MINISTÉRIO DA CIÊNCIA E TECNOLOGIA
INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS

Severe Weather Prediction:
Integrating Partial Differential and Machine Learning Models

Haroldo F. de Campos Velho (COPDT-INPE)

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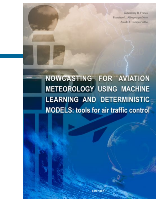
XI CIMAC (Congreso Internacional de Matemática Aplicada y Computacional)

Summary

- Weather prediction: PDE x Data
- A false dilemma
- Hybrid prediction:
  Differential. equations + Machine learning (data-driven)
- Hybrid prediction for convective events
- Next actions for Hybrid Prediction
- Final remarks

Numerical weather prediction



Scientific challenges

- **Before** the 20th Centrury:
  We want to know the "Laws of Nature"

- **During** the 20th Centrury:
  We know the Laws, but how can we solve the equations?

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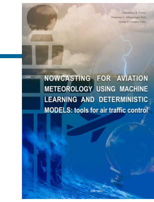
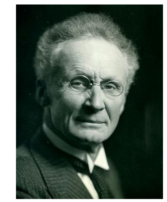
  The first decades of this century show that one of the challenges is the extraction of knowledge from a tsunami mass of data: "*Data Scince*".



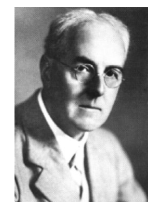
Numerical weather prediction

A scientific achievement of the 20th century

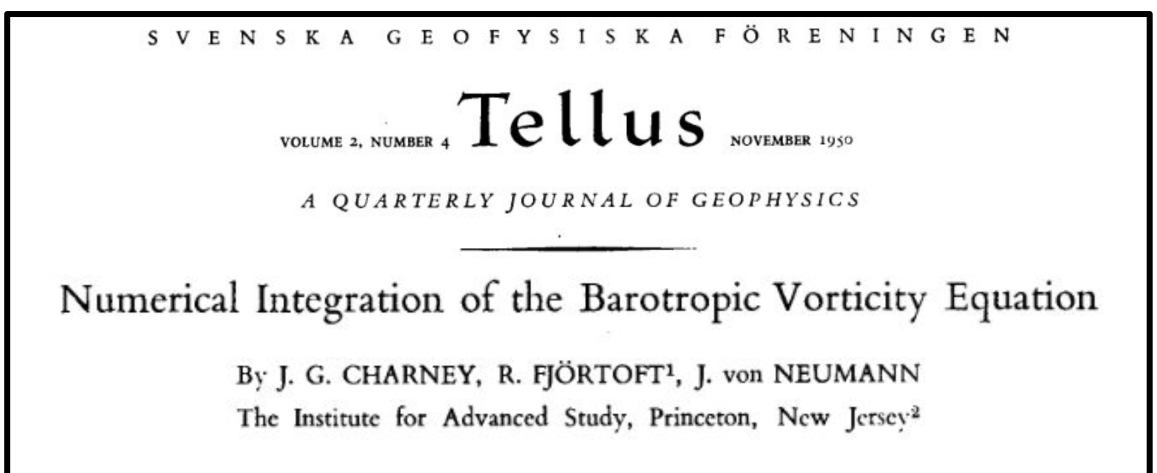
- The Vilhelm Bjerknes' Theorem (1904)



- Book: Lewis Fry Richardson (1922)



- Paper: Charney, Fjørtoft, von Neumann (1950)



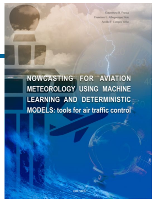
SVENSKA GEOFYSISKA FÖRENINGEN

VOLUME 2, NUMBER 4 **Tellus** NOVEMBER 1950

A QUARTERLY JOURNAL OF GEOPHYSICS

Numerical Integration of the Barotropic Vorticity Equation

By J. G. CHARNEY, R. FJÖRTOFT[1], J. von NEUMANN
The Institute for Advanced Study, Princeton, New Jersey[2]



Numerical weather prediction

A scientific achievement of the 20th century

- Weather prediction by Differential Equations

$$\frac{\partial \zeta}{\partial t} = -\nabla \cdot (\zeta + f)\mathbf{U} - \mathbf{k} \cdot \nabla \times \left(RT'\nabla lp + \dot{\sigma}\frac{\partial \mathbf{U}}{\partial \sigma} + \mathbf{F} \right)$$

$$\frac{\partial D}{\partial t} = \mathbf{k} \cdot \nabla \times (\zeta + f)\mathbf{U} - \nabla \cdot \left(RT'\nabla lp + \dot{\sigma}\frac{\partial \mathbf{U}}{\partial \sigma} + \mathbf{F} \right) - \nabla^2 (\Phi' + RT_0\, lp + \frac{1}{2}\mathbf{U} \cdot \mathbf{U})$$

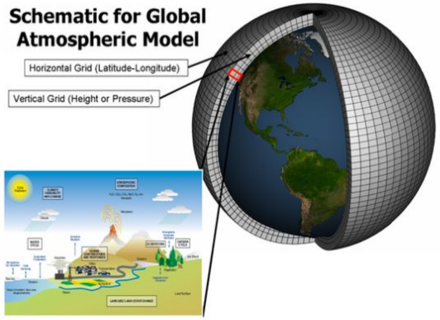
$$\frac{\partial T}{\partial t} = -\nabla \cdot \mathbf{U}T' + T'D + \dot{\sigma}\gamma - \frac{RT}{c_p}\left(D + \frac{\partial \dot{\sigma}}{\partial \sigma} \right)$$

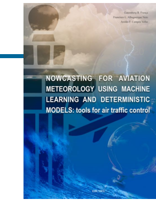
{with: $\phi = gh$; and: $\sigma = p/p_0$}

$$\frac{\partial q}{\partial t} = -D - \frac{\partial \dot{\sigma}}{\partial \sigma} - \mathbf{U} \cdot \nabla\, lp$$

{with: $q = \log(p_0)$}

(a) ζ: vorticity
(b) D: divergence
(c) T: temperature
(d) q: moisture





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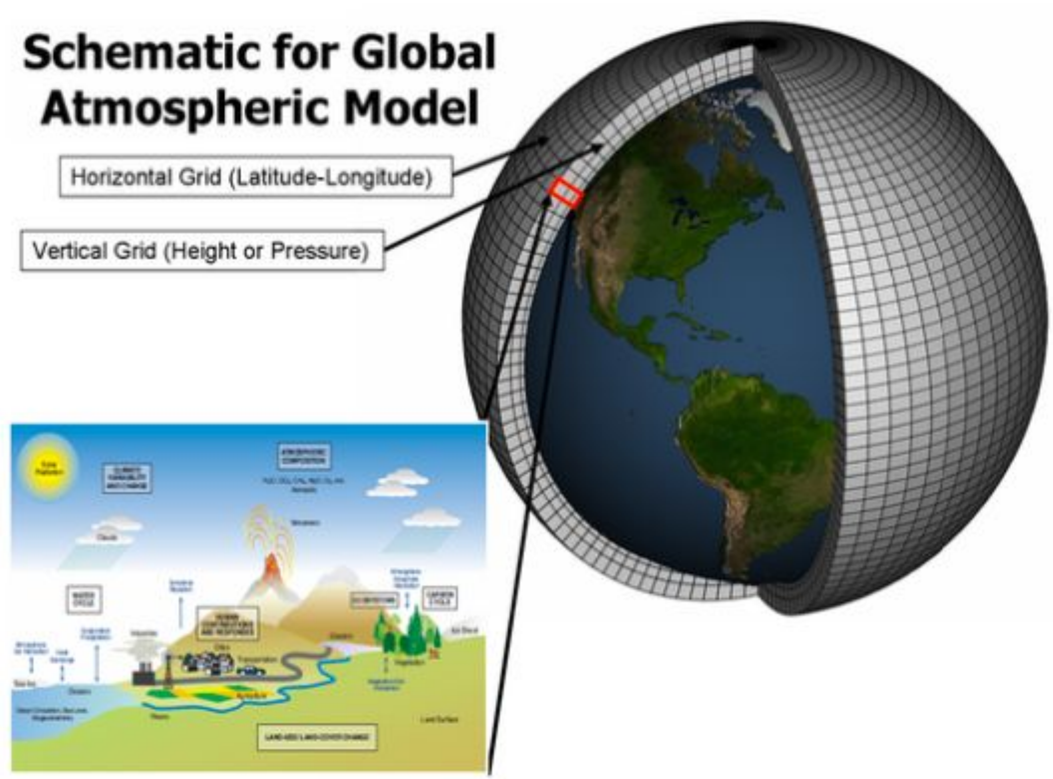
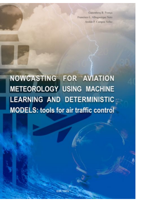


Numerical weather prediction



A scientific achievement of the 20th century

- Solving differential equations: Finite Difference

$$\frac{\partial \Lambda(\alpha_i)}{\partial \alpha_i} \approx \frac{\Lambda(\alpha_i + \Delta\alpha_i) - \Lambda(\alpha_i)}{\Delta\alpha_i} + O\left(\Delta\alpha_i\right) \ ,$$

$$\frac{\partial \Lambda(\alpha_i)}{\partial \alpha_i} \approx \frac{\Lambda(\alpha_i) - \Lambda(\alpha_i - \Delta\alpha_i)}{\Delta\alpha_i} + O\left(\Delta\alpha_i\right) \ ,$$

$$\frac{\partial \Lambda(\alpha_i)}{\partial \alpha_i} \approx \frac{\Lambda(\alpha_i + \Delta\alpha_i) - \Lambda(\alpha_i - \Delta\alpha_i)}{2\,\Delta\alpha_i} + O\left(\Delta\alpha_i^2\right) \ ,$$

$$\frac{\partial^2 \Lambda(\alpha_i)}{\partial \alpha_i^2} \approx \frac{\Lambda(\alpha_i + \Delta\alpha_i) - 2\Lambda(\alpha_i) + \Lambda(\alpha_i - \Delta\alpha_i)}{\Delta\alpha_i^2} + O\left(\Delta\alpha_i^2\right) \ .$$

$$\frac{d\mathbf{\Lambda}_F}{dt} + \mathbf{D}\,\mathbf{\Lambda}_F + N^F(\mathbf{\Lambda}_F) + \mathbf{K} = \mathbf{0} \ .$$

Numerical weather prediction

A scientific achievement of the 20th century

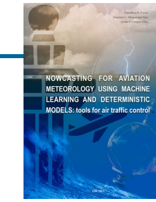
- Solving differential equations: Spectral Method

$$\Lambda(\lambda,\mu,t)=\sum_{m=-J}^{+J}\sum_{\ell=|m|}^{|m|+J+\alpha} c_\ell^m \Lambda_\ell^m(t) Y_\ell^m$$

$$Y_\ell^m = Y(\lambda_\ell,\mu_m) = P_\ell^m(\mu)\, e^{im\lambda}$$

$$c_\ell^m = \begin{cases} a^2\ , & \text{for: } \psi\ ,\ \chi\ ,\ \phi \\ a\ , & \text{for: } u\ ,\ v \\ 1\ , & \text{for: } T\ ,\ r_h\ ,\ q \end{cases} \qquad \alpha = \begin{cases} 1\ , & \text{for: } u\ ,\ v \\ 0\ , & \text{otherwise} \end{cases}$$

$$\frac{d\mathbf{\Lambda}_S(t)}{dt} + \mathbf{L}\,\mathbf{\Lambda}_S + N^S(\mathbf{\Lambda}_S) + \mathbf{C} = \mathbf{0}$$



Numerical weather prediction

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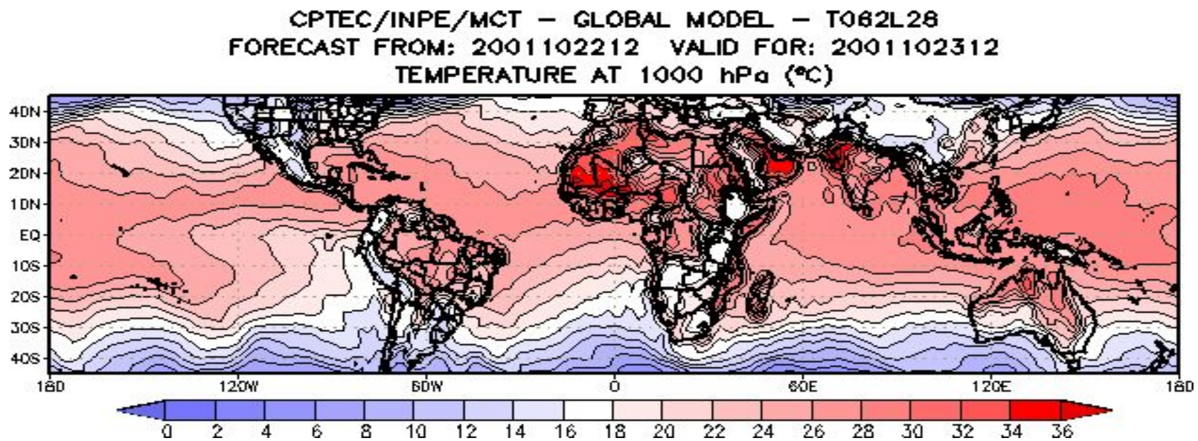
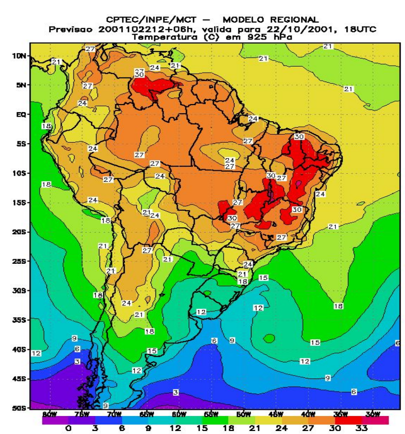
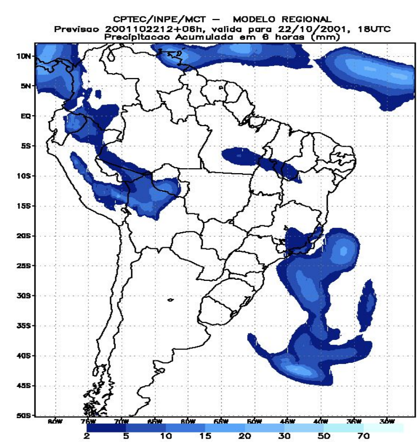
- Weather prediction by differential equations







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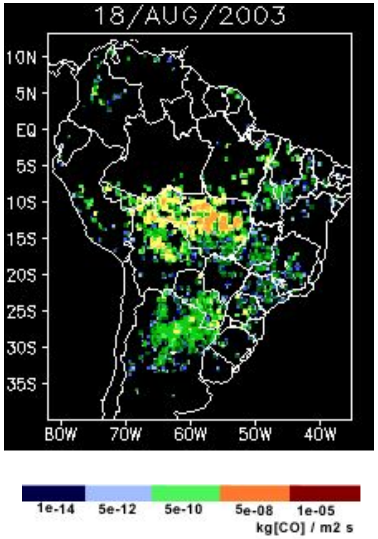
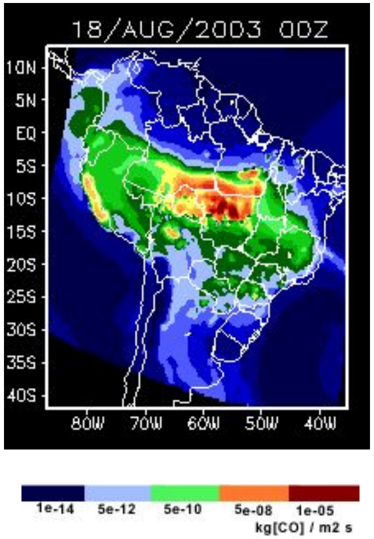
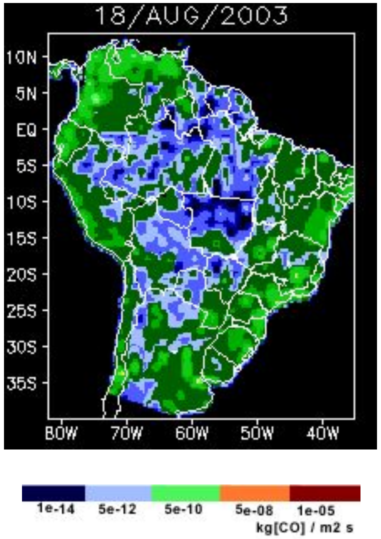


Fire emission

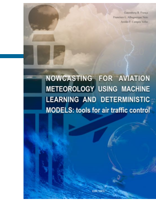


Total emission ratio



Antropogenic emission

Numerical weather prediction



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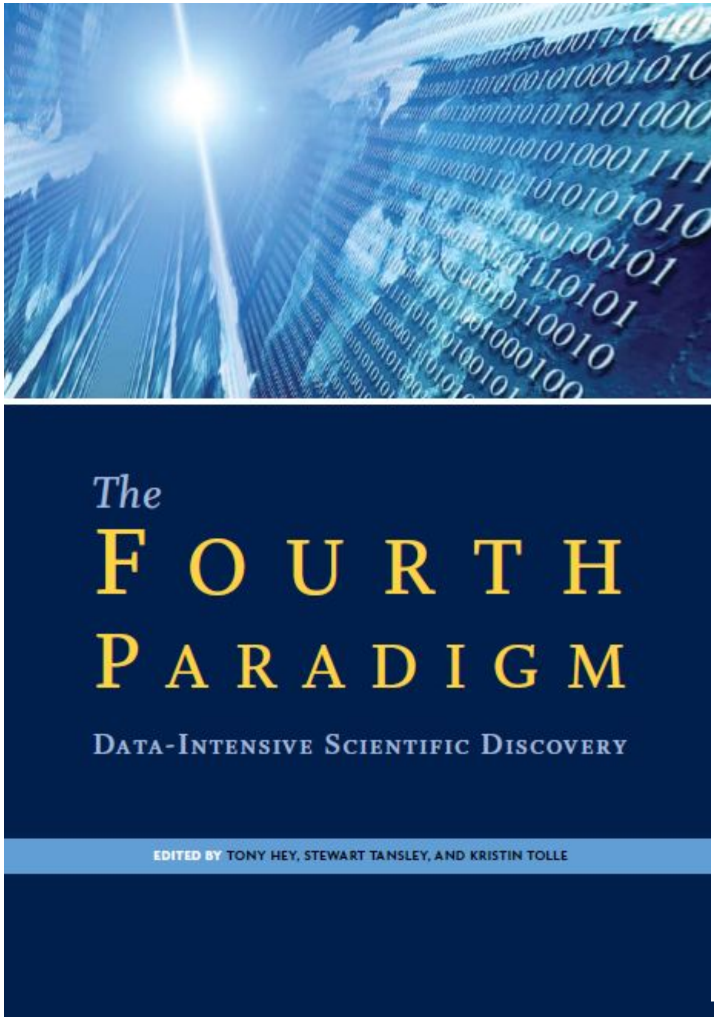
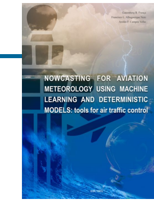


The

FOURTH PARADIGM

DATA-INTENSIVE SCIENTIFIC DISCOVERY

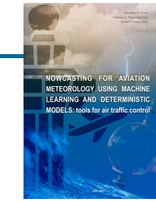
EDITED BY
TONY HEY, STEWART TANSLEY,
AND KRISTIN TOLLE



Data weather prediction

Challenges for the 21-th Century

- Severe weather prediction: "Data Science"



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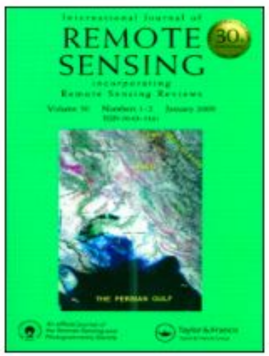

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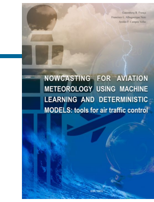
Short-range forecasting system for meteorological convective events in Rio de Janeiro using remote sensing of atmospheric discharges

Vinícius Albuquerque de Almeida, Gutemberg Borges França & Haroldo Fraga de Campos Velho

Data weather prediction



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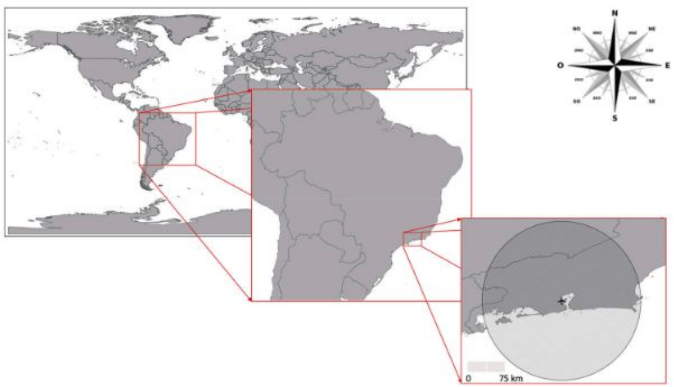

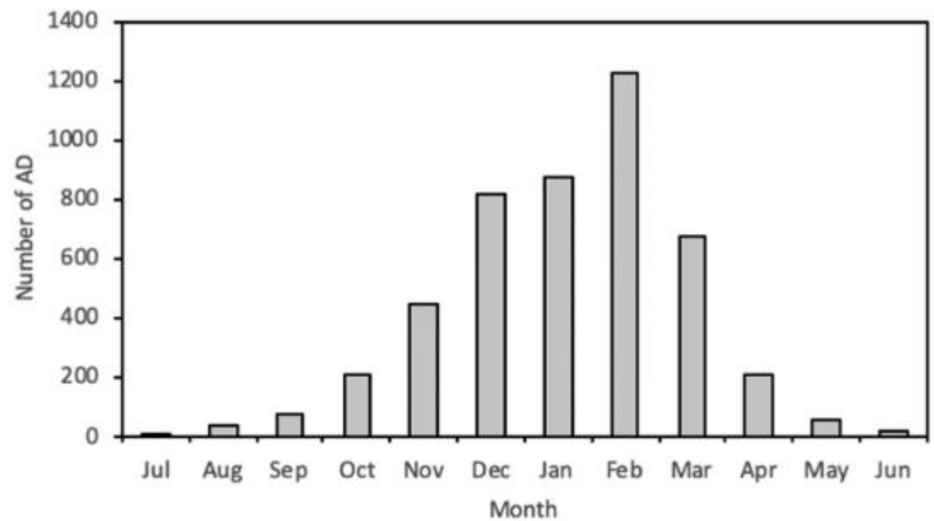

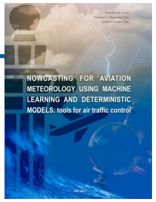

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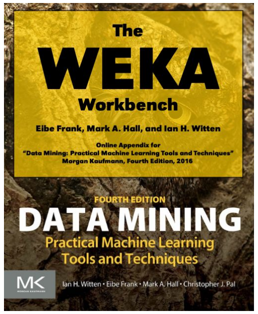
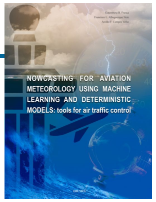


Table 4. Classifiers and configurations used for training the algorithms.

Classifier	Description	Configuration	Reference
Random forest	Creates decision trees trained on different subsets of input features.	Default configuration with 100 trees using the standard variance reduction as split selection criterion	Leo Breiman (2001)
Decision tree (J48)	Creates single decision tree based on all available input features	Unpruned decision tree with a minimum of two instances per leaf.	Ross Quinlan (1993)
Multilayer Perceptron (MLP) Classifier	Multilayer perceptron with one hidden layer with customized number of hidden units	Standard perceptron with ten hidden units using the sigmoid activation function and optimization by the minimization of the squared error loss function.	Eibe Frank (2016)
Radial Basis Function (RBF) Classifier	Class implementing radial basis function networks	Radial basis function classifier with ten hidden units trained by minimizing squared error.	Eibe Frank (2014)
Voting committee	Class for combining classifiers	Used default configuration for RandomForest and J48 and the customized versions of MLPClassifier and RBFClassifier with ten hidden units	Ludmila I. Kuncheva (2014)
Deep Learning fully-connected (DL-FC) layers with dropout	Keras sequential models for deep learning.	Python implementation using the tensorflow framework. Two fully-connected (dense) layers with twenty-five units each, dropout regularization between dense layers, adam optimizer, sparse categorical crossentropy loss function, activation ReLu for intermediate layers and softmax for the output layer.	TensorFlow Authors

Data weather prediction



Challenges for the 21-th Century

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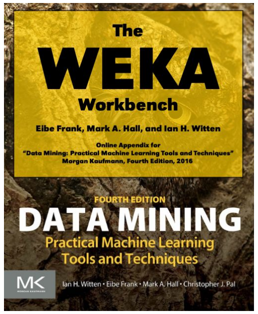
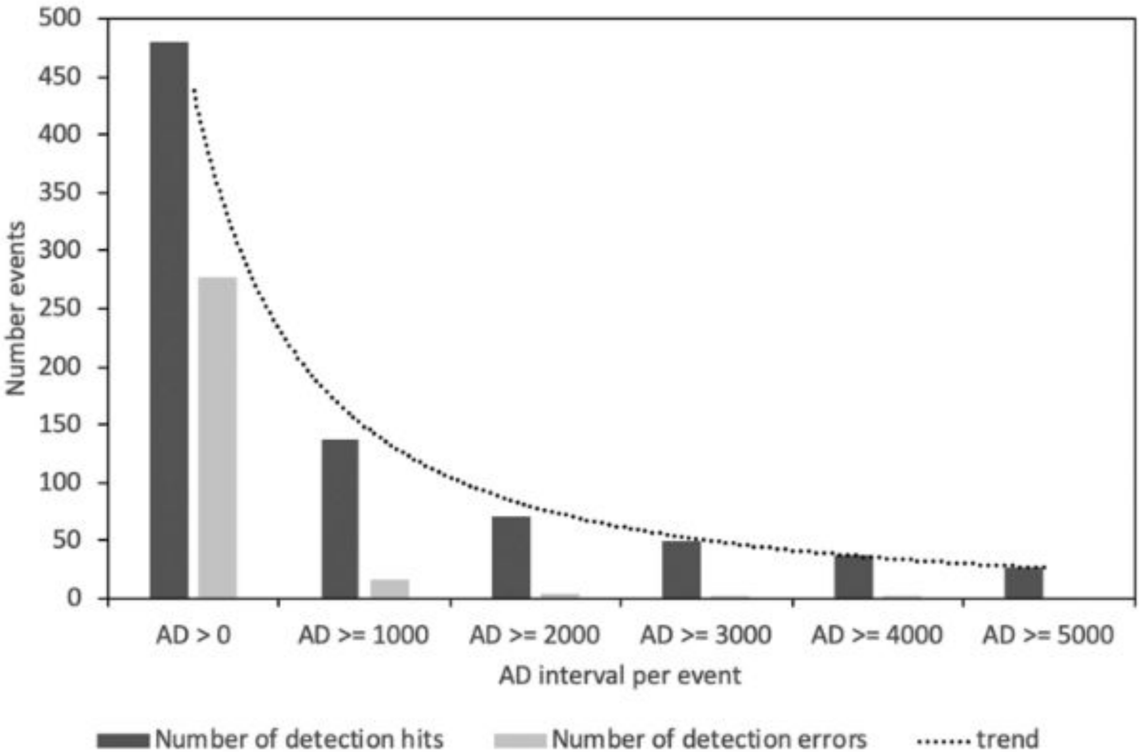
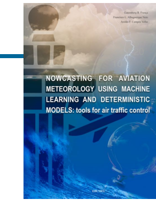
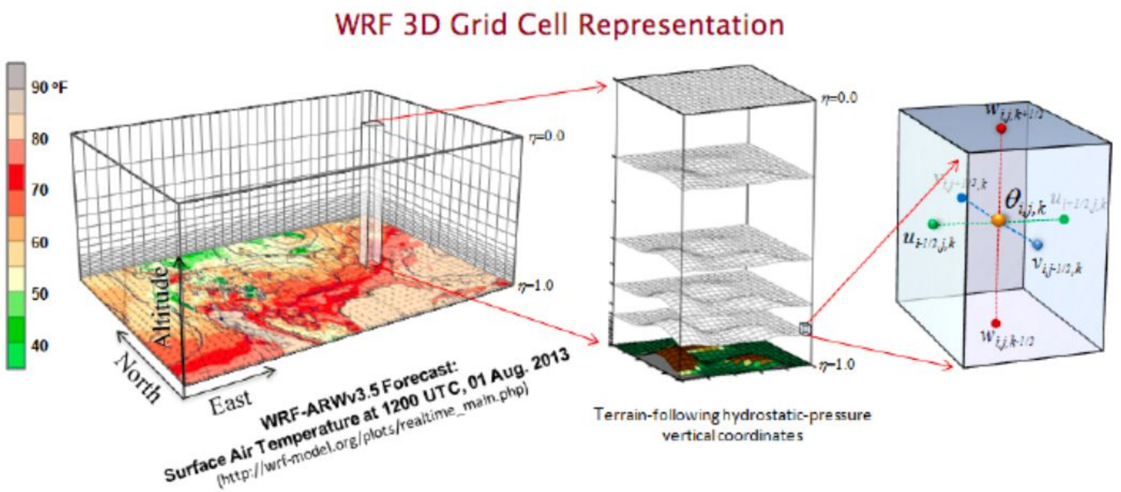






Numerical/Data weather prediction

Hybrid prediction: Differential Eqs. + Data Science



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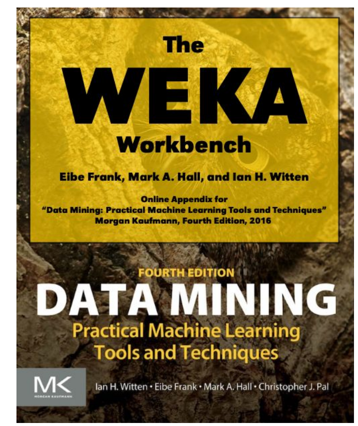

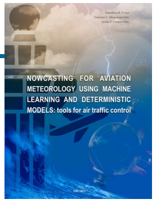

Numerical/Data weather prediction

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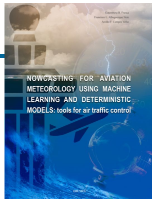

Numerical/Data weather prediction

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Applied Computing and Geosciences 16 (2022) 100099

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Check for updates

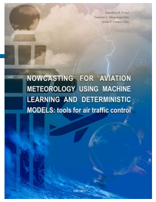
Forecast of convective events via hybrid model: WRF and machine learning algorithms

Yasmin Uchôa da Silva [a,*], Gutemberg Borges França [a], Heloisa Musetti Ruivo [b], Haroldo Fraga de Campos Velho [b]

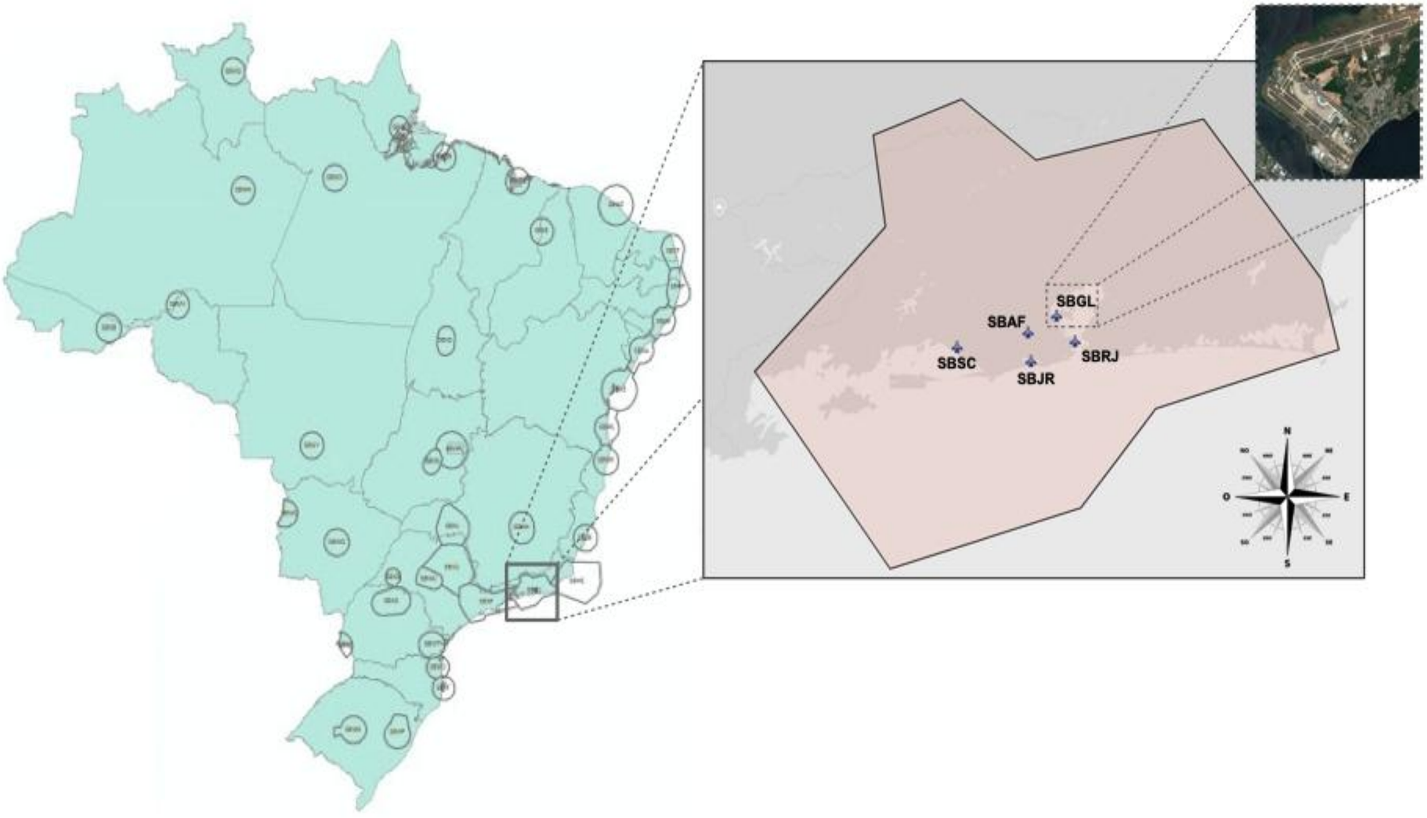
[a] *Laboratório de Meteorologia Aplicada, Departamento de Meteorologia-IGEO-CCMN, Universidade Federal do Rio de Janeiro (UFRJ), Rio De Janeiro, Brazil*

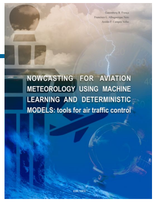
[b] *Instituto Nacional de Pesquisas Espaciais (INPE), São Paulo, Brazil*

Numerical/Data weather prediction



Hybrid prediction: Differential Eqs. + Data Science





Numerical/Data weather prediction

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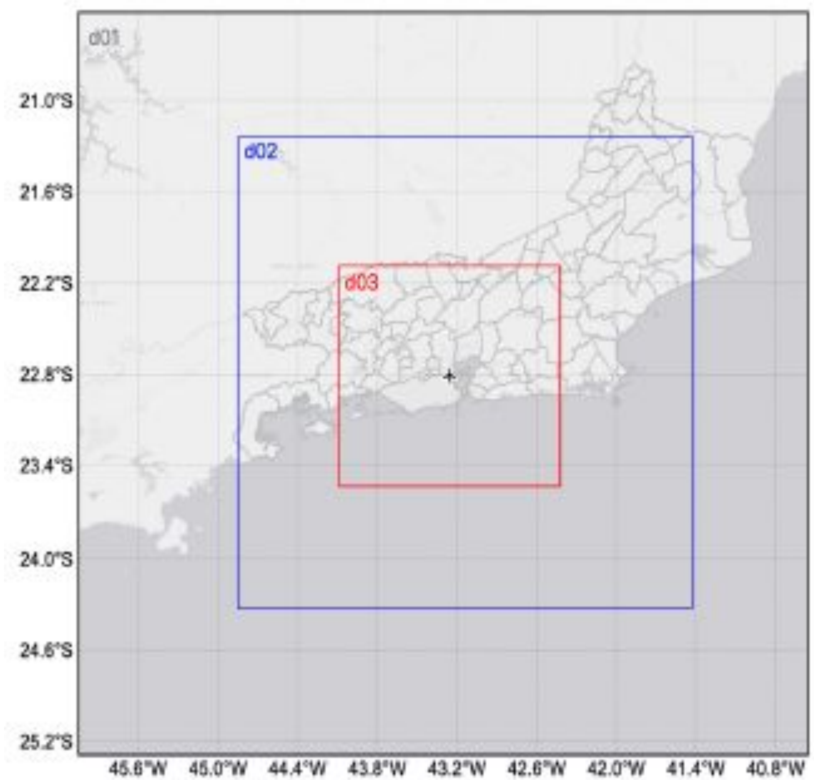


Período: Fev. 2008-2020;

Frequência entre as previsões: 3h

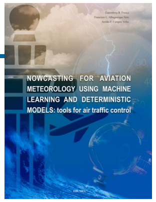
Resolução horizontal: 18 km (90x90)

Níveis na vertical: 33

Projeção: 'Mercator'

Lat/Lon do ponto central da grade: -22.8136 , -43.2675

Time step: 180s



Numerical/Data weather prediction

Hybrid prediction: Differential Eqs. + Data Science

- Attribute analysis: “p-value”

- Data dimension reduction
  - **WRF outputs: 1.8 x 10^6 attributes**
  - **Selection by p-value: 36 attributes**

Atributo	Nível	Latitude	Longitude	Valor-p
sh	400	-22.5S	320W	9.2E-05
sh	300	-20S	317.5W	1.7E-04
sh	400	-25S	322.5W	3.2E-04
sh	850	-20S	315W	4.2E-04
sh	850	-20S	312.5W	8.5E-04
sh	300	-20S	320W	1.4E-03
sh	400	-25S	320W	1.4E-03
sh	400	-27.5S	322.5W	1.4E-03
sh	300	-22.5S	320W	1.5E-03
omega	600	-20S	317.5W	1.6E-03
omega	300	-20S	315W	2.0E-03
u	925	-25S	317.5W	2.3E-03
v	925	-25S	317.5W	2.5E-03
sh	925	-22.5S	317.5W	3.2E-03
omega	600	-20S	317.5W	3.4E-03
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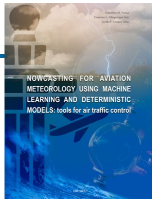
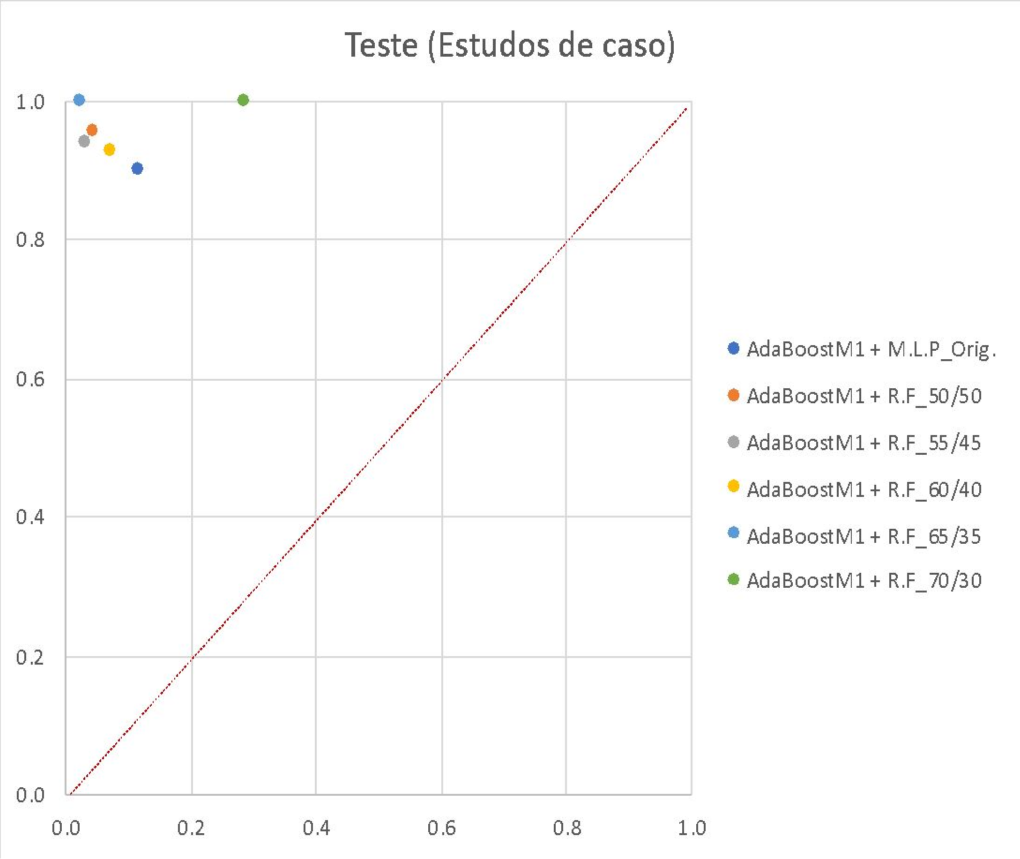
sh	500	-27.5S	322.5W	4.8E-03
sh	600	-22.5S	317.5W	4.9E-03
omega	700	-20S	312.5W	5.7E-03
omega	500	-27.5S	312.5W	6.0E-03
omega	600	-27.5S	312.5W	6.5E-03
omega	700	-27.5S	312.5W	6.7E-03
v	400	-27.5S	322.5W	6.8E-03
sh	400	-20S	320W	7.1E-03
sh	850	-20S	317.5W	7.2E-03
v	700	-25S	322.5W	8.0E-03
sh	500	-25S	320W	8.1E-03
v	500	-25S	322.5W	8.6E-03
omega	850	-20S	310W	8.8E-03
sh	700	-27.5S	322.5W	8.8E-03
u	500	-27.5S	322.5W	8.9E-03
u	700	-22.5S	322.5W	8.9E-03
omega	400	-27.5S	312.5W	9.2E-03
u	850	-22.5S	317.5W	9.4E-03

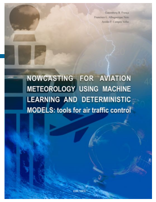
Numerical/Data weather prediction



Hybrid prediction: Differential Eqs. + Data Science

- Machine learning (ML) algorithms - performance:



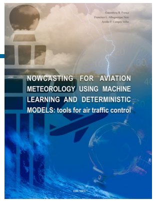


Numerical/Data weather prediction

Hybrid prediction: Differential Eqs. + Data Science

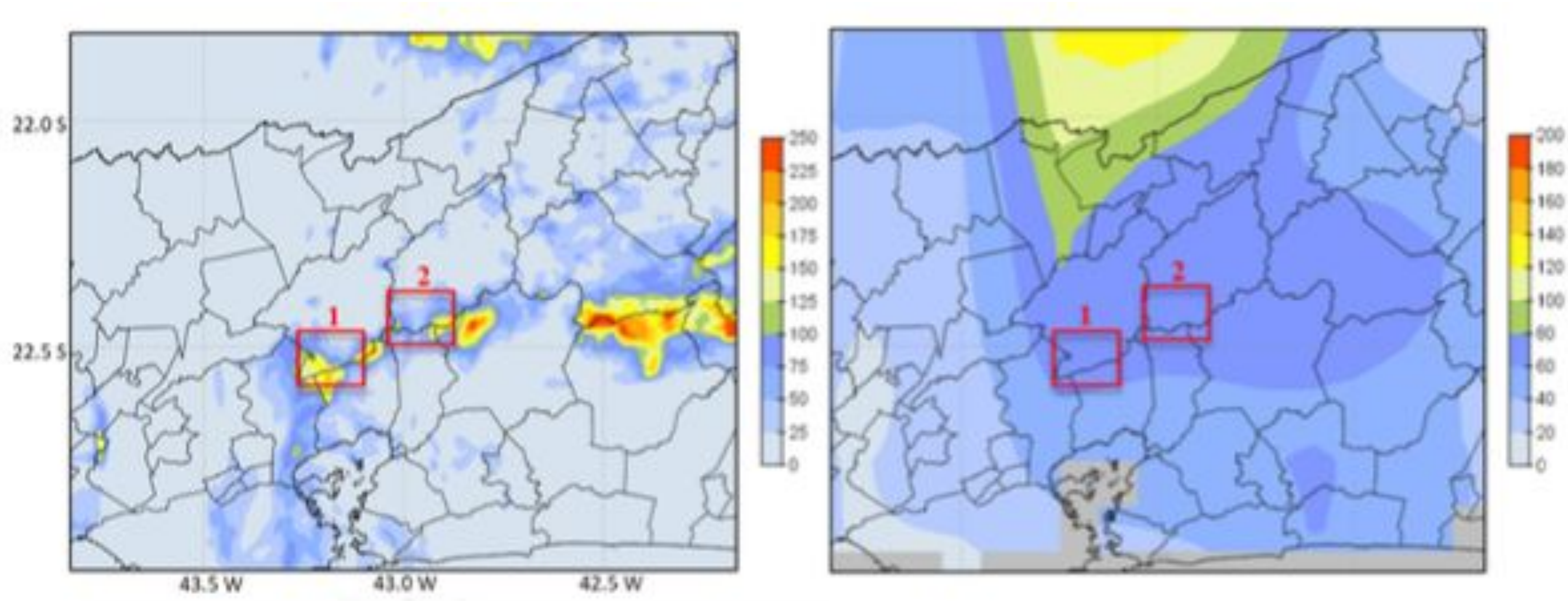
- Extreme event at RJ State mountain region (March/2022)

Numerical/Data weather prediction



Hybrid prediction: Differential Eqs. + Data Science

- Extreme event at RJ State mountain region (March/2022)



Precipitação: (a) WRF (b) Eras-5

Numerical/Data weather prediction

Hybrid prediction: Differential Eqs. + Data Science

- EExtreme event at RJ State mountain region (March/2022)

DAY		20															21									
CITY - AREA		Petrópolis - Area 1																								
HOUR (Local time)		9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	0	1	2	3	4	5	6	7	8	9
OBS	**Mean Hourly Precipitation**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**7.6**	**100.2**	**91.0**	**47.6**	**29.1**	**0.4**	**27.3**	**72**	**67.0**	**28.7**	**22.6**	**17.5**	**7.2**	**3.8**	**1.6**	**1.0**	**0.0**	**0.0**	**0.0**
	Standard Deviation	0.0	0.1	0.0	0.0	0.0	0.0	2.7	9.2	11.4	9.6	9.2	0.6	17	13	12	13.4	9.2	6.3	2.0	2.1	1.9	0.9	0.0	0.0	0.0
	Maximum	0.0	0.2	0.0	0.0	0.0	0.0	11.9	117.1	####	59	37.1	1.4	46	89	84	50.6	33.8	24.7	11.3	7.1	4.8	2.5	0.0	0.0	0.0
	Minimum	0.0	0.0	0.0	0.0	0.0	0.0	4.2	88.8	71.2	30	14.3	0	7.9	56	51	15.8	9.9	9.8	5.5	1.8	0.0	0.0	0.0	0.0	0.0
WRF	**Mean Hourly Precipitation**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**33.7**	**69.4**	**60.1**	**15.0**	**20.2**	**50.4**	**24.6**	**4.5**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Standard Deviation	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.3	7.4	9.8	6.3	7.6	7.9	17	1.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Maximum	0.0	0.0	0.0	0.0	0.0	0.0	0.0	53.1	82.5	75	23.7	30	59	42	7.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Minimum	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.3	63.0	49	9.8	9.9	39	7.9	2.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Event Occurrence		N	N	N	N	N	N	N	Y	Y	Y	Y	N	Y	Y	Y	Y	N	N	N	N	N	N	N	N	N
Models	**NaiveBayes* (6)**																									
	MultilayerPerceptron* (1)																									
	LMT* (4)																									
	RandomForest* (2)																									
	RandomForest* (3)																									
	RandomForest* (4)																									
	RandomForest* (5)																									
	RandomForest* (6)																									

Numerical/Data weather prediction

Hybrid prediction: Differential Eqs. + Data Science

- Extreme event at RJ State mountain region (March/2022)

CITY - AREA		Teresópolis - Area 2																								
HOUR (Local time)		9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	0	1	2	3	4	5	6	7	8	9
OBS	**Mean Hourly Precipitation**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**12.8**	**28.2**	**89.6**	**32.0**	**15.4**	**25.6**	**27.8**	**0.0**	**0.0**	**0.0**	**2.6**	**8.2**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Standard Deviation	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.67	5.8	5.6	6.7	4.0	5.2	17.1	0.0	0.0	0.0	1.6	3.1	0.0	0.0	0.0	0.0	0.0	0.0
	Maximum	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.6	33	97.2	42.8	20.6	32.4	41.8	0.0	0.0	0.0	4.6	12.8	0.0	0.0	0.0	0.0	0.0	0.0
	Minimum	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.3	17.2	80.8	24.3	10.1	18.7	7.9	0.0	0.0	0.0	0.2	3.7	0.0	0.0	0.0	0.0	0.0	0.0
WRF	**Mean Hourly Precipitation**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**15.2**	**60.2**	**30.8**	**22.6**	**11.1**	**18.2**	**0.0**	**0.0**	**0.0**	**0.0**	**14.7**	**3.2**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Standard Deviation	0.0	0.0	0.0	0.0	0.0	0.0	17.7	8.3	16.1	13.9	8.4	17.2	0.0	0.0	0.0	0.0	12.5	5.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Maximum	0.0	0.0	0.0	0.0	0.0	0.0	47.2	63.0	41.8	30.9	22.1	42.5	0.0	0.0	0.0	0.0	33.2	14.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Minimum	0.0	0.0	0.0	0.0	0.0	0.0	5.6	42.2	1.1	0.4	0.0	1.8	0.0	0.0	0.0	0.0	2.4	1.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Event Occurrence		N	N	N	N	N	N	N	N	Y	Y	Y	N	Y	Y	N	N	N	N	N	N	N	N	N	N	N
Models	**NaiveBayes* (6)**																									
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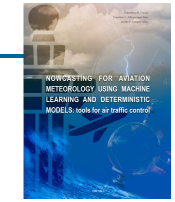
Numerical/Data weather prediction

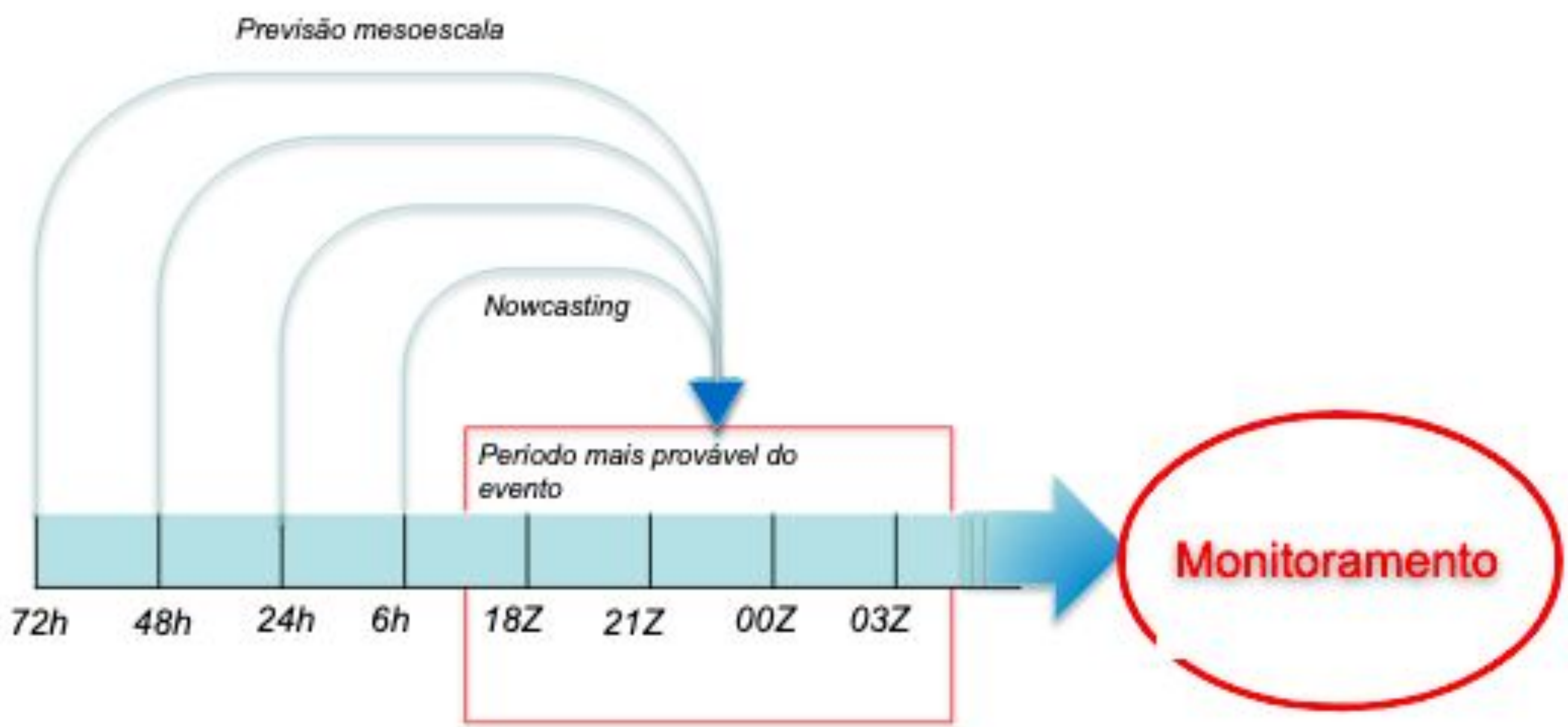


Hybrid prediction: Differential Eqs. + Data Science

Modelos	24 horas			48 horas			72 horas		
	POD	FAR	CSI	POD	FAR	CSI	POD	FAR	CSI
NaiveBayes* (6)	0.88	0.12	0.78	0.86	0.25	0.67	0.69	0.32	0.52
MultilayerPerceptron* (1)	0.89	0.11	0.80	0.89	0.20	0.73	0.73	0.31	0.55
LMT* (4)	0.89	0.07	0.84	0.70	0.30	0.54	0.61	0.39	0.44
RandomForest* (2)	0.93	0.07	0.88	0.80	0.11	0.73	0.73	0.30	0.56
RandomForest* (3)	0.90	0.04	0.90	0.86	0.25	0.67	0.74	0.29	0.59
RandomForest* (4)	0.95	0.03	0.92	0.90	0.18	0.75	0.78	0.28	0.63
RandomForest* (5)	**0.97**	**0.02**	**0.94**	**0.92**	**0.11**	**0.82**	**0.77**	**0.25**	**0.65**
RandomForest* (6)	0.95	0.09	0.86	0.84	0.17	0.72	0.75	0.30	0.58

Numerical/Data weather prediction

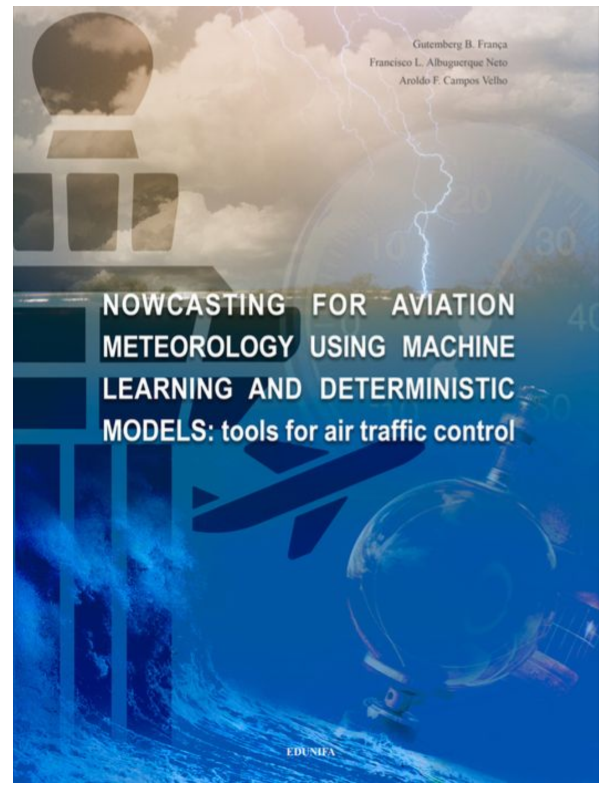
Hybrid prediction: Differential Eqs. + Data Science



Numerical/Data weather prediction

Hybrid prediction: Differential Eqs. + Data Science

Book:
Compilation of computacional methods for nowcasting with focus on commercial aviation traffic.



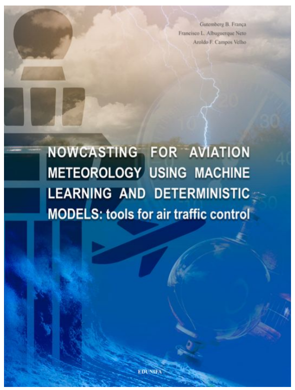
A person to say thank you

Prof. Ubidio Rubio
Universidad Nacional de Trujillo
President of the SPMAC

SPMAC: Sociedad Peruana de Matemática Aplicada y Computacional

Numerical Weather Prediction

Hybrid prediction: Differential Eqs. + Data Science

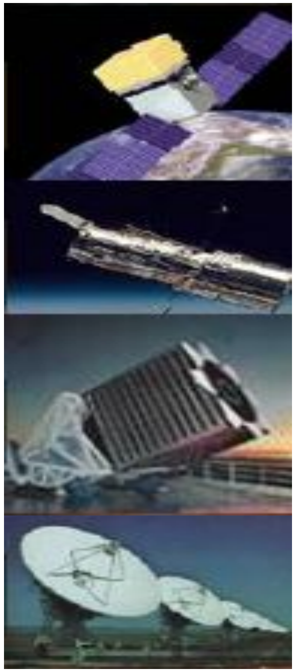


Gracias!

Why VO?

Traditional (old faschion) scheme in astronomy:

1. The astronomer asks a time to use a telescope
2. The astronomer colects his/her data
3. Data analysis for colected data: publishing a report (paper)



New schemes:

1. One observatory does a survey of astronomical data
2. Astronomical community can access the data
3. Which is the most efficient strategy to share data?

Astronomical survey

Sloan Digital Sky Survey

SDSS

Goal

Create the most detailed map of the Northern sky

"The Cosmic Genome Project"

Two surveys in one

Photometric survey in 5 bands

Spectroscopic redshift survey

Automated data reduction

150 man-years of development

High data volume

40 TB of raw data

5 TB processed catalogs

Data is public

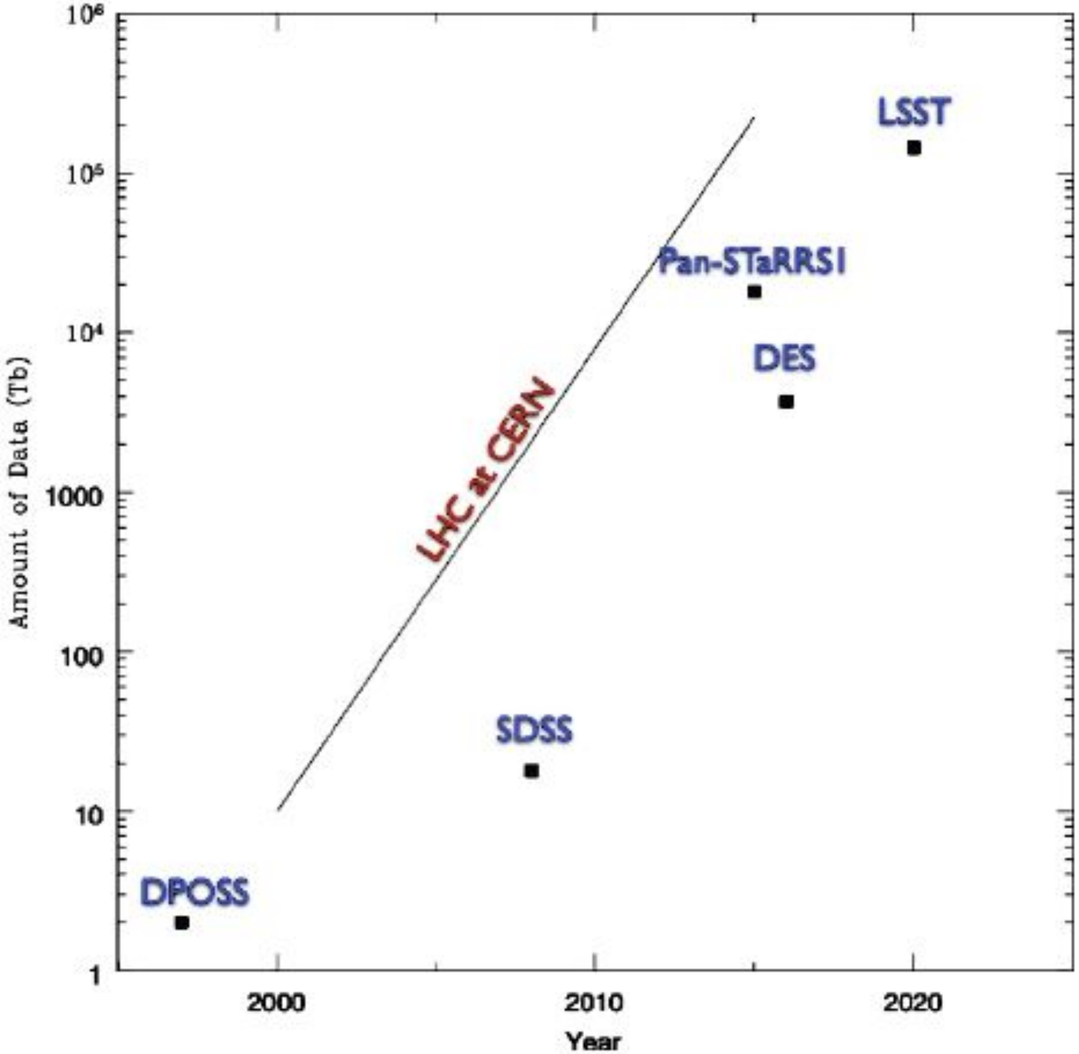
2.5 Terapixels of images

The University of Chicago
Princeton University
The Johns Hopkins University
The University of Washington
New Mexico State University
Fermi National Accelerator Laboratory
US Naval Observatory
The Japanese Participation Group
The Institute for Advanced Study
Max Planck Inst, Heidelberg

Sloan Foundation, NSF, DOE, NASA

From: Alex Szalay, AustraliAsia e-Research Conference, 2007

Increase of astronomical data



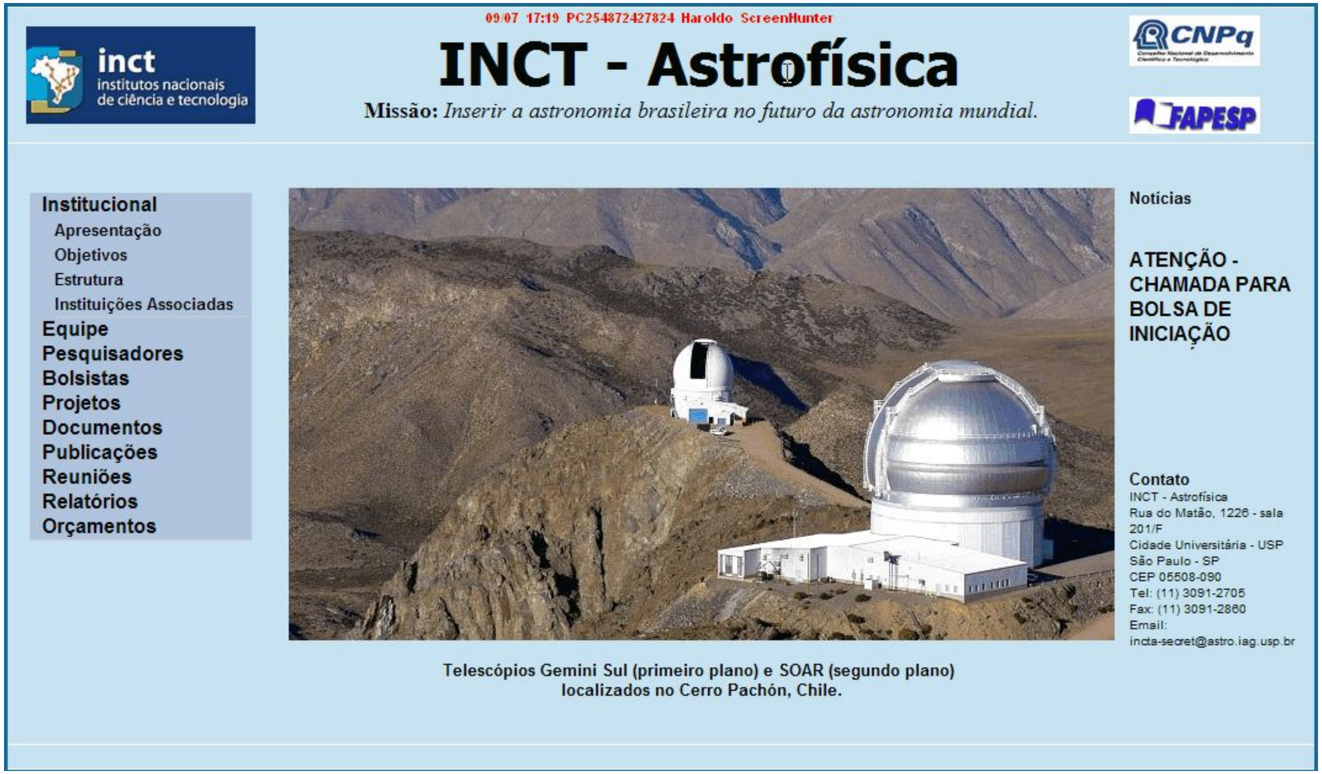
VO communities: IVOA

From: http://www.ivoa.net/

The BraVO project

Declaration of intentions: signed at August 18, 2006

The super-structure: INCT-Astrophysics



http://www.astro.iag.usp.br/~incta/

Brazilian effort for VO: The BraVO project

http://www.lna.br/bravo

Instituto de Astronomia, Geofísica e Ciências Atmosféricas
Departamento de Astronomia

INPE
Talk to us
BRAVO
Brazilian Virtual Observatory @ INPE

SOARVO
SOAR TELESCOPE
The Southern Astrophysical Research Telescope Virtual Observatory

SEAGal

Starlight
Spectral Synthesis Code

GRUPO DE ASTROFÍSICA
GAS - UFSC
BRASIL

Cyclops
Cyclotron Emission of Polars

INPE
MINISTÉRIO DA CIÊNCIA E TECNOLOGIA
INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS

The BraVO project

Description

PAN-AMERICAN ASSOCIATION OF COMPUTATIONAL INTERDISCIPLINARY SCIENCES

Journal of Computational Interdisciplinary Sciences (2009) 1(3): 187-206

ISSN 1983-8409
http://epacis.org

The Brazilian Virtual Observatory – A New Paradigm for Astronomy

R.R. de Carvalho[1], R.R. Gal[2], H.F. de Campos Velho[1], H.V. Capelato[1], F. La Barbera[3], E.C. Vasconcellos[1], R.S.R. Ruiz[1], J.L. Kohl-Moreira[4], P.A.A. Lopes[5] and M. Soares-Santos[6]

Manuscript received on September 09, 2009 / accepted on January 20, 2010

http://epacis.org/jcis.php

BraVO@INPE

2. Decision tree for astronomical data classification

Classification Star/galaxy is not easy task!

BraVO@INPE

2. Decision tree for astronomical data classification

Classification

Star/galaxy

It is not easy task

See the figure:

(a) Easy

BraVO@INPE

2. Decision tree for astronomical data classification

Classification

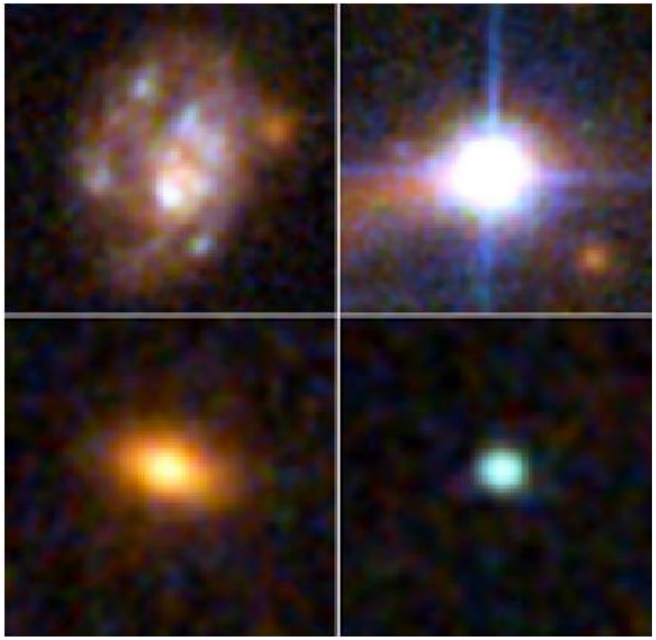
Star/galaxy

It is not easy task

See the figure:

(a) Easy

(b) More complicated



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2. Decision tree for astronomical data classification

Classification

Star/galaxy

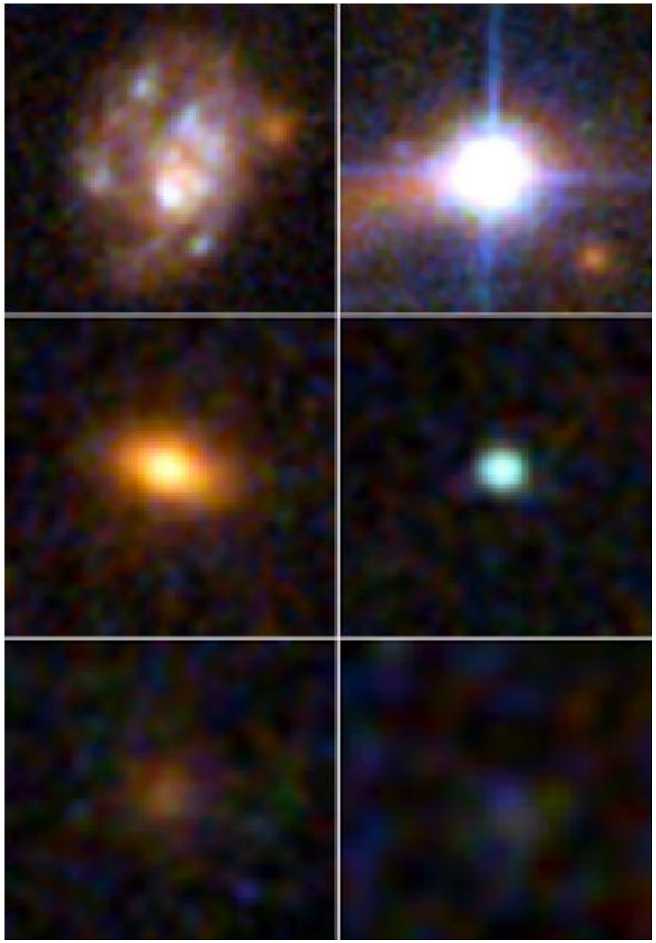
It is not easy task

See the figure:

(a) Easy

(b) More complicated

(c) How to classify?



BraVO@INPE

The Astronomical Journal, 141:189 (12pp), 2011 June
doi:10.1088/0004-6256/141/6/189

DECISION TREE CLASSIFIERS FOR STAR/GALAXY SEPARATION

E. C. Vasconcellos[1], R. R. de Carvalho[2], R. R. Gal[3], F. L. LaBarbera[4], H. V. Capelato[2], H. Frago Campos Velho[5], M. Trevisan[6], and R. S. R. Ruiz[1]
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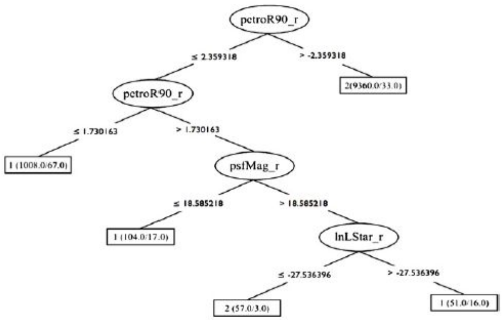

(with use of committee machine)