

Results on the indicators

For practical purposes, we would prefer :

- relevant metrics –> sector status

$\Longrightarrow$ Evaluate the metrics of each relevant component.

Component	Metrics
C_2	**avg_vs**, $\frac{\sigma_{gs}}{\overline{gs}}$, σ^2_{gs}, N_{cl}, N_{ds}
C_3	F_5, $\mathbf{F_{15}}$, F_{30}, $\mathbf{F_{60}}$
C_4	**inter_hori**, *insen_c*, *Conv*, *creed_ok*, *creed_pb*

Classification rates

Correct classification rates

- with the most relevant indicators $\{V, Nb, avg\_vs, F_{60}, F_{15}, inter\_hori\}$
- using a neural network with 15 hidden units

Set	Global	Merged	Armed	Split
Train	83.47%	89.07%	65.58%	91.91%
Test	83.24%	89.14%	64.56%	91.75%

Discussion C_2 indicators

C_2 : ground speed variance and altitude changes

- the component is relevant,
- this contradicts previous works by [Malasonis, Callaham, Wanke, 2003]
  –> nature of data ?
  relationship sector volume / type of traffic ?
- the average vertical speed **avg_vs** is the most relevant in C_2
- but $\frac{\sigma_{gs}}{gs}$ and σ_{gs}^2 gave fairly close results

The average vertical speed is a dynamic indicator
Could it be replaced by a static sector typology, like : *en route*, *arrival*, *departure*, *mixed* ?
–> classify the sectors according to **avg_vs**.

Discussion C_3 indicators

C_3 : incoming flows

- F_5 gave the worse results,
- $\mathbf{F_{15}}$ is relevant
  –> consistent with working methods : strips distributed about 15 minutes before sector entry,
- $\mathbf{F_{60}}$ came as a surprise
  –> smoothing effect ? compensate the variations of the other variables ?

Discussion C_4 indicators

C_4 : flows convergence and anticipation of conflicts

- **inter_hori** (number of aircraft pairs with crossing angle greater than 20 degrees) is the most relevant,
- other "convergence" indicators also performed well,
- the indicators related to the anticipation of conflicts
  - between converging aircraft
  - in the horizontal plane

  perform well, but do not improve the results
  –> too much correlated to the airspace structure ?

More general conflict detection indicators may be useful (not only converging aircraft, not only in horizontal plane)

Conclusion

27 metrics + sector volume $\longrightarrow$ 6 relevant indicators

Best model for the indicators :

- V : sector volume,
- Nb : number of aircraft,
- *avg_vs* : average vertical speed,
- F_{15}, F_{60} : incoming flows,
- *inter_hori* : Number of aircraft pairs crossing with an angle greater than 20 degrees.

Not an absolute truth !

- *combined effects* of the different indicators
- adding or removing some metrics may change the picture.

Conclusion

Method

- Neural networks proved efficient.
- Consistent results on *train* and *test* data
  $\Longrightarrow$ ability to generalize on fresh inputs
- Output : probability to belong to a class
  (*merged*, *armed*, or *split*).

Simple relationship :
$\{V, Nb, avg\_vs, F_{60}, F_{15}, inter\_hori\} \longrightarrow$ sector status

$$y_k = \Psi(\sum_{j=1}^{q} w_{jk}\Phi(\sum_{i=1}^{p} w_{ij}x_i + w_{0j}) + w_{0k})$$

with the weights of the trained network.

Conclusion

About 83% of correct classifications,
with the best model and with 15 hidden units

Classification rates or cross-entropy
are not good criteria for model selection

Selection criterion

- The Schwartz's *Bayesian Information Criterion* allowed model's selection,
- not biased by the increasing number of weights in the NN.

Further work

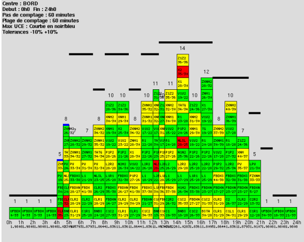
Dynamic indicators : high variations in time
Sector status : few changes

Research options

- Could static indicators replace dynamic metrics :
  - average vertical speed $\longrightarrow$ sector class (en-route, arrival,...),
  - pairs of crossing aircraft $\longrightarrow$ sector class (crossing / parallel) ?
- Use "smoothed" metrics ?
- Time series processing ?

Other methods could be tested
(logistic regression, dynamic discrete choice models).

Further work



Application : optimal sector configurations

Use air traffic complexity metrics
instead of incoming flows / sector capacities.

End of presentation...

... any questions ?