



# PROYECTO IA: *PREDICCIÓN DE APROBACIÓN DE PRÉSTAMOS BANCARIOS*

Santiago Camargo Ardila - 2211873  
Luis Carlos Benavides Torres - 2211925

Inteligencia Artificial I - F1



# OBJETIVO

El presente proyecto tiene como objetivo predecir de forma eficiente y precisa la aprobación de un préstamo bancario, considerando el perfil del solicitante y diversos aspectos de su historial crediticio mediante diversos modelos de aprendizaje automático y aprendizaje profundo.



# DEFINICIÓN DEL PROBLEMA

Se trata de un problema de clasificación binaria, ya que la variable objetivo solo puede tomar dos valores: préstamo aprobado o préstamo no aprobado.

Este enfoque permite automatizar y optimizar la toma de decisiones en procesos crediticios.



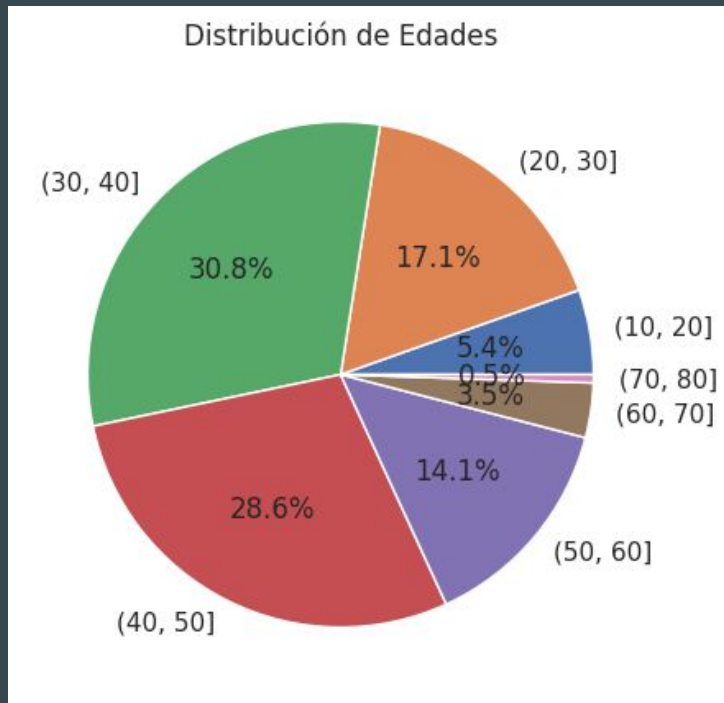
# ACERCA DEL DATASET

El dataset fue obtenido en Kaggle a través del siguiente enlace <https://www.kaggle.com/datasets/lorenzozoppelletto/financial-risk-for-loan-approval?select=Loan.csv>

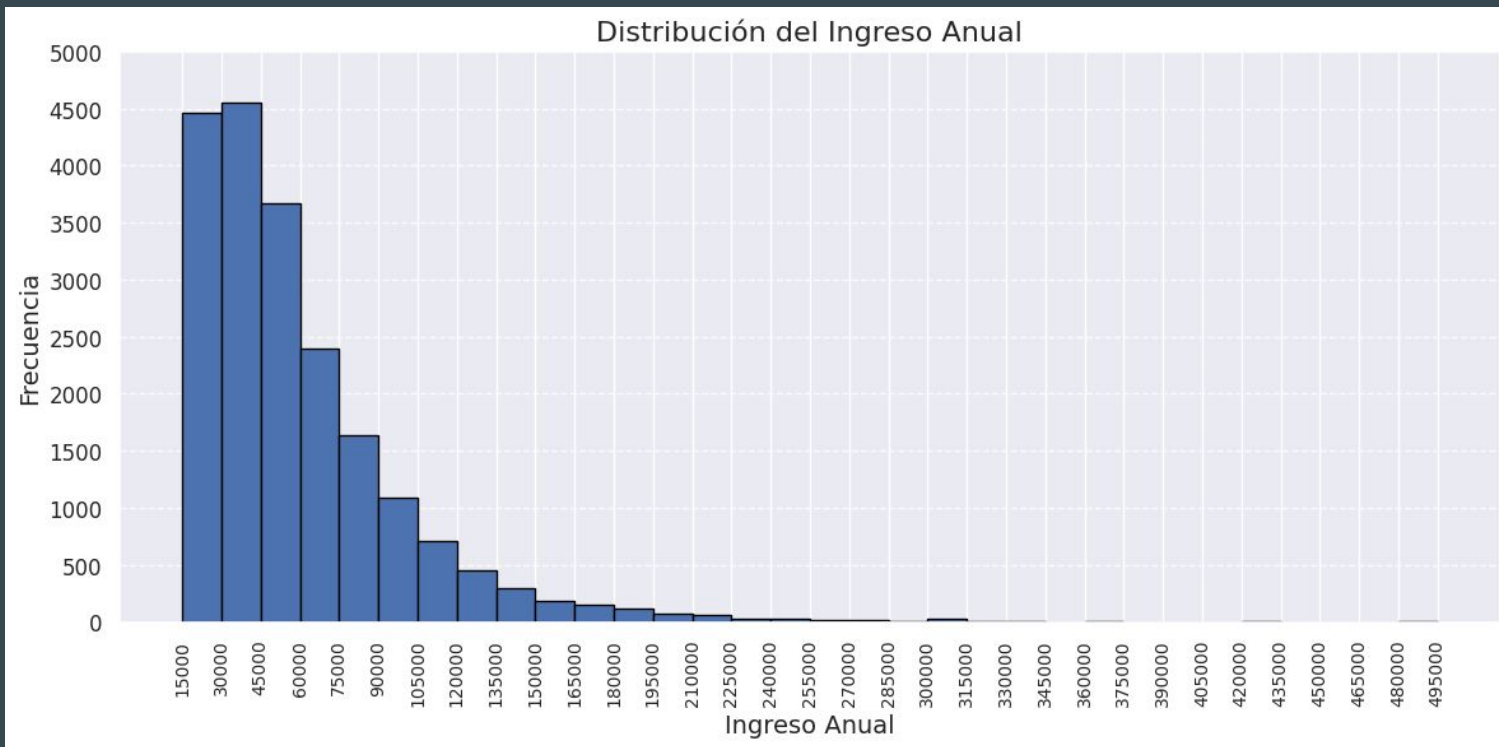
El conjunto de datos está conformado por 20.000 registros y 36 columnas que incluyen información sobre la edad, nivel de ingresos, historial crediticio, situación laboral, entre otros, lo que proporciona una base sólida para análisis predictivos y toma de decisiones en el ámbito crediticio.



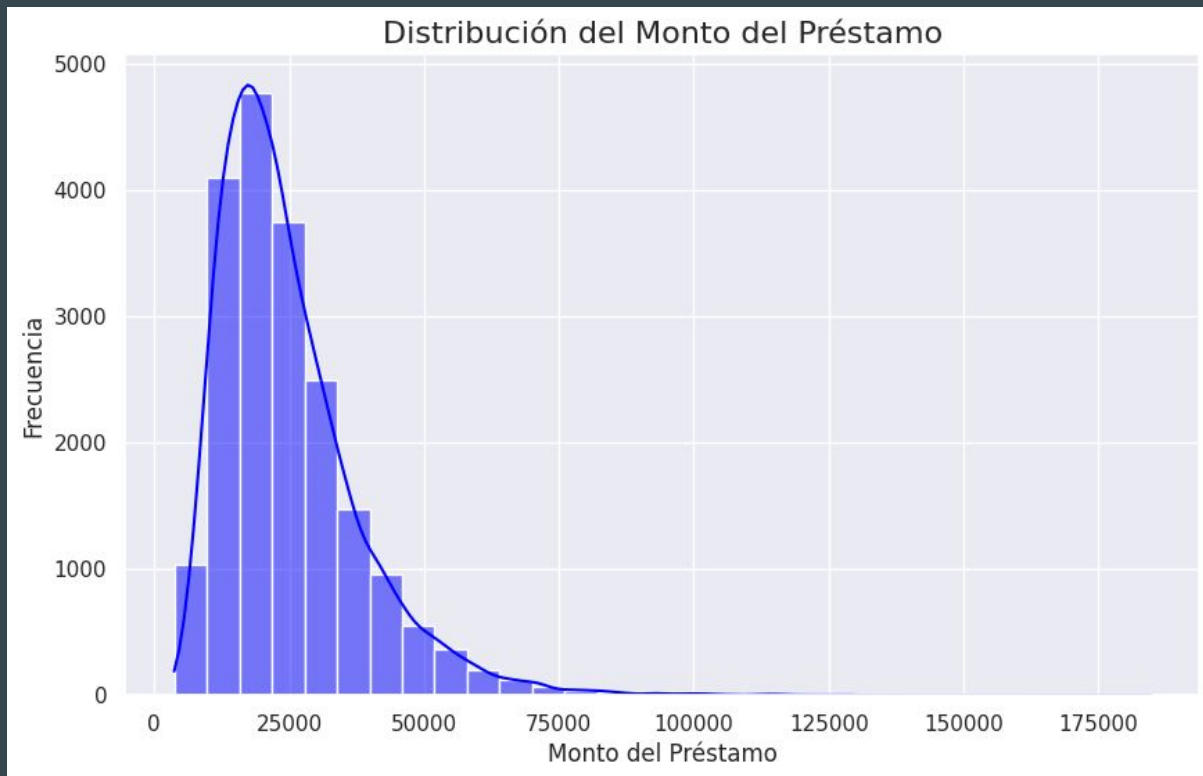
# ACERCA DEL DATASET



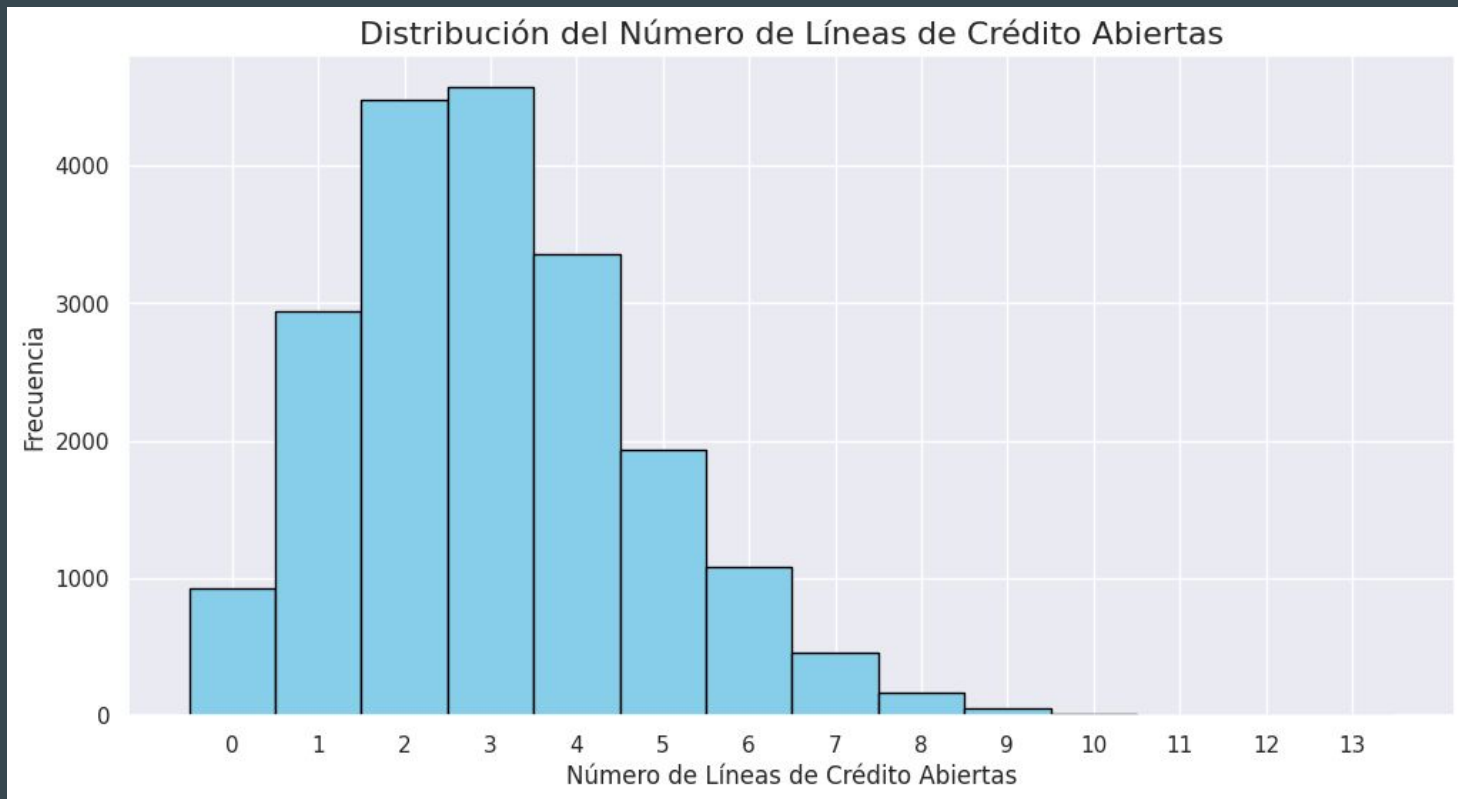
# ACERCA DEL DATASET



# ACERCA DEL DATASET

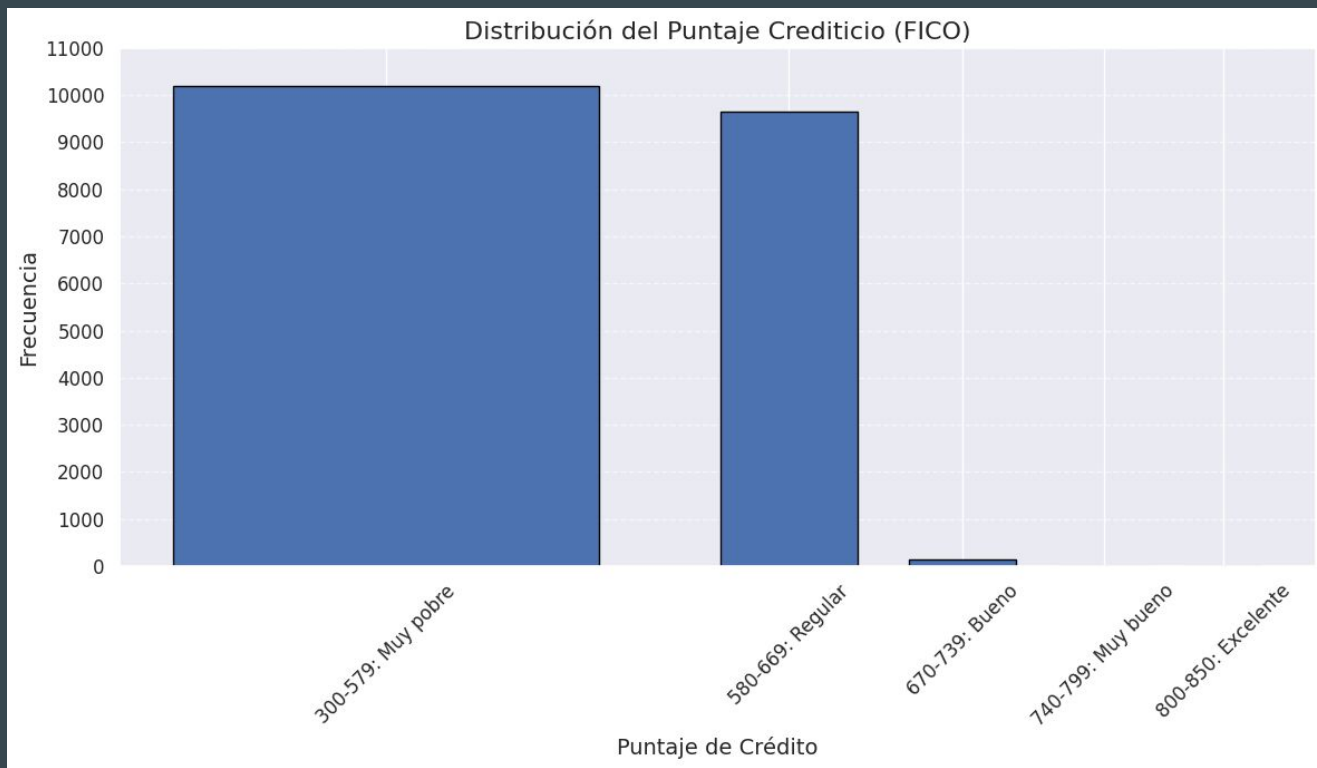


# ACERCA DEL DATASET

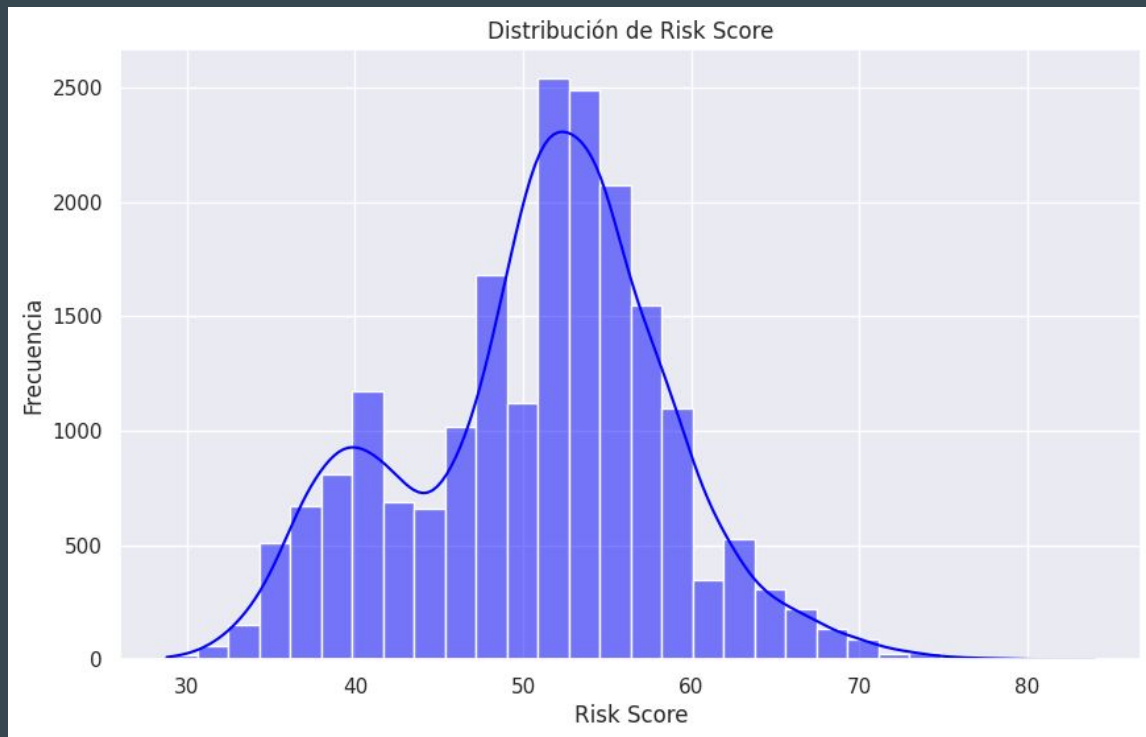




# ACERCA DEL DATASET



# ACERCA DEL DATASET

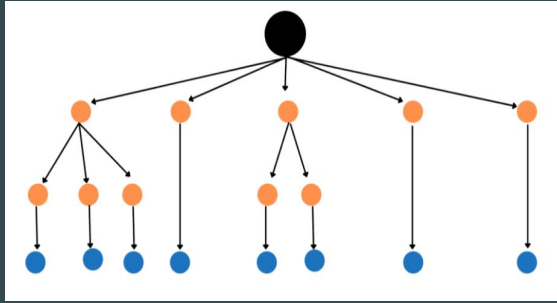


# ACERCA DEL DATASET

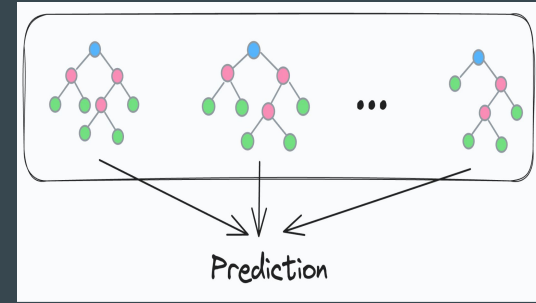


# Modelos implementados

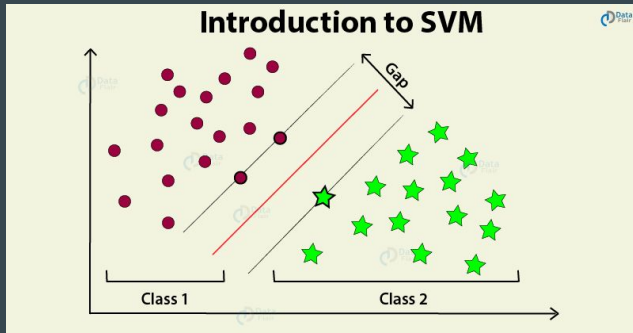
*Decision Tree*



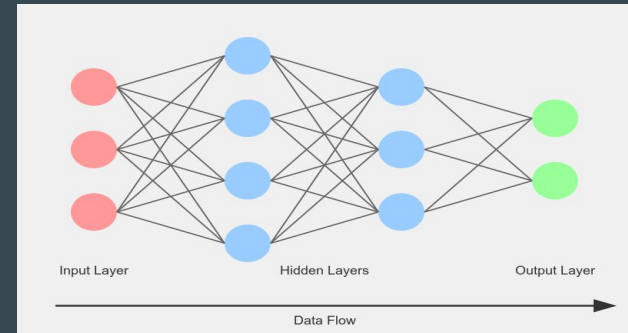
*Random Forest*



*SVM*



*DeepLearning*



# CONVERSIÓN DE DATOS CATEGÓRICOS A VALORES NUMÉRICOS

```
# Identificar columnas categóricas
categorical_columns = df.select_dtypes(include=['object', 'category']).columns

# Mostrar las columnas categóricas y sus valores únicos
for col in categorical_columns:
    print(f"Columna: {col}")
    print(f"Valores únicos: {df[col].unique()}")
    print()

# Convertir las columnas categóricas a números
for col in categorical_columns:
    df[col] = df[col].astype('category').cat.codes

# Verificar los cambios
print(df.head())
```

*Ejemplo:*


```
⇒ Columna: EmploymentStatus
Valores únicos: ['Employed' 'Self-Employed' 'Unemployed']
```

0

1

2

# PARTICIONADO [train\_test\_split]

```
 x = df.drop(columns=['LoanApproved'])  
y = df['LoanApproved']  
|  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

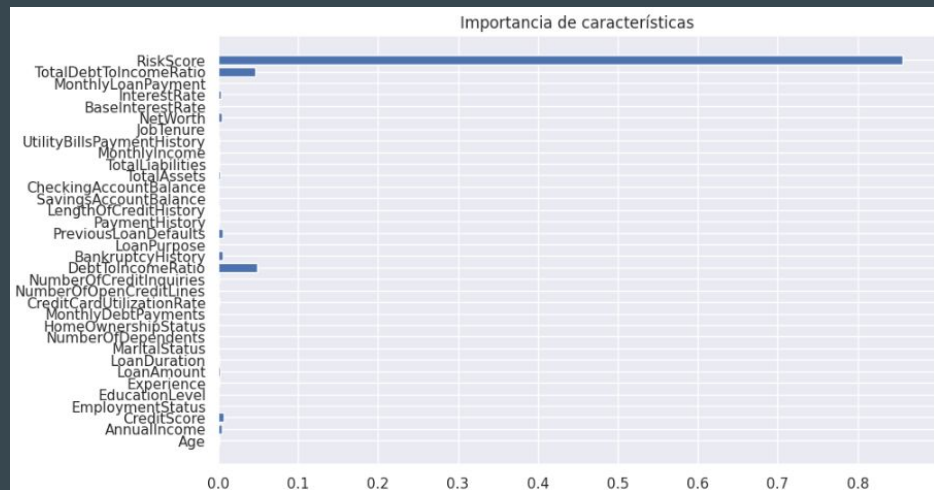
- *Ground truth (y): 'LoanApproved'*
- *Training size: 80%*
- *Test size: 20%*

# ESTIMADORES - Accuracy: Decision Tree

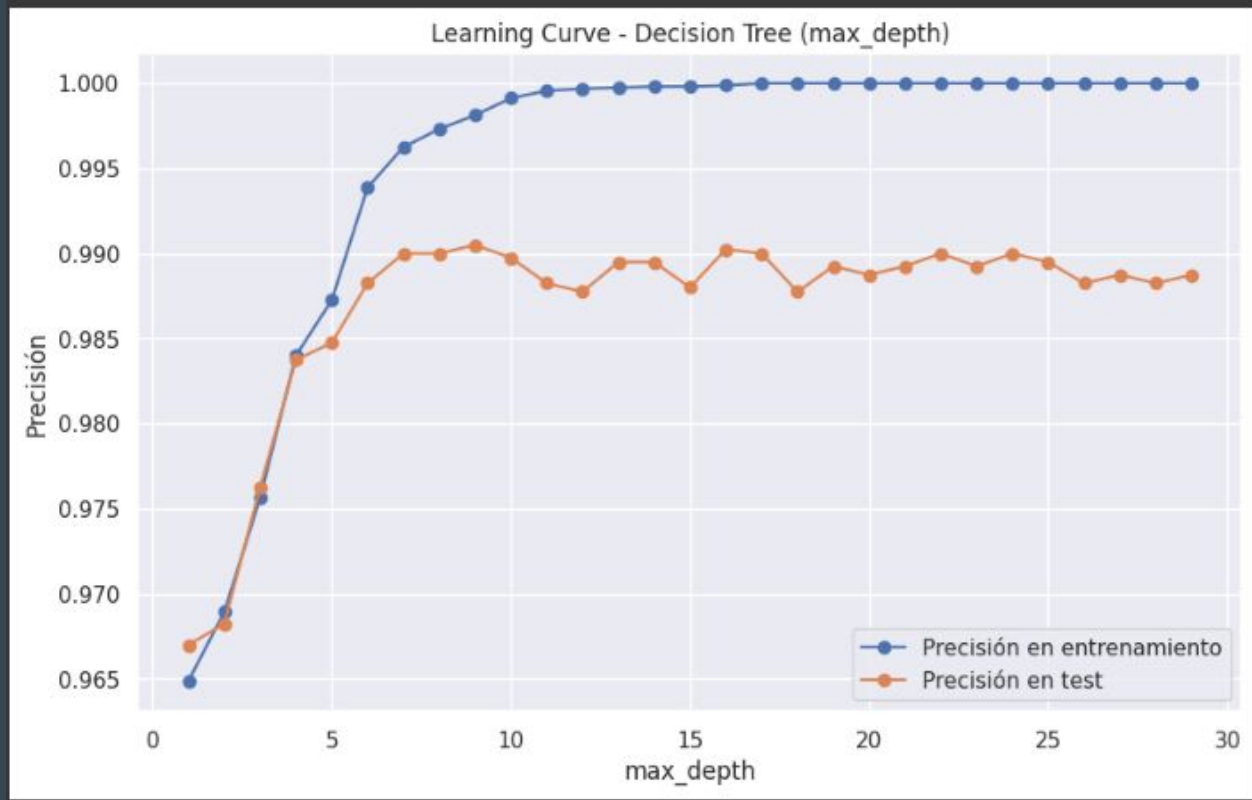
```
est = DecisionTreeClassifier()  
est.fit(X_train,y_train)  
print(accuracy_score(est.predict(X_test), y_test))
```

0.98975

*est.feature\_importances\_*



# LEARNING CURVE [Decision Tree - max depth]





# ESTIMADORES - Accuracy: Random Forest y SVM

## *Random Forest*

```
✓ [51] est = RandomForestClassifier()  
4 s est.fit(X_train,y_train)  
print(accuracy_score(est.predict(X_test), y_test))
```

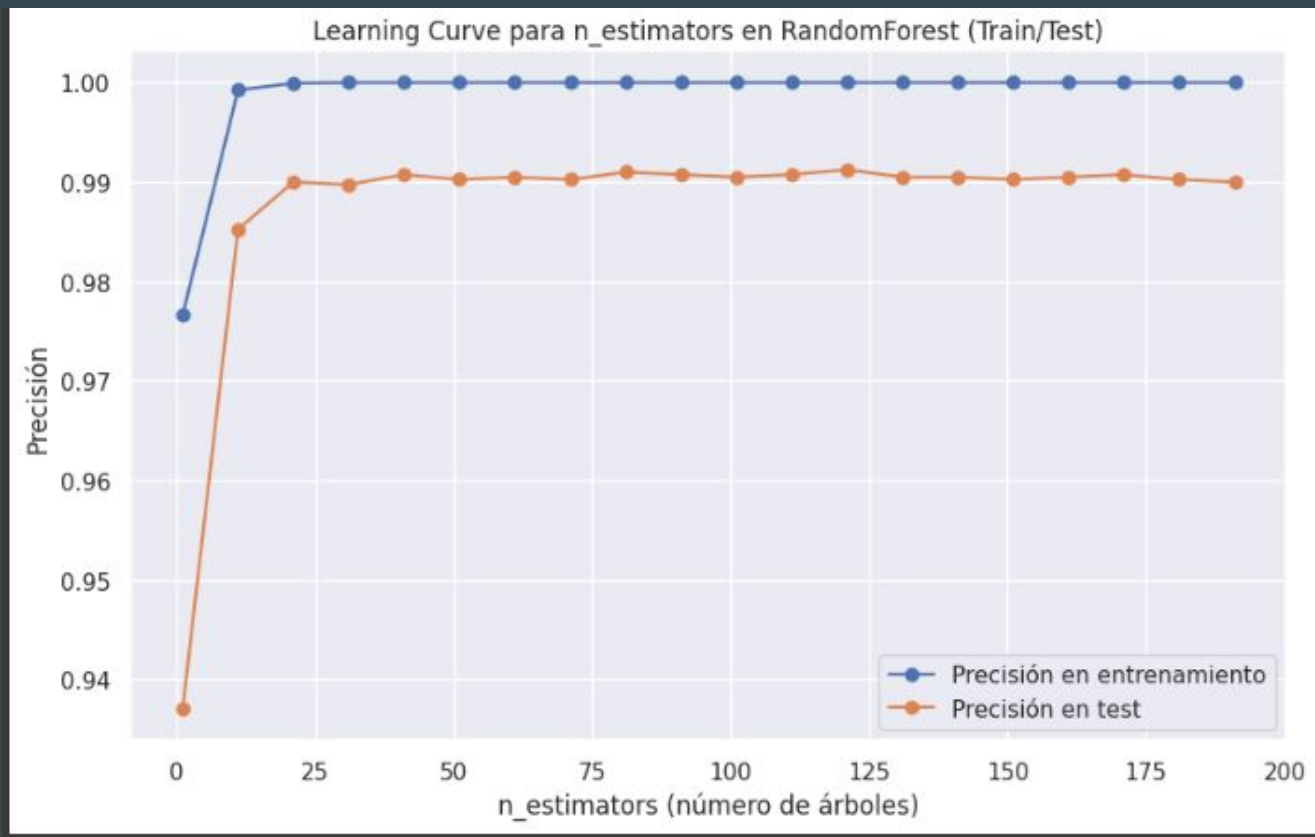
0.992

## *SVM*

```
✓ 6 s from sklearn.svm import SVC  
est = SVC()  
est.fit(X_train,y_train)  
print(accuracy_score(est.predict(X_test), y_test))
```

0.88125

# LEARNING CURVE [Random Forest - $n_{\text{estimators}}$ ]



# SVM - Kernel

*rbf*

```
✓ [29] from sklearn.svm import SVC  
4 s  est = SVC(kernel="rbf", random_state=1)  
     est.fit(X_train, y_train)  
     print(accuracy_score(est.predict(X_test), y_test))
```

→ 0.88125

*poly*

```
✓ [52] from sklearn.svm import SVC  
7 s  est = SVC(kernel="poly", random_state=1)  
     est.fit(X_train, y_train)  
     print(accuracy_score(est.predict(X_test), y_test))
```

→ 0.87025

*linear*

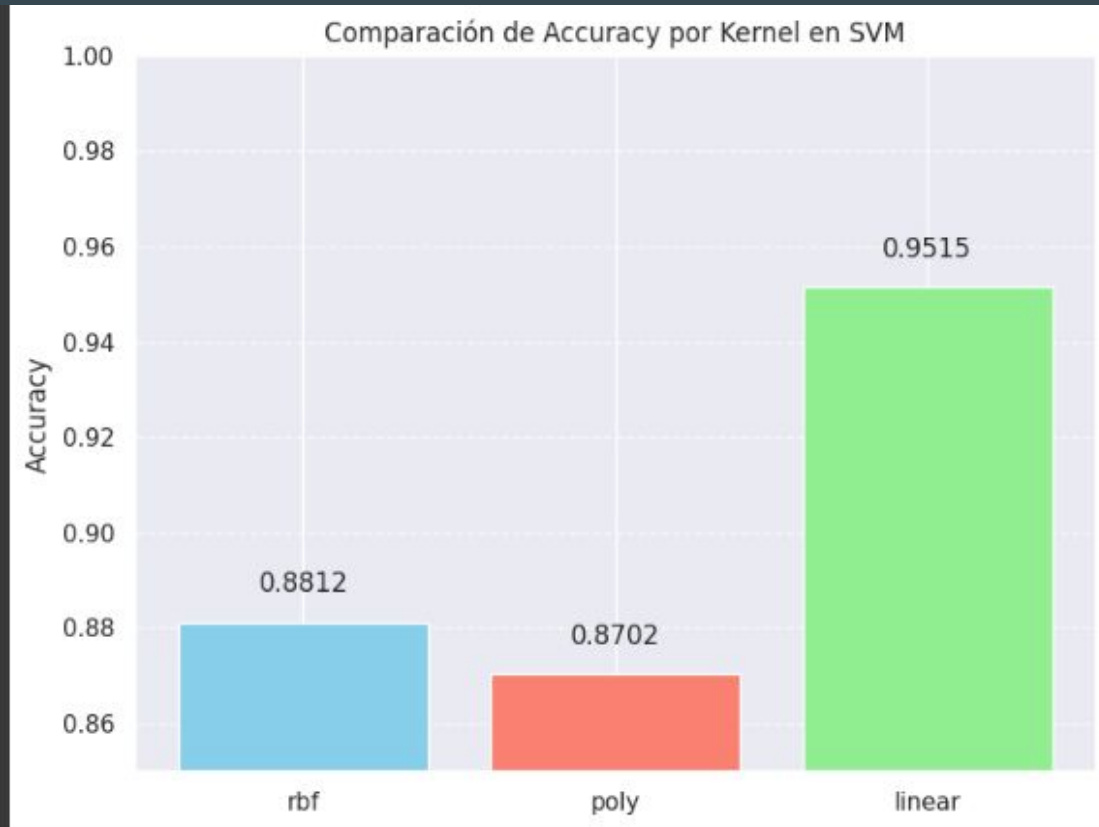
```
✓ [29] from sklearn.svm import SVC  
7 m  X_small = X_train[:1000]  
     y_small = y_train[:1000]  
  
     est = SVC(kernel="linear", random_state=1)  
     est.fit(X_small, y_small)  
     print(accuracy_score(est.predict(X_test), y_test))
```

→ 0.93475

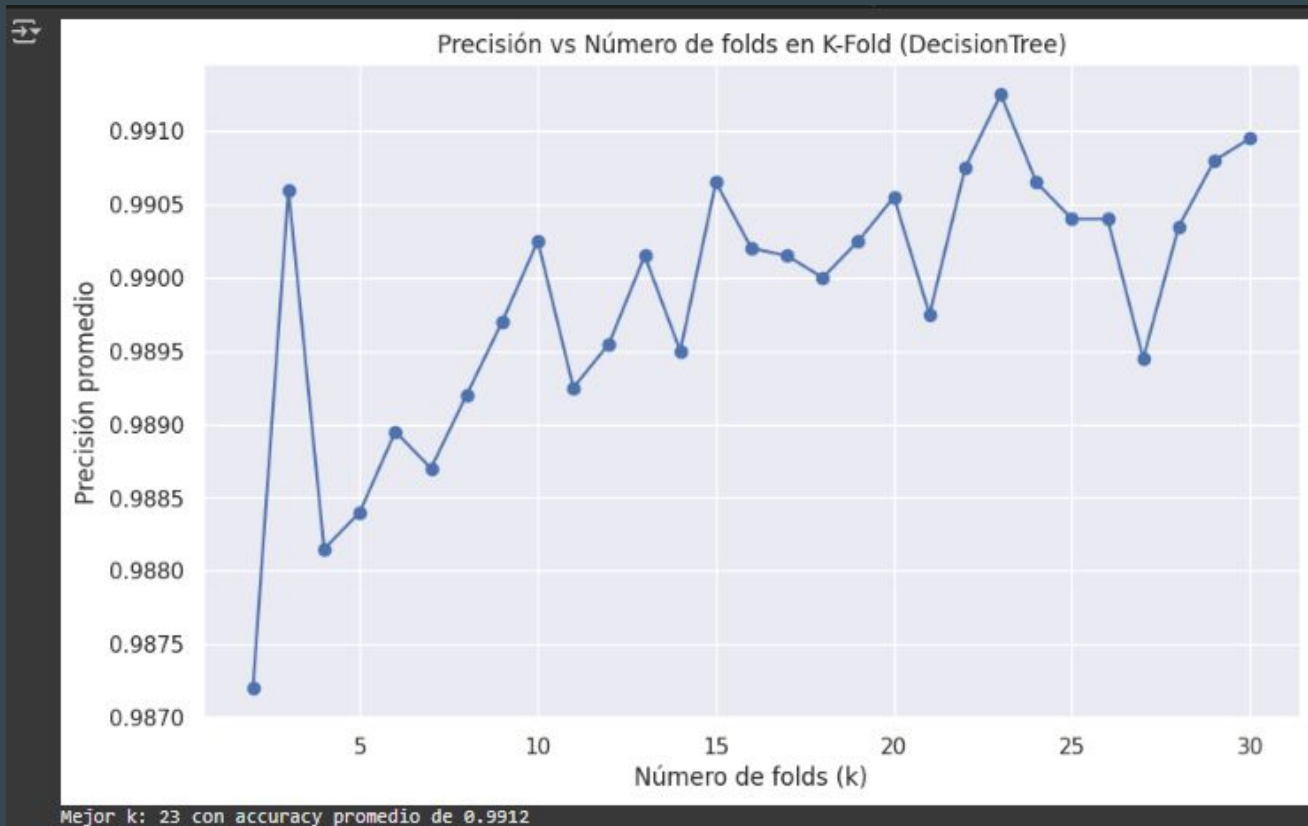
```
✓ [58] from sklearn.svm import SVC  
53 m est = SVC(kernel="linear", random_state=1)  
     est.fit(X_train, y_train)  
     print(accuracy_score(est.predict(X_test), y_test))
```

→ 0.9515

# SVM - Kernel



# LEARNING CURVE [Cross Validation - Decision Tree]



# RED NEURONAL - Perceptrón de 3 capas

```
X = df.drop(columns=['LoanApproved'])
y = df['LoanApproved']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Normalización de datos
mean = X_train.mean(axis=0)
std = X_train.std(axis=0)
X_train = (X_train - mean) / std
X_test = (X_test - mean) / std

model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=(X_train.shape[1],)),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(2, activation=tf.nn.softmax)
])

model.compile(optimizer='adam', loss='crossentropy', metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10)
```

```
Epoch 1/10
/usr/local/lib/python3.11/dist-packages/keras/src/layers/reshaping/flatten.py:37:
```

Do not pass an `input\_shape`/`input\_dim` argument to a layer. When using Sequential

```
500/500 ————— 3s 4ms/step - accuracy: 0.9489 - loss: 0.1180
Epoch 2/10
500/500 ————— 2s 2ms/step - accuracy: 0.9970 - loss: 0.0079
Epoch 3/10
500/500 ————— 1s 2ms/step - accuracy: 0.9985 - loss: 0.0092
Epoch 4/10
500/500 ————— 1s 2ms/step - accuracy: 0.9979 - loss: 0.0039
Epoch 5/10
500/500 ————— 1s 2ms/step - accuracy: 1.0000 - loss: 9.4836e-05
Epoch 6/10
500/500 ————— 1s 2ms/step - accuracy: 1.0000 - loss: 3.6514e-05
Epoch 7/10
500/500 ————— 1s 2ms/step - accuracy: 1.0000 - loss: 9.5012e-06
Epoch 8/10
500/500 ————— 1s 2ms/step - accuracy: 1.0000 - loss: 4.2292e-06
Epoch 9/10
500/500 ————— 1s 2ms/step - accuracy: 1.0000 - loss: 2.9318e-06
Epoch 10/10
500/500 ————— 2s 4ms/step - accuracy: 1.0000 - loss: 1.9669e-06
<keras.src.callbacks.history.History at 0x7d87dc1d65d0>
```

# RED NEURONAL - Perceptrón de 6 capas

```
X = df.drop(columns=['LoanApproved'])
y = df['LoanApproved']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Normalización de datos
mean = X_train.mean(axis=0)
std = X_train.std(axis=0)
X_train = (X_train - mean) / std
X_test = (X_test - mean) / std

model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=(X_train.shape[1],)),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(2, activation=tf.nn.softmax)
])

model.compile(optimizer='adam', loss='crossentropy', metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10)
```

Epoch 1/10  
/usr/local/lib/python3.11/dist-packages/keras/src/layers/reshaping/flatten.py:37: UserWarning

Do not pass an `input\_shape`/`input\_dim` argument to a layer. When using Sequential model

```
500/500 ————— 4s 3ms/step - accuracy: 0.9426 - loss: 0.1305
Epoch 2/10
500/500 ————— 3s 3ms/step - accuracy: 0.9982 - loss: 0.0059
Epoch 3/10
500/500 ————— 3s 3ms/step - accuracy: 0.9987 - loss: 0.0045
Epoch 4/10
500/500 ————— 3s 4ms/step - accuracy: 1.0000 - loss: 4.6508e-04
Epoch 5/10
500/500 ————— 3s 5ms/step - accuracy: 0.9994 - loss: 0.0022
Epoch 6/10
500/500 ————— 2s 3ms/step - accuracy: 0.9994 - loss: 0.0022
Epoch 7/10
500/500 ————— 3s 3ms/step - accuracy: 1.0000 - loss: 1.6682e-04
Epoch 8/10
500/500 ————— 3s 3ms/step - accuracy: 0.9994 - loss: 0.0032
Epoch 9/10
500/500 ————— 2s 3ms/step - accuracy: 1.0000 - loss: 3.6108e-06
Epoch 10/10
500/500 ————— 4s 5ms/step - accuracy: 1.0000 - loss: 4.1828e-07
<keras.src.callbacks.history.History at 0x7d87ed11b1d0>
```

# RED NEURONAL - Perceptrón de 10 capas

```
X = df.drop(columns=['LoanApproved'])
y = df['LoanApproved']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Normalización de datos
mean = X_train.mean(axis=0)
std = X_train.std(axis=0)
X_train = (X_train - mean) / std
X_test = (X_test - mean) / std

model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=(X_train.shape[1],)),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(2, activation=tf.nn.softmax)
])

model.compile(optimizer='adam', loss='crossentropy', metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10)
```

```
Epoch 1/10
/usr/local/lib/python3.11/dist-packages/keras/src/layers/reshaping/flatten.py:37: UserWarning:
Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer
500/500 ————— 5s 4ms/step - accuracy: 0.9218 - loss: 0.1673
Epoch 2/10
500/500 ————— 3s 4ms/step - accuracy: 0.9971 - loss: 0.0111
Epoch 3/10
500/500 ————— 3s 4ms/step - accuracy: 0.9989 - loss: 0.0047
Epoch 4/10
500/500 ————— 3s 6ms/step - accuracy: 0.9991 - loss: 0.0022
Epoch 5/10
500/500 ————— 2s 4ms/step - accuracy: 0.9996 - loss: 4.7294e-04
Epoch 6/10
500/500 ————— 2s 4ms/step - accuracy: 1.0000 - loss: 1.3048e-06
Epoch 7/10
500/500 ————— 2s 4ms/step - accuracy: 1.0000 - loss: 9.3266e-07
Epoch 8/10
500/500 ————— 3s 4ms/step - accuracy: 1.0000 - loss: 6.1626e-07
Epoch 9/10
500/500 ————— 3s 6ms/step - accuracy: 1.0000 - loss: 6.4575e-07
Epoch 10/10
500/500 ————— 4s 4ms/step - accuracy: 1.0000 - loss: 1.3756e-07
<keras.src.callbacks.history.History at 0x7d87d9e59490>
```

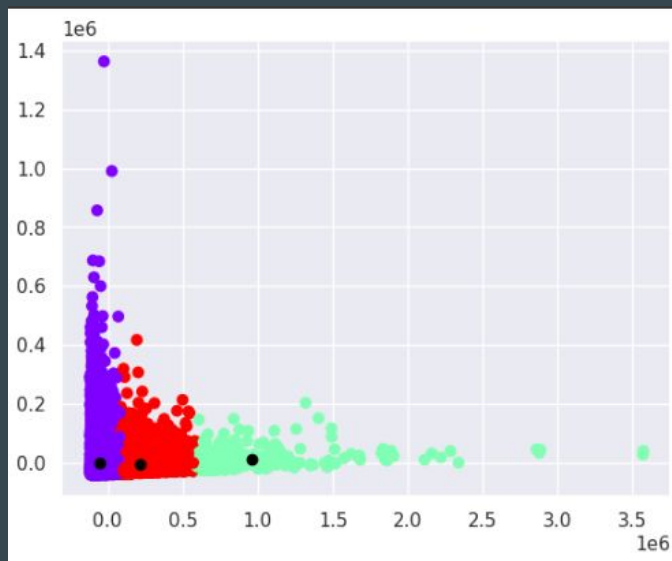


# REDUCCIÓN DE DIMENSIONALIDAD - PCA

```
from sklearn.decomposition import PCA  
  
X = df.drop(columns=['LoanApproved'])  
pca = PCA(n_components=2)  
X_pca = pca.fit_transform(X)
```

# APRENDIZAJE NO SUPERVISADO - K-means

```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=3)
kmeans.fit(X_pca)
plt.scatter(X_pca[:,0],X_pca[:,1], c=kmeans.labels_, cmap='rainbow')
plt.scatter(kmeans.cluster_centers_[0],kmeans.cluster_centers_[1], color='black')
```

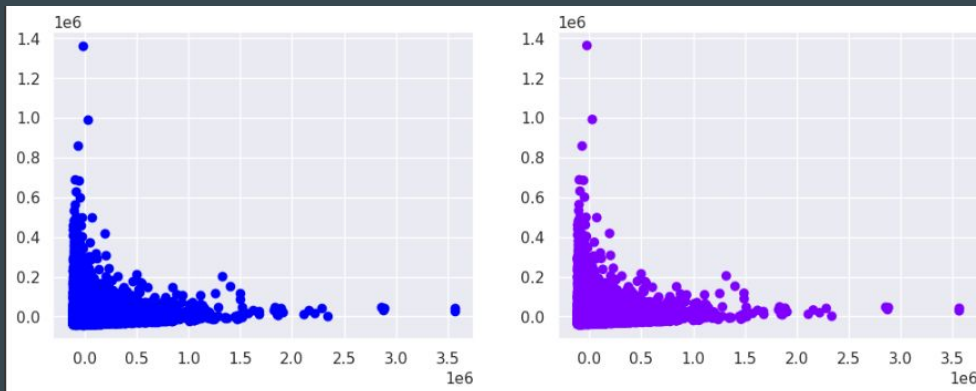


# APRENDIZAJE NO SUPERVISADO - DBSCAN

```
from sklearn.cluster import DBSCAN

DBS = DBSCAN(min_samples=2)
DBS.fit(X_pca)

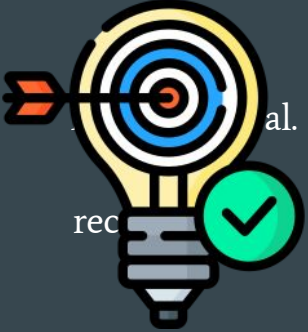
plt.figure(figsize=(12,4))
plt.subplot(121)
plt.scatter(X_pca[:,0], X_pca[:,1], c="blue", cmap='rainbow');
plt.subplot(122)
plt.scatter(X_pca[:,0], X_pca[:,1], c=DBS.labels_, cmap='rainbow');
```



# CONCLUSIONES

Los modelos alcanzaron una precisión casi perfecta, lo que se debe en gran parte a la simplicidad del dataset, con variables limpias, bien estructuradas y altamente correlacionadas con el resultado. Esto facilitó la tarea de predicción, pero también implica que los resultados podrían no generalizar bien a contextos más complejos o reales.

Aunque los resultados son prometedores, se recomienda:

- Probar los modelos en datos más diversos o con  al.
- Usar validación cruzada y métricas adicionales (precision, recall, etc.).
- Considerar aspectos éticos en la toma de decisiones automatizada.

El sistema tiene potencial para aplicaciones reales, pero requiere pruebas adicionales antes de su implementación práctica.