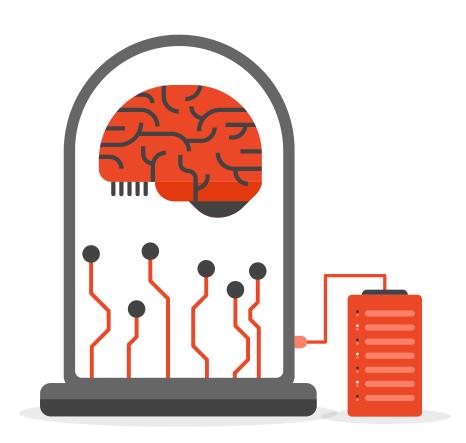


# TP3 Autoencoders

Alejandro Rolandelli Benjamin Delasoie Facundo Zimbimbakis Malena Vasquez Currie Santiago Larroude Alvarez

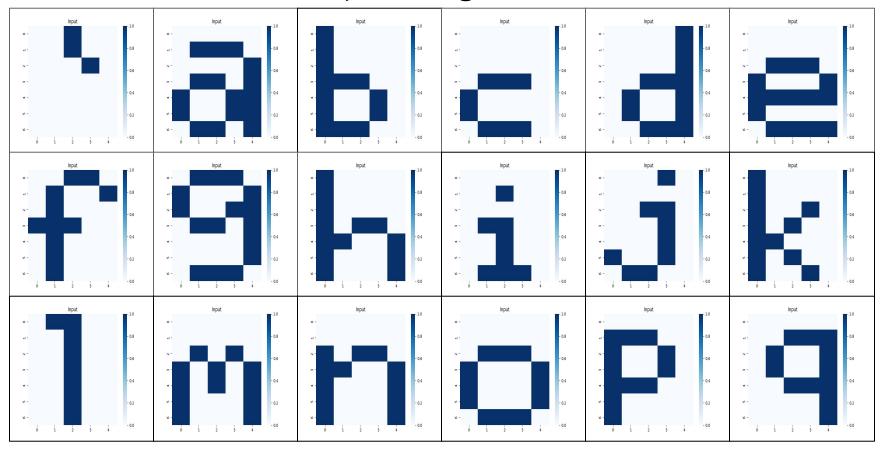
EJ1a. Autoencoder Básico



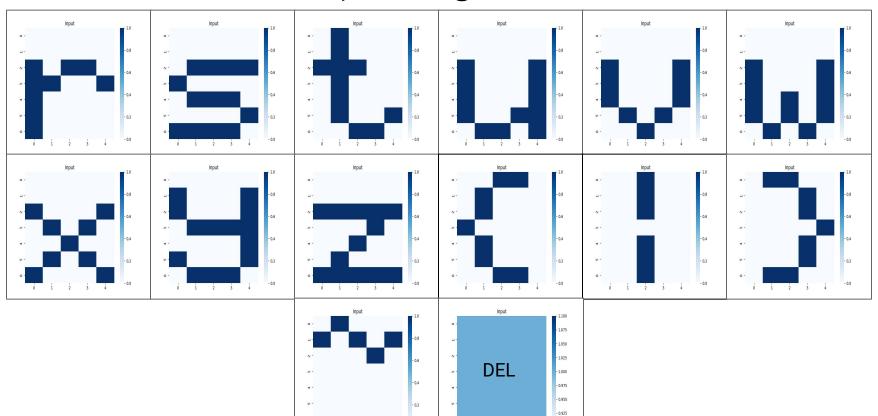


## Representación de las fuentes

## **Conjunto Original (1/2)**



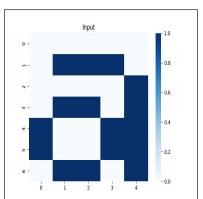
## **Conjunto Original (2/2)**

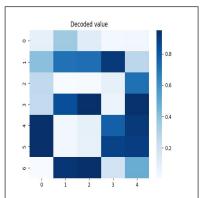


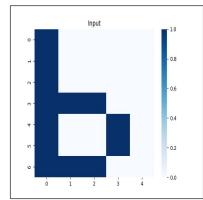


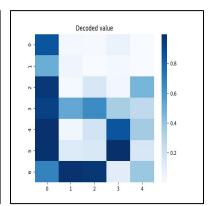
## Subconjunto {a, b, e, n}

**Comparación Original vs Generado** 

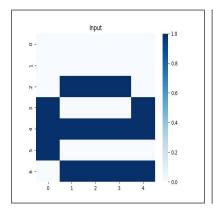


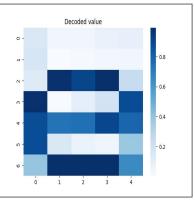


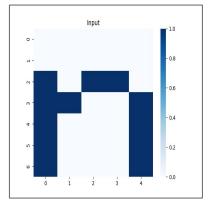


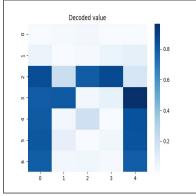


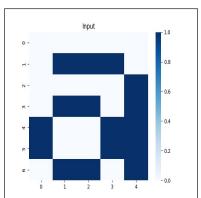
Error: 11.03

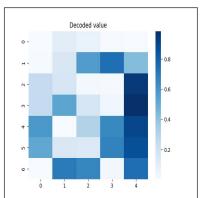


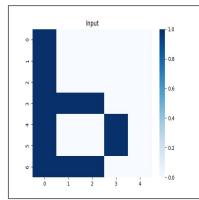


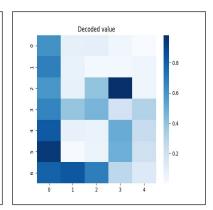




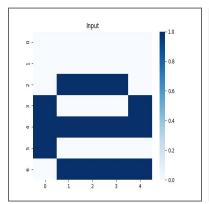


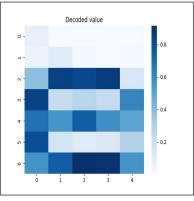


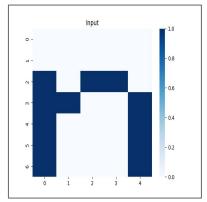


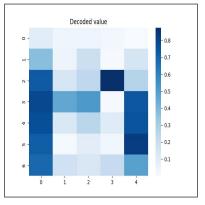


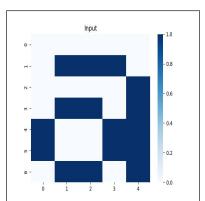
Error: 25.02

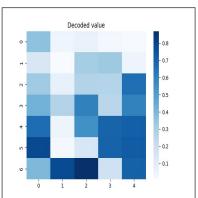


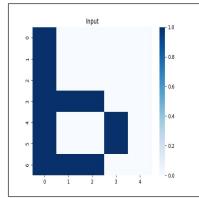


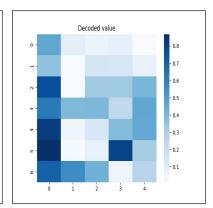




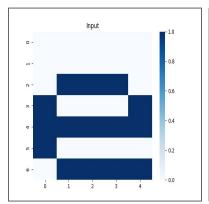


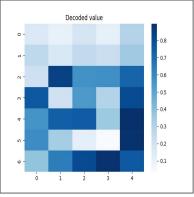


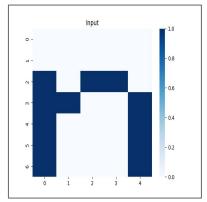


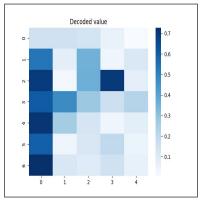


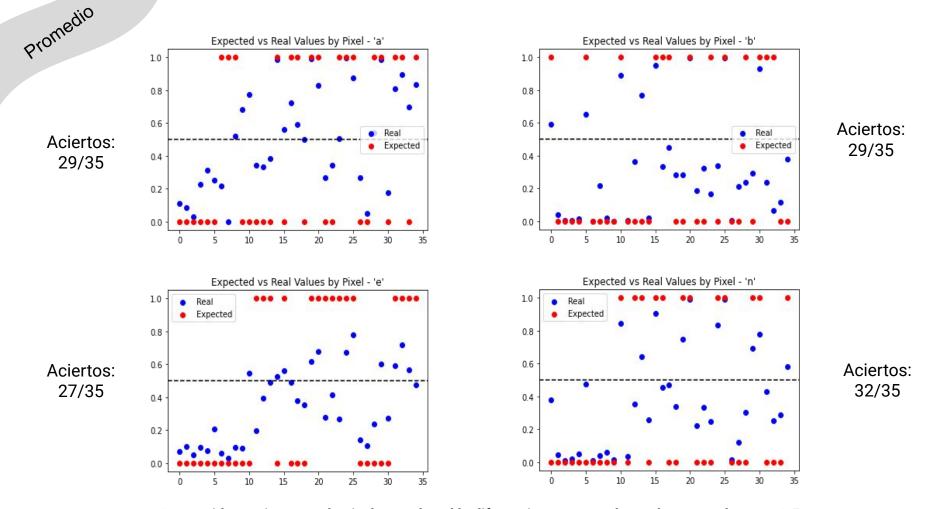
Error: 72.38





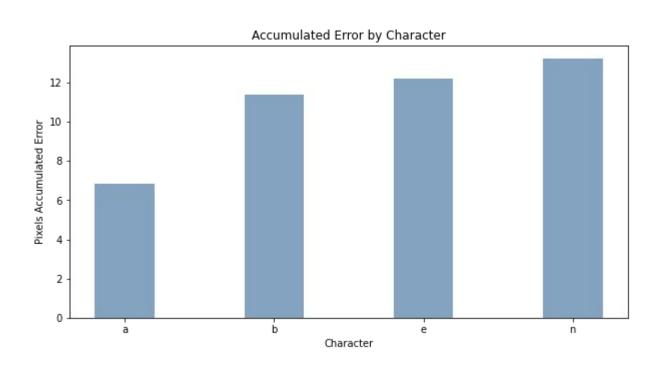






Se considera acierto a todo pixel para el cual la diferencia entre su valor real y esperado es <= 0.5

#### **Evolución de los Errores**

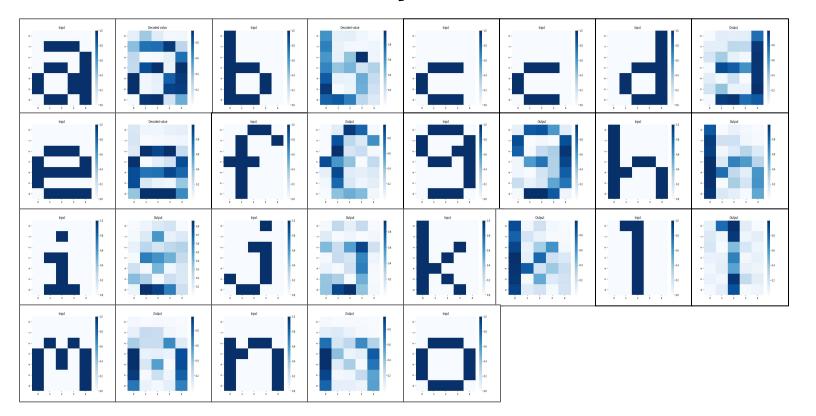


### Puede aprender todo? Afecta la calidad del aprendizaje?

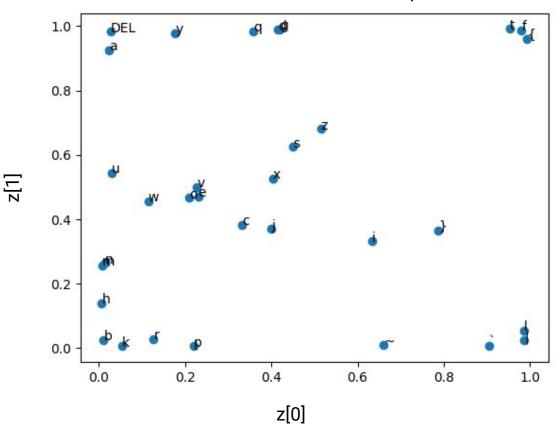


## **Conjunto Completo**

**Comparación Original vs Generado** 



Character classes in the latent space

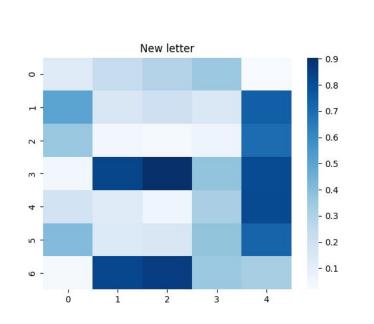




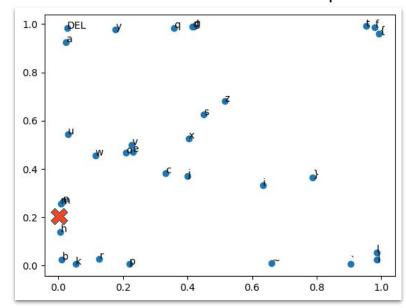
### Creación de nuevas letras

### Usando el conjunto completo (0, 0.2)

z[1]



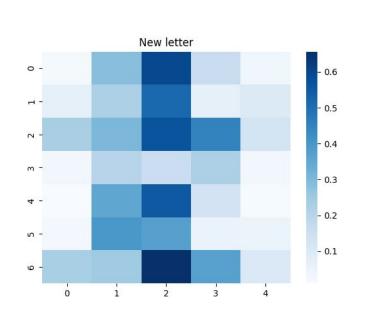
#### Character classes in the latent space



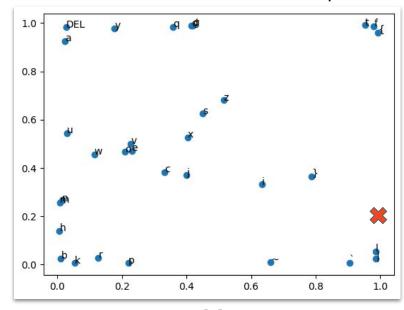
z[0]

## Usando el conjunto completo (1, 0.2)

z[1]



#### Character classes in the latent space



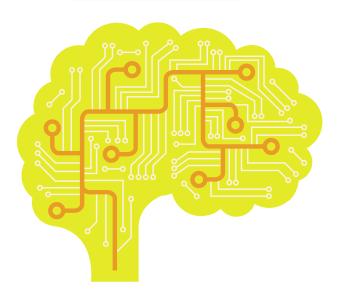
z[0]

#### **Conclusiones**

Aprendizaje diferente

El AE aprende algunos caracteres mejor que otros





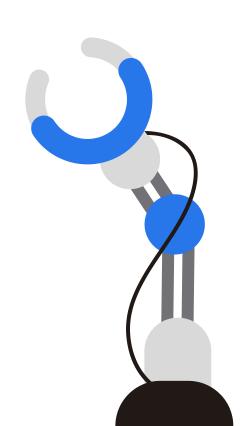
La capa latente tiene un rol importante.

Mientras mayor su dimensión, menor el error

 El autoencoder no solo tiene la habilidad de aprender el conjunto completo sino también crear nuevos elementos a partir de lo aprendido.

## EJ1b. Denoising Autoencoder

[35, 25, 9, 12, 4, 12, 9, 25, 35]

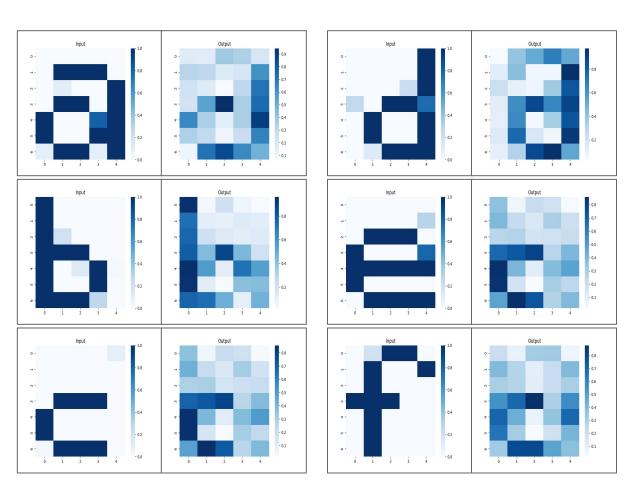


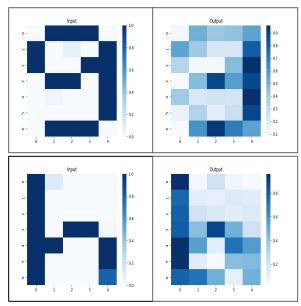
## Capacidad de eliminación del ruido

Variación de la probabilidad de mutación y el ruido máximo

#### **Mutation Prob: 0.1**

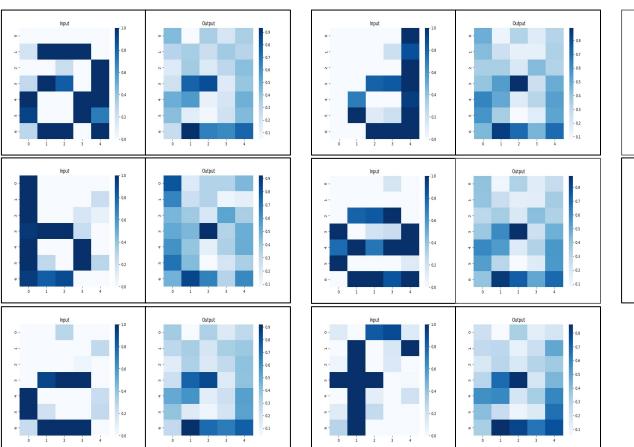
#### Max Noise: 0.3

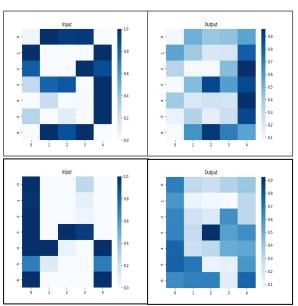




Error 18.11

#### **Mutation Prob: 0.3 Max Noise: 0.3**

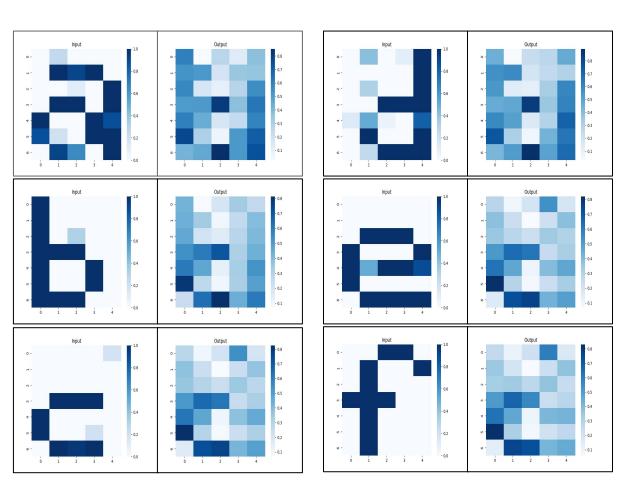


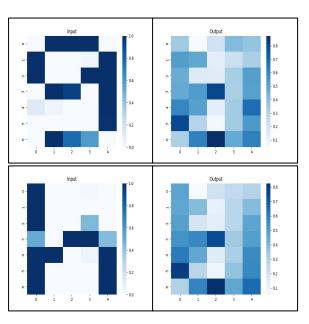


Error 25.56

#### **Mutation Prob: 0.1**

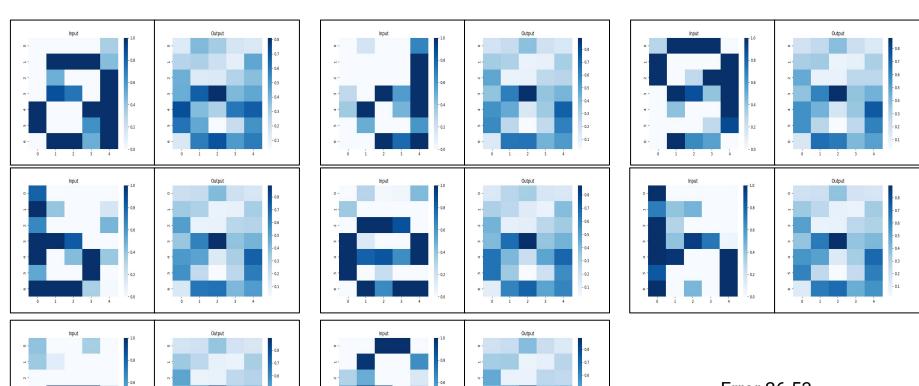
#### **Max Noise: 0.5**





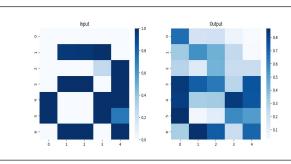
Error 25.34

#### **Mutation Prob: 0.3** Max Noise: 0.5

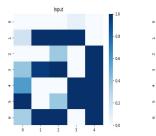


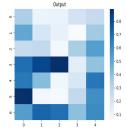
Error 26.53

## Otra arquitectura?

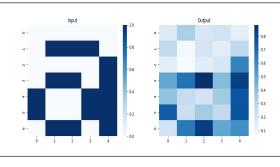


Mut Prob: 0.1 Max Noise: 0.3

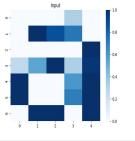


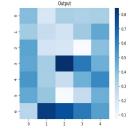


Mut Prob: 0.3 Max Noise: 0.3



Mut Prob: 0.1 Max Noise: 0.5





Mut Prob: 0.3 Max Noise: 0.5

## **Resumen y Conclusiones**



[35, 25, 9, 12, 4, 12, 9, 25, 35]			[ <b>35, 25, 12,</b> 12, <b>12, 25, 35</b> ]		
Mut. Prob	Max Noise	Error	Mut. Prob	Max Noise	Error
0.1	0.3	18.11	0.1	0.3	22.31
0.1	0.5	25.34	0.1	0.5	24.31
0.3	0.3	25.26	0.3	0.3	23.85
0.3	0.5	26.53	0.3	0.5	27.03



#### **Muchos factores**

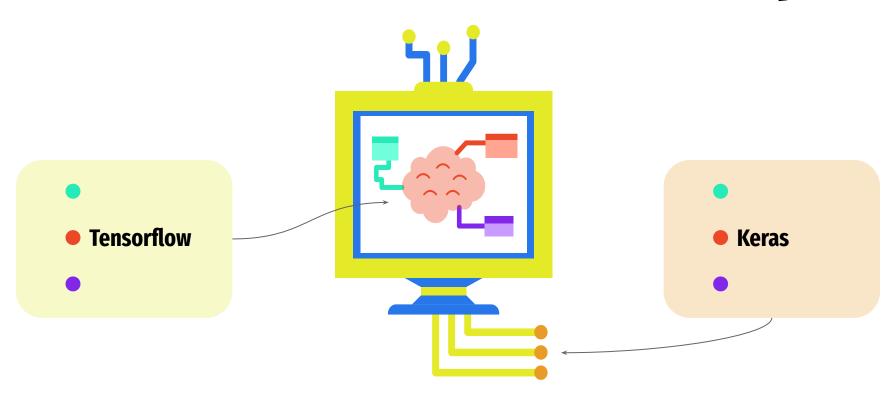
El error puede variar en base a una combinación de factores



#### + Ruido, + Error

Parece que existe una correlación directa entre ruido y error.

## **EJ.2 Autoencoder Variacional Simple**



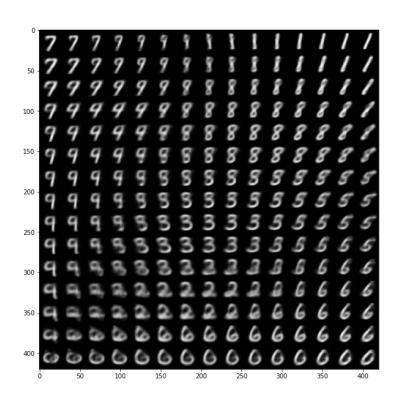
**MNIST Digit Dataset** 

#### Métodos de Optimización: Adam, RMS Prop

## **RMS Prop (1/2)**

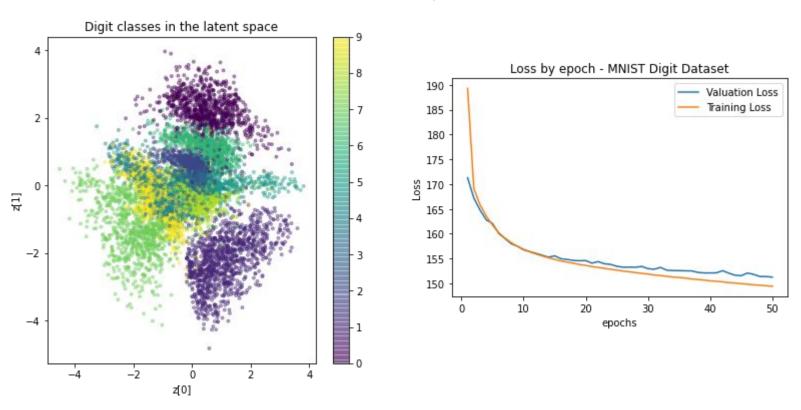


Original

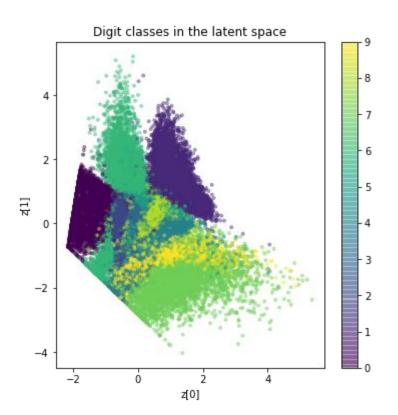


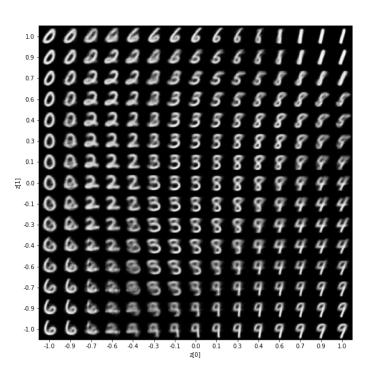
Generado

## **RMS Prop (2/2)**



#### **Adam**





## **Análisis y Conclusiones**

#### **RMS**

Se forman agrupaciones separadas de dígitos. La separación entre ellas indica que el autoencoder puede distinguirlos correctamente.

01

03

#### Adam

Mayor agrupamiento entre clases. Indica que el autoencoder no los puede reconocer bien. Se podría aumentar la cantidad de capas ocultas.

SIA

#### **Errores**

La valuation loss y la training loss tienen un camino parecido. Indica que el modelo es bueno, ya que no hay demasiado overfitting o underfitting.

02

## Gracias! Preguntas?

