Laboratorio 8

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Link del repo: https://github.com/alee2602/LAB8-DS

Importación de librerías

In [ ]:

```
import warnings, numpy as np, pandas as pd
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt

from sklearn.datasets import fetch_covtype
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.metrics import (
    roc_auc_score, average_precision_score, f1_score,
    precision_score, recall_score, confusion_matrix,
    roc_curve, precision_recall_curve
)

from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
```

Cargar CoverType

In [3]:

```
cov = fetch_covtype(as_frame=True)
X_full: pd.DataFrame = cov.data.copy()
y_full: pd.Series = cov.target.copy()
```

Exploración breve de features

In [4]:

```
print("Número total de columnas:", X_full.shape[1])
print("\nPrimeras 10 columnas:")
print(X_full.columns[:10].tolist())

print("\nÚltimas 10 columnas:")
print(X_full.columns[-10:].tolist())

X_full.info()

X_full.head()
```

```
Número total de columnas: 54

Primeras 10 columnas:
['Elevation', 'Aspect', 'Slope', 'Horizontal_Distance_To_Hydrology', 'Vertical_Dista
nce_To_Hydrology', 'Horizontal_Distance_To_Roadways', 'Hillshade_9am', 'Hillshade_No
on', 'Hillshade_3pm', 'Horizontal_Distance_To_Fire_Points']

Últimas 10 columnas:
['Soil_Type_30', 'Soil_Type_31', 'Soil_Type_32', 'Soil_Type_33', 'Soil_Type_34', 'So
il_Type_35', 'Soil_Type_36', 'Soil_Type_37', 'Soil_Type_38', 'Soil_Type_39']
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 581012 entries, 0 to 581011
Data columns (total 54 columns):
 #   Column                              Non-Null Count   Dtype  
---  ------                              --------------   -----  
 0   Elevation                           581012 non-null  float64
 1   Aspect                              581012 non-null  float64
 2   Slope                               581012 non-null  float64
 3   Horizontal_Distance_To_Hydrology    581012 non-null  float64
 4   Vertical_Distance_To_Hydrology      581012 non-null  float64
 5   Horizontal_Distance_To_Roadways     581012 non-null  float64
 6   Hillshade_9am                       581012 non-null  float64
 7   Hillshade_Noon                      581012 non-null  float64
 8   Hillshade_3pm                       581012 non-null  float64
 9   Horizontal_Distance_To_Fire_Points  581012 non-null  float64
 10  Wilderness_Area_0                   581012 non-null  float64
 11  Wilderness_Area_1                   581012 non-null  float64
 12  Wilderness_Area_2                   581012 non-null  float64
 13  Wilderness_Area_3                   581012 non-null  float64
 14  Soil_Type_0                         581012 non-null  float64
 15  Soil_Type_1                         581012 non-null  float64
 16  Soil_Type_2                         581012 non-null  float64
 17  Soil_Type_3                         581012 non-null  float64
 18  Soil_Type_4                         581012 non-null  float64
 19  Soil_Type_5                         581012 non-null  float64
 20  Soil_Type_6                         581012 non-null  float64
 21  Soil_Type_7                         581012 non-null  float64
 22  Soil_Type_8                         581012 non-null  float64
 23  Soil_Type_9                         581012 non-null  float64
 24  Soil_Type_10                        581012 non-null  float64
 25  Soil_Type_11                        581012 non-null  float64
 26  Soil_Type_12                        581012 non-null  float64
 27  Soil_Type_13                        581012 non-null  float64
 28  Soil_Type_14                        581012 non-null  float64
 29  Soil_Type_15                        581012 non-null  float64
 30  Soil_Type_16                        581012 non-null  float64
 31  Soil_Type_17                        581012 non-null  float64
 32  Soil_Type_18                        581012 non-null  float64
 33  Soil_Type_19                        581012 non-null  float64
 34  Soil_Type_20                        581012 non-null  float64
 35  Soil_Type_21                        581012 non-null  float64
 36  Soil_Type_22                        581012 non-null  float64
 37  Soil_Type_23                        581012 non-null  float64
 38  Soil_Type_24                        581012 non-null  float64
 39  Soil_Type_25                        581012 non-null  float64
 40  Soil_Type_26                        581012 non-null  float64
```

```
 41  Soil_Type_27                        581012 non-null  float64
 42  Soil_Type_28                        581012 non-null  float64
 43  Soil_Type_29                        581012 non-null  float64
 44  Soil_Type_30                        581012 non-null  float64
 45  Soil_Type_31                        581012 non-null  float64
 46  Soil_Type_32                        581012 non-null  float64
 47  Soil_Type_33                        581012 non-null  float64
 48  Soil_Type_34                        581012 non-null  float64
 49  Soil_Type_35                        581012 non-null  float64
 50  Soil_Type_36                        581012 non-null  float64
 51  Soil_Type_37                        581012 non-null  float64
 52  Soil_Type_38                        581012 non-null  float64
 53  Soil_Type_39                        581012 non-null  float64
dtypes: float64(54)
memory usage: 239.4 MB
```

Out[4]:

	Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	Vertical_Distance_To_Hydrolc
0	2596.0	51.0	3.0	258.0	
1	2590.0	56.0	2.0	212.0	-
2	2804.0	139.0	9.0	268.0	6
3	2785.0	155.0	18.0	242.0	11
4	2595.0	45.0	2.0	153.0	-

5 rows × 54 columns

Distribución de la variable objetivo

In [5]:

```python
y_full.value_counts().sort_index()
```

Out[5]:

```
Cover_Type
1    211840
2    283301
3     35754
4      2747
5      9493
6     17367
7     20510
Name: count, dtype: int64
```

Descripción de las variables del conjunto de datos

- `Elevation:` Representa la altitud del terreno en metros sobre el nivel del mar, con valores aproximados entre 1850 y 3858 m.
- `Aspect:` Indica la orientación del terreno en grados, donde 0–360° corresponden al ángulo respecto al norte.

- `Slope:` Pendiente o inclinación del terreno expresada en grados, con un rango típico de 0–60°.
- `Hillshade_9am, Hillshade_Noon, Hillshade_3pm:` Miden el nivel de iluminación o sombra del terreno (valores entre 0 y 255) a distintas horas del día, calculados a partir de un modelo digital de elevación.
- `Horizontal_Distance_To_Hydrology / Vertical_Distance_To_Hydrology:` Distancias horizontales y verticales al cuerpo de agua más cercano, medidas en metros.
- `Horizontal_Distance_To_Roadways y Horizontal_Distance_To_Fire_Points:` Distancias horizontales hacia la carretera y al punto de incendio más cercano, respectivamente.
- `Wilderness_Area1-4:` Cuatro variables binarias (variables dummy) que identifican la zona silvestre a la que pertenece cada observación; solo una toma el valor 1 por registro.
- `Soil_Type1-40:` Cuarenta variables binarias que codifican el tipo de suelo; igualmente, solo una está activa (valor 1) para cada muestra.
- `Cover_Type:` Variable objetivo que clasifica la cobertura forestal en siete tipos (1–7). En este laboratorio, la clase 2 se considera “normal”, y las demás se tratan como anomalías. Por lo tanto, existe un desbalanceo grande entre clases.

Etiquetar datos normales vs anómalos

In [6]:
```python
y = (y_full == 2).astype(int).values
```

Definir columnas numéricas y binarias

In [7]:
```python
numeric_cols = [
    "Elevation", "Aspect", "Slope",
    "Horizontal_Distance_To_Hydrology", "Vertical_Distance_To_Hydrology",
    "Horizontal_Distance_To_Roadways",
    "Hillshade_9am", "Hillshade_Noon", "Hillshade_3pm",
    "Horizontal_Distance_To_Fire_Points",
]
binary_cols = [c for c in X_full.columns if c not in numeric_cols]

print("Numéricas:", len(numeric_cols))
print("Binarias:", len(binary_cols))
```

```
Numéricas: 10
Binarias: 44
```

Escalar variables numéricas

In [8]:
```python
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler

ct = ColumnTransformer(
    transformers=[
        ("num", StandardScaler(), numeric_cols),
        ("bin", "passthrough", binary_cols),
    ],
    remainder="drop"
)

X = ct.fit_transform(X_full).astype("float32")

print("X shape:", X.shape)
print("Proporción de normales (y==1):", y.mean())
```

```
X shape: (581012, 54)
Proporción de normales (y==1): 0.48759922342395684
```

Separación de conjuntos de entrenamiento, prueba y validación

In [16]:
```python
SEED = 16

idx_norm = np.where(y == 1)[0]
idx_anom = np.where(y == 0)[0]

# Normales: 60% Train, 10% Val, 10% TuneNorm, 20% TestNorm
idx_train_norm, idx_rest_norm = train_test_split(idx_norm, test_size=0.40, random_s
idx_val_norm, idx_rest_norm2 = train_test_split(idx_rest_norm, test_size=0.75, rand
idx_tune_norm, idx_test_norm = train_test_split(idx_rest_norm2, test_size=0.6667, r

# Anómalos: 70% Tune, 30% Test
idx_anom_tune, idx_anom_test = train_test_split(idx_anom, test_size=0.30, random_st

# Construcción de conjuntos
X_train = X[idx_train_norm];  y_train = y[idx_train_norm]
X_val   = X[idx_val_norm];    y_val   = y[idx_val_norm]

# Tune mixto = TuneNorm + AnomTune
X_tune = np.vstack([X[idx_tune_norm], X[idx_anom_tune]])
y_tune = np.concatenate([y[idx_tune_norm], y[idx_anom_tune]])

# Test mixto = TestNorm + AnomTest
X_test = np.vstack([X[idx_test_norm], X[idx_anom_test]])
y_test = np.concatenate([y[idx_test_norm], y[idx_anom_test]])

print("Shapes:")
print("  X_train:", X_train.shape, " y_train sum:", y_train.sum())
print("  X_val  :", X_val.shape,   " y_val sum:",   y_val.sum())
print("  X_tune :", X_tune.shape,  " proporción normales:", y_tune.mean())
print("  X_test :", X_test.shape,  " proporción normales:", y_test.mean())
```

```
Shapes:
  X_train: (169980, 54)  y_train sum: 169980
  X_val  : (28330, 54)  y_val sum: 28330
  X_tune : (236724, 54)  proporción normales: 0.11966256061911762
  X_test : (145978, 54)  proporción normales: 0.38816808012166215
```

En los autocodificadores, el objetivo principal es que el modelo aprenda a reconstruir correctamente los patrones normales de los datos. Por esa razón, los conjuntos de entrenamiento y validación deben incluir únicamente observaciones normales. Si el modelo se entrena con ejemplos anómalos, también aprendería a reconstruir esos comportamientos atípicos y dejaría de distinguirlos del resto, perdiendo su capacidad para detectar anomalías. En cambio, al entrenarlo solo con datos normales, el error de reconstrucción aumenta significativamente cuando se encuentra con observaciones inusuales, lo que permite utilizarlas como indicador de anomalía. Por este motivo, únicamente el conjunto de prueba debe contener tanto observaciones normales como anómalas, ya que se usa para evaluar qué tan bien el modelo logra diferenciarlas.

Utilidades comunes para la evaluación de los modelos

In [17]:
```python
def precision_at_k(scores_anom, y_true_anom, k):
    order = np.argsort(-scores_anom)
    topk = order[:k]
    return float(y_true_anom[topk].mean())

def best_f1_threshold(scores_anom, y_true_anom, n_steps=200, greater_is_anom=True):
    ths = np.linspace(scores_anom.min(), scores_anom.max(), n_steps)
    best = (0.0, ths[0], 0.0, 0.0)  # f1, th, p, r
    for th in ths:
        y_hat = (scores_anom >= th).astype(int) if greater_is_anom else (scores_ano
        f1 = f1_score(y_true_anom, y_hat, zero_division=0)
        if f1 > best[0]:
            p = precision_score(y_true_anom, y_hat, zero_division=0)
            r = recall_score(y_true_anom, y_hat, zero_division=0)
            best = (f1, th, p, r)
    return {"F1": best[0], "th": best[1], "P": best[2], "R": best[3]}

def plot_roc_pr(y_true_anom, scores, title_prefix):
    fpr, tpr, _ = roc_curve(y_true_anom, scores)
    plt.figure(); plt.plot(fpr, tpr); plt.plot([0,1],[0,1],'--')
    plt.xlabel("FPR"); plt.ylabel("TPR"); plt.title(f"{title_prefix} · ROC"); plt.s

    p, r, _ = precision_recall_curve(y_true_anom, scores)
    plt.figure(); plt.plot(r, p)
    plt.xlabel("Recall"); plt.ylabel("Precision"); plt.title(f"{title_prefix} · Pre

def eval_with_threshold(scores_anom, y_true_anom, th):
    y_hat = (scores_anom >= th).astype(int)
    return {
        "F1": f1_score(y_true_anom, y_hat, zero_division=0),
        "ROC-AUC": roc_auc_score(y_true_anom, scores_anom),
        "PR-AUC": average_precision_score(y_true_anom, scores_anom),
        "CM": confusion_matrix(y_true_anom, y_hat),
```

```
        "y_hat": y_hat
    }
```

Autoencoder simétrico

In [18]:
```
input_dim = X_train.shape[1]

def build_autoencoder(d):
    inputs = keras.Input(shape=(d,))
    x = layers.Dense(64, activation="relu")(inputs)
    x = layers.Dense(32, activation="relu")(x)
    bottleneck = layers.Dense(16, activation="relu")(x)
    x = layers.Dense(32, activation="relu")(bottleneck)
    x = layers.Dense(64, activation="relu")(x)
    outputs = layers.Dense(d, activation="linear")(x)
    ae = keras.Model(inputs, outputs)
    ae.compile(optimizer="adam", loss="mse")
    return ae

ae = build_autoencoder(input_dim)
early = keras.callbacks.EarlyStopping(monitor="val_loss", patience=5, restore_best_

hist = ae.fit(
    X_train, X_train,
    validation_data=(X_val, X_val),
    epochs=100, batch_size=512, callbacks=[early], verbose=1
)

print("Mejor val_loss:", np.min(hist.history["val_loss"]))
```

```
Epoch 1/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0523 - val_loss: 0.0157
Epoch 2/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0112 - val_loss: 0.0083
Epoch 3/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0066 - val_loss: 0.0052
Epoch 4/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0042 - val_loss: 0.0034
Epoch 5/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0030 - val_loss: 0.0028
Epoch 6/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0026 - val_loss: 0.0025
Epoch 7/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0024 - val_loss: 0.0023
Epoch 8/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0022 - val_loss: 0.0022
Epoch 9/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0021 - val_loss: 0.0021
Epoch 10/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0020 - val_loss: 0.0019
Epoch 11/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0017 - val_loss: 0.0017
Epoch 12/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0016 - val_loss: 0.0016
Epoch 13/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0016 - val_loss: 0.0016
Epoch 14/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0015 - val_loss: 0.0015
Epoch 15/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0015 - val_loss: 0.0015
Epoch 16/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0015 - val_loss: 0.0015
Epoch 17/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0014 - val_loss: 0.0014
Epoch 18/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 19/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 20/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 21/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 22/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 23/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 24/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 25/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0012 - val_loss: 0.0013
Epoch 26/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 27/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 28/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0012 - val_loss: 0.0012
```

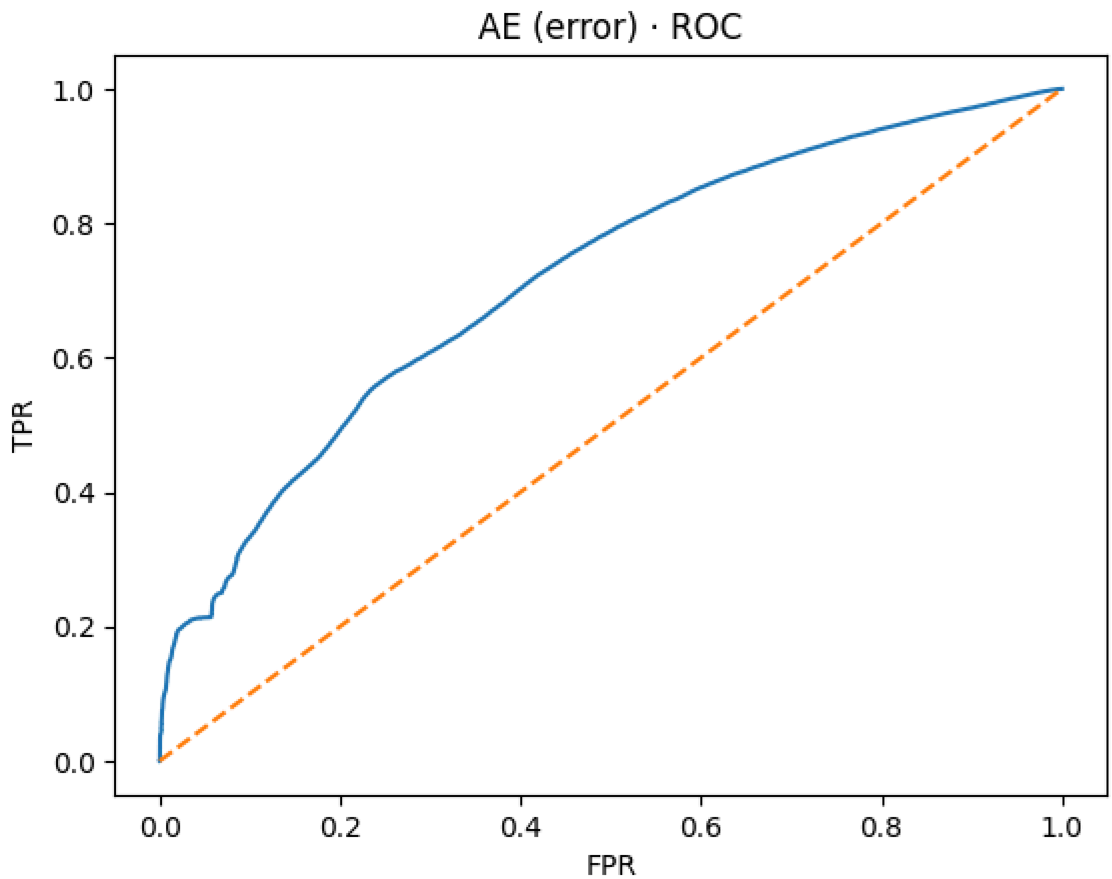
```
Epoch 29/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 30/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 31/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 32/100
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0012 - val_loss: 0.0012
Mejor val_loss: 0.0011653261026367545
```

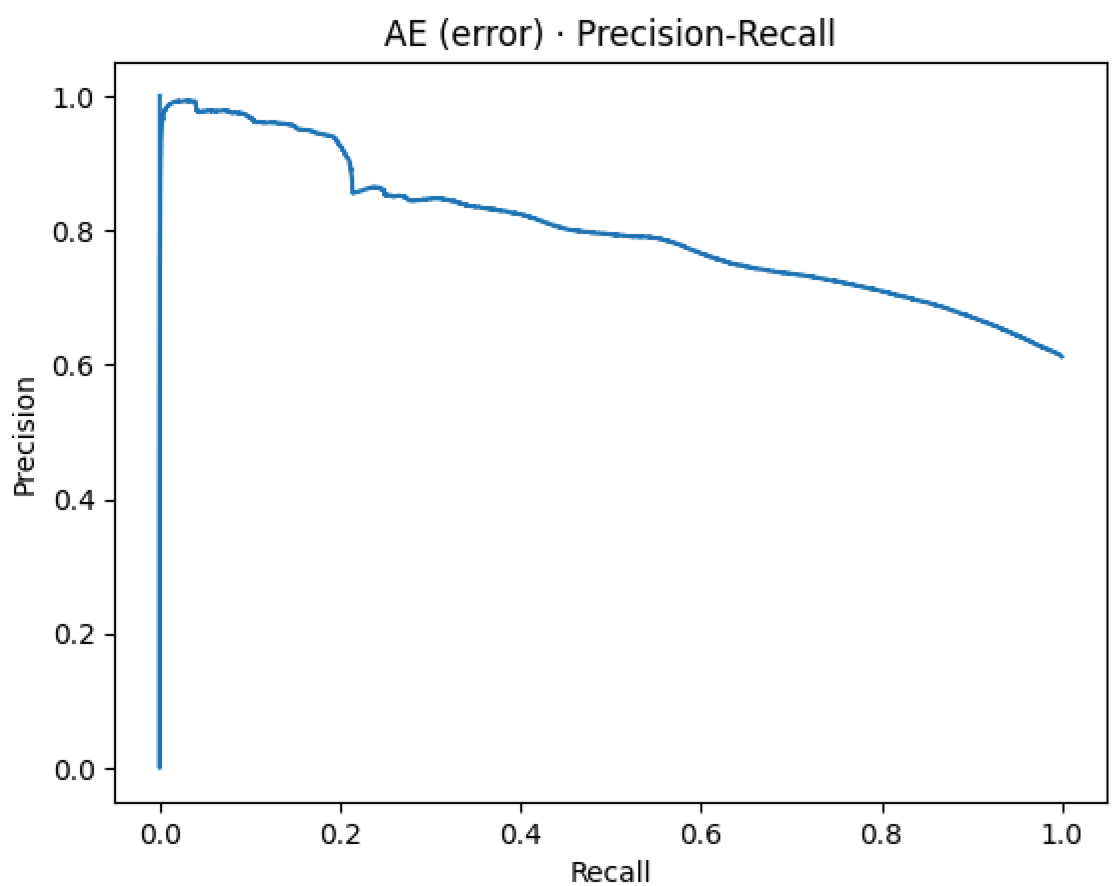
Evaluación del Autoencoder

In [19]:

```python
def recon_error(model, Xarr):
    X_hat = model.predict(Xarr, verbose=0)
    return np.mean(np.square(Xarr - X_hat), axis=1)

err_val  = recon_error(ae, X_val)
err_tune = recon_error(ae, X_tune)
err_test = recon_error(ae, X_test)

# Umbrales
th_pct = float(np.percentile(err_val, 95.0))
best   = best_f1_threshold(err_tune, (1 - y_tune), n_steps=200, greater_is_anom=Tru
th_f1  = best["th"]

print(f"AE th_percentil95={th_pct:.6f}  | AE th_F1={th_f1:.6f}  (Tune F1={best['F1'

# Evaluación en Test
ae_pct = eval_with_threshold(err_test, (1 - y_test), th_pct)
ae_f1  = eval_with_threshold(err_test, (1 - y_test), th_f1)

print("AE (percentil):", {k:v for k,v in ae_pct.items() if k!='CM' and k!='y_hat'})
print("CM (percentil):\n", ae_pct["CM"])
print("AE (F1 tune):", {k:v for k,v in ae_f1.items() if k!='CM' and k!='y_hat'})
print("CM (F1 tune):\n", ae_f1["CM"])

# Curvas usando el score de anomalía
plot_roc_pr((1 - y_test), err_test, "AE (error)")
```

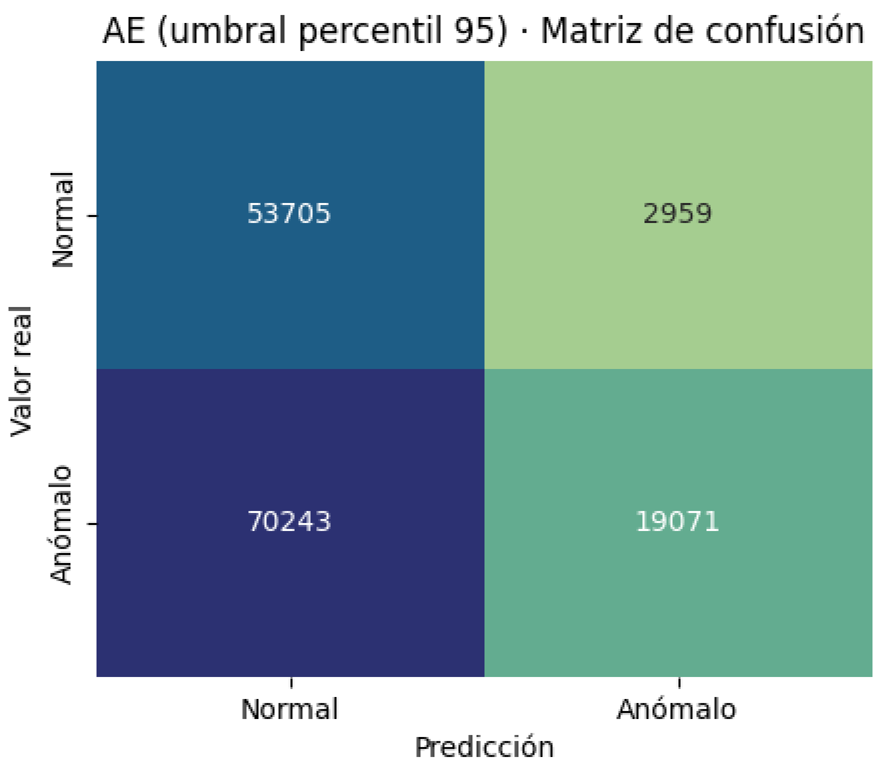
```
AE th_percentil95=0.015155  | AE th_F1=0.000014  (Tune F1=0.936)
AE (percentil): {'F1': 0.3425599942520477, 'ROC-AUC': 0.7167684055610144, 'PR-AUC':
0.8022073257862314}
CM (percentil):
 [[53705  2959]
 [70243 19071]]
AE (F1 tune): {'F1': 0.7591758325824932, 'ROC-AUC': 0.7167684055610144, 'PR-AUC': 0.
8022073257862314}
CM (F1 tune):
 [[    0 56664]
 [    0 89314]]
```

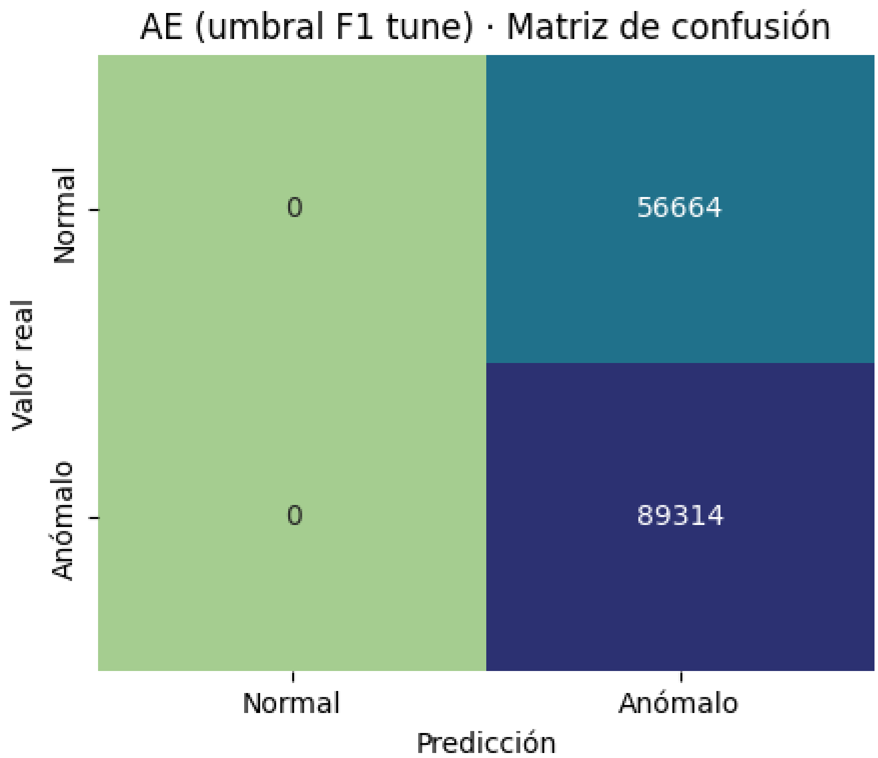

AE (error) · ROC
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0


AE (error) · Precision-Recall
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

In [49]:

```
import seaborn as sns
from sklearn.metrics import confusion_matrix

def plot_confusion_heatmap(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(5,4))
    sns.heatmap(
        cm,
        annot=True, fmt="d", cmap="crest", cbar=False,
        xticklabels=["Normal", "Anómalo"], yticklabels=["Normal", "Anómalo"]
    )
    plt.title(title)
    plt.xlabel("Predicción")
    plt.ylabel("Valor real")
    plt.show()

plot_confusion_heatmap((1 - y_test), ae_pct["y_hat"], "AE (umbral percentil 95) · M
plot_confusion_heatmap((1 - y_test), ae_f1["y_hat"], "AE (umbral F1 tune) · Matriz
```





Entrenamiento con Isolation Forest

In [47]:
```python
grid = {
    "n_estimators": [100, 200, 300],
    "max_samples": ["auto", 1024, 2048],
    "max_features": [0.5, 1.0]
}

candidatos = []
for n in grid["n_estimators"]:
    for ms in grid["max_samples"]:
        for mf in grid["max_features"]:
            if_model = IsolationForest(
                n_estimators=n, max_samples=ms, max_features=mf,
                contamination="auto", random_state=SEED, n_jobs=-1
            ).fit(X_train)

            # Scores de anomalía
            s_tune = -if_model.decision_function(X_tune)
            s_test = -if_model.decision_function(X_test)

            # Umbral por F1 en Tune
            best = best_f1_threshold(s_tune, (1 - y_tune), n_steps=200, greater_is_
            th = best["th"]

            # Métricas en Test
            ev = eval_with_threshold(s_test, (1 - y_test), th)
            candidatos.append({
                "params": {"n_estimators": n, "max_samples": ms, "max_features": mf
                "th": th, "eval": ev, "s_test": s_test
            })
```

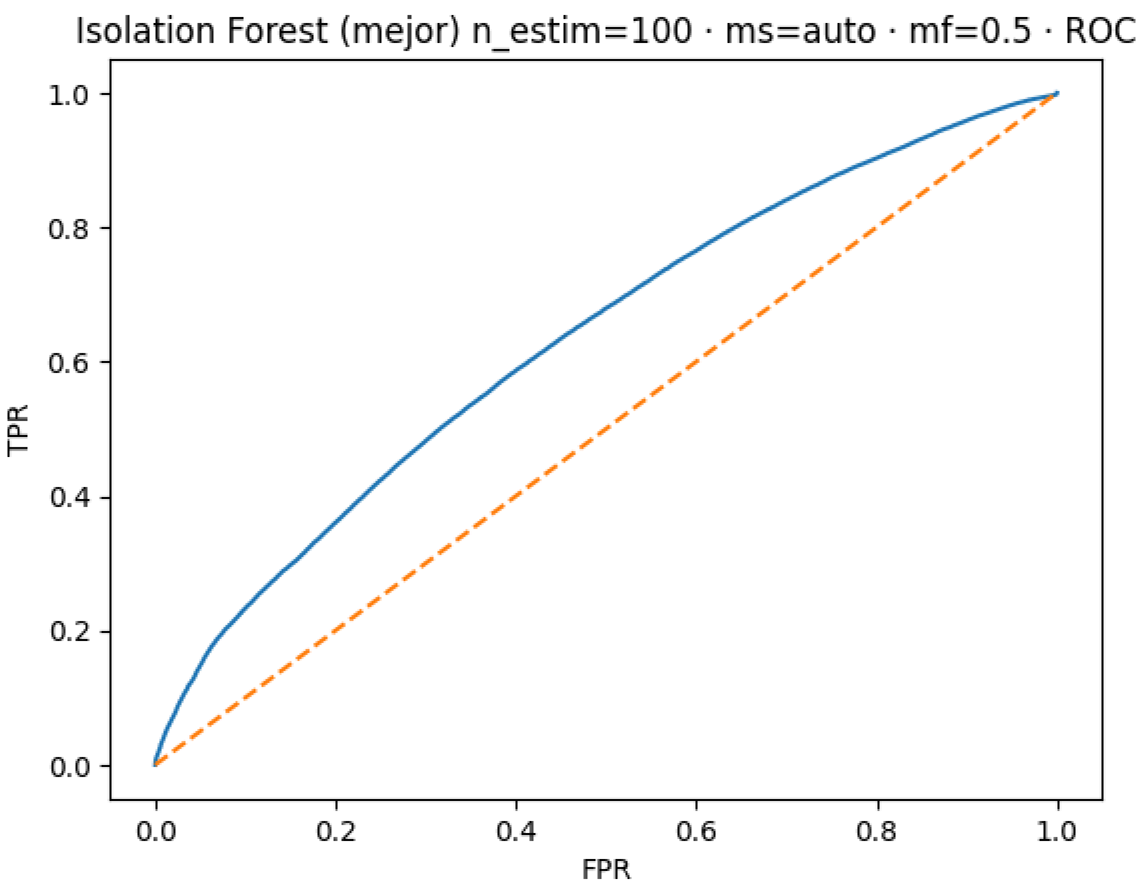
```
# Elegir el mejor por F1 en Test
mejor = max(candidatos, key=lambda c: c["eval"]["F1"])
p = mejor["params"]; th_if = mejor["th"]; if_eval = mejor["eval"]; s_test_if = mejo
```

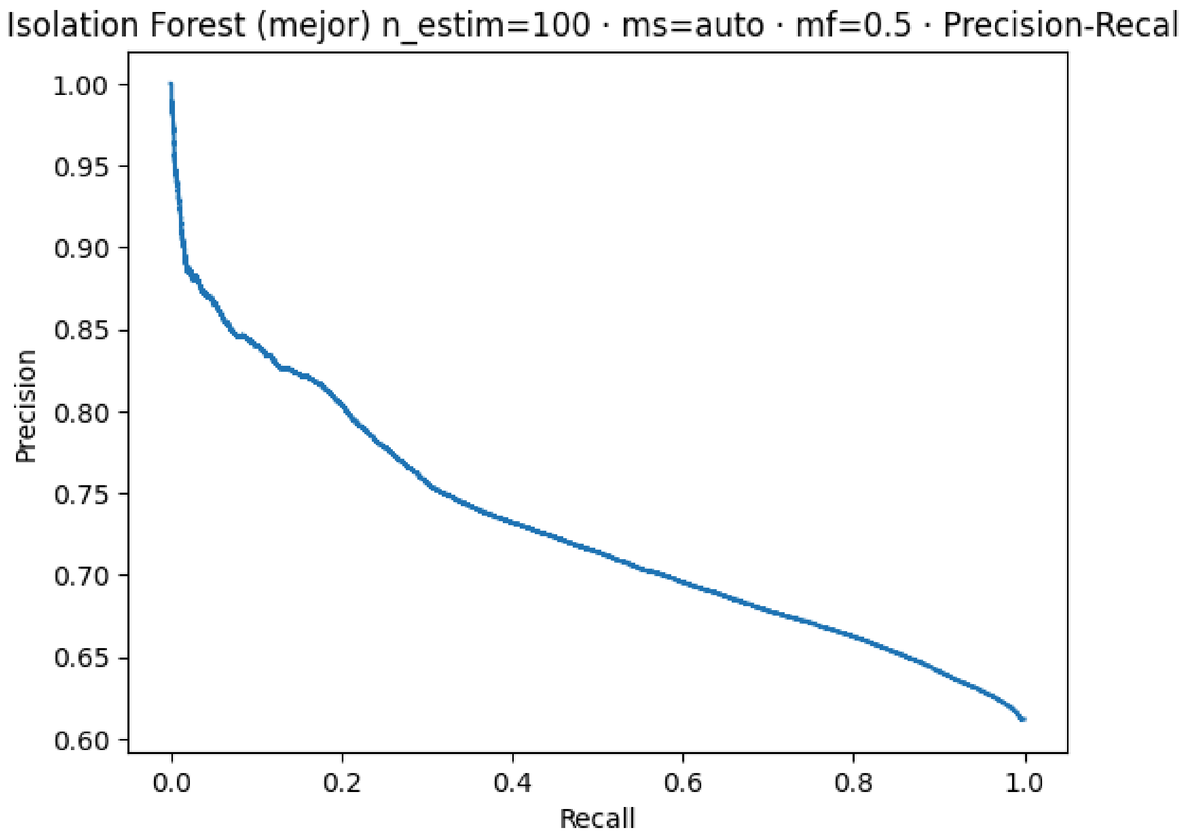
Mostrar métricas de entrenamiento para Isolation Forest

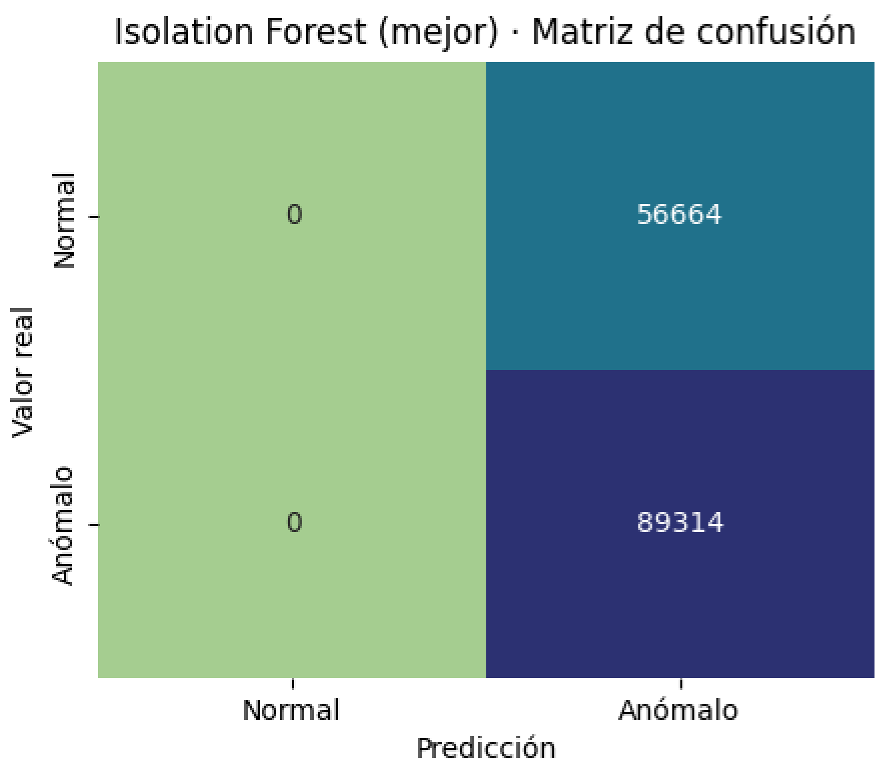
In [50]:

```
print(">>> Isolation Forest (MEJOR por F1)")
print("Parámetros:", p, "| Umbral(F1 Tune):", th_if)
print({k:v for k,v in if_eval.items() if k not in ["CM","y_hat"]})

plot_roc_pr((1 - y_test), s_test_if, f"Isolation Forest (mejor) n_estim={p['n_estim
cm_if = plot_confusion_heatmap((1 - y_test), if_eval["y_hat"], "Isolation Forest (m

# Precision@k del mejor
k = max(1, int(0.01 * len(y_test)))
print(f"Isolation Forest (mejor) Precision@{k}:", precision_at_k(s_test_if, (1 - y_
```

```
>>> Isolation Forest (MEJOR por F1)
Parámetros: {'n_estimators': 100, 'max_samples': 'auto', 'max_features': 0.5} | Umbr
al(F1 Tune): -0.151893792434666
{'F1': 0.7591758325824932, 'ROC-AUC': 0.6340325562470167, 'PR-AUC': 0.72830783526093
17}
```








```
Isolation Forest (mejor) Precision@1459: 0.9026730637422893
```

Entrenamiento con LOF

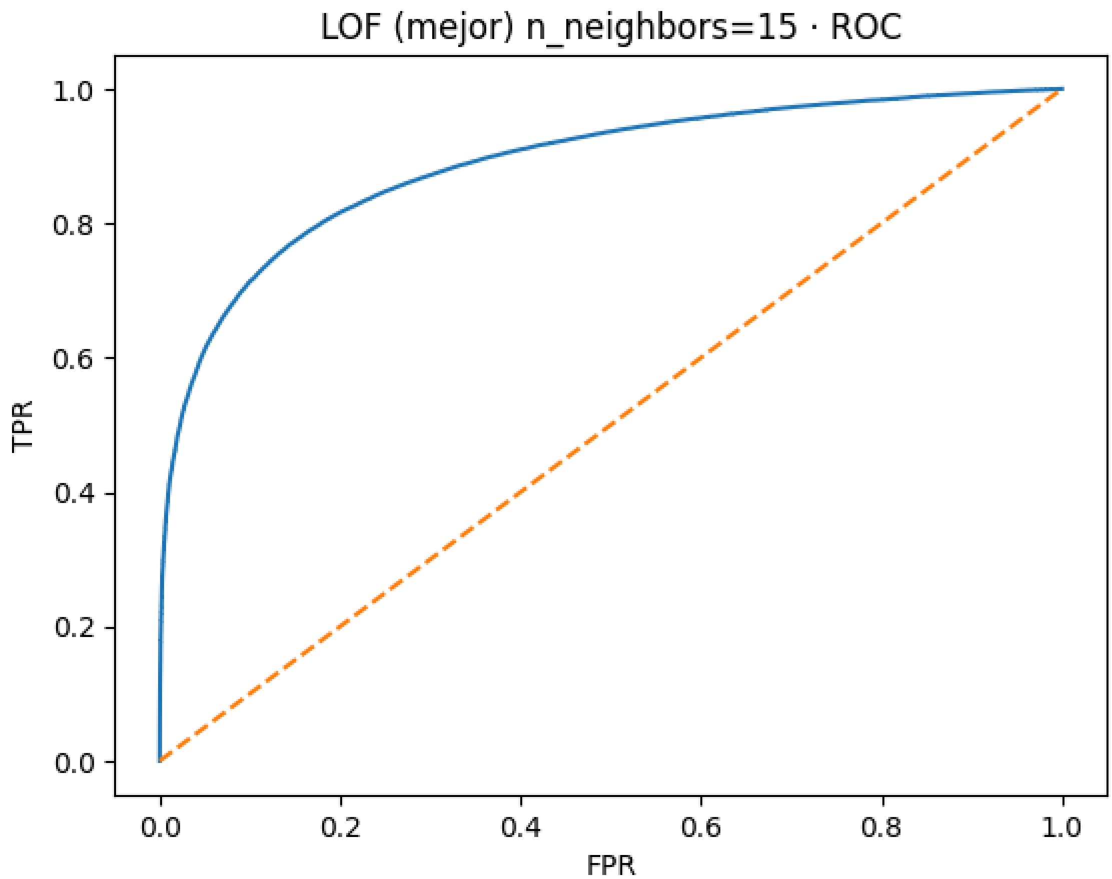
In [51]:
```
neighbors_grid = [15, 25, 35, 50]
```

```python
candidatos = []
for nn in neighbors_grid:
    lof = LocalOutlierFactor(n_neighbors=nn, novelty=True, contamination="auto").fi

    s_tune = -lof.decision_function(X_tune)
    s_test = -lof.decision_function(X_test)

    # Umbral por F1 en Tune
    best = best_f1_threshold(s_tune, (1 - y_tune), n_steps=200, greater_is_anom=Tru
    th = best["th"]

    # Métricas en Test
    ev = eval_with_threshold(s_test, (1 - y_test), th)
    candidatos.append({"nn": nn, "th": th, "eval": ev, "s_test": s_test})

# Elegir el mejor por F1 en Test
mejor = max(candidatos, key=lambda c: c["eval"]["F1"])
nn_best = mejor["nn"]; th_lof = mejor["th"]; lof_eval = mejor["eval"]; s_test_lof =
```

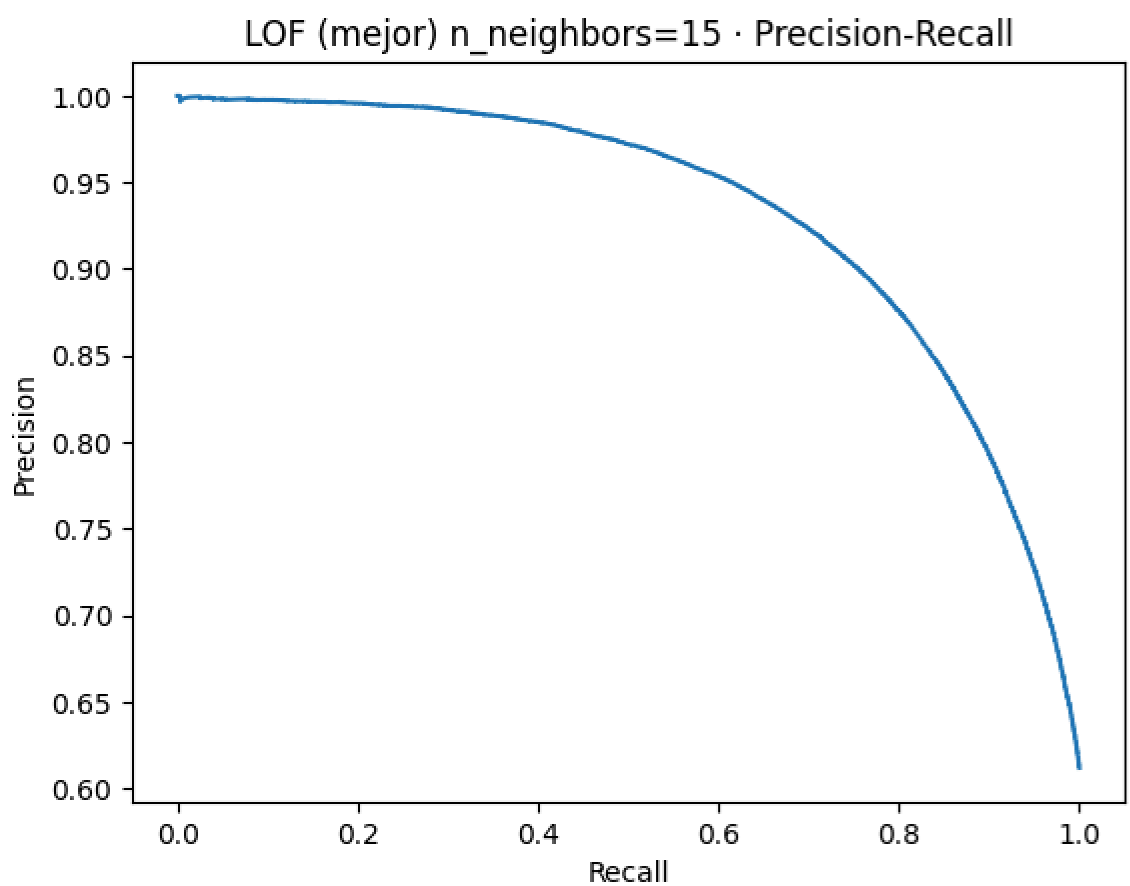
In [52]:

```python
print(">>> LOF (MEJOR por F1)")
print(f"n_neighbors={nn_best} | Umbral(F1 Tune): {th_lof}")
print({k:v for k,v in lof_eval.items() if k not in ["CM","y_hat"]})

# Gráficos SOLO del mejor
plot_roc_pr((1 - y_test), s_test_lof, f"LOF (mejor) n_neighbors={nn_best}")
cm_lof = plot_confusion_heatmap((1 - y_test), lof_eval["y_hat"], "LOF (mejor) · Mat

# Precision@k del mejor
k = max(1, int(0.01 * len(y_test)))
print(f"LOF (mejor) Precision@{k}:", precision_at_k(s_test_lof, (1 - y_test), k))
```

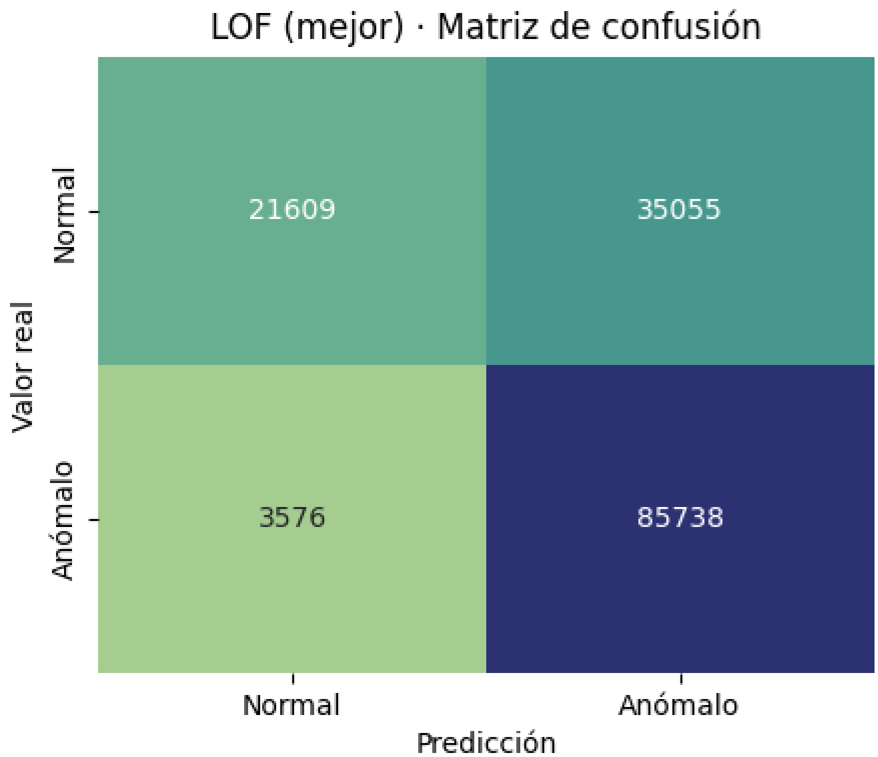
```
>>> LOF (MEJOR por F1)
n_neighbors=15 | Umbral(F1 Tune): -0.4821498394012451
{'F1': 0.8161365399534523, 'ROC-AUC': 0.8884447459282652, 'PR-AUC': 0.93185026297798
85}
```



LOF (mejor) n_neighbors=15 · ROC
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0



LOF (mejor) n_neighbors=15 · Precision-Recall
Precision
Recall
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00
0.0
0.2
0.4
0.6
0.8
1.0




```
LOF (mejor) Precision@1459: 0.9993145990404386
```

Comparación y mejor modelo

In [53]:
```
k = max(1, int(0.01 * len(y_test)))

rows = [
    ("AE (percentil)", ae_pct["F1"], ae_pct["ROC-AUC"], ae_pct["PR-AUC"], precision
    ("AE (F1 tune)",  ae_f1["F1"],  ae_f1["ROC-AUC"],  ae_f1["PR-AUC"],  precision_
    ("Isolation Forest", if_eval["F1"], if_eval["ROC-AUC"], if_eval["PR-AUC"], prec
    ("LOF", lof_eval["F1"], lof_eval["ROC-AUC"], lof_eval["PR-AUC"], precision_at_k
]
df = pd.DataFrame(rows, columns=["Modelo","F1","ROC-AUC","PR-AUC",f"Precision@{k}",
display(df[["Modelo","F1","ROC-AUC","PR-AUC",f"Precision@{k}"]])

# Elegir mejor por F1
best_idx = df["F1"].idxmax()
best_name = df.loc[best_idx, "Modelo"]
best_cm = df.loc[best_idx, "CM"]
print(f"\n>>> MEJOR MODELO (por F1): {best_name}")
print("Matriz de confusión del mejor modelo:\n", best_cm)
```

	Modelo	F1	ROC-AUC	PR-AUC	Precision@1459
0	AE (percentil)	0.342560	0.716768	0.802207	0.991090
1	AE (F1 tune)	0.759176	0.716768	0.802207	0.991090
2	Isolation Forest	0.759176	0.634033	0.728308	0.902673
3	LOF	0.816137	0.888445	0.931850	0.999315

```
>>> MEJOR MODELO (por F1): LOF
Matriz de confusión del mejor modelo:
 [[21609 35055]
 [ 3576 85738]]
```

In [54]:
```python
def plot_cm_heatmap(cm, title):
    plt.figure(figsize=(5,4))
    sns.heatmap(
        cm, annot=True, fmt="d", cmap="crest", cbar=False,
        xticklabels=["Normal", "Anómalo"], yticklabels=["Normal", "Anómalo"]
    )
    plt.title(title)
    plt.xlabel("Predicción")
    plt.ylabel("Valor real")
    plt.tight_layout()
    plt.show()

# Heatmap del mejor modelo
plot_cm_heatmap(best_cm, f"Matriz de confusión · {best_name}")
```