A01633376

Modelos de Regresión

```
[2] import csv
import numpy as np
             import numpy as np
import matplotlib.pyplot as plt
from sklearn import linear_model
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.feature_selection import SelectKBest, r_regression
from sklearn.feature_selection import SequentialFeatureSelector, RFE
             from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neural_network import MLPRegressor
              from sklearn.svm import SVR
    [3] # Archivo CSV
    csv_file = 'parkinsons_updrs.data'
             exclude_columns = ['subject#']
exclude_independent = ['subject#', 'total_UPDRS', 'Jitter(%)', 'Jitter:DDP', 'Shimmer:APQ5', 'HNR']
             with open(csv_file, mode='r') as file:
    csv_reader = csv.DictReader(file)
                     columns = [column for column in csv_reader.fieldnames if column not in exclude_columns]
independent = [column for column in csv_reader.fieldnames if column not in exclude_independent]
dependent = 'total_UPDRS'
                     data = {column: [] for column in independent}
total_UPDRS = []
                              for column in independent:
    if row[column]:
        data[column].append(float(row[column]))
                                           data[column].append(None)
                           if row[dependent]:
    total_UPDRS.append(float(row[dependent]))
             X = np.array([data[column] for column in independent]).T
y = np.array(total_UPDRS)
os [17] def filter_method(X, y, feature_names, k=5):
fselection = SelectKBest(r_regression, k=k)
                     rectaction - selection estimates and, and fished constitutions, selected features = fselection.get_support() selected_feature_names = np.array(independent)[fselection.get_support()] return selected_features, selected_feature_names
    [6] def wrapper_method(X, y, model, feature_names, n_features_to_select='auto', direction='forward'):
sfs = SequentialFeatureSelector(model, n_features_to_select=n_features_to_select, direction=direction, cv=5)
                     sfs.fit(X, y)
selected_features = sfs.get_support()
                     selected_feature_names = np.array(independent)[sfs.get_support()]
return selected_features, selected_feature_names
    selected_features = rfe.get_support()
selected_feature_names = np.array(independent)[rfe.support_]
return selected_features, selected_feature_names
```

```
[8] # Función para evaluar el rendimiento del modelo usando validación cruzada
def evaluate_model(X, y, selected_features, model):
    X_selected = X[:, selected_features]
    kf = KFold(n_splits=S, shuffle=True)

    mse_cv = []
    mae_cv = []
    for train_index, test_index in kf.split(X_selected):
        X_train, X_test = X_selected[frain_index], X_selected[test_index]
        y_train, y_test = y[train_index], y[test_index]

    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    mse_cv.append(mean_squared_error(y_test, y_pred))
    mse_cv.append(mean_sbsolute_error(y_test, y_pred))
    r2_cv.append(r2_score(y_test, y_pred))

    return np.mean(mse_cv), np.mean(mae_cv), np.mean(r2_cv)
```

```
[9] def evaluate_with_optimal_features(X, y, selected_features, model):
    X_selected = X[:, selected_features]
    model.fit(X_selected, y)
    y_pred = model.predict(X_selected)

    mse = mean_squared_error(y, y_pred)
    mae = mean_absolute_error(y, y_pred)
    r2 = r2_score(y, y_pred)
    return mse, mae, r2
```

```
print('\middelo Regresión Lineal')
model = linear_model.LinearRegression()

# Método Filter

# Método Filter

# Método Filter

# Primera evaluación

ms. filter, selected_feature_names_filter = filter_method(X, y, feature_names=independent, k=5)

# Primera evaluación

ms. filter, mac_filter, p2_filter = evaluate_model(X, y, selected_features_filter)

# Segunda evaluación

ms. filter, method - MSE: (ses_filter), MAE: (mes_filter), RP: (r2_filter)")

# Segunda evaluación

ms. filter.opt, me_filter_opt, r2_filter_opt = evaluate_with_optimal_features(X, y, selected_features_filter, model)

print("OptimalFeatures MSE: (mse_filter_opt, PAE: (mee_filter_opt), RP: (r2_filter_opt)")

# Método Mrapper

# Primera evaluación

ms. wrapper, mea_urapper, p2_wrapper = evaluate_model(X, y, selected_features_wrapper, nodel)

print("Metodo Mrapper")

# Primera evaluación

mse_wrapper, mea_urapper, r2_wrapper = evaluate_model(X, y, selected_features_wrapper, model)

print("Mrapper Method - MSE: (mse_wrapper), MAE: (mse_wrapper), RP: (r2_wrapper)")

# Segunda evaluación usando las canarcterístics optimas seleccionadas

mse_wrapper_opt, mse_wrapper_opt, r2_wrapper_opt = evaluate_with_optimal_features(X, y, selected_features_wrapper, model)

print("Optimal Features MSE: (mse_wrapper, opt), NAE: (mse_wrapper_opt), RP: (r2_wrapper_opt)")

# Método Recursivo

# Primera evaluación

print("Neteodo Recursivo")

# Método Recursivo

# Primera evaluación usando las canarcterístics optimas selectionadas

mse_wrapper_opt, mse_wrapper_opt, r2_wrapper_opt), valected_feature_names_recursive)

# Primera evaluación usando las canarcterístics optimas selectionadas

mse_mercursive, mse_recursive, p2_recursive = evaluate_model(X, y, selected_features_recursive, model)

## primera evaluación usando las canarcterístics optimas selectionadas

mse_recursive, mse_recursive, mse_recursive, optimas l_features_recursive, model)

## primt("Netecdo Recursivo")

## Segunda evaluación usando las canarcterístics optimas selectionadas

mse_recursive_opt, mse_recursiv
```

```
Metodo Filter
Predictores óptimos (Filter): ['age' 'motor_UPDRS' 'Shimmer:APQ11' 'RPDE' 'PPE']
Filter Method - MSE: 11.203078880535486, MAE: 2.450747170700032, R^2: 0.9019909862716391
OptimalFeatures MSE: 11.184730607028982, MAE: 2.448218768411101, R^2: 0.9022967729109506

Metodo Wrapper
Predictores óptimos (Wrapper): ['sex' 'test_time' 'motor_UPDRS' 'Jitter:RAP' 'Shimmer:DDA']
Wrapper Method - MSE: 11.256079556683371, MAE: 2.4331868990162913, R^2: 0.9015480041789216
Optimal Features MSE: 11.234534606172055, MAE: 2.4331868990162913, R^2: 0.9018617144719784

Metodo Recursivo
Predictores óptimos (Recursivo): ['Jitter(Abs)' 'Jitter:RAP' 'Jitter:PPQ5' 'Shimmer:APQ3' 'Shimmer:DDA']
Recursive Method - MSE: 113.87364772968245, MAE: 8.643033954527201, R^2: 0.005023989680104046
Optimal Features - MSE: 113.69703636743088, MAE: 8.63390328026619, R^2: 0.0050839573350126774
```

```
Modelo DecisionTree

Metodo Filter
Predictores óptimos (Filter): ['age' 'motor_UPDRS' 'Shimmer:APQ11' 'RPDE' 'PPE']
Filter Method - MSE: 1.1286488519829787, MAE: 0.35511302127659583, R^2: 0.9901153673338328
OptimalFeatures MSE: 2.3441589248252635e-30, MAE: 4.456765925576118e-16, R^2: 1.0

Metodo Wrapper
Predictores óptimos (Wrapper): ['sex' 'test_time' 'motor_UPDRS' 'Jitter:PPO5' 'Shimmer']
Wrapper Method - MSE: 2.076702392771064, MAE: 0.3123425191489363, R^2: 0.9818483809640629
Optimal Features MSE: 2.7656456280573923e-30, MAE: 5.14160817940447e-16, R^2: 1.0

Metodo Recursivo
Predictores óptimos (Recursivo): ['age' 'sex' 'test_time' 'motor_UPDRS' 'DFA']
Recursive Method - MSE: 0.1498962853940426, MAE: 0.0417515304255320444, R^2: 0.998690459275543
Optimal Features - MSE: 3.358466206193693e-30, MAE: 6.391861035731285e-16, R^2: 1.0
```

```
print("\mModelo RandomForest")
model = RandomForestRegressor(n_estimators=100)

# Método Filter

print("\mModelo filter")
selected_features_filter, selected_feature_names_filter = filter_method(X, y, feature_names=independent, k=5)
print("Predictores optimos (Filter):", selected_feature_names_filter)
# Primera evaluación

me_filter, me_filter, pr.g.filter = evaluate_model(X, y, selected_features_filter, model)
print("Filter Nethod - MSE: (mse_filter), MSE: (mse_filter), RYE: (fr2_filter)")
# Segunda evaluación usando las caracteriaticas optimas seleccionadas

mse_filter, pot, mse_filter_opt, r2_filter opt = evaluate_with_optimal_features(X, y, selected_features_filter, model)
print(f'OptimalFeatures MSE: (mse_filter_opt), MAE: (mse_filter_opt), RYE: (r2_filter)")

# Método Minapper
print("\mMetodo Minapper")
selected_features_wrapper, selected_feature_names_wrapper = wrapper_method(X, y, model, feature_names=independent, n_features_to_select=5)
print("Predictores optimos ((Mrapper"); selected_feature_names_wrapper)
# Primera evaluación
mse_wrapper, me_wrapper_opt_wrapper_opt_select=0.

mse_wrapper_opt, mse_wrapper_opt, r2_wrapper_opt = evaluate_with_optimal_features(X, y, selected_features_wrapper, model)
print("f'optimal Features MSE: (mse_wrapper_opt = evaluate_with_optimal_features(X, y, selected_features_wrapper, model)
print("Optimal Features MSE: (mse_wrapper_opt, MAE: (mse_wrapper_opt), RYE: (r2_wrapper_opt)")

# Metodo Recursivo
print("Netodo Recursivo")
selected_feature_names_recursive = recursive_method(X, y, model, feature_names=independent, n_features_to_select=5)
print("Optimal Features MSE: (mse_wrapper_opt), RYE: (mse_wrapper_opt), RYE: (r2_wrapper_opt)")

# Metodo Recursivo
print("Netodo Recursivo")
selected_feature_names_recursive = recursive_method(X, y, model, feature_names=independent, n_features_to_select=5)
print("Predictores optimos (Recursivo):", selected_feature_names_recursive)
# Primera evaluación
mse_recursive, mse_recursive_opt, r2_recursive_opt = evaluate_with_optimal_features(X, y
```

```
Modelo RandomForest
           Predictores óptimos (Filter): ['age' 'motor_UPDRS' 'Shimmer:APQ11' 'RPDE' 'PPE']
Filter Method - MSE: 0.6837927679891348, MAE: 0.450980964425532, R^2: 0.9940189035296536
OptimalFeatures MSE: 0.07672788389307474, MAE: 0.139107479659575, R^2: 0.9993297503420103
           Predictores óptimos (Wrapper): ['motor_UPDRS' 'Jitter(Abs)' 'Jitter:PPQ5' 'RPDE' 'DFA']
Wrapper Method - MSE: 3.759719358458436, MAE: 1.232757962842553, R^2: 0.9670870819155404
Optimal Features MSE: 0.48379026732291197, MAE: 0.43083481072340435, R^2: 0.9957738928175868
            Metodo Recursivo
Predictores óptimos (Recursivo): ['age' 'sex' 'test_time' 'motor_UPDRS' 'DFA']
Recursive Method - MSE: 0.04868141092181374, MAE: 0.0827340350638309, R^2: 0.9995752638230542
Optimal Features - MSE: 0.0047230285202215375, MAE: 0.02021453106383698, R^2: 0.9999587424012011
/<sub>7m</sub> [16]
                           model = SVR(kernel='rbf')
                         selected_features_filter, selected_feature_names_filter = filter_method(X, y, feature_names=independent, k=5) print("Predictores óptimos (Filter):", selected_feature_names_filter)
                         # Primera evaluation
mse_filter, mae_filter, r2_filter = evaluate_model(X, y, selected_features_filter, model)
print(f"Filter Method - MSE: {mse_filter}, MAE: {mse_filter}, R02: {r2_filter}")
# Segunda evaluación usando las características óptimas seleccionadas
mse_filter_opt, mse_filter_opt, r2_filter_opt = evaluate_with_optimal_features(X, y, selected_features_filter, model)
print(f"OptimalFeatures MSE: {mse_filter_opt}, MAE: {mse_filter_opt}, R^2: {r2_filter_opt}")
                         selected_features_wrapper, selected_feature_names_wrapper = wrapper_method(X, y, model, feature_names=independent, n_features_to_select=5)
print("Predictores óptimos (Wrapper):", selected_feature_names_wrapper)
                         mse_wrapper, mae_wrapper, r2_wrapper = evaluate_model(X, y, selected_features_wrapper, model)
print(f"Wrapper Method - MSE: {mse_wrapper}, MAE: {mse_wrapper}, R^2: {r2_wrapper}")
# Segunda evaluación usando las características óptimas seleccionadas
                         mse_wrapper_opt, mae_wrapper_opt, r2_wrapper_opt = evaluate_with_optimal_features(X, y, selected_features_wrapper, model)
print(f"Optimal Features MSE: {mse_wrapper_opt}, MAE: {mae_wrapper_opt}, R^2: {r2_wrapper_opt}")
               Modelo Support Vector Machines
                Predictores óptimos (Filter): ['agg' 'motor_UPDRS' 'Shimmer:APQ11' 'RPDE' 'PPE']
Filter Method - MSE: 12.095384238076184, MAE: 2.4768780492418285, R^2: 0.894408597520804
OptimalFeatures MSE: 12.068029169584687, MAE: 2.472023613334542, R^2: 0.8945807962748593
               Metodo Wrapper
Predictores óptimos (Wrapper): ['sex' 'motor_UPDRS' 'RPDE' 'DFA' 'PPE']
Wrapper Method - MSE: 11.221245214310715, MAE: 2.3698793498035, R^2: 0.9020594606139847
Optimal Features MSE: 11.089456849694683, MAE: 2.351285224844805, R^2: 0.9031290284095864
                           print("\nModelo NeuralNetwork Regressor")
                                                                                                                                                                                                                                                                                                                            ↑ ↓ ⊖ 🗏 ‡ 🗓 🗓 :
        0
                            model = MLPRegressor(hidden_layer_sizes=(1000,), max_iter=10000)
                           # Método Filter
print("\nMetodo Filter")
                           selected_features_filter, selected_feature_names_filter = filter_method(X, y, feature_names=independent, k=5) print("Predictores óptimos (Filter):", selected_feature_names_filter)
                          # MPIMERA eValuacion
mse_filter, mae_filter, r2_filter = evaluate_model(X, y, selected_features_filter, model)
print(f"filter Method - MSE: {mse_filter}, MAE: {mse_filter}, R^2: {r2_filter}")
# Segunda evaluación usando las características óptimas seleccionadas
mse_filter_opt, mse_filter_opt, r2_filter_opt = evaluate_with_optimal_features(X, y, selected_features_filter, model)
print(f"OptimalFeatures MSE: {mse_filter_opt}, MAE: {mse_filter_opt}, R^2: {r2_filter_opt}")
                           print("\nMetodo Wrapper")
                           selected_features_wrapper, selected_feature_names_wrapper = wrapper_method(X, y, model, feature_names=independent, n_features_to_select=5)
print("Predictores óptimos (Wrapper):", selected_feature_names_wrapper)
                           mse_wrapper, mae_wrapper, r2_wrapper = evaluate_model(X, y, selected_features_wrapper, model)
print(f"Wrapper Method - MSE: {mse_wrapper}, MAE: {mae_wrapper}, R^2: {r2_wrapper}")
# Segunda evaluación usando las características óptimas seleccionadas
                           mse_wrapper_opt, mae_wrapper_opt, r2_wrapper_opt = evaluate_with_optimal_features(X, y, selected_features_wrapper, model)
print(f"Optimal Features MSE: {mse_wrapper_opt}, MAE: {mae_wrapper_opt}, R^2: {r2_wrapper_opt}")
                           # Método Recursivo
print("\nMetodo Recursivo")
                           selected_features_recursive, selected_feature_names_recursive = recursive_method(X, y, model, feature_names=independent, n_features_to_select=5)
print("Predictores óptimos (Recursivo):", selected_feature_names_recursive)
                           mse_recursive, mae_recursive, r2_recursive = evaluate_model(X, y, selected_features_recursive, model)
print(f"Recursive Method - MSE: {mse_recursive}, MAE: {mae_recursive}, R^2: {r2_recursive}")
# Segunda evaluación usando las características óptimas seleccionadas
```

mse_recursive_opt, mae_recursive_opt, r2_recursive_opt = evaluate_with_optimal_features(X, y, selected_features_recursive, model)
print(f"Optimal Features - MSE: {mse_recursive_opt}, MAE: {mae_recursive_opt}, R^2: {r2_recursive_opt}")

```
Metodo Filter
Predictores óptimos (Filter): ['age' 'motor_UPDRS' 'Shimmer:APQ11' 'RPDE' 'PPE']
Filter Method - MSE: 11.513498629847252, MAE: 2.485760263472933, R^2: 0.8993740500559412
OptimalFeatures MSE: 10.775593719326158, MAE: 2.4392900012722083, R^2: 0.9058707520843617
```

Consideras que el modelo de regresión lineal es adecuado para los datos. ¿Por qué?

El mejor R^2 obtenido con regresión lineal fue el de Filter, con 0.9022, ya ajustando el modelo con las optimal features. Este en mi opinión es un resultado aceptable, sin embargo con un valor de 11.18 para el MMSE, y 2.45 de MAE, está lejos de ser el mejor modelo para los datos.

2. ¿Qué método de selección de características consideras que funciona bien con los datos? ¿Por qué?

El método de RandomForest (Recursivo) dio uno de los mejores resultados con un MSE de 0.004 y un MAE de 0.02.

Sin embargo el método de DecisionTree (Recursivo) fue el que ha dado los mejores resultados con valores de MSE y MAE elevados a la -30 y -16 respectivamente, dando por mucho el mejor margen de error, y r cuadrada.

3. Del proceso de selección de características, ¿puedes identificar algunas que sean sobresalientes? ¿Qué información relevantes observas de dichas características?

De las características seleccionadas, age, sex y test_time fueron las que más se repitieron, con Shimmer:APQ11, motor_UPDRS y PPE repitiendose menos pero de igual manera aparecieron en varios modelos. Lo cual me hace pensar que son las más importantes en ese orden.

4. ¿Los modelos de regresión no lineal funcionaron mejor que el lineal? ¿Por qué?

En este caso nuestro conjunto de datos probablemente tiene relaciones entre varias variables, por lo que un modelo lineal no es lo suficientemente preciso.

5. ¿Se puede concluir algo interesante sobre los resultados de modelar estos datos con regresión?

Todo apunta a que la regresión lineal no es un buen candidato para realizar el análisis de nuestros datos. Las redes neuronales, siendo el último modelo que probé, requieren de un tiempo de procesamiento exagerado y al menos con parametros de hidden_layer_sizes=(1000) y max_iter=10000 no ofrece una buena predicción a comparación de modelos como random forest y decision tree.