

# Representación temporal de alertas ZTF

-Presentación Intermedia-

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Grupo: 8a

# Motivación

ALeRCE es un broker de alertas astronómicas provenientes del survey ZTF

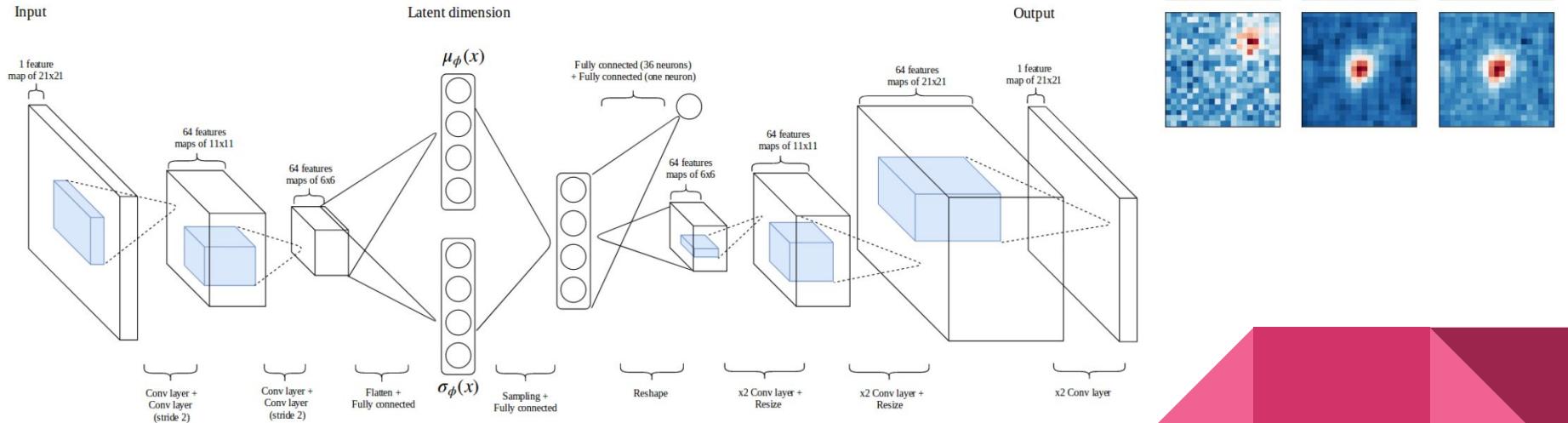
- Existe una gran cantidad de datos
- Interés en detección de transientes efímeros en alza
- Oportunidad para aplicar Machine Learning

Objetivo del proyecto:

- Replicar AutoEncoder Convolucional y explorar representación del espacio latente
- Modelo recurrente para clasificar y comparar los resultados con literatura
- Mejorar los modelos existentes

# Estado del Arte

- Arquitectura del modelo: **Variational Auto Encoder**
- Stamps dataset: **Augmentation**



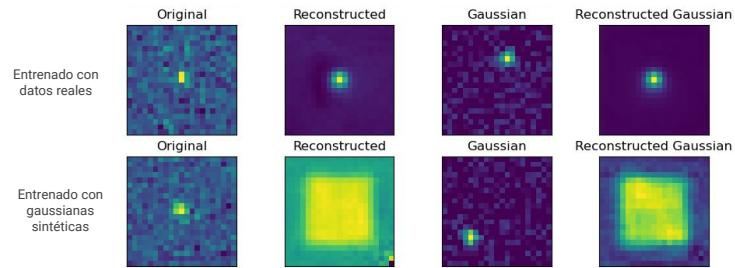
# Variational Auto Encoder v/s Auto Encoder

Se implementó VAE:

- Espacio latente: sigue una **distribución probabilística** ( $\mu, \sigma$ ).
- Función de pérdida: Reconstrucción + **KL Divergence**

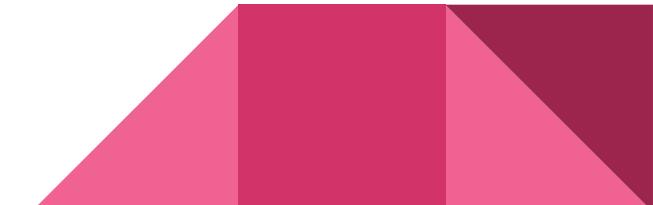
Se cambió a un AE:

- Espacio latente: **determinista**
- Función de pérdida: Reconstrucción (**MSE**)



# Arquitectura del Modelo: AutoEncoder

1. **Encoder**: Input imagen 21x21p con **2 channels**:
  - 4 capas convolucionales
  - 1 capa Fully Connected (FCL)
2. **Decoder**: Input **variables latentes z**:
  - 1 capa Fully Connected (FCL)
  - 6 capas convolucionales



# Experimentos con el Modelo

Experimentos realizados con dataset de **5 clases** → Training 72710, Validation 500, Test 500

Valores default de entrenamiento:

- 300 epochs
- EarlyStop tolerance = 15
- Batch size = 100
- Learning rate = 0.333e-4
- Augmentation = True
- Shuffling = False
- Latent dim = 42

Se experimentó con:

1. Augmentation
2. Latent Dimensions
3. Learning Rate

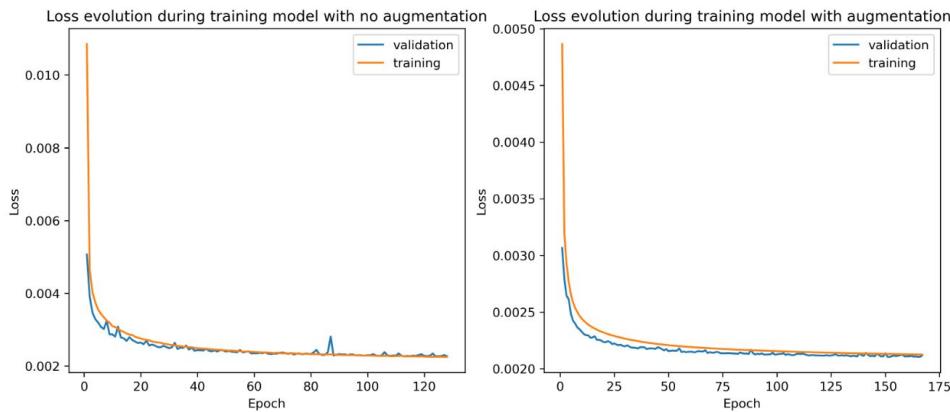
Métricas de comparación:

1. Curvas de entrenamiento
2. Linear Probing (200 epochs)
3. Proyecciones UMAP
4. Ejemplos de Reconstrucción

# Augmentation

Técnicas de augmentation:

- Flip Horizontal y Vertical
- Rotación 90°, 180° y 270°
- Tile shuffling



Se entrenaron 3 modelos:

- No augmentation
- Flip y rotación (Augmentation)
- Flip, rotación y shuffling (Augmentation + shuffle)

Modelo	MSE
Model sin augm.	0.00257473
Model con augm.	0.00222773
Model con augm. y shuffling	0.00226179

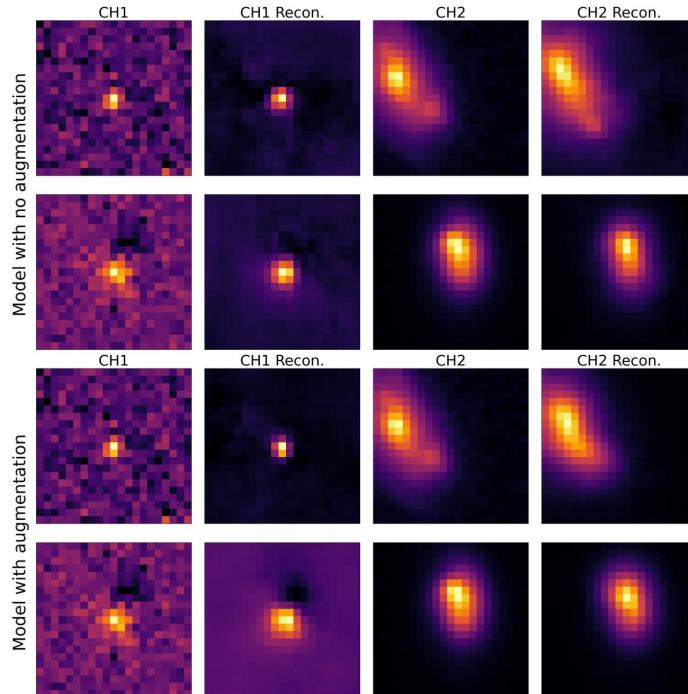
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Técnicas de augmentation:

- **Flip** Horizontal y Vertical
- **Rotación** 90°, 180° y 270°
- **Tile shuffling**

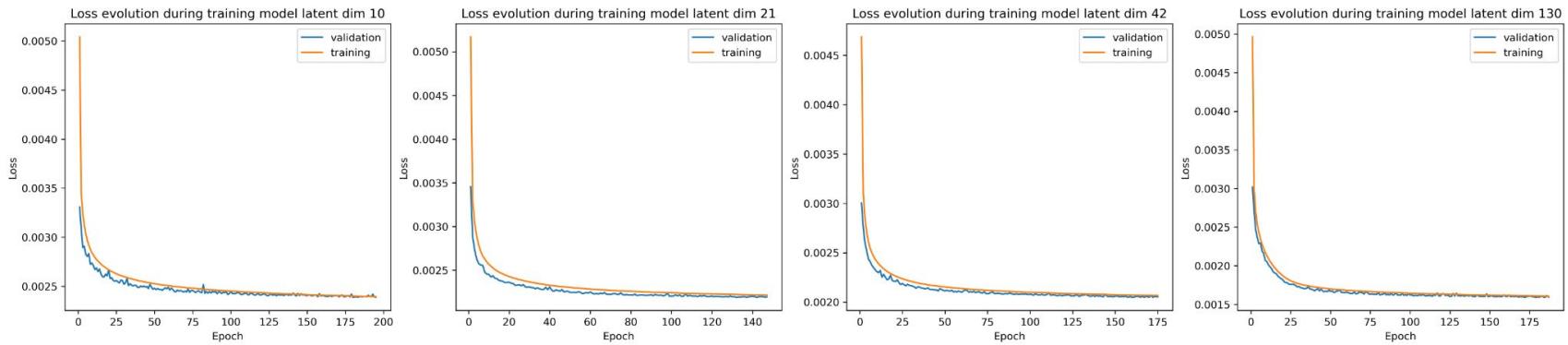
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# Latent Dimensions

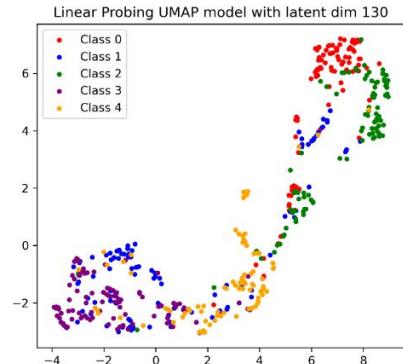
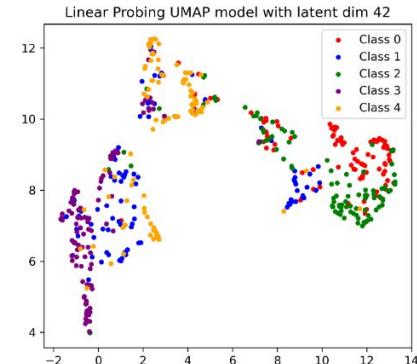
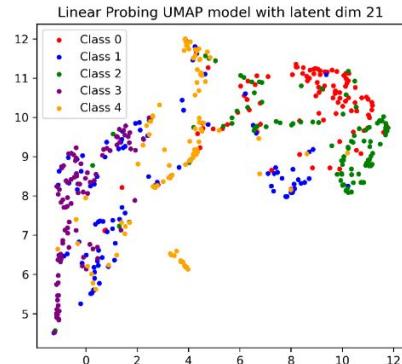
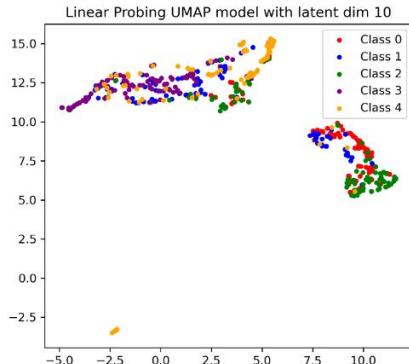
Se entrenaron 4 modelos → Latent Dimension = 10, 21, 42 y 130



Modelo	Precisión (%)	Recall (%)	F1-Score (%)	MSE
Model lat. dim. 10	64.673	62.684	62.403	0.002516
Model lat. dim. 21	72.409	71.397	71.152	0.002337
Model lat. dim. 42	72.857	72.454	72.281	0.002168
Model lat. dim. 130	76.275	75.439	75.238	0.001730

# Latent Dimensions

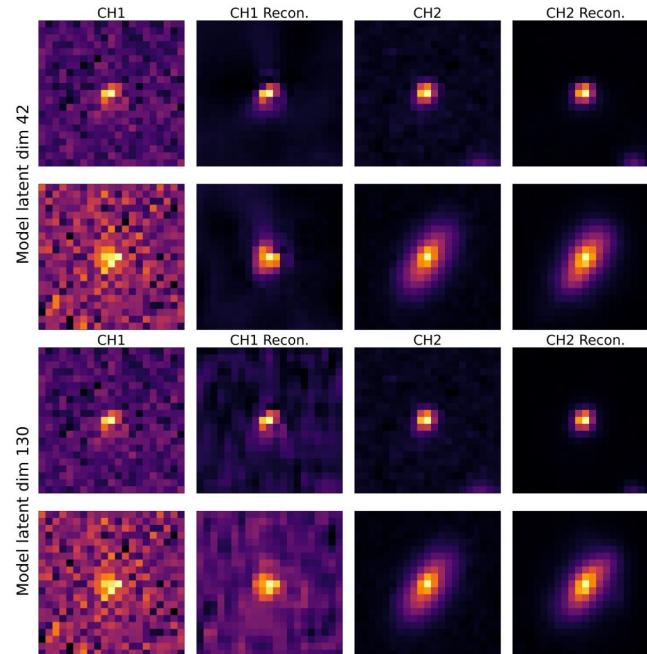
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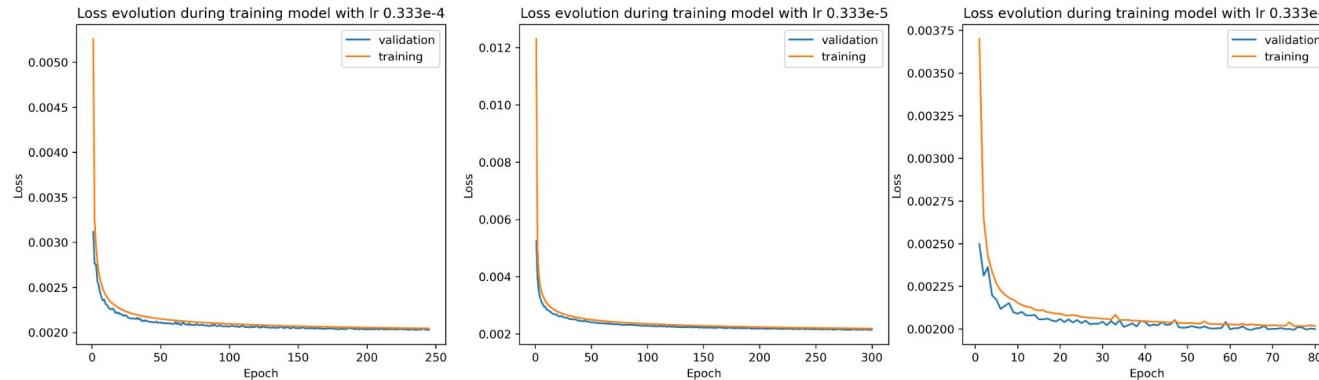
Se entrenaron 4 modelos  $\longrightarrow$  Latent Dimension = 10, 21, 42 y 130



# Learning Rate

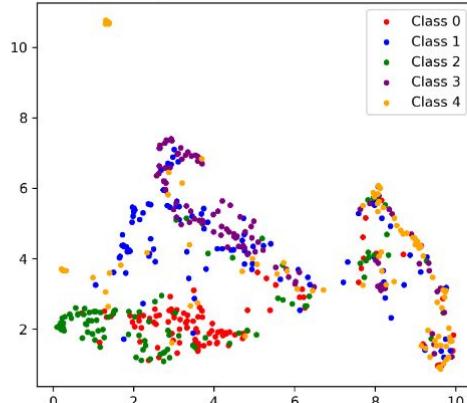
Utilizando el valor presentado por Astorga:  $0.333\text{e-}4$

Se entrenaron 3 modelos  $\longrightarrow \text{LR} = 0.333\text{e-}4, 0.333\text{e-}5 \text{ y } 0.333\text{e-}3$

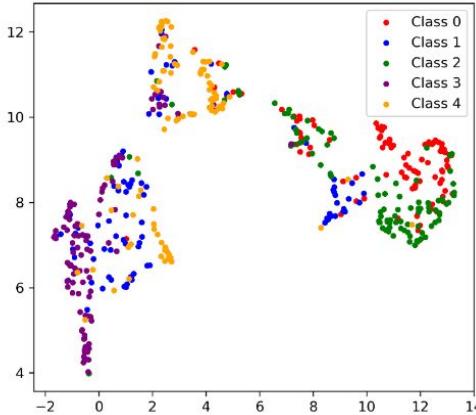


Modelo	Precisión (%)	Recall (%)	F1-Score (%)	MSE
Model lr $0.333\text{e-}4$	73.416	72.111	71.898	0.002137
Model lr $0.333\text{e-}5$	70.180	69.560	69.362	0.002409
Model lr $0.333\text{e-}3$	72.083	71.792	71.584	0.002098

Latent space UMAP model latent dim 42



Linear Probing UMAP model with latent dim 42

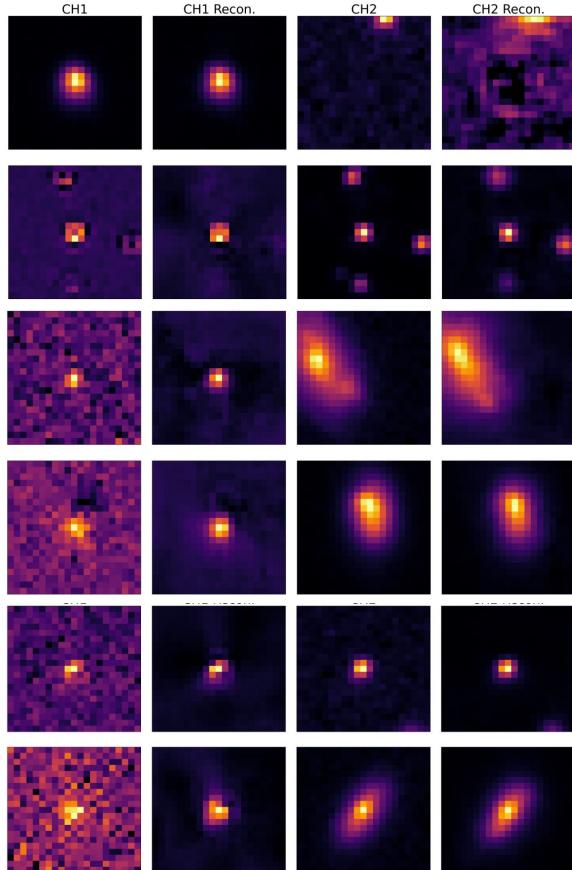


# Resultados del AutoEncoder

Finalmente, se decide en:

- Learning rate = 0.333e-4
- Augmentation = True
- Shuffling = False
- Latent dim = 42

Precisión (%)	Recall (%)	F1-Score (%)	MSE
72.857	72.454	72.281	0.002168



# Resultados del AutoEncoder

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- Learning rate = 0.333e-4
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- Latent dim = 42

Precisión (%)	Recall (%)	F1-Score (%)	MSE
72.857	72.454	72.281	0.002168

# Objetivos completados y siguientes pasos:

- Replicar AutoEncoder Convolucional y comprar reconstrucciones
- Analizar espacio latente (clustering)
- Entrenar y comparar resultados de modelo entrenado con los dataset grande (3 clases)
- Agregar modelo recurrente para clasificación
- Mejorar los modelos existentes

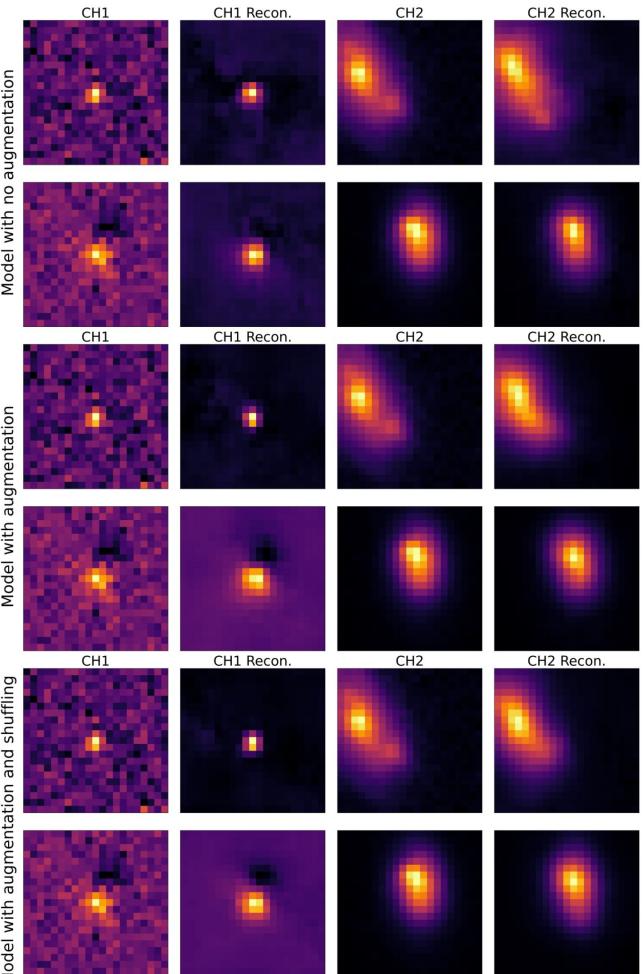
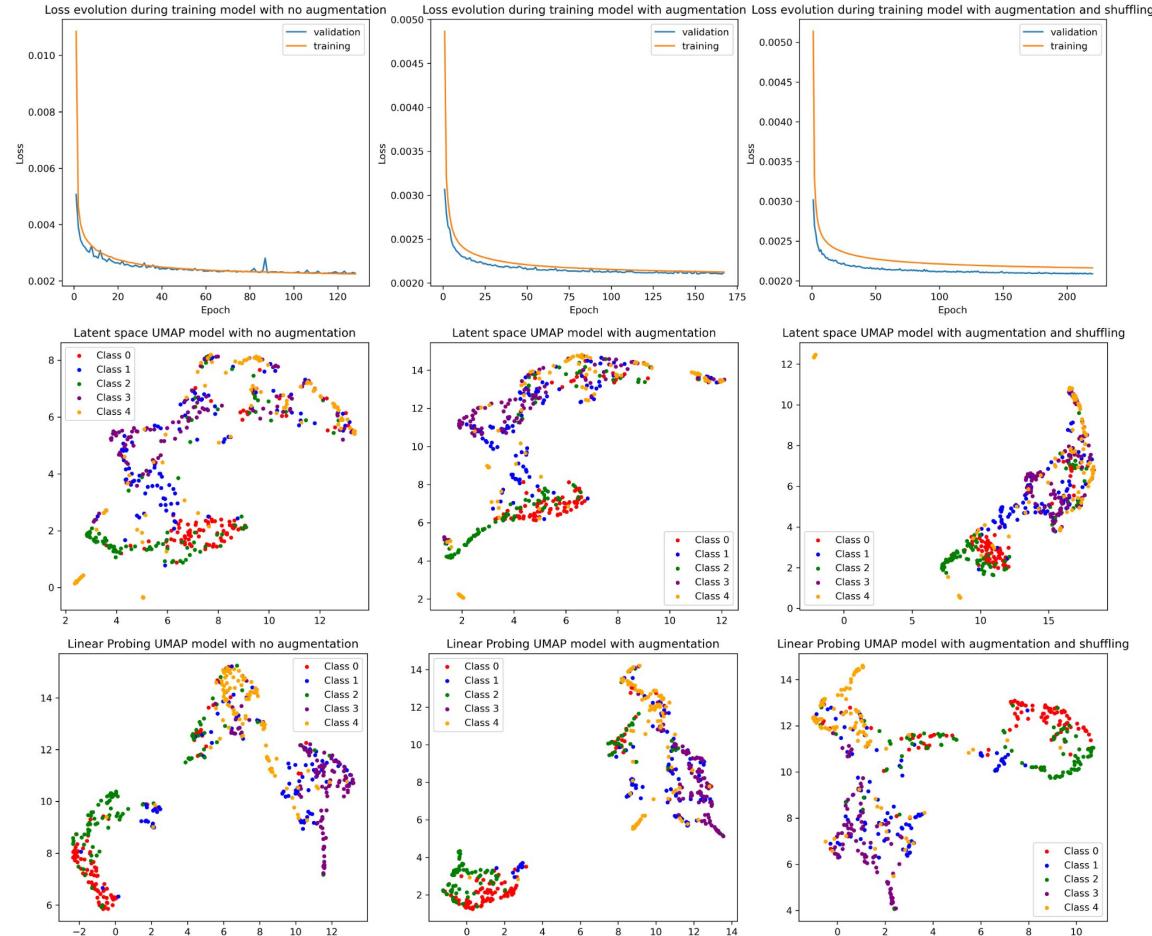
# Bibliografía

- [1] Astorga, N., Huijse, P., Estévez, P. A., Forster, F. (2018, July). Clustering of Astronomical Transient Candidates Using Deep Variational Embedding. In 2018 International Joint Conference on Neural Networks (IJCNN). IEEE
- [2] Carrasco-Davis, Rodrigo, et al. "Alert Classification for the ALeRCE Broker System: The Real-time Stamp Classifier." arXiv preprint arXiv:2008.03309 (2020).

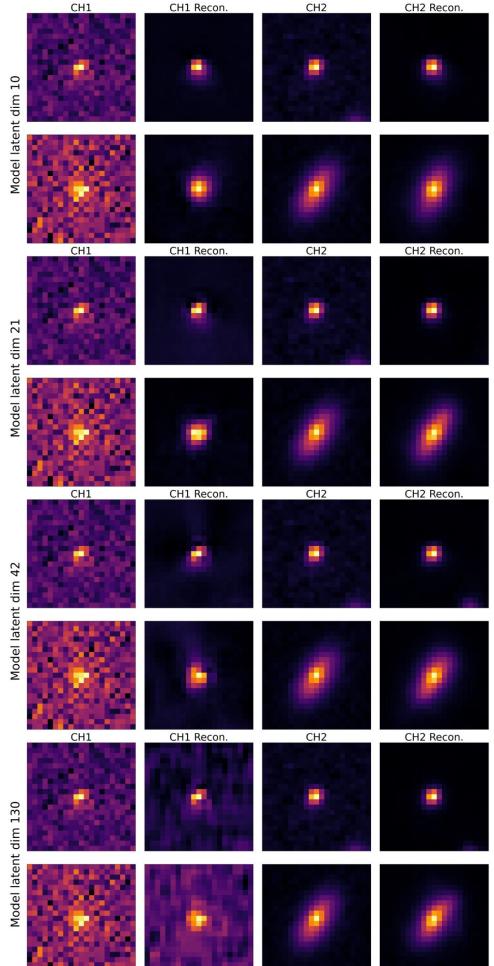
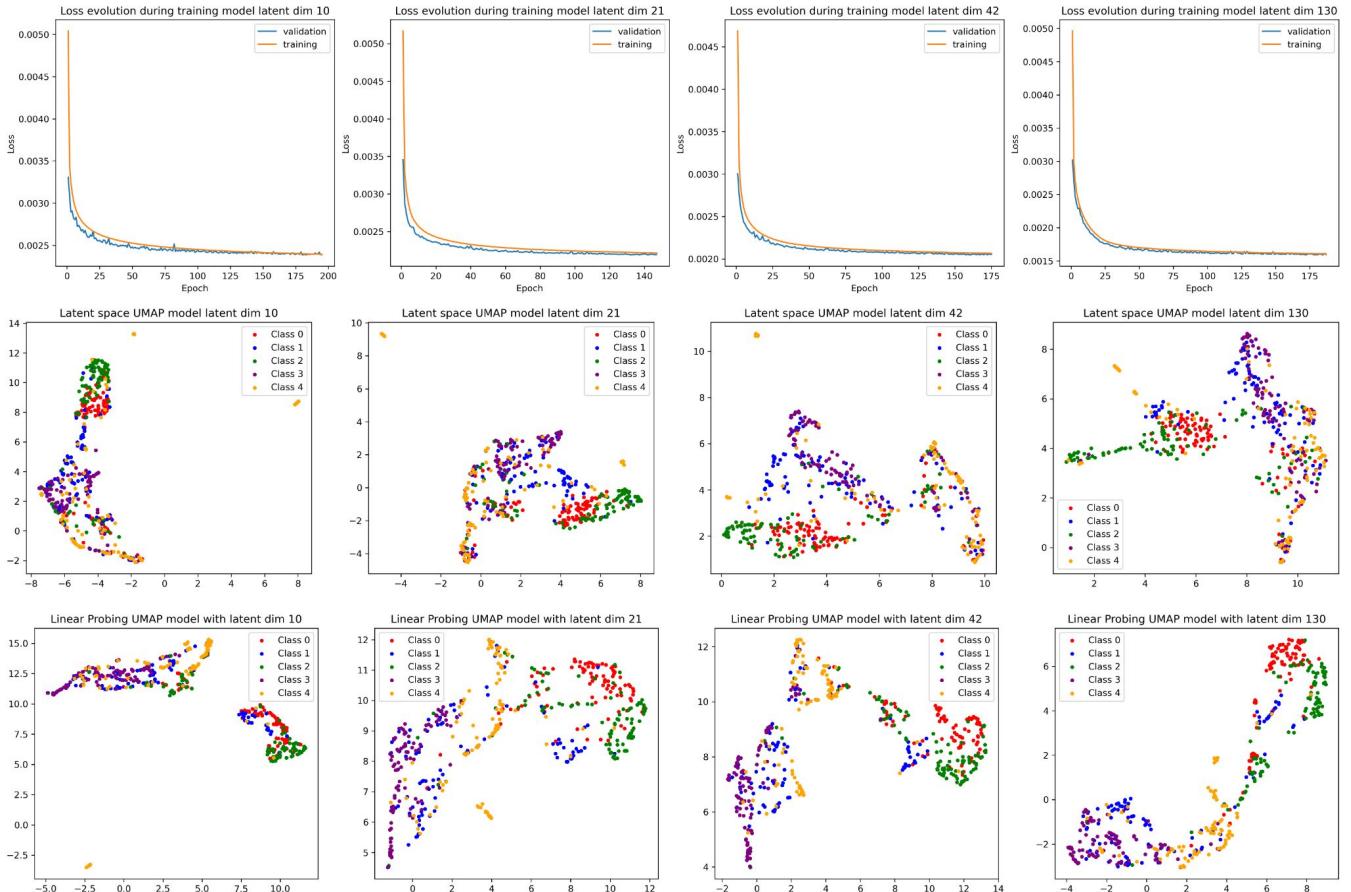
# Anexo

Modelo	Precisión (%)	Recall (%)	F1-Score (%)	MSE
Model sin augm.	72.795	71.298	71.086	0.002574
Model con augm.	72.623	71.702	71.389	0.002228
Model con augm. y shuffling	72.450	71.246	71.088	0.002262
Model lat. dim. 10	64.673	62.684	62.403	0.002516
Model lat. dim. 21	72.409	71.397	71.152	0.002337
Model lat. dim. 42	72.857	72.454	72.281	0.002168
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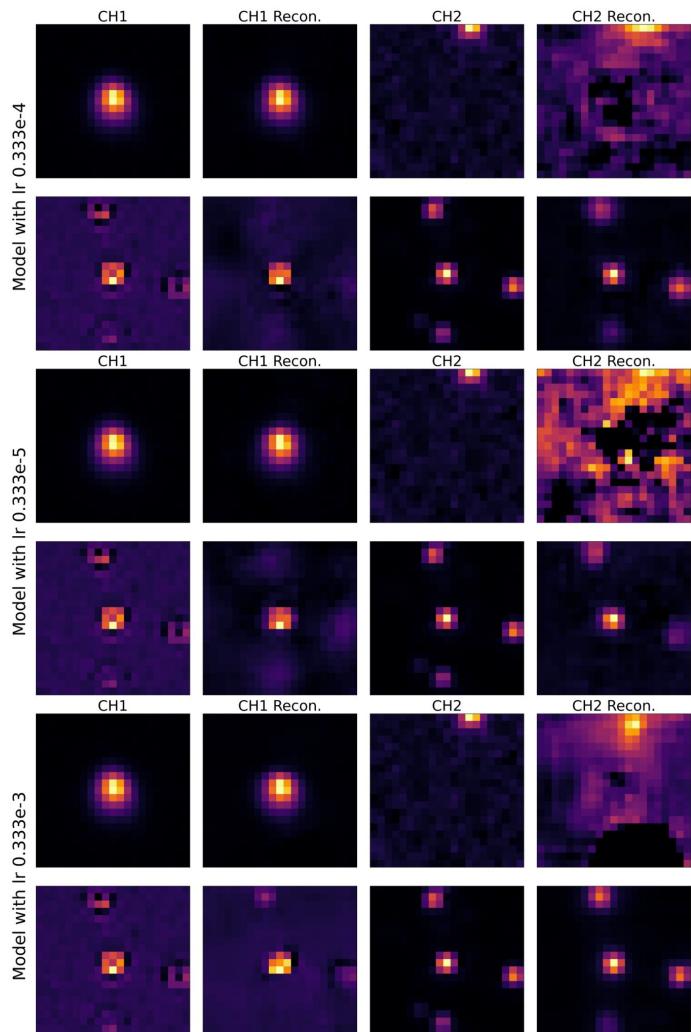
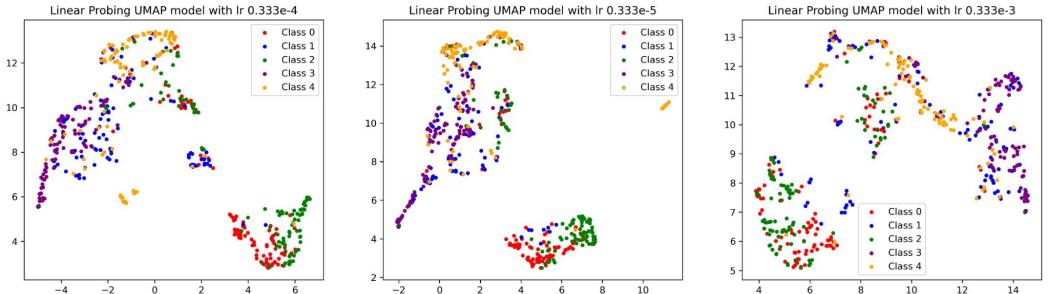
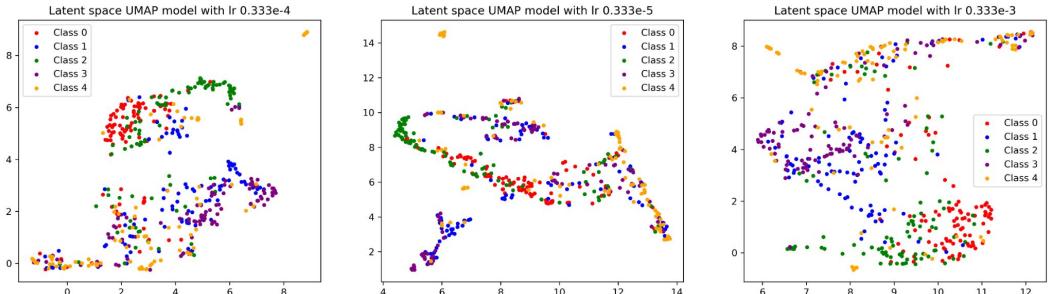
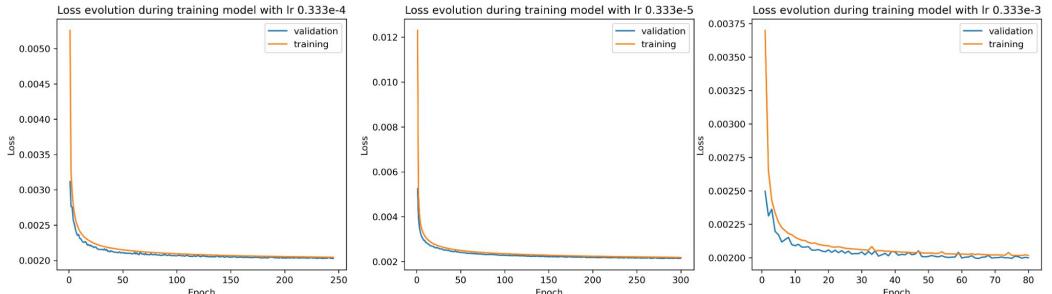
# Anexo Exp.1



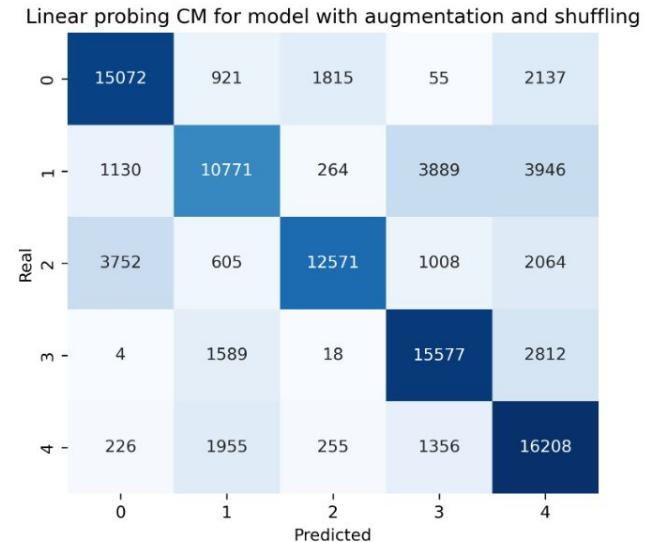
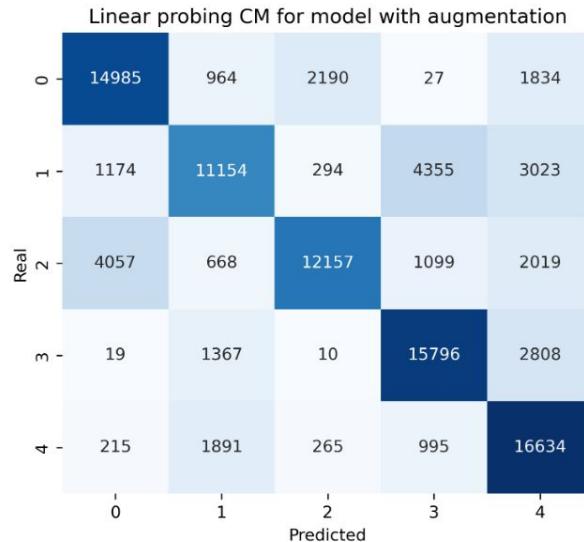
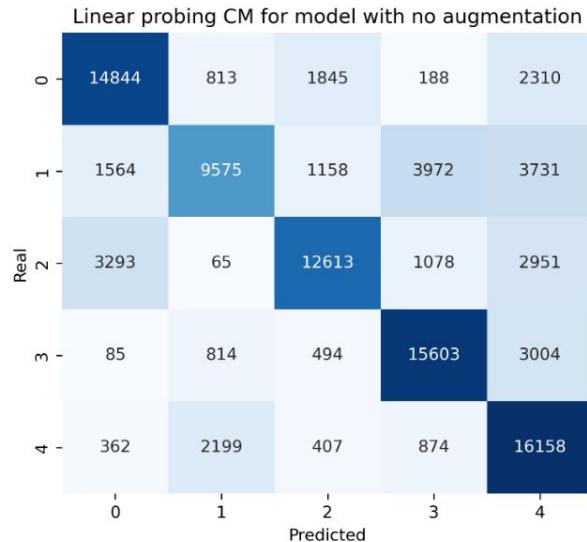
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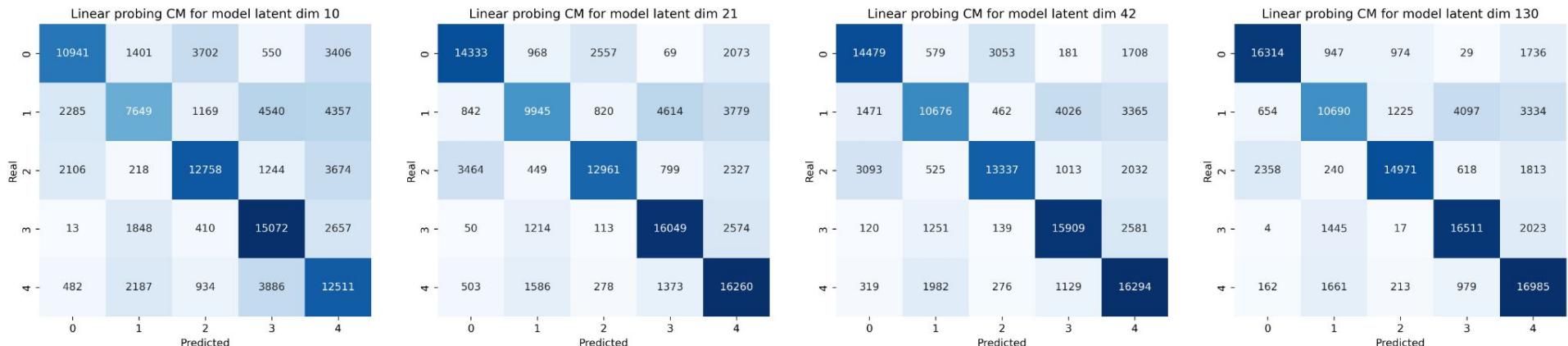
# Anexo Exp.1



# CM Exp.1



# CM Exp.2



# CM Exp.3

		Linear probing CM for model with lr 0.333e-4				
		0	1	2	3	4
Real	0	15603	968	1525	14	1890
	1	1198	11433	357	3792	3220
	2	4079	702	11830	884	2505
	3	50	1676	27	15719	2528
	4	391	1892	270	858	16589

		Linear probing CM for model with lr 0.333e-5				
		0	1	2	3	4
Real	0	13424	844	3059	168	2505
	1	1671	9058	1251	3950	4070
	2	2403	528	13369	842	2858
	3	438	1939	578	14315	2730
	4	212	1996	253	1409	16130

		Linear probing CM for model with lr 0.333e-3				
		0	1	2	3	4
Real	0	13918	977	3286	69	1750
	1	890	11135	853	4239	2883
	2	3352	771	13300	698	1879
	3	210	1853	257	15233	2447
	4	260	2071	250	784	16635