Simposio Científico de Inteligencia Artificial y Aplicaciones (SCIAA-UdeSA)
Universidad de San Andrés
4 de octubre de 2023 – CABA – República Argentina

One class to rule them all

Aplicaciones de clasificación a una clase en visión artificial y medicina

José Ignacio Orlando, PhD
CONICET / PLADEMA-UNICEN

* Este trabajo corresponde a parte de las tesis doctoral en curso de Duilio Deangeli

@ignaciorlando

José Ignacio Orlando

Nuestra charla de hoy va ser la

Historia de una ida y una vuelta

A la ida, un problema

Caracterizar asimetría normativa

Un repaso de los clásicos

Algoritmos estadísticos para novelty detection

Nuestra solución, bien clásica

NORHA: Caracterización de asimetrías y OC-SVM

Luego, un repaso de los nuevos métodos

Algoritmos deep para novelty detection

Para mejorar nuestra solución

NORAH: Deep characterization y Deep SVDD

Pensar escenarios nuevos

Los sí y los no de Deep SVDD

Y quedarnos charlando un rato!

A la ida, un problema

Caracterizar asimetría normativa

- El **cerebro humano** se divide en **dos hemisferios contralaterales** con distintas **funciones**

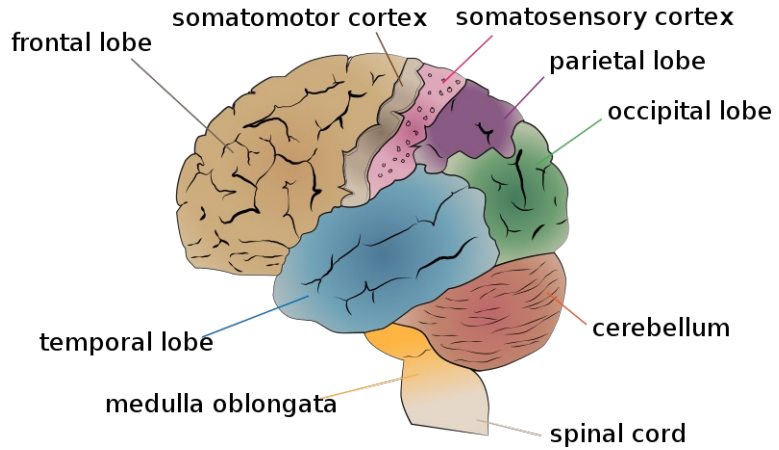
A la ida, un problema

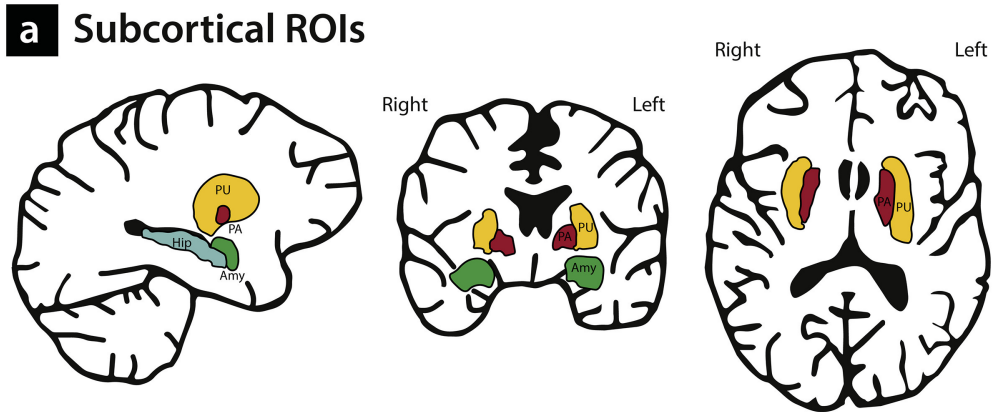
Caracterizar asimetría normativa

- El **cerebro humano** se divide en **dos hemisferios contralaterales** con distintas **funciones**
- Estructuras **corticales** y **subcorticales**

Corticales = corteza
Funciones de alto nivel (lenguaje, toma de decisiones, ...)

Subcorticales = debajo de la corteza
Funciones primitivas (emociones, **memoria**, ...)





A la ida, un problema

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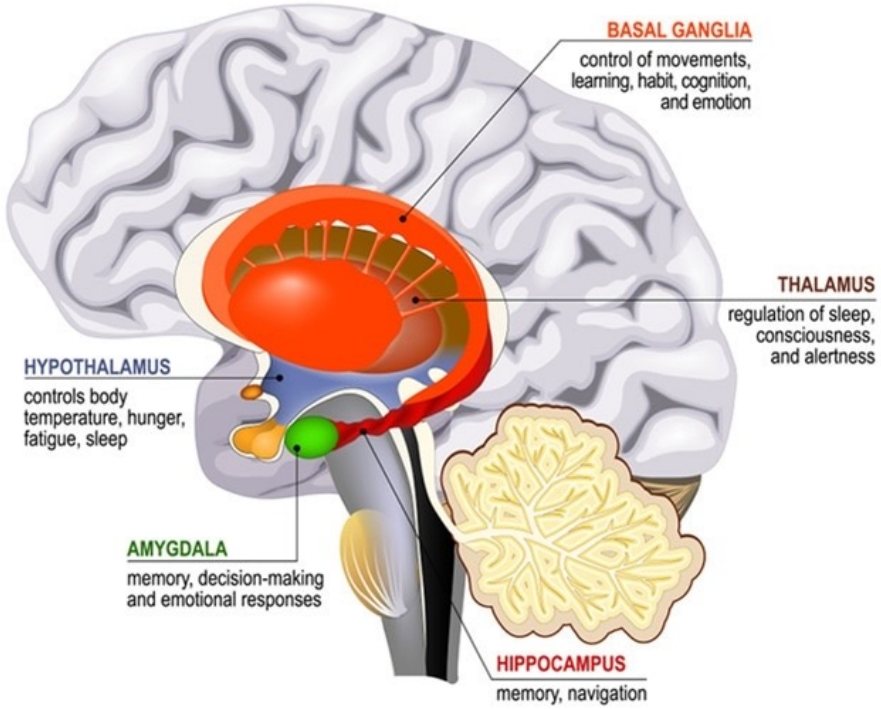
- **Asimetrías del hipocampo**

  En condiciones normales los hipocampos tienen **asimetría propias**.

  Fenómenos **naturales** (envejecimiento) y **condiciones neurodegenerativas** (Alzheimer) introducen **cambios en esta asimetría**

  Estudios vinculando **asimetría estructural y comportamiento**



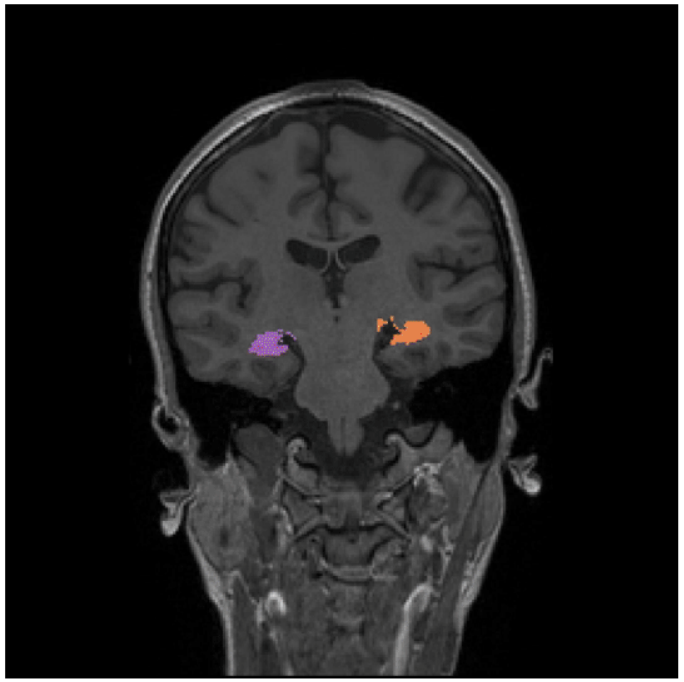
¿Cómo podemos determinar cuándo estas diferencias son patológicas?

A la ida, un problema

Caracterizar asimetría normativa

¿Cómo podemos determinar cuándo estas diferencias son patológicas?

1. **Extracción de la morfología hipocampal**
   - Imágenes de Resonancia Magnética **(MRI)**
2. **Caracterización de la asimetría**



A la ida, un problema

Caracterizar asimetría normativa

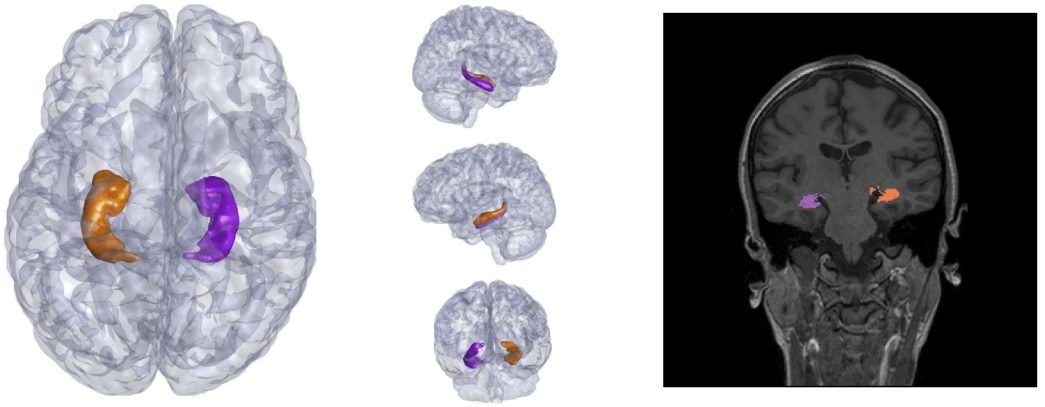
¿Cómo podemos determinar cuándo estas diferencias son patológicas?

1 Extracción de la morfología hipocampal

- Imágenes de Resonancia Magnética **(MRI)**
- **Segmentación 3D** de la región de interés

  FreeSurfer (Reuter et al. 2012), **FastSurfer** (Henschel et al. 2020), **hippmapp3r** (Goubran et al. 2020), ...

2 Caracterización de la asimetría



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Caracterizar asimetría normativa

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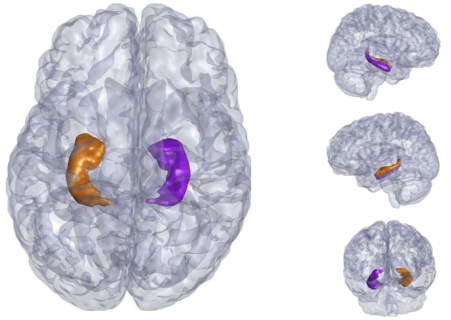
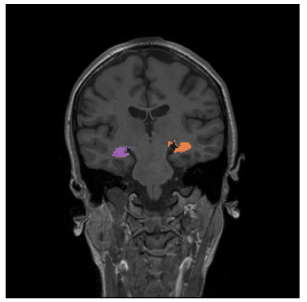
2 Caracterización de la asimetría

- Análisis de **volumetría** y comparación poblacional

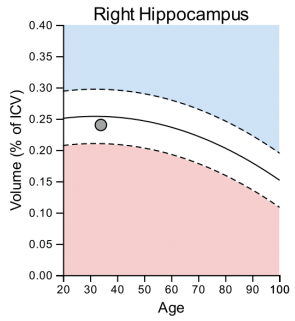
  volBrain (Manjón et al. 2016)

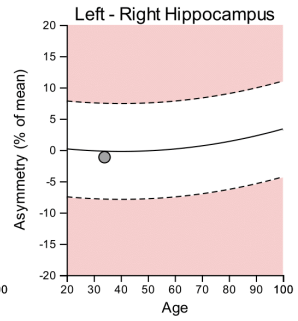
  👍 Fácil de interpretar 👎 Tipos de asimetría limitados

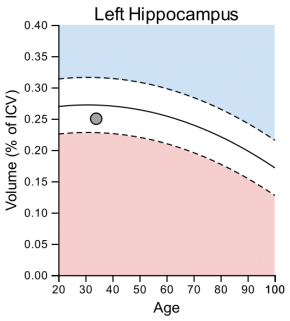




Hippocampus	Absolute Volume (mL)		Relative Volume (% of ICV)		Left-Right Asymmetry
	Right	Left	Right	Left	
	3.48	3.70	0.24	0.25	-1.15 %







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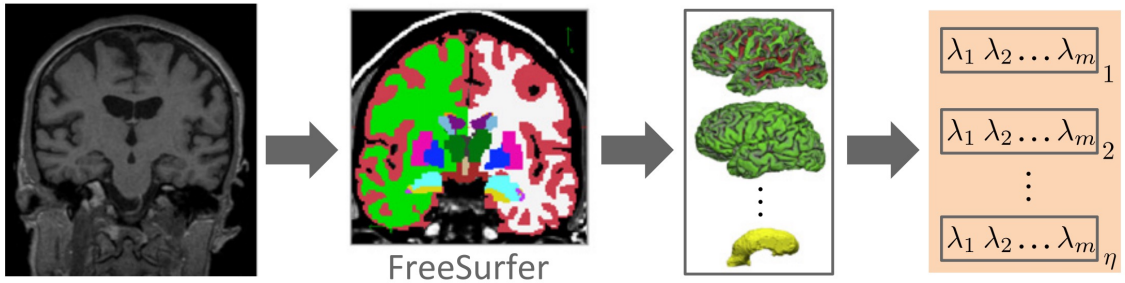
  👍 Fácil de interpretar 👎 Tipos de asimetría limitados

- **Representaciones** morfológicas vectoriales + **aprendizaje supervisado**

  Wachinger et al. 2015

  👍 Más asimetrías 👎 Modelos específicos por enfermedad, menos interpretables

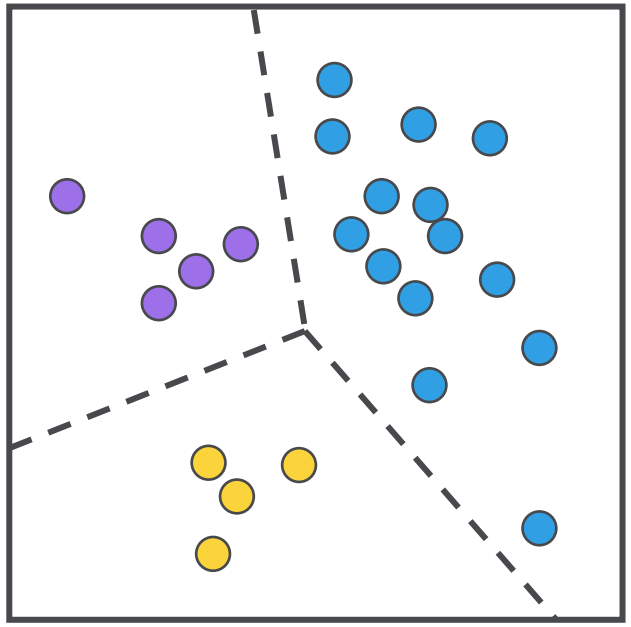


¿Y si usamos novelty detection?

Un repaso de los clásicos:

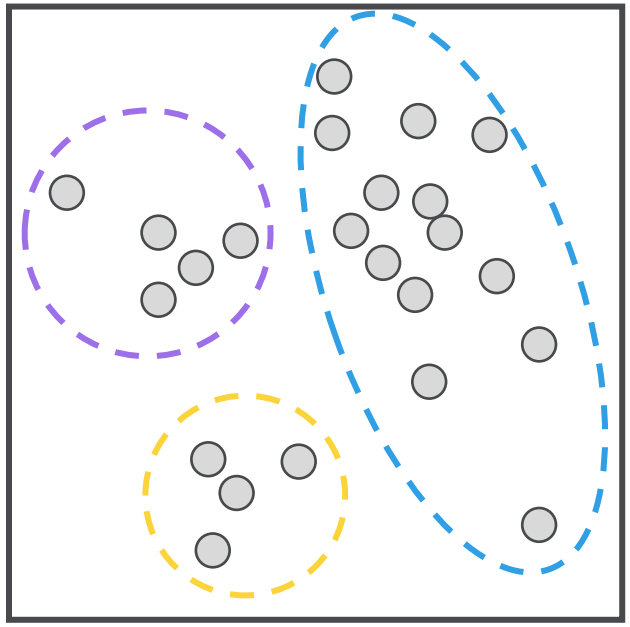
Algoritmos estadísticos para novelty detection

Supervised learning
(clasificación, regresión, ...)



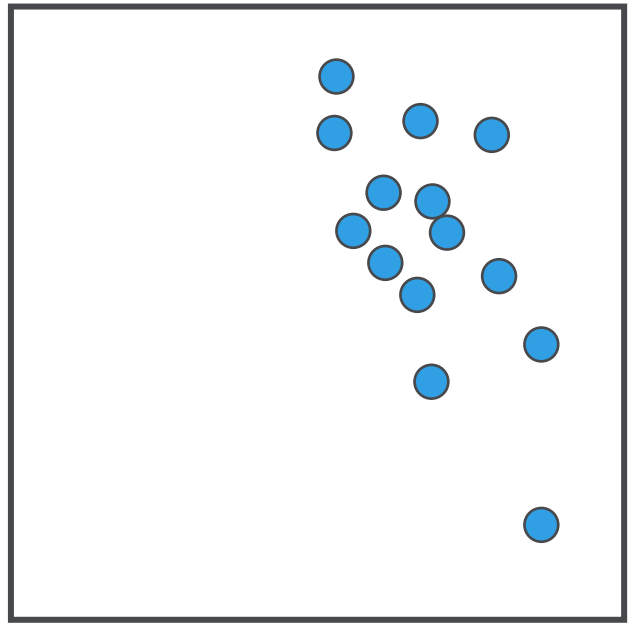
Etiquetas asociadas
a cada muestra

Unsupervised learning
(representation learning, clustering, ...)



Desconocemos a qué clase
pertenece cada muestra

One-class classification
(anomaly or novelty detection)



Solamente tenemos
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Un repaso de los clásicos:

Algoritmos estadísticos para novelty detection

One-class classification
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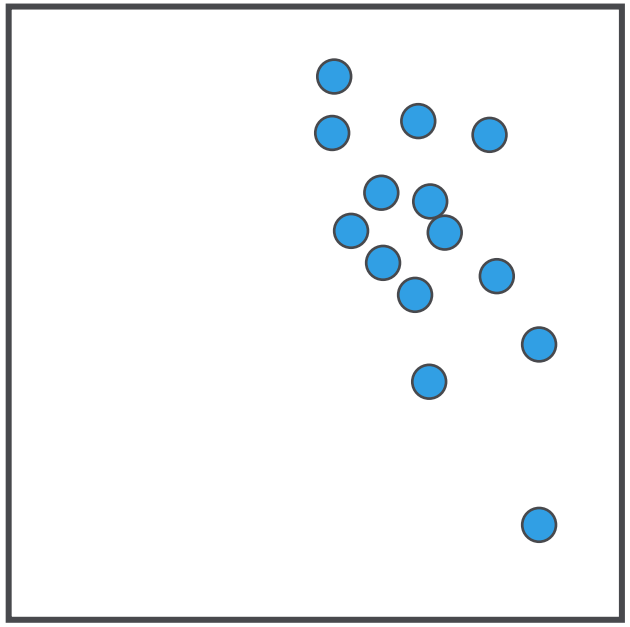
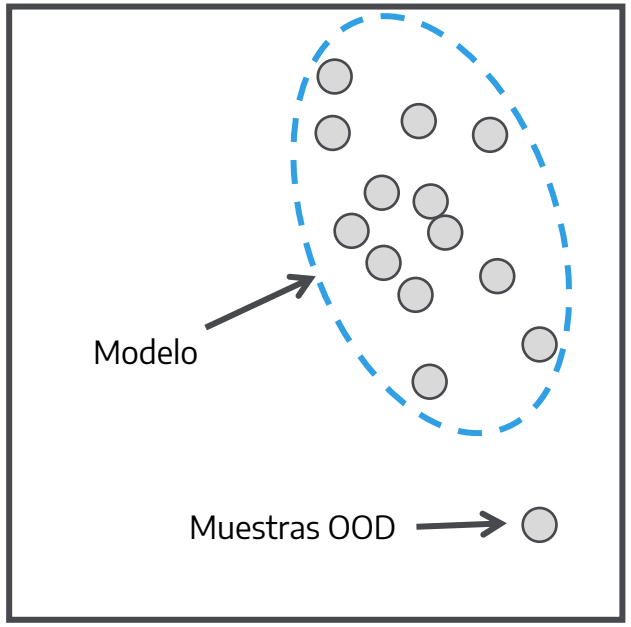


Solamente tenemos muestras de una única clase

Anomaly detection
Detectar muestras espurias en los datos disponibles



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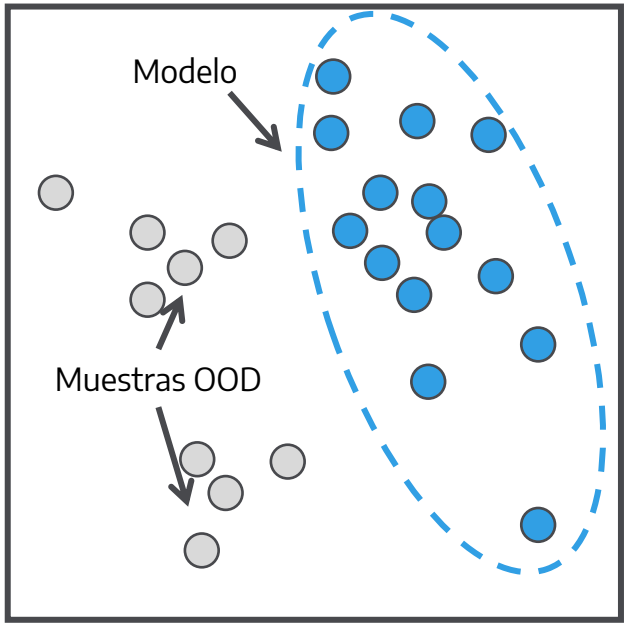
Novelty detection
Detectar muestras que no se ajustan a la distribución original



Mismo tipo de modelos, cambia sólo el momento de aplicarlos
Puede asumirse o no la presencia de OOD simples en la muestra
Algoritmos que describen la distribución de los datos → Unsupervised

Un repaso de los clásicos:

Algoritmos estadísticos para novelty detection

One-class Support Vector Machine (OC-SVM)

Un **hiperplano** que **aisla** a (casi) todas las muestras de entrenamiento por encima

$$\min_{\mathbf{w},\xi} \quad \frac{1}{2}\|\mathbf{w}\|^2 - \frac{1}{\nu N}\sum_{i=1}^{N}\xi_i - \rho$$
$$\text{s.t.} \quad \langle \mathbf{w}, \phi(\mathbf{x}_i)\rangle_{\mathcal{F}_k} \geq \rho - \xi_i,$$
$$\xi_i \geq 0$$

Schölkopf et al. 2001

con

$$\phi_k : \mathcal{X} \to \mathcal{F}_k$$
$$k(\mathbf{x}, \tilde{\mathbf{x}}) = \langle \phi(\mathbf{x}), \tilde{\mathbf{x}}\rangle_{\mathcal{F}_k}$$

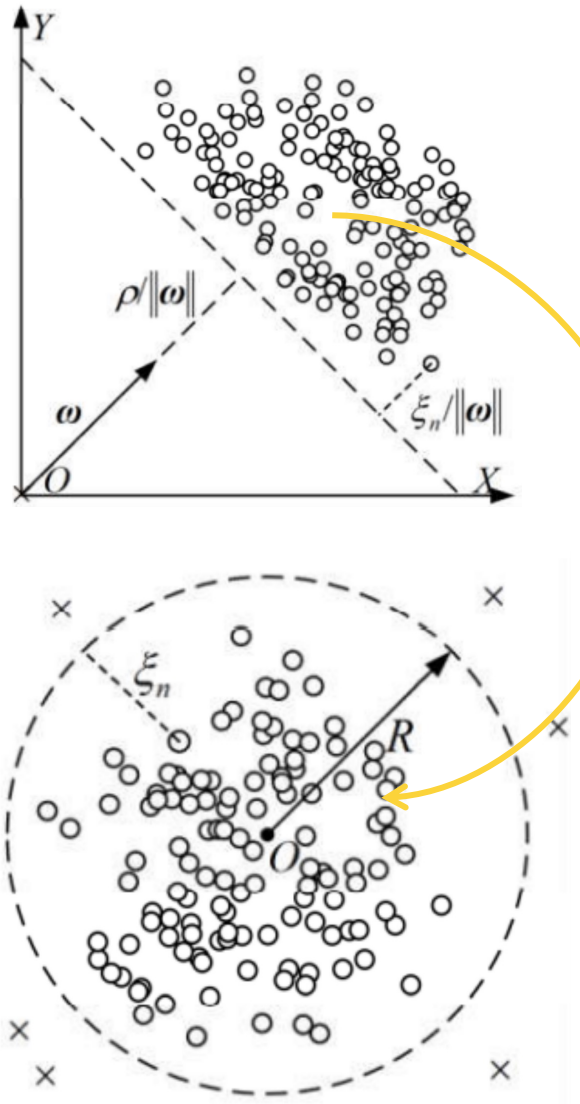
Support Vector Data Description (SVDD)

Una **hiperesfera** que **rodea** a (casi) todas las muestras de entrenamiento

$$\min_{R,\mathbf{c},\xi} \quad R^2 + \frac{1}{\nu N}\sum_{i=1}^{N}\xi_i$$
$$\text{s.t.} \quad \|\phi(\mathbf{x}_i) - \mathbf{c}\|^2_{\mathcal{F}_k} \leq R^2 + \xi_i$$
$$\xi_i \geq 0$$

Tax & Duin. 2004

Entrenamiento | **Test**



Muestras anómalas

$$\langle \mathbf{w}, \phi(\mathbf{x}_i)\rangle_{\mathcal{F}_k} < \rho$$

Usando un kernel RBF:

$$K(\mathbf{x}, \tilde{\mathbf{x}}) = \exp\left(-\frac{\|\mathbf{x} - \tilde{\mathbf{x}}\|^2}{2\sigma^2}\right)$$

Muestras anómalas

$$\|\phi(\mathbf{x}_i) - \mathbf{c}\|^2_{\mathcal{F}_k} > R^2$$

Nuestra solución, bien clásica:

NORHA: Caracterización de asimetrías y OC-SVM

Journal of Alzheimer's Disease 43 (2015) 201–212
DOI 10.3233/JAD-140189
IOS Press

Defining Multivariate Normative Rules for Healthy Aging using Neuroimaging and Machine Learning: An Application to Alzheimer's Disease

Ailton Andrade de Oliveira[a], Maria Teresa Carthery-Goulart[a],
Pedro Paulo de Magalhães Oliveira Júnior[b], Daniel Carneiro Carrettiero[c],
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[a]*Center of Mathematics, Computation and Cognition, Universidade Federal do ABC, Santo André, Brazil*
[b]*NIF-LIM44, Department of Radiology, Faculdade de Medicina da Universidade de São Paulo, São Paulo, Brazil*
[c]*Center of Natural and Human Sciences, Universidade Federal do ABC, Santo André, Brazil*

Accepted 29 May 2014

Abstract.
Background: Neuroimaging techniques combined with computational neuroanatomy have been playing a role in the investigation of healthy aging and Alzheimer's disease (AD). The definition of normative rules for brain features is a crucial step to establish typical and atypical aging trajectories.
Objective: To introduce an unsupervised pattern recognition method; to define multivariate normative rules of neuroanatomical measures; and to propose a brain abnormality index.
Methods: This study was based on a machine learning approach (one class classification or novelty detection) to neuroanatomical measures (brain regions, volume, and cortical thickness) extracted from the Alzheimer's Disease Neuroimaging Initiative (ADNI)'s database. We applied a ν-One-Class Support Vector Machine (ν-OC-SVM) trained with data from healthy subjects to build an abnormality index, which was compared with subjects diagnosed with mild cognitive impairment and AD.
Results: The method was able to classify AD subjects as outliers with an accuracy of 84.3% at a false alarm rate of 32.5%. The proposed brain abnormality index was found to be significantly associated with group diagnosis, clinical data, biomarkers, and future conversion to AD.
Conclusion: These results suggest that one-class classification may be a promising approach to help in the detection of disease conditions. Our findings support a framework considering the continuum of brain abnormalities from healthy aging to AD, which is correlated with cognitive impairment and biomarkers measurements.

Keywords: Dementia, neurodegeneration, neuroimaging, normative, outliers, pattern recognition, support vector machines

- Espesor de estructuras corticales
- Volumen de estructuras subcorticales y cerebrales

Andrade de Oliveira et al. 2015

- Parches en la imagen
- Modelos generativos para extraer embeddings
- One-class SVM

13 March 2019

Modeling normal brain asymmetry in MR images applied to anomaly detection without segmentation and data annotation

Samuel Botter Martins, Barbara Caroline Benato, Bruna Ferreira Silva, Clarissa Lyn Yasuda, Alexandre Xavier Falcão

Author Affiliations +

Proceedings Volume 10950, Medical Imaging 2019: Computer-Aided Diagnosis; 109500C (2019)
https://doi.org/10.1117/12.2512873
Event: SPIE Medical Imaging, 2019, San Diego, California, United States

ARTICLE | FIGURES & TABLES | REFERENCES | CITED BY

Abstract

While the human brain presents natural structural asymmetries between left and right hemispheres in MR images, most neurological diseases are associated with abnormal brain asymmetries. Due to the great variety of such anomalies, we present a framework to model normal structural brain asymmetry from control subjects only, independent of the neurological disease. The model dismisses data annotation by exploiting generative deep neural networks and one-class classifiers. We also propose a patch-based model to localize volumes of interest with reduced background sizes around selected brain structures and a one-class classifier based on an optimum-path forest. This model makes the framework independent of segmentation, which may fail, especially in abnormal images, or may not be available for a given structure. We validate the first method to the detection of abnormal hippocampal asymmetry using distinct groups of Epilepsy patients and testing controls. The results of validation using the original feature space and a two-dimensional space based on non-linear projection show the potential to extend the framework for abnormal asymmetry detection in other parts of the brain and develop intelligent and interactive virtual environments. For instance, the approach can be used for screening, inspection, and annotation of the detected anomaly type, allowing the development of CADx systems.

Botter Martins et al. 2019

Nuestra solución, bien clásica:

NORHA: Caracterización de asimetrías y OC-SVM

Brain Topography (2023) 36:644–660
https://doi.org/10.1007/s10548-023-00985-6

ORIGINAL PAPER

NORHA: A NORmal Hippocampal Asymmetry Deviation Index Based on One-Class Novelty Detection and 3D Shape Features

Duilio Deangeli[1,2] · Francisco Iarussi[1] · Hernán Külsgaard[1,2] · Delfina Braggio[1,2] · Juan Pablo Princich[3] · Mariana Bendersky[3,4] · Emmanuel Iarussi[2,5] · Ignacio Larrabide[1,2] · José Ignacio Orlando[1,2]

Received: 12 September 2022 / Accepted: 21 June 2023 / Published online: 29 June 2023

Abstract
Radiologists routinely analyze hippocampal asymmetries in magnetic resonance (MR) images as a biomarker for neurodegenerative conditions like epilepsy and Alzheimer's Disease. However, current clinical tools rely on either subjective evaluations, basic volume measurements, or disease-specific models that fail to capture more complex differences in normal shape. In this paper, we overcome these limitations by introducing NORHA, a novel NORmal Hippocampal Asymmetry deviation index that uses machine learning novelty detection to objectively quantify it from MR scans. NORHA is based on a One-Class Support Vector Machine model learned from a set of morphological features extracted from automatically segmented hippocampi of healthy subjects. Hence, in test time, the model automatically measures how far a new unseen sample falls with respect to the feature space of normal individuals. This avoids biases produced by standard classification models, which require being trained using diseased cases and therefore learning to characterize changes produced only by the ones. We evaluated our new index in multiple clinical use cases using public and private MRI datasets comprising control individuals and subjects with different levels of dementia or epilepsy. The index reported high values for subjects with unilateral atrophies and remained low for controls or individuals with mild or severe symmetric bilateral changes. It also showed high AUC values for discriminating individuals with hippocampal sclerosis, further emphasizing its ability to characterize unilateral abnormalities. Finally, a positive correlation between NORHA and the functional cognitive test CDR-SB was observed, highlighting its promising application as a biomarker for dementia.

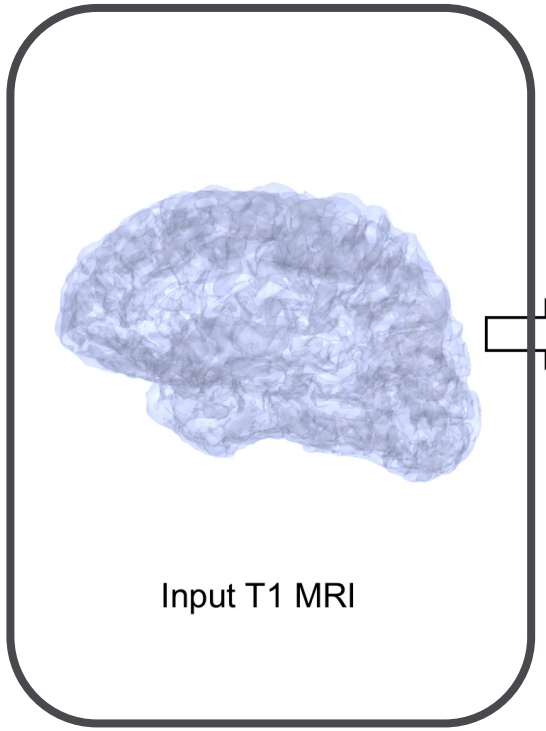
Keywords Hippocampus · Normal asymmetries · Machine learning · Novelty detection

Segmentación + Caracterización + Asimetría + OC-SVM

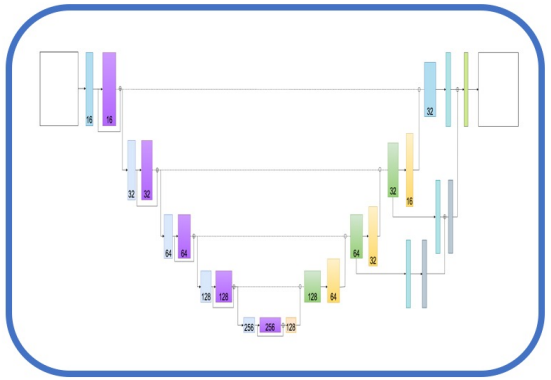
Nuestra solución, bien clásica:

NORHA: Caracterización de asimetrías y OC-SVM

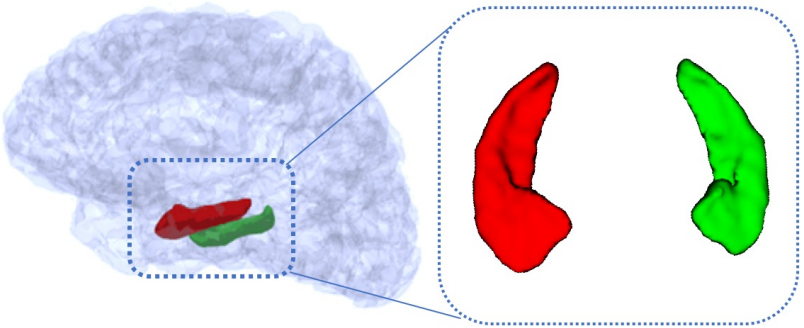
Normalización
a espacio estándar
usando templates
de MNI (SPM12)



Input T1 MRI



HippMapp3r
(Goubran et al. 2020)



Hippocampal segmentation

Segmentación + Caracterización + Asimetría + OC-SVM

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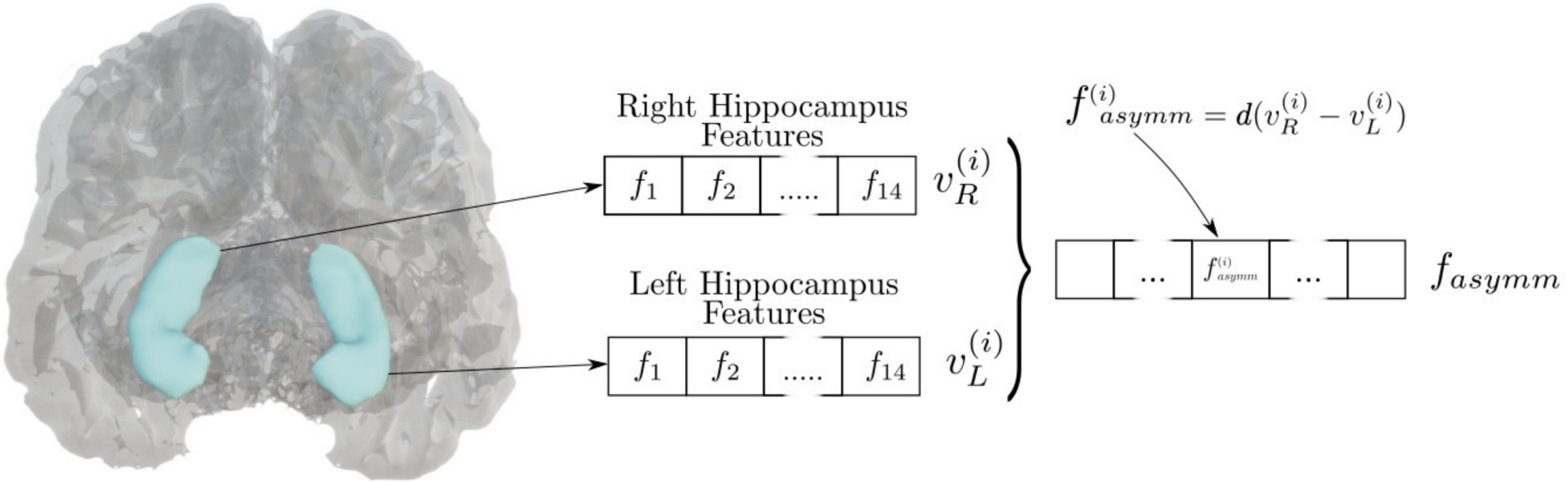

Segmentación + Caracterización + Asimetría + OC-SVM

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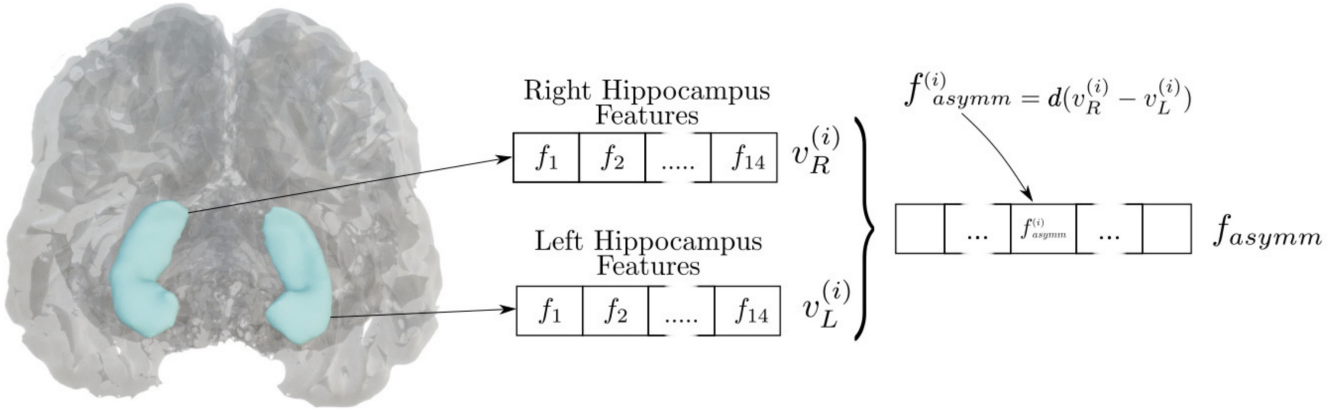
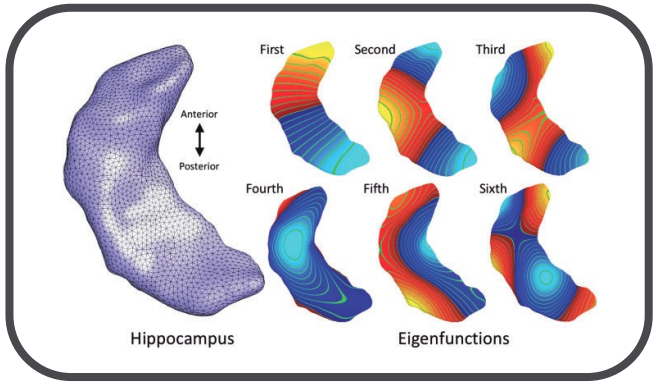
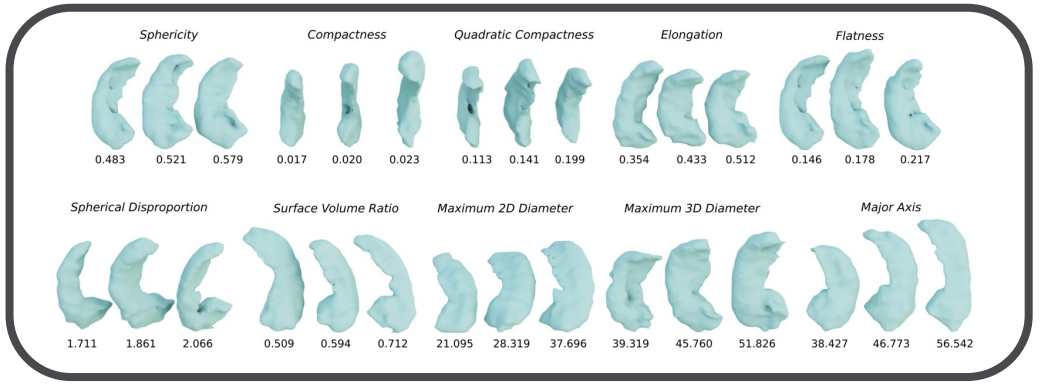


Distancia Euclidea y de Mahalanobis de ShapeDNA
(Wachinger et al. 2016)



Diferencias morfológicas
(Pyradiomics)



Diferencia volumétrica

Diferencia volumétrica (crudas y normalizadas)
(Trimesh)

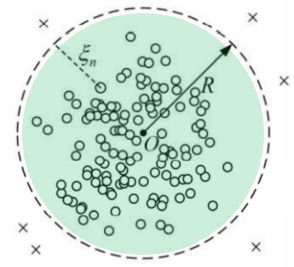
Segmentación + Caracterización + Asimetría + OC-SVM

Nuestra solución, bien clásica:

NORHA: Caracterización de asimetrías y OC-SVM

OC-SVM entrenada con **datos sanos** (NC)

Partitions		Gender (M/F)	Mean age [min-max]	NC	AD	MCI	HSL	HSR	Total
Train		1284/838	60 [19-95]	1500 (OASIS) + 539 (IXI) + 83 (ROFFO)	-	-	-	-	2122
Test	OASIS	434/429	65 [45-88]	717	146	-	-	-	863
	ADNI	74/83	75 [56-89]	53	33	71	-	-	157
	HEC	43/58	32 [18-63]	53	-	-	32	16	101



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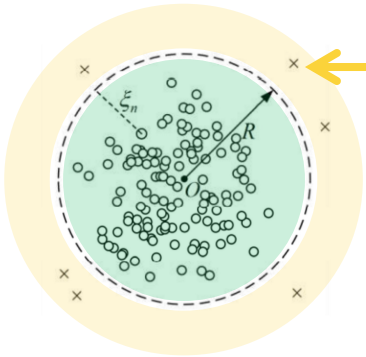
	HEC	43/58	32 [18-63]	53	-	-	32	16	101

Casos con enfermedades neurodegenerativas deberían caer **fuera del espacio de normalidad**



Segmentación + Caracterización + Asimetría + OC-SVM

Nuestra solución, bien clásica:

NORHA: Caracterización de asimetrías y OC-SVM

OC-SVM entrenada con **datos sanos** (NC)

Partitions		Gender (M/F)	Mean age [min-max]	NC	AD	MCI	HSL	HSR	Total
Train		1284/838	60 [19-95]	1500 (OASIS) + 539 (IXI) + 83 (ROFFO)	-	-	-	-	2122
Test	OASIS	434/429	65 [45-88]	717	146	-	-	-	863
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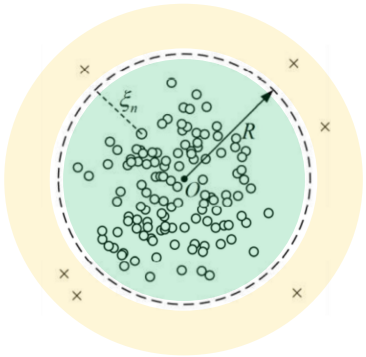
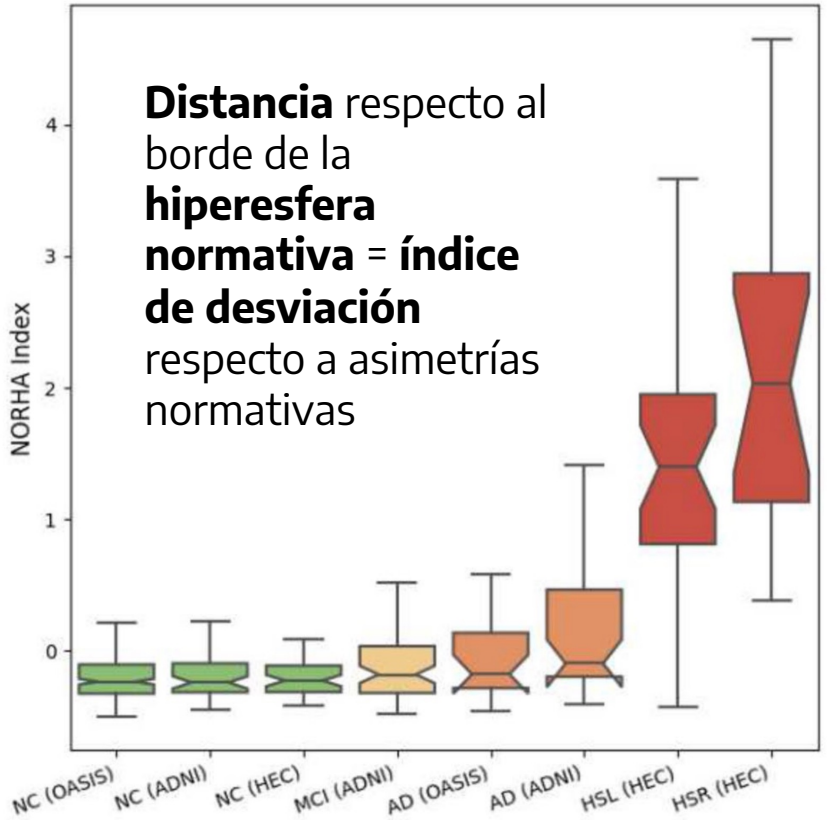


Distancia respecto al borde de la **hiperesfera normativa** = **índice de desviación** respecto a asimetrías normativas



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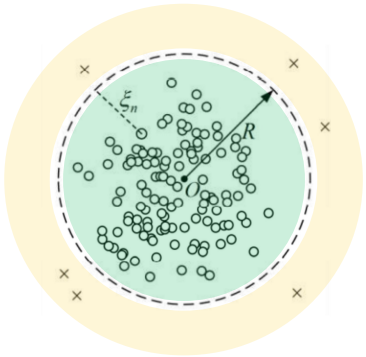

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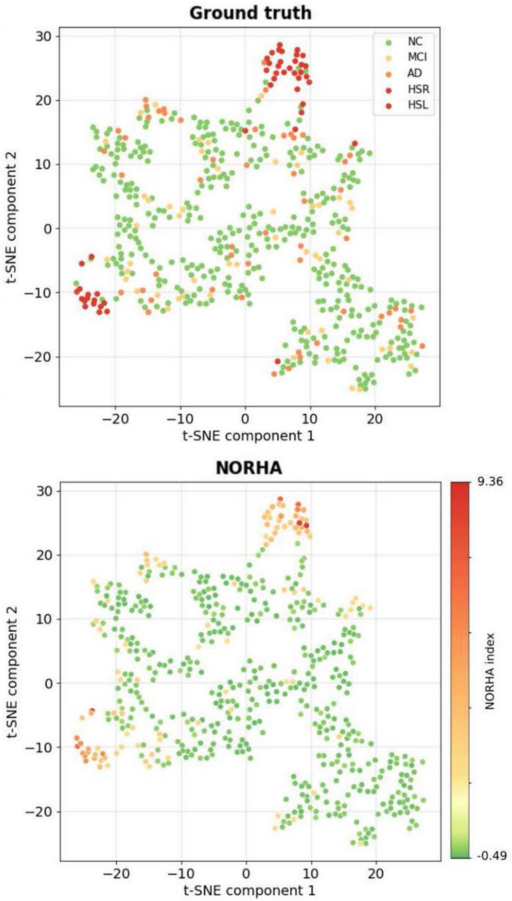


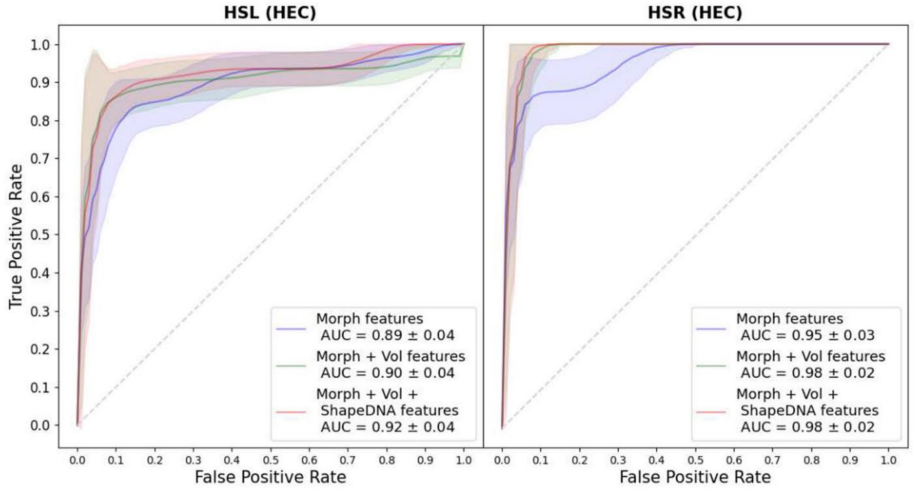
Segmentación + Caracterización + Asimetría + OC-SVM

Nuestra solución, bien clásica:

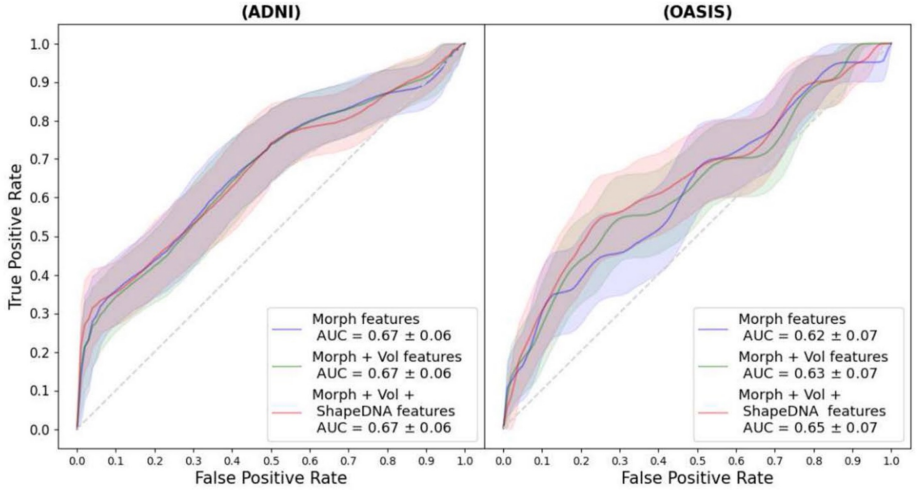
NORHA: Caracterización de asimetrías y OC-SVM

Distancia como **indicador diagnóstico** para condiciones que provocan **cambios significativos en la asimetría**

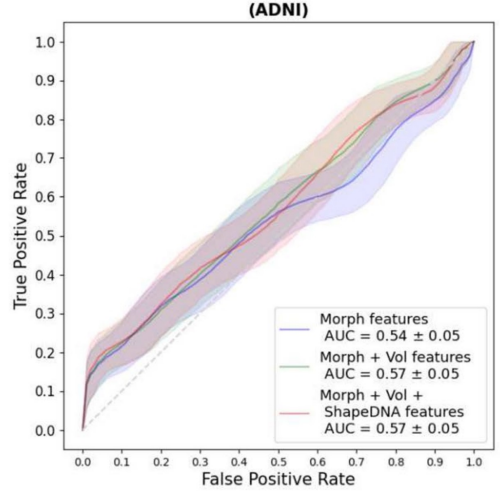
Esclerosis hippocampal izquierda (HSL) o derecha (HSR)



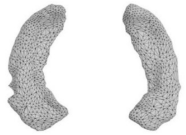
Enfermedad de Alzheimer (AD)



Deterioro cognitivo leve (MSI)

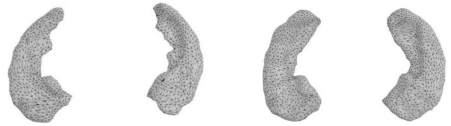


Caso **sano**:



Caso **HSL**:

Casos **MSI**:

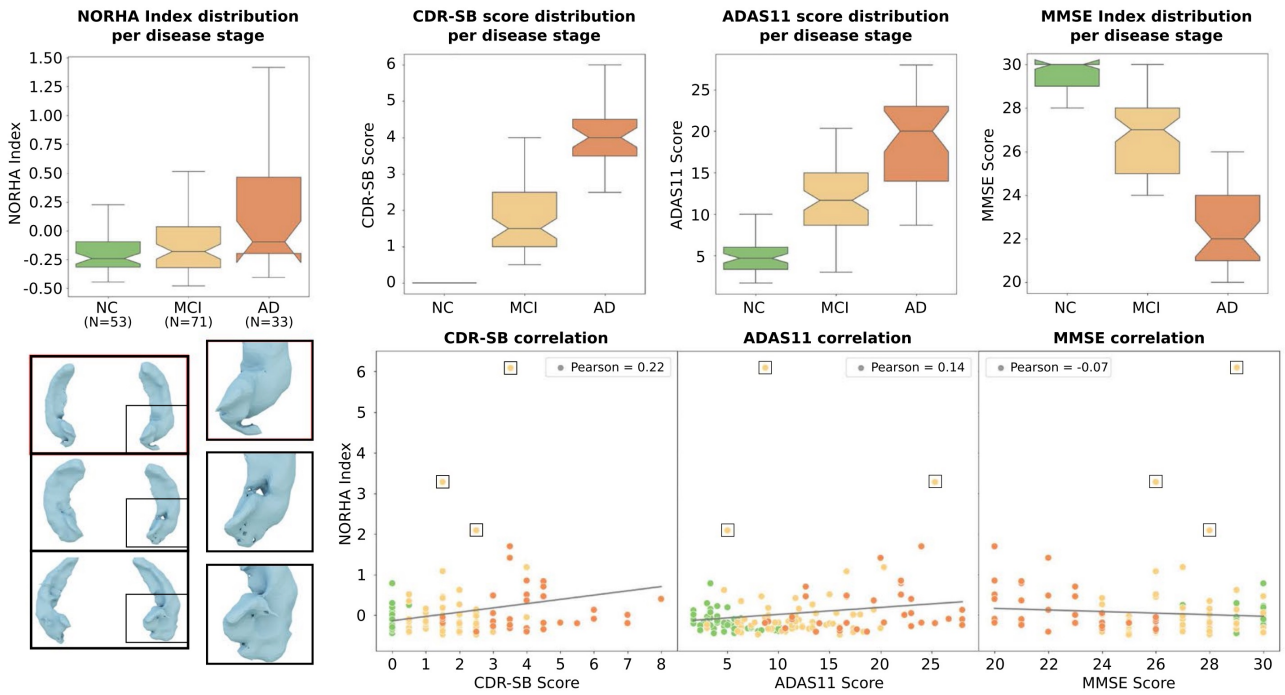


Segmentación + Caracterización + Asimetría + OC-SVM

Nuestra solución, bien clásica:

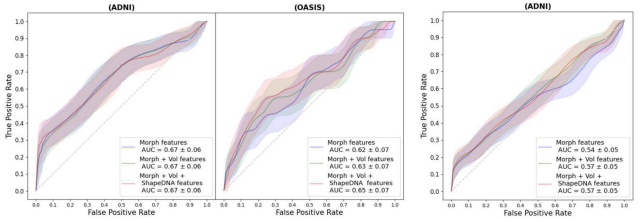
NORHA: Caracterización de asimetrías y OC-SVM

Distancia que **correlaciona levemente** con los resultados de **estudios cognitivos estándar** para diagnóstico

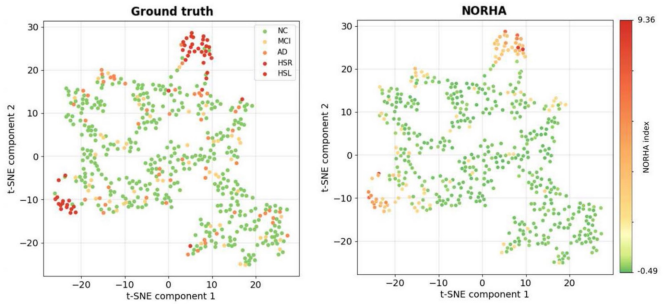


Outliers por mala segmentación

Poder diagnóstico limitado para reconocer **MSI y AD**



Las **características** parecen **no ser suficientemente discriminativas**



Probemos algo deep!

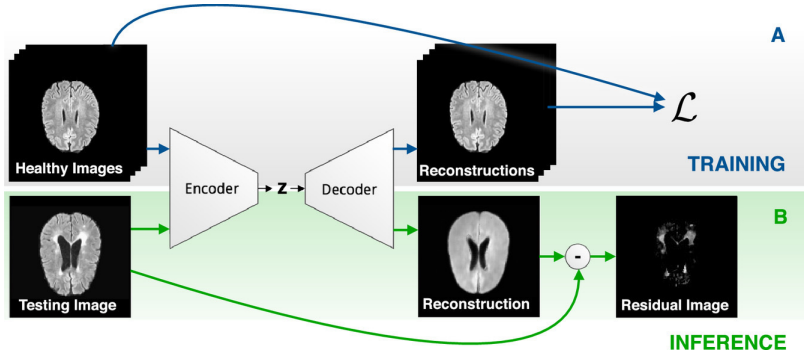
Luego, un repaso de los nuevos métodos:

Algoritmos deep para novelty detection

(Convolutional) Autoencoder (CAE) + Reconstruction error

Un CAE entrenado **únicamente con datos de una clase** debería **fallar** si tratamos de reconstruir **clases nunca vista**.

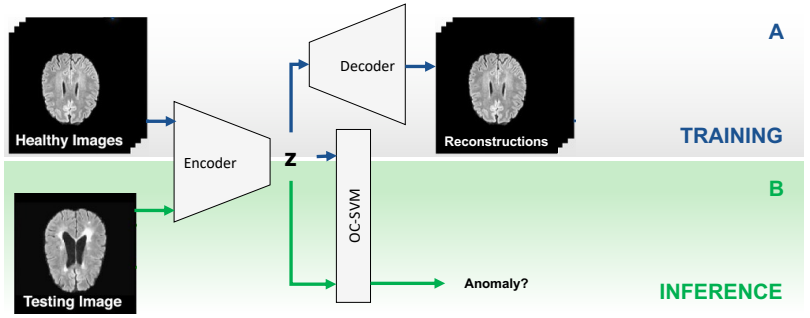
Explicabilidad a través de la reconstrucción	Ignora representaciones, no está calibrado	*Baur et al. 2021*, An & Cho 2015, Chen et al. 2017, ...



CAE latent representations + One-class classifiers

Un CAE entrenado **únicamente con datos de una clase** debería producir **representaciones latentes espurias** en muestras de clases nunca vistas.

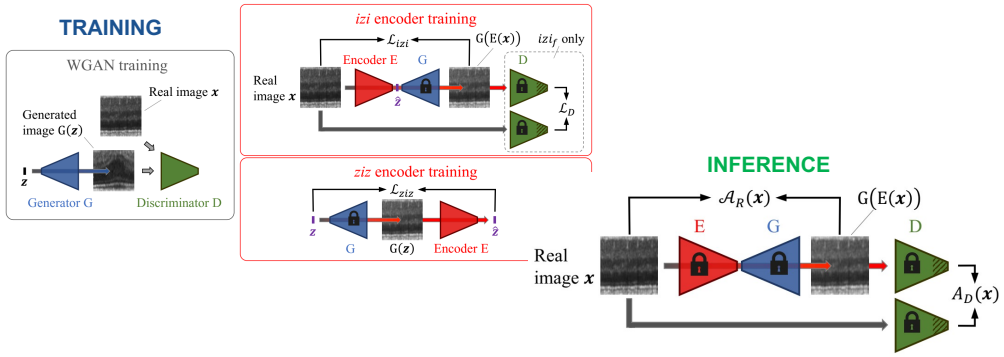
Usa representaciones, calibrado	No hay explicabilidad, entrenamiento separado	Xu et al. 2015, Andrews et al 2016, Erfani et al. 2016, ...



Combinar GANs y embeddings: AnoGAN y f-AnoGAN

GAN entrenada en datos normales, predicción que combina error de reconstrucción y diferencias en el discriminador.

Usa representaciones, explicabilidad	Poco calibrado, embeddings no compactos	Schlegl et al. 2017, Schlegl et al. 2019



Luego, un repaso de los nuevos métodos:

Algoritmos deep para novelty detection

Una única red, con una loss para detección de anomalías

Una red convolucional entrenada con una función de pérdida que produce **representaciones compactas:**

$$\min_{\mathcal{W}} \frac{1}{n}\sum_{i=1}^{n}\underbrace{\|\phi(\mathbf{x}_i;\mathcal{W})-\mathbf{c}\|^2}_{\text{Features lo más cercanas posibles al centro } \mathbf{c}} + \underbrace{\frac{\lambda}{2}\sum_{l=1}^{L}\|\mathbf{W}^l\|_F^2}_{\text{Weight Decay}}$$

Ruff et al. 2018, Ruff et al. 2021.

👍 Utiliza representaciones, aprende todo a la vez!

👎 No tiene explicabilidad (por ahora ;-))

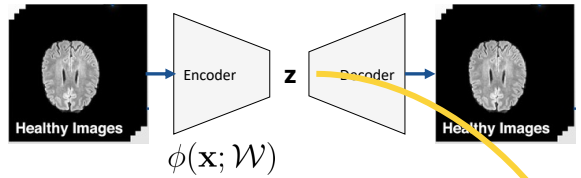
¿Y si diseñamos algo con esto?

Deep One-Class Classification

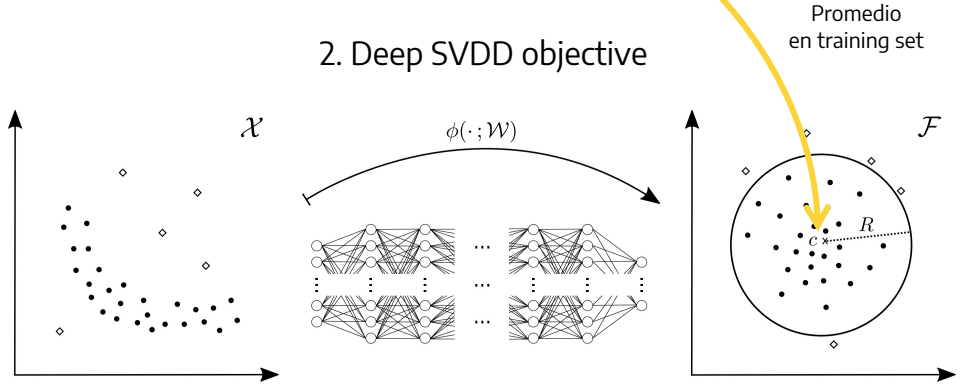
Lukas Ruff [*1] Robert A. Vandermeulen [*2] Nico Görnitz [3] Lucas Deecke [4] Shoaib A. Siddiqui [2 5]
Alexander Binder [6] Emmanuel Müller [1] Marius Kloft [2]

Entrenamiento

1. Preentrenamiento como CAE



2. Deep SVDD objective



Test

Muestras anómalas

$$s(\mathbf{x}) = \|\phi(\mathbf{x};\mathcal{W}^*)-\mathbf{c}\|^2$$

Para mejorar nuestra solución:

NORAH: Deep characterization y Deep SVDD

Regularized siamese neural network for unsupervised outlier detection on brain multiparametric magnetic resonance imaging: Application to epilepsy lesion screening

Zaruhi Alaverdyan[a], Julien Jung[b], Romain Bouet[b], Carole Lartizien[a,*]

[a] Univ Lyon, INSA-Lyon, Université Claude Bernard Lyon 1, UJM-Saint Etienne, CNRS, Inserm, CREATIS UMR 5220, U1206, F69621, Lyon, France
[b] Lyon Neuroscience Research Center, CRNL, INSERM U1028, CNRS UMR5292, University Lyon 1, Lyon, France

ARTICLE INFO

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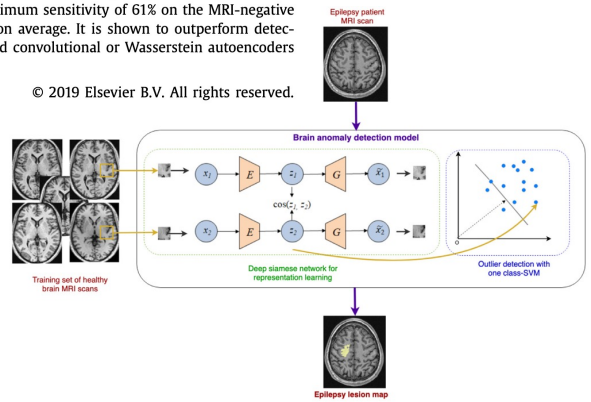
Keywords:
Regularized siamese network
Wasserstein autoencoder
Unsupervised representation learning
Brain lesions
Anomaly detection
Deep learning

ABSTRACT

In this study, we propose a novel anomaly detection model targeting subtle brain lesions in multiparametric MRI. To compensate for the lack of annotated data adequately sampling the heterogeneity of such pathologies, we cast this problem as an outlier detection problem and introduce a novel configuration of unsupervised deep siamese networks to learn normal brain representations using a series of non-pathological brain scans. The proposed siamese network, composed of stacked convolutional autoencoders as subnetworks is designed to map patches extracted from healthy control scans only and centered at the same spatial localization to 'close' representations with respect to the chosen metric in a latent space. It is based on a novel loss function combining a similarity term and a regularization term compensating for the lack of dissimilar pairs. These latent representations are then fed into oc-SVM models at voxel-level to produce anomaly score maps. We evaluate the performance of our brain anomaly detection model to detect subtle epilepsy lesions in multiparametric (T1-weighted, FLAIR) MRI exams considered as normal (MRI-negative). Our detection model trained on 75 healthy subjects and validated on 21 epilepsy patients (with 18 MRI-negatives) achieves a maximum sensitivity of 61% on the MRI-negative lesions, identified among the 5 most suspicious detections on average. It is shown to outperform detection models based on the same architecture but with stacked convolutional or Wasserstein autoencoders as unsupervised feature extraction mechanisms.

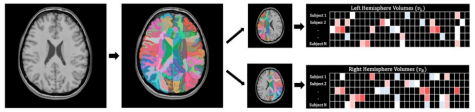
- Parches de la imagen
- CAE siamés para extraer features
- One-class SVM no integrada al entrenamiento



Using deep Siamese neural networks for detection of brain asymmetries associated with Alzheimer's Disease and Mild Cognitive Impairment

Chin-Fu Liu[a,b,1], Shreyas Padhy[a,b,1], Sandhya Ramachandran[a,b], Victor X. Wang[a,b], Andrew Efimov[a,b,c], Alonso Bernal[a,b], Linyuan Shi[a,d], Marc Vaillant[i], J. Tilak Ratnanather[a,b], Andreia V. Faria[e], Brian Caffo[b,g,h], Marilyn Albert[f], Michael I. Miller[a,b,h,*], the BIOCARD Research Team, for the Alzheimer's Disease Neuroimaging Initiative[2]

[a] Center for Imaging Science, Institute for Computational Medicine, Johns Hopkins University, Baltimore, MD, USA
[b] Department of Biomedical Engineering, Johns Hopkins University, Baltimore, MD, USA
[c] Department of Electrical and Computer Engineering, Johns Hopkins University, Baltimore, MD, USA
[d] Department of Neuroscience, Johns Hopkins University, Baltimore, MD, USA
[e] Department of Radiology, School of Medicine, Johns Hopkins University, Baltimore, MD
[f] Department of Neurology, Johns Hopkins University, Baltimore, MD, USA
[g] Department of Biostatistics, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA
[h] Kavli Neuroscience Discovery Institute, Johns Hopkins University, Baltimore, MD, USA
[i] Animetrics Inc., Conway, NH, USA



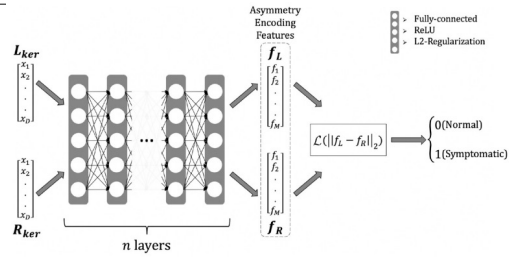
ARTICLE INFO

Keywords:
Structural magnetic resonance imaging
Alzheimer's Disease
Mild Cognitive Impairment
Machine learning
Deep learning
Siamese networks

ABSTRACT

In recent studies, neuroanatomical volume and shape asymmetries have been seen during the course of Alzheimer's Disease (AD) and could potentially be used as preclinical imaging biomarkers for the prediction of Mild Cognitive Impairment (MCI) and AD dementia. In this study, a deep learning framework utilizing Siamese neural networks trained on paired lateral inter-hemispheric regions is used to harness the discriminative power of whole-brain volumetric asymmetry. The method uses the MRICloud pipeline to yield low-dimensional volumetric features of pre-defined atlas brain structures, and a novel non-linear kernel trick to normalize these features to reduce batch effects across datasets and populations. By working with the low-dimensional features, Siamese networks were shown to yield comparable performance to studies that utilize whole-brain MR images, with the advantage of reduced complexity and computational time, while preserving the biological information density. Experimental results also show that Siamese networks perform better in certain metrics by explicitly encoding the asymmetry in brain volumes, compared to traditional prediction methods that do not use the asymmetry, on the ADNI and BIOCARD datasets.

- Volumetría de estructuras subcorticales
- Red fully connected siamesa



Para mejorar nuestra solución:

NORAH: Deep characterization y Deep SVDD

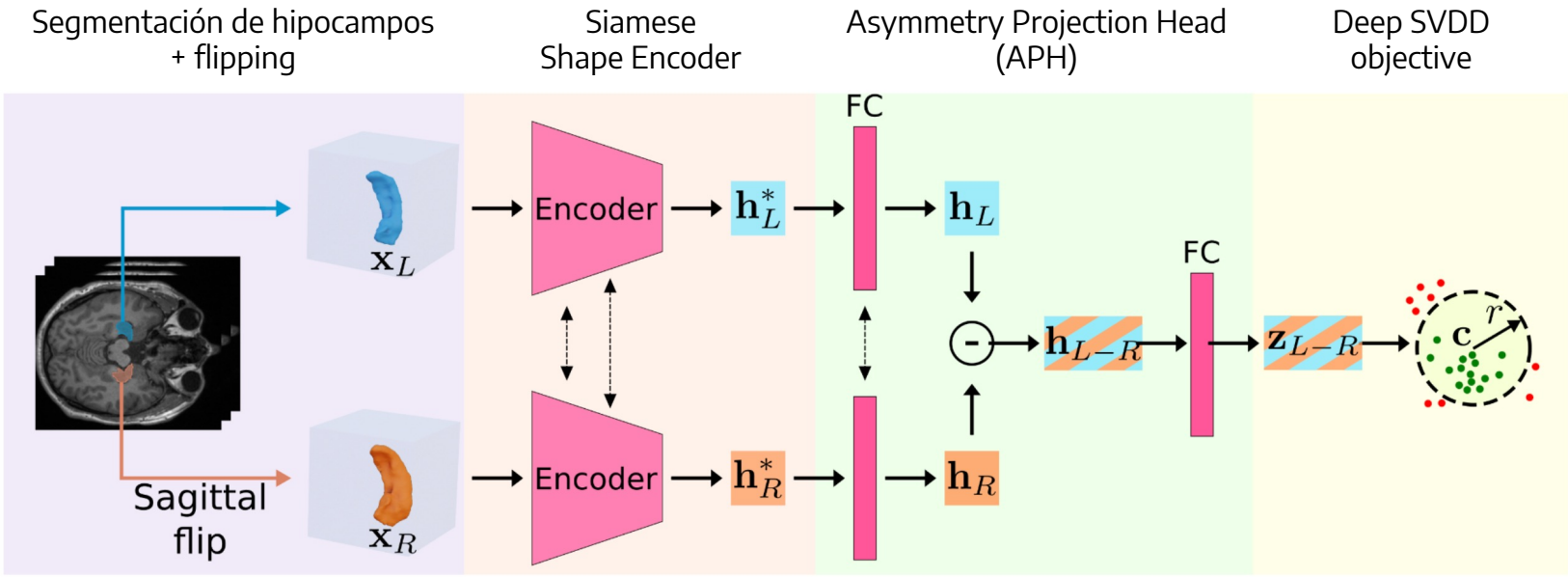
Learning normal asymmetry representations for homologous brain structures

Duilio Deangeli[1,2], Emmanuel Iarussi[2,3], Juan Pablo Princich[4], Mariana Bendersky[3,4], Ignacio Larrabide[1,2], and José Ignacio Orlando[1,2]

[1] Yatiris, PLADEMA, UNICEN, Tandil, Buenos Aires, Argentina
[2] CONICET, Buenos Aires, Argentina
[3] Universidad Torcuato Di Tella, CABA, Argentina
[4] ENyS, CONICET-HEC-UNAJ, Florencio Varela, Buenos Aires, Argentina
[5] Normal Anatomy Department, UBA, CABA, Argentina

Abstract. Although normal homologous brain structures are approximately symmetrical by definition, they also have shape differences due to e.g. natural ageing. On the other hand, neurodegenerative conditions induce their own changes in this asymmetry, making them more pronounced or altering their location. Identifying when these alterations are due to a pathological deterioration is still challenging. Current clinical tools rely either on subjective evaluations, basic volume measurements or disease-specific deep learning models. This paper introduces a novel method to learn normal asymmetry patterns in homologous brain structures based on anomaly detection and representation learning. Our framework uses a Siamese architecture to map 3D segmentations of left and right hemispherical sides of a brain structure to a normal asymmetry embedding space, learned using a support vector data description objective. Being trained using healthy samples only, it can quantify deviations-from-normal-asymmetry patterns in unseen samples by measuring the distance of their embeddings to the center of the learned normal space. We demonstrate in public and in-house sets that our method can accurately characterize normal asymmetries and detect pathological alterations due to Alzheimer's disease and hippocampal sclerosis, even though no diseased cases were accessed for training. Our source code is available at https://github.com/duiliod/DeepNORHA.

Keywords: Normal asymmetry · Brain MRI · Anomaly detection.



Segmentación + Red siamesa + CAE + Deep SVDD

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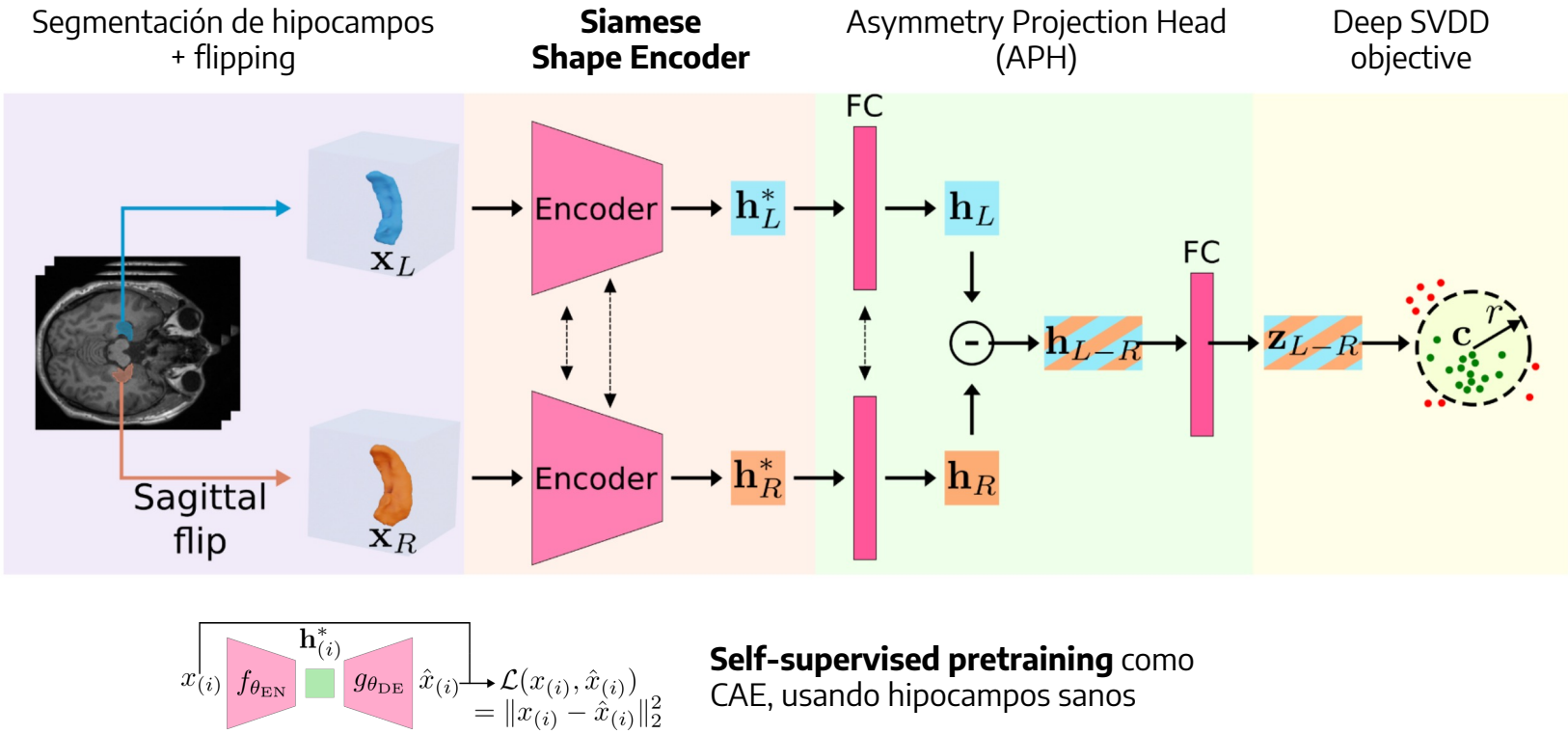

Self-supervised pretraining como CAE, usando hipocampos sanos

Segmentación + Red siamesa + CAE + Deep SVDD

Para mejorar nuestra solución:

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Learning normal asymmetry representations for homologous brain structures

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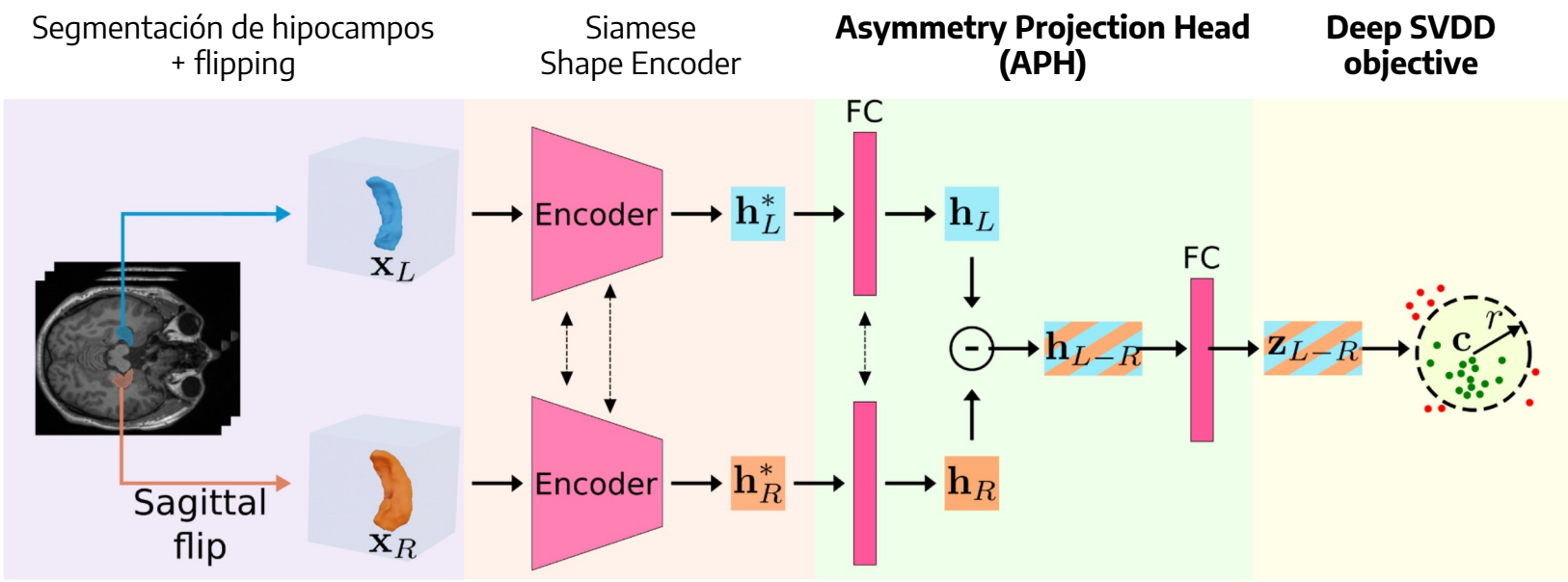
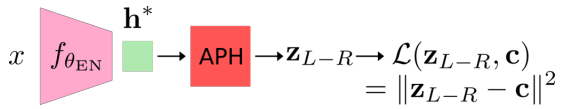


Deep SVDD fine tuning como red siamesa, minimizando distancia respecto al centro **c** (promedio de encoder)



Segmentación + Red siamesa + CAE + Deep SVDD

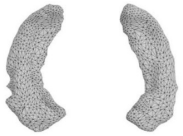
Para mejorar nuestra solución:

NORAH: Deep characterization y Deep SVDD

Distancia al **centro** como **indicador diagnóstico** para **todas las enfermedades neurodegenerativas consideradas**

Method	Synthetic	MCI	AD (ADNI)	AD (OASIS)	HSL	HSR
AVD	0.72 (0.62-0.81)	0.56 (0.46-0.66)	0.55 (0.42-0.67)	0.62 (0.51-0.74)	0.95 (0.89-0.99)	0.94 (0.82-1.00)
NVD	0.82 (0.74-0.89)	0.58 (0.48-0.68)	0.62 (0.49-0.74)	0.64 (0.53-0.74)	0.95 (0.88-1.00)	0.94 (0.83-1.00)
ShapeDNA + OC-SVM	0.66 (0.56-0.74)	0.52 (0.42-0.60)	0.66 (0.55-0.76)	0.47 (0.35-0.60)	0.80 (0.69-0.90)	0.90 (0.81-0.98)
LFV + OC-SVM	0.93 (0.89-0.97)	0.58 (0.49-0.66)	0.67 (0.57-0.76)	0.65 (0.53-0.77)	0.92 (0.88-0.96)	0.98 (0.95-1.00)
LeNet-CAE + OC-SVM	0.95 (0.91-0.98)	0.48 (0.38-0.58)	0.50 (0.37-0.61)	0.46 (0.40-0.51)	0.77 (0.67-0.86)	0.69 (0.56-0.81)
Oktay *et al.* + OC-SVM	0.94 (0.90-0.98)	0.45 (0.35-0.56)	0.48 (0.35-0.59)	0.47 (0.42-0.53)	0.80 (0.69-0.88)	0.76 (0.65-0.86)
AD classification	0.49 (0.47-0.50)	0.64 (0.56-0.70)	0.73 (0.63-0.83)	(Used for training)	0.52 (0.48-0.56)	0.54 (0.48-0.61)
Deep NORAH (w/o CAE pretr.)	0.79 (0.71-0.87)	0.59 (0.48-0.69)	0.99 (0.99-1.00)	0.76 (0.67-0.84)	**1.00** (0.99-1.00)	**1.00** (0.99-1.00)
Deep NORAH (w/o FC dim. red.)	0.98 (0.94-1.00)	0.70 (0.60-0.79)	0.76 (0.65-0.87)	0.65 (0.54-0.76)	**1.00** (1.00-1.00)	**1.00** (1.00-1.00)
Deep NORAH (with CAE pretr.)	**0.99** (0.99-1.00)	**0.93** (0.87-0.97)	**1.00** (0.99-1.00)	**0.92** (0.86-0.96)	**1.00** (1.00-1.00)	**1.00** (1.00-1.00)

Volumen (diferencia absoluta –AVD – o normalizada –NVD –)
solamente útil para reconocer **atrofias** evidentes

Caso **sano**: 

Caso **HSL**: 

Segmentación + Red siamesa + CAE + Deep SVDD

Para mejorar nuestra solución:

NORAH: Deep characterization y Deep SVDD

Distancia al **centro** como **indicador diagnóstico** para **todas las enfermedades neurodegenerativas consideradas**

Method	Synthetic	MCI	AD (ADNI)	AD (OASIS)	HSL	HSR
AVD	0.72 (0.62-0.81)	0.56 (0.46-0.66)	0.55 (0.42-0.67)	0.62 (0.51-0.74)	0.95 (0.89-0.99)	0.94 (0.82-1.00)
NVD	0.82 (0.74-0.89)	0.58 (0.48-0.68)	0.62 (0.49-0.74)	0.64 (0.53-0.74)	0.95 (0.88-1.00)	0.94 (0.83-1.00)
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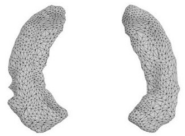
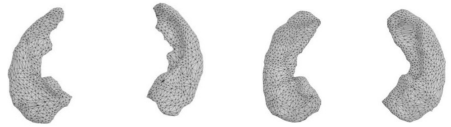
NORHA (Deangeli et al. 2023) tiene **limitaciones** para reconocer **MCI y AD** en todos los datasets

Caso **sano**:



Casos **MSI**:



Segmentación + Red siamesa + CAE + Deep SVDD

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Deep NORAH (with CAE pretr.)	**0.99** (0.99-1.00)	**0.93** (0.87-0.97)	**1.00** (0.99-1.00)	**0.92** (0.86-0.96)	**1.00** (1.00-1.00)	**1.00** (1.00-1.00)

Separar el aprendizaje de las **características** (CAE) del detector de anomalías **no mejora resultados**

Segmentación + Red siamesa + CAE + Deep SVDD

Para mejorar nuestra solución:

NORAH: Deep characterization y Deep SVDD

Distancia al **centro** como **indicador diagnóstico** para **todas las enfermedades neurodegenerativas consideradas**

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Un **modelo supervisado entrenado** únicamente para detectar **AD**
no puede detectar otras condiciones

Segmentación + Red siamesa + CAE + Deep SVDD

Para mejorar nuestra solución:

NORAH: Deep characterization y Deep SVDD

Distancia al **centro** como **indicador diagnóstico** para **todas las enfermedades neurodegenerativas consideradas**

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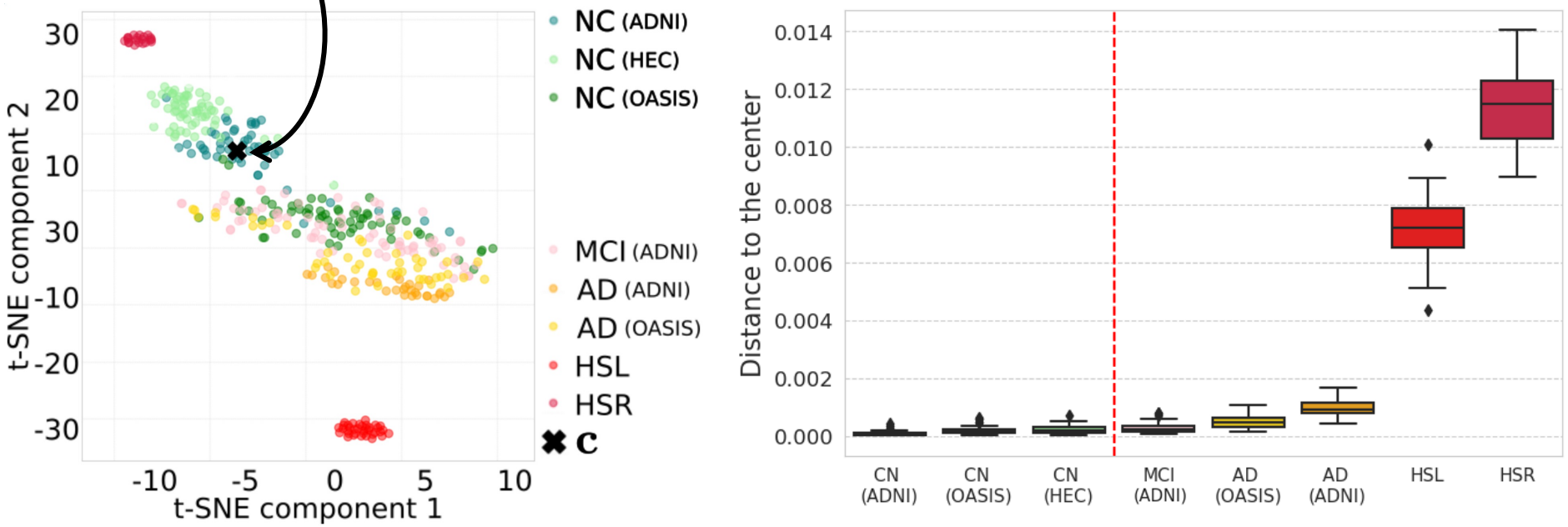
Nuestro modelo es capaz de reconocer **todas las enfermedades neurodegenerativas** que analizamos!

Segmentación + Red siamesa + CAE + Deep SVDD

Para mejorar nuestra solución:

NORAH: Deep characterization y Deep SVDD

Distancia al centro como **indicador diagnóstico** para **todas las enfermedades neurodegenerativas consideradas**



Segmentación + Red siamesa + CAE + Deep SVDD

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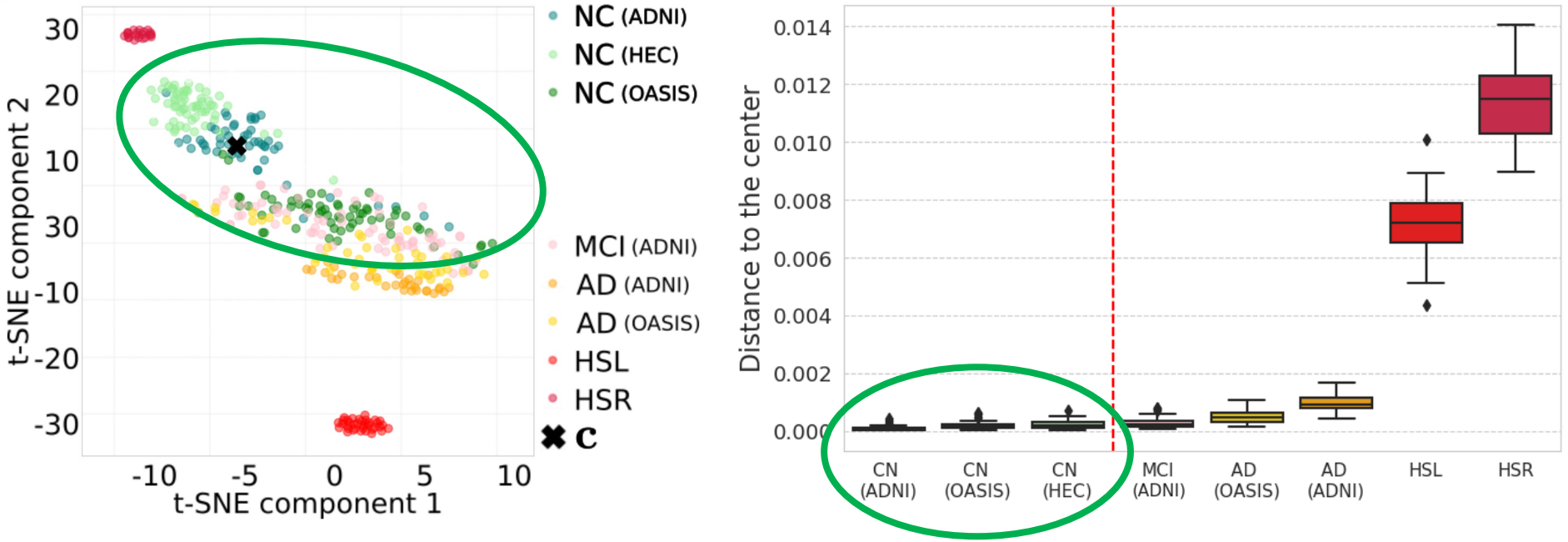

Segmentación + Red siamesa + CAE + Deep SVDD

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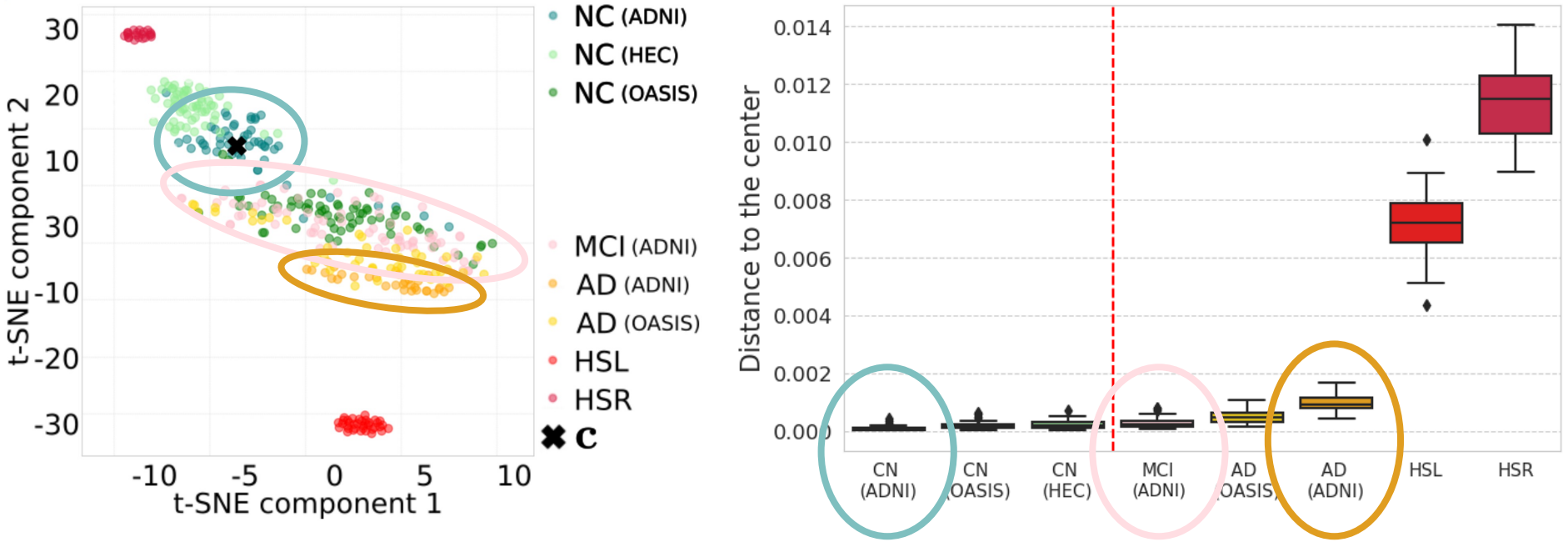

Segmentación + Red siamesa + CAE + Deep SVDD

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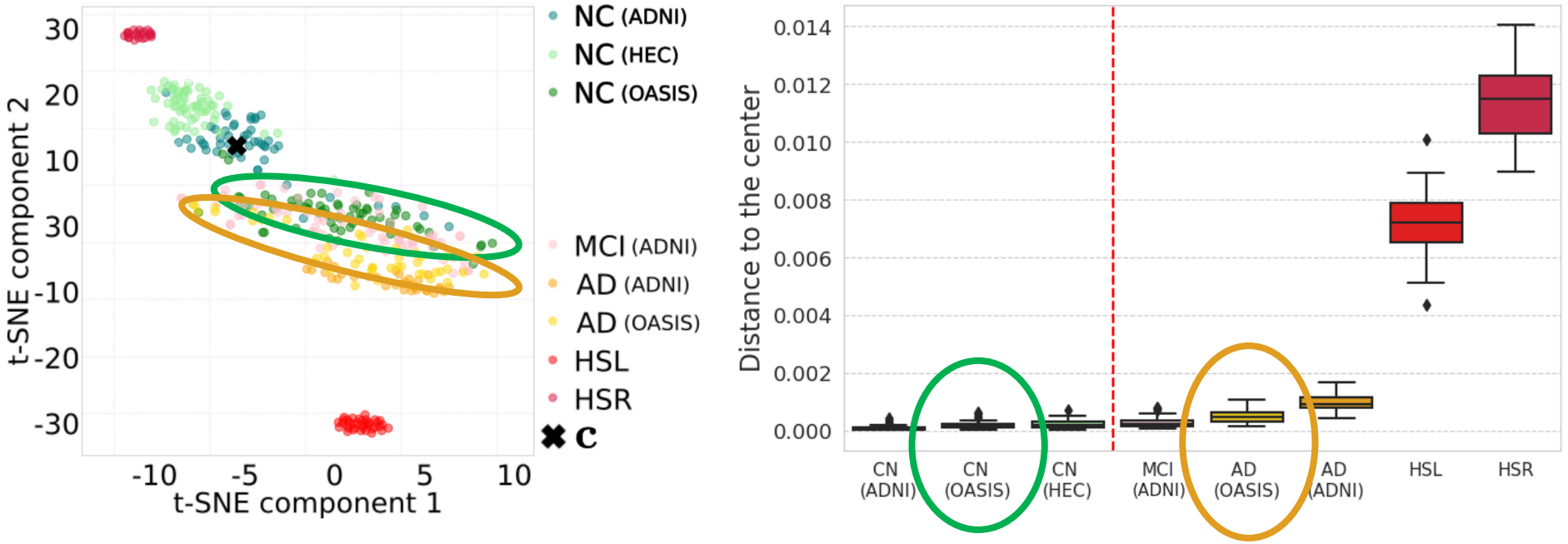

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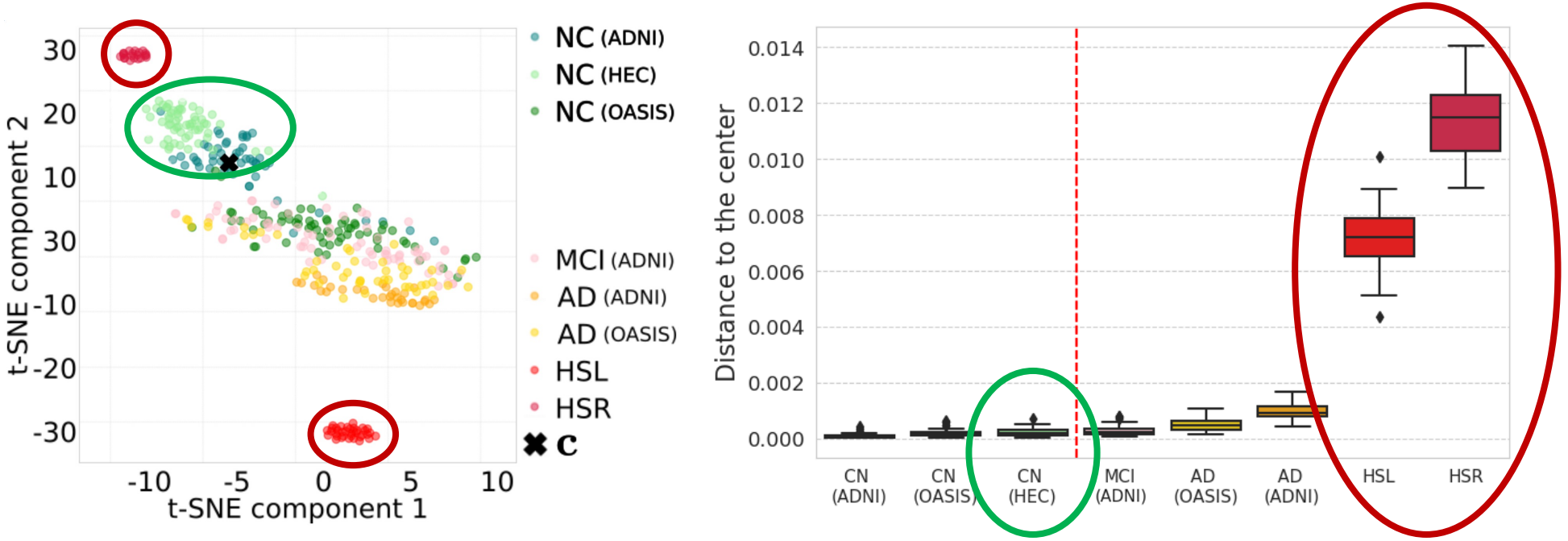
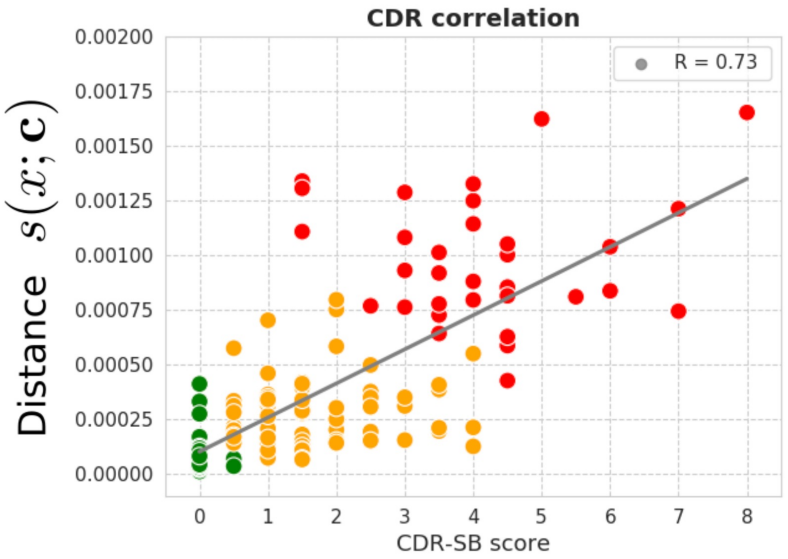


Segmentación + Red siamesa + CAE + Deep SVDD

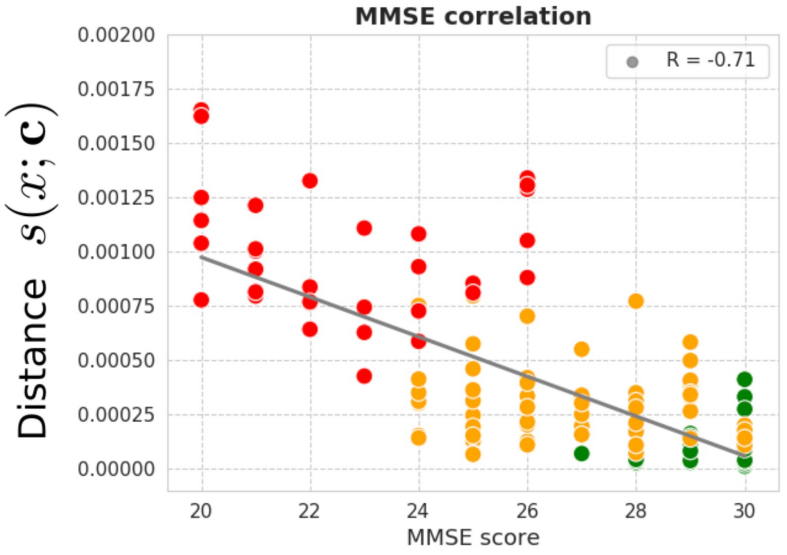
Para mejorar nuestra solución:

NORAH: Deep characterization y Deep SVDD

Nuestro índice **correlaciona fuertemente** con los **estudios funcionales** más utilizados para diagnóstico de enfermedades neurodegenerativas



(Clasificación Clínica de Demencia de Hughes)



(Test Mini Mental de Folstein)

- **Explicabilidad** a través de occlusion maps.
- Estudios **sectorizados por región** del hipocampo
- Experimentos sobre **otras estructuras homólogas**

Segmentación + Red siamesa + CAE + Deep SVDD

Pensar escenarios nuevos

Los sí y los no de Deep SVDD

Te lo resumo así nomás!

- **Che, ¿esto funciona para cualquier imagen?**

  NO! En imágenes naturales, su propio contenido / estructura multiescala hace que el modelo no pueda diferenciar anomalías.

- **¿Cómo hago entonces con imágenes naturales?**

  Outlier Exposure (OE). Juntar (poquitos nomás) datos que nada que ver (outliers) y entrenar algún bicho de esos. Hendrycks et al., 2019a

- **¿Y cuándo puede servir esto, entonces?**

  Datos simples. Con segmentaciones, MNIST, etc. la cosa funca hermosa. ¿Será un tema de capacidad?

- **¿Qué onda el espacio de características?**

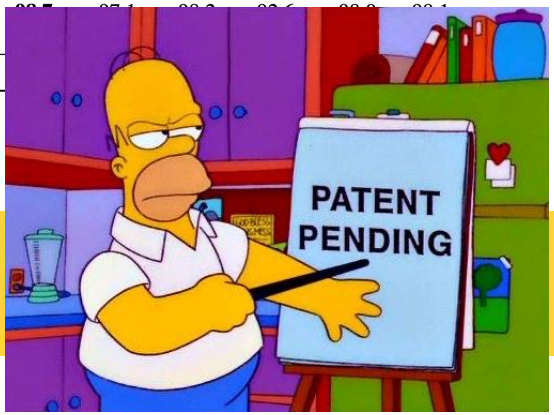
  Muy compacto. ¿Podrá servir como discriminador en GANs? ¿Podrá usarse para medir calidad de segmentación?

Rethinking Assumptions in Deep Anomaly Detection

Lukas Ruff [1 *] Robert A. Vandermeulen [2 *] Billy Joe Franks [3] Klaus-Robert Müller [2 4 5] Marius Kloft [3]

Table 4. Mean AUC detection performance in % (over 10 seeds) for all individual classes and methods on the CIFAR-10 one vs. rest benchmark with 80MTI OE from Section 3.1.

	Unsupervised					Unsupervised OE			Supervised OE		
Class	SVDD*	DSVDD*	GT*	IT*	GT+*	GT+*	DSAD	HSC	Focal*	Focal	BCE
Airplane	65.6	61.7	74.7	78.5	77.5	90.4	94.2	96.3	87.6	95.9	**96.4**
Automobile	40.9	65.9	95.7	89.8	96.9	**99.3**	98.1	98.7	93.9	98.7	98.8
Bird	65.3	50.8	78.1	86.1	87.3	**93.7**	89.8	92.7	78.6	92.3	93.0
Cat	50.1	59.1	72.4	77.4	80.9	88.1	87.4	89.8	79.9	88.8	**90.0**
Deer	75.2	60.9	87.8	90.5	92.7	**97.4**	95.0	96.6	81.7	96.6	97.1
Dog	51.2	65.7	87.8	84.5	90.2	**94.3**	93.0	94.2	85.6	94.1	94.2
Frog	71.8	67.7	83.4	89.2	90.9	97.1	96.9	97.9	93.3	97.8	**98.0**
Horse	51.2	67.3	95.5	92.9	96.5	**98.8**	96.8	97.6	87.9	97.6	97.6
Ship	67.9	75.9	93.3	92.0	95.2						
Truck	48.5	73.1	91.3	85.5	93.3						
Mean AUC	58.8	64.8	86.0	86.6	90.1						



Estamos en eso!

Slides acá!

¡Gracias por su atención!

¿Tienen alguna duda? Charlemos!

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Simposio Científico de Inteligencia Artificial y Aplicaciones (SCIAA-UdeSA)
Universidad de San Andrés
4 de octubre de 2023 – CABA – República Argentina

One class to rule them all

Aplicaciones de clasificación a una clase en visión artificial y medicina

José Ignacio Orlando, PhD
CONICET / PLADEMA-UNICEN

* Este trabajo corresponde a parte de las tesis doctorales en curso de Duilio Deangeli

@ignaciorlando

José Ignacio Orlando