Descripción del proyecto

La compañía Sweet Lift Taxi ha recopilado datos históricos sobre pedidos de taxis en los aeropuertos. Para atraer a más conductores durante las horas pico, necesitamos predecir la cantidad de pedidos de taxis para la próxima hora. Construye un modelo para dicha predicción.

La métrica RECM en el conjunto de prueba no debe ser superior a 48.

Indice

Introducción

En el presente proyecto se realizara un analisis de los datos de una compañia de servicios de transporte (taxis), para que se realizara una limpieza, busqueda de tendencias entre otras metricas.

La finalidad del proyecto es entrenar un modelo que de una metrica RECM menor a 48.

En este proyecto se utilizan Regresiones lineales, Bosque Aleatorio, XGBoost, CatBoost LGBMregression.

```
# Manipulación de datos
import pandas as pd
import numpy as np
from statsmodels.tsa.seasonal import seasonal_decompose

# Visualización
import matplotlib.pyplot as plt
import plotly.express as px

# Modelado
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from lightgbm import LGBMRegressor
from sklearn.preprocessing import MaxAbsScaler
from xgboost import XGBRegressor
from catboost import CatBoostRegressor
from sklearn.model_selection import RandomizedSearchCV
```

```
# Evaluación del rendimiento
from sklearn.metrics import mean_squared_error

# Desactivación de advertencias
import warnings
warnings.filterwarnings("ignore")
```

Preparación de datos

```
# Carga del dataset
df =  pd.read_csv('taxi.csv', index_col=[0], parse_dates=[0])
```

```
df = df.resample('H').sum()
```

```
df.head()
```

	num_orders
datetime	
2018-03-01 00:00:00	124
2018-03-01 01:00:00	85
2018-03-01 02:00:00	71
2018-03-01 03:00:00	66
2018-03-01 04:00:00	43

Los datos se muestran cada 10 minutos, junto con el número de ordenes en esa temporalidad, originalmente, en el anterior codigo, se hizo un resample para que este el numero de ordenes por horas.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 4416 entries, 2018-03-01 00:00:00 to 2018-08-31 23:00:00
Freq: h
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   num_orders  4416 non-null   int64
dtypes: int64(1)
memory usage: 69.0 KB
```

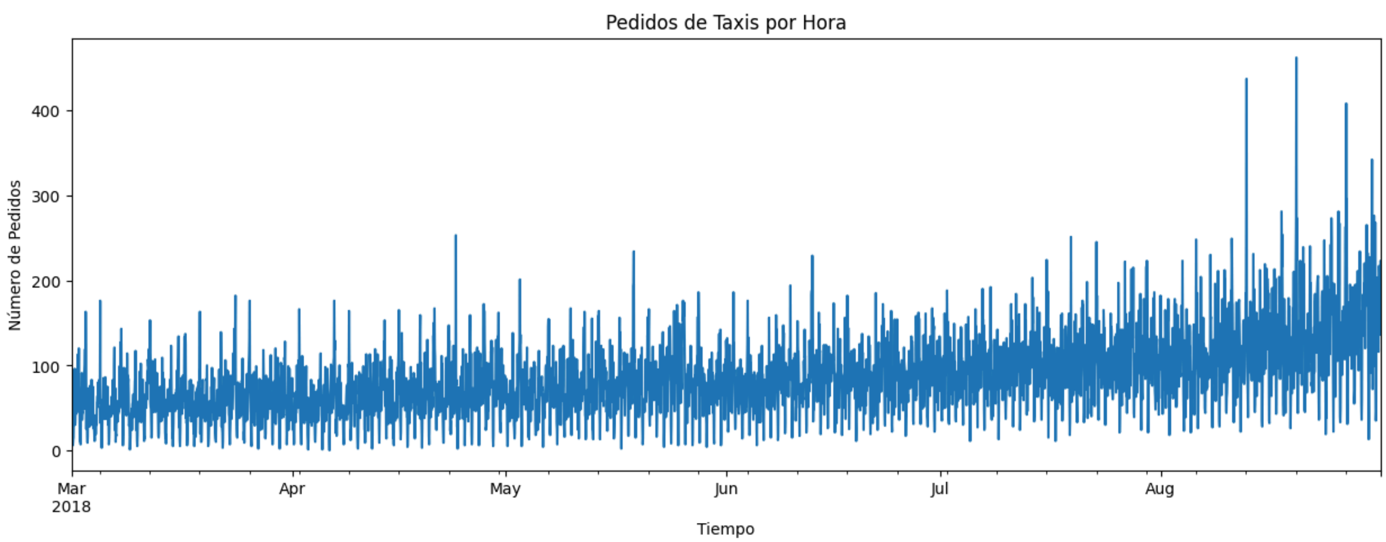
Veo en general datos limpios, hay que cambiar la columna datetime a tipo date para que sea compatible con la libreria pandas para la manipulación por zonas temporales, esto ya se hizo prevaiemente al cargar el dataset

```
df.describe()
```

	num_orders
count	4416.000000
mean	84.422781
std	45.023853
min	0.000000
25%	54.000000
50%	78.000000
75%	107.000000
max	462.000000

Se observan algunos datos bastante grandes, el 75% de los datos se encuentran por de bajo de 19 ordenes y la media es de 14 ordenes por cada 10 minutos

```
# Graficar la serie temporal de pedidos por hora
df['num_orders'].plot(figsize=(15, 5), title='Pedidos de Taxis por Hora')
plt.xlabel('Tiempo')
plt.ylabel('Número de Pedidos')
plt.show()
```



Como se observa en el anterior grafico vemos que la tendencia desde marzo Dciembre esta en aumento

```
min_date = df.index.min()

max_date = df.index.max()

print(min_date)
print(max_date)
```

```
2018-03-01 00:00:00
2018-08-31 23:00:00
```

```python
decomposed = seasonal_decompose(df['num_orders'], model='additive')

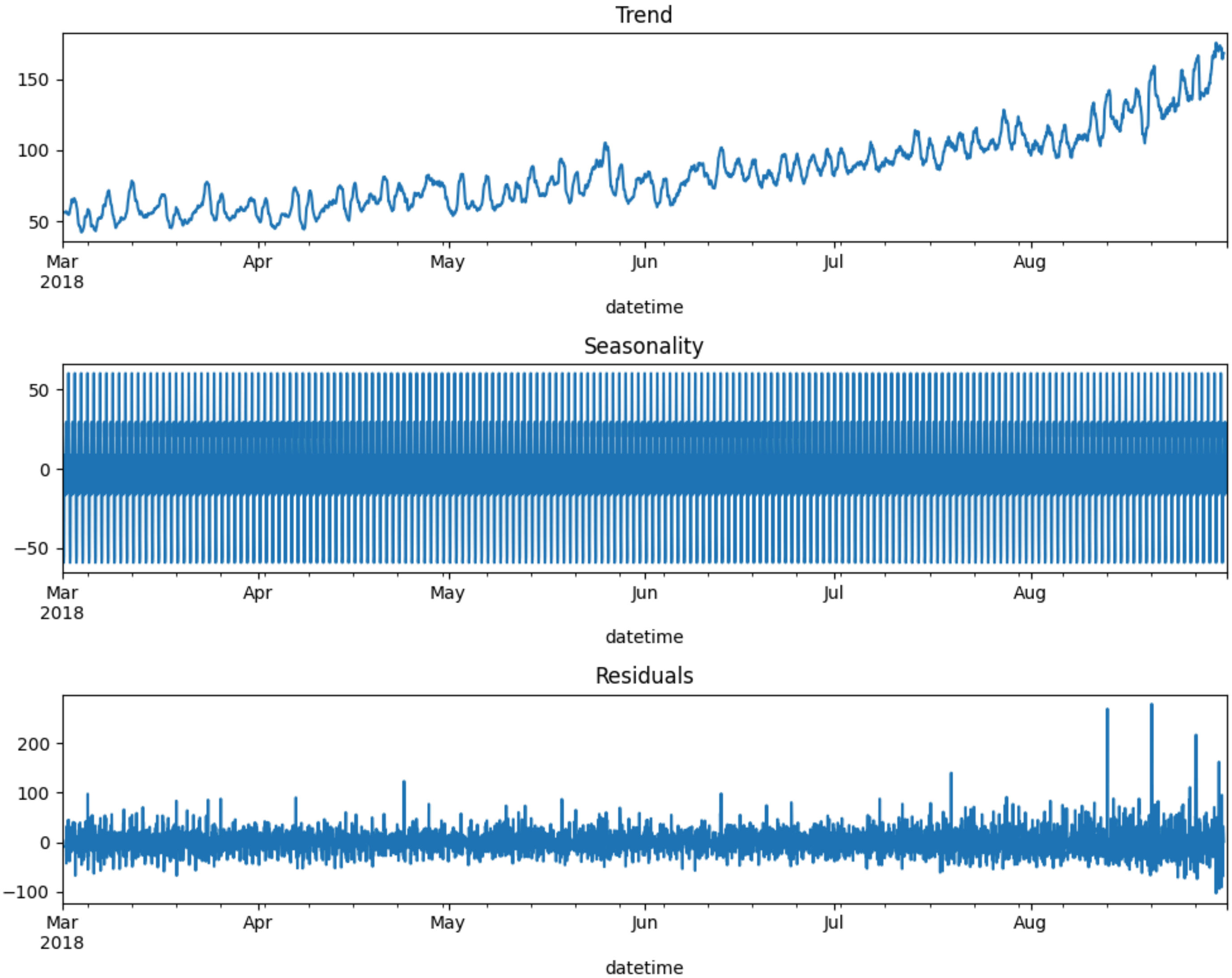
# Graficar las componentes
plt.figure(figsize=(10, 8))

# Tendencia
plt.subplot(311)
decomposed.trend.plot(ax=plt.gca())
plt.title('Trend')

# Estacionalidad
plt.subplot(312)
decomposed.seasonal.plot(ax=plt.gca())
plt.title('Seasonality')

# Residuos
plt.subplot(313)
decomposed.resid.plot(ax=plt.gca())
plt.title('Residuals')

plt.tight_layout()
plt.show()
```



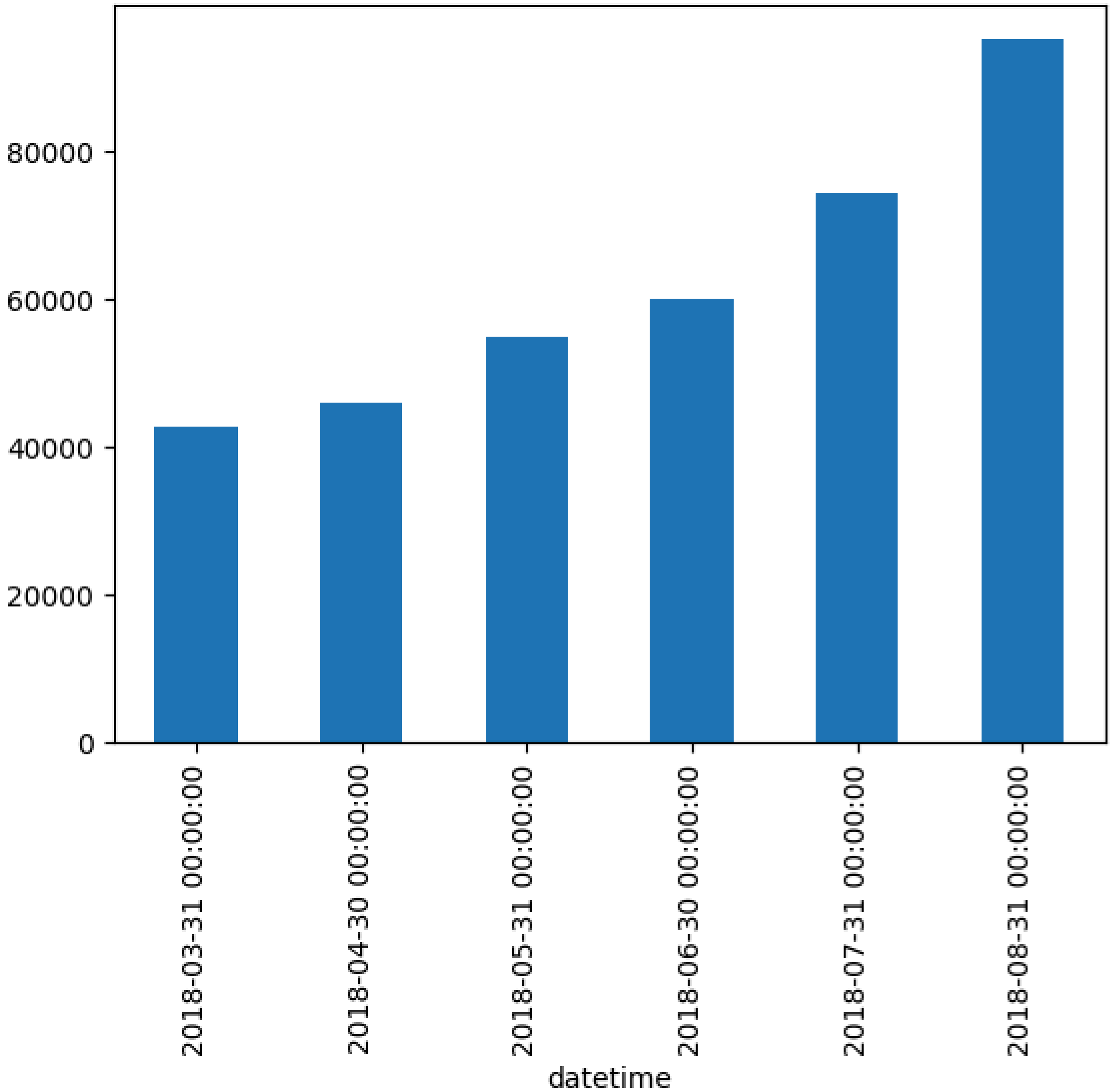
Por lo que se puede observar en los graficos anteriores existe una tendencia alcista del numero de pedidos del servicio de taxis haciendo esta descomposición con seasonal_descompose.

Además vemos que se muestra un patron regular, por lo tanto la estacionalidad es evidente.

A continuación analizare los pedidos del servicio por mes

```
volume_per_month = df['num_orders'].resample('M').sum()

volume_per_month.plot(kind='bar')
```



En efecto se denota una tencia al alza desde el comienzo de los datos a finales de marzo hasta finales de Agosto

A continuación observare el número dee pedidos por día de la semana.

```
import pandas as pd
import matplotlib.pyplot as plt


df_dayofweek = df.copy()
df_dayofweek['dayofweek'] = df.index.dayofweek

# Agrupar los pedidos por día de la semana
volume_per_dayofweek = df_dayofweek.groupby('dayofweek')['num_orders'].sum().reset_index()

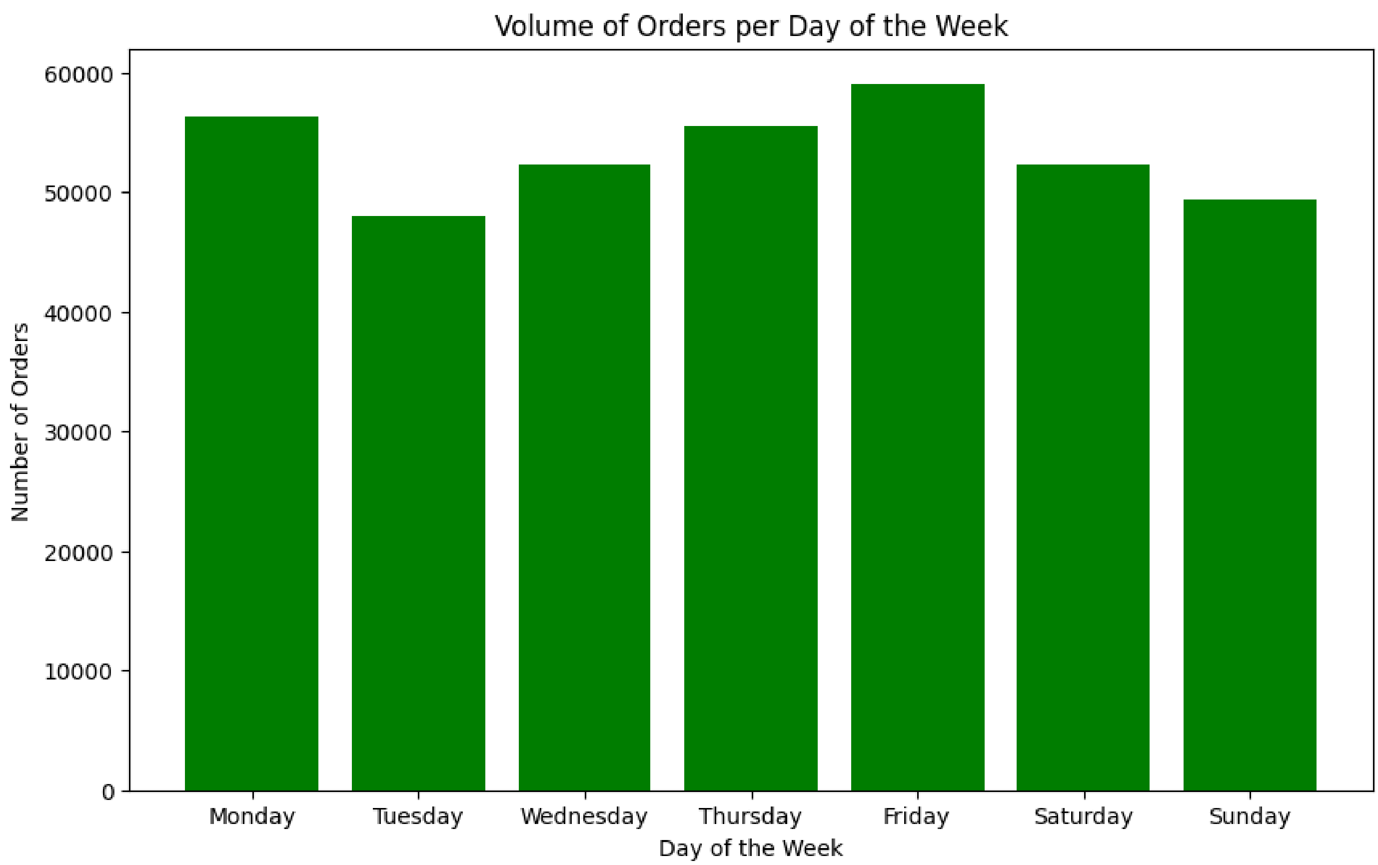

plt.figure(figsize=(10, 6))
plt.bar(volume_per_dayofweek['dayofweek'], volume_per_dayofweek['num_orders'], color='green')

# Configurar los ejes x
```

```
plt.xticks(ticks=range(7), labels=['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Satur
plt.xlabel('Day of the Week')
plt.ylabel('Number of Orders')
plt.title('Volume of Orders per Day of the Week')



# Mostrar el gráfico
plt.show()
```



Los días con mayor demanda son Lunes y Viernes, parece que el día martes cae abruptamente la demanda, esta comienza a ascender tendencialmente hasta el dia Viernes para llegar a su pico y posteriormente descender hasta el día domingo, el peor día es para el Martes.

A continuación realizare un grafico por pedidos por hora

```
import pandas as pd
import matplotlib.pyplot as plt



df_hour_graph = df.copy()
df_hour_graph['hour'] = df_hour_graph.index.hour

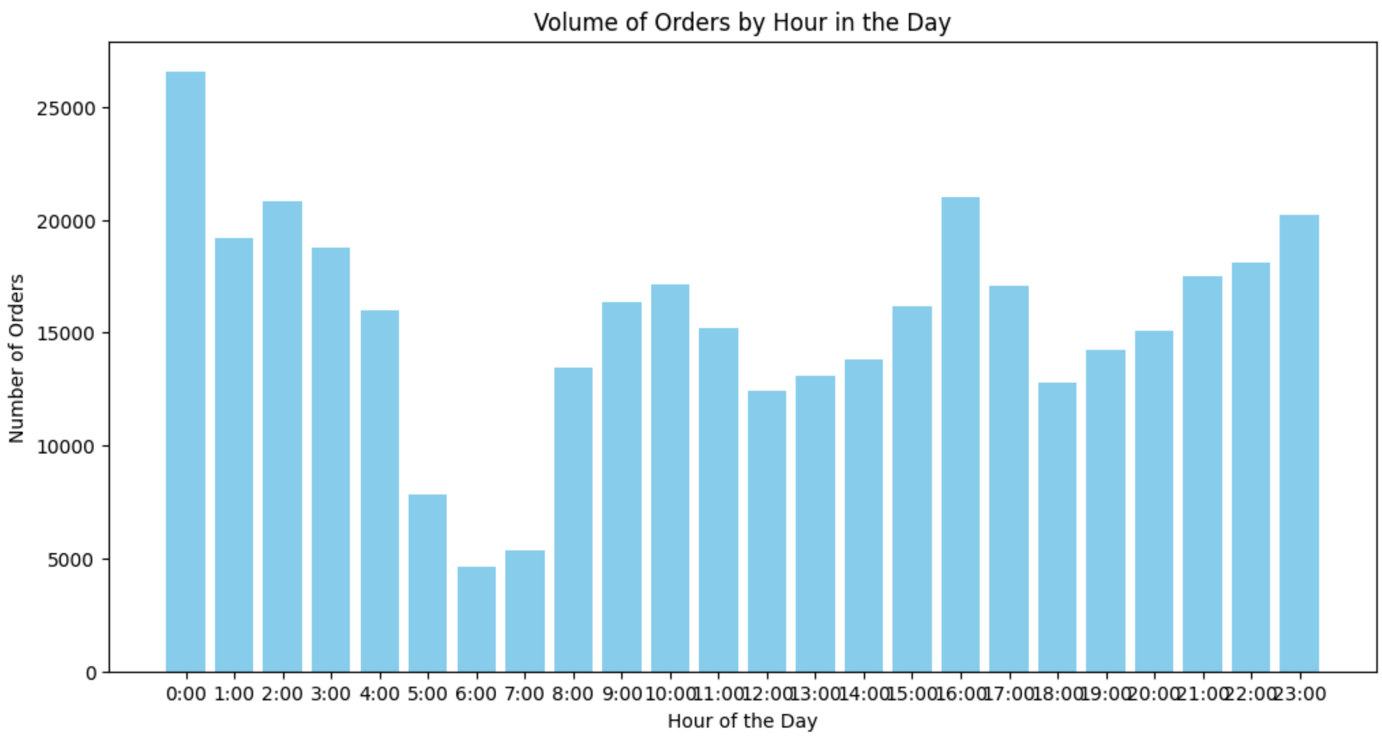
# Agrupar los pedidos por hora
Orders_by_hour = df_hour_graph.groupby('hour')['num_orders'].sum().reset_index()
```

```
# Crear el gráfico con Matplotlib
plt.figure(figsize=(12, 6))
plt.bar(Orders_by_hour['hour'], Orders_by_hour['num_orders'], color='skyblue')

# Configurar los ejes x
plt.xticks(ticks=range(24), labels=[f'{hour}:00' for hour in range(24)])
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Orders')
plt.title('Volume of Orders by Hour in the Day')

# Exportar el gráfico como imagen
plt.savefig("volume_orders_by_hour.png")  # Guarda como PNG

# Mostrar el gráfico
plt.show()
```



Se observa que en el promedio de días hay una alta demanda en las primeras horas del día y a partir de las 03:00 am derece sustancialmente hasta las 6 donde hay solo 4632 pedidos registrados en esta hora, posteriormente se mantiene constante y aumenta hasta las 10:00 horas y vuelve a crear el 2do pico mas alto a las 16:00 horas se reduce la demanda hasta las 18:00 horas y comienza a ascender hora por hora hasta las 23:00 horas

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 4416 entries, 2018-03-01 00:00:00 to 2018-08-31 23:00:00
Freq: h
Data columns (total 1 columns):
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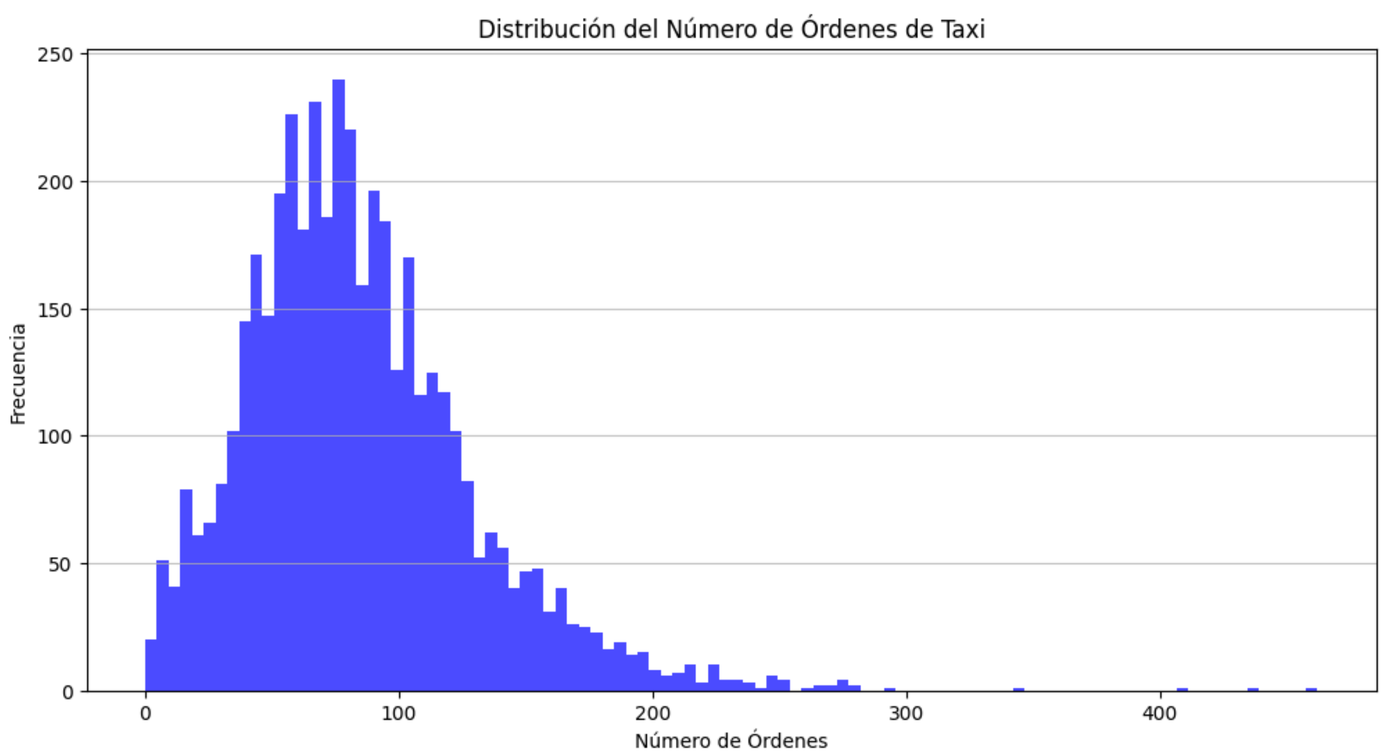
```
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   num_orders  4416 non-null   int64
dtypes: int64(1)
memory usage: 69.0 KB
```

```
import pandas as pd
import matplotlib.pyplot as plt


# Crear el histograma con Matplotlib
plt.figure(figsize=(12, 6))
plt.hist(df['num_orders'], bins=100, color='blue', alpha=0.7)

# Configurar los títulos y etiquetas
plt.title('Distribución del Número de Órdenes de Taxi')
plt.xlabel('Número de Órdenes')
plt.ylabel('Frecuencia')

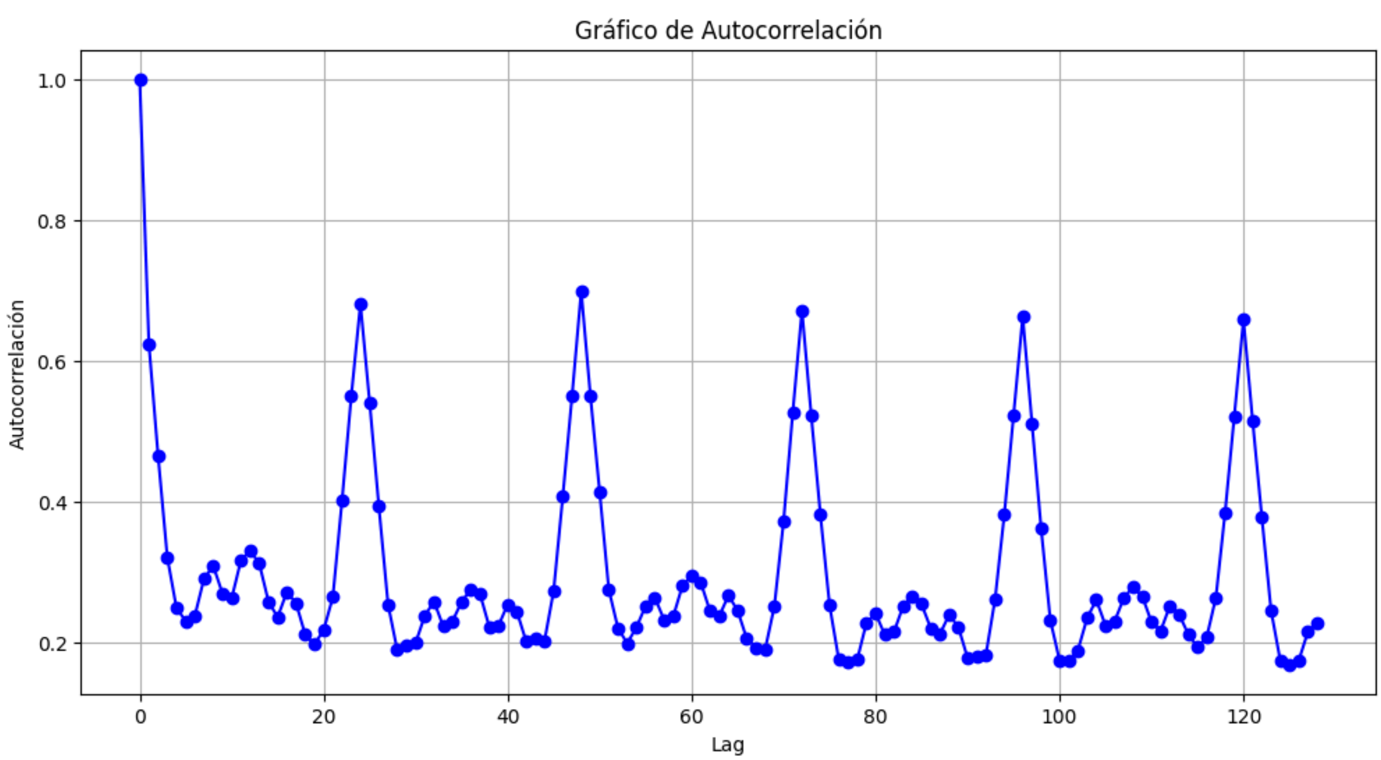
# Mostrar el gráfico
plt.grid(axis='y', alpha=0.75)
plt.show()
```




```
<Figure size 640x480 with 0 Axes>
```

Se observa regularmente hay alrededor entre 55 a 84 ordenes por hora ya que hay alrededor de 1300 registros de 4416 que hay lo cual es un porcentaje importante.

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import acf


# Calcular la autocorrelación
autocorr_values = acf(df['num_orders'], nlags=128)

# Crear el gráfico de autocorrelación
plt.figure(figsize=(12, 6))
plt.plot(autocorr_values, marker='o', linestyle='-', color='blue')

# Añadir detalles al gráfico
plt.title('Gráfico de Autocorrelación')
plt.xlabel('Lag')
plt.ylabel('Autocorrelación')
plt.grid()

# Mostrar el gráfico
plt.show()

# Exportar el gráfico como imagen (opcional)
plt.savefig("grafico_autocorrelacion.png")  # Guarda como PNG
```




```
<Figure size 640x480 with 0 Axes>
```

- Vemos una fuerte autocorrelación en los primeros lags (de 1 a 4), lo que significa que los valores recientes están muy correlacionados entre sí, los pedidos en horas consececutivas tienden a estar

correlacionados.
- Hay un patron diario de los datos cada 24 horas.
- La Disminución gradual de la correlación indica que horas mas alejadas de otras no estan tan correlacionadas.

En conclusión podemos ver que hay una correlación entre horas colindantes y un patron con fuerte correlación cada 24 horas mencionando tambén que horas alejadas como podrían ser las 5 de la mañana con las 5 de la tarde no suelen estar relacionadas entre si.

Entrenamiento de modelo

```
# Adición de caracteristicas

# Función para crear características
def make_features(data, max_lag, rolling_mean_size, target_column):
    data['year'] = data.index.year
    data['month'] = data.index.month
    data['day'] = data.index.day
    data['dayofweek'] = data.index.dayofweek
    data['hour'] = data.index.hour

    for lag in range(1, max_lag + 1):
        data[f'lag_{lag}'] = data[target_column].shift(lag)

    data['rolling_mean'] = (
        data[target_column].shift().rolling(rolling_mean_size).mean()
    )
    return data
```

```
# División en conjunto de prueba, validación y entrenamoiento

df_train, df_test = train_test_split(df, shuffle=False, test_size=0.1)
```

```
def best_leg_rolling(data_train, data_test, target_column, model, param_dist=None, n_iter=10, ran
    """
    Encuentra la mejor combinación de `max_lag` y `rolling_size` para un modelo de predicción bas

    Parámetros:
    -----------
    data_train : pd.DataFrame
        Conjunto de datos de entrenamiento.
    data_test : pd.DataFrame
        Conjunto de datos de prueba.
    target_column : str
        Nombre de la columna objetivo que se quiere predecir.
```

```
    model : estimator object
        Modelo de Machine Learning que se utilizará. Puede ser un modelo lineal o uno que requiera
    param_dist : dict, opcional
        Distribución de parámetros para la búsqueda aleatoria. Solo se usa si el modelo no es line
    n_iter : int, opcional
        Número de iteraciones para RandomizedSearchCV. Por defecto es 10.
    random_state : int, opcional
        Semilla para la generación de números aleatorios. Por defecto es 42.

    Devuelve:
    ---------
    tuple
        Una tupla con el mejor RMSE, `max_lag`, `rolling_size` y los mejores parámetros del modelo

    Descripción:
    ------------
    Esta función busca la mejor combinación de `max_lag` y `rolling_size` para el modelo proporcio
    los mejores hiperparámetros del modelo no lineal. Calcula el RMSE para cada combinación de `ma
    que minimizan el RMSE.
    """
    best_rmse = float('inf')
    best_max_lag = 0
    best_rolling_size = 0
    best_model_params = None

    scaler = MaxAbsScaler()

    # Optimización: precomputar las características
    feature_dict_train = {}
    feature_dict_test = {}

    for max_lag in range(1, 7):
        for rolling_size in range(1, 7):
            df_copy_train = data_train.copy()
            df_copy_test = data_test.copy()

            df_copy_train = make_features(df_copy_train, max_lag, rolling_size, target_column)
            df_copy_test = make_features(df_copy_test, max_lag, rolling_size, target_column)

            df_copy_train = df_copy_train.dropna()
            df_copy_test = df_copy_test.dropna()

            X_train = df_copy_train.drop(target_column, axis=1)
            y_train = df_copy_train[target_column]

            X_test = df_copy_test.drop(target_column, axis=1)
            y_test = df_copy_test[target_column]

            feature_dict_train[(max_lag, rolling_size)] = (X_train, y_train)
            feature_dict_test[(max_lag, rolling_size)] = (X_test, y_test)
```

```
    for max_lag in range(1, 7):
        for rolling_size in range(1, 7):
            X_train, y_train = feature_dict_train[(max_lag, rolling_size)]
            X_test, y_test = feature_dict_test[(max_lag, rolling_size)]

            # Escalado de características
            X_train_scaled = scaler.fit_transform(X_train)
            X_test_scaled = scaler.transform(X_test)

            if isinstance(model, LinearRegression):
                current_model = LinearRegression()
                current_model.fit(X_train_scaled, y_train)
                predictions = current_model.predict(X_test_scaled)
                current_params = None
            else:
                search = RandomizedSearchCV(model, param_dist, n_iter=n_iter, scoring='neg_mean_s
                search.fit(X_train_scaled, y_train)
                best_model = search.best_estimator_
                predictions = best_model.predict(X_test_scaled)
                current_params = search.best_params_

            rmse = mean_squared_error(y_test, predictions, squared=False)

            if rmse < best_rmse:
                best_rmse = rmse
                best_max_lag = max_lag
                best_rolling_size = rolling_size
                if current_params is not None:
                    best_model_params = current_params

    if best_model_params is None:
        return best_rmse, best_max_lag, best_rolling_size
    else:
        return best_rmse, best_max_lag, best_rolling_size, best_model_params
```

```
# Regresión Lineal

best_rmse, best_max_lag, best_rolling_size = best_leg_rolling(df_train, df_test, 'num_orders', Li

model_name = 'Regresion Lineal'

print('Para el modelo de {}, el mejor rmse es {}, con el max_lag de {} y la mejor media movil de
```

Para el modelo de Regresion Lineal, el mejor rmse es 52.511927147300746, con el max_lag de 3 y la mejor media movil de 2

```
# Bosque aleatorio

param_dist = {
    'n_estimators': [10,100,500],
    'max_depth': [5,10,20],
    'min_samples_split': [3,5],
    'min_samples_leaf': [3,5,10]
}

best_rmse, best_max_lag, best_rolling_size, best_model_params = best_leg_rolling(
    df_train,
    df_test,
    'num_orders',
    RandomForestRegressor(random_state=42),
    param_dist
)

print(f'El mejor RMSE es {best_rmse:.2f}, con un max_lag de {best_max_lag} y una media móvil de {
print(f'Mejores hiperparámetros del modelo: {best_model_params}')
```

```
El mejor RMSE es 45.25, con un max_lag de 6 y una media móvil de 4.
Mejores hiperparámetros del modelo: {'n_estimators': 500, 'min_samples_split': 3,
'min_samples_leaf': 5, 'max_depth': 20}
```

```
# LGBMRegressor

param_dist = {
    'n_estimators': [15, 25, 50, 100, 200, 500],
    'learning_rate': [0.01, 0.05, 0.1, 0.3],
    'num_leaves': [20, 31, 40, 50],
    'min_child_samples': [10, 20, 30, 40],
    'subsample': [0.6, 0.8, 1.0],
    'colsample_bytree': [0.6, 0.8, 1.0]
}

best_rmse, best_max_lag, best_rolling_size, best_model_params = best_leg_rolling(
    df_train,
    df_test,
    'num_orders',
    LGBMRegressor(random_state=12345),
    param_dist
)

print(f'El mejor RMSE es {best_rmse:.2f}, con un max_lag de {best_max_lag} y una media móvil de {
print(f'Mejores hiperparámetros del modelo: {best_model_params}')
```

```
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000161
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 450
[LightGBM] [Info] Number of data points in the train set: 3973, number of used features: 6
[LightGBM] [Info] Start training from score 78.279134
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.000072
seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 515
[LightGBM] [Info] Number of data points in the train set: 3972, number of used features: 6
[LightGBM] [Info] Start training from score 78.277442
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000124
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 515
[LightGBM] [Info] Number of data points in the train set: 3971, number of used features: 6
[LightGBM] [Info] Start training from score 78.279275
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000151
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 515
[LightGBM] [Info] Number of data points in the train set: 3970, number of used features: 6
[LightGBM] [Info] Start training from score 78.282368
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.000158
seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 515
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 6
[LightGBM] [Info] Start training from score 78.291257
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000128
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 515
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 6
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000415
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 640
[LightGBM] [Info] Number of data points in the train set: 3972, number of used features: 7
[LightGBM] [Info] Start training from score 78.277442
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000114
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 705
[LightGBM] [Info] Number of data points in the train set: 3972, number of used features: 7
[LightGBM] [Info] Start training from score 78.277442
```

```
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000141
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 705
[LightGBM] [Info] Number of data points in the train set: 3971, number of used features: 7
[LightGBM] [Info] Start training from score 78.279275
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000130
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 705
[LightGBM] [Info] Number of data points in the train set: 3970, number of used features: 7
[LightGBM] [Info] Start training from score 78.282368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000142
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 705
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 7
[LightGBM] [Info] Start training from score 78.291257
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000145
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 705
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 7
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000138
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 830
[LightGBM] [Info] Number of data points in the train set: 3971, number of used features: 8
[LightGBM] [Info] Start training from score 78.279275
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000140
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 895
[LightGBM] [Info] Number of data points in the train set: 3971, number of used features: 8
[LightGBM] [Info] Start training from score 78.279275
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000140
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 895
[LightGBM] [Info] Number of data points in the train set: 3971, number of used features: 8
[LightGBM] [Info] Start training from score 78.279275
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000166
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 895
[LightGBM] [Info] Number of data points in the train set: 3970, number of used features: 8
[LightGBM] [Info] Start training from score 78.282368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000165
seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 895
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 8
[LightGBM] [Info] Start training from score 78.291257
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000172
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 895
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 8
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000167
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1020
[LightGBM] [Info] Number of data points in the train set: 3970, number of used features: 9
[LightGBM] [Info] Start training from score 78.282368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000177
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1085
[LightGBM] [Info] Number of data points in the train set: 3970, number of used features: 9
[LightGBM] [Info] Start training from score 78.282368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000174
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1085
[LightGBM] [Info] Number of data points in the train set: 3970, number of used features: 9
[LightGBM] [Info] Start training from score 78.282368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000151
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1085
[LightGBM] [Info] Number of data points in the train set: 3970, number of used features: 9
[LightGBM] [Info] Start training from score 78.282368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000246
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1085
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 9
[LightGBM] [Info] Start training from score 78.291257
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000151
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1085
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 9
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000154
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1210
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 10
[LightGBM] [Info] Start training from score 78.291257
```

```
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000160
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1275
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 10
[LightGBM] [Info] Start training from score 78.291257
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000152
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1275
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 10
[LightGBM] [Info] Start training from score 78.291257
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000214
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1275
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 10
[LightGBM] [Info] Start training from score 78.291257
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000168
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1275
[LightGBM] [Info] Number of data points in the train set: 3969, number of used features: 10
[LightGBM] [Info] Start training from score 78.291257
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000134
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1275
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 10
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000171
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1400
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 11
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000200
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1465
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 11
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000219
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1465
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 11
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000178
seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 1465
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 11
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000196
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1465
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 11
[LightGBM] [Info] Start training from score 78.309476
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000189
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1465
[LightGBM] [Info] Number of data points in the train set: 3968, number of used features: 11
[LightGBM] [Info] Start training from score 78.309476
El mejor RMSE es 43.00, con un max_lag de 1 y una media móvil de 1.
Mejores hiperparámetros del modelo: {'subsample': 0.8, 'num_leaves': 50, 'n_estimators': 500,
'min_child_samples': 20, 'learning_rate': 0.01, 'colsample_bytree': 0.8}
```

```python
# XGBoost

param_dist = {
    'n_estimators': [50, 100, 200, 300],
    'learning_rate': [0.01, 0.1],
    'max_depth': [3, 5],
    'min_child_weight': [1, 5],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0],
    'gamma': [0, 0.1],
    'reg_alpha': [0, 0.5],
    'reg_lambda': [0.01, 1]
}

best_rmse, best_max_lag, best_rolling_size, best_model_params = best_leg_rolling(
    df_train,
    df_test,
    'num_orders',
    XGBRegressor(random_state=12345),
    param_dist
)

print(f'El mejor RMSE es {best_rmse:.2f}, con un max_lag de {best_max_lag} y una media móvil de {
print(f'Mejores hiperparámetros del modelo: {best_model_params}')
```

```
El mejor RMSE es 40.78, con un max_lag de 4 y una media móvil de 3.
Mejores hiperparámetros del modelo: {'subsample': 0.8, 'reg_lambda': 0.01, 'reg_alpha': 0.5,
'n_estimators': 300, 'min_child_weight': 5, 'max_depth': 3, 'learning_rate': 0.1, 'gamma': 0,
'colsample_bytree': 1.0}
```

```
# CatBoost

param_dist = {
    'iterations': [15, 25, 50, 100, 200, 300],
    'learning_rate': [0.01, 0.05, 0.1, 0.3],
    'depth': [3, 5, 7],
    'l2_leaf_reg': [1, 3, 5, 7],
    'border_count': [32, 50, 100, 200]
}


best_rmse, best_max_lag, best_rolling_size, best_model_params = best_leg_rolling(
    df_train,
    df_test,
    'num_orders',
    CatBoostRegressor(random_state=12345),
    param_dist
)

print(f'El mejor RMSE es {best_rmse:.2f}, con un max_lag de {best_max_lag} y una media móvil de {
print(f'Mejores hiperparámetros del modelo: {best_model_params}')
```

```
0:  learn: 37.3014265   total: 2.43ms   remaining: 726ms
1:  learn: 35.6302910   total: 4.06ms   remaining: 605ms
2:  learn: 34.2161660   total: 4.94ms   remaining: 490ms
3:  learn: 33.0723182   total: 5.79ms   remaining: 429ms
4:  learn: 32.0900990   total: 6.57ms   remaining: 387ms
5:  learn: 31.3205376   total: 7.33ms   remaining: 359ms
6:  learn: 30.6195684   total: 8.26ms   remaining: 346ms
7:  learn: 29.8982506   total: 9.36ms   remaining: 341ms
8:  learn: 29.2078661   total: 10.1ms   remaining: 325ms
9:  learn: 28.8937459   total: 10.8ms   remaining: 313ms
10: learn: 28.4205612   total: 11.5ms   remaining: 302ms
11: learn: 27.9330910   total: 12.2ms   remaining: 292ms
12: learn: 27.5093594   total: 12.8ms   remaining: 283ms
13: learn: 27.2200676   total: 13.7ms   remaining: 280ms
14: learn: 26.8524924   total: 15ms remaining: 285ms
15: learn: 26.5526620   total: 15.9ms   remaining: 283ms
16: learn: 26.3857728   total: 16.8ms   remaining: 280ms
17: learn: 26.1703828   total: 17.6ms   remaining: 276ms
18: learn: 26.0196384   total: 18.4ms   remaining: 272ms
19: learn: 25.7583061   total: 19.2ms   remaining: 269ms
20: learn: 25.5520029   total: 20.2ms   remaining: 269ms
21: learn: 25.3423068   total: 21ms remaining: 266ms
22: learn: 25.2090925   total: 21.8ms   remaining: 263ms
23: learn: 25.0534294   total: 22.6ms   remaining: 260ms
24: learn: 24.9595206   total: 23.3ms   remaining: 257ms
25: learn: 24.8197656   total: 24ms remaining: 253ms
26: learn: 24.6823738   total: 24.7ms   remaining: 250ms
```

```
170:	learn: 16.9859937	total: 455ms	remaining: 77.2ms
171:	learn: 16.9435453	total: 457ms	remaining: 74.4ms
172:	learn: 16.8942704	total: 459ms	remaining: 71.6ms
173:	learn: 16.8756192	total: 462ms	remaining: 69.1ms
174:	learn: 16.8506916	total: 465ms	remaining: 66.4ms
175:	learn: 16.8305703	total: 468ms	remaining: 63.8ms
176:	learn: 16.8051142	total: 470ms	remaining: 61.1ms
177:	learn: 16.7654424	total: 473ms	remaining: 58.4ms
178:	learn: 16.7491772	total: 476ms	remaining: 55.8ms
179:	learn: 16.7161011	total: 478ms	remaining: 53.1ms
180:	learn: 16.7129148	total: 481ms	remaining: 50.5ms
181:	learn: 16.7106398	total: 483ms	remaining: 47.7ms
182:	learn: 16.6768215	total: 485ms	remaining: 45ms
183:	learn: 16.6548389	total: 488ms	remaining: 42.4ms
184:	learn: 16.6385108	total: 490ms	remaining: 39.7ms
185:	learn: 16.6197126	total: 493ms	remaining: 37.1ms
186:	learn: 16.5683291	total: 495ms	remaining: 34.4ms
187:	learn: 16.5334552	total: 498ms	remaining: 31.8ms
188:	learn: 16.5026834	total: 501ms	remaining: 29.1ms
189:	learn: 16.4777843	total: 504ms	remaining: 26.5ms
190:	learn: 16.4474703	total: 510ms	remaining: 24ms
191:	learn: 16.4302325	total: 515ms	remaining: 21.5ms
192:	learn: 16.3987773	total: 519ms	remaining: 18.8ms
193:	learn: 16.3723116	total: 523ms	remaining: 16.2ms
194:	learn: 16.3288709	total: 526ms	remaining: 13.5ms
195:	learn: 16.2884243	total: 529ms	remaining: 10.8ms
196:	learn: 16.2668359	total: 532ms	remaining: 8.1ms
197:	learn: 16.2473491	total: 535ms	remaining: 5.41ms
198:	learn: 16.2315245	total: 538ms	remaining: 2.7ms
199:	learn: 16.1761063	total: 540ms	remaining: 0us
El mejor RMSE es 41.35, con un max_lag de 4 y una media móvil de 2.
Mejores hiperparámetros del modelo: {'learning_rate': 0.1, 'l2_leaf_reg': 1, 'iterations': 300,
'depth': 5, 'border_count': 50}
```

```python
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error
import numpy as np
import pandas as pd

# Definición del modelo con los mejores hiperparámetros encontrados
best_model = XGBRegressor(random_state=12345, subsample=0.8, reg_lambda=0.01, reg_alpha=0.5, n_es


# Creación de las características de entrenamiento y prueba
df_copy_train = df_train.copy()
df_copy_test = df_test.copy()

df_copy_train = make_features(df_copy_train, 4, 3, 'num_orders')
df_copy_test = make_features(df_copy_test, 4, 3, 'num_orders')
```

```python
df_copy_train = df_copy_train.dropna()
df_copy_test = df_copy_test.dropna()

X_train = df_copy_train.drop('num_orders', axis=1)
y_train = df_copy_train['num_orders']

X_test = df_copy_test.drop('num_orders', axis=1)
y_test = df_copy_test['num_orders']

# Entrenamiento del modelo
best_model.fit(X_train, y_train)

# Predicciones y cálculo del RMSE
predictions = best_model.predict(X_test)
rmse = np.sqrt(mean_squared_error(predictions, y_test))
print(f"RMSE: {rmse}")
```

```
RMSE: 40.784867202604026
```

```python
# Crear dataframe para plotly express
df_plot = pd.DataFrame({
    'Fecha': y_test.index,
    'Valores_Reales': y_test.values,
    'Predicciones': predictions
})

# Crear gráfico interactivo con Plotly Express
fig = px.scatter(df_plot,
                 x='Fecha',
                 y=['Valores_Reales', 'Predicciones'],
                 labels={'Fecha': 'Fecha y Hora', 'value': 'Número de Órdenes'},
                 color_discrete_sequence=['blue', 'red'])

fig.update_layout(title='Comparación de Predicciones y Valores Reales',
                  xaxis_title='Fecha y Hora',
                  yaxis_title='Número de Órdenes',
                  legend_title='Datos',
                  hovermode='x unified')

fig.show()

from scipy.stats import pearsonr

# Calcular correlación de Pearson entre predicciones y valores reales
correlation, _ = pearsonr(predictions, y_test)
print(f"Correlación de Pearson: {correlation}")
```

```
Unable to display output for mime type(s): application/vnd.plotly.v1+json
```

```
Correlación de Pearson: 0.7238395111147611
```

Observamos que hay un interesante correlación de pearson

Conclusión

En este proyecto se realizo unn analisis exploratorio de datos y de visualización para una empresa de servicios de transporte de taxis en la que se concluyeron los siguientes puntos:

- La tendencia general de los pedidos por servicios de taxi tienen una tendencia al alza
- A las ultimas y primeras horas del día se encuentra una alta demanda que baja alrededor de las 6:00 horas y repunta hasta las 16:00 horas
- El mejor modelo fue el XGBoost seguido del CatBoost, aunque este ultimo tiene una mayor tiempo de entrenamiento
- En el grafico anterior entre las predicciones y los datos reales del conjunto de testing, hay una fuerte correlación del 0.7238

Conclusión final A la vista posterior de entrenar y evaluar los modelos con la metrica RECM podemos observa que XGBoost es extremadamente superior a los demás en terminos tanto de velocidad de entrenamiento como en calidad de predicción, se pudo observar un RMSE de: 40.784867202604026, bastante bueno para el objetivo que se había marcado previamente (RECM = 48)

```
max_lag de 4 y una media móvil de 3.
Mejores hiperparámetros del modelo: {'subsample': 0.8, 'reg_lambda': 0.01, 'reg_alpha': 0.5,
'n_estimators': 300, 'min_child_weight': 5, 'max_depth': 3, 'learning_rate': 0.1, 'gamma': 0,
'colsample_bytree': 1.0
```