LGBMRegressor

April 7, 2023

0.1 #Introducción

TFM: Aplicación de ciencia de datos en el sector de producción animal para la predicción y explicación de óptimos en ganado porcino.

Titulo: **LGBMRegressor**

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0.2 Importar paquetes

[1]:
```
# Importación de paquetes
import numpy as np
import pandas as pd
import seaborn as sns

import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import matplotlib
from matplotlib.pyplot import figure

from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.datasets import make_regression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler

from sklearn.ensemble import HistGradientBoostingRegressor

sns.set(style="darkgrid")
```

[2]:
```
from google.colab import files
# Cargamos el fichero del dataset gmd_02.csv
uploaded = files.upload()
# Leemos el fichero csv con los datos
df = pd.read_csv('gmd_02.csv', sep=';')
# Revisar la raza si se agrupan las razas con menos ocurrencias
```

```
agrupar_razas = {93 : 93, 85 : 93, 90 : 93, 95 : 93, 94 : 93, 82 : 93, 80 : 80,␣
↪96 : 80, 88 : 88, 0 : 0, 23 : 0,
                 84 : 0, 66 : 0, 18 : 0, 68 : 88, 7 : 7, 89 : 7, 65 : 7, 15 :␣
↪15, 97 : 7, 69 : 69, 81 : 81}
df.replace({'ct_raza' : agrupar_razas}, inplace=True)
df["bajas"] = df["NumBajas"] / (df["NumAnimales"] * df["DiasMedios"])
# Convertimos los tipos
df["ct_integra"] = df["ct_integra"].astype("category")
#df["ct_tipo"] = df["ct_tipo"].astype("category")
df["ct_raza"] = df["ct_raza"].astype("category")
df["ct_fase"] = df["ct_fase"].astype("category")
df['EntradaInicial']= pd.to_datetime(df['EntradaInicial'])
df['EntradaFinal']= pd.to_datetime(df['EntradaFinal'])
df["na_rega"] = df["na_rega"].astype("category")
df["NumBajas"] = df["NumBajas"].astype("int64")
df["gr_codpos"] = df["gr_codpos"].astype("category")
df["gr_poblacion"] = df["gr_poblacion"].astype("category")
df["na_nombre2"] = df["na_nombre2"].astype("category")

# Funcion para convertir en One Hot Encoding
def encode_and_bind(original_dataframe, feature_to_encode):
    dummies = pd.get_dummies(original_dataframe[[feature_to_encode]])
    res = pd.concat([original_dataframe, dummies], axis=1)
    res = res.drop([feature_to_encode], axis=1)
    return(res)
# Cargamos las variables objetivo y las usadas (15 variables seleccionadas, una␣
↪de ellas categórica con 8 valores).
y = df['GMD']
x0 = df[['ct_integra','ct_tipo', 'ct_raza', 'IncPeso', 'NumAnimales', 'na_rega',
         'PesoEntMedio', 'PesoRecMedio', 'bajas', 'GPS_Longitud', 'GPS_Latitud',
         'semanaEntrada', 'añoEntrada', 'PorcHembras', 'PiensoCerdaDia']]
features_to_encode = ['ct_raza']   # , 'na_rega']
x1 = x0.copy()
x1.drop(['ct_integra','na_rega'], inplace=True, axis=1)
for feature in features_to_encode:
    x1 = encode_and_bind(x1, feature)
```

```
<IPython.core.display.HTML object>
```

```
Saving gmd_02.csv to gmd_02.csv
```

[3]:
```
X_train, X_test, y_train, y_test = train_test_split(x1, y, test_size = 0.2,␣
↪random_state = 123)
# Vemos de escalar las variables para que no se vean influenciadas por los␣
↪outliers.
scaler = RobustScaler()
scaler.fit(X_train)
X_train_s = scaler.transform(X_train)
```

```
X_test_s = scaler.transform(X_test)
```

[6]:
```
import lightgbm as lgb

# Definiendo parámetros del Modelo
params = {
    'task': 'train',
    'boosting': 'gbdt',
    'objective': 'regression',
    'num_leaves': 200,
    'learnnig_rage': 0.01,
    'metric': None,
    'verbose': -100
}

# Cargando Datos
lgb_train = lgb.Dataset(X_train_s, y_train, silent=True)
lgb_eval = lgb.Dataset(X_test_s, y_test, reference=lgb_train, silent=True)

# Ajustando el modelo
model = lgb.train(params,
                  train_set=lgb_train,
                  valid_sets=lgb_eval,
                  num_boost_round=20000,
                  early_stopping_rounds=500,
                  verbose_eval=-100)
```

```
/usr/local/lib/python3.9/dist-packages/lightgbm/engine.py:181: UserWarning:
'early_stopping_rounds' argument is deprecated and will be removed in a future
release of LightGBM. Pass 'early_stopping()' callback via 'callbacks' argument
instead.
  _log_warning("'early_stopping_rounds' argument is deprecated and will be
removed in a future release of LightGBM. "
/usr/local/lib/python3.9/dist-packages/lightgbm/engine.py:239: UserWarning:
'verbose_eval' argument is deprecated and will be removed in a future release of
LightGBM. Pass 'log_evaluation()' callback via 'callbacks' argument instead.
  _log_warning("'verbose_eval' argument is deprecated and will be removed in a
future release of LightGBM. "
/usr/local/lib/python3.9/dist-packages/lightgbm/basic.py:1491: UserWarning:
'silent' argument is deprecated and will be removed in a future release of
LightGBM. Pass 'verbose' parameter via 'params' instead.
  _log_warning("'silent' argument is deprecated and will be removed in a future
release of LightGBM. "
```

```
[LightGBM] [Warning] Unknown parameter: learnnig_rage
Training until validation scores don't improve for 500 rounds
Early stopping, best iteration is:
[70]	valid_0's l2: 0.00114773
```

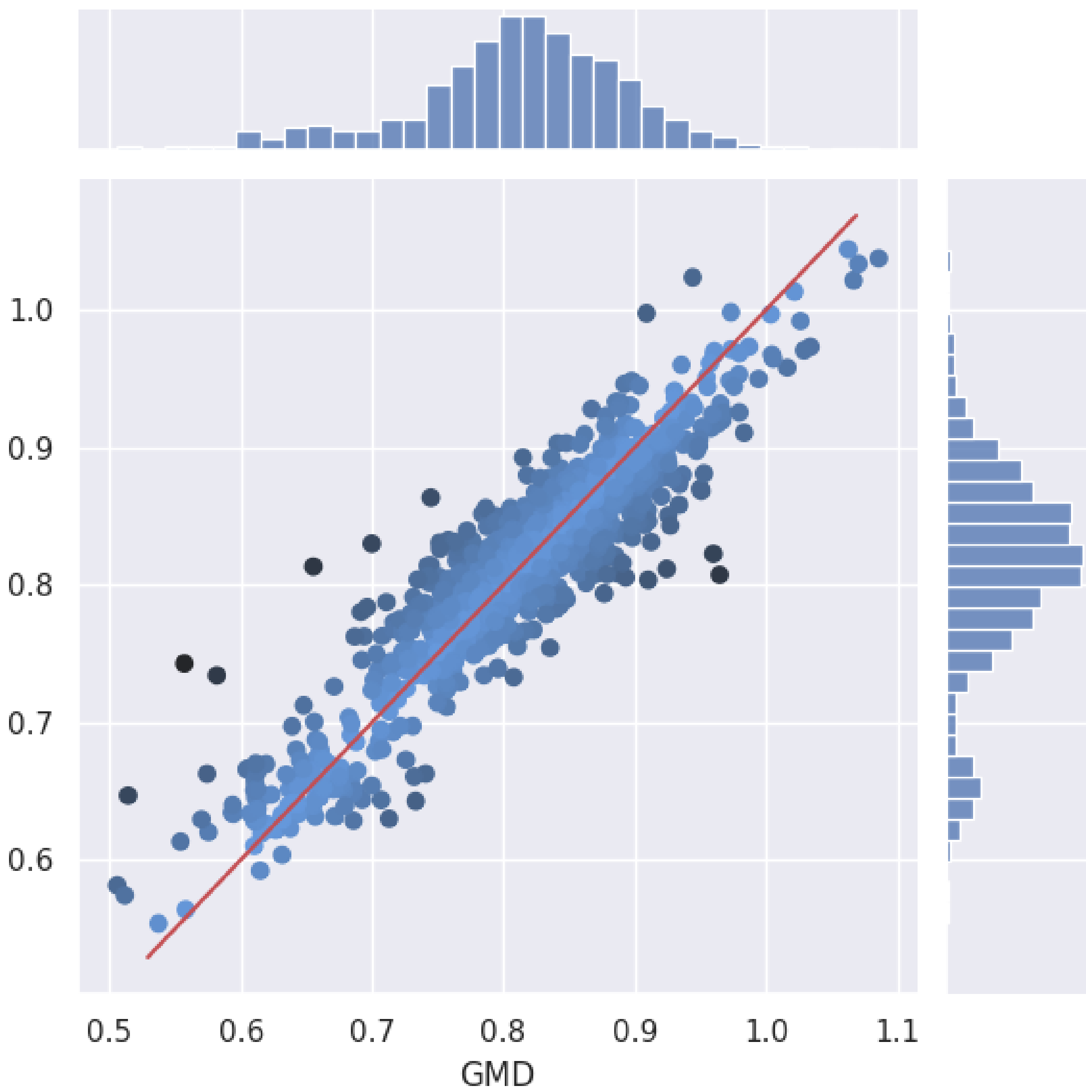
[7]:

```
# Analizamos otros errores del método
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import max_error
y_pred = model.predict(X_test_s)
# Definimos la función con las métricas a mostrar
def mostrar_metricas(y_test, y_pred):
   print("Metr.\t Valor\t\t\t Descripción")
   print("R^2 \t", r2_score(y_test, y_pred), "\t (Coeficiente de␣
 ↪Determinación)")
   print("RMSE\t", mean_squared_error(y_test, y_pred, squared=True), "\t (Raíz␣
 ↪de error cuadrático medio)")
   print("MAE \t", mean_absolute_error(y_test, y_pred), "\t (Error absoluto␣
 ↪medio)")
   print("MAX \t", max_error(y_test, y_pred), "\t (Error Máximo)")
# Pedimos que muestre las métricas para el modelo de RandomForest
print("Métricas para RandomForest v1")
mostrar_metricas(y_test, y_pred)
```

```
Métricas para RandomForest v1
Metr.    Valor                   Descripción
R^2      0.8398283101724142      (Coeficiente de Determinación)
RMSE     0.0011477341160718545   (Raíz de error cuadrático medio)
MAE      0.025661958893514223    (Error absoluto medio)
MAX      0.18576502841184117     (Error Máximo)
```

[8]:

```
# Función para Graficar diferencias entre valor predicho y real en datos de␣
 ↪test del modelo pasado
def graficoDiferencias(modelo, X_test_s, y_test):
    y_pred = modelo.predict(X_test_s)
    diferencia = abs(y_pred - y_test)
    g = sns.jointplot(x=y_test, y=y_pred)
    # Draw a line of x=y
    x0, x1 = g.ax_joint.get_xlim()
    y0, y1 = g.ax_joint.get_ylim()
    lims = [max(x0, y0), min(x1, y1)]
    g.ax_joint.plot(lims, lims, '-r')
    g.ax_joint.scatter(x=y_test, y=y_pred, c=diferencia.values, cmap=sns.
 ↪dark_palette("#69d", reverse=True, as_cmap=True))
    plt.show()

# Graficar las diferencias
modelo = model # rs_cv.best_estimator_
#print('Score R2:',modelo.score(X_test_s, y_test))
graficoDiferencias(modelo, X_test_s, y_test)
```



[9]:
```
### NO DA TIEMPO A TERMINAR ###

### Búscamos los mejores hiperparámetros (no da tiempo a buscar en Colab lo␣
↪hago en local y guardo el mejor modelo)
from sklearn.model_selection import RandomizedSearchCV
import lightgbm as lgb
np.random.seed(0)

rs_params = {
        'task': ['train'],
        'boosting_type': ['gbdt', 'dart', 'rf'],
        'objective': ['regression'],
        'num_leaves': [20, 31, 100, 500, 1000],
```

```
        'learning_rate': [0.001, 0.01, 0.1, 0.2, 0.4],
        'n_estimators': [50, 100, 200, 500, 1000, 1500],
        'num_boost_round': [20000],
        'early_stopping_rounds': [500],
        'verbose': [0]
}

# Initialize a RandomizedSearchCV object using 5-fold CV-
rs_cv = RandomizedSearchCV(estimator=lgb.LGBMRegressor(),␣
 ↪param_distributions=rs_params, cv=3, n_iter=200,␣
 ↪scoring="neg_mean_squared_error", verbose=0, n_jobs=-1)

# Train on training data-
rs_cv.fit(X_train_s, y_train, eval_set=[(X_test_s, y_test)], eval_metric="rmse")
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-9-2ac9745f7f89> in <cell line: 24>()
     22
     23 # Train on training data-
---> 24 rs_cv.fit(X_train_s, y_train, eval_set=[(X_test_s, y_test)],␣
 ↪eval_metric="rmse")

/usr/local/lib/python3.9/dist-packages/sklearn/model_selection/_search.py in␣
 ↪fit(self, X, y, groups, **fit_params)
    872                     return results
    873
--> 874             self._run_search(evaluate_candidates)
    875
    876             # multimetric is determined here because in the case of a␣
 ↪callable

/usr/local/lib/python3.9/dist-packages/sklearn/model_selection/_search.py in␣
 ↪_run_search(self, evaluate_candidates)
   1766     def _run_search(self, evaluate_candidates):
   1767         """Search n_iter candidates from param_distributions"""
-> 1768         evaluate_candidates(
   1769             ParameterSampler(
   1770                 self.param_distributions, self.n_iter, random_state=self.
 ↪random_state

/usr/local/lib/python3.9/dist-packages/sklearn/model_selection/_search.py in␣
 ↪evaluate_candidates(candidate_params, cv, more_results)
    819                         )
    820
```

```
--> 821                 out = parallel(
    822                     delayed(_fit_and_score)(
    823                         clone(base_estimator),

/usr/local/lib/python3.9/dist-packages/sklearn/utils/parallel.py in␣
 ↪__call__(self, iterable)
     61             for delayed_func, args, kwargs in iterable
     62         )
---> 63         return super().__call__(iterable_with_config)
     64 
     65 

/usr/local/lib/python3.9/dist-packages/joblib/parallel.py in __call__(self,␣
 ↪iterable)
   1059 
   1060             with self._backend.retrieval_context():
-> 1061                 self.retrieve()
   1062             # Make sure that we get a last message telling us we are done
   1063             elapsed_time = time.time() - self._start_time

/usr/local/lib/python3.9/dist-packages/joblib/parallel.py in retrieve(self)
    936             try:
    937                 if getattr(self._backend, 'supports_timeout', False):
--> 938                     self._output.extend(job.get(timeout=self.timeout))
    939                 else:
    940                     self._output.extend(job.get())

/usr/local/lib/python3.9/dist-packages/joblib/_parallel_backends.py in␣
 ↪wrap_future_result(future, timeout)
    540         AsyncResults.get from multiprocessing."""
    541         try:
--> 542             return future.result(timeout=timeout)
    543         except CfTimeoutError as e:
    544             raise TimeoutError from e

/usr/lib/python3.9/concurrent/futures/_base.py in result(self, timeout)
    439                     return self.__get_result()
    440 
--> 441                 self._condition.wait(timeout)
    442 
    443                 if self._state in [CANCELLED, CANCELLED_AND_NOTIFIED]:

/usr/lib/python3.9/threading.py in wait(self, timeout)
    310         try:    # restore state no matter what (e.g., KeyboardInterrupt
    311             if timeout is None:
--> 312                 waiter.acquire()
    313                 gotit = True
```

```
    314             else:

KeyboardInterrupt:
```

Como en Colab tardaba mucho y terminaba abortando el proceso, decido hacerlo en mi PC local y guardar el mejor modelo obtenid con un R2=85%. Ahora veo de replicar los parámetros de ese mejor modelo bajo la optimización de hiperparámetros escogida y de entrenarlo en este cuaderno con aún más iteraciones.

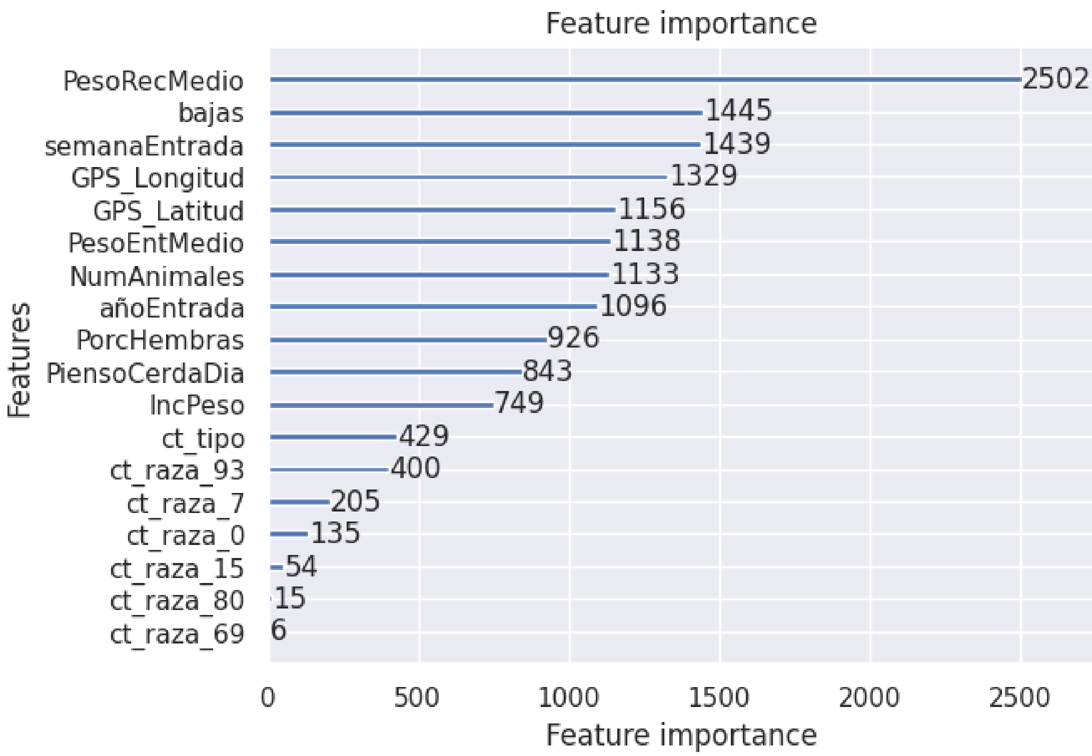
[50]:

```
# Definiendo parámetros del Modelo
params = {
    'task': 'train',
    'boosting': 'dart',
    'objective': 'regression',
    'num_leaves': 31,
    'learnnig_rate': 0.4,
    'metric': 'rmse',
    'n_estimators': 500,
    'verbose': -100
}

# Cargando Datos
lgb_train = lgb.Dataset(X_train_s, y_train, silent=True)
lgb_eval = lgb.Dataset(X_test_s, y_test, reference=lgb_train, silent=True)

# Ajustando el modelo
model = lgb.train(params,
                  train_set=lgb_train,
                  valid_sets=lgb_eval,
                  num_boost_round=20000,
                  verbose_eval=-100,
                  feature_name=list(x1.columns))
y_pred = model.predict(X_test_s)
mostrar_metricas(y_test, y_pred)
```

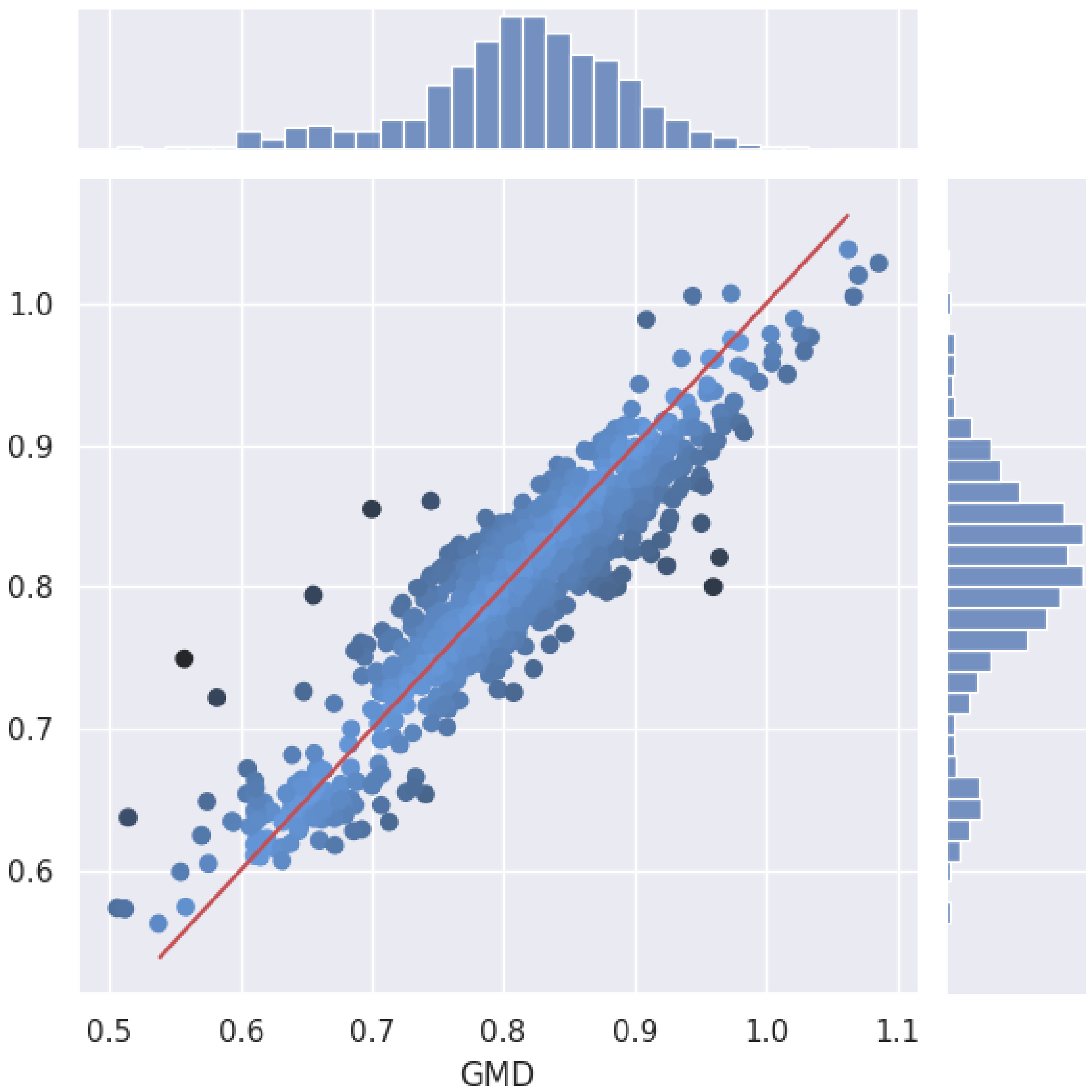
```
/usr/local/lib/python3.9/dist-packages/lightgbm/engine.py:177: UserWarning:
Found `n_estimators` in params. Will use it instead of argument
  _log_warning(f"Found `{alias}` in params. Will use it instead of argument")
/usr/local/lib/python3.9/dist-packages/lightgbm/engine.py:239: UserWarning:
'verbose_eval' argument is deprecated and will be removed in a future release of
LightGBM. Pass 'log_evaluation()' callback via 'callbacks' argument instead.
  _log_warning("'verbose_eval' argument is deprecated and will be removed in a
future release of LightGBM. "
/usr/local/lib/python3.9/dist-packages/lightgbm/basic.py:1491: UserWarning:
'silent' argument is deprecated and will be removed in a future release of
LightGBM. Pass 'verbose' parameter via 'params' instead.
  _log_warning("'silent' argument is deprecated and will be removed in a future
release of LightGBM. "
```

```
[LightGBM] [Warning] Unknown parameter: learnnig_rate
Metr.    Valor                   Descripción
R^2      0.8417945814651489      (Coeficiente de Determinación)
RMSE     0.001133644506063036    (Raíz de error cuadrático medio)
MAE      0.025451588780438125    (Error absoluto medio)
MAX      0.1922229409128967      (Error Máximo)
```

[52]:
```
lgb.plot_importance(model)
plt.show()
```



[53]:
```
graficoDiferencias(model, X_test_s, y_test)
```



[36]:
```
y_pred = model.predict(X_test_s)
mostrar_metricas(y_test, y_pred)
```

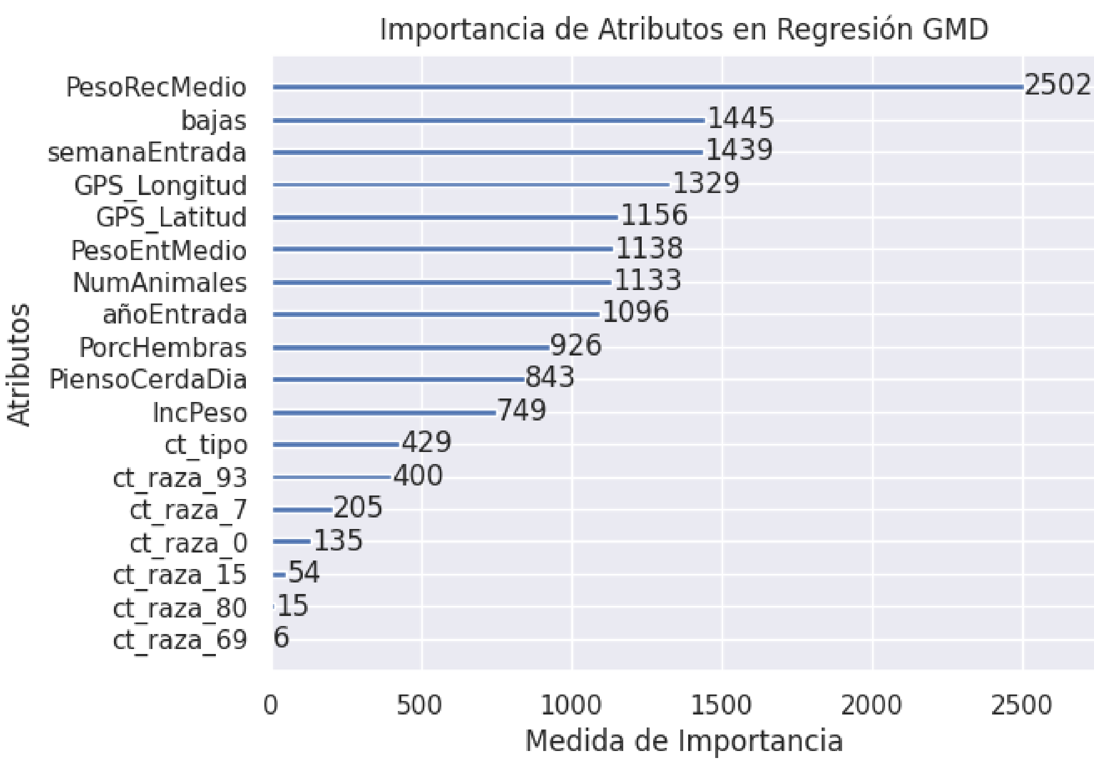
```
Metr.    Valor                   Descripción
R^2      0.8417945814651489      (Coeficiente de Determinación)
RMSE     0.001133644506063036    (Raíz de error cuadrático medio)
MAE      0.025451588780438125    (Error absoluto medio)
MAX      0.1922229409128967      (Error Máximo)
```

1 Cargamos el modelo optimizado anteriormente

[54]:
```
# Cargamos el fichero del modelo lightgbm.model.txt
uploaded = files.upload()
model2 = lgb.Booster(model_file='lightgbm.model.txt')

y_pred = model2.predict(X_test_s)
mostrar_metricas(y_test, y_pred)
```

```
<IPython.core.display.HTML object>

Saving lightgbm.model.txt to lightgbm.model.txt
Metr.    Valor                    Descripción
R^2      0.8506920300138257       (Coeficiente de Determinación)
RMSE     0.0010698885123771175    (Raíz de error cuadrático medio)
MAE      0.024500069116363023     (Error absoluto medio)
MAX      0.1980376163023514       (Error Máximo)
```

[56]:
```
lgb.plot_importance(model)
plt.title('Importancia de Atributos en Regresión GMD')
plt.ylabel('Atributos')
plt.xlabel('Medida de Importancia')
plt.show()
```



[57]:
```
graficoDiferencias(model2, X_test_s, y_test)
```