AI vs Real Image

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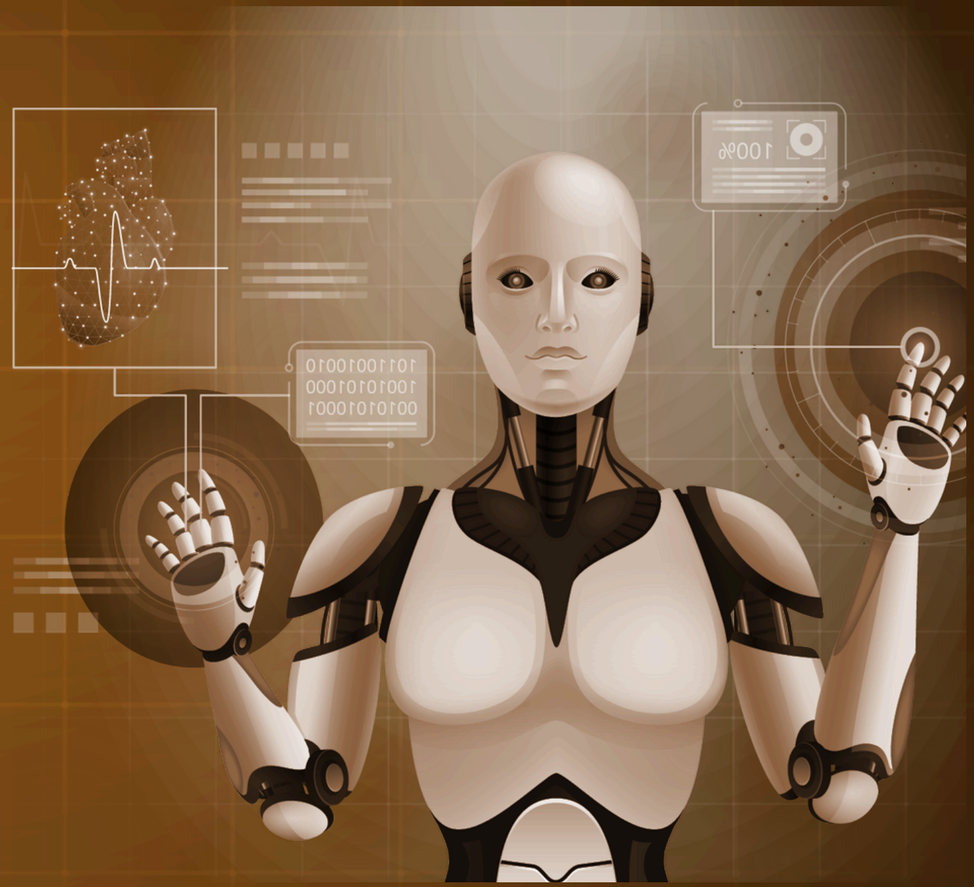
ENFOQUE

Clasificar imágenes entre reales y generadas por inteligencia artificial

Generación de imágenes por IA

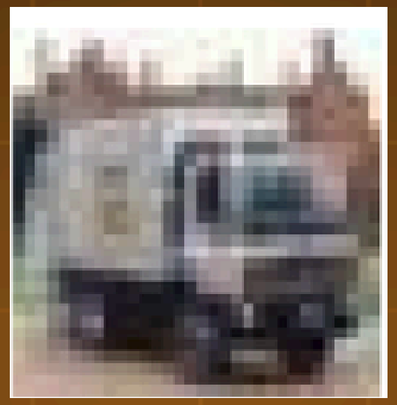
- Redes Sociales
- Ciberseguridad
- Evidencia Legal



The Data-Set (CIFAKE)

REAL

60,000 realy taken images



FAKE

60,000 synthetically-generated images

SPLIT

20,000 were used for testing
100,000 were used for training

Images were normalized (vals beetwen 0-1)

Pre-Procesamiento

Carga de Imágenes y Etiquetado

```
real_images, real_labels = load_image_data(os.path.join(TRAIN_PATH, 'REAL'), [0, 1])
fake_images, fake_labels = load_image_data(os.path.join(TRAIN_PATH, 'FAKE'), [1, 0])
```

Se definen funciones para cargar imágenes de las carpetas REAL y FAKE, asignando etiquetas personalizadas:

Normalización de Datos

Las imágenes se normalizan dividiendo los valores de píxeles por 255, para que estén en el rango [0, 1].

```
X_train = np.concatenate((real_images, fake_images)).astype('float32') / 255.0
y_train = np.concatenate((real_labels, fake_labels))
X_test = np.concatenate((test_real_images, test_fake_images)).astype('float32') / 255.0
y_test = np.concatenate((test_real_labels, test_fake_labels))
```

Esto mejora la eficiencia del entrenamiento.

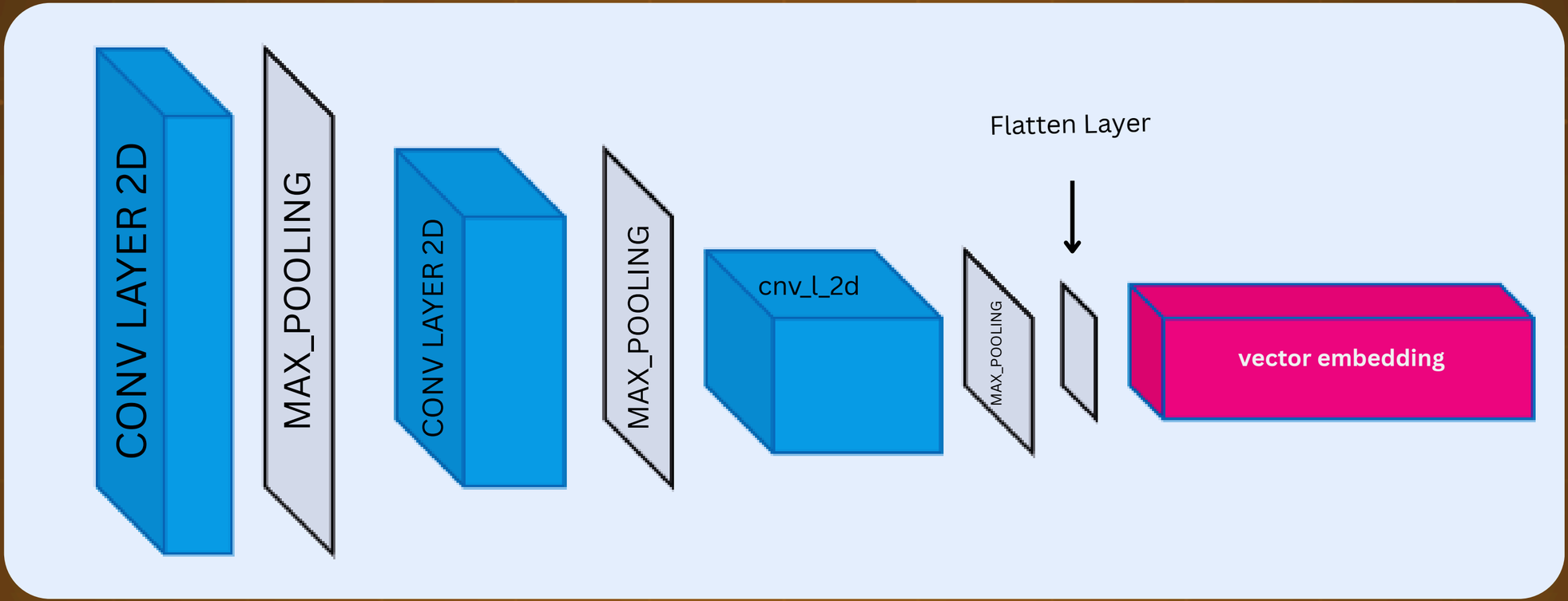
División del Dataset

El conjunto de entrenamiento se divide en entrenamiento y validación usando train_test_split.

(90% / 10%)

```
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.1, random_state=21)
```

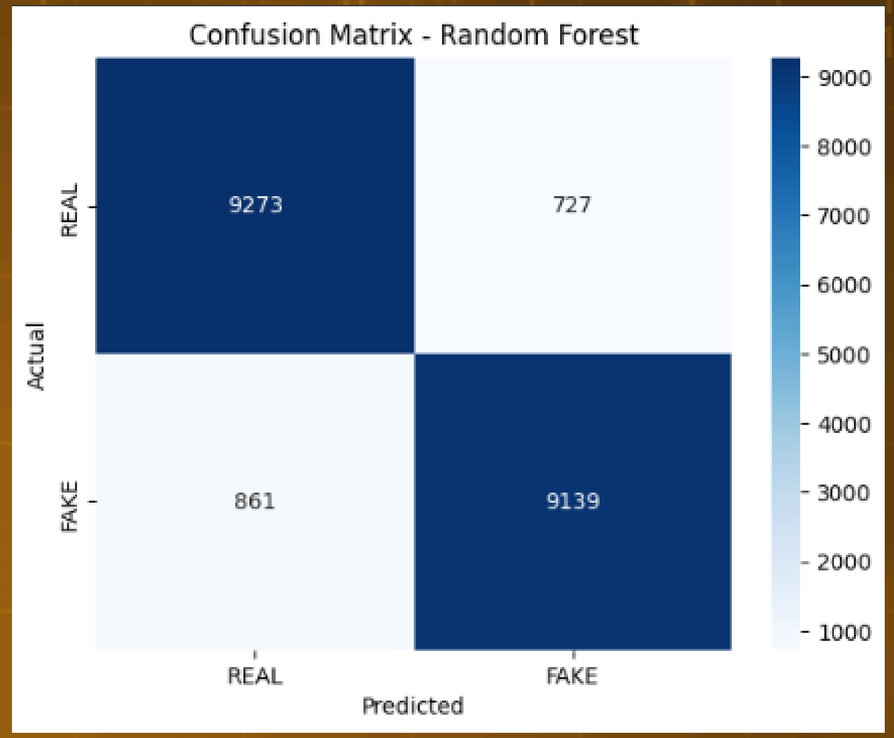
Convolutional Pretraining



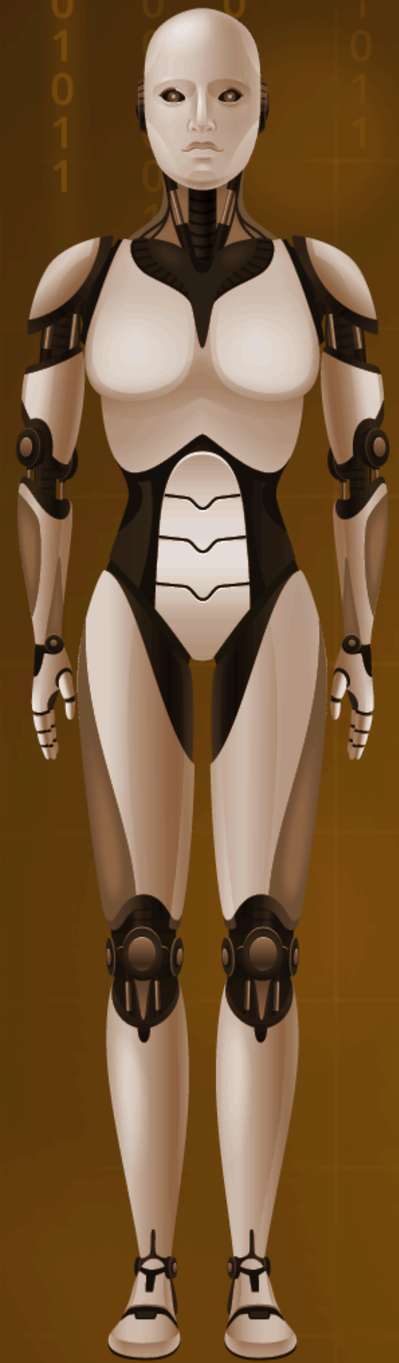
Metodos Machine Learning

Random Forest

Accuracy: 0.9282
Precision: 0.9222
Recall: 0.9352



- Vectores de Características
- Diferencias Detectables



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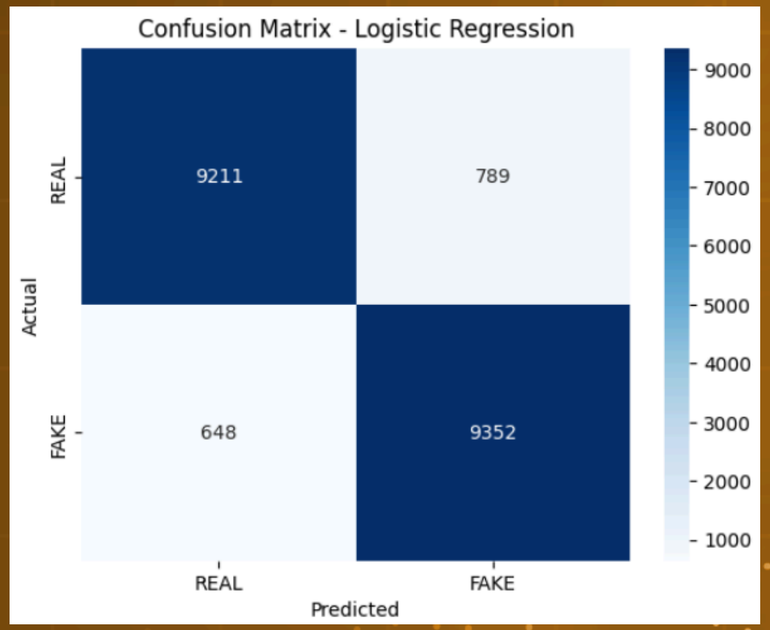


Logistic Regression

REAL / FAKE

Captura la relacion sin sobreajustarse

Datos Lineales

XGBoost

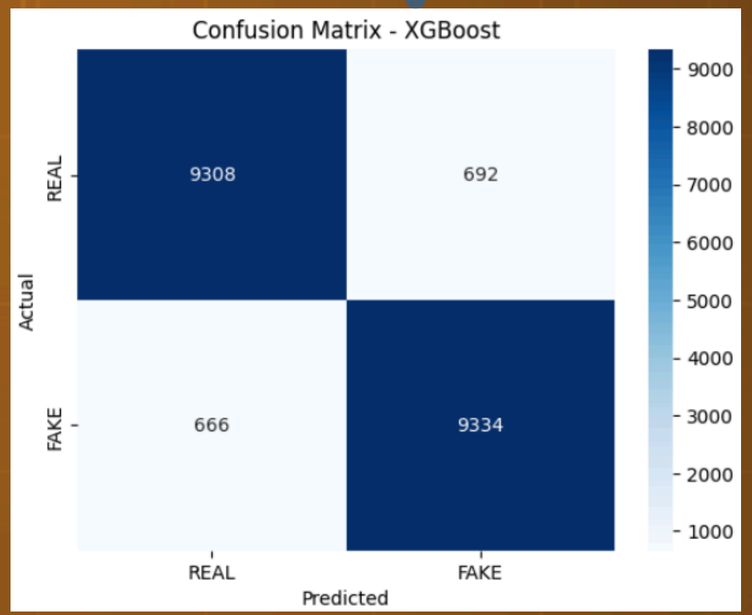
Boosting

Extrae Features de las imagenes

Aprende Patrones Lineales

Caracteristicas Densas → Embeddings

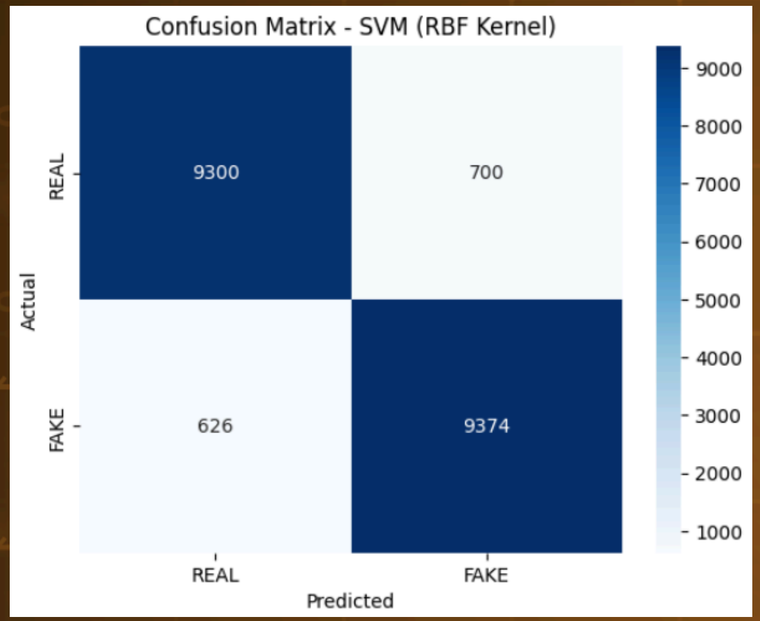
Accuracy: 0.9321
Precision: 0.9310
Recall: 0.9334



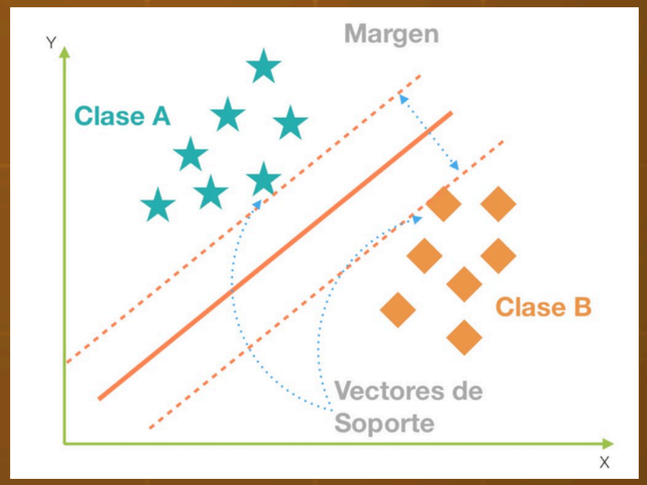
SVW

RBF KERNEL

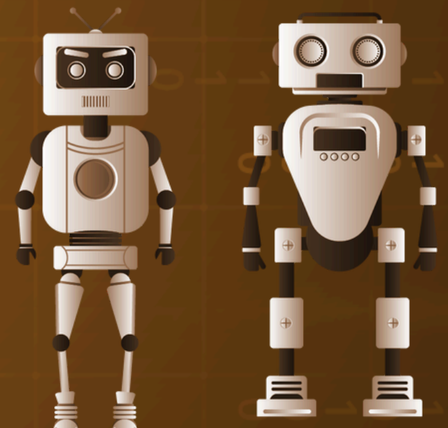
Accuracy: 0.9337
Precision: 0.9305
Recall: 0.9374



Embeddings



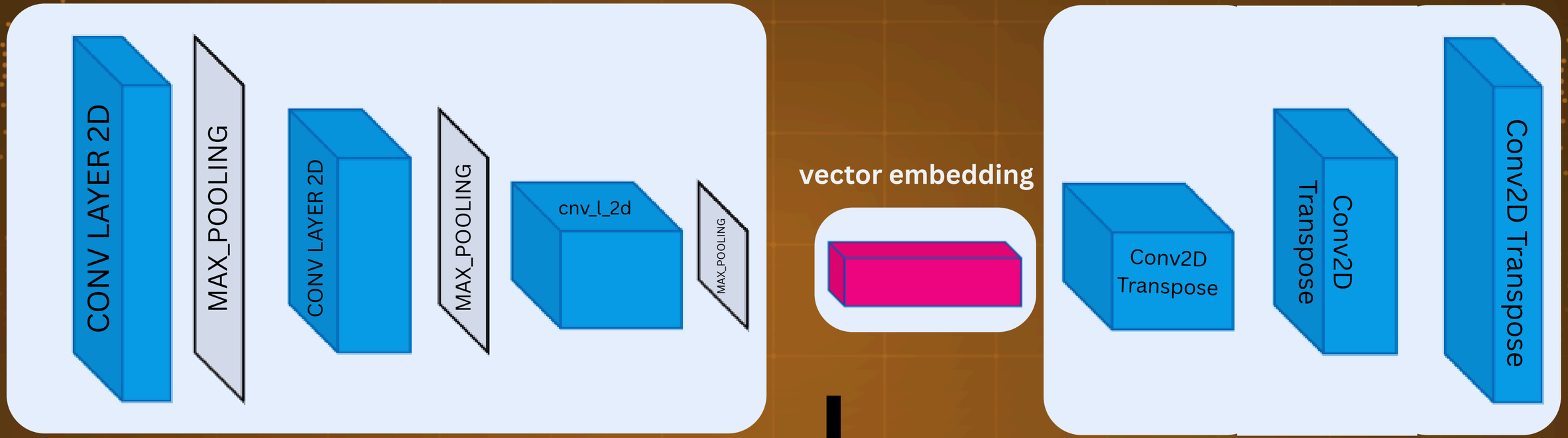
Hiperplano



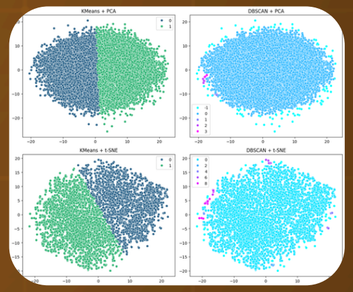
Trabajo futuro

- Modelo no supervisado
- Hacer inferencia en otros datasets
- Aumentar las dimensiones y resolución de las imagenes
- Experimentar Que tan bien generaliza el modelo

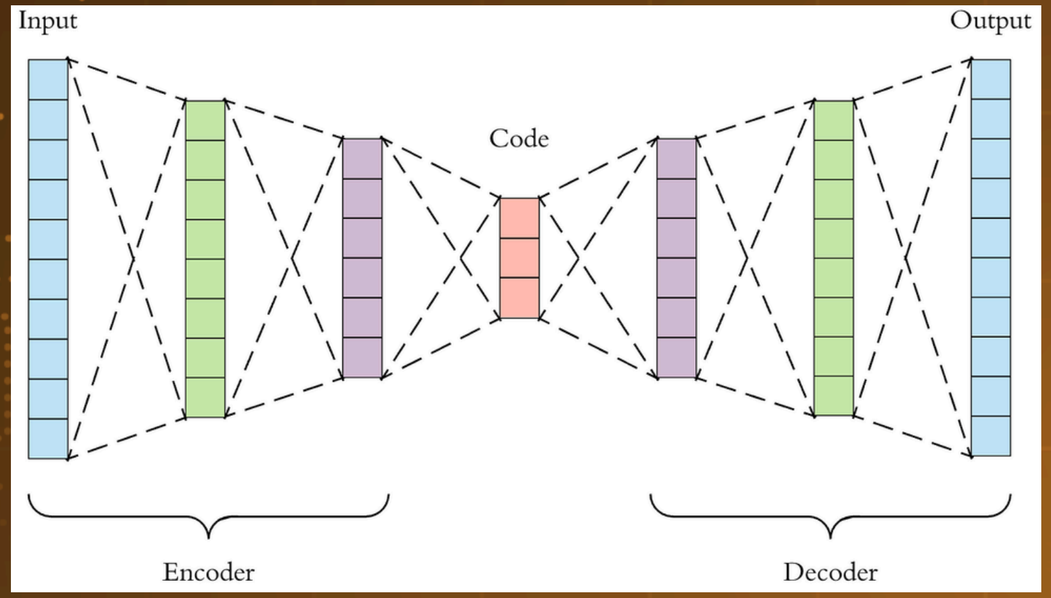
Autoencoder architecture

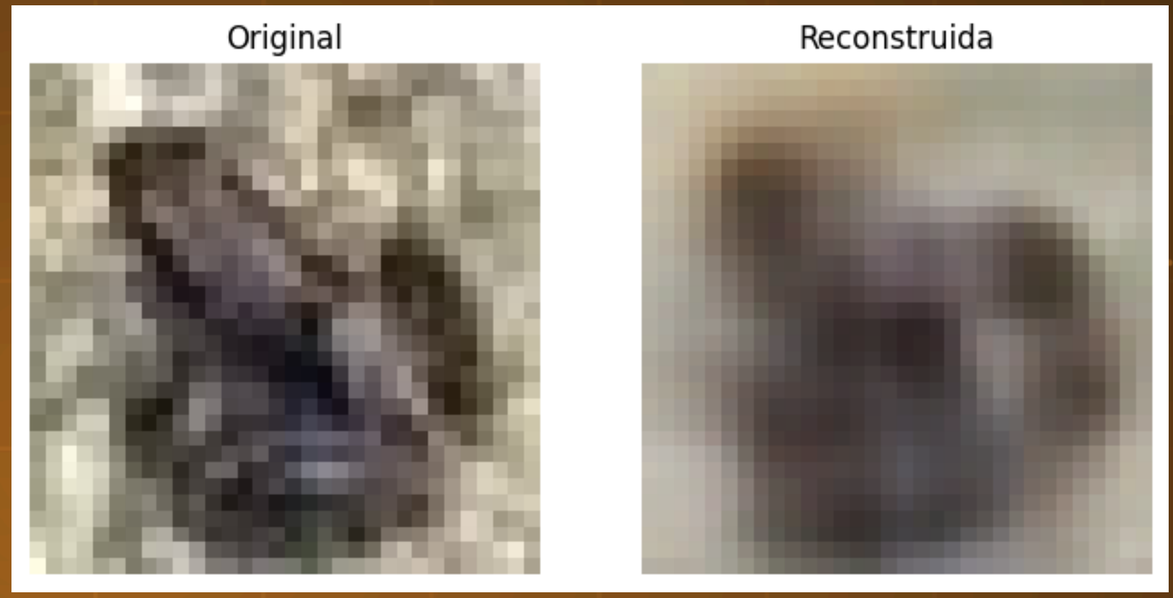


Clustering methods



Autoencoder



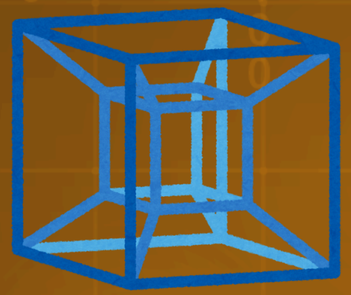



```
Training model...
Epoch 1/5
2813/2813 ━━━━━━━━━━━━━━━━━━━━ 727s 255ms/step - loss: 0.0286 - psnr_metric: 16.4029
Epoch 2/5
2813/2813 ━━━━━━━━━━━━━━━━━━━━ 729s 251ms/step - loss: 0.0152 - psnr_metric: 18.8291
Epoch 3/5
2813/2813 ━━━━━━━━━━━━━━━━━━━━ 704s 237ms/step - loss: 0.0135 - psnr_metric: 19.3530
Epoch 4/5
2813/2813 ━━━━━━━━━━━━━━━━━━━━ 719s 250ms/step - loss: 0.0126 - psnr_metric: 19.6502
Epoch 5/5
2813/2813 ━━━━━━━━━━━━━━━━━━━━ 744s 251ms/step - loss: 0.0121 - psnr_metric: 19.8452
```

Metodos No Supervisados

Reduccion Dimensionalidad

- PCA
- t-SNE

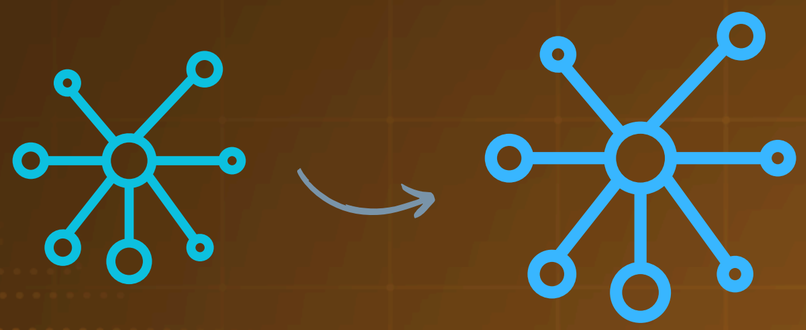


Clustering

- KMeans
- DBSCAN

→ Silhouette Score, Calinski-Harabasz y Davies-Bouldin.

Silhouette Score



Cohesion vs Separacion

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

1 - Mejor Agrupamiento

Calinski-Harabasz Score

Dispersión entre clústeres y la dispersión dentro de los clústeres.

$$\mathrm{CH} = \frac{\text{Between-cluster dispersion}}{\text{Within-cluster dispersion}} \times \frac{n-k}{k-1}$$

Mejor Separación y Agrupamiento

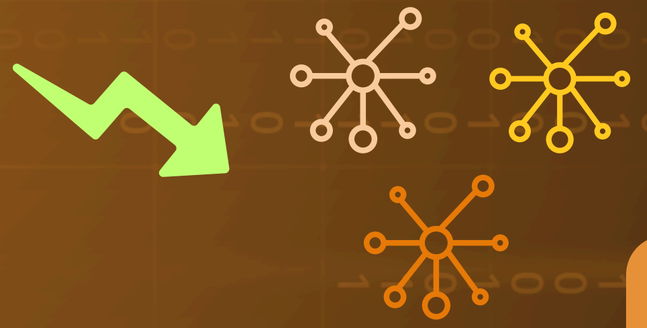
Davies-Bouldin Score

La similitud promedio entre cada clúster y su clúster más similar.

DB Score

Razón entre:

- Dispersión dentro del clúster i
- Distancia a su clúster más cercano j



KMeans + PCA

Clusters encontrados: 2

Silhouette Score: 0.331

Calinski-Harabasz Score: 49418.195

Davies-Bouldin Score: 1.179

DBSCAN + PCA

Clusters encontrados: 4

Silhouette Score: 0.370

Calinski-Harabasz Score: 24.856

Davies-Bouldin Score: 2.755

KMeans + t-SNE

Clusters encontrados: 2

Silhouette Score: 0.401

Calinski-Harabasz Score: 4117.347

Davies-Bouldin Score: 0.995

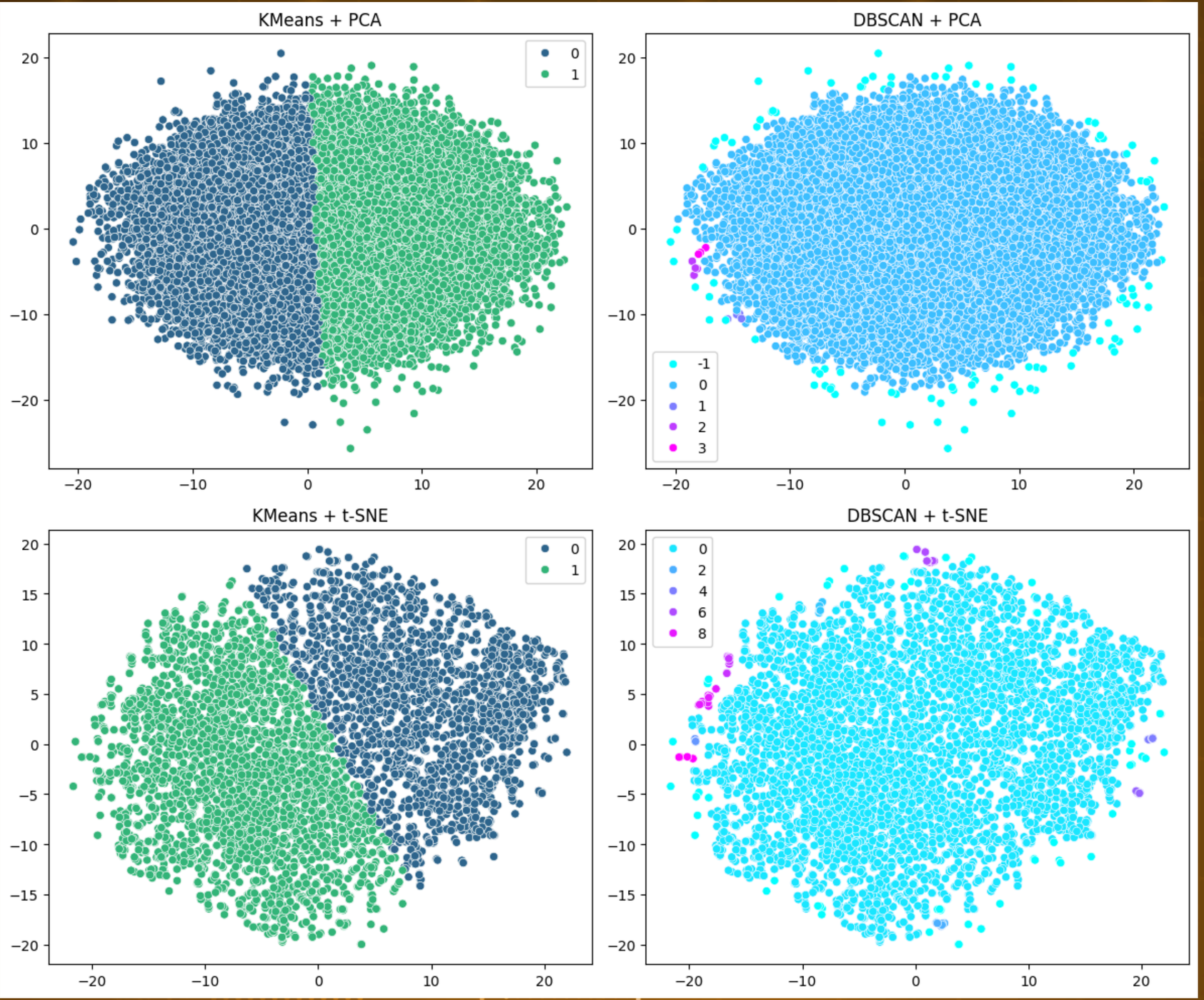
DBSCAN + t-SNE

Clusters encontrados: 10

Silhouette Score: -0.365

Calinski-Harabasz Score: 15.556

Davies-Bouldin Score: 3.775


KMeans + PCA
0
1
DBSCAN + PCA
-1
0
1
2
3
KMeans + t-SNE
0
1
DBSCAN + t-SNE
0
2
4
6
8

KMeans + t-SNE

Clusters encontrados: 2

Silhouette Score: 0.401

Calinski-Harabasz Score: 4117.347

Davies-Bouldin Score: 0.995

Preserva relaciones locales entre puntos

KMeans

Clústeres convexos y bien separados

DBSCAN + t-SNE

Clusters encontrados: 10

Silhouette Score: -0.365

Calinski-Harabasz Score: 15.556

Davies-Bouldin Score: 3.775

DBSCAN

Necesita densidades y distancias reales

No preserva distancias globales ni densidades reales

```
KMeans + PCA - Metricas Supervisadas
  Accuracy:  0.558
  Precision: 0.573
  Recall:    0.463

DBSCAN + PCA - Metricas Supervisadas
  Accuracy:  0.500
  Precision: 0.500
  Recall:    0.999

KMeans + t-SNE - Metricas Supervisadas
  Accuracy:  0.547
  Precision: 0.561
  Recall:    0.494

DBSCAN + t-SNE - Metricas Supervisadas
  Accuracy:  0.512
  Precision: 0.510
  Recall:    0.993
```

Identificar patrones útiles en los embebidos sin necesidad de etiquetas.

GRACIAS!