MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E INOVAÇÃO
INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS
São José dos Campos, SP, BRAZIL

ASTRONOMY WORKSHOP 2016
BRICS
7-9 Sep, Russia

Improving intensive data analysis in astronomy using many-core heterogeneous computing

Reinaldo R. Rosa
Computational Space Physics Program (GFEC)
Lab for Computing and Applied Math (LAC)
reinaldo.rosa @pq.cnpq.br / rrrosa.inpe@gmail.com

R.R. de Carvalho, M.D. Weinberg, G. Mamon, A. Krone-Martins, M. Soares-Santos,
F. La Barbera, J.I. Silk,
D. Stalder, A. Bonfim, R. Bertollini, R. Sautter & N. Joshi

http://cosmobook.com.br/

1. *Morphology* in Gravitational Physics (50 Kpc-150Mpc)
2. **Big Data**: Computational Features Required
3. *U-Morphometrika* : Applications & Preliminary Results

FAPESP
CNPq Conselho Nacional de Desenvolvimento Científico e Tecnológico
CAPES
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1. *Morphology* in Gravitational Physics (50 Kpc-150Mpc) $>128^2$
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1. *Morphology* in Gravitational Physics (50 Kpc-150Mpc) $>128^2$ $>256^3$
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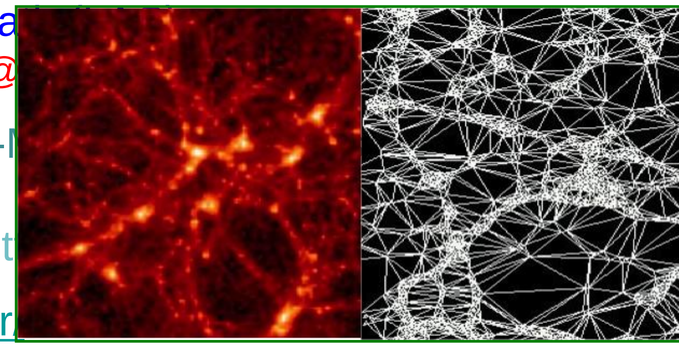

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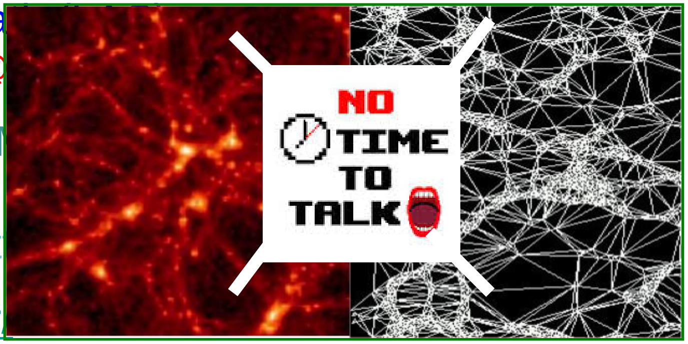

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NO TIME TO TALK

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DATA SCIENCE (Holt et al. 2010) ➔ relevant scientific discoveries and its theoretical paradigm evolution depend on intensive analysis and high resolution interpretation on ***BIG DATA*** ***(ex. CMB and Supernova)***

1. *Morpholog*
2. **Big Data**: C
3. *U-Morphometrika* : Applications & Preliminary Results

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Morphology in Gravitational Physics

- Interdisciplinary Approach:
  - Extragalactic Astrophysics & Cosmology
  - Big Data & Data Science
  - Computational Statistical Analysis
  - High Performance Computing

- Imaging Processing ➔ Structural Analysis (space, time and frequency)

  ➔ Pattern Recognition / Classification (data science paradigm)

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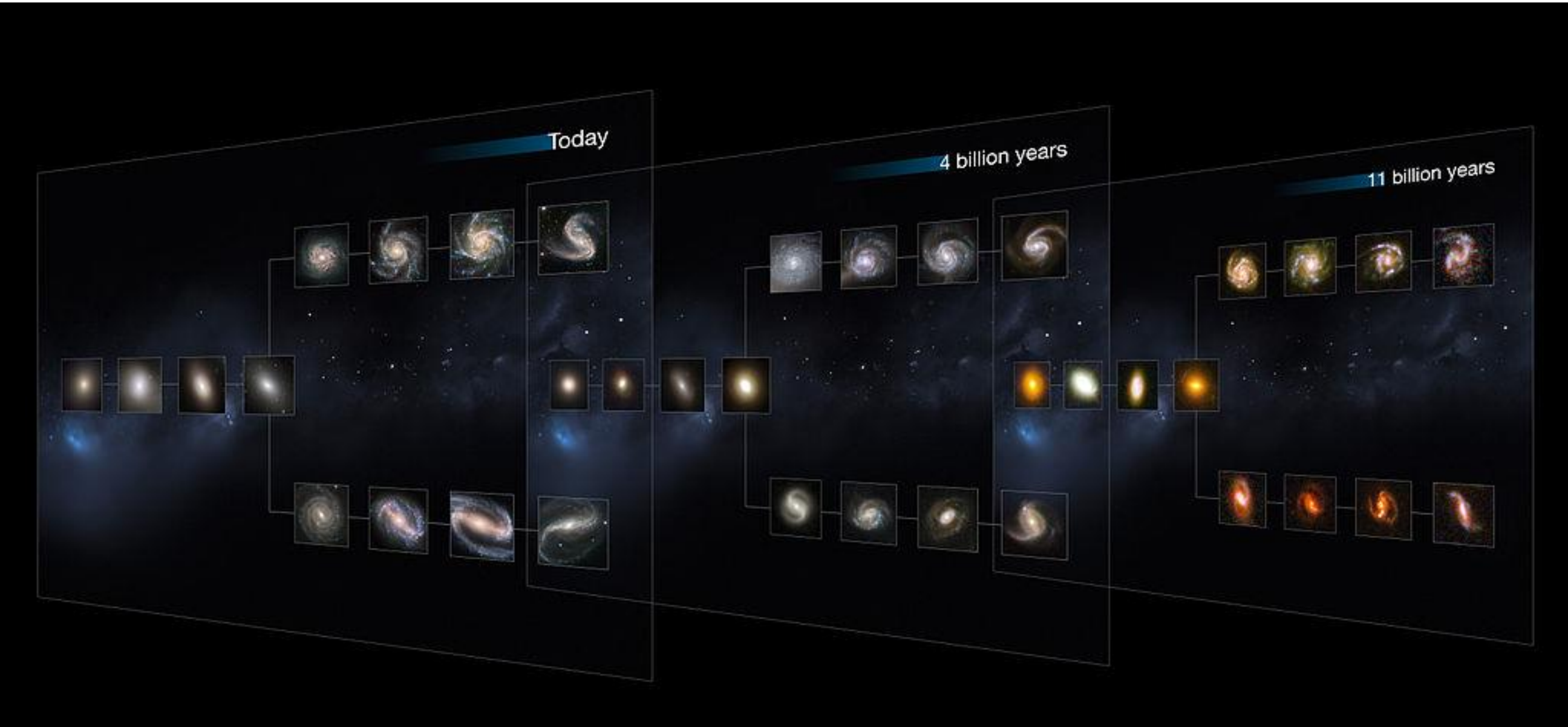

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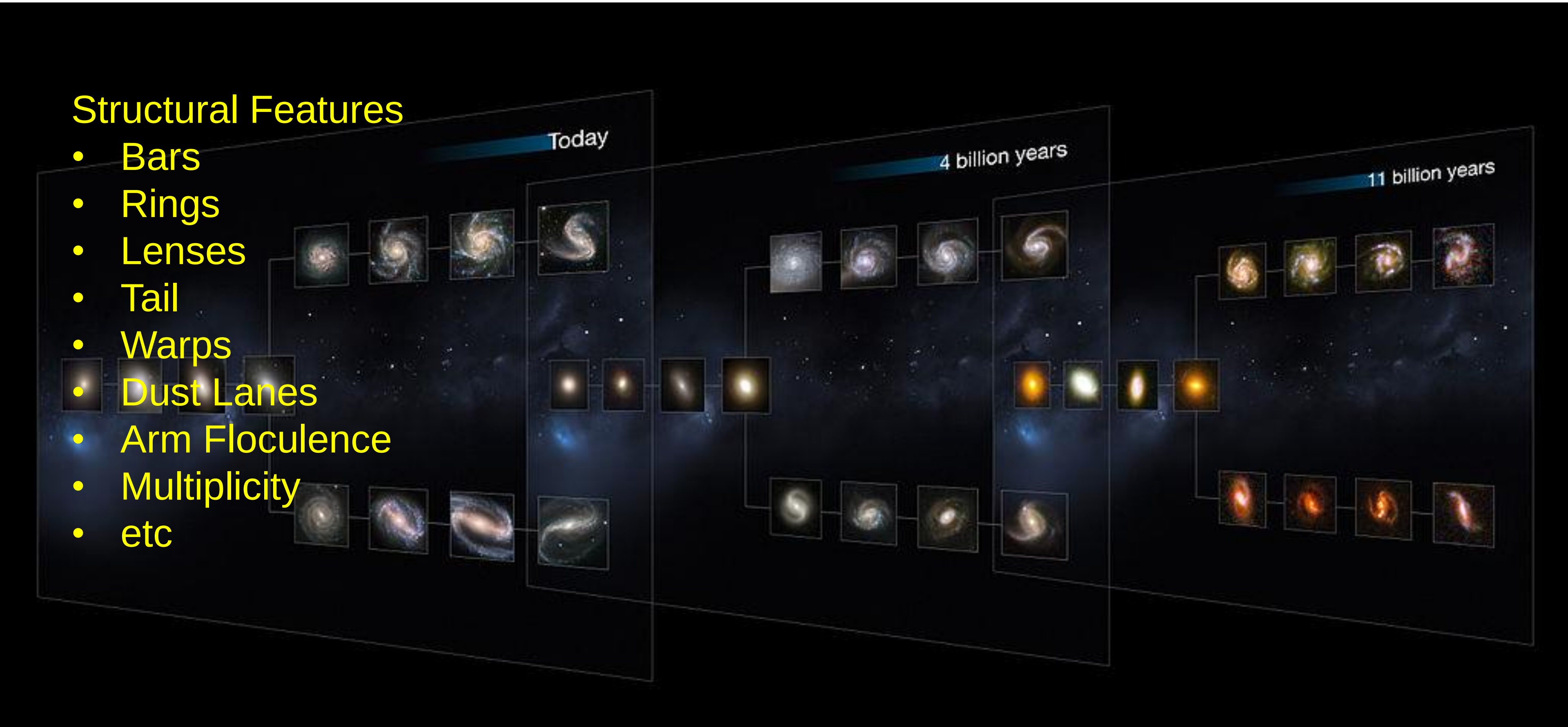

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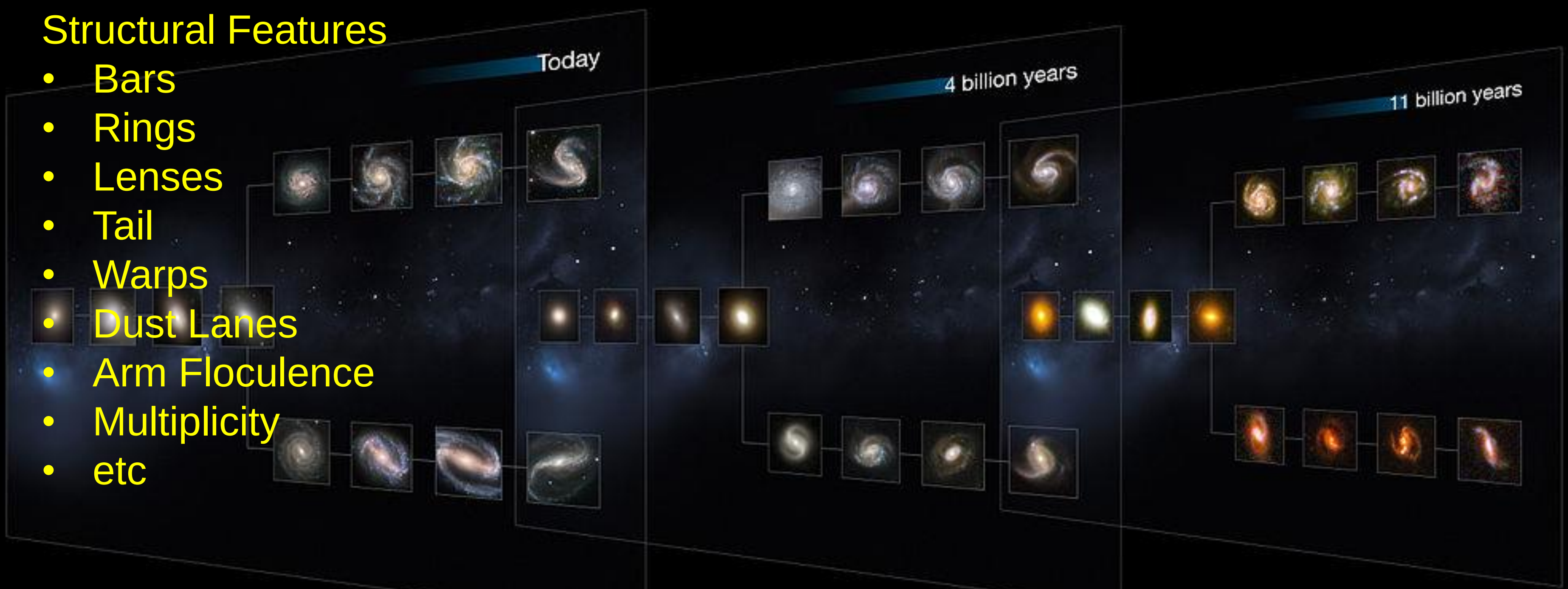
Structural Features
- Bars
- Rings
- Lenses
- Tail
- Warps
- Dust Lanes
- Arm Floculence
- Multiplicity
- etc



How to characterize the structural environment of a galaxy for Data Science?

Morphology in Gravitational Physics

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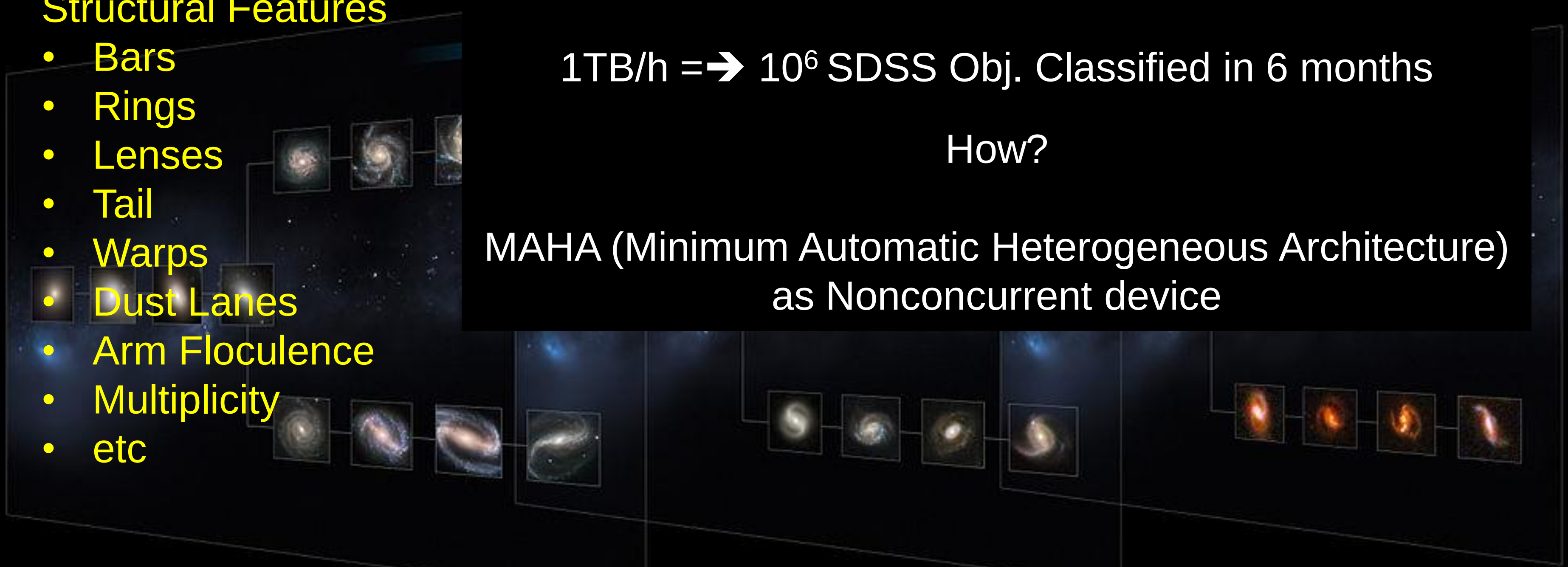

Big Data: Volume, Velocity, Variety and Value

1TB/h =➔ 10^6 SDSS Obj. Classified in 6 months

How?

MAHA (Minimum Automatic Heterogeneous Architecture)
as Nonconcurrent device

Structural Features

- Bars
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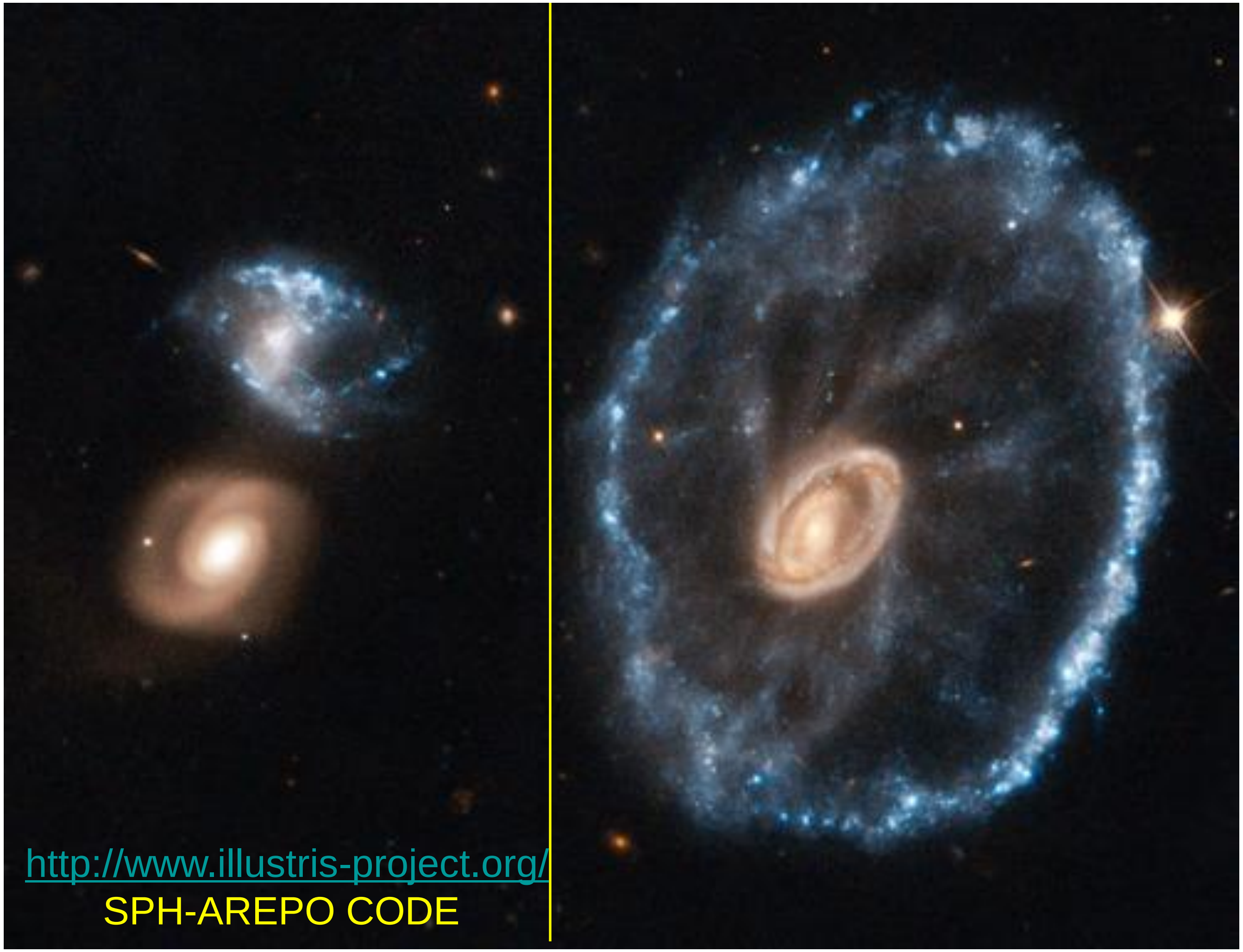
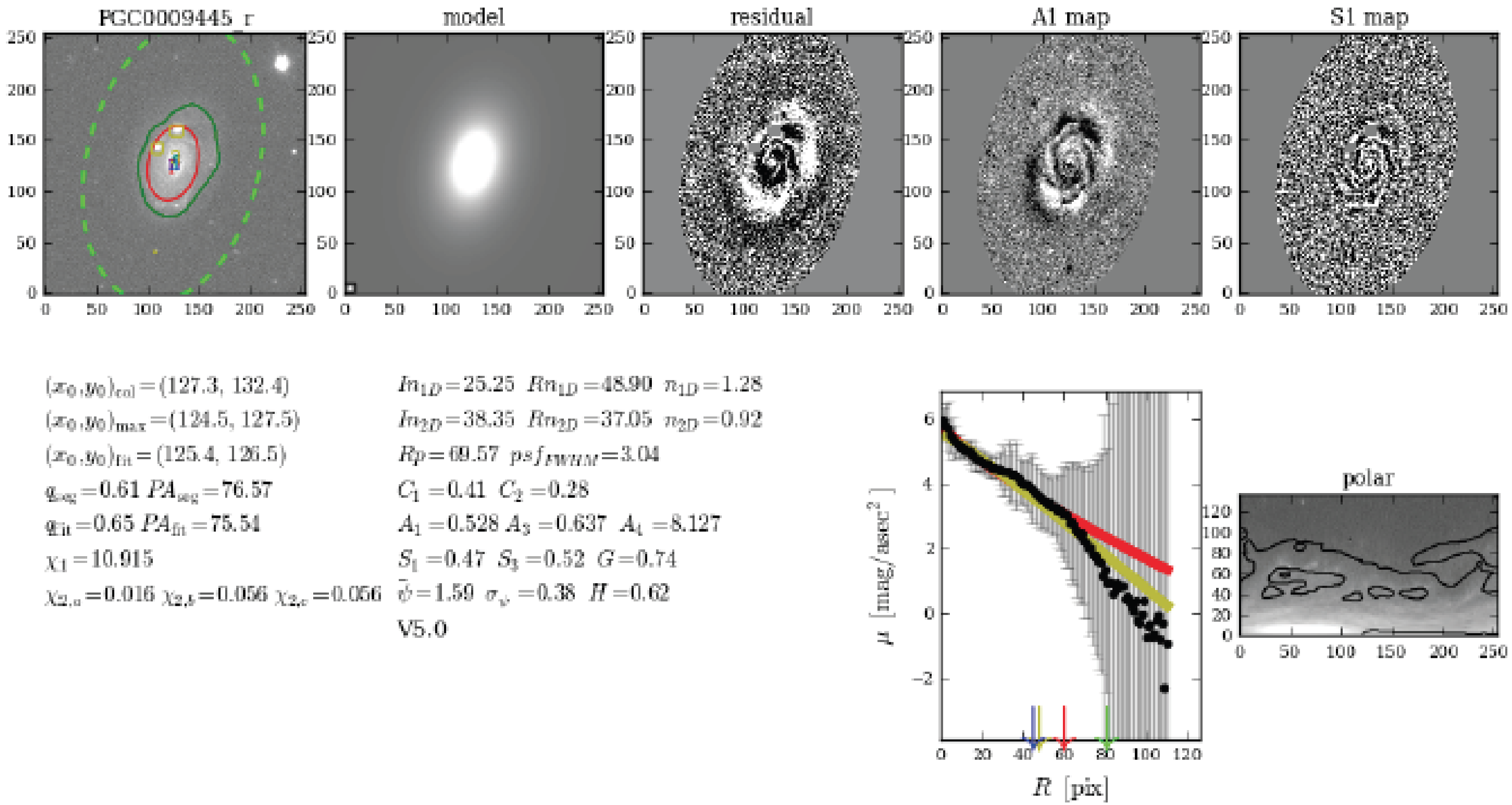
- etc

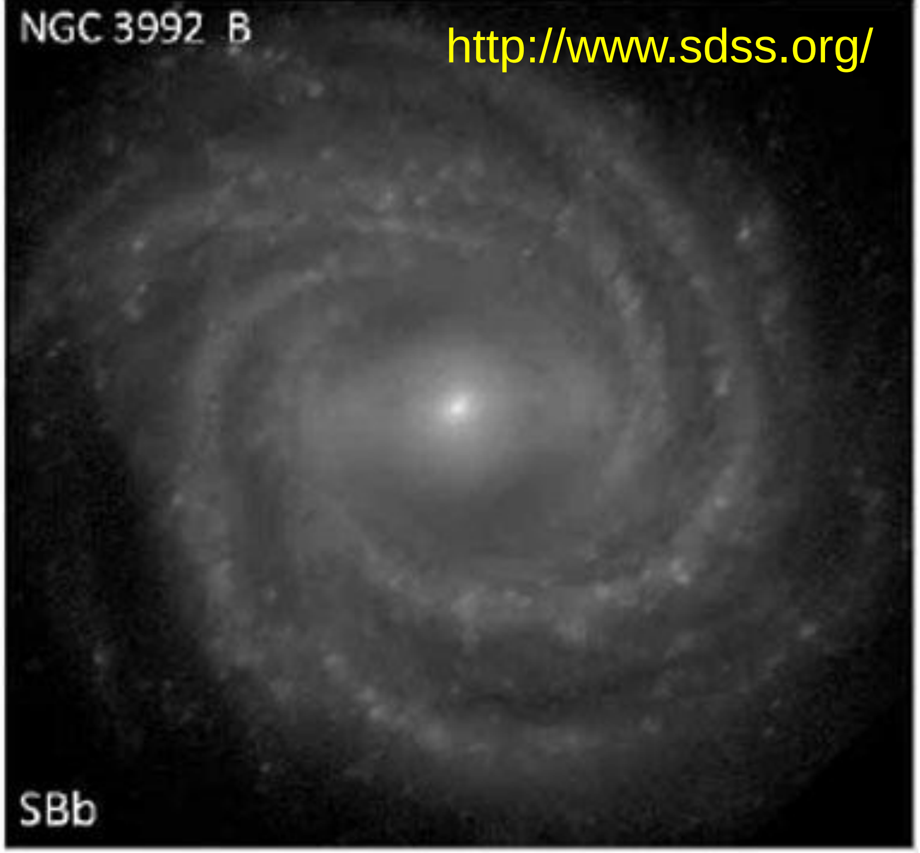
How to characterize the structural environment of a galaxy for Data Science?

MORPHOLOGICAL CLASSIFICATION IS NOT A SIMPLE TASK!!

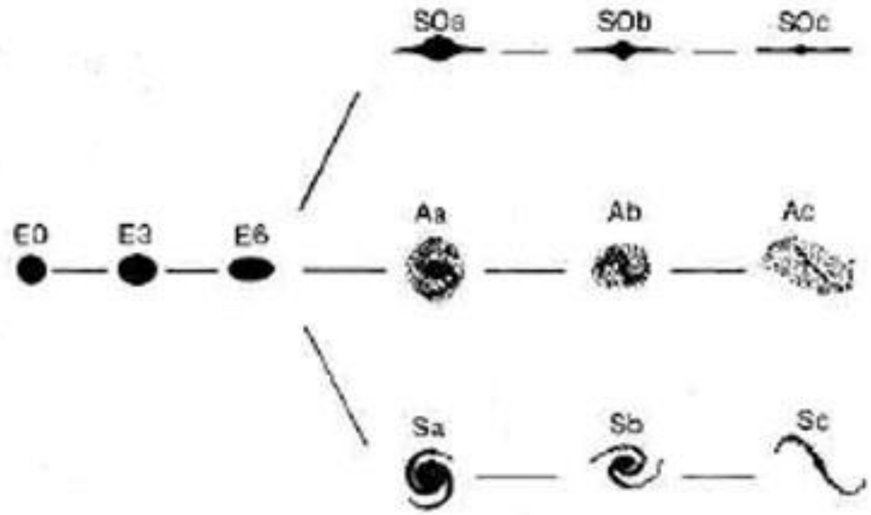


MORPHOLOGICAL CLASSIFICATION IS NOT A SIMPLE **COMPUTATIONAL** TASK!!





http://www.sdss.org/



Structural Features

- Bars
- Arms
- Floculence

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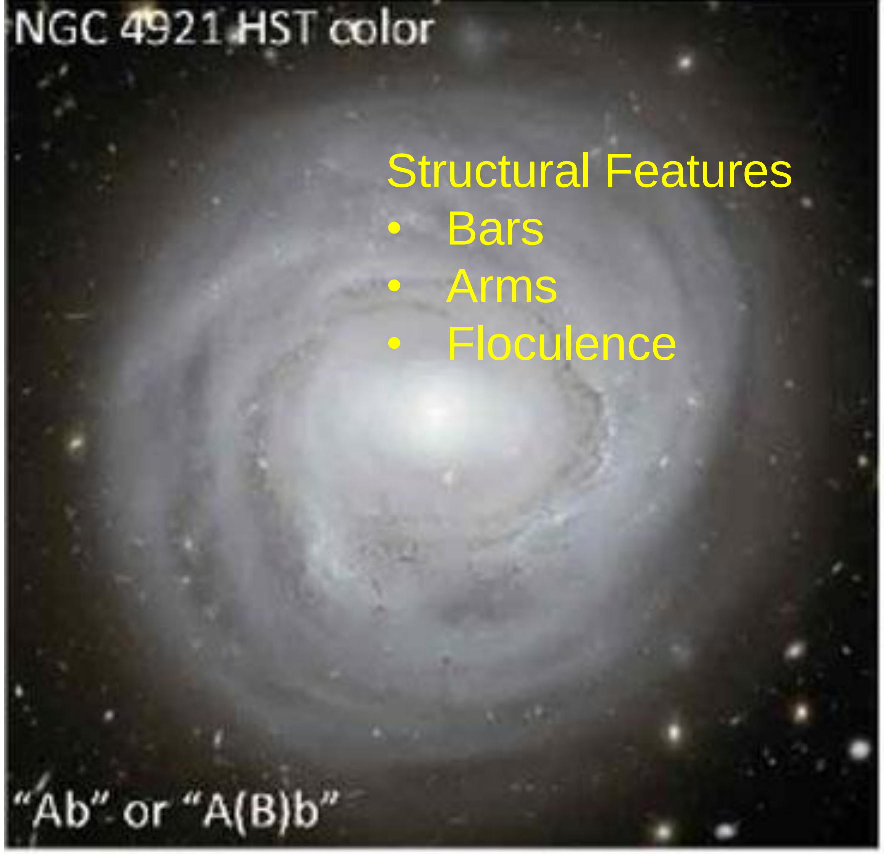

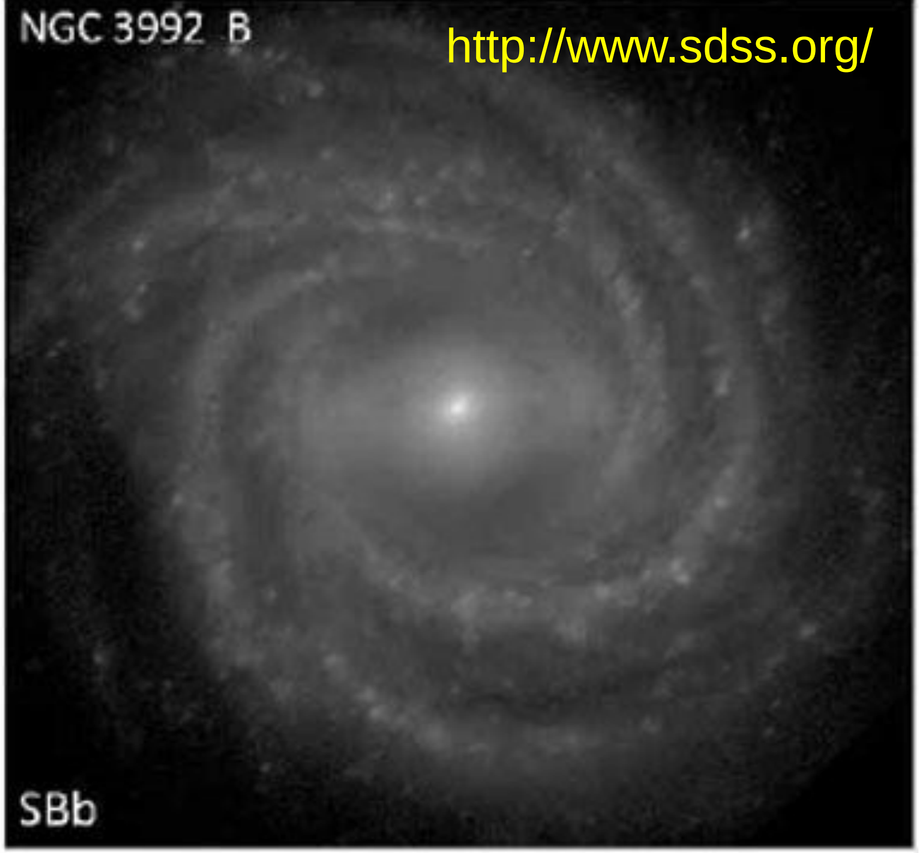

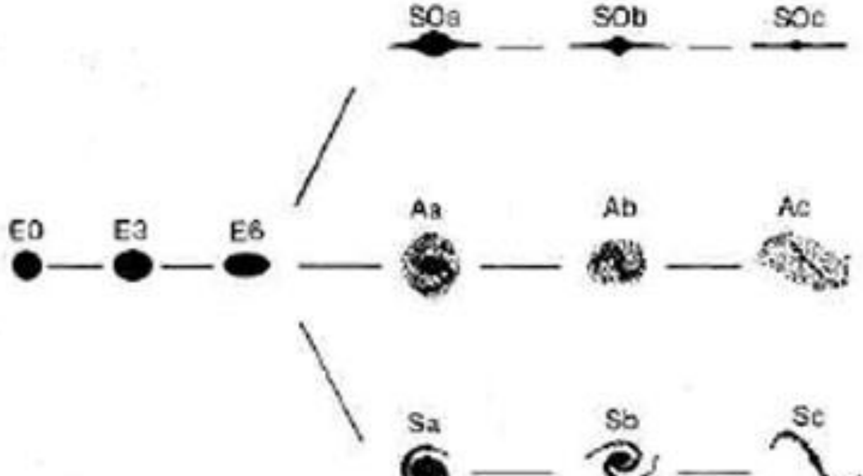

Structural Features
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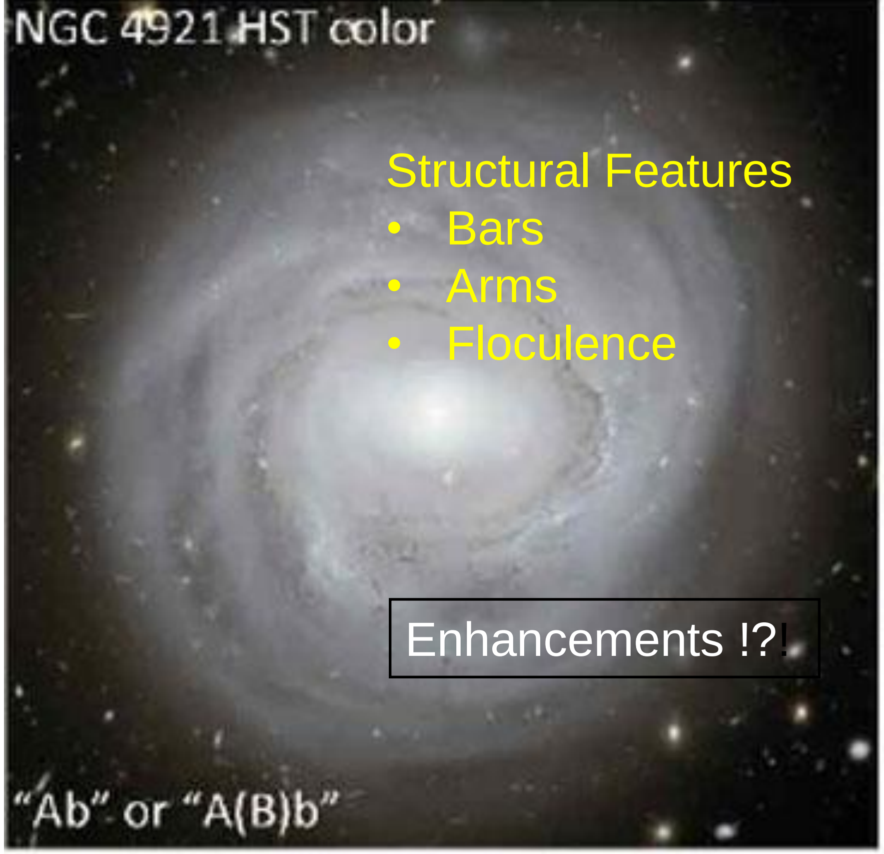
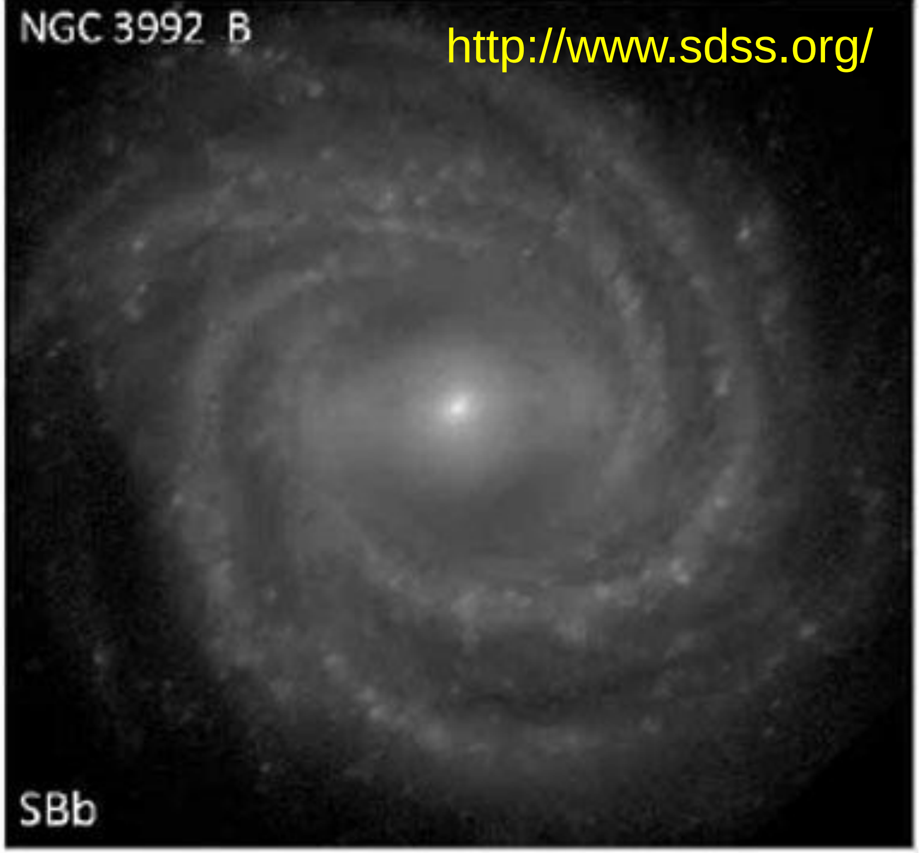
Enhancements !?!





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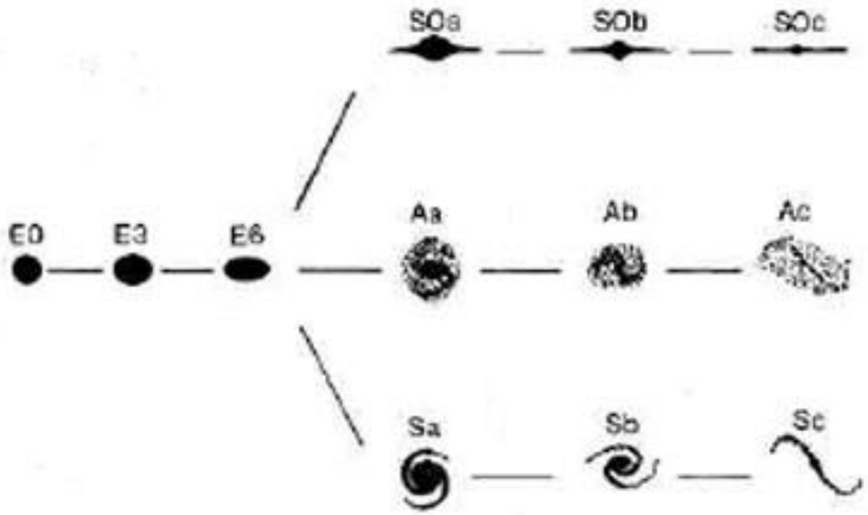

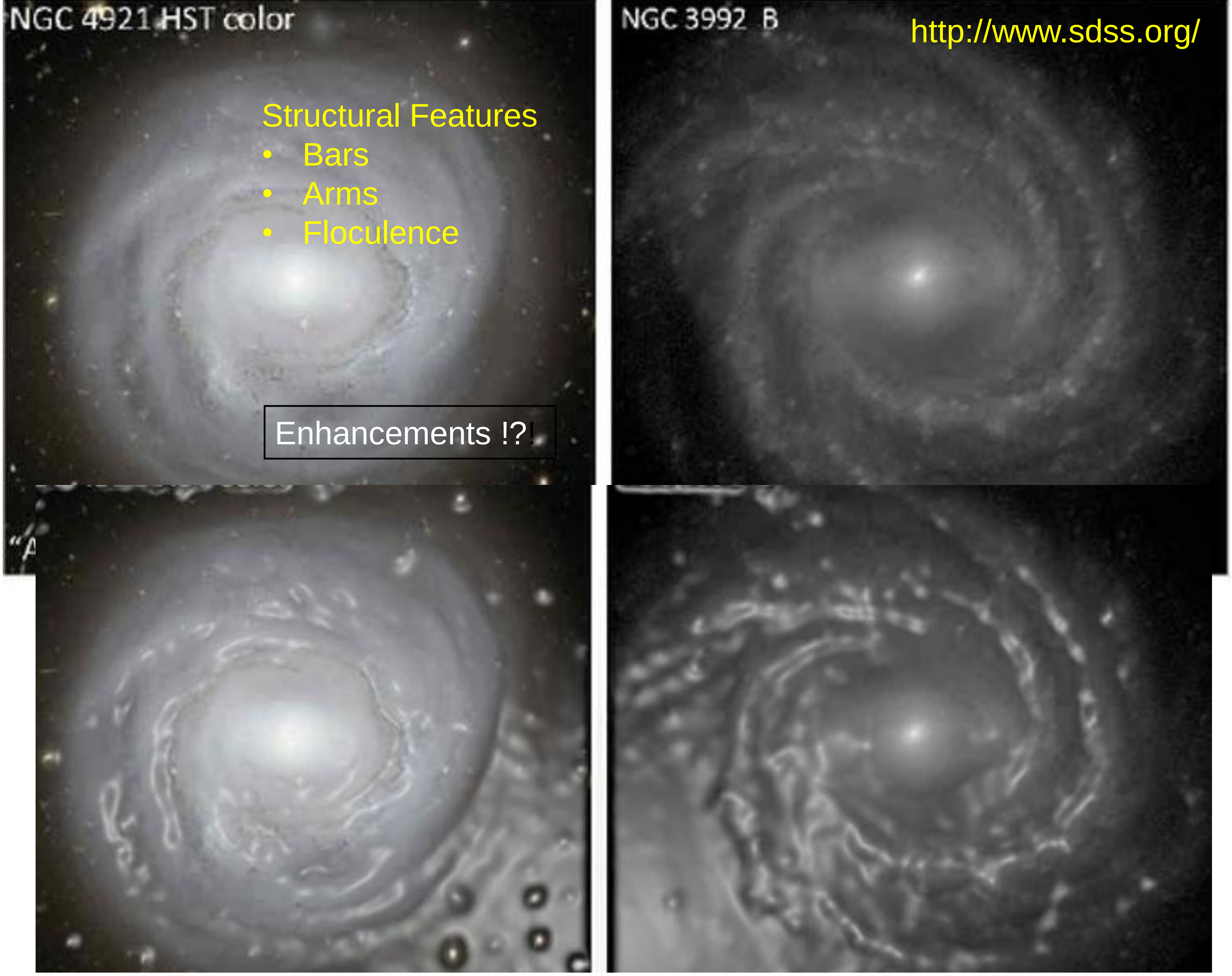
NGC 4921 HST color
NGC 3992 B
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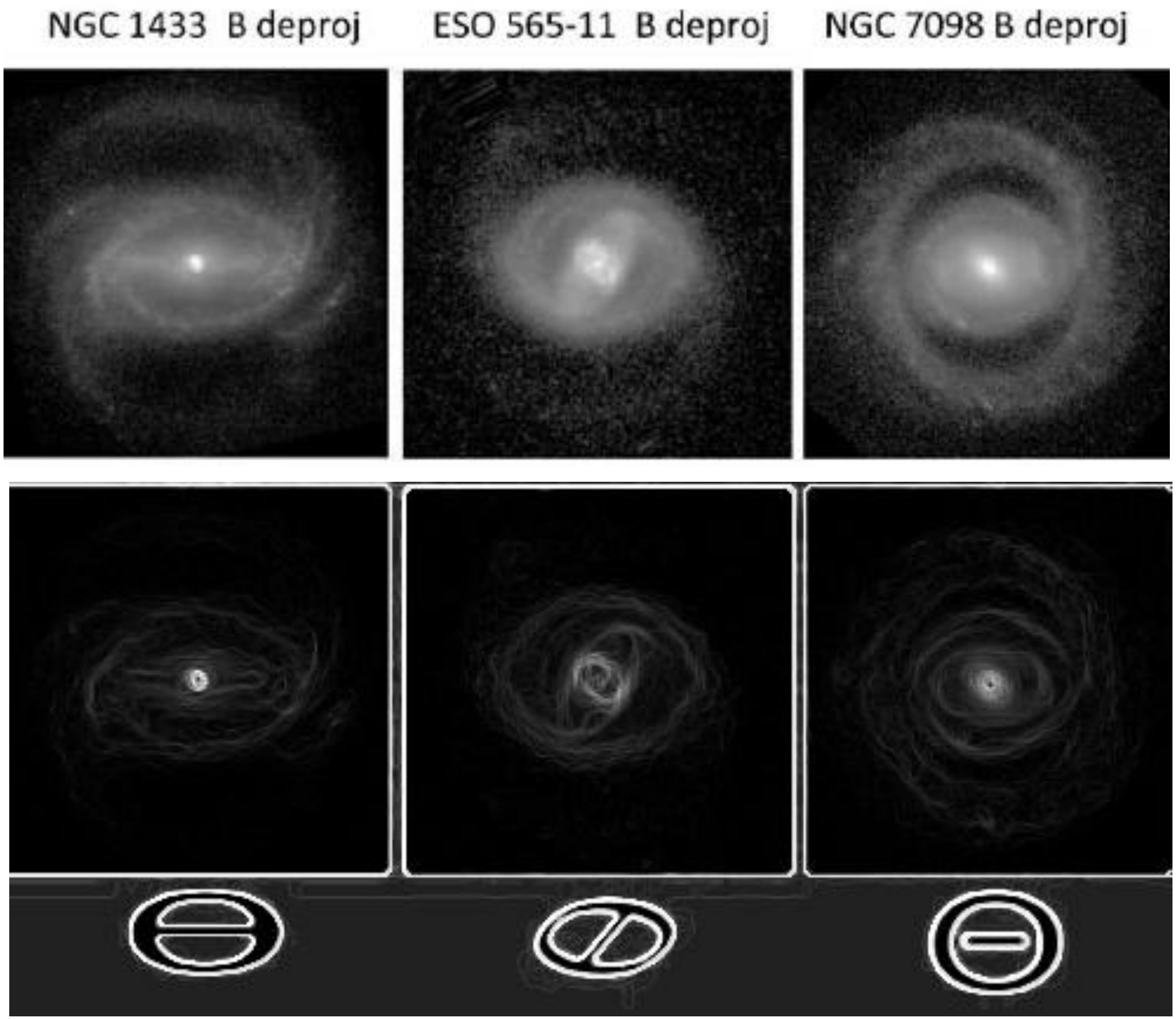

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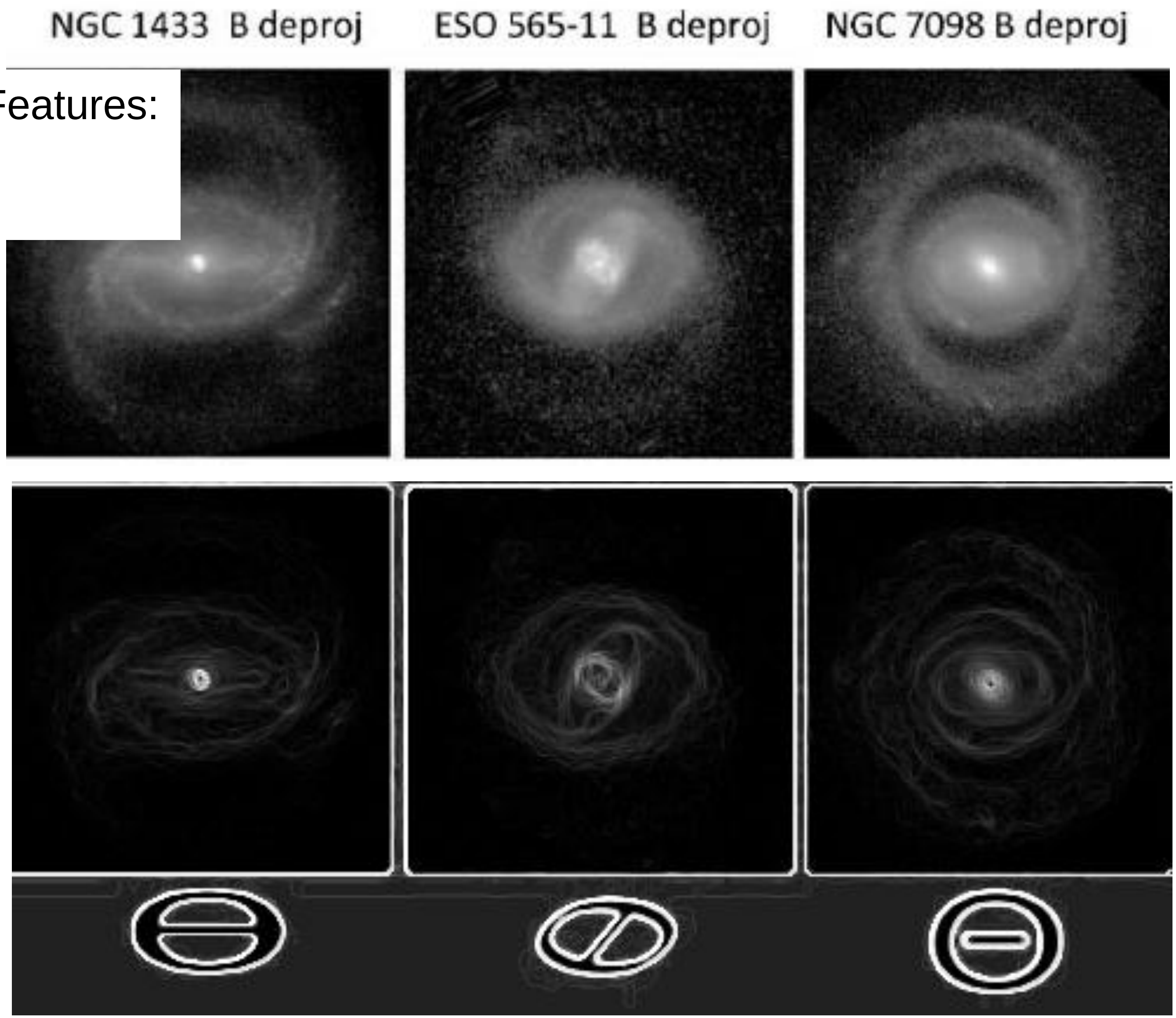

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Structural Features:

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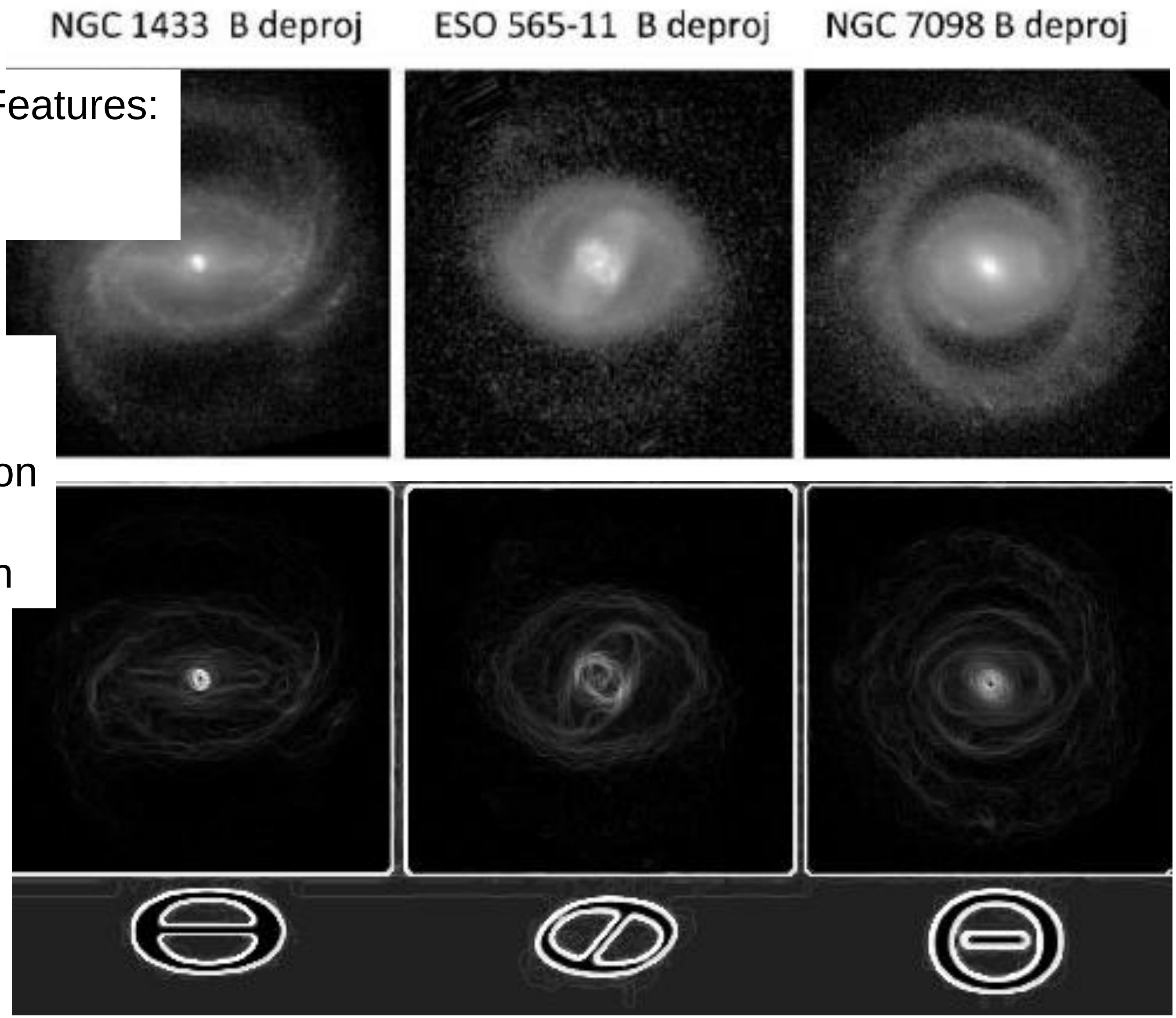
Filtering

&

Segmentation

&

Information



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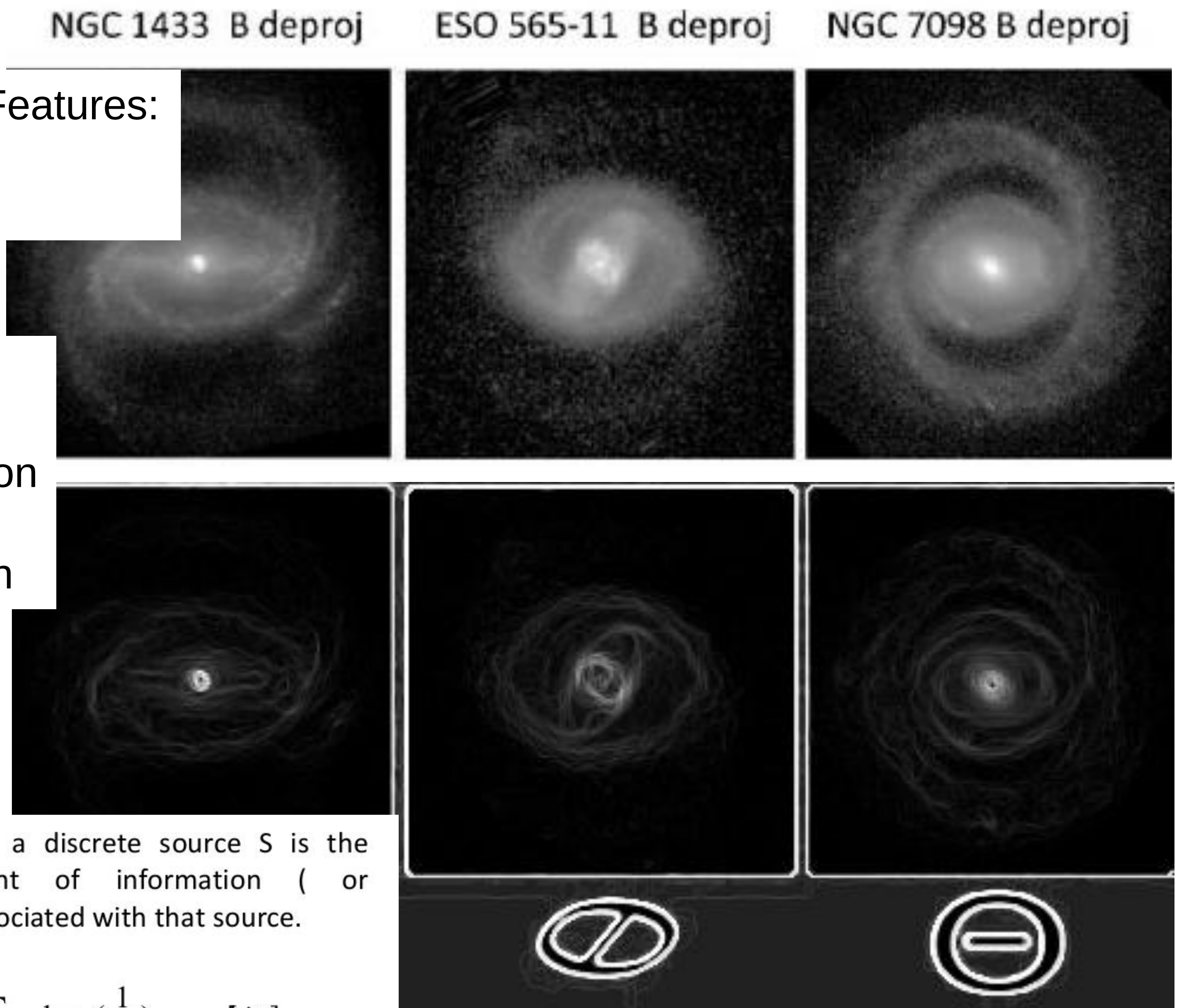

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$$H(s) = \sum_{j=1}^{m} p_j \log_2\left(\frac{1}{p_j}\right) \qquad [bits]$$

- m = number of possible outcomes
- Pj = probability of the j^{th} message

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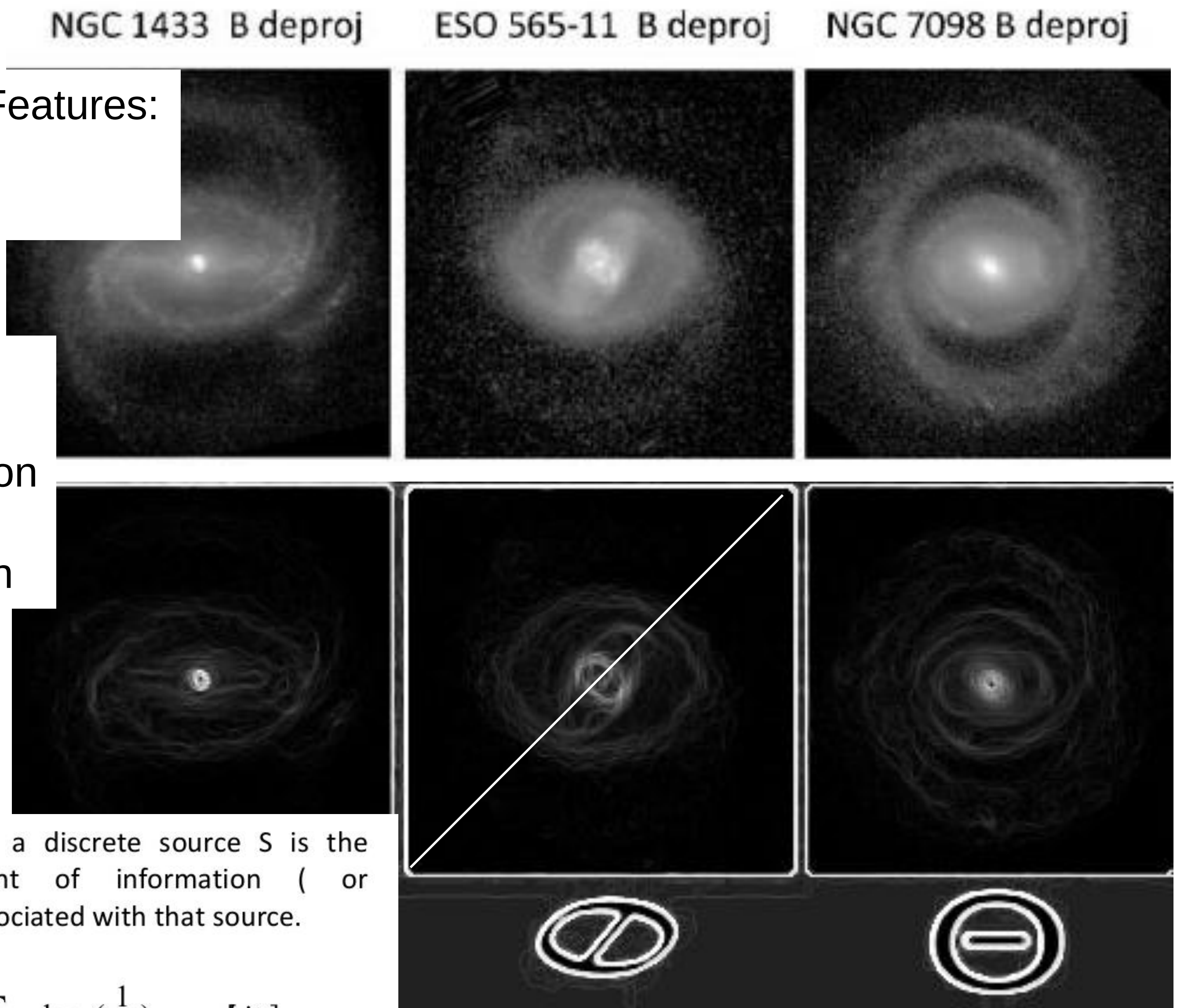

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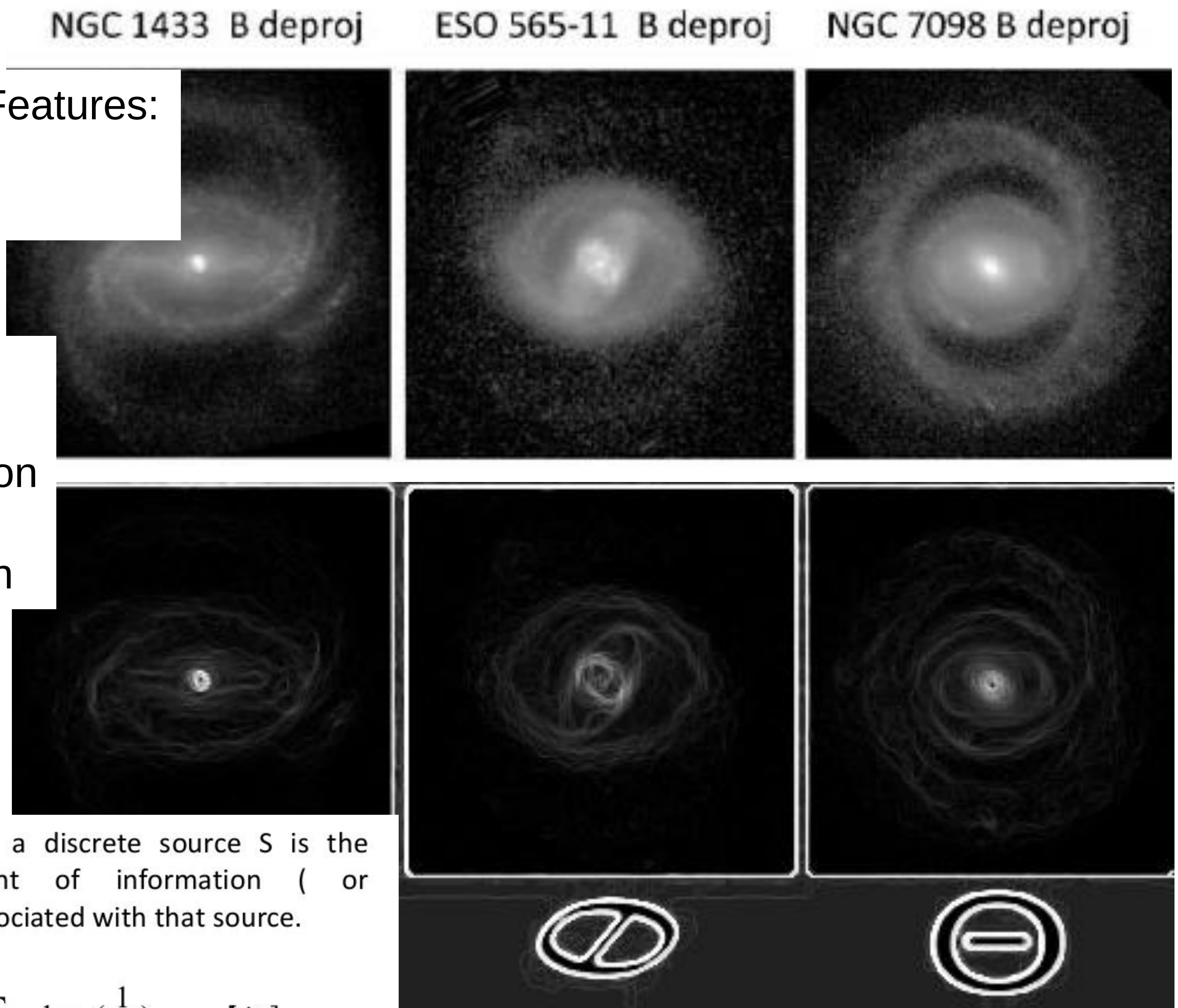

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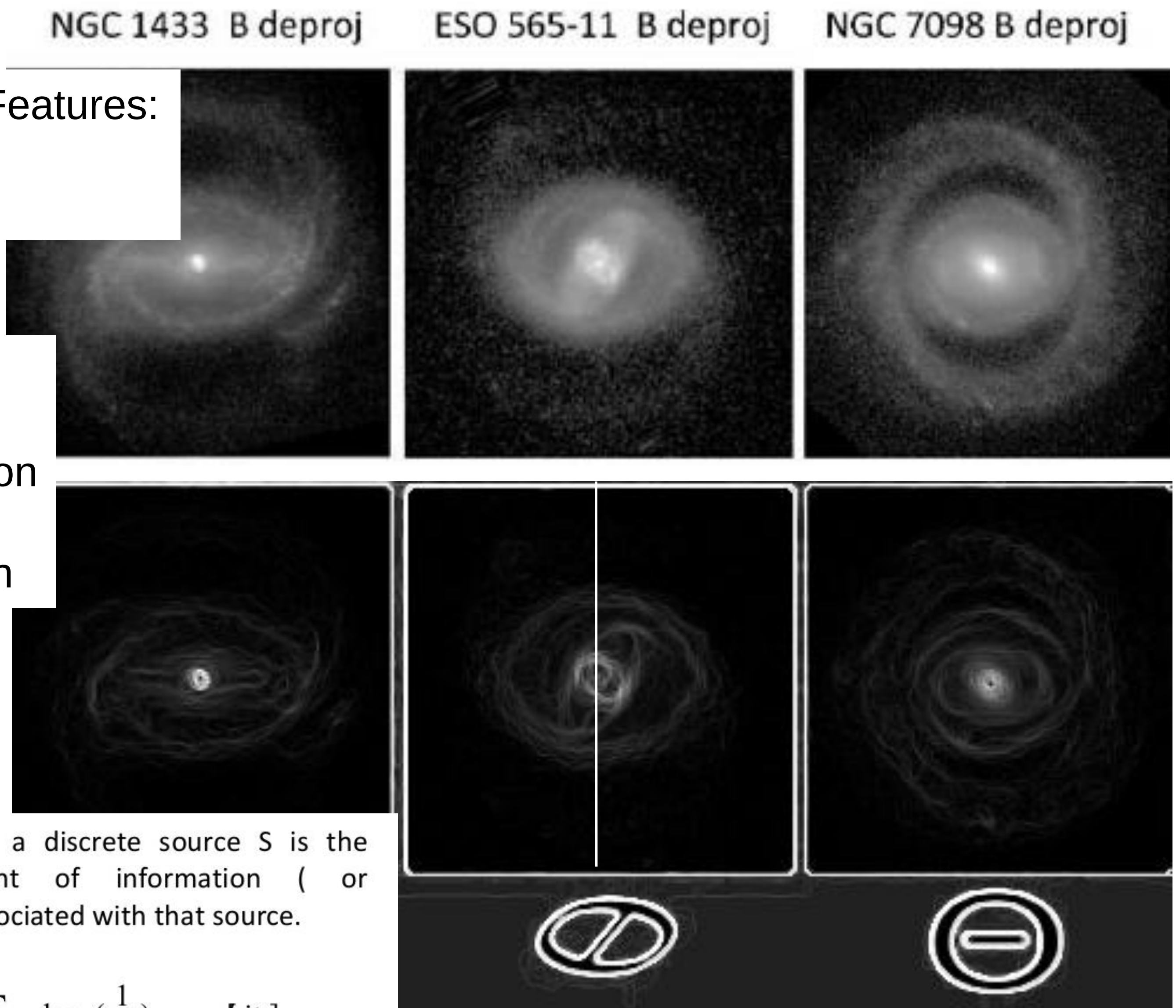

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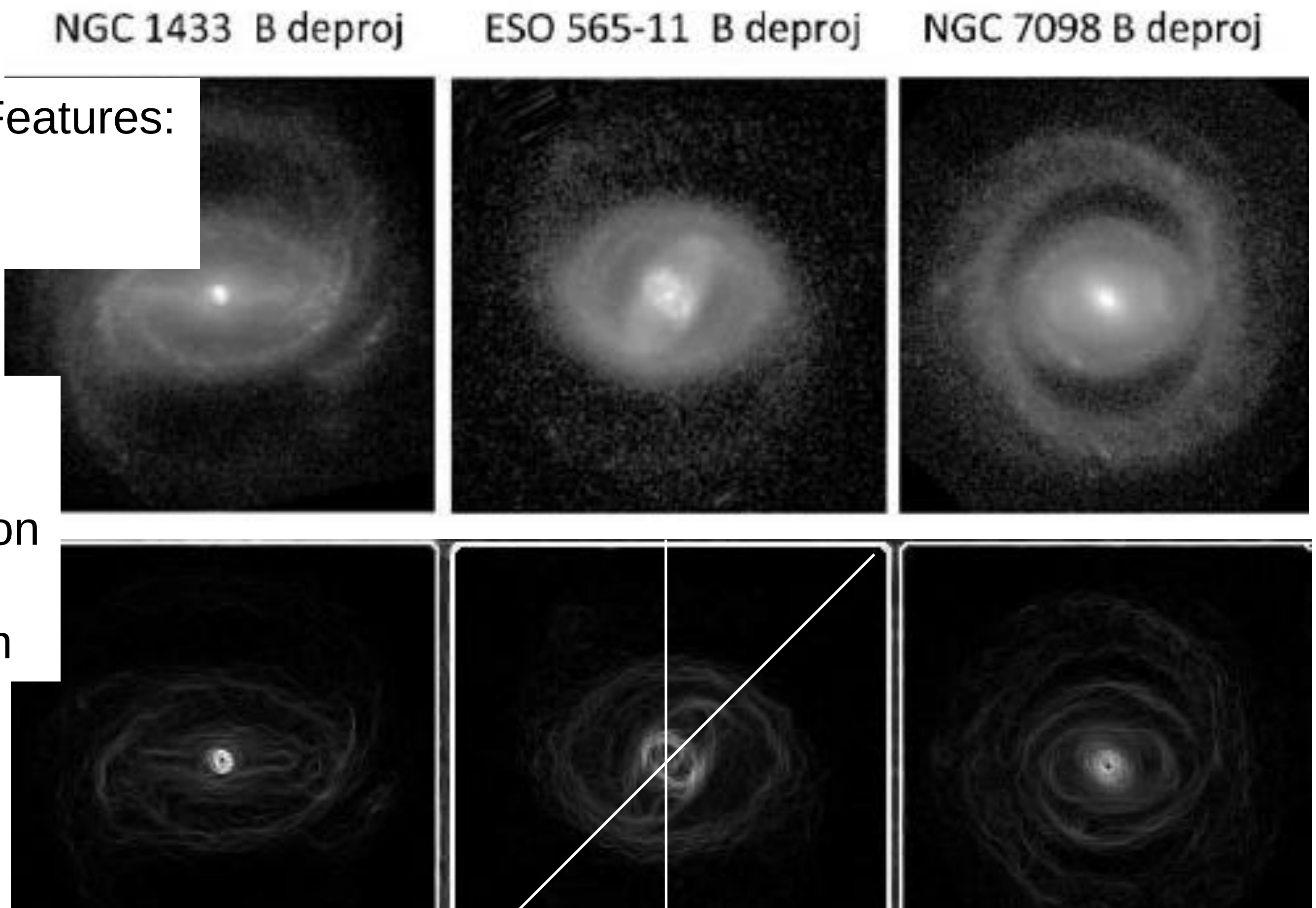

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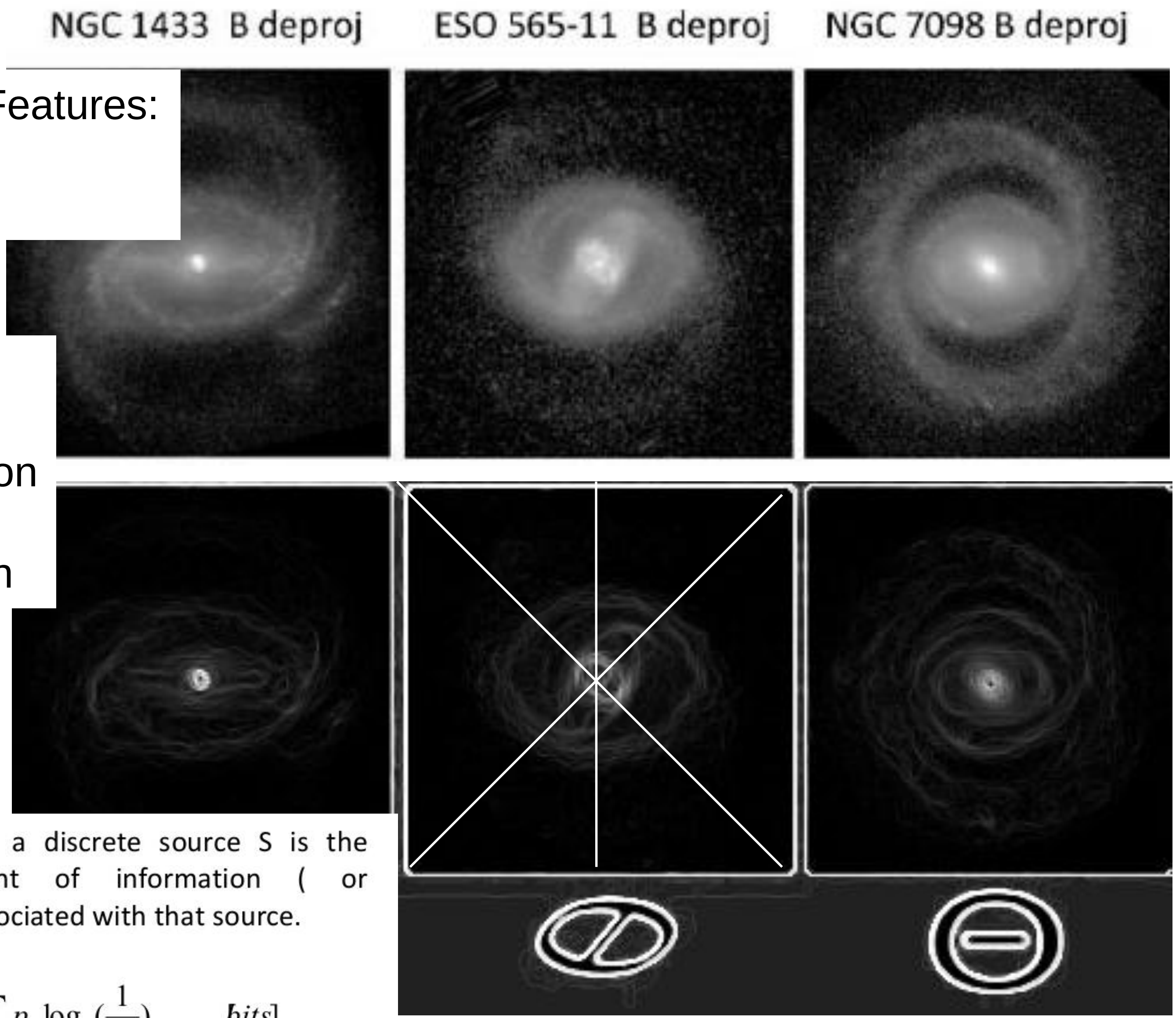

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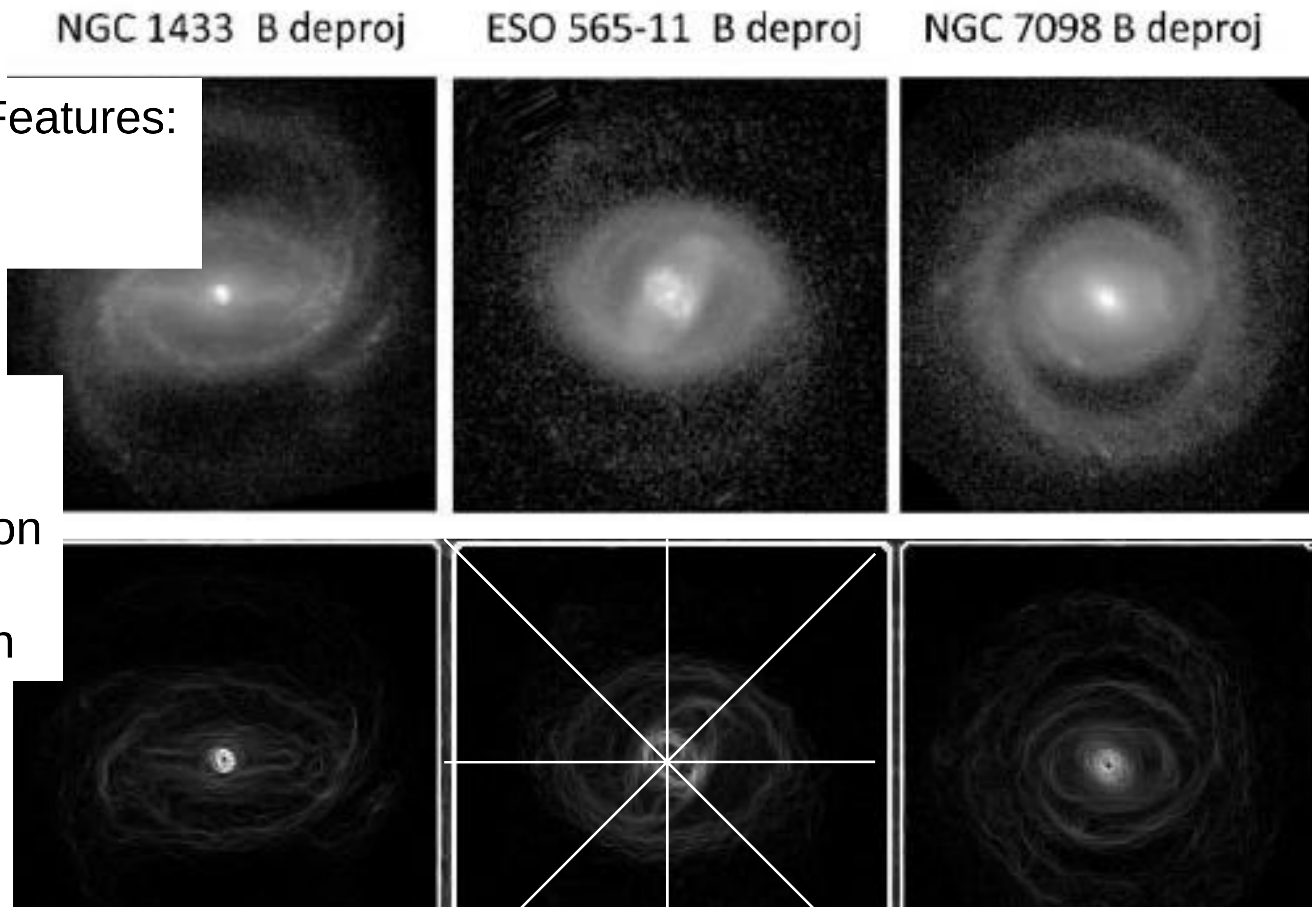

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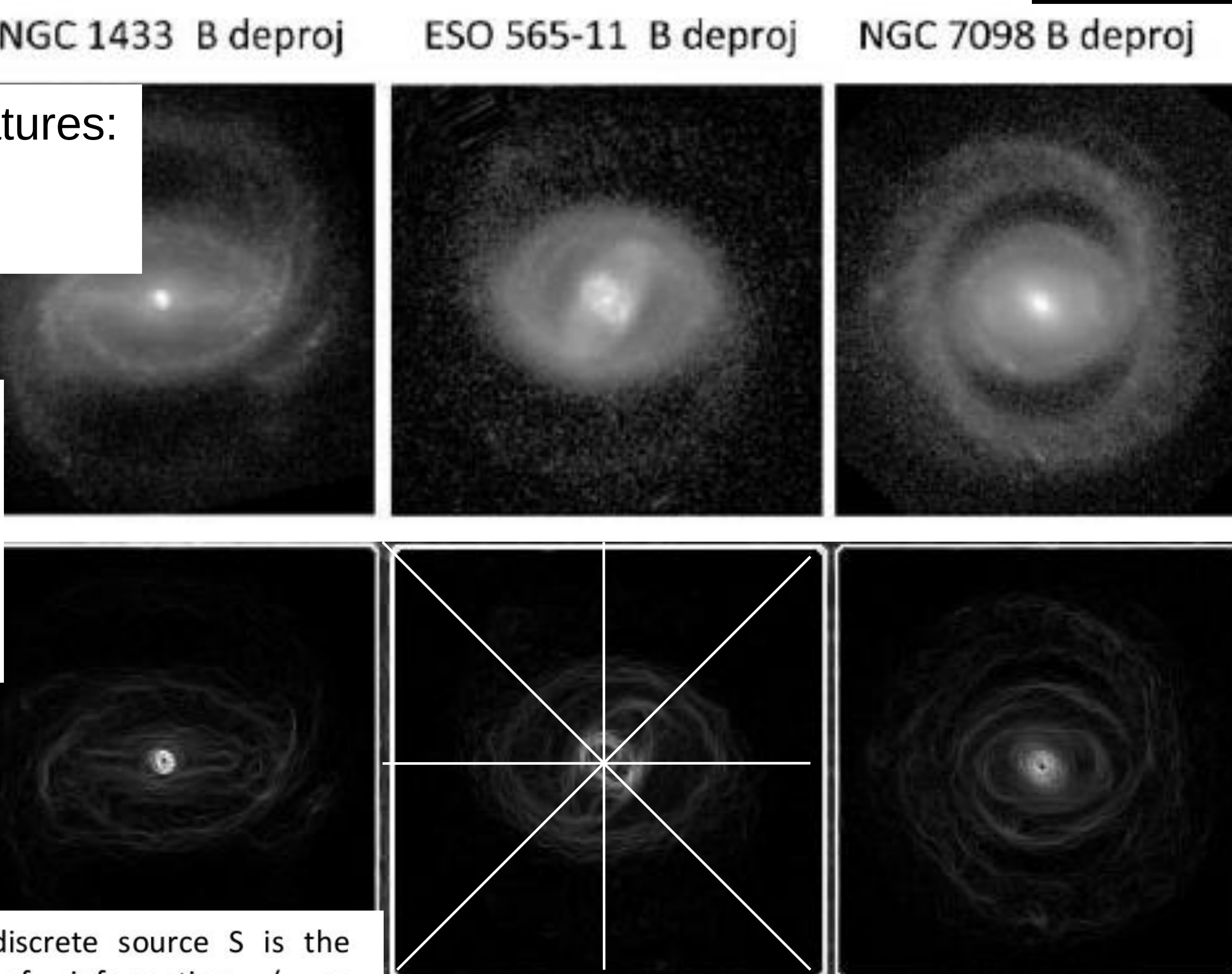

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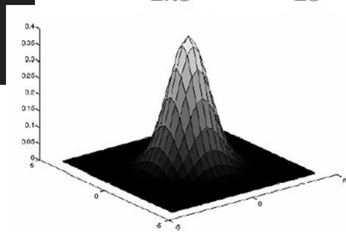
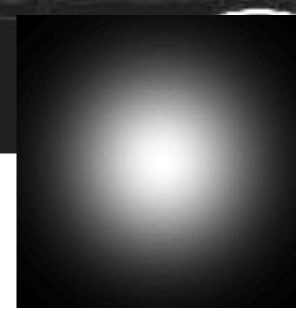
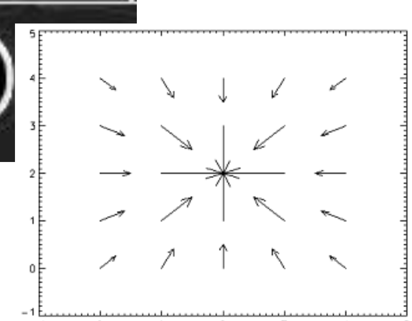
$$k_{2D}(\vec{x}) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{\vec{x}'\vec{x}}{2\sigma^2}\right)$$





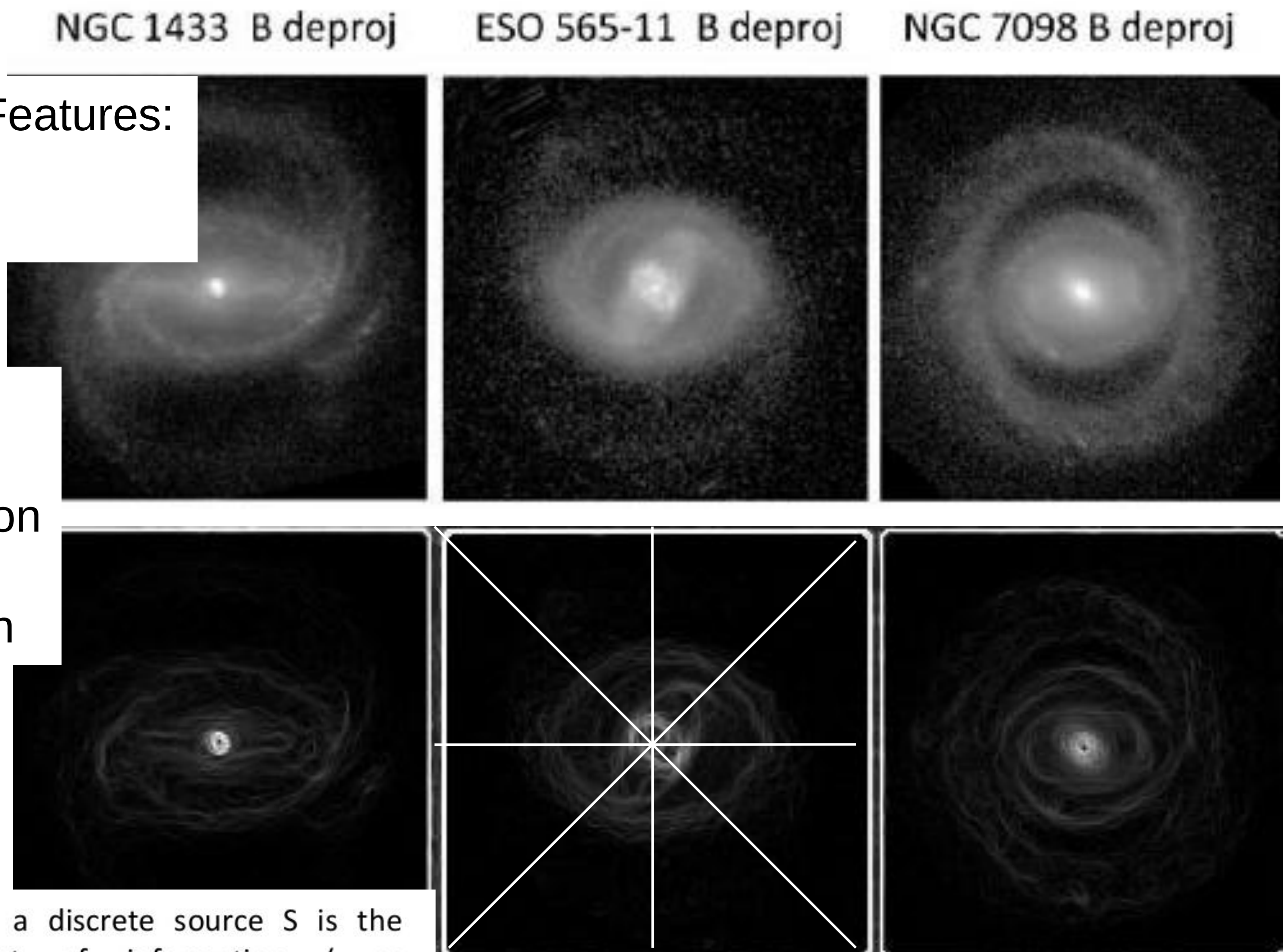


http://www.sdss.org/

Structural Features:

- Rings
- Bars

Filtering
&
Segmentation
&
Information

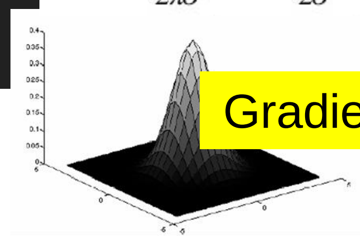


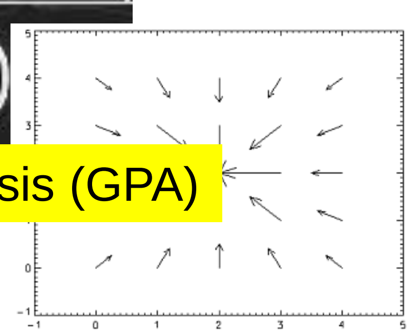
- The entropy of a discrete source S is the average amount of information (or uncertainty) associated with that source.

$$H(s) = \sum_{j=1}^{m} p_j \log_2\left(\frac{1}{p_j}\right) \qquad [bits]$$

- m = number of possible outcomes
- Pj = probability of the jth message

$$k_{2D}(\vec{x}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\vec{x}'\vec{x}}{2\sigma^2}\right)$$





Gradient Pattern Analysis (GPA)

GRADIENT PATTERN ANALYSIS (GPA)

http://en.wikipedia.org/wiki/Gradient_pattern_analysis

International Journal of Modern Physics C, Vol. 10, No. 1 (1999) 147–163

CHARACTERIZATION OF ASYMMETRIC FRAGMENTATION PATTERNS IN SPATIALLY EXTENDED SYSTEMS

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†Astronomy and Physics Departments, University of Maryland
College Park-MD, 20742-2421, USA
§E-mail: ssh@avl.umd.edu

-Rosa et al., Int. J. Mod. Phys. C, 10(1)(1999):147.
-Rosa et al.; Braz. J. Phys. 33 (2003):605
-Assireu et al., Physica D, 2002
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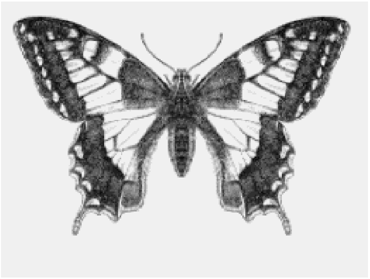
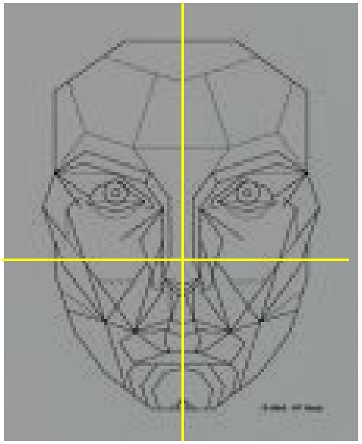
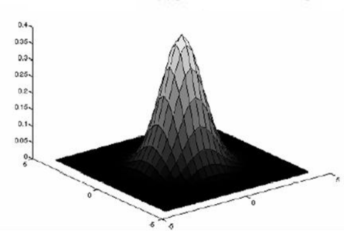
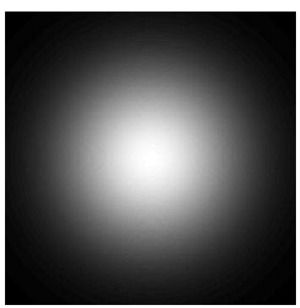
-Sawant et al., Adv. Spaace Rese., 2013

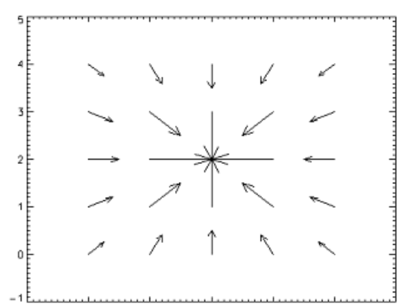




$$k_{2D}(\vec{x}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\vec{x}'\vec{x}}{2\sigma^2}\right)$$







GRADIENT PATTERN ANALYSIS (GPA)

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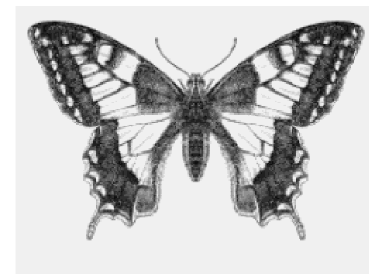
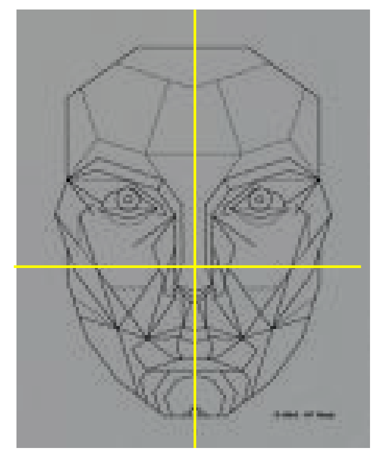
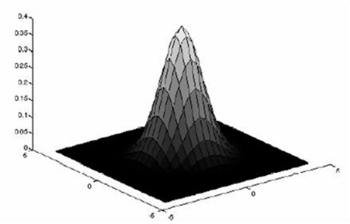
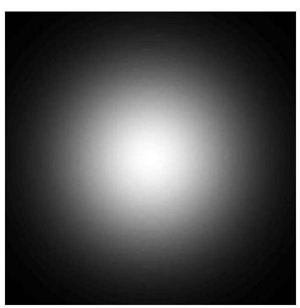
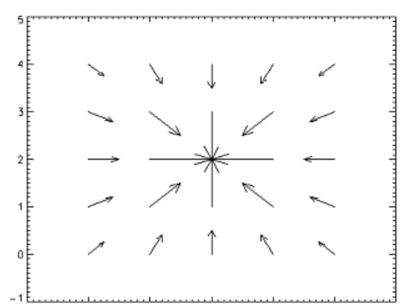




$$k_{2D}(\vec{x}) = \frac{1}{2\pi\sigma^2}\exp(-\frac{\vec{x}'\vec{x}}{2\sigma^2})$$

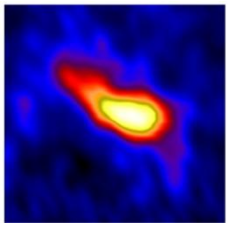


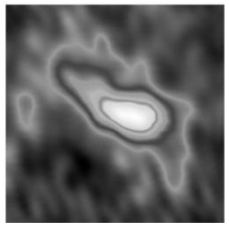


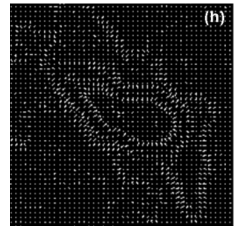


"Structural Bilateral/Concentric Asymmetries" ➔ "non-zero gradients pairs"

$$\Omega_1(\mathbf{M}) \rightarrow M_N \,;\, \Omega_2(M_N) \rightarrow \mathbf{G}_N \,;\, \Omega_3(\mathbf{G}_N) \rightarrow \mathbf{G}_{NA} \,;\, \Omega_4(\mathbf{G}_{NA}) \rightarrow \mathbf{D}_N \text{ e } \Omega_s(\mathbf{D}_N) \rightarrow G_A$$

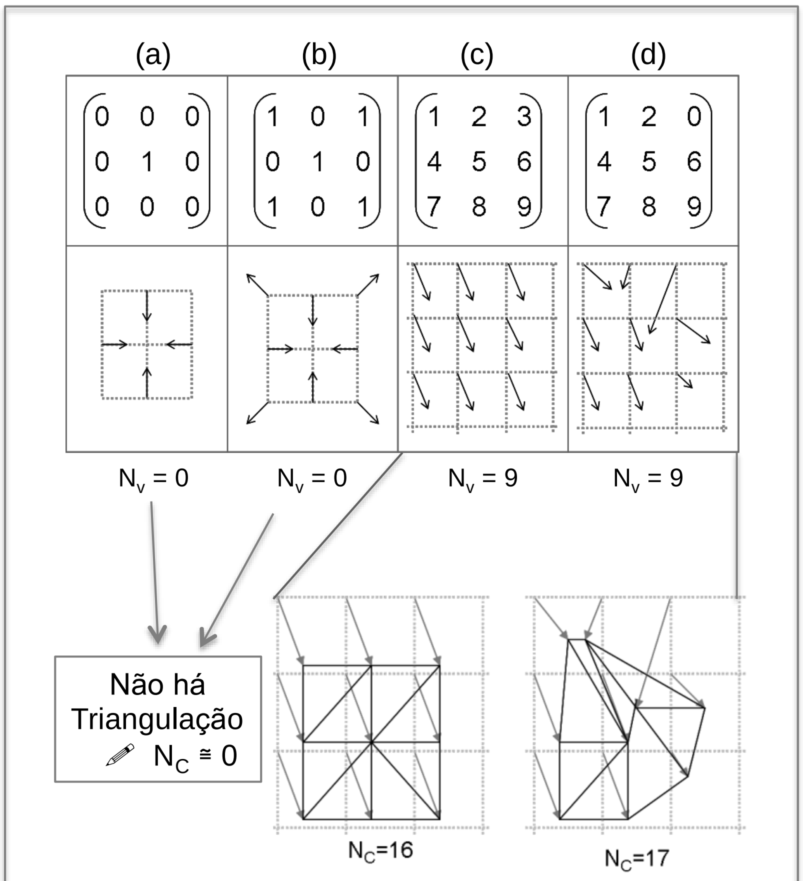


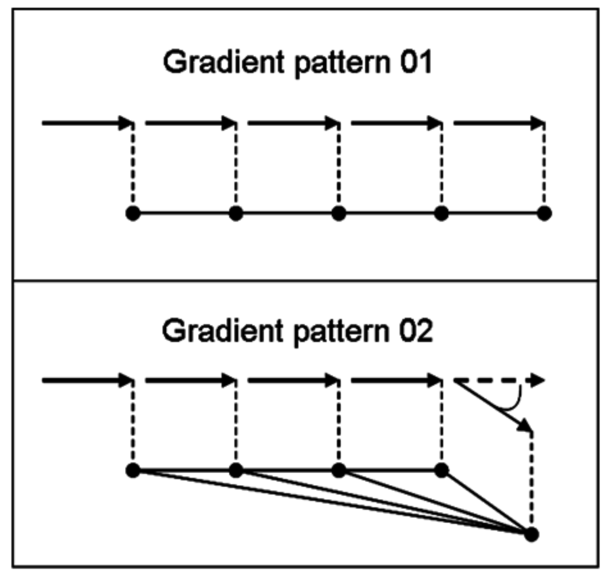




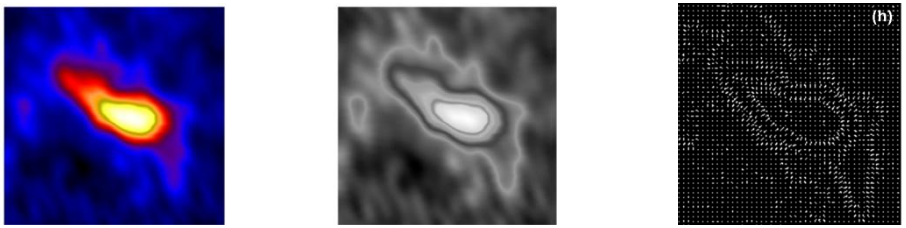
$$G_A \equiv \frac{N_C - N_V}{N_V} \text{ with } N_C > N_V$$

Gradient Asymmetry Index



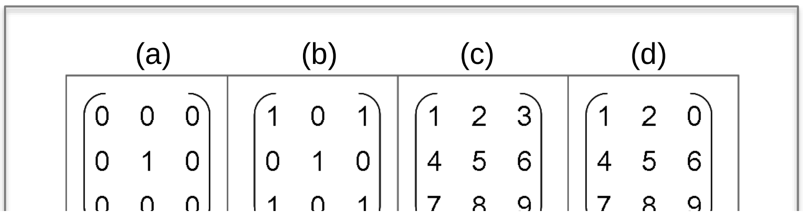


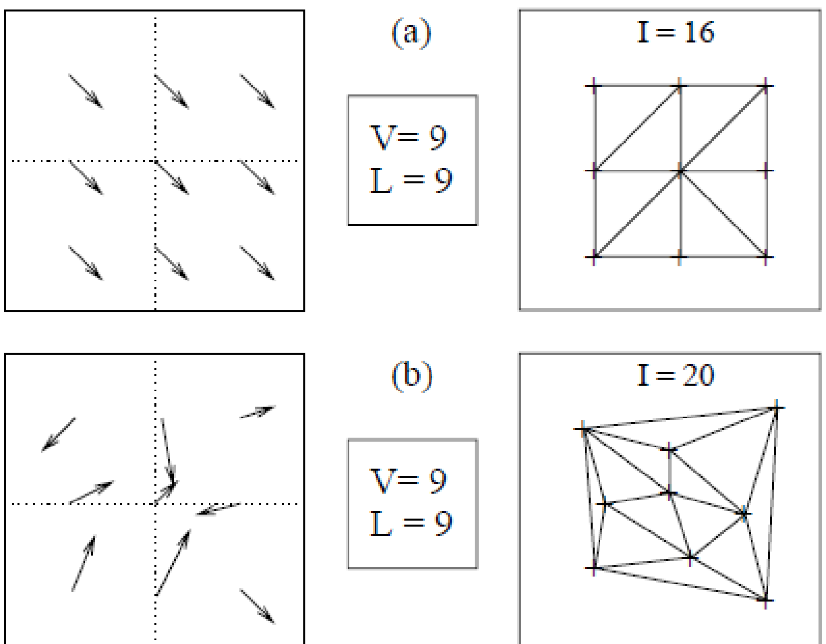
$$\boxed{\Omega_1(\mathbf{M}) \rightarrow M_{\mathrm{N}}\,;\, \Omega_2(M_{\mathrm{N}}) \rightarrow \mathbf{G}_{\mathrm{N}}\,;\, \Omega_3(\mathbf{G}_{\mathrm{N}}) \rightarrow \mathbf{G}_{\mathrm{NA}}\,;\, \Omega_4(\mathbf{G}_{\mathrm{NA}}) \rightarrow \mathbf{D}_{\mathrm{N}} \text{ e } \Omega_s(\mathbf{D}_{\mathrm{N}}) \rightarrow \mathrm{G}_{\mathrm{A}}}$$

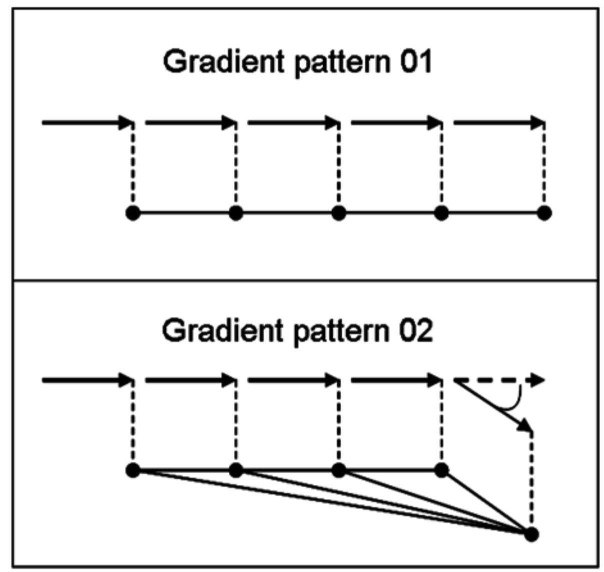


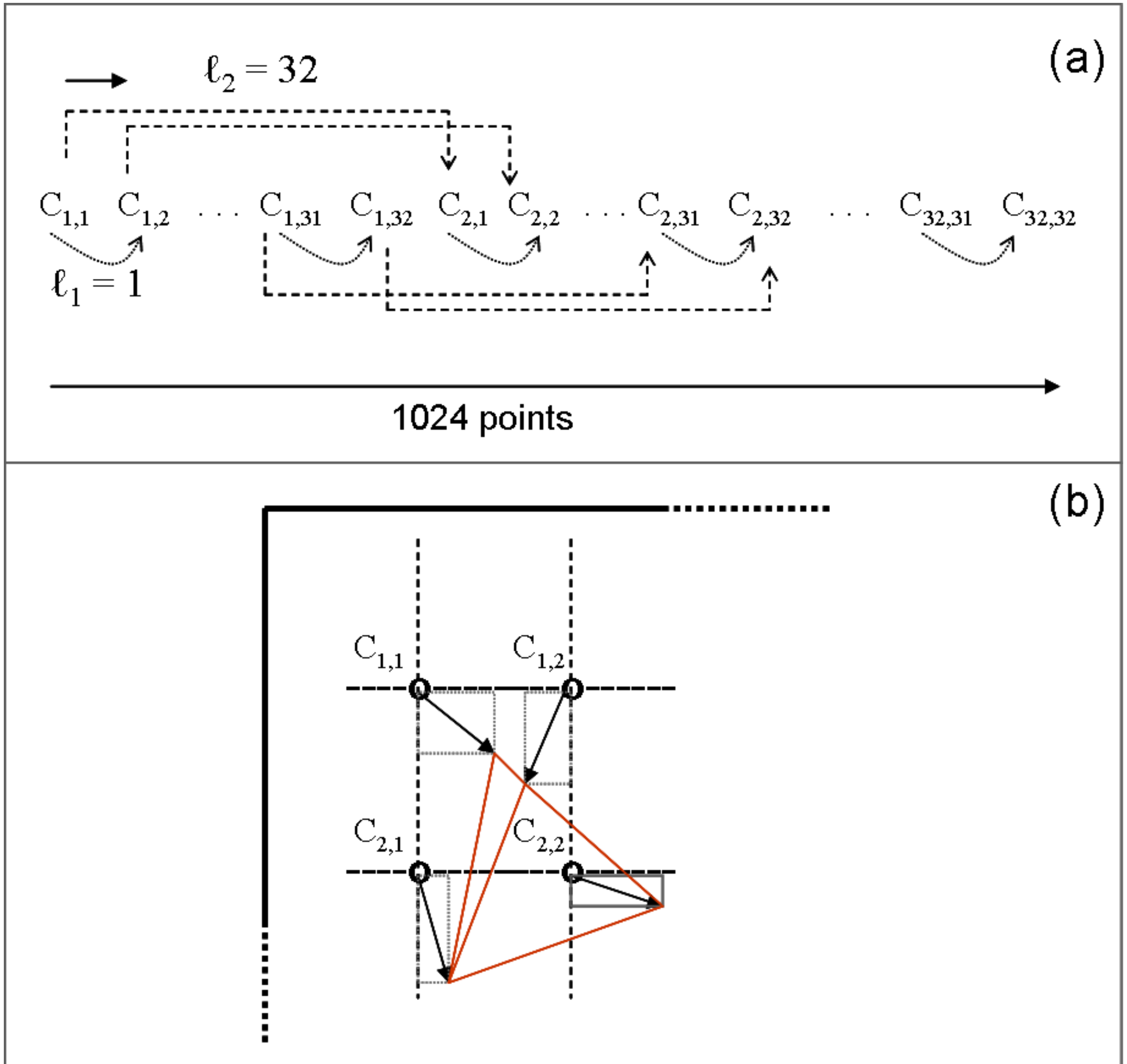
$$G_A \equiv \frac{N_C - N_V}{N_V} \text{ with } N_C > N_V$$

Gradient Asymmetry Index

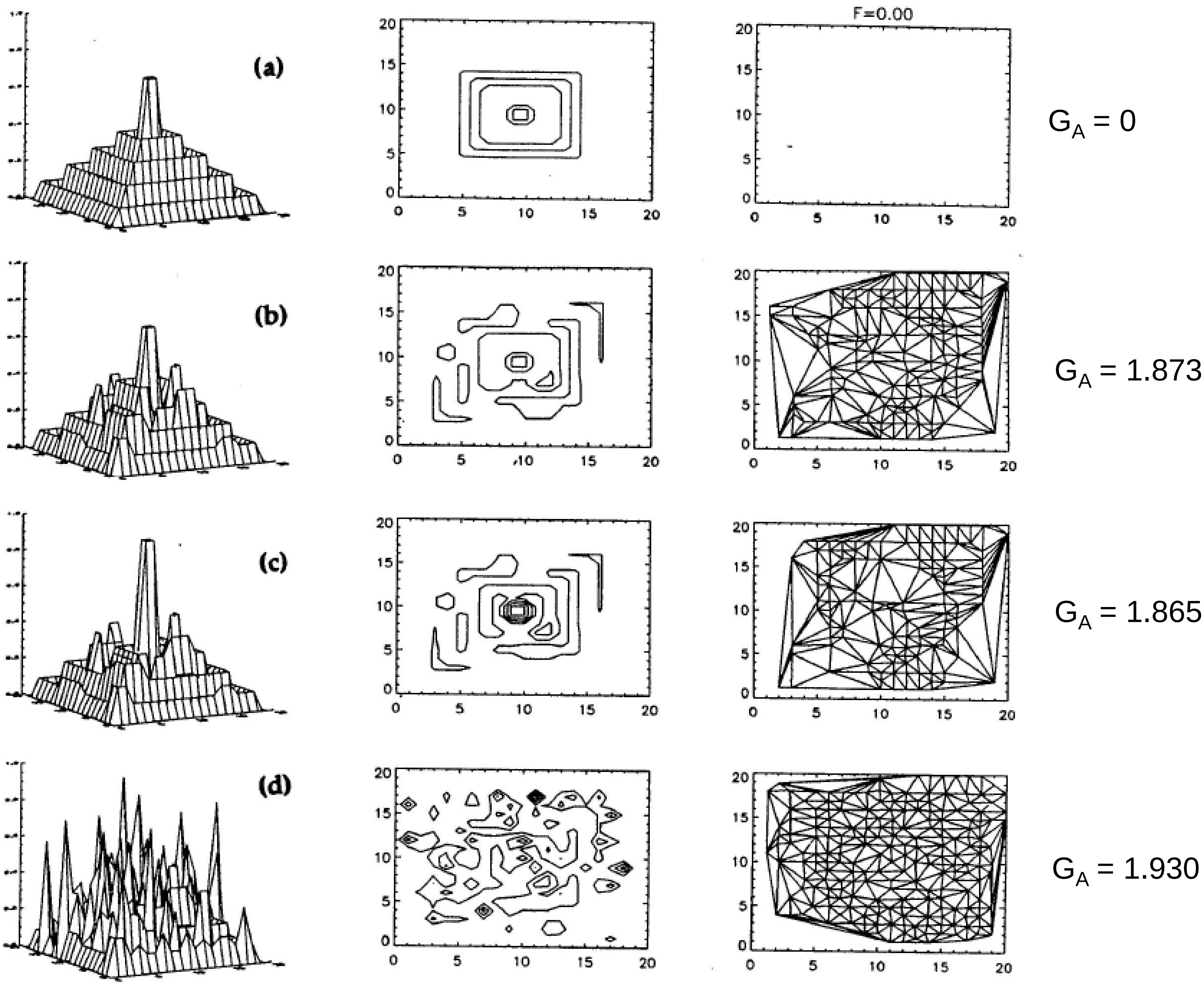




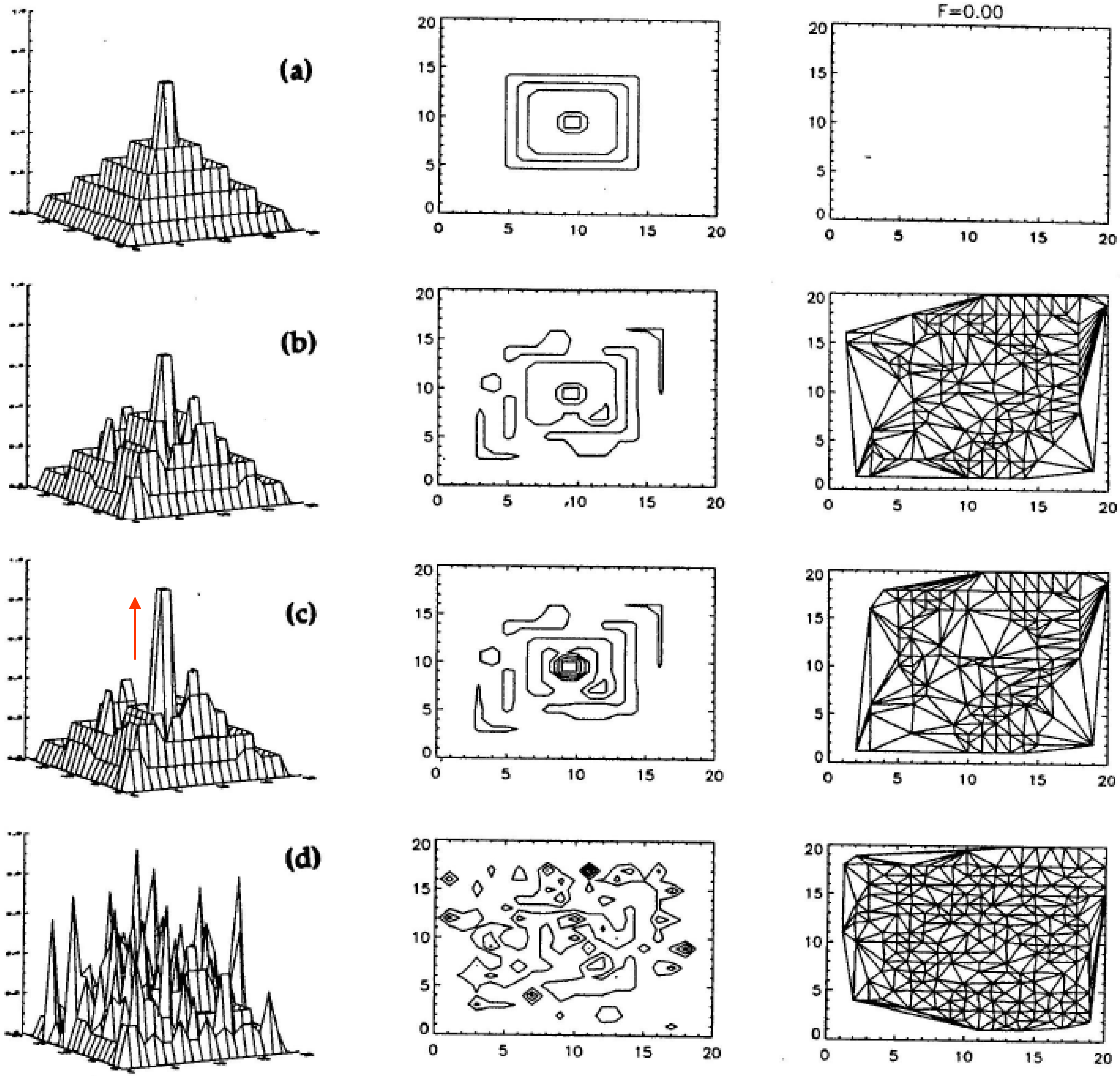




(a)
ℓ2 = 32
C1,1 C1,2 . . . C1,31 C1,32 C2,1 C2,2 . . . C2,31 C2,32 . . . C32,31 C32,32
ℓ1 = 1
1024 points
(b)
C1,1
C1,2
C2,1
C2,2



(a)
F=0.00
$G_A = 0$
(b)
$G_A = 1.873$
(c)
$G_A = 1.865$
(d)
$G_A = 1.930$

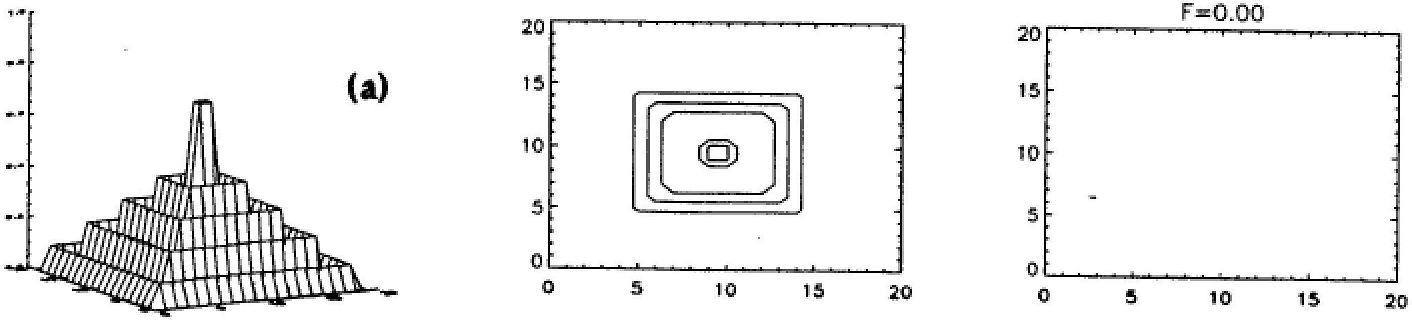


$G_A = 0$

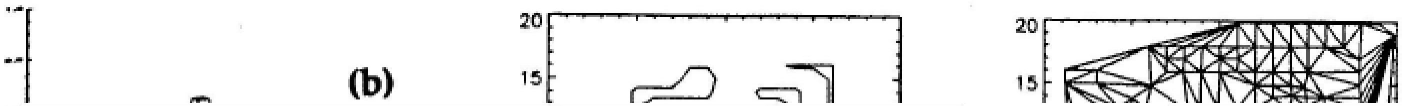
$G_A = 1.873$

$G_A = 1.865$

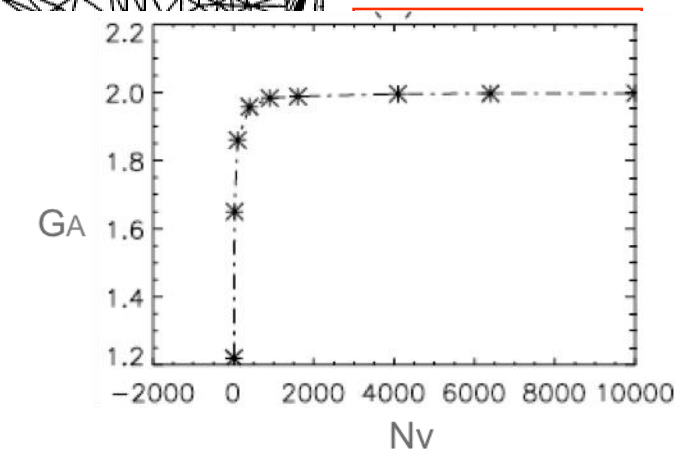
$G_A = 1.930$

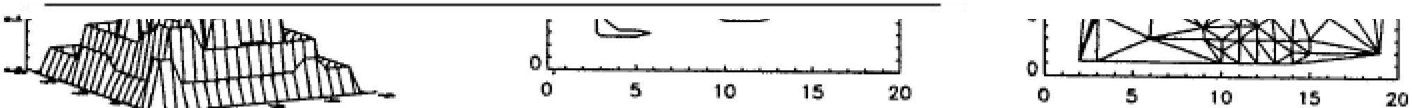


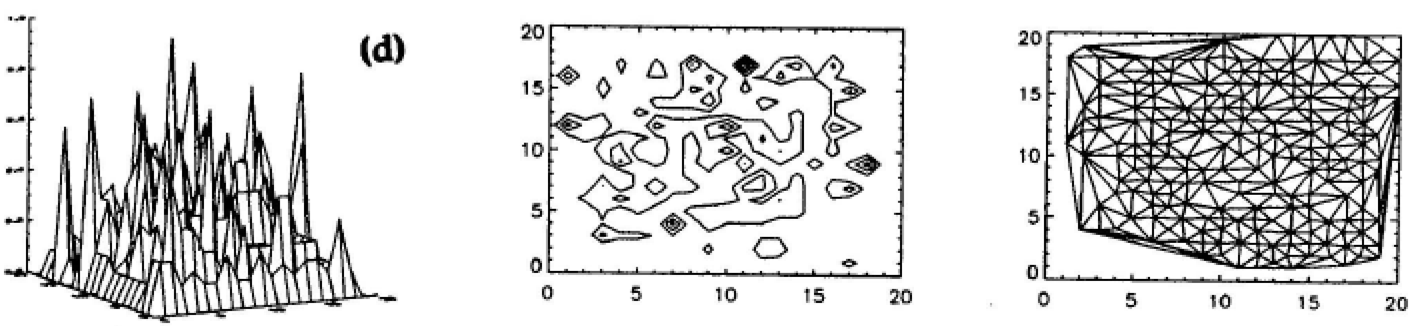
$G_A = 0$



3 × 3	9	18	1.2200	0.2200
5 × 5	25	65	1.6500	0.1700
10 × 10	100	285	1.8600	0.0120
20 × 20	400	1186	1.9575	0.0076
30 × 30	900	2685	1.9833	0.0031
40 × 40	1600	4781	1.9881	0.0016
64 × 64	4096	12269	1.9954	0.0009
80 × 80	6400	19199	1.9968	0.0003
100 × 100	10000	29975	1.9974	0.0002
128 × 128	16384	49140	1.9992	0.0001





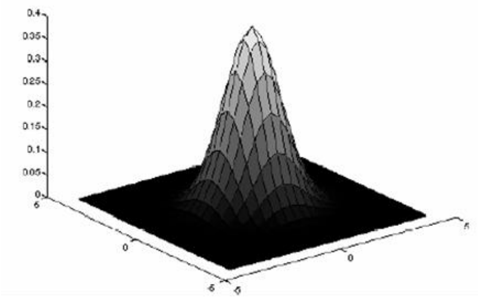


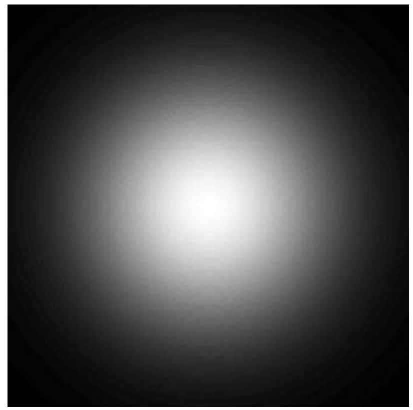
$G_A = 1.930$

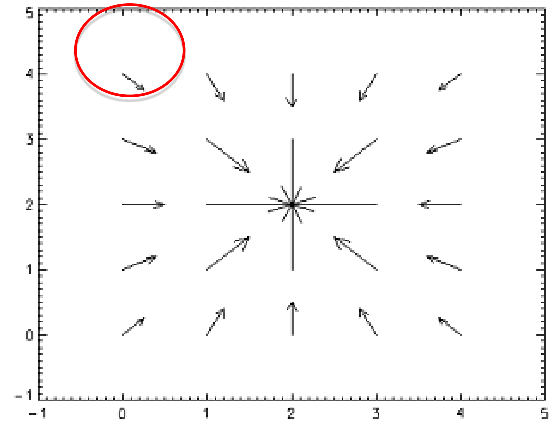
pyCUDA-GPA

:

$$k_{2D}(\vec{x}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\vec{x}'\vec{x}}{2\sigma^2}\right)$$



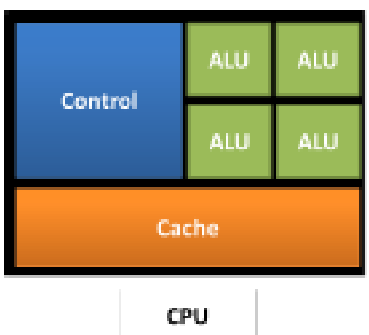


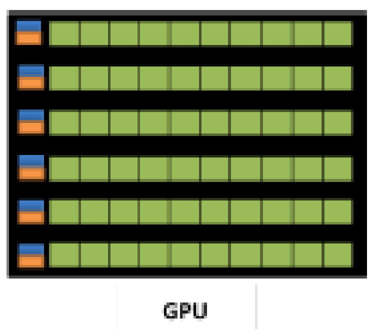


!

!

GPGPU





2 threads:

- gradM
- gradM_A

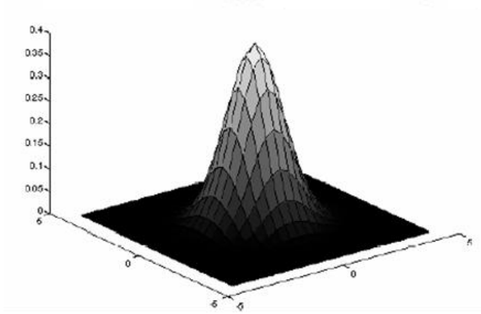
$$t(R,N) = \frac{0{,}35}{\sqrt{R}} + \frac{0{,}65}{N}$$

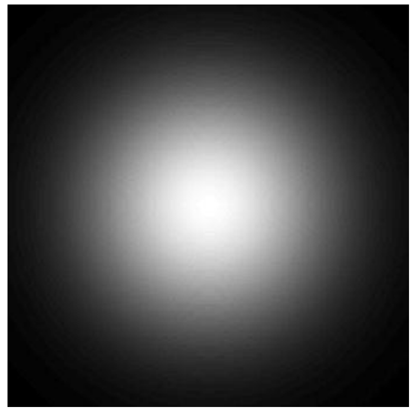
$$\Omega_1(\mathbf{M}) \rightarrow M_N\,;\ \boxed{\Omega_2(M_N) \rightarrow \mathbf{G}_N}\,;\ \boxed{\Omega_3(\mathbf{G}_N) \rightarrow \mathbf{G}_{NA}}\,;\ \Omega_4(\mathbf{G}_{NA}) \rightarrow \mathbf{D}_N \text{ e } \Omega_5(\mathbf{D}_N) \rightarrow G_A$$

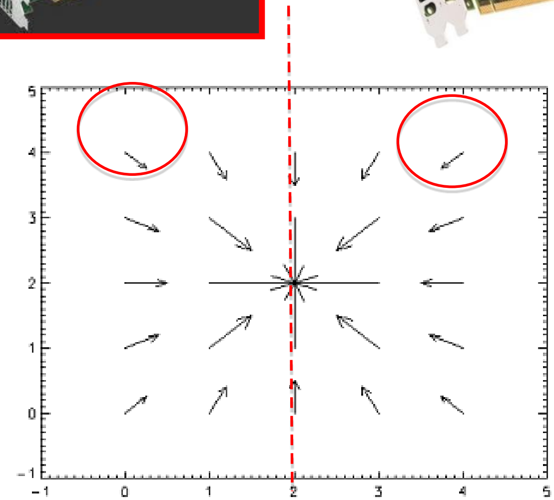
pyCUDA-GPA

:

$$k_{2D}(\vec{x}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\vec{x}'\vec{x}}{2\sigma^2}\right)$$







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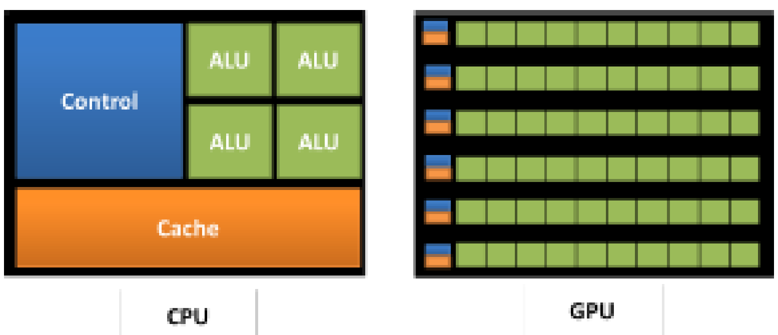
!

GPGPU



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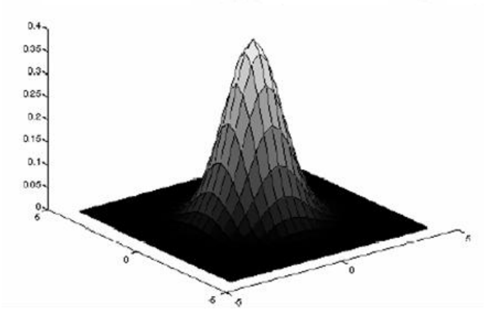
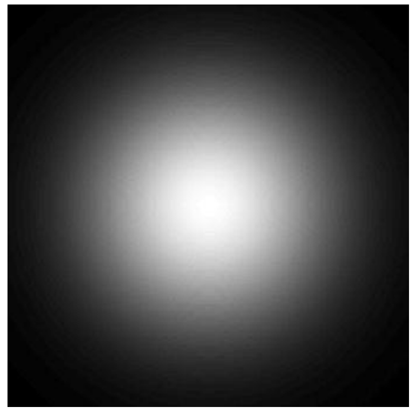
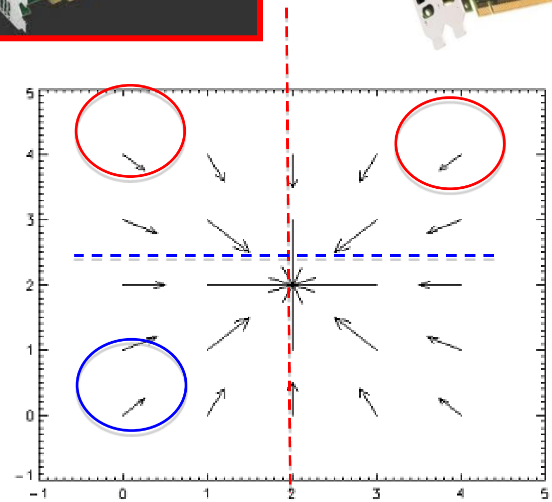
pyCUDA-GPA

:

$$k_{2D}(\vec{x}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\vec{x}'\vec{x}}{2\sigma^2}\right)$$







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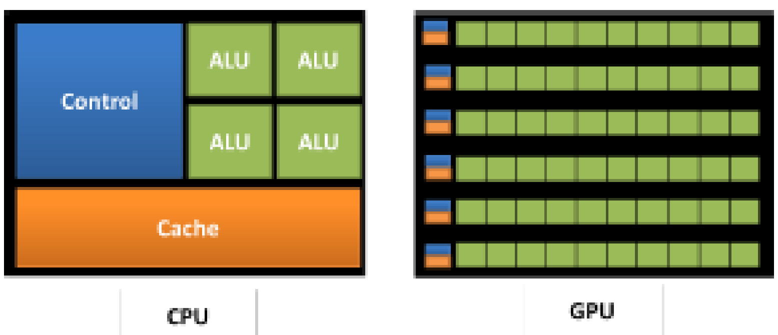
GPGPU



2 threads:

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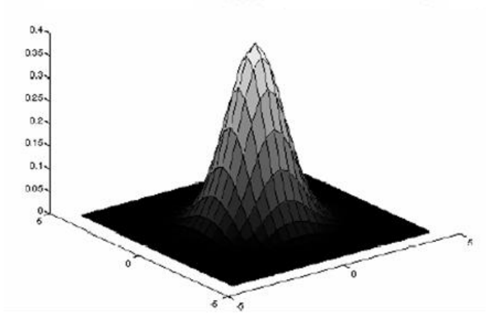
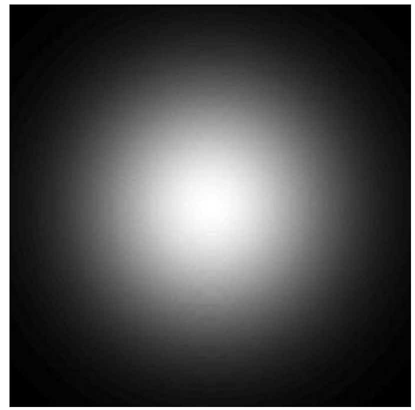
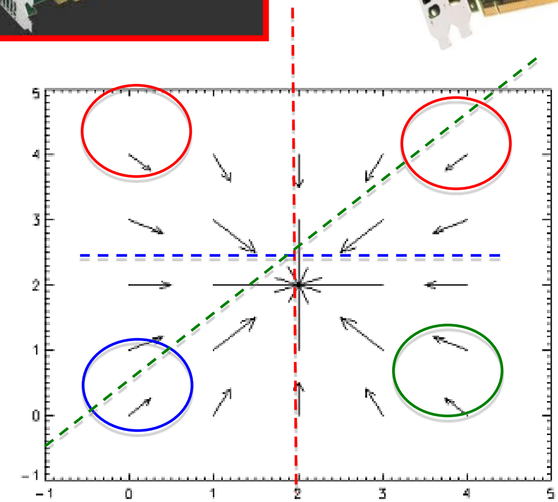
pyCUDA-GPA

:

$$k_{2D}(\vec{x}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\vec{x}'\vec{x}}{2\sigma^2}\right)$$



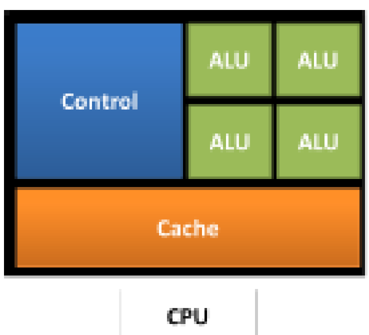


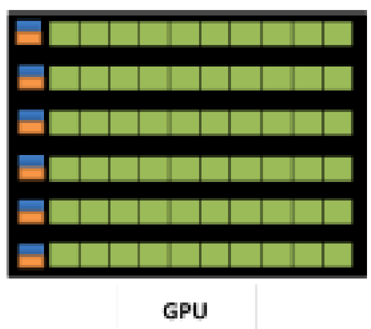


!

!

GPGPU





2 threads:

- gradM
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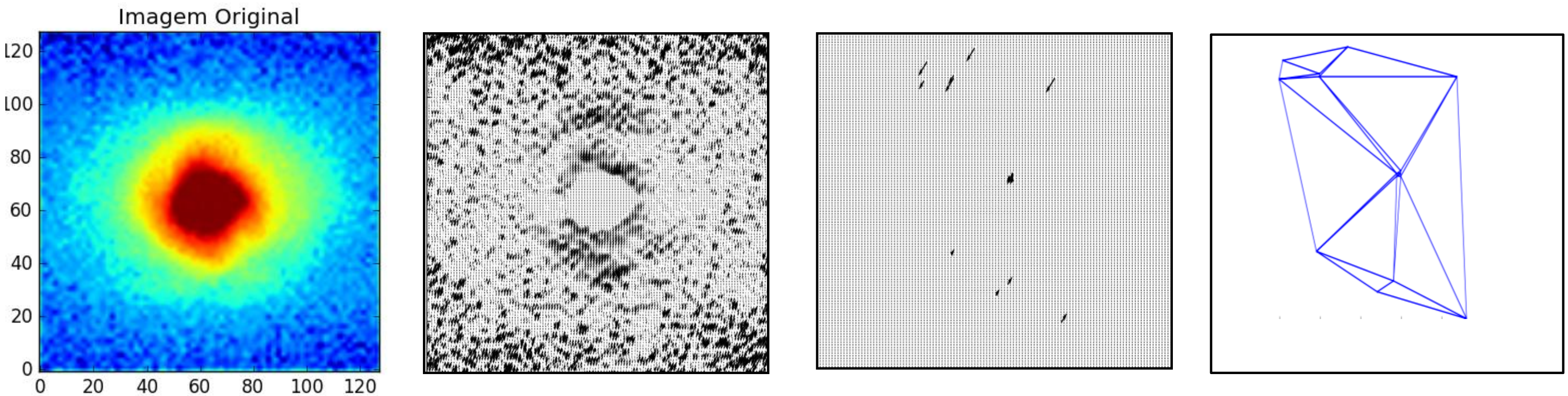
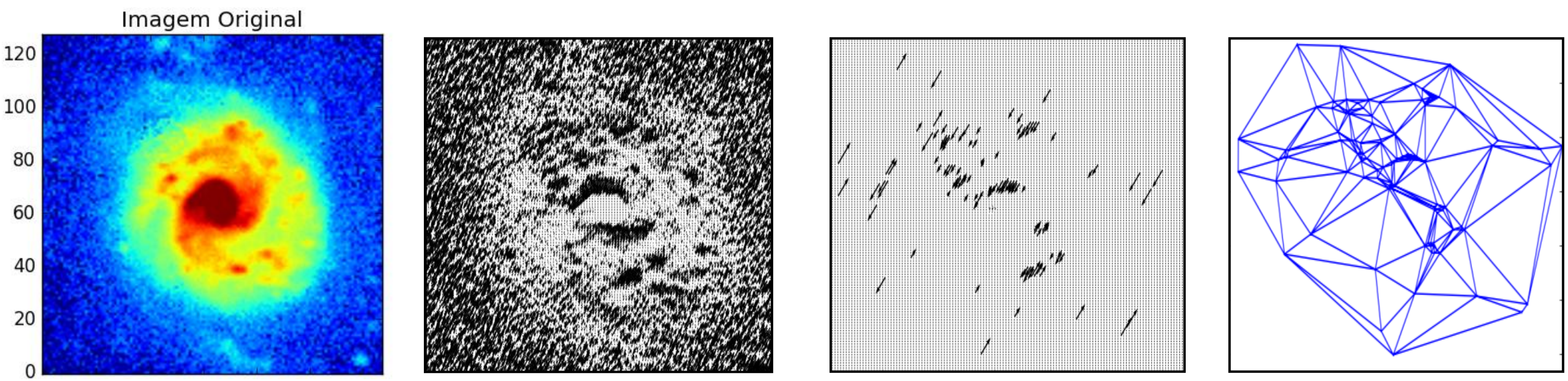
$$t(R,N) = \frac{0{,}35}{\sqrt{R}} + \frac{0{,}65}{N}$$

$$\Omega_1(\mathbf{M}) \to M_N \,;\, \boxed{\Omega_2(M_N) \to \mathbf{G}_N} \,;\, \boxed{\Omega_3(\mathbf{G}_N) \to \mathbf{G}_{NA}} \,;\, \Omega_4(\mathbf{G}_{NA}) \to \mathbf{D}_N \text{ e } \Omega_s(\mathbf{D}_N) \to \mathrm{G}_A$$



$G_A = 1.8543 \pm 0.0005$



$G_A = 1.9842 \pm 0.0005$

$t(2{,}680) < 7.5 \times 10^{-2}$ s ➔ $S_p > 82$

Ferrari et al. ApJ 2015
Doi: 10.1088/0004-637X/814/1/55

Morfometry / Morphology

Classification x Characterization

AI (Machine Learning) “Metrics” (*Pattern Recognition)*

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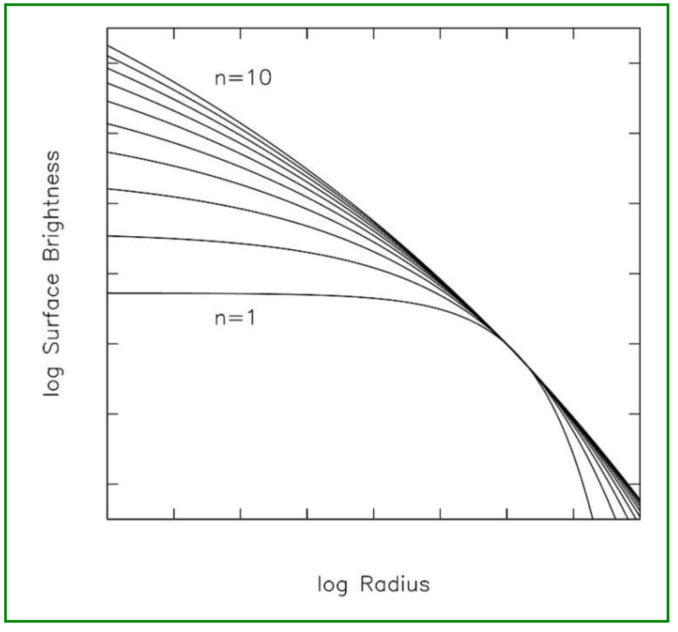

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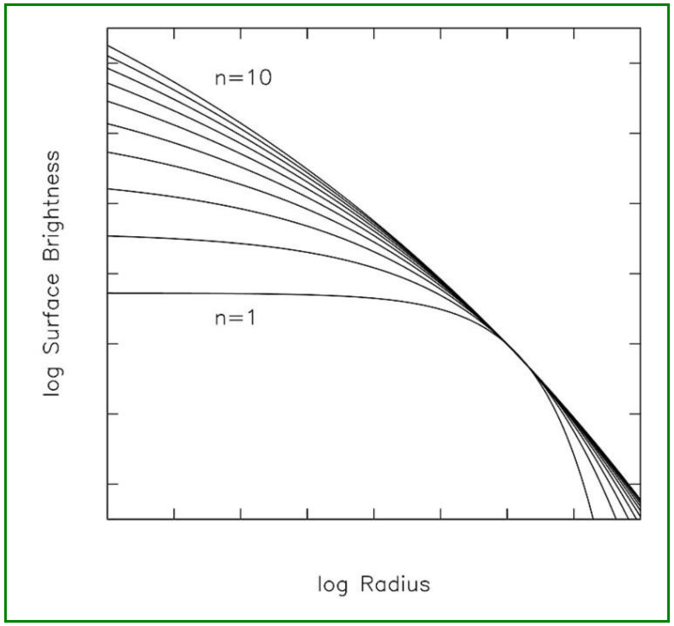

① E
② C
③ S
④ E
⑤ σ
⑥ G_A

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Structural Features (S)

- Bars
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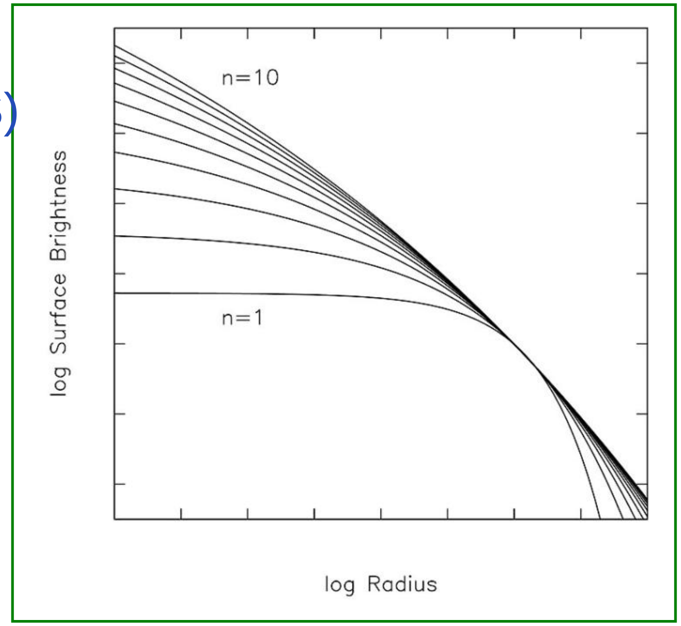
- etc



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1 E Entropy
2 C Axis rate
3 S Smoothness
4 E Concentration
5 σ Spirality
6 G_A **Gradient Asymmetry**

Morfometry / Morphology

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$\mu_6 \times \mu_i \times n$

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MORPHOMETRIKA
U-MORPHOMETRIKA
65% // for
Multicore Architectures

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Morphology in Gravitational Physics

- Interdisciplinary Approach:
  - Extragalactic Astrophysics & Cosmology
  - Big Data & Data Science
  - Computational Statistical Analysis
  - High Performance Computing

- Imaging Processing ➔ Structural Analysis (space, time and frequency)

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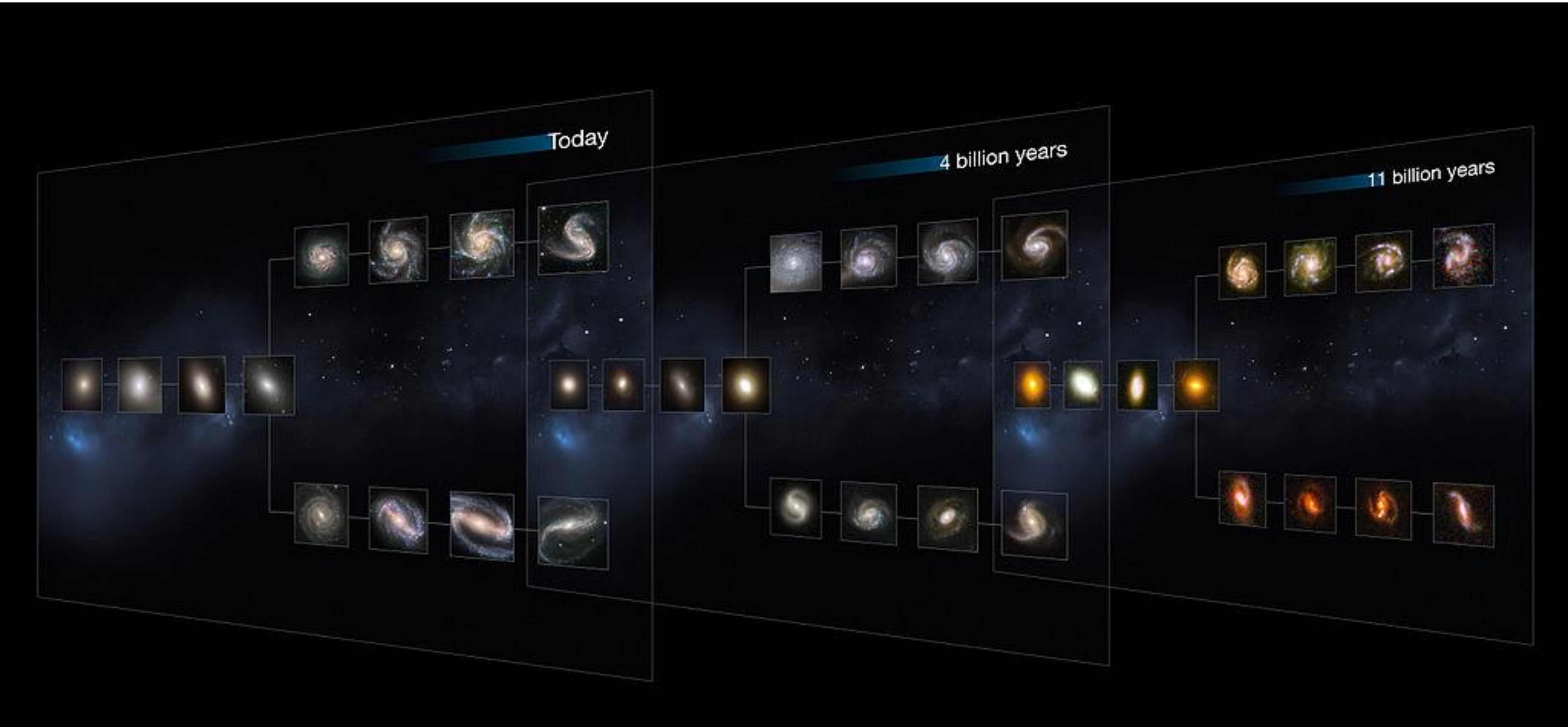

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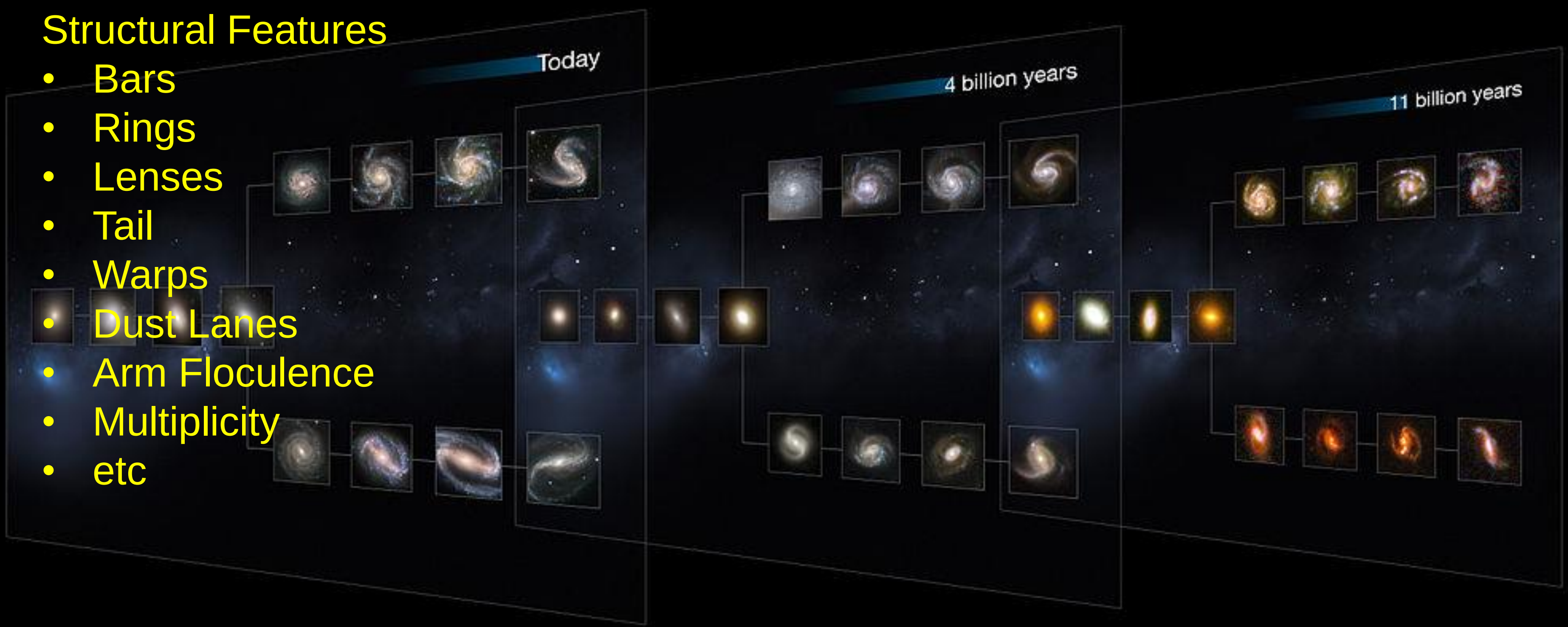

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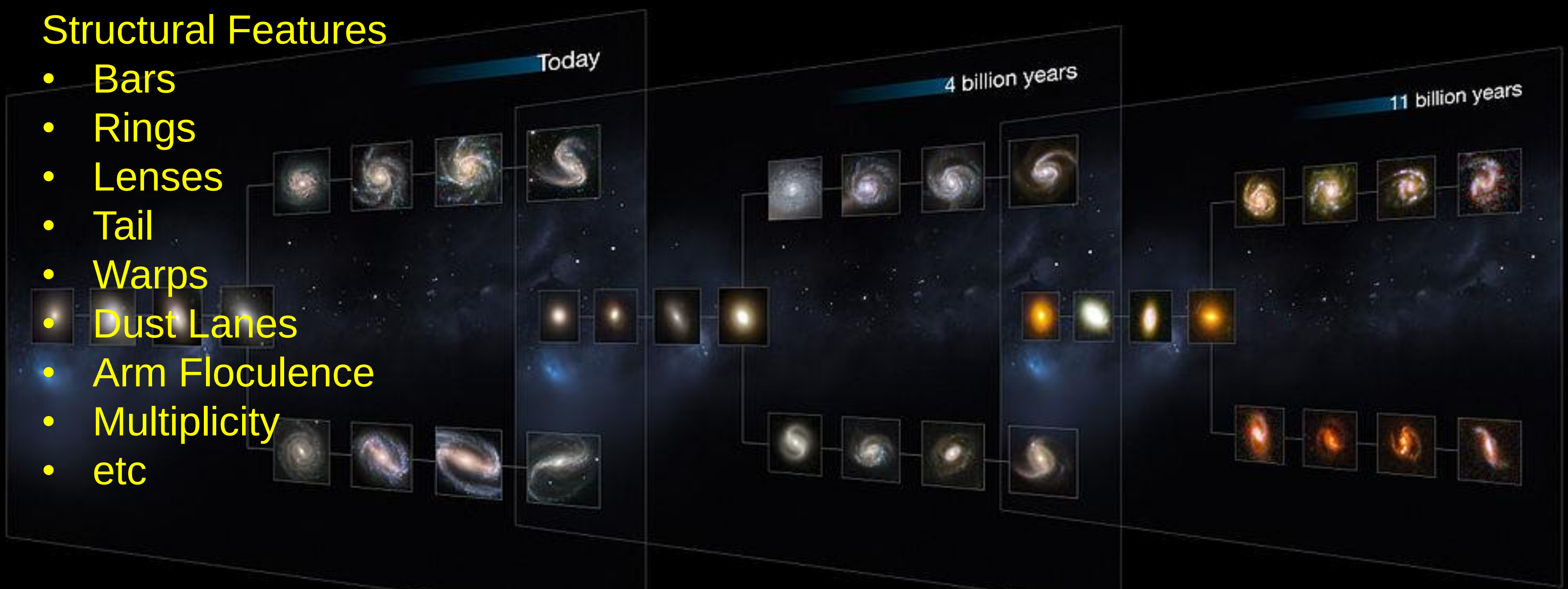

How to characterize the structural environment of a galaxy for Data Science?

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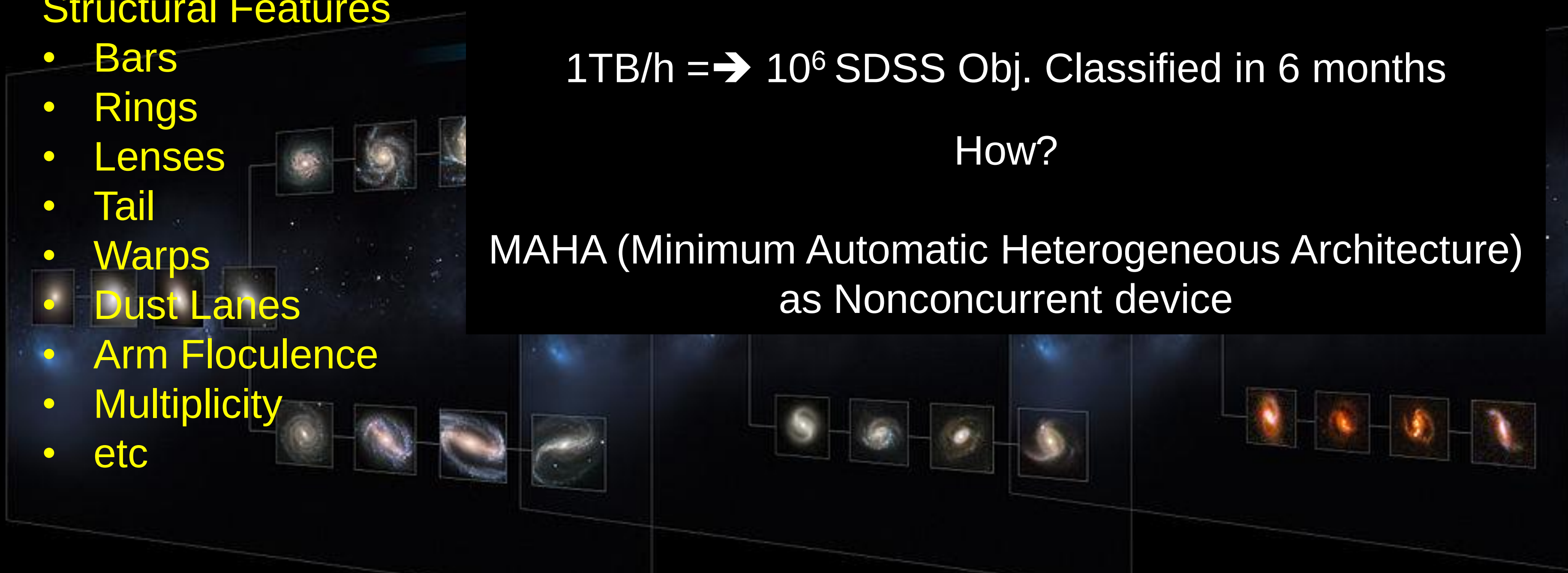

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Big Data: Volume, Velocity, Variety and Value

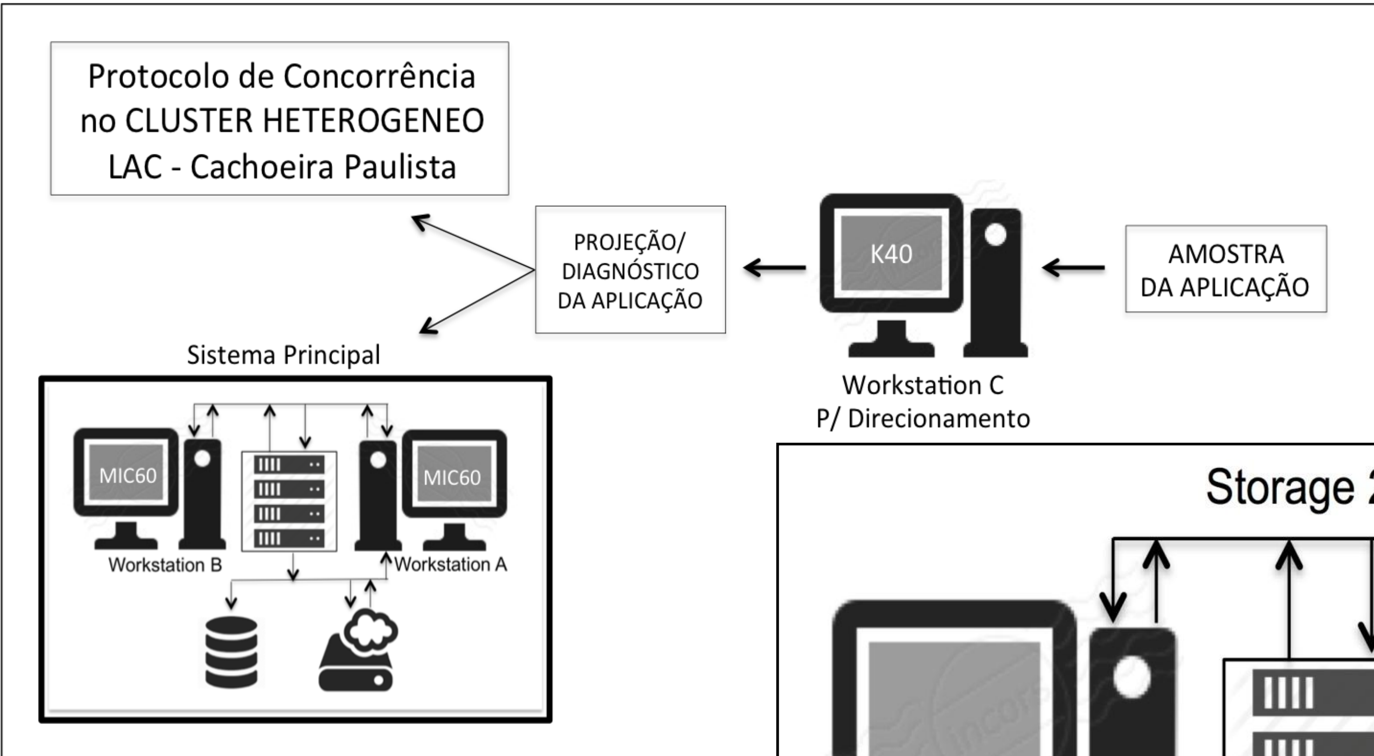
1TB/h =➔ 10^6 SDSS Obj. Classified in 6 months

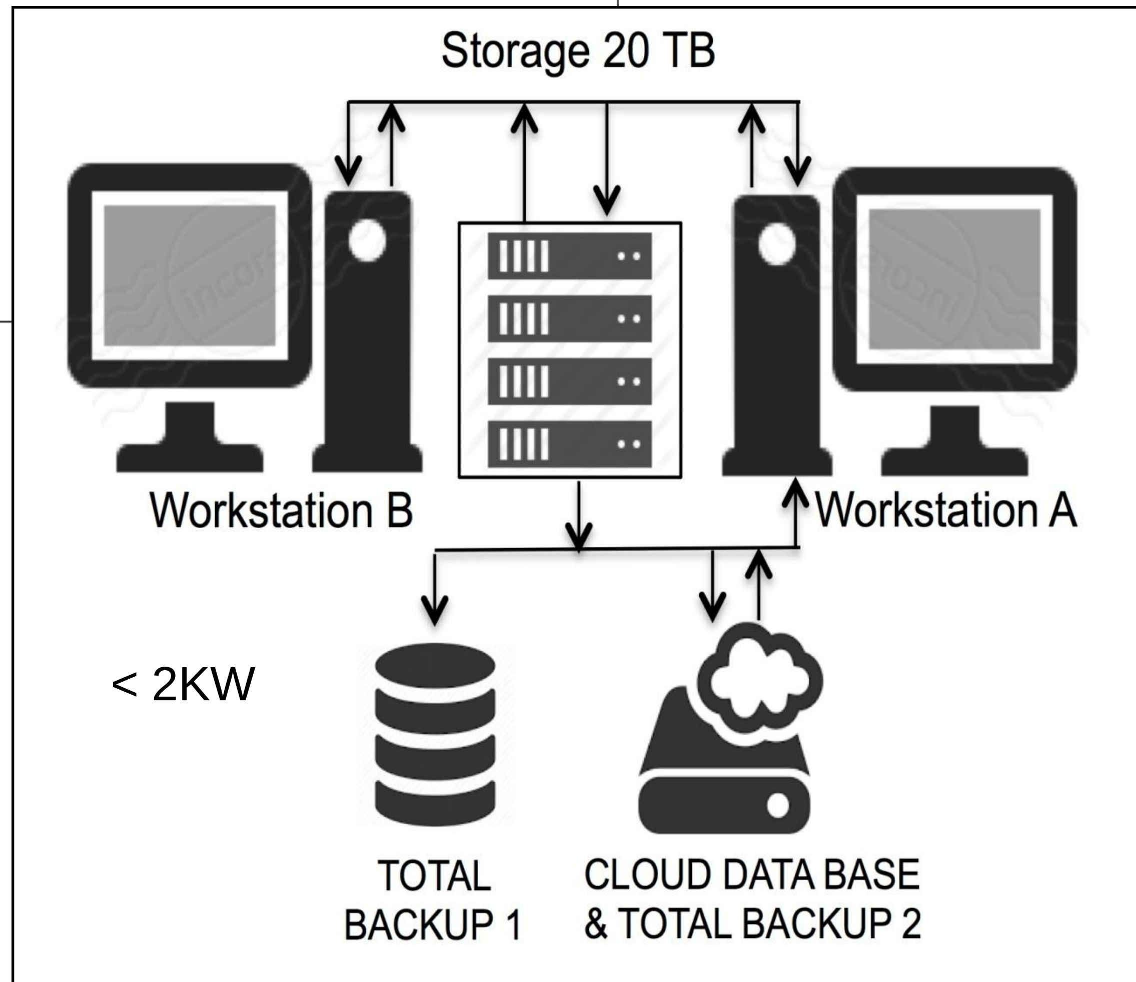
How?

MAHA (Minimum Automatic Heterogeneous Architecture) as Nonconcurrent device

How to characterize the structural environment of a galaxy for Data Science?

WORKLOAD &
WORKFLOW
OPTIMIZED
USING
NoSQL
For DATA BASE





$$t(R,N) = \frac{0{,}35}{\sqrt{R}} + \frac{0{,}65}{N}$$

R = 2 e N=60 (Intel Xeon Phi 5510P)

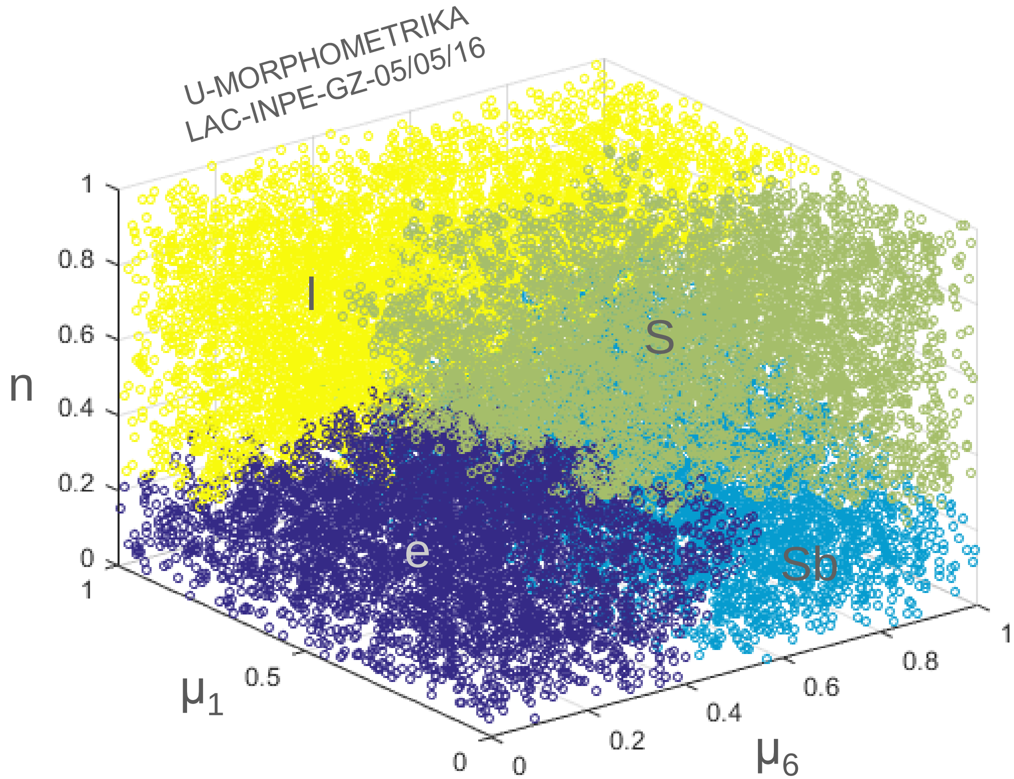
0,26s/file ➔ > 10^3 /day

x 0,22s/f from K40

Simplest Preliminary Search

https://www.galaxyzoo.org/

FILE RB0115: 64.328



14,2 hours (K40)

Accuracy: 86,4 %

Sautter et al, JCIS, 2016

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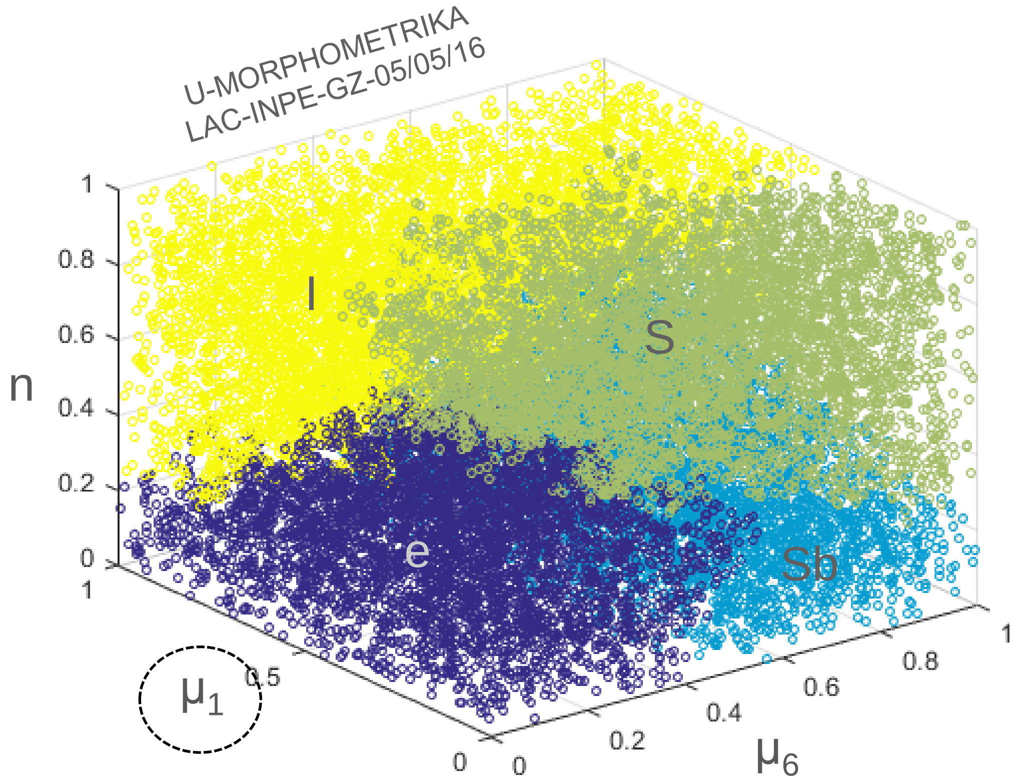

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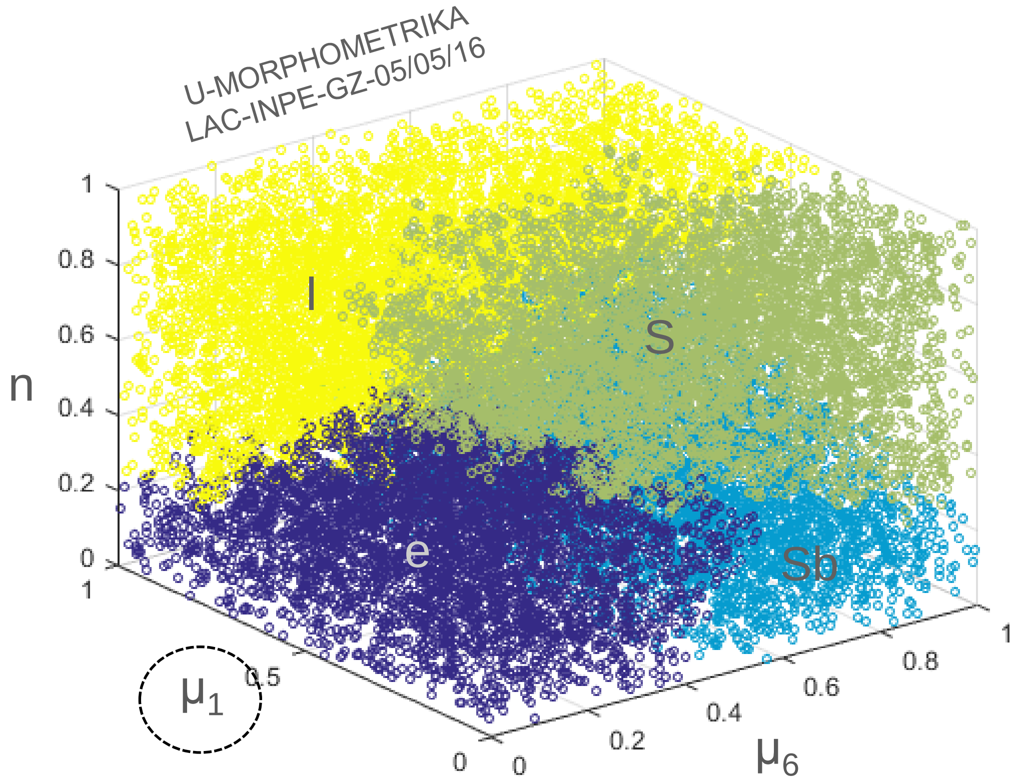

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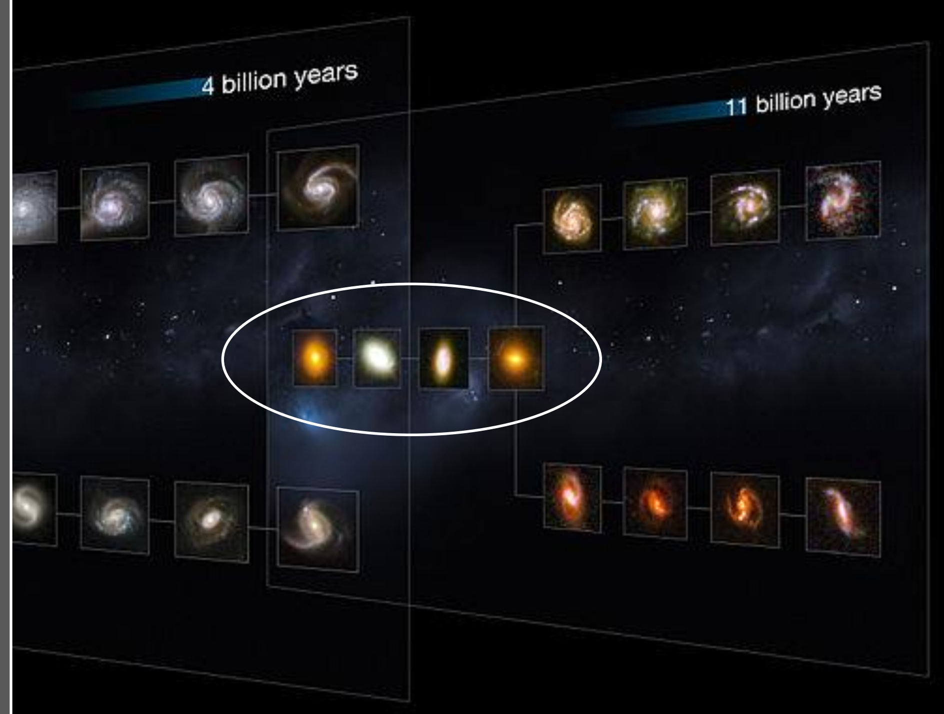
CONCLUDING REMARK: FOR BIG DATA ANALYSIS IN ASTRONOMY MAHA AS NONCONCURRENT MACHINE IS MORE APPROPRIATE THAN BIG CLUSTERS!!!

MAIN CONCLUDING REMARK FOR EXTRA-GALACTIC ASTROPHYSICS

By studying global properties of local ETGs, from Big Data Files, such as color gradients, the fundamental plane, stellar populations, their initial mass function (IMF) and their **morphometric properties**, it should be able to constrain and improve models of galaxy formation and cosmic evolution.

It is important to characterize these **galaxies' environments** using a physically meaningful and consistent measure of the host group/cluster velocity distributions into the context of **high resolution galaxy morphology**, so that we can begin to separate the effects of environment (nurture) and individual galaxy properties(nature).



http://www.epacis.net/ccis2016/en/index.php

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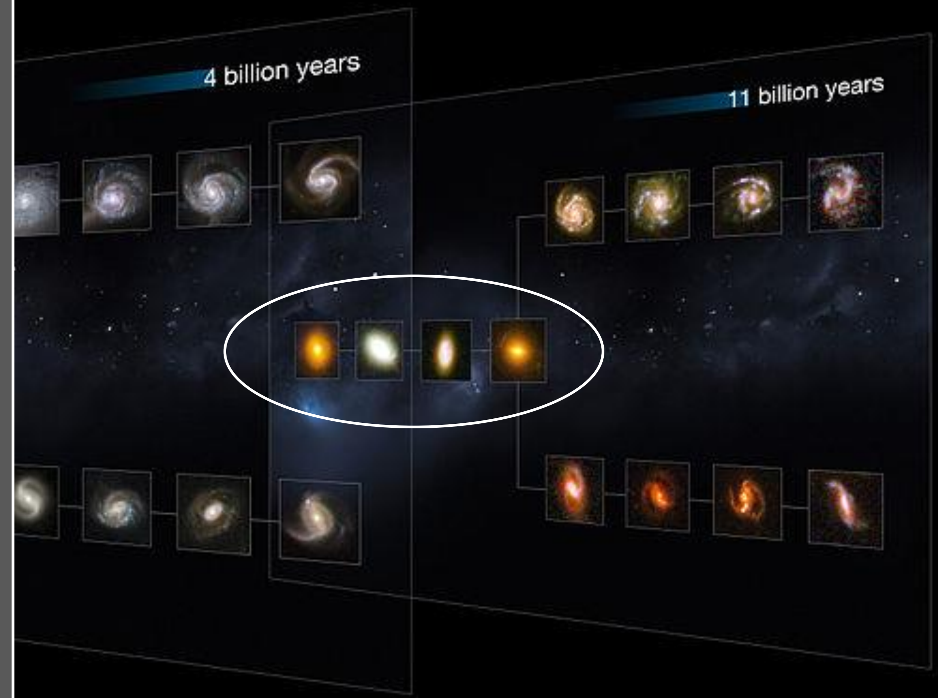

CCiS 2016

São José dos Campos - SP, Brazil
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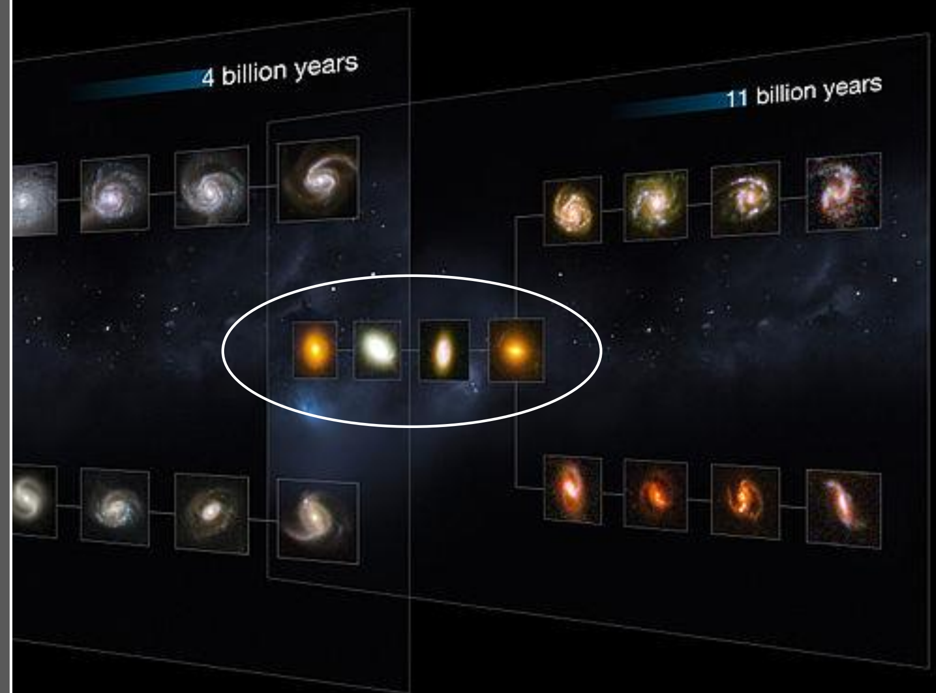

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Thank you!

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UPDATING MORFOMETRIKA: SOFTWARE (GFEC-LAC-CTE)

Algoritmo	Técnica	Versão Original	Pacote/Programa	Versão Paralelizada	Referências Principais
SQB	Espaço de Parâmetros p/ Inferencia Bayesiana	C/C++ Python	GALPHAT	OpenMP (em implementação) CUDA (em implementacao)	Yoon, I., Weinberg, M. D., and Katz, N.. (2011). Monthly Notices of the Royal Astronomical Society, 414:1625-1655. doi:1365-2966.2011.18501.x
GPA	Coeficiente de Assimetria Gradiente	C/C++ IDL	GPA++ GFEC_CODES	OpenMP (a ser implementada) CUDA (em implementação)	R.R. Rosa, A.S. Sharma, J.A. Valdivia, Int. J. Mod. Phys.C, 10(1), 147 (1999). doi: 10.1142/S0129183199000103 R.R. Rosa et al. Physica A 283, 156 (2000). doi: 10.1016.S0378-4371(00)00144-8
MDFA	Histogramas Espectrais e FFT2D	Matlab Python	PHYSIONET JURICA GFEC_CODES	OpenMP (a ser implementada) CUDA (a ser implementada)	Rong-Guan Yeh et al., doi:10.1155/2012/947191 M. Baroni, A. De Wit, R.R. Rosa EPL (Europhysics Letters) 92 (6), 2011. doi:10.1209/0295-5075/92/64002
E+	Entropia estrutural e medidas relacionadas	Python	MORFOMETRYKA	OpenMP (a ser implementada) CUDA (em implementação)	Ferrari et al. arXiv:1509.05430v1
SPIRAL	Identificar e quatificar espiralidade	C	GANALYZER	OpenMP (a ser implementada) CUDA (a ser implementada)	L. Shamir, Ap. J., 736:141, 2011 doi:10.1088/0004-637X/736/2/141
EULERCHAR	Funcionais de Minkowski para Caracterização de Padrões Filamentares	C/C++	CRAL/WGM GFEC_CODES	OpenMP (a ser implementada) CUDA (a ser implementada)	M. France, 2010 WGM Memorandum. R.Rosa et al., Physica A, 386(2):666, 2007. doi:10.1016/j.physa.2007.08.044

Workstation Abax Gamma	**Componentes** • 2 Processadores Intel Xeon Octa Core E52630v3 2.4-3.2GHZ (16 núcleos reais 32 Threads) • 1 Placa-mãe Supermicro X10DRG-Q • 128 GB Memória Kingston DDR4 KVR21R15D4/16 128GB RDIMM • Chassis Workstation Supermicro CSE-732D4-1200 1200Watts Platinum • 5 Disco Seagate Barracuda 2TB SATA III Seagate 7200RPM e 64MB Buffer • 2 Units Intel Xeon Phi 5110P 31 MB L2 Cache PCI Express x16 245 W SC5110P (60 Cores)
Softwares	• Intel® Parallel Studio XE 2016 Professional Edition
Custo	O custo do equipamento com é de R$ 84.900,00. Orçamento válido por 21 dia. Entrega em 60 dias. Frete Incluso.
Requerimentos	• Requer 1200 Watts de potência elétrica.
Serviços	• Todos os serviços de despacho e instalação estão inclusos neste orçamento • Suporte técnico por telefone e email 24/7 por 1 ano incluindo instalação de pacotes (sujeito a verificação de compatibilidade).
Garantia	**Garantia** Garantia Abax de 3 anos.