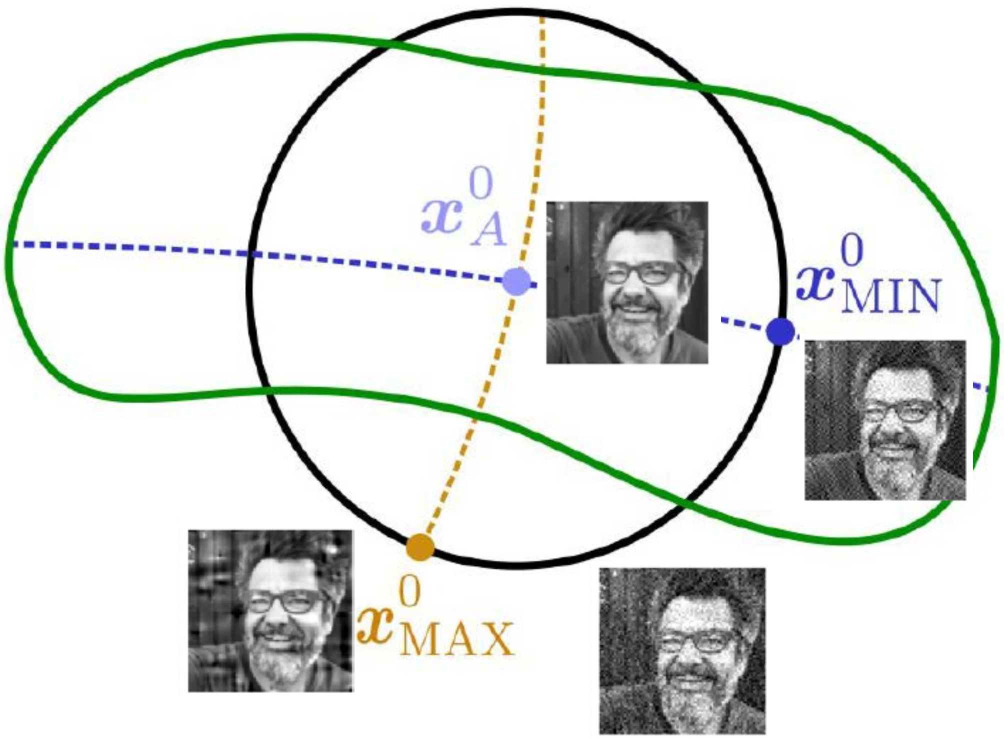
GEOMETRY OF THE SPACE OF VISUAL STIMULI: PSYCHOPHYSICS AND NEURAL MODELS

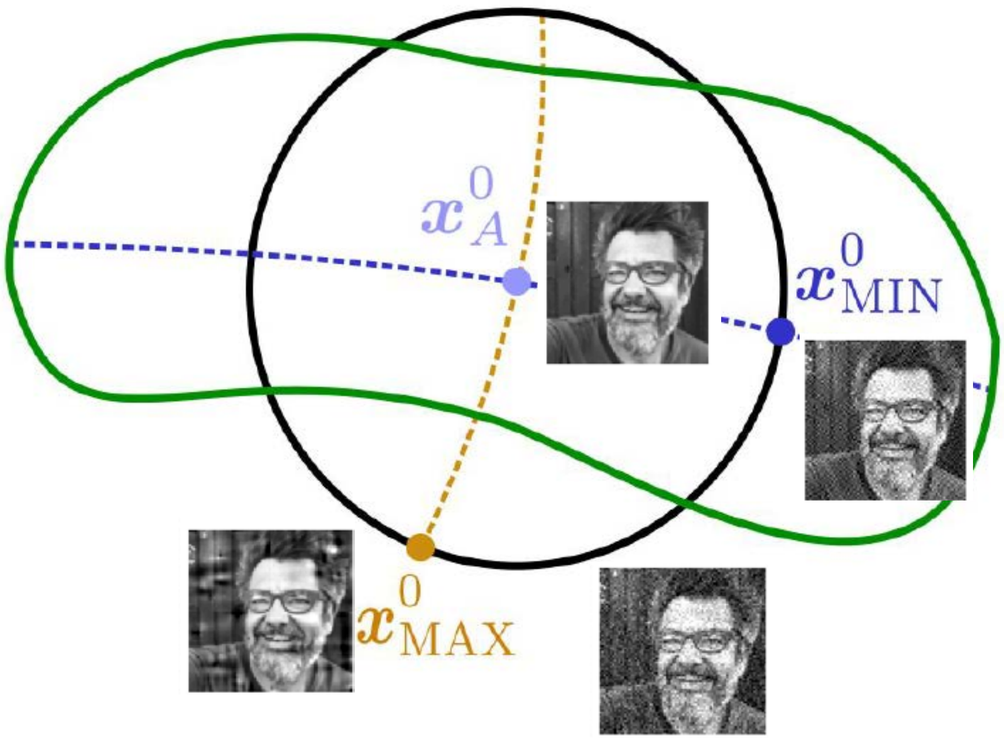


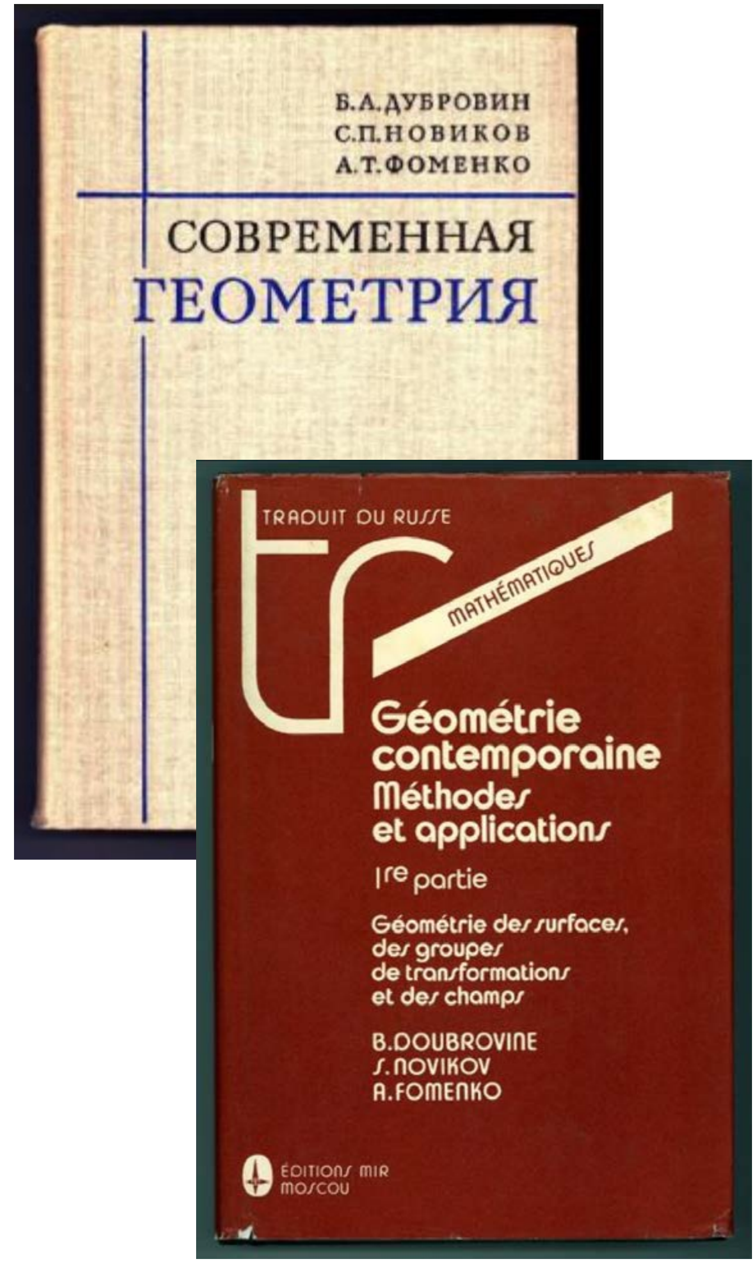
JESÚS MALO

VNIVERSITAT DE VALÈNCIA

SPAIN

WORKSHOP: GEOMETRY OF COLOR PERCEPTION, CORTICAL MODELS OF VISUAL PERCEPTION AND IMAGING APPLICATIONS SORBONNE UNIVERSITÉ PARIS, NOV. 2018





SORBONNE UNIVERSITE PARIS, NOV. 2018

GEOMETRY OF THE SPACE OF VISUAL STIMULI: PSYCHOPHYSICS AND NEURAL MODELS

1. Space is more than color!
2. Geometry may make you a star! SSIM
3. Geometry and neural models (I) $g = \nabla S^{\top} \nabla S$
4. Geometry is more than deep-nets
5. Some psychophysics for you! DOWNLOAD!
6. Geometry and neural models (II) ∇S DOWNLOAD!
7. Conclusions

1. Space is more than color!
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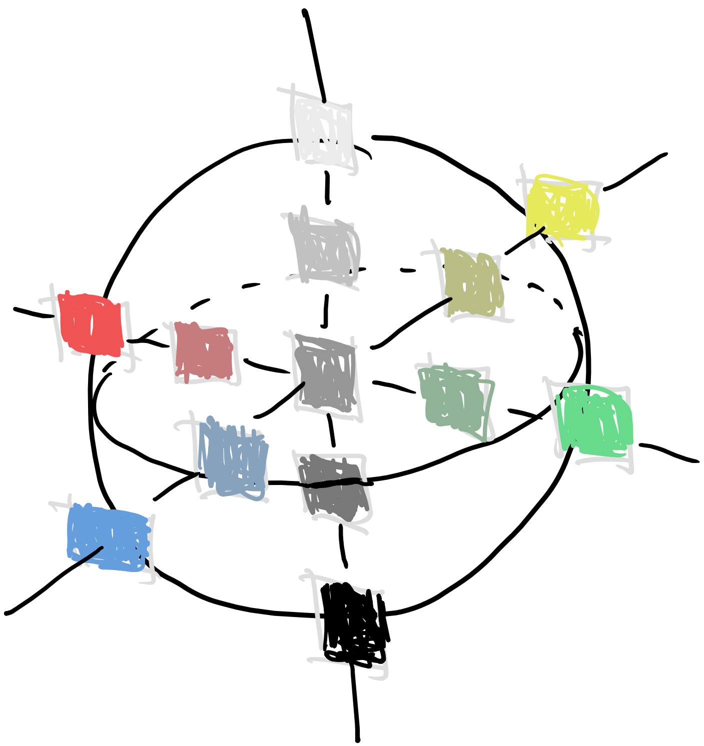
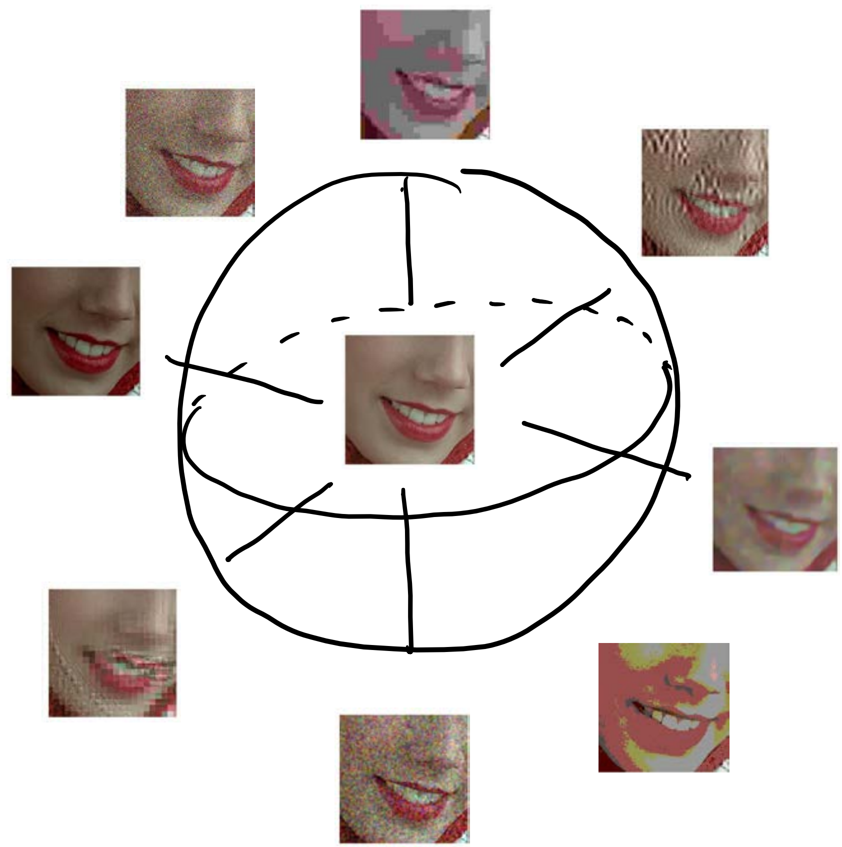
① Space is more than color! Dimensionality & Distance

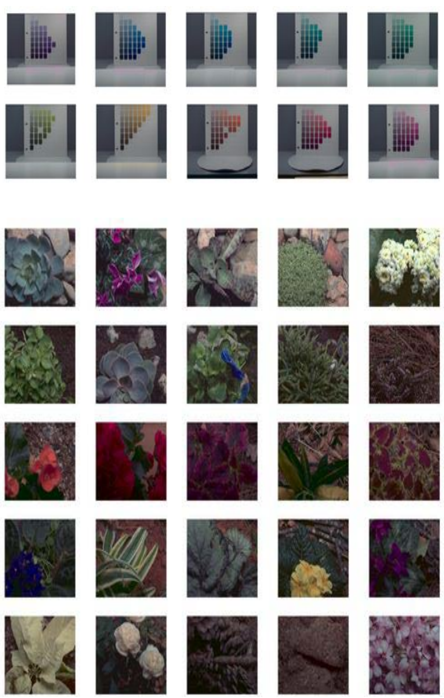


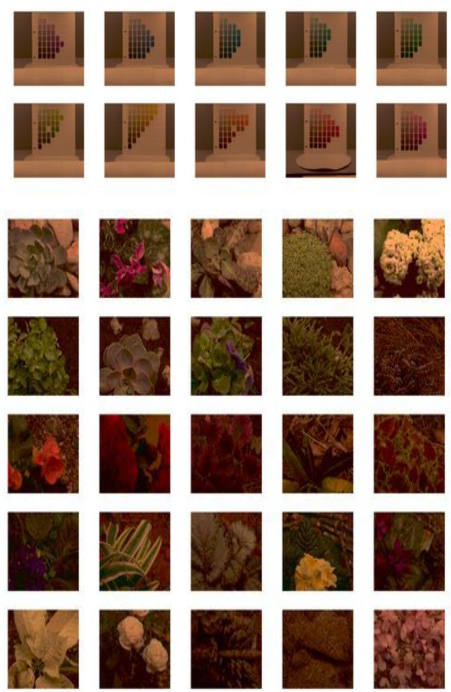


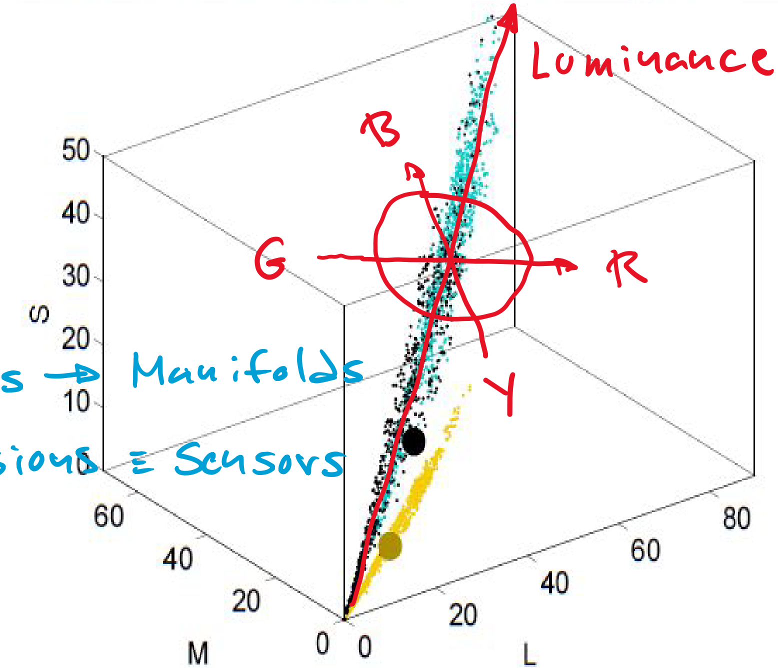
① Space is more than color !

Environment A:
CIE D65 illumination

Environment B:
CIE A illumination





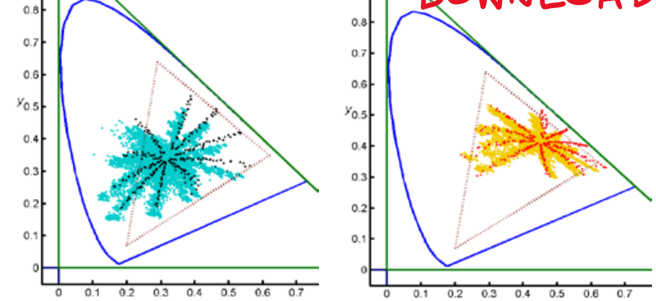


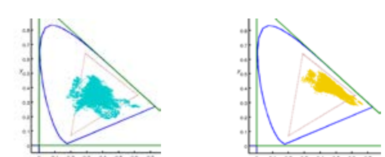
Physics → Manifolds
Dimensions = Sensors

http://isp.uv.es/data_color.htm

Laparra & Malo Neural Comput. 2012
Gutmann, Laparra, Hyvarinen & Malo PLoS 2014
Laparra & Malo Front. Neurosci. 2015

DOWNLOAD!

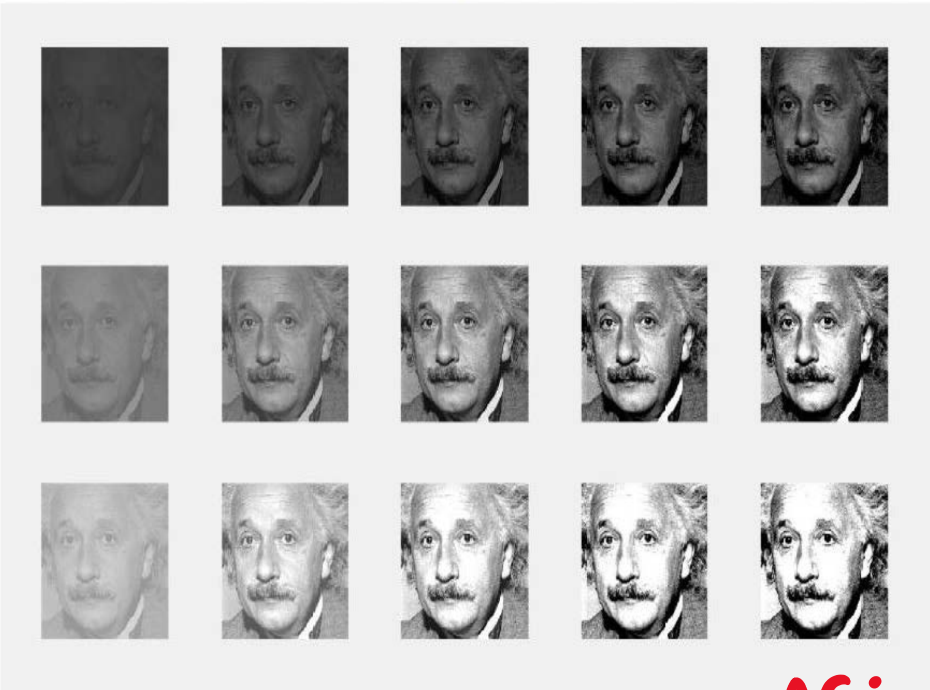


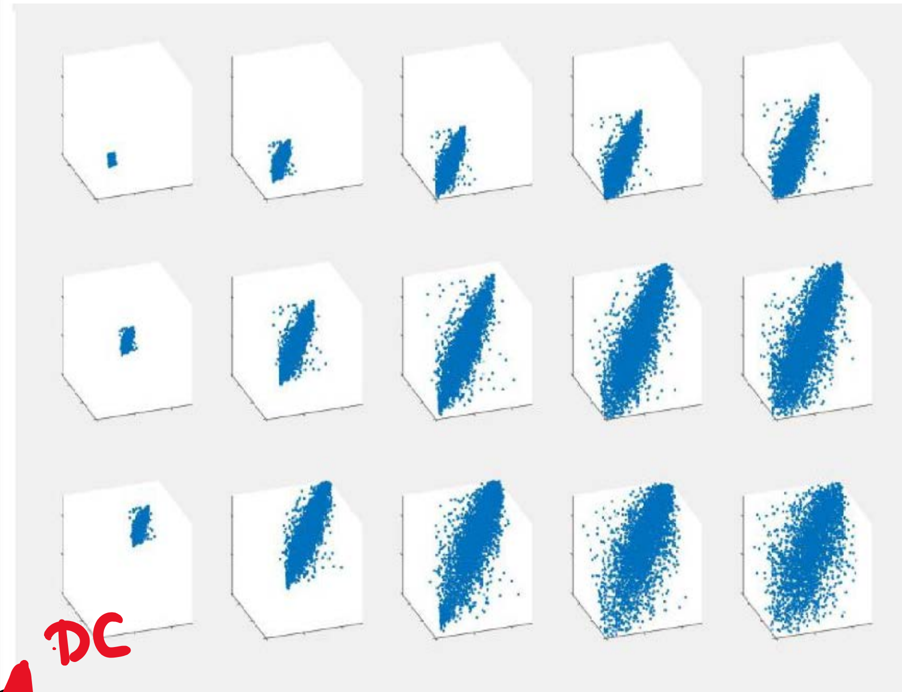


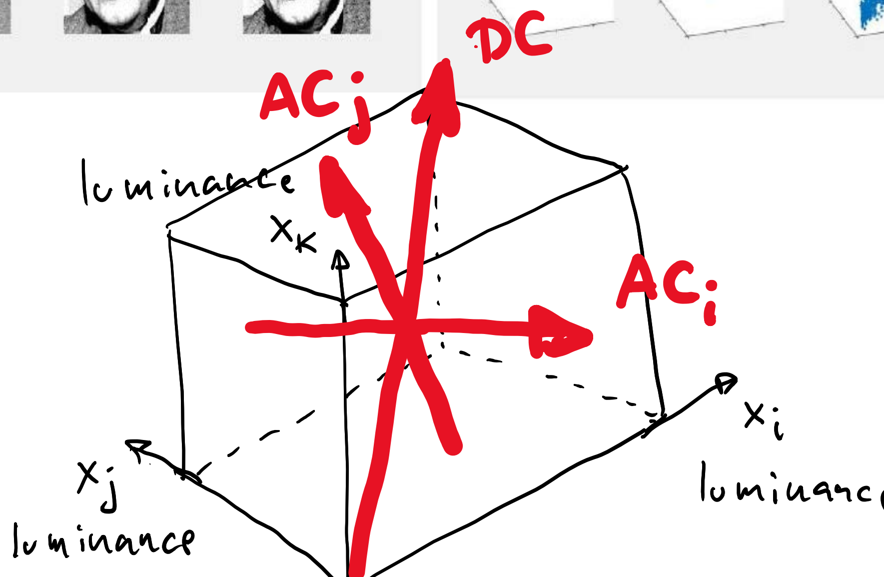
① Space is more than color!

Physics → Manifolds

Dimensions ≡ Sensors



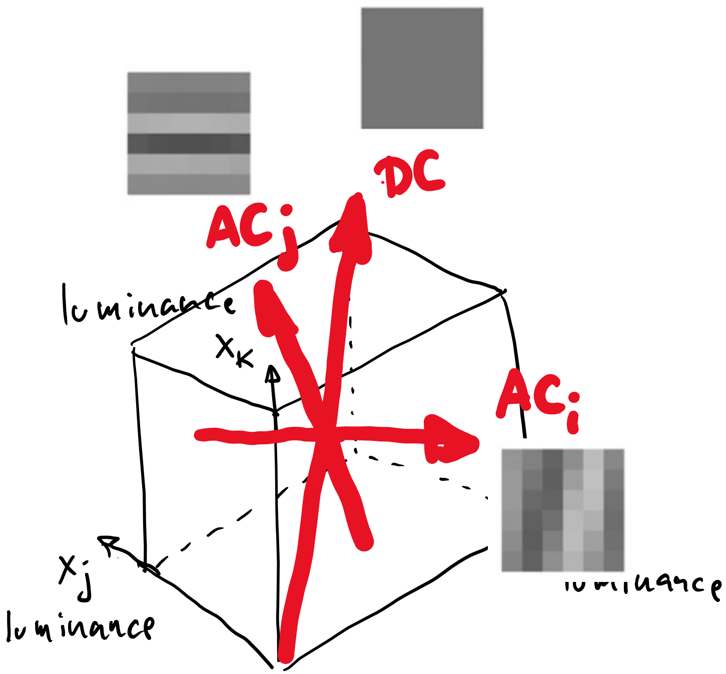


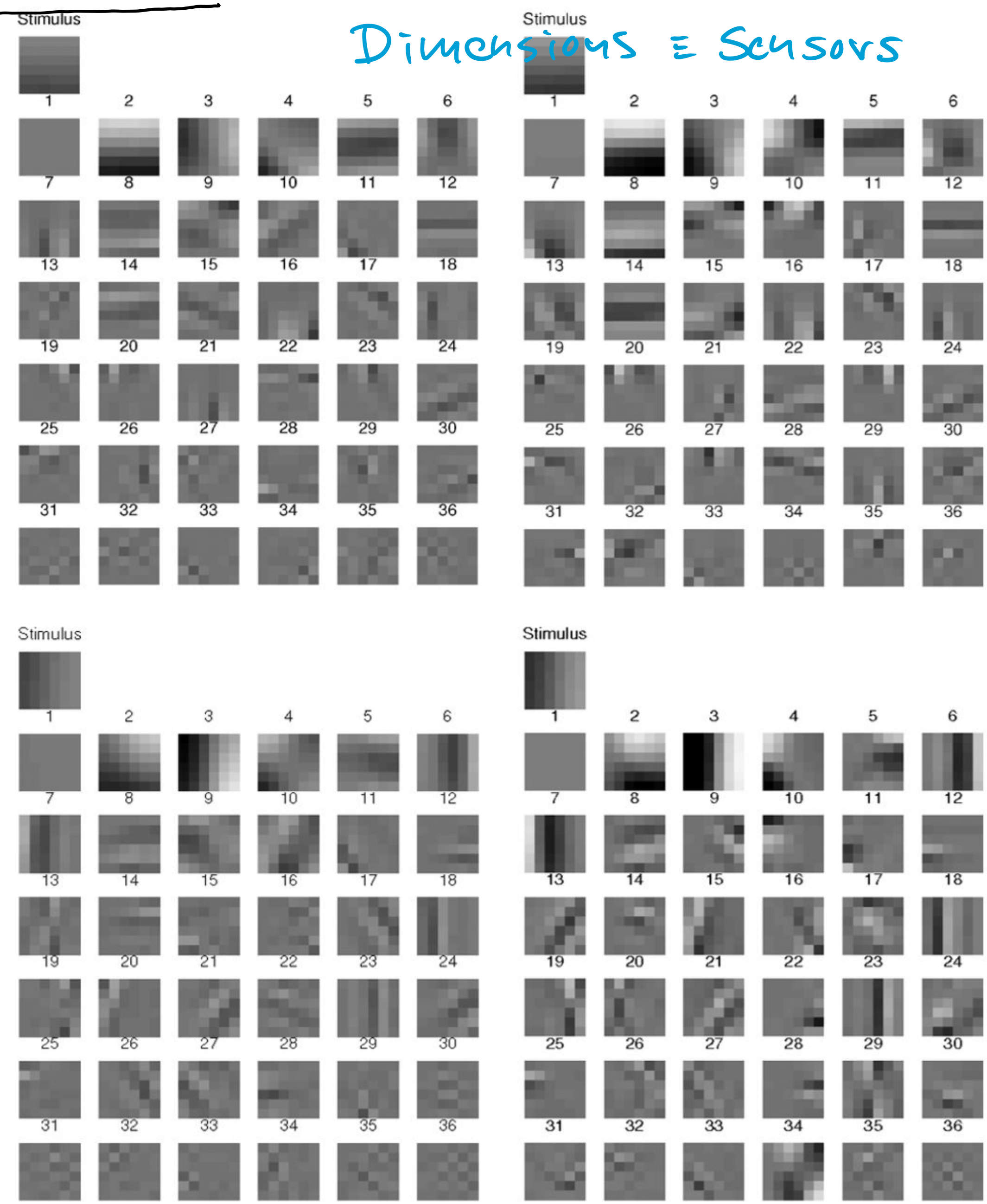


① Space is more than color!

Physics → Manifolds

Dimensions ≡ Sensors

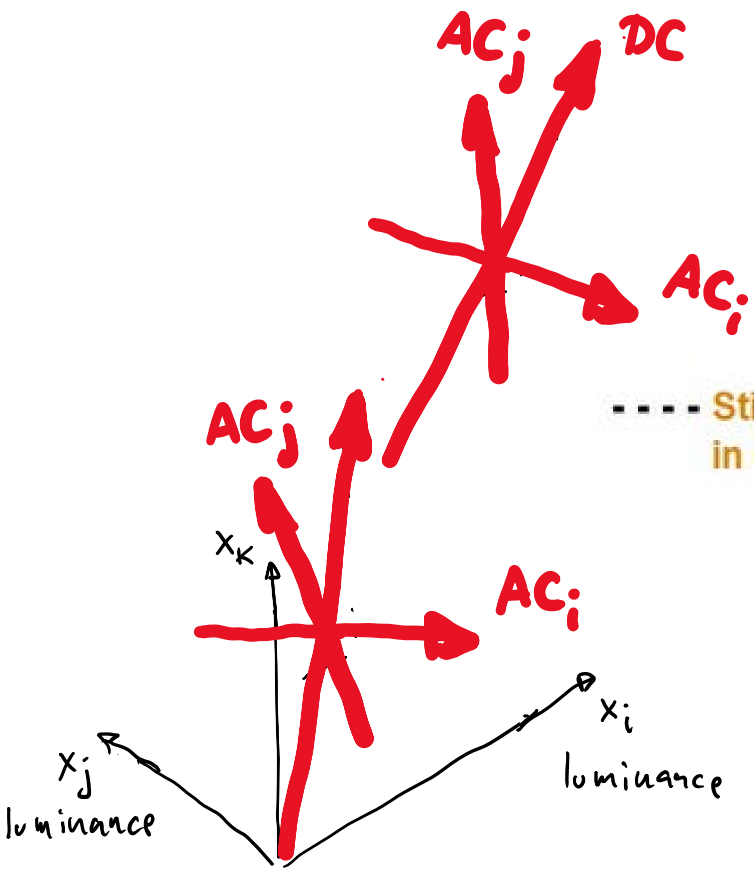


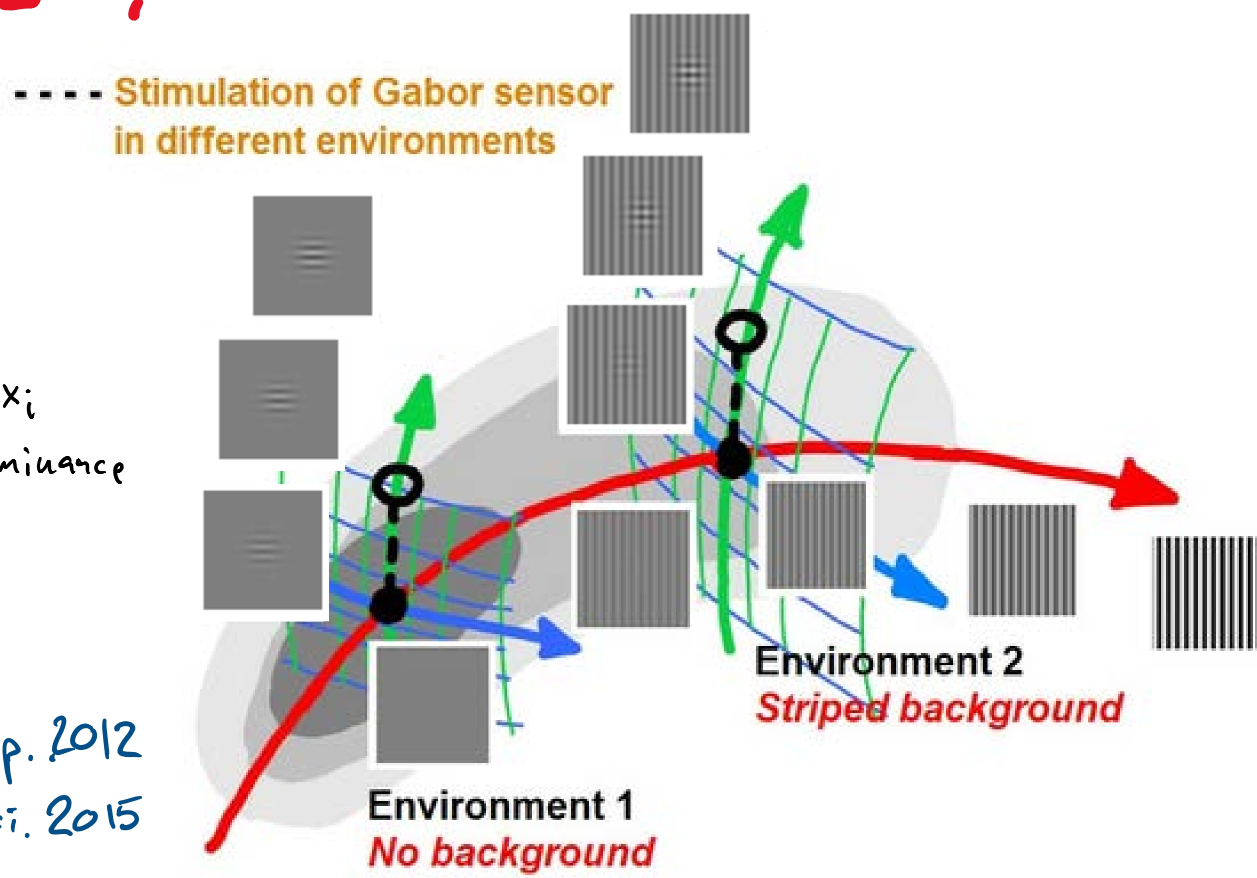


Malo & Gutierrez Network 2006

Local ICA

① Space is more than color ! Adaptation ≡ local basis





Laparra & Malo Neural Comp. 2012
Laparra & Malo Front. Neurosci. 2015

Sequential PCA

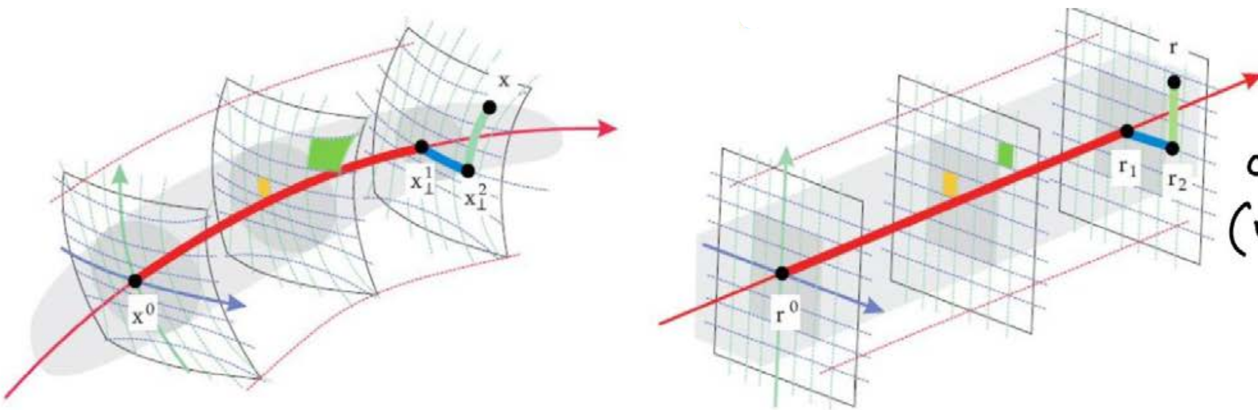
① Space is more than color!

Adaptation ≡ local basis

STIMULUS $\xrightarrow{S}$ RESPONSE

$x \underset{S^{-1}}{\overset{S}{\rightleftarrows}} r$

INPUT (signal) x



OUTPUT (response) r

* INFOMAX
* ERROR MINIMIZATION

$$\mathbf{r} = S(\mathbf{x}) = C \cdot \int_{\mathbf{x}^o}^{\mathbf{x}} \nabla S(\mathbf{x}') \cdot d\mathbf{x}' = C \cdot \int_{\mathbf{x}^o}^{\mathbf{x}} D(\mathbf{x}') \cdot \nabla U(\mathbf{x}') \cdot d\mathbf{x}'$$

$$r_i = C_{ii} \cdot \int_{\mathbf{x}_\perp^{i-1}}^{\mathbf{x}_\perp^{i}} D(\mathbf{x}') \cdot \nabla U(\mathbf{x}') \cdot d\mathbf{x}' = C_{ii} \int_0^{u_{i\perp}^{i}} p_{u_i}(u_i')^{\gamma} \, du_i'$$

Laparra & Malo Neural Comp. 2012

Laparra & Malo Front. Neurosci. 2015

Sequential PCA

1. Space is more than color!
   - Dimensionality & Distance
   - Physics/Manifold & Sensors
   - Adaptation ≡ local basis
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1. Space is more than color!
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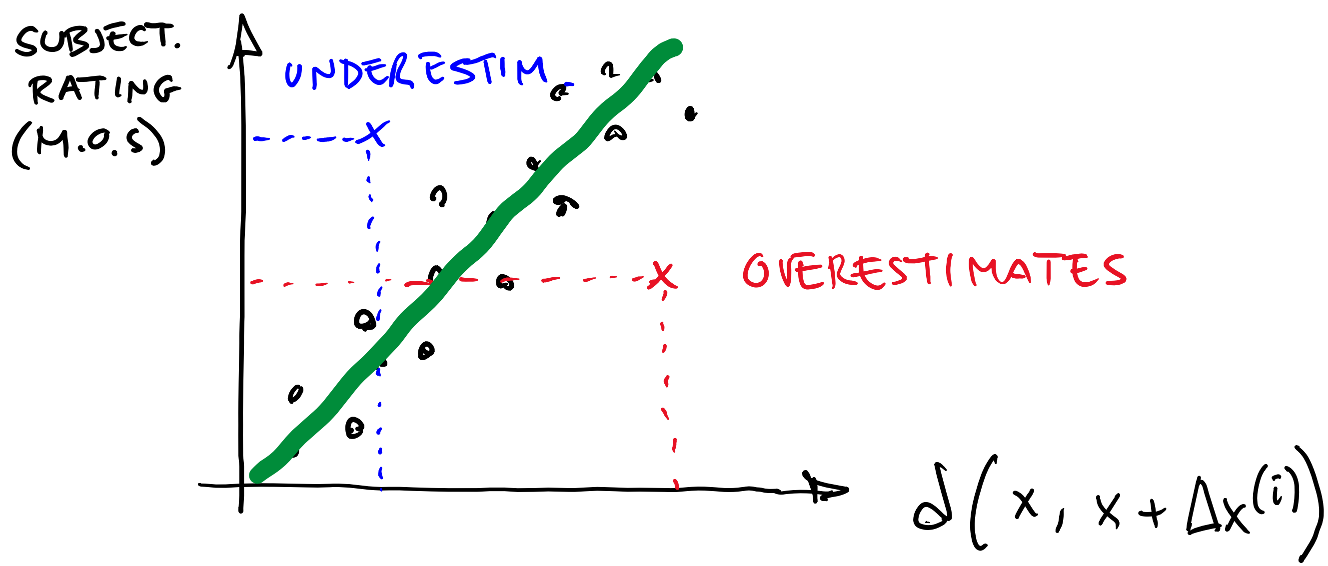
② Geometry may make you a star! The image quality community

x

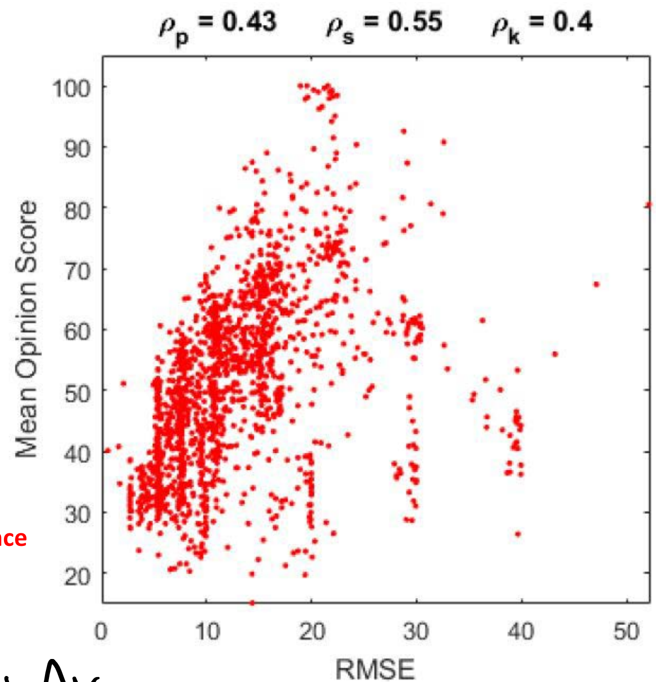
$y^{(1)} = x + \Delta x^{(2)}$

$y^{(2)} = x + \Delta x^{(1)}$



(2) Geometry may make you a star!

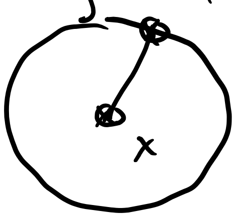
Euclides vs SSIM



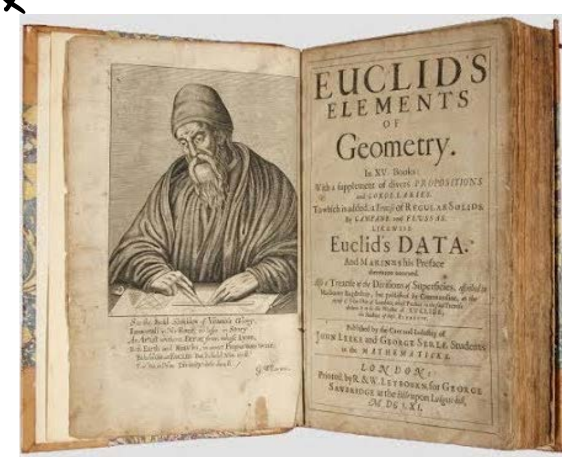
RMSE

Euclidean Distance

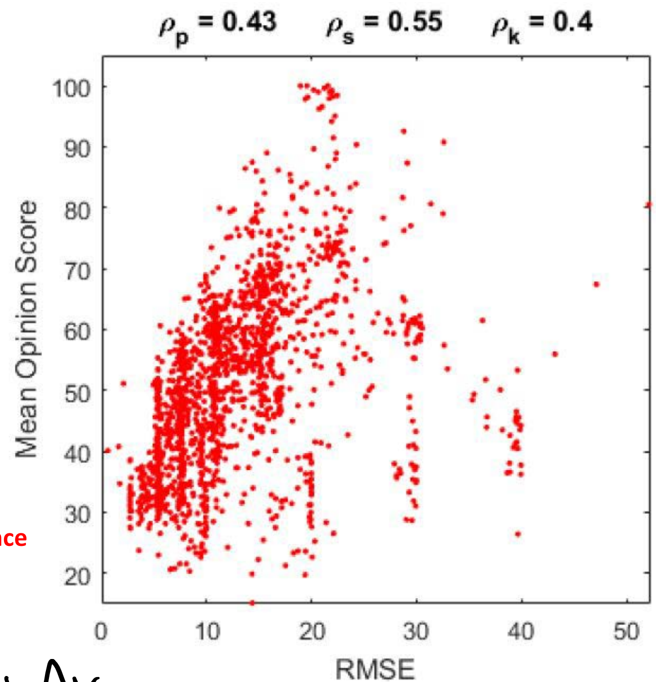
$y = x + \Delta x$



$d = \|\Delta x\|_2$



(2) Geometry may make you a star! Euclides vs SSIM



RMSE

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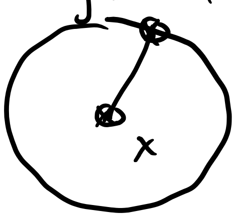
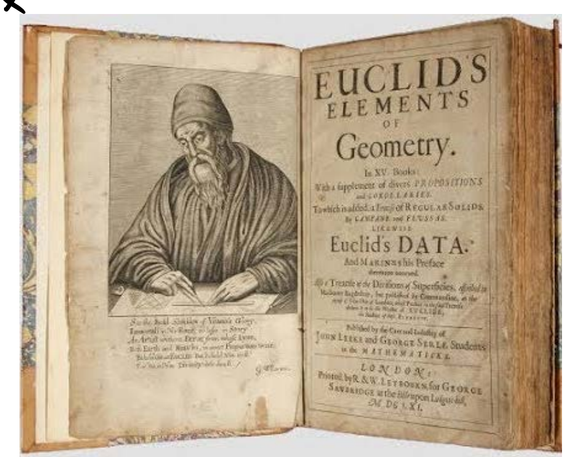


$d = \|\Delta x\|_2$



IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 13, NO. 4, APRIL 2004

Image Quality Assessment: From Error Visibility to Structural Similarity

Zhou Wang, *Member, IEEE*, Alan C. Bovik, *Fellow, IEEE*
Hamid R. Sheikh, *Student Member, IEEE*, and Eero P. Simoncelli, *Senior Member, IEEE*

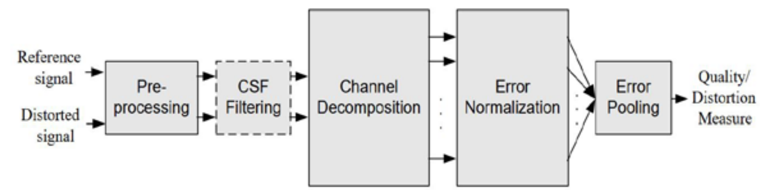
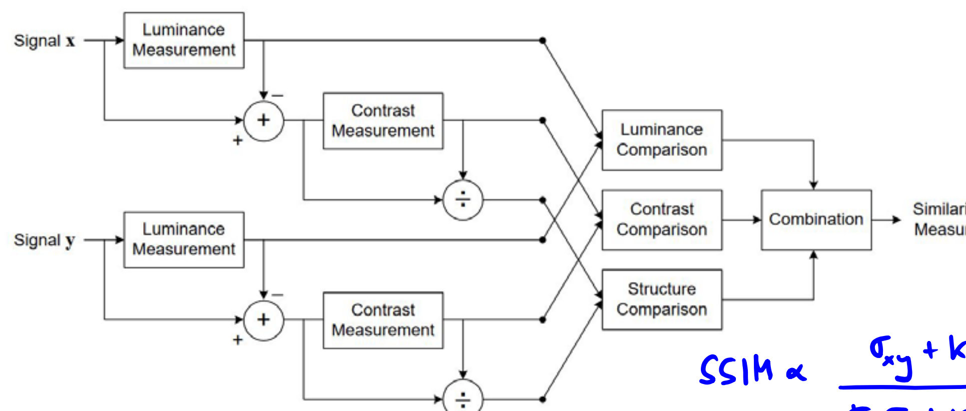


Fig. 1. A prototypical quality assessment system based on error sensitivity. Note that the CSF feature can be implemented either as a separate stage (as shown) or within "Error Normalization".

A. New Philosophy

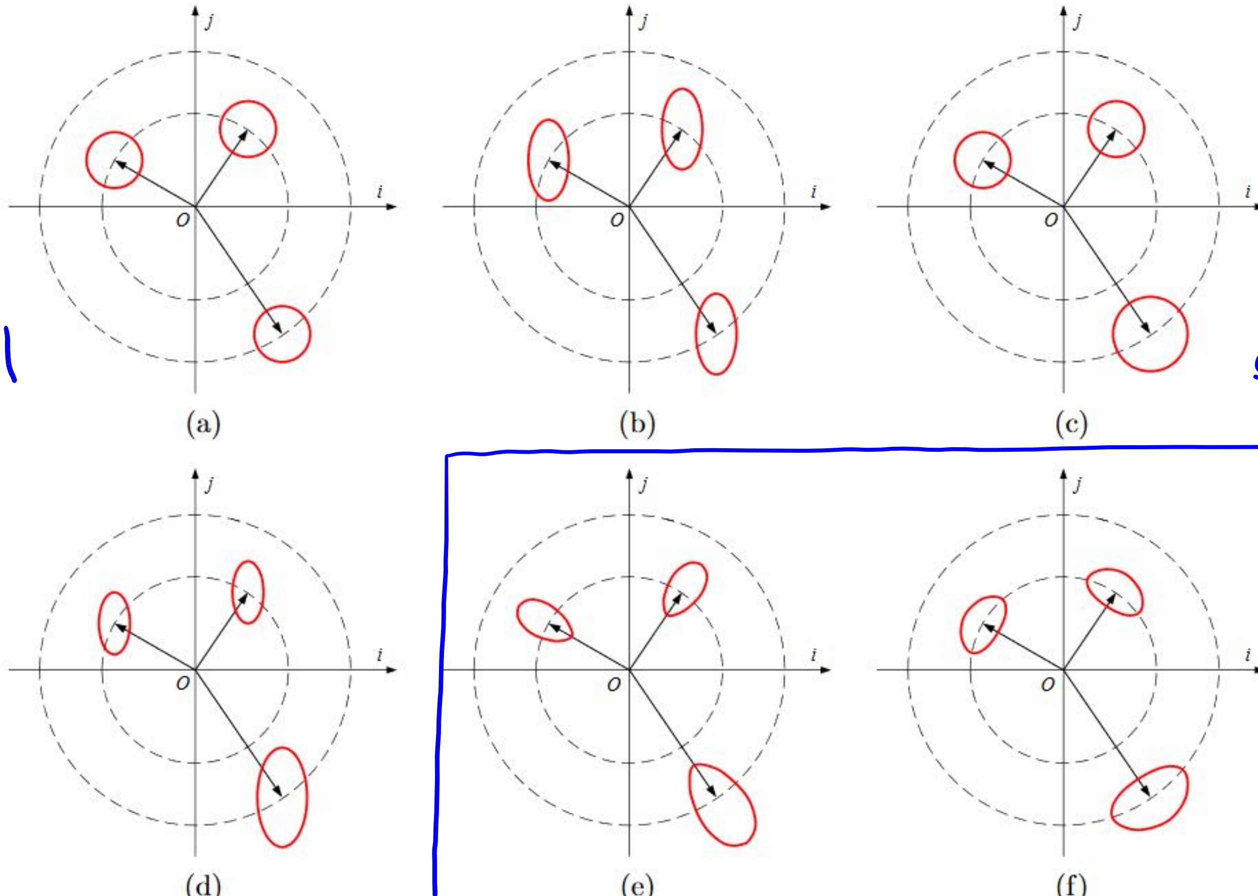


$$\mathrm{SSIM} \propto \frac{\sigma_{xy} + k}{\sigma_x \sigma_y + k}$$

Fig. 3. Diagram of the structural similarity (SSIM) measurement system.

(2) Geometry may make you a star! Euclides vs SSIM

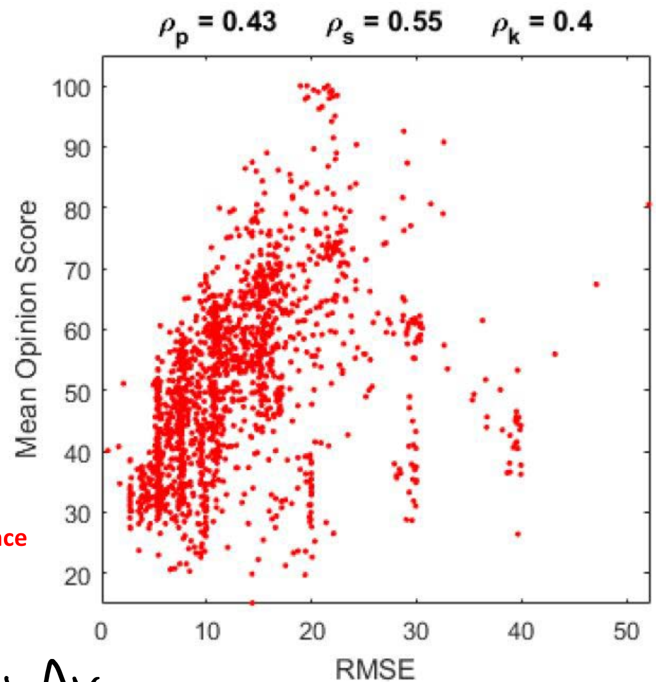
Euclid $= |x-y|$



SSIM $\propto \dfrac{\sigma_{xy}+k}{\sigma_x \sigma_y + k}$

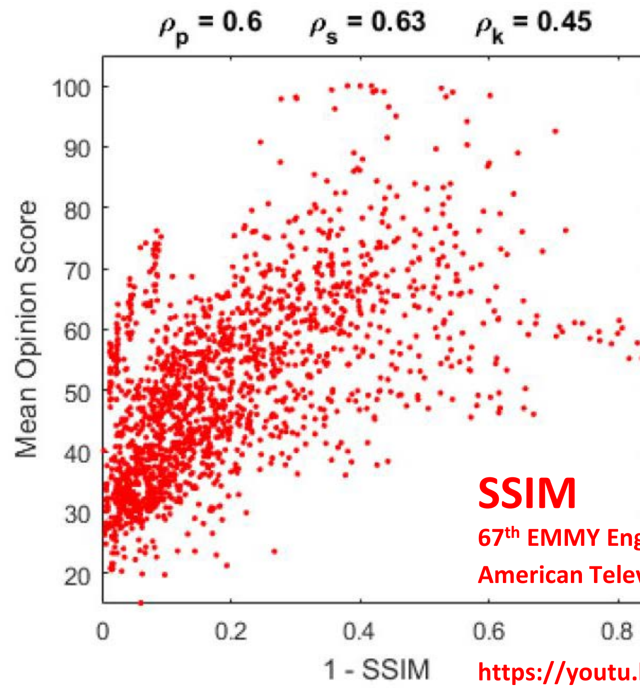
Fig. 4. Three example equal-distance contours for different quality metrics. (a) Minkowski error measurement systems; (b) component-weighted Minkowski error measurement systems; (c) magnitude-weighted Minkowski error measurement systems; (d) magnitude and component-weighted Minkowski error measurement systems; (e) the proposed system (a combination of Eqs. (9) and (10)) with more emphasis on $s(\mathbf{x},\mathbf{y})$; (f) the proposed system (a combination of Eqs. (9) and (10)) with more emphasis on $c(\mathbf{x},\mathbf{y})$. Each image is represented as a vector, whose entries are image components. Note: this is an illustration in 2-D space. In practice, the number of dimensions should be equal to the number of image components used for comparison (e.g, the number of pixels or transform coefficients).

② Geometry may make you a star! Euclides vs SSIM



RMSE

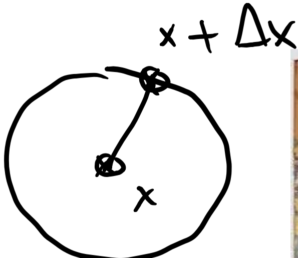
Euclidean Distance



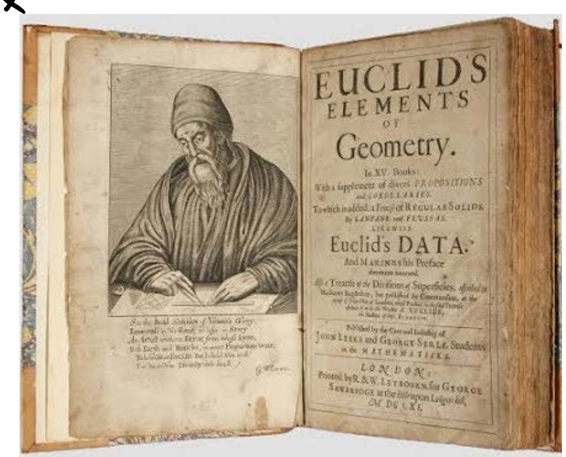
SSIM

67th EMMY Engineering Award of the American Television Academy 2015 !

https://youtu.be/e5-LCFGdgMA



$d = \|\Delta x\|_2$



(2) Geometry may make you a star! Euclides vs SSIM

Google Scholar

Alan Bovik

FOLLOW

Cockrell Family Regents Endowed Chair Professor, The University of Texas at Austin
Verified email at ece.utexas.edu - Homepage

Image Processing Video Processing Visual Perception Vision Science Video Quality

TITLE	CITED BY	YEAR
Image quality assessment: From error visibility to structural similarity Z Wang, A Bovik, H Sheikh, E Simoncelli IEEE Transactions on Image Processing 13 (4), 600-612	20022	2004
A universal image quality index Z Wang, AC Bovik IEEE Signal Processing Letters 9 (3), 81-84	4719	2002
Image information and visual quality HR Sheikh, AC Bovik IEEE Transactions on Image Processing 15 (2), 430-444	2430	2006
Multiscale structural similarity for image quality assessment Z Wang, EP Simoncelli, AC Bovik The Thirty-Seventh Asilomar Conference on Signals, Systems & Computers, 2003 ...	2301	2003

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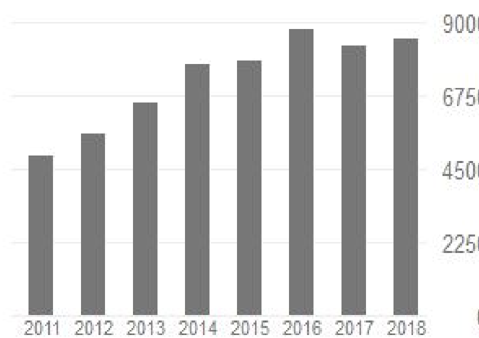
i10-index	433	298



Co-authors VIEW ALL

Zhou Wang
Professor, Electrical and Comput...

(2) Geometry may make you a star!

the review

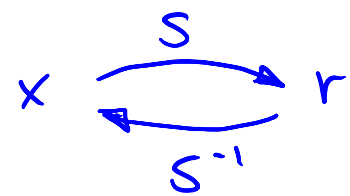
What about proper neural models?

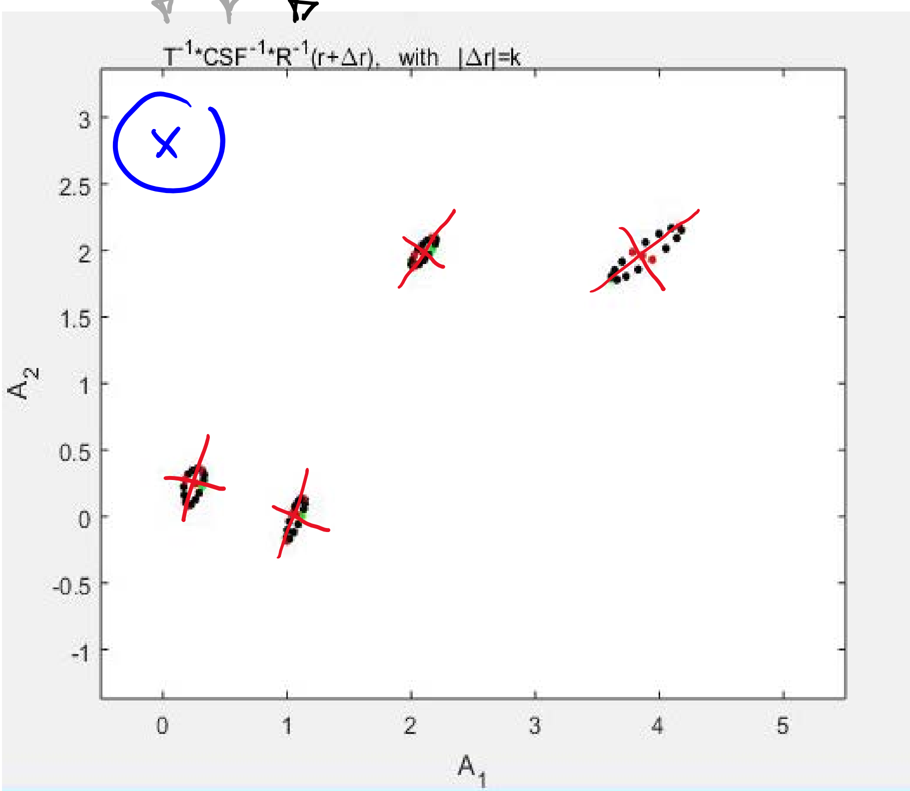
(such as Carandini & Heeger Divisive Normalization)

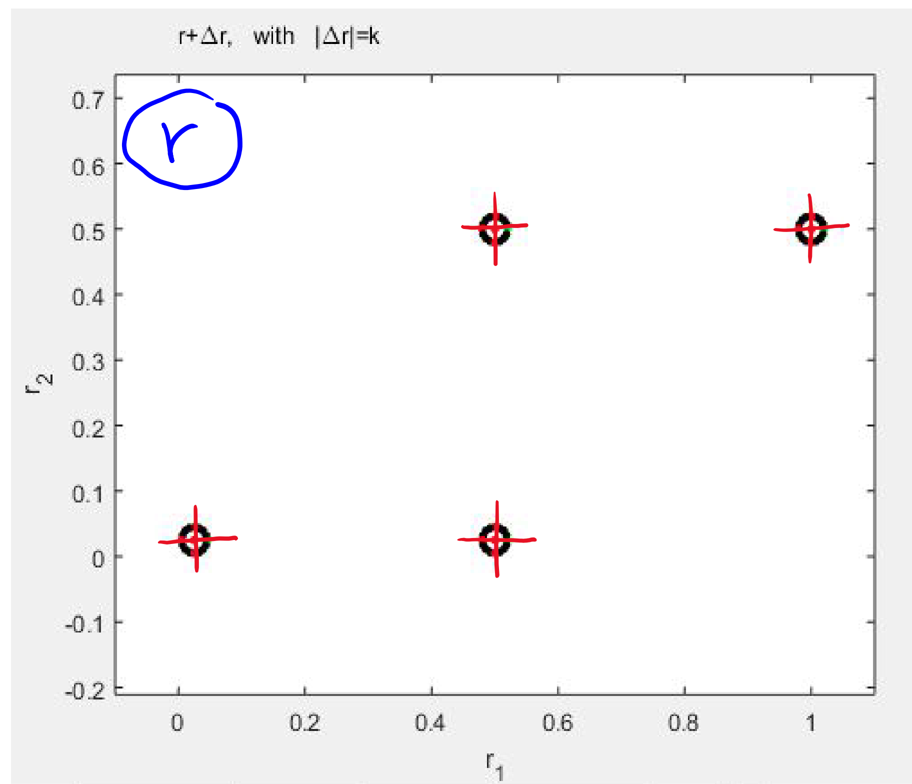
$$x \underset{s^{-1}}{\overset{s}{\rightleftarrows}} r$$

(2) Geometry may make you a star!

the review







Proper neural models S also give the right input dependent behavior!

1. Space is more than color!
2. **Geometry may make you a star!**
   - Image Quality
   - Euclides vs SSIM
   - Don't forget S!
3. Geometry and neural models (I)
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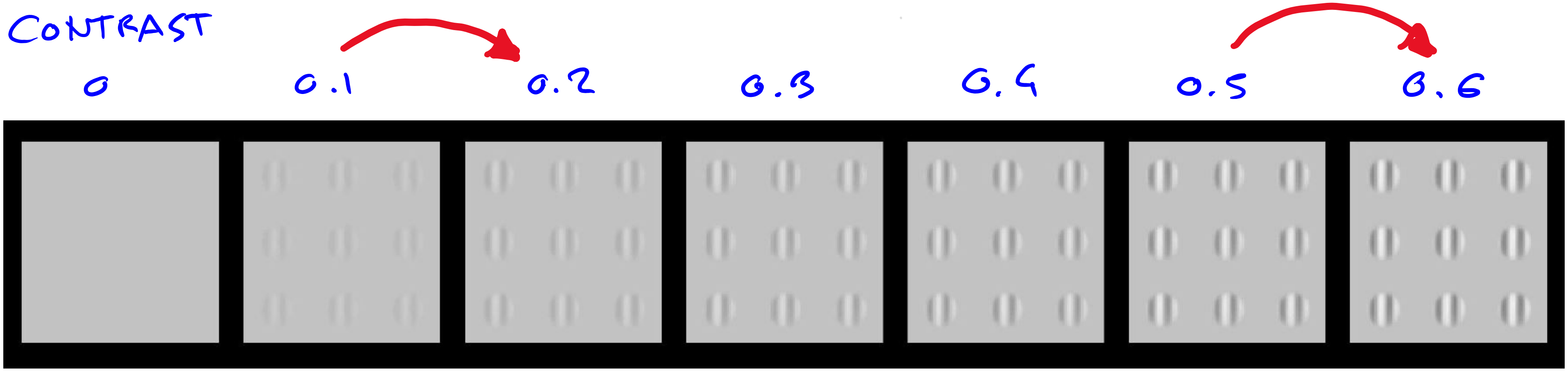
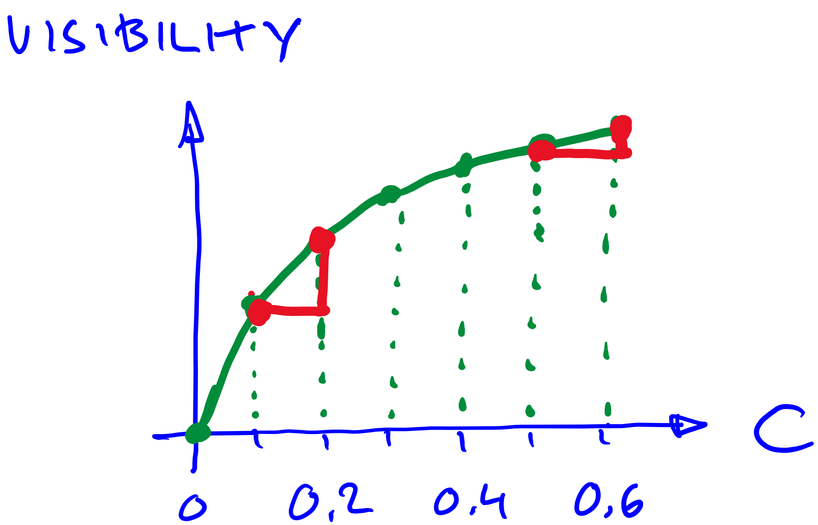
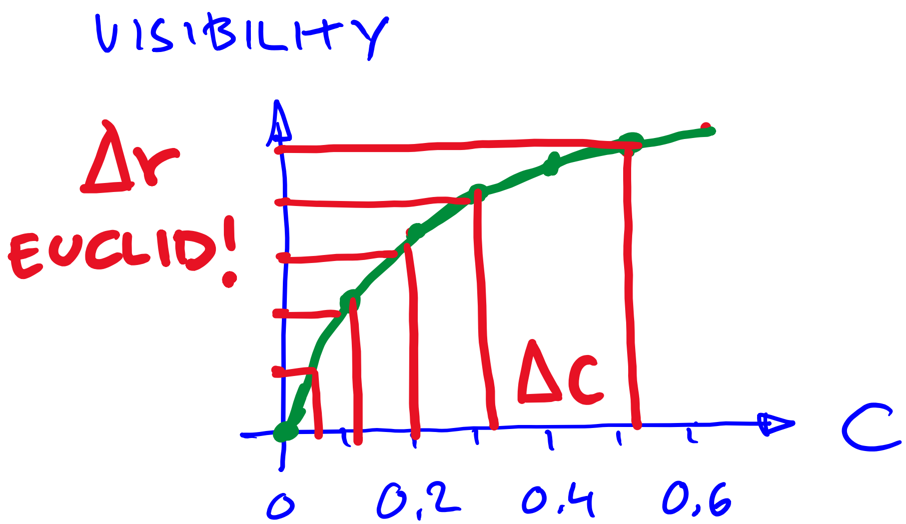
③ Geometry and neural models (I)

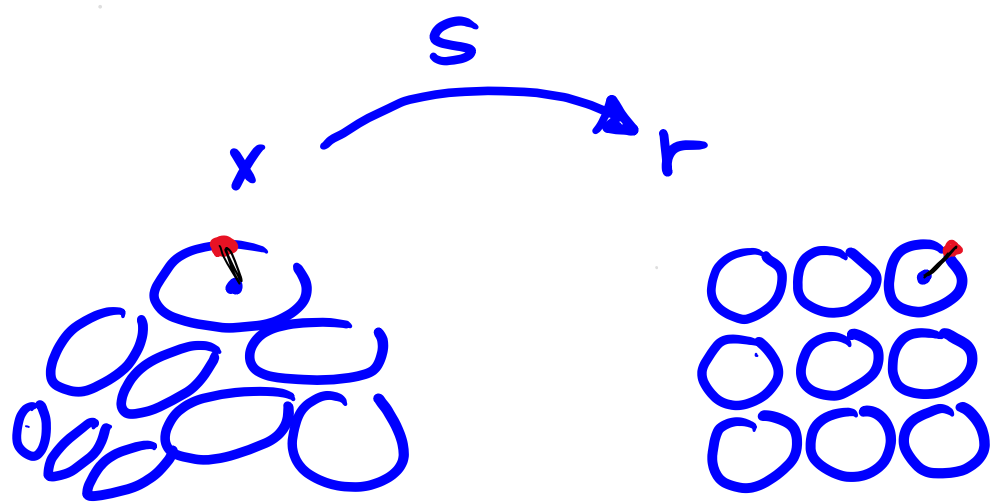
Euclides is right (in the proper domain)







③ Geometry and neural models (I)



Euclidean distance in the response domain

+

Distance preservation under transforms

+

Taylor

$$d^2(r, r+\Delta r) = \Delta r^T \cdot \Delta r$$

$$d^2(x, x+\Delta x) = d^2(r, r+\Delta r) = \Delta x^T \underbrace{\nabla S^T \cdot \nabla S}_{\text{NON TRIVIAL METRIC!}} \cdot \Delta x$$

$$\Delta r \simeq \nabla_x S(x) \cdot \Delta x$$

NON TRIVIAL METRIC!

$\equiv$

JACOBIAN OF NEURAL MODEL!

Malo et al. Disp. 99, IEEE TIP 06, JOSA 10, PLoS 18

③ Geometry and neural models (I)

Divisive Normalization neural models — Dynamic models (e.g. Wilson-Cowan)

[Carandini & Heeger Nature Rev. Neurosci. 2012] [Malo & Bertalmio arXiv 18]

$$\begin{tikzcd} x \arrow[r, "\mathcal{L}"'] \arrow[rr, bend left, "S"] & e \arrow[r, "\mathcal{N}"'] & r \end{tikzcd}$$

T = wavelet basis matrix

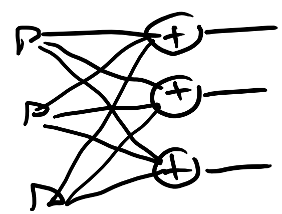
e = wavelet vector

b = semisaturation

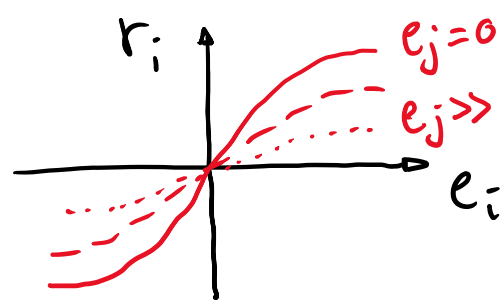
H = interaction kernel

k = constant → dyn. range

$\mathcal{L}$ $\quad e = T \cdot x$



$\mathcal{N}$ $\quad r = k \cdot \dfrac{e}{b + H \cdot e}$



Masking and adaptation

$$\nabla_x S \sim \left[I - D_{r(x)} H \right] \cdot D_e \cdot T \Rightarrow g = \nabla_x S^T \nabla_x S$$

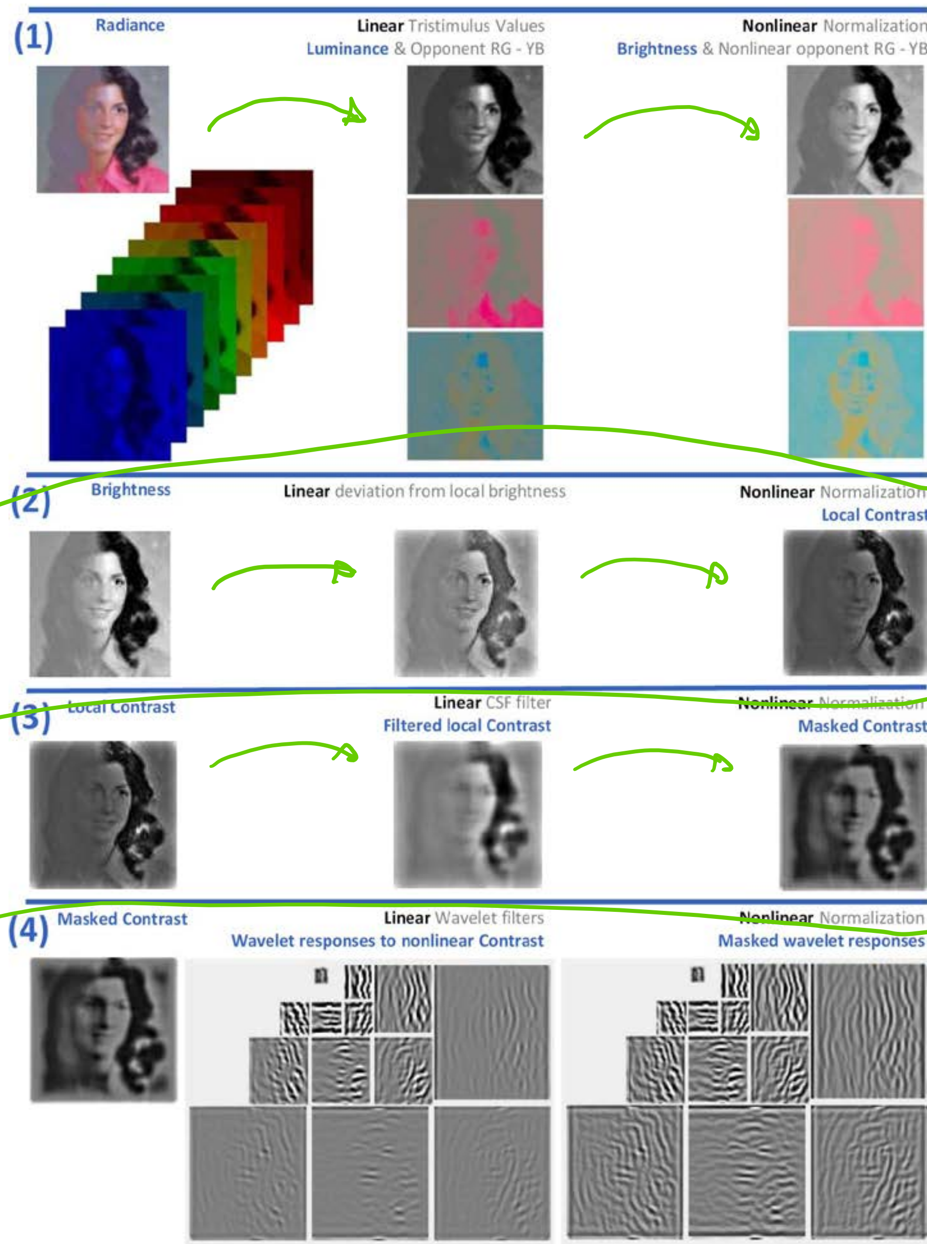
NON DIAGONAL!
INPUT DEPENDENT!

③ Geometry and neural models (I)

Divisive Normalization

Martinez, Bertalmio & Malo PLoS 2018

CASCADE
L + N



COLOR

Spectral integration
Adaptation
Oponency
Saturation

SPATIAL TEXTURE

Contrast

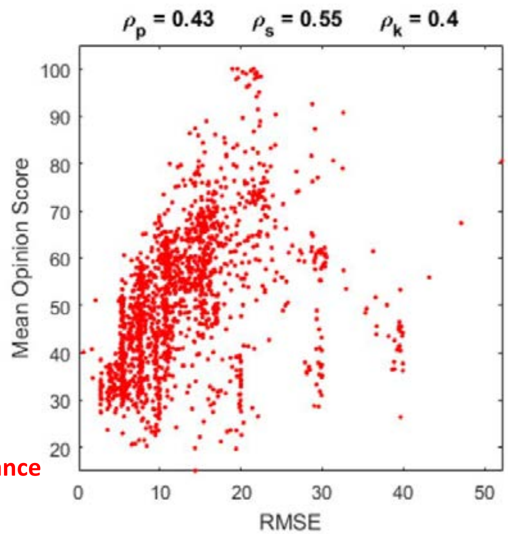
CSFs
Global masking

Wavelet
Cross-band masking

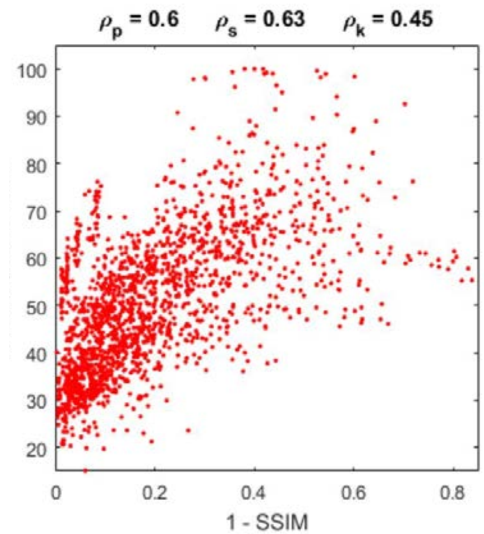
③ Geometry and neural models (I)

Divisive Normalization

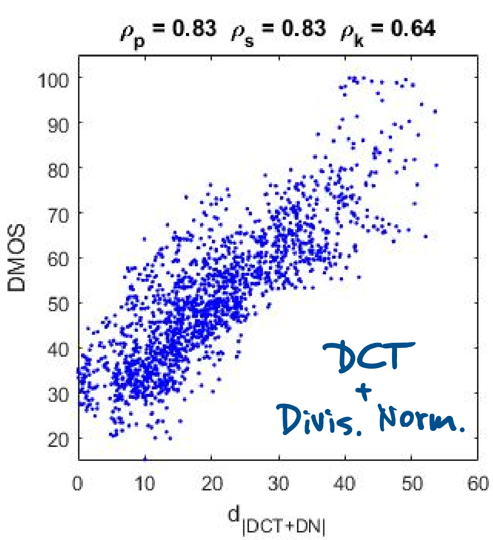
Martinez, Bertalmio & Malo PLoS 2018
Laparra & Simoncelli JOSA 2017



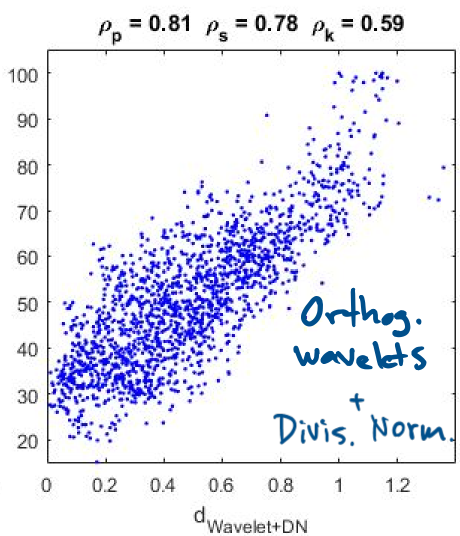
RMSE
Euclidean Distance



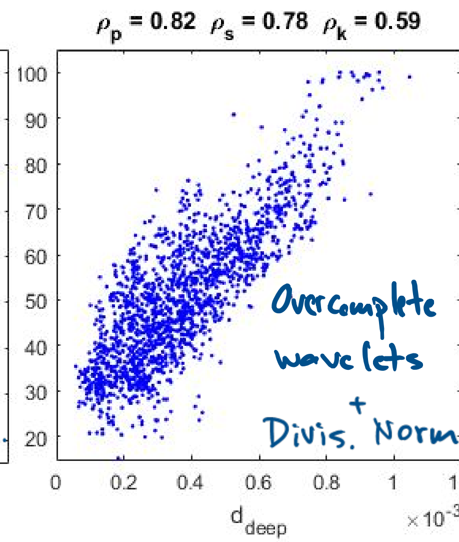
SSIM Paper 2004
67th EMMY Engineering Award of the American Television Academy 2015 !



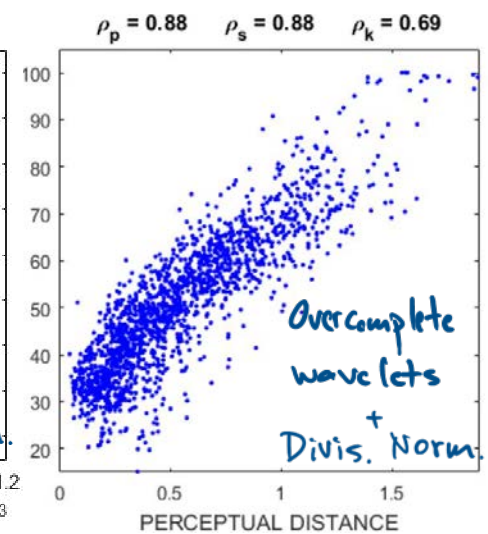
V1_model_DCT_DN_color
. Im. Vis. Comp. 1997
IEEE Trans. Im. Proc. 2006 ....



V1_model_wavelet_DN_color
JOSA A 2010
Neural Comput. 2010



BioMultiLayer_L_NL_color
Front. Neurosci. 2018 a



BioMultiLayer_L_NL_color
(partially optimized)
PLoS ONE 2018

1. Space is more than color!
2. Geometry may make you a star!
3. Geometry and neural models (I)
4. Geometry is more than deep-nets
5. Some psychophysics for you!
6. Geometry and neural models (II)
7. Conclusions

$$g(x) = \nabla S(x)^T \nabla S(x)$$

Excellent behavior!

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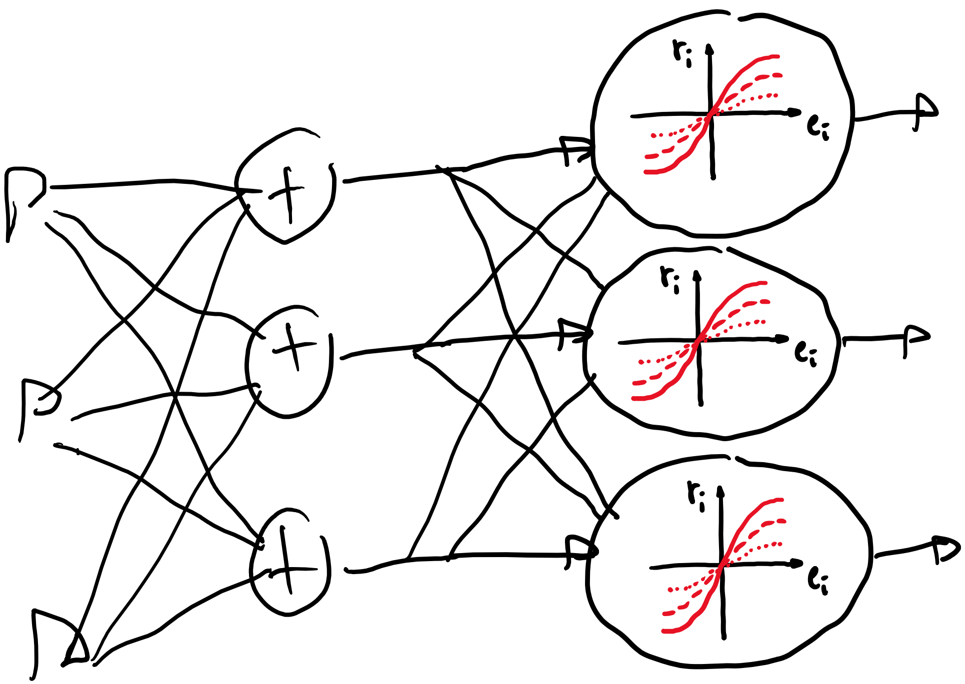
④ Geometry is more than deep-nets

[Proper neural models is more than regression]

(T) (H)

WAVELET – KERNEL BALANCE !



T H

$$r = K \cdot \frac{T \cdot x}{b + \underbrace{\left[D_l \cdot H \cdot_G D_r\right]}_{H} \cdot T \cdot x}$$

4 Geometry is more than deep-nets

[Proper neural models is more than regression]

WAVELET - KERNEL BALANCE !

Gedanken psychophysics [Martinez, Bertalmio, Malo, Under Review. 18]
arXiv

4.1 Expected behavior

4.2 Naive Divisive Normalization

Malo et al. Neural Comp. 2010
JOSA A 2010
PLoS ONE 2018

4.3 Unit norm Watson & Solomon Kernel

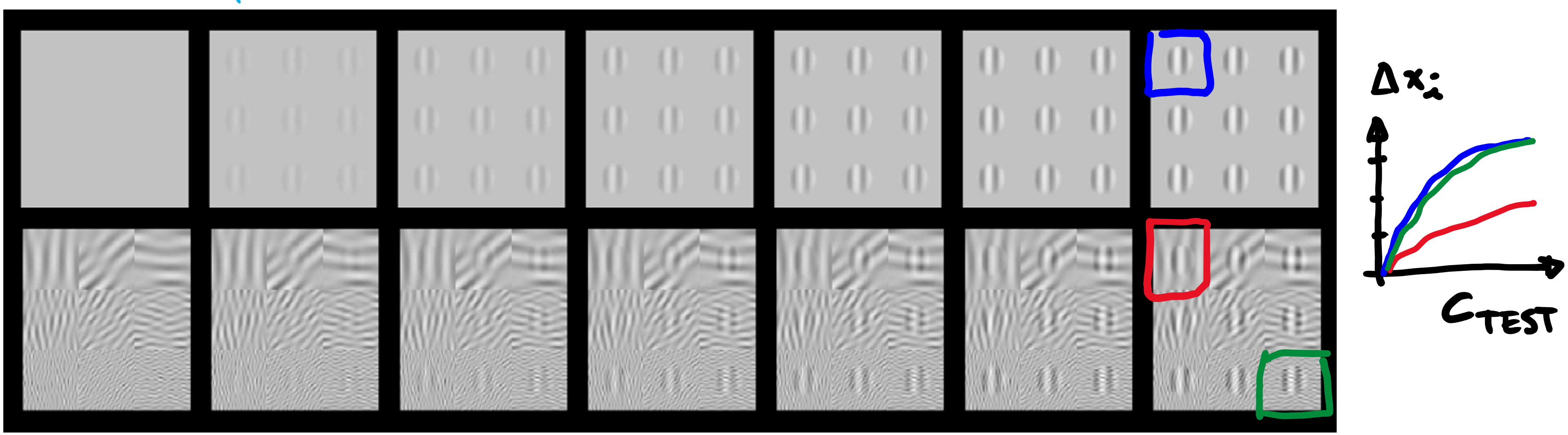
Watson & Solomon JOSA A 1997

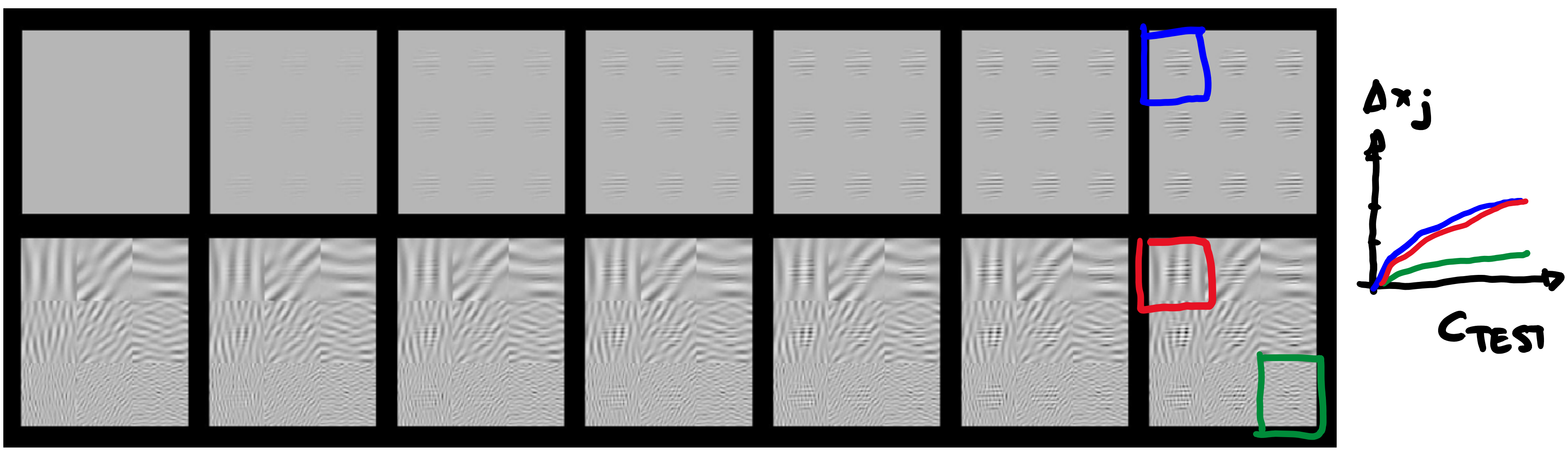
4.4 Changes for by-hand tuning

4 Geometry is more than deep-nets

[Proper neural models is more than regression]

4.1 Expected behavior



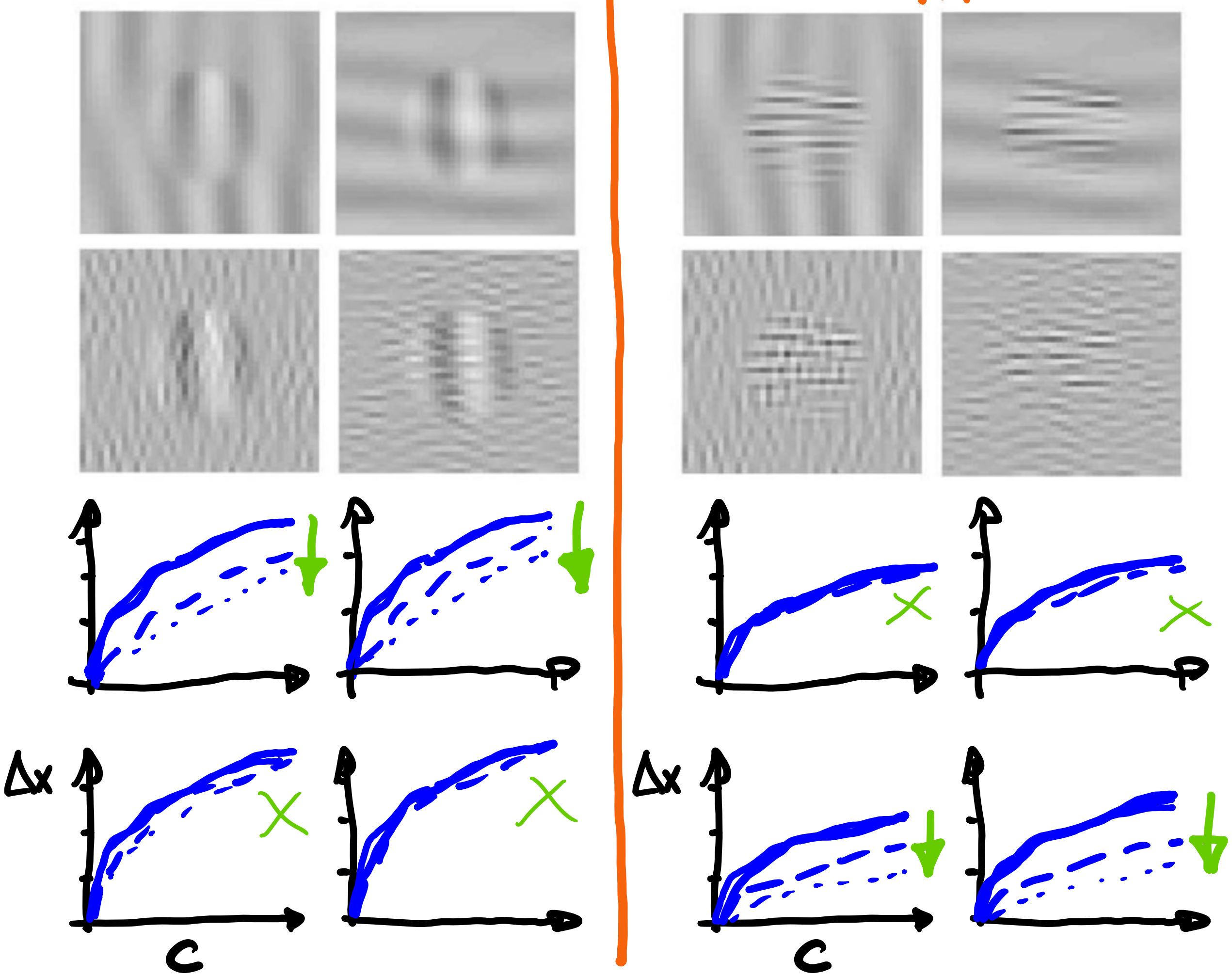


(4) Geometry is more than deep-nets

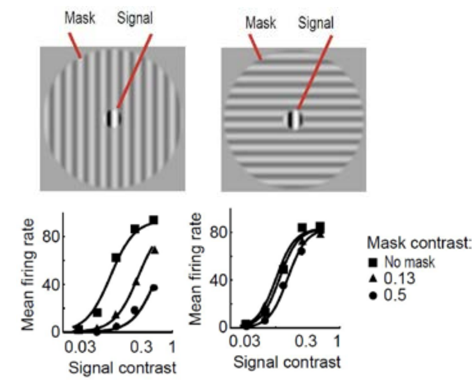
[Proper neural models is more than regression]

4.1 Expected behavior

LOW | HIGH



Cavanagh 00



$c_M = 0$

$c_M \ll$

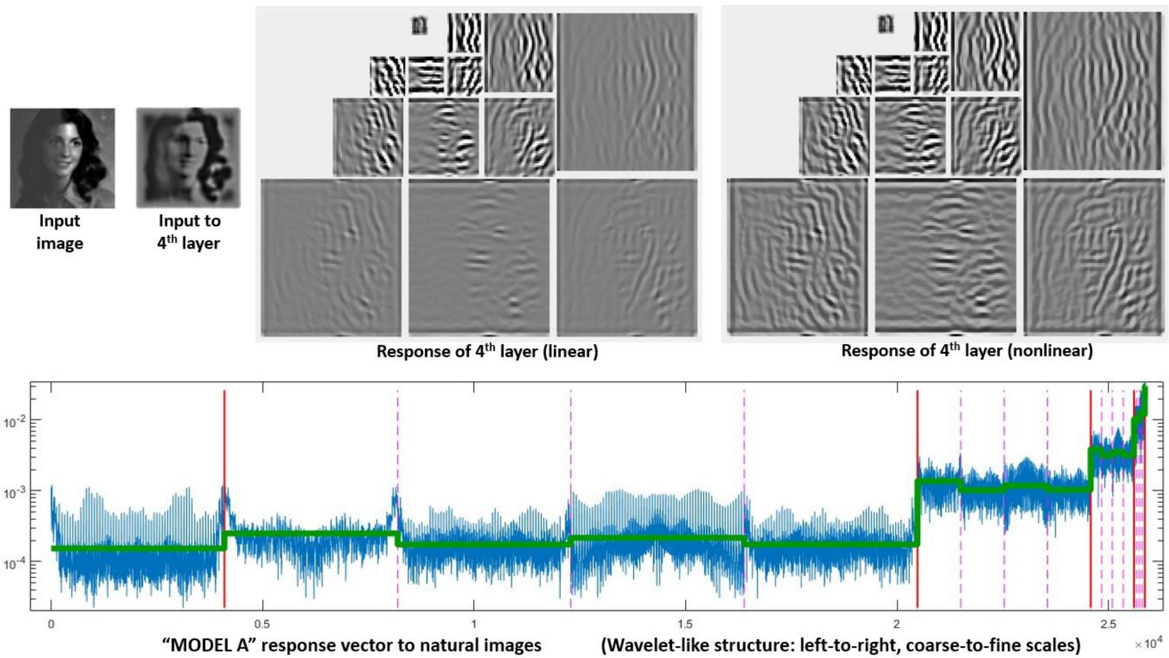
$c_M \gg$

④ Geometry is more than deep-nets

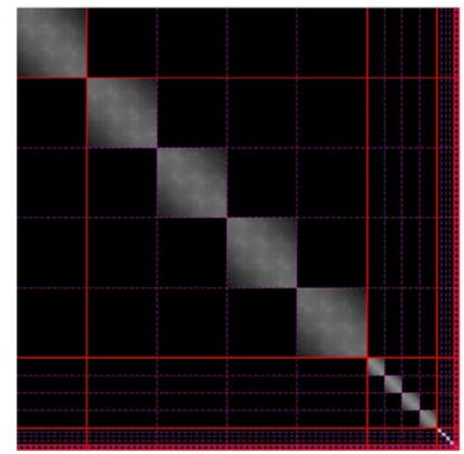
[Proper neural models is more than regression]

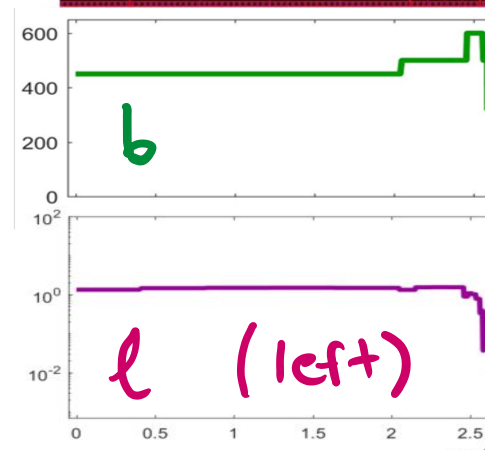
4.2 Naive Divisive Normalization

Malo et al. Neural Comp. 2010
JOSA A 2010
PLoS 2018



H =





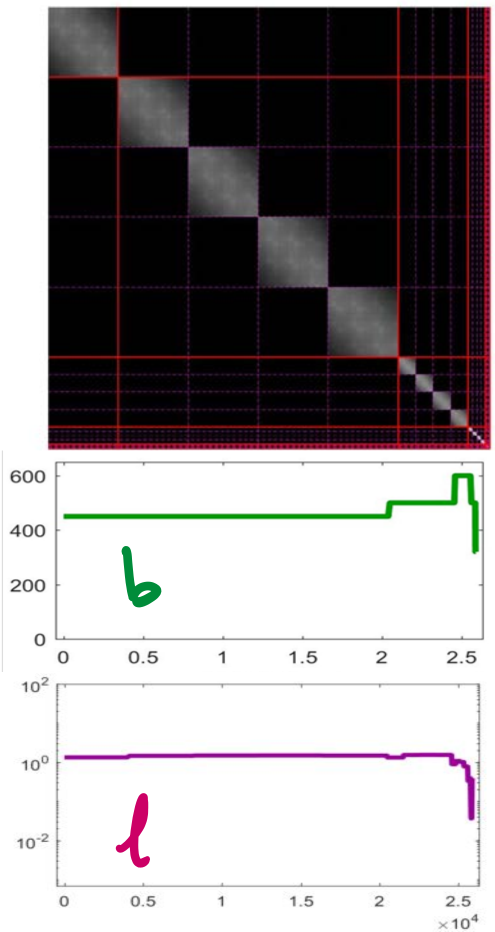
$$r = k \frac{e}{b + [D_e \cdot H] \cdot e}$$

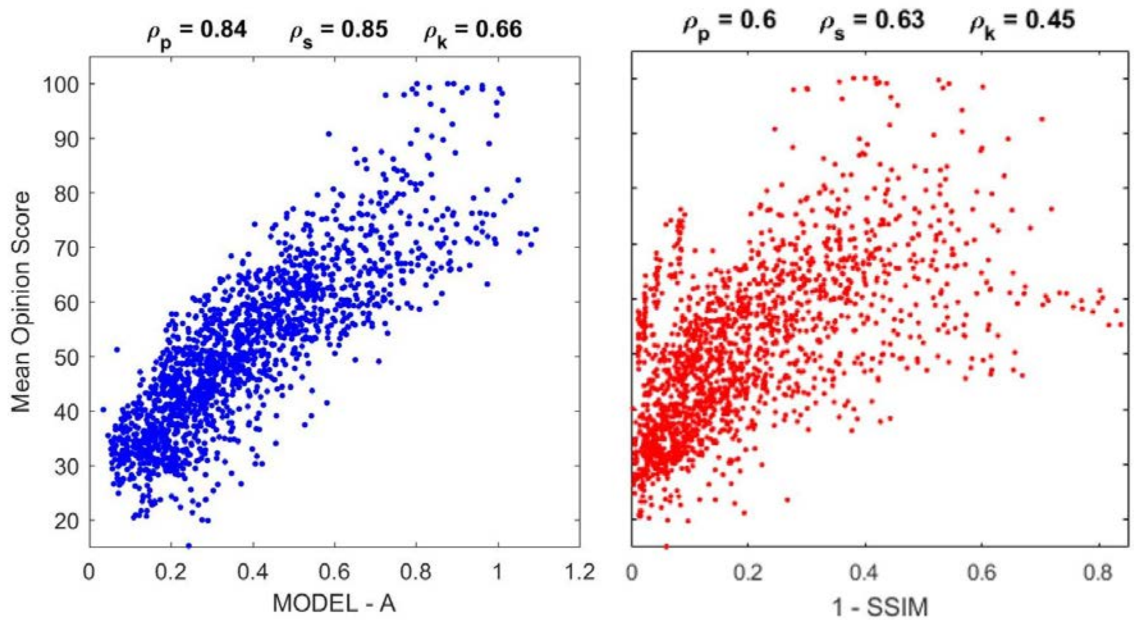
4 Geometry is more than deep-nets

[Proper neural models is more than regression]

4.2 Naive Divisive Normalization

Malo et al. Neural Comp. 2010
JOSA A 2010
PLoS 2018





Performance of MODEL – A (compared to SSIM)

④ Geometry is more than deep-nets

[Proper neural models is more than regression]

4.2 Naive Divisive Normalization

Malo et al. Neural Comp. 2010
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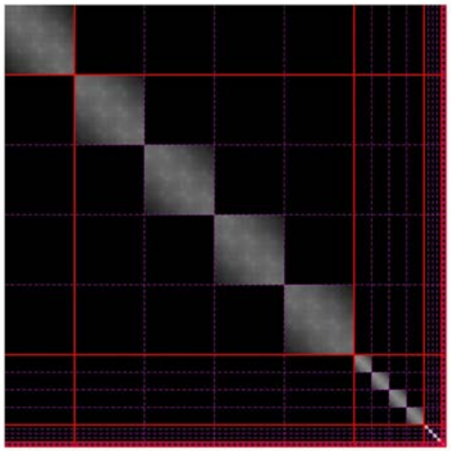
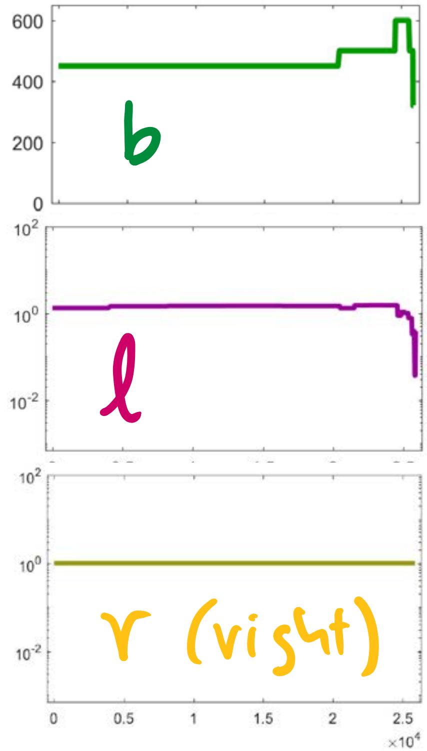
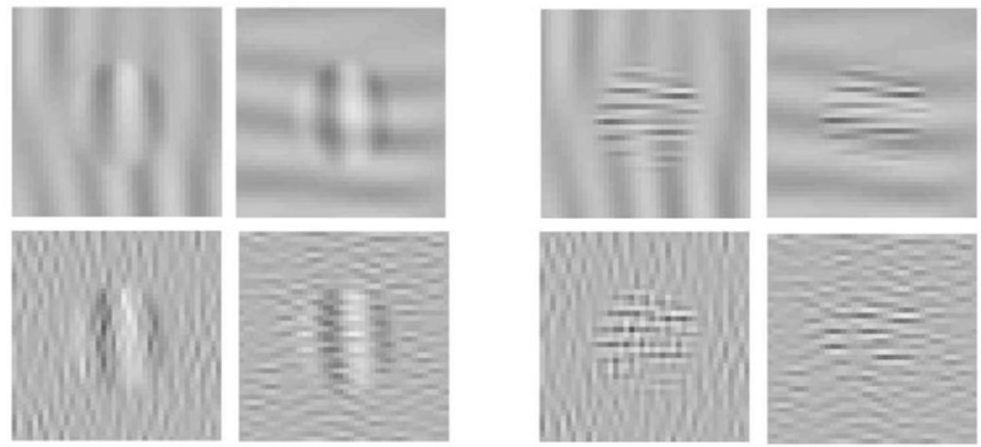
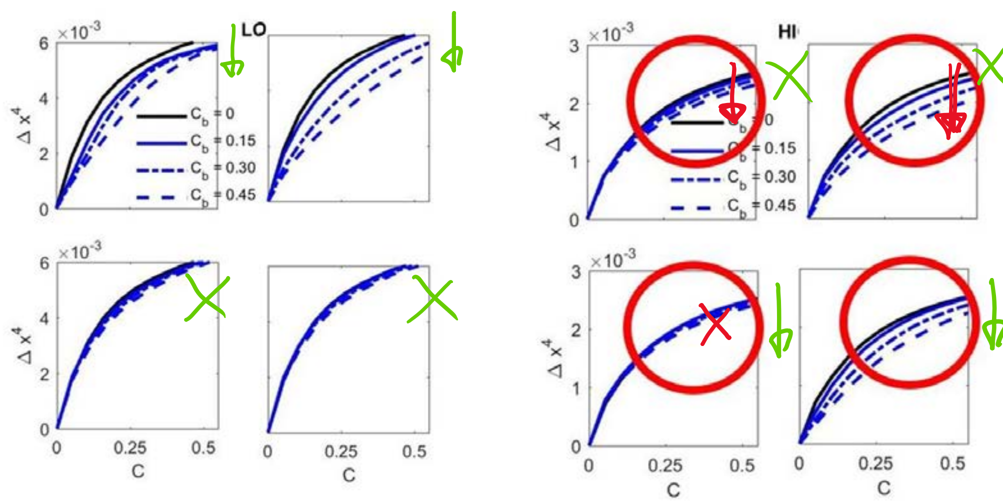
PLoS 2018





r=1 ≡ NOTHING

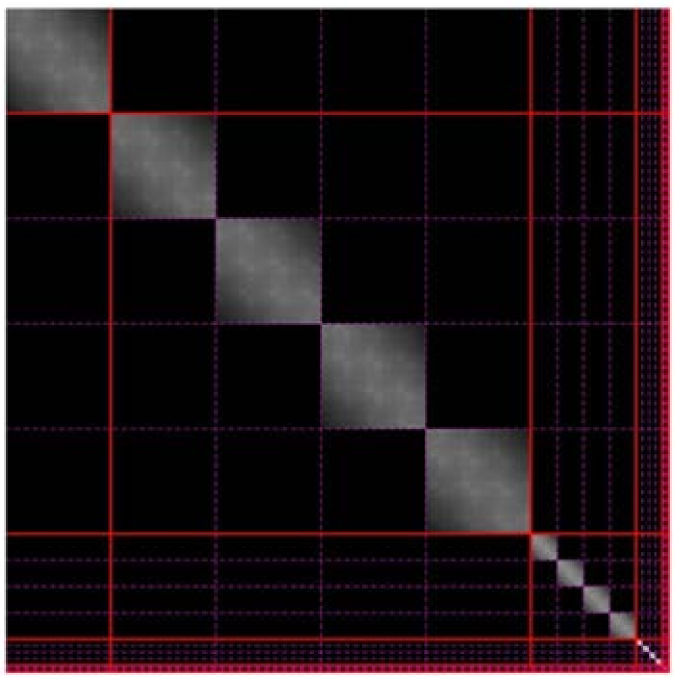


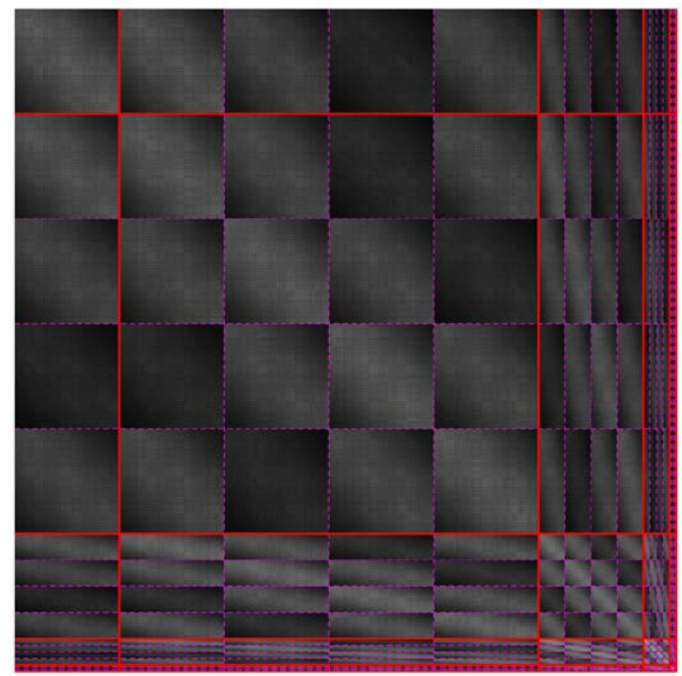


④ Geometry is more than deep-nets

[Proper neural models is more than regression]

4.3 Use unit-norm Gaussian Kernel   Watson & Solomon JOSA 97





$\sigma_\theta \sim 30^\circ$

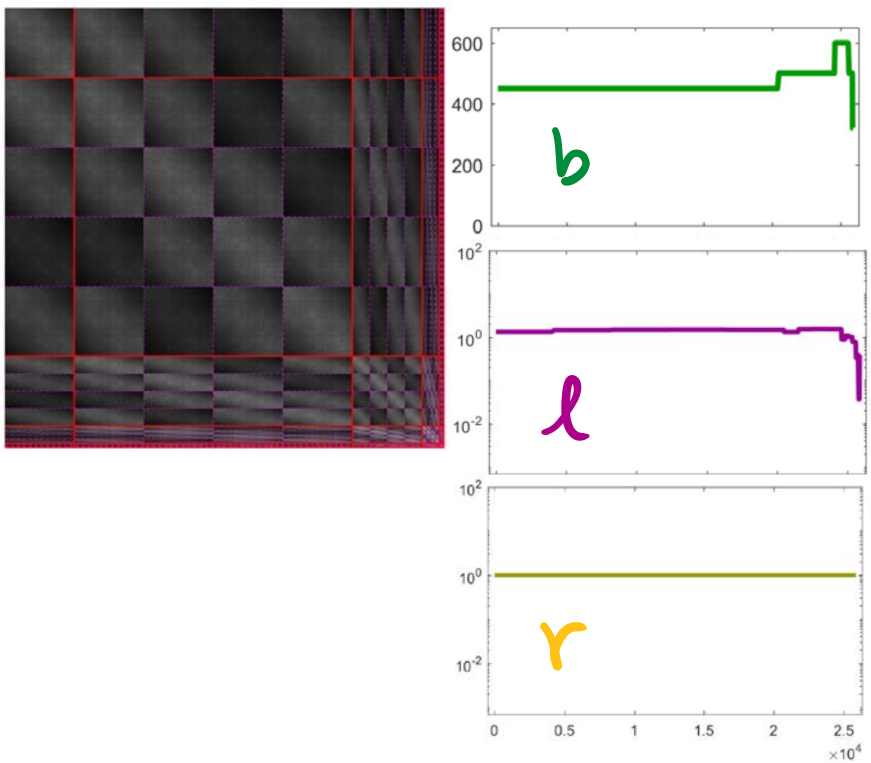
Keep σ_x and

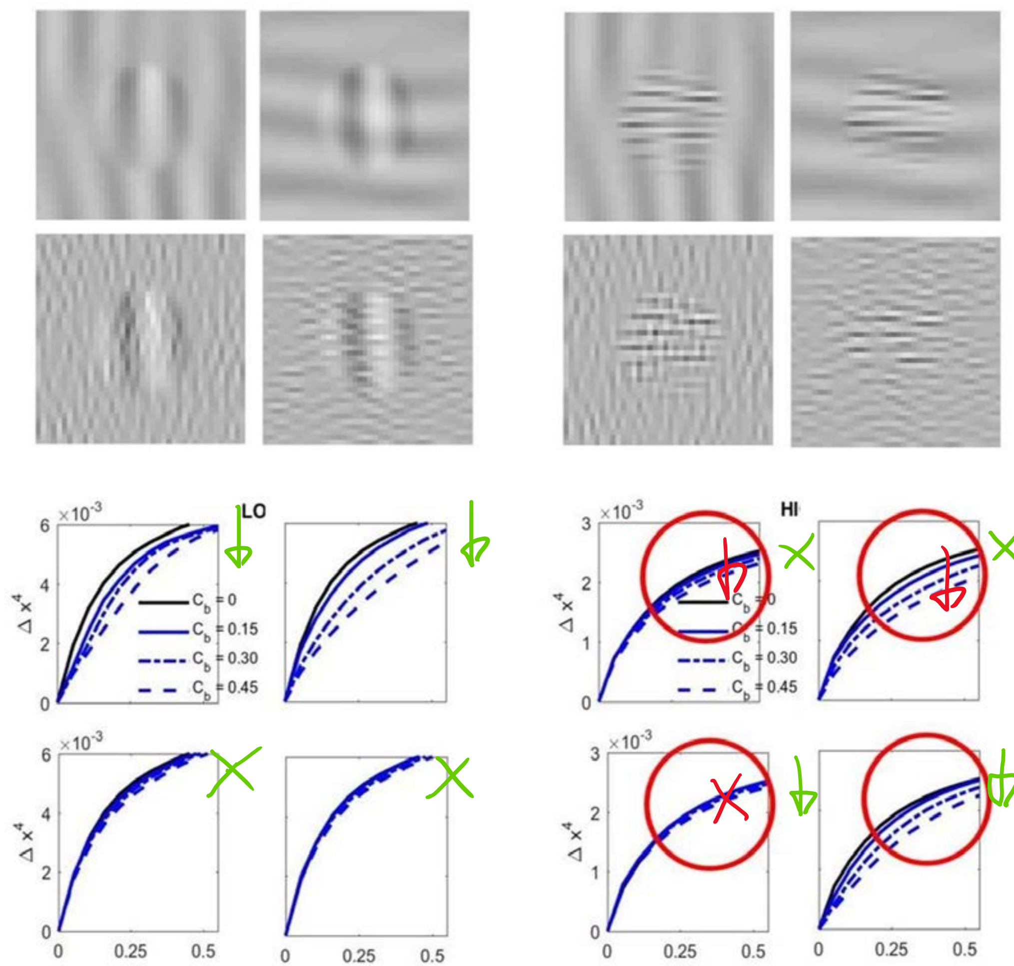
$\sigma_f \sim 1$ octave

4 Geometry is more than deep-nets

[Proper neural models is more than regression]

4.3 Use unit-norm Gaussian Kernel Watson & Solomon JOSA 97

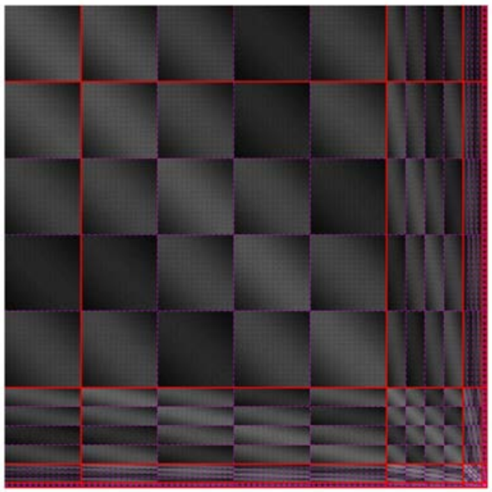




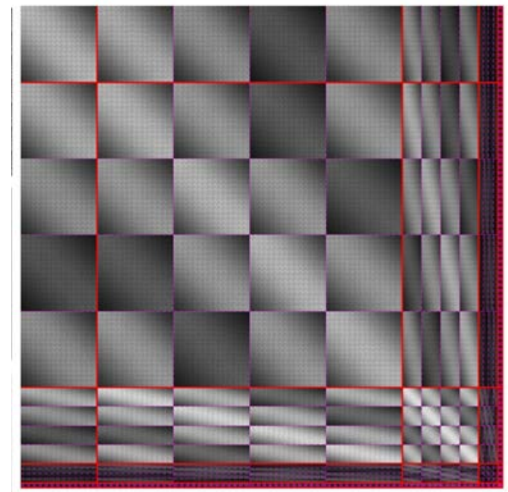
4 Geometry is more than deep-nets

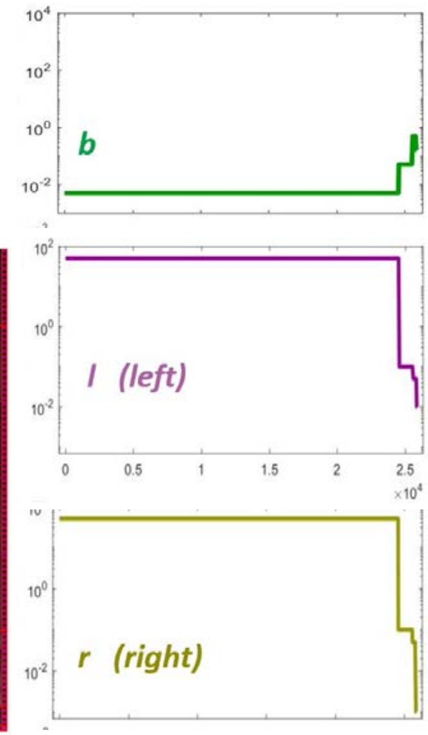
[Proper neural models is more than regression]

4.4 By-hand tuning



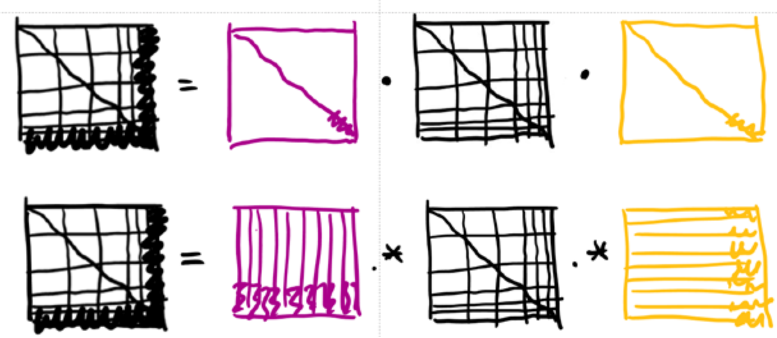
MODEL B (naive)





$$H = D_l \cdot H_{GAUSS} \cdot D_r$$

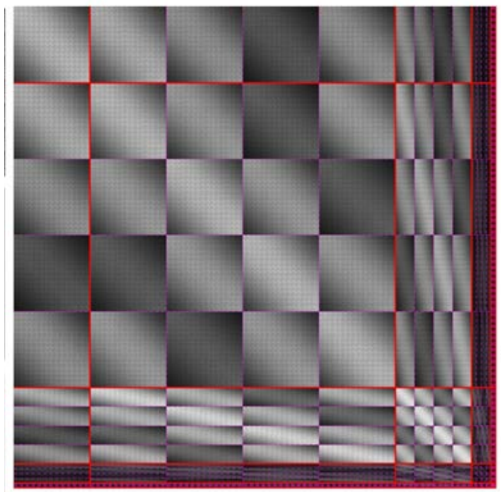
$$r = K \cdot \frac{T \cdot x}{b + \underbrace{\left[D_l \cdot H_G \cdot D_r \right]}_{H} \cdot T \cdot x}$$

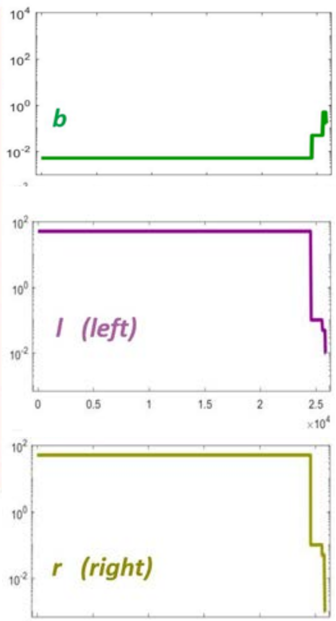


(4) Geometry is more than deep-nets

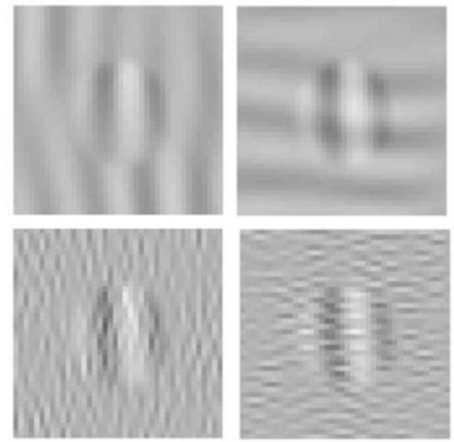
[Proper neural models is more than regression]

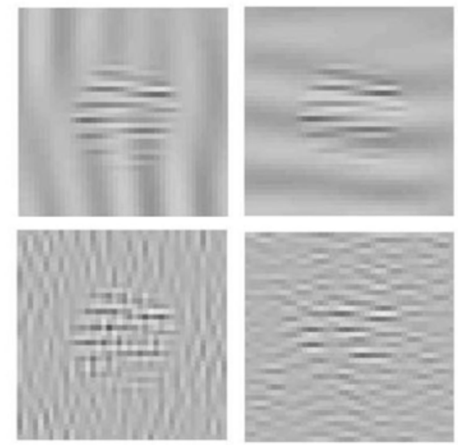
4.4 By-hand tuning

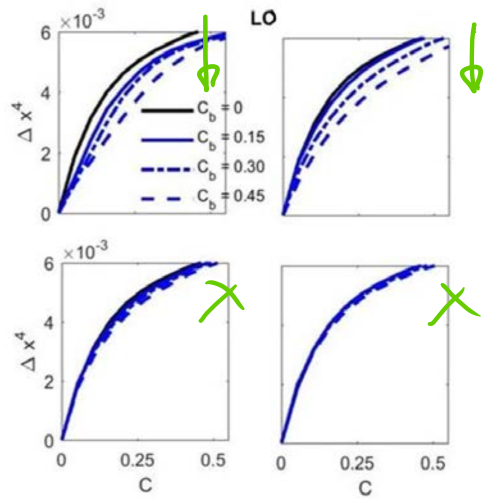


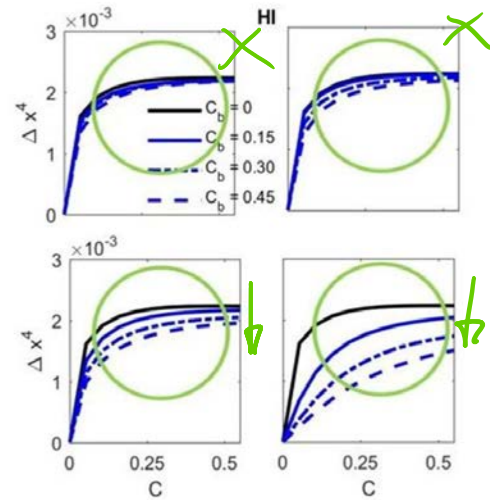


ok!





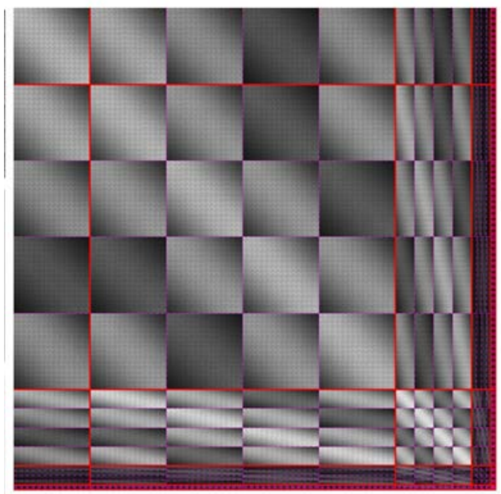


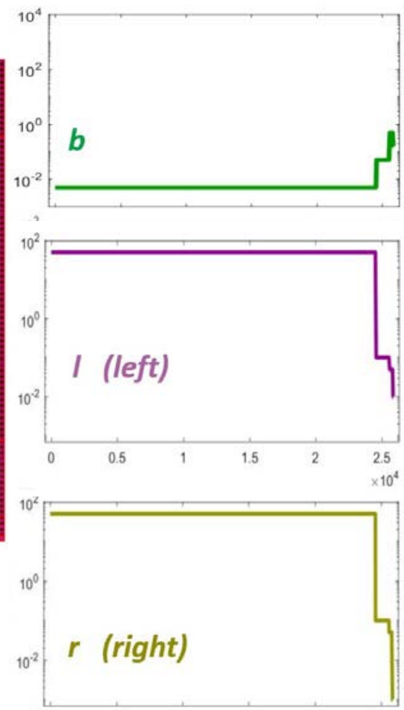


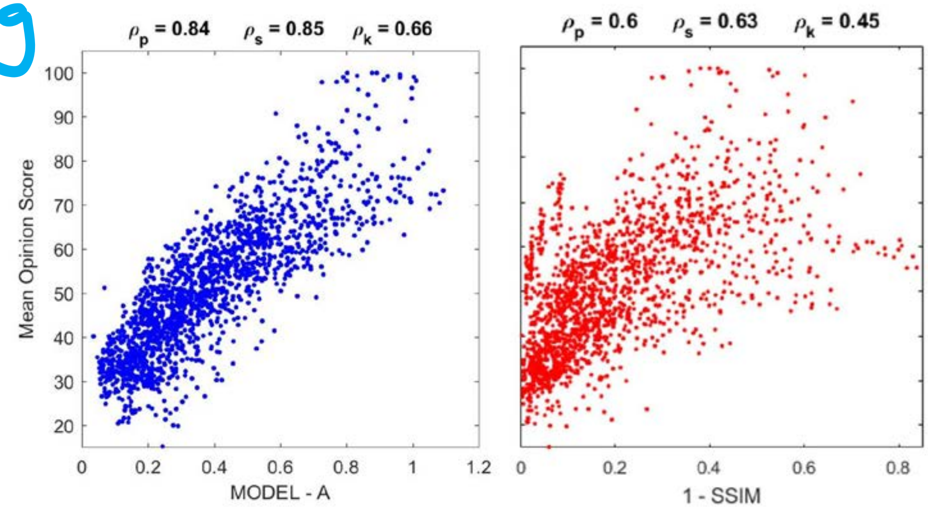
4 Geometry is more than deep-nets

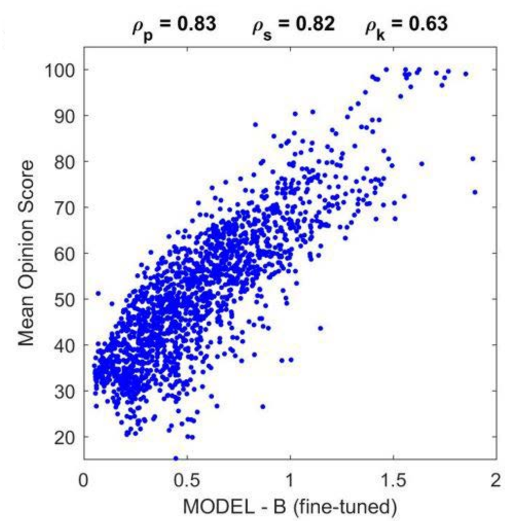
[Proper neural models is more than regression]

4.4 By-hand tuning

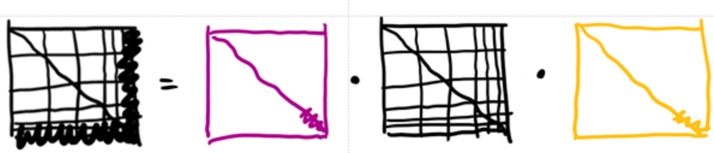








$$H = D_l \cdot H_{GAUSS} \cdot D_r$$

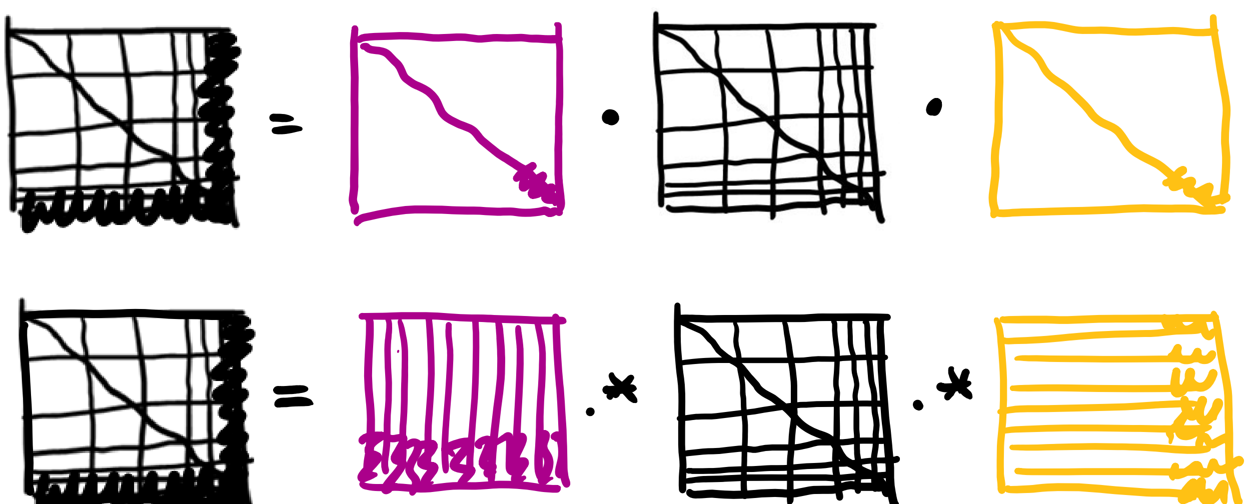


Equivalence of Divsive Normaliz. & Wilson-Cowan

The question

Where does this come from?

$$H = D_l \cdot H_{GAUSS} \cdot D_r$$



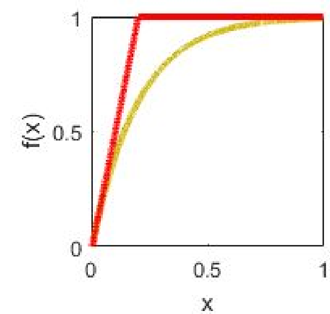
Equivalence of Divsive Normaliz. & Wilson-Cowan

(Wilson-Cowan)

Assumptions: $\dot{x} = e - D_\alpha x - W \cdot f(x)$

* Equivalence in steady state

* Piece-wise linear $f(\cdot)$ in WC



$$e = D_\alpha x + W \cdot f(x)$$

$$\hookrightarrow \quad e = (D_\alpha + W) \cdot x$$

* Truncation of inverse in DN

$$(I - D_{(\frac{x}{k})} H)^{-1} = I + \sum_{n=1}^{\infty} (D_{(\frac{x}{k})} H)^n \simeq I + D_{(\frac{x}{k})} H$$

$$e = (1 - D_{(\frac{x}{k})} H)^{-1} D_{(\frac{b}{k})} x \quad \Longrightarrow \quad e = \left(D_{(\frac{b}{k})} + D_{(\frac{x}{k})} H\right) \cdot x$$

Equivalence of Divsive Normaliz. & Wilson-Cowan

Parameters of Div. Norm. from Wilson-Cowan

$$\Rightarrow \begin{cases} b = k \odot \alpha \\ H = D_{\left(\frac{k}{x}\right)} \cdot W \cdot D_{\left(\frac{k}{b}\right)} \end{cases}$$

AHA!

$$H = D_{\ell} \cdot H_{GAUSS} \cdot D_{r}$$

- Signal dependence
- Wiring

1. Space is more than color!
2. Geometry may make you a star!
3. Geometry and neural models (I)
4. **Geometry is more than deep-nets**
   - No blind. fitting!
   - Balance problem
   - Always check visibil.!
   - Relation DN - WC
5. Some psychophysics for you!
6. Geometry and neural models (II)
7. Conclusions

1. Space is more than color!
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5. Some psychophysics for you! DOWNLOAD!
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(5) Some psychophysics for you!

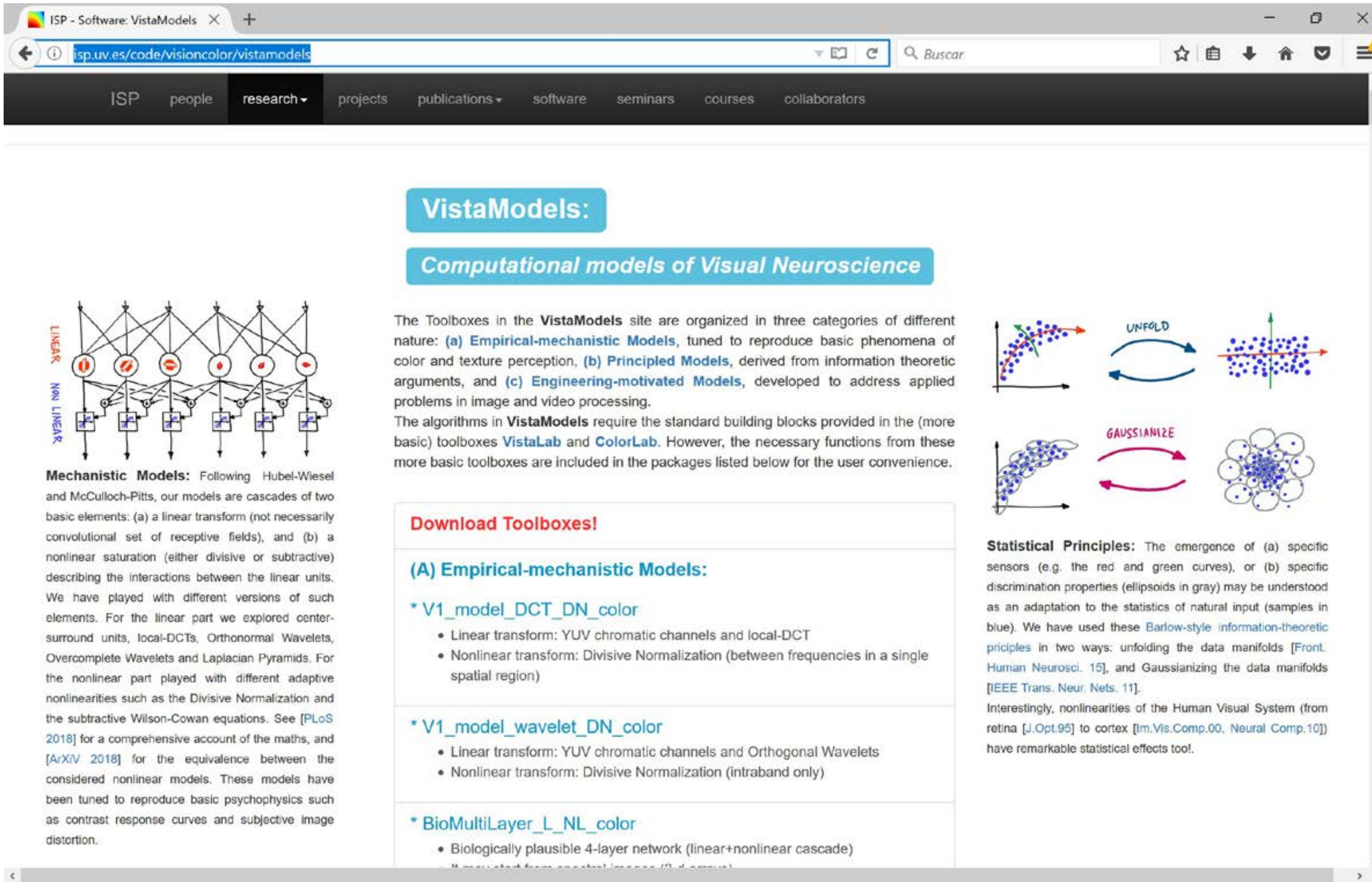
DOWNLOAD! BASIC FACTS TO FALSIFY MODELS

http://isp.uv.es/code/visioncolor/vistamodels

Frequency (CSFs)

Contrast (mask)

Noise


ISP - Software: VistaModels

isp.uv.es/code/visioncolor/vistamodels

Buscar

ISP people research projects publications software seminars courses collaborators

VistaModels:

Computational models of Visual Neuroscience

Mechanistic Models: Following Hubel-Wiesel and McCulloch-Pitts, our models are cascades of two basic elements: (a) a linear transform (not necessarily convolutional set of receptive fields), and (b) a nonlinear saturation (either divisive or subtractive) describing the interactions between the linear units. We have played with different versions of such elements. For the linear part we explored center-surround units, local-DCTs, Orthonormal Wavelets, Overcomplete Wavelets and Laplacian Pyramids. For the nonlinear part played with different adaptive nonlinearities such as the Divisive Normalization and the subtractive Wilson-Cowan equations. See [PLoS 2018] for a comprehensive account of the maths, and [ArXiV 2018] for the equivalence between the considered nonlinear models. These models have been tuned to reproduce basic psychophysics such as contrast response curves and subjective image distortion.

The Toolboxes in the **VistaModels** site are organized in three categories of different nature: **(a) Empirical-mechanistic Models**, tuned to reproduce basic phenomena of color and texture perception, **(b) Principled Models**, derived from information theoretic arguments, and **(c) Engineering-motivated Models**, developed to address applied problems in image and video processing.
The algorithms in **VistaModels** require the standard building blocks provided in the (more basic) toolboxes **VistaLab** and **ColorLab**. However, the necessary functions from these more basic toolboxes are included in the packages listed below for the user convenience.

Download Toolboxes!

(A) Empirical-mechanistic Models:

* V1_model_DCT_DN_color
  - Linear transform: YUV chromatic channels and local-DCT
  - Nonlinear transform: Divisive Normalization (between frequencies in a single spatial region)

* V1_model_wavelet_DN_color
  - Linear transform: YUV chromatic channels and Orthogonal Wavelets
  - Nonlinear transform: Divisive Normalization (intraband only)

* BioMultiLayer_L_NL_color
  - Biologically plausible 4-layer network (linear+nonlinear cascade)

Statistical Principles: The emergence of (a) specific sensors (e.g. the red and green curves), or (b) specific discrimination properties (ellipsoids in gray) may be understood as an adaptation to the statistics of natural input (samples in blue). We have used these Barlow-style information-theoretic priciples in two ways: unfolding the data manifolds [Front. Human Neurosci. 15], and Gaussianizing the data manifolds [IEEE Trans. Neur. Nets. 11].
Interestingly, nonlinearities of the Human Visual System (from retina [J.Opt.95] to cortex [Im.Vis.Comp.00, Neural Comp.10]) have remarkable statistical effects too!.

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6. Geometry and neural models (II) ∇S DOWNLOAD!
7. Conclusions

6 Geometry and neural models (II)

MORE REFINED GEOMETRY-BASED PSYCHOPYSICS

ALSO DOWNLOAD!

$\nabla_x S$

MAXIMUM DIFFERENTIATION

FALSIFY MODELS (OR PARAMETERS)

BY ASSESING MODEL-BASED EXTREME DISTORTIONS

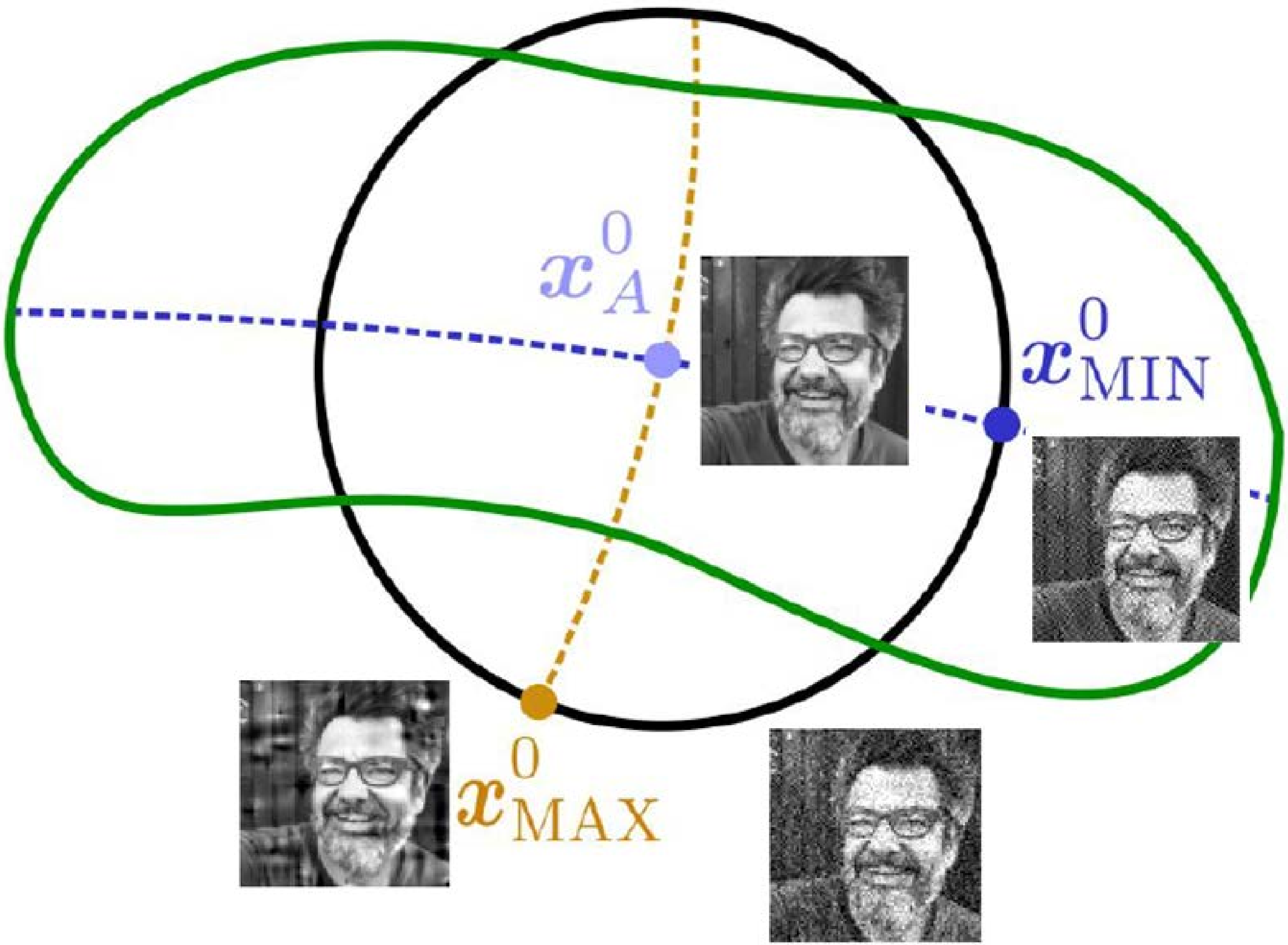
⑥ Geometry and neural models (II)

MORE REFINED GEOMETRY-BASED PSYCHOPYSICS

ALSO DOWNLOAD!

$\nabla_x S$

MAXIMUM DIFFERENTIATION



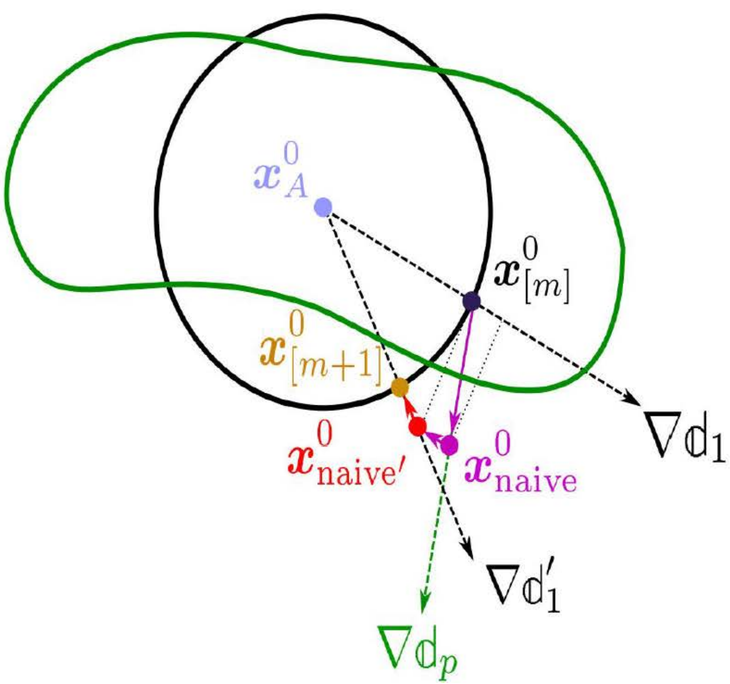
(6) Geometry and neural models (II)

MORE REFINED GEOMETRY-BASED PSYCHOPYSICS

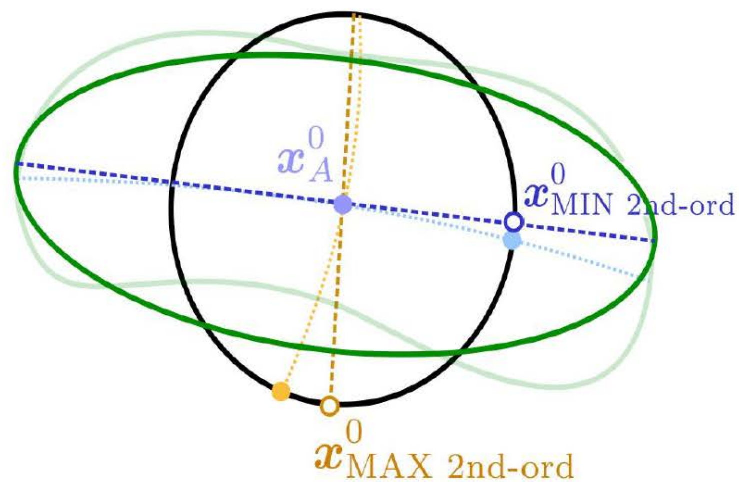
ALSO DOWNLOAD! $\nabla_x S$

MAXIMUM DIFFERENTIATION

The original algorithm [Wang & Simoncelli JoV 2008]



The aproximation [Malo & Simoncelli: SPIE 2013 Martinez et al. PLoS 2018]



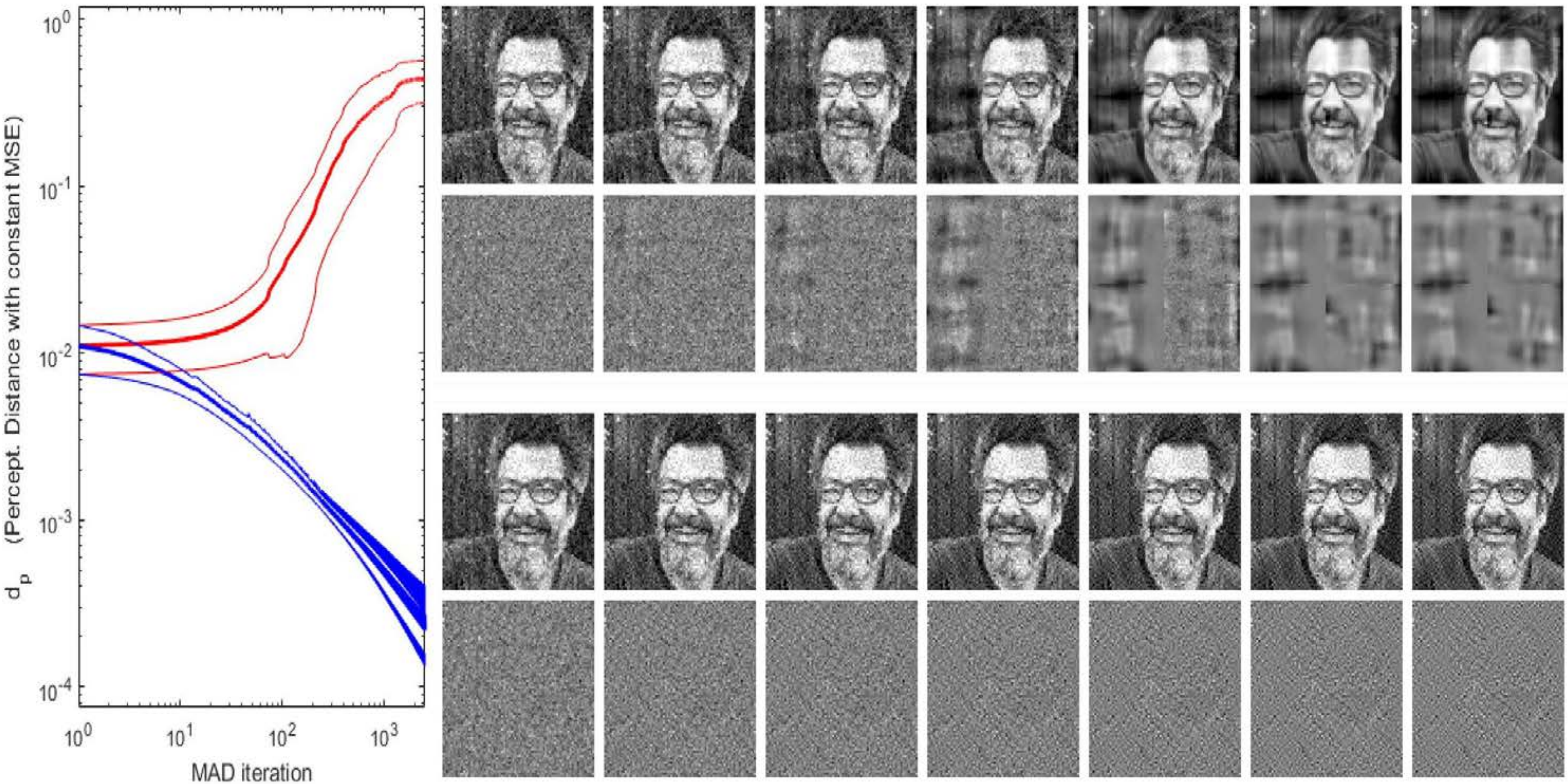
$$g(x) = \nabla_x S(x)^T \cdot \nabla_x S(x)$$

6 Geometry and neural models (II)

MAXIMUM DIFFERENT

ALSO DOWNLOAD $\nabla_x S$!

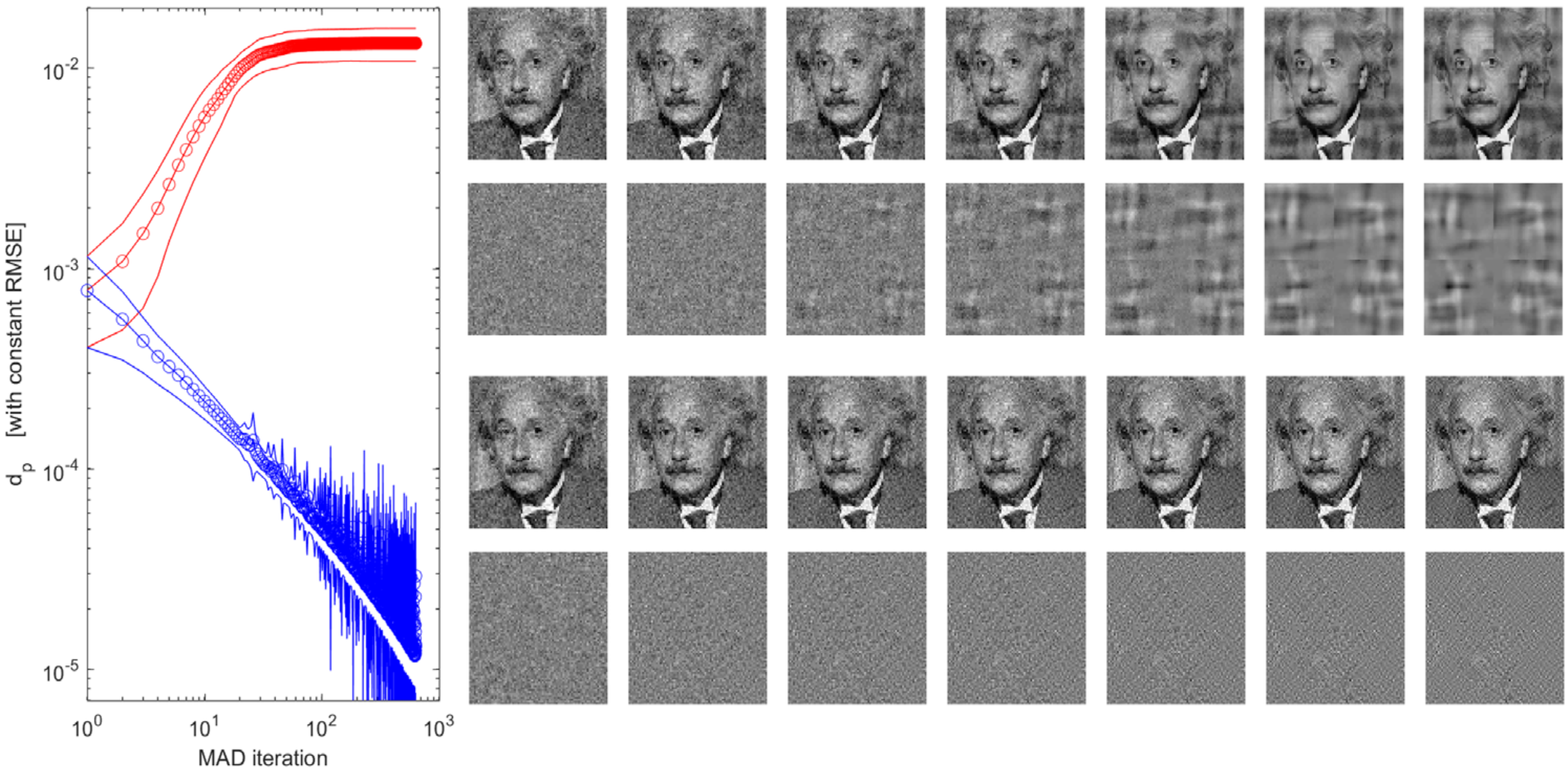
Iterative: SAME ENERGY, PROGRESSIVELY DIFFERENT VISIBILITY



⑥ Geometry and neural models (II)

MAXIMUM DIFFERENT

ALSO DOWNLOAD $\nabla_x S$!



⑥ Geometry and neural models (II)

MAXIMUM DIFFERENT

ALSO DOWNLOAD $\nabla_x S$!

iterative

Eigen vectors of metric

MIN. VISIB. MAX VISIB.

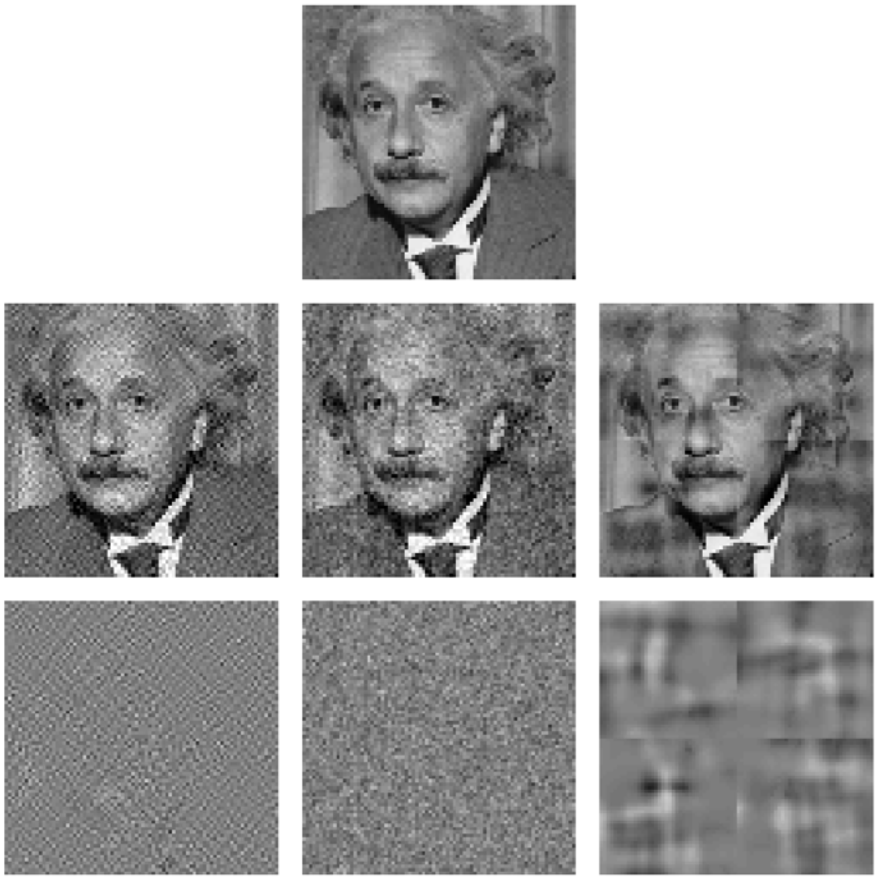
MIN VISIB. MAX VISIB.

(6) Geometry and neural models (II)

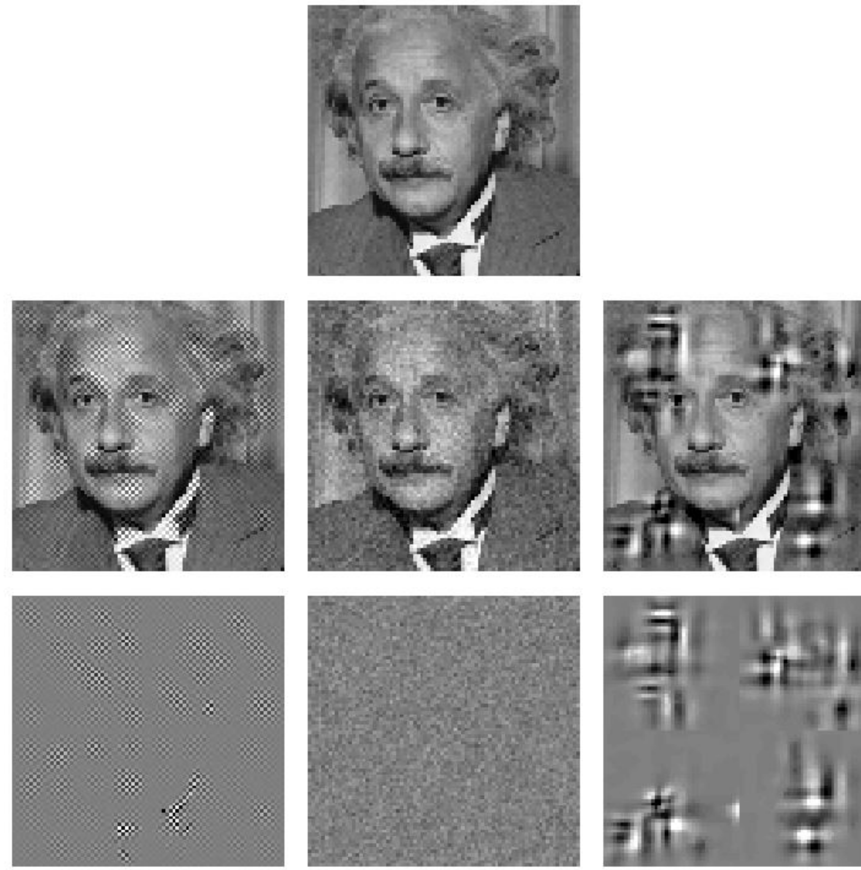
MAXIMUM DIFFERENT

ALSO DOWNLOAD $\nabla_x S$!

iterative



Eigen vectors of metric



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7) Conclusions

[PLoS 2018]

Derivatives and inverse of Linear+Nonlinear Neural models
http://arxiv.org/abs/1711.00526

* Neural models are relevant for geometry

  Div. Norm. / Wilson-Cowan

  $g(x) = \nabla_x S(x)^T \cdot \nabla_x S(x)$

* Metric ⇒ New psychophysics

  Maximum Differentiation

* Other implications of $\nabla_x S$

  - Adaptive receptive fields
  - Information theory
  - Decoding

[Under Review, arXiv, 2018]

In praise of artifice reloaded http://arxiv.org/abs/1801.09632

* Do not trust blind optimization

  - Check with psychophysics
  - Arquitecture changes may be required

[Under Review, arXiv, 2018]

Appropriate kernels for Divisive Normalization explained by Wilson-Cowan equations http://arxiv.org/abs/1804.05964

* Divisive Normalization from Wilson-Cowan

JESUS

JUAN GUTIERREZ

VALERO LAPARRA

MARINA MARTINEZ

UV

MARCELO BERTALMIO

PRAVEEN CYRIAC

THOMAS BATARD

UPF

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NYU