## Introduction

Nixtla's TimeGPT is a generative pre-trained forecasting model for time series data. TimeGPT can produce accurate forecasts for new time series without training, using only historical values as inputs. TimeGPT can be used across a plethora of tasks including demand forecasting, anomaly detection, financial forecasting, and more.

The TimeGPT model "reads" time series data much like the way humans read a sentence – from left to right. It looks at windows of past data, which we can think of as "tokens", and predicts what comes next. This prediction is based on patterns the model identifies in past data and extrapolates into the future.

The API provides an interface to TimeGPT, allowing users to leverage its forecasting capabilities to predict future events. TimeGPT can also be used for other time series-related tasks, such as what-if scenarios, anomaly detection, and more.

## **Usage**

```
In [ ]: # / hide
        from dotenv import load_dotenv
In [ ]: # / hide
        load dotenv()
Out[]: True
In [ ]: from nixtlats import TimeGPT
        import os
        You can instantiate the TimeGPT class providing your credentials.
In [ ]: timegpt = TimeGPT(token=os.getenv("TIMEGPT TOKEN"))
In [ ]: # / hide
        timegpt = TimeGPT()
        You can test the validate of your token calling the validate_token method:
In [ ]: timegpt.validate_token()
       INFO:nixtlats.timegpt:Happy Forecasting! :), If you have questions or need support,
       please email ops@nixtla.io
Out[]: True
```

Now you can start making forecasts! Let's import an example on the classic

AirPassengers dataset. This dataset contains the monthly number of airline passengers in

Australia between 1949 and 1960. First, let's load the dataset and plot it:

```
In [ ]:
        import pandas as pd
        df = pd.read csv(
In [ ]:
            "https://raw.githubusercontent.com/Nixtla/transfer-learning-time-series/main/da
        df.head()
Out[]:
           timestamp value
          1949-01-01
                        112
          1949-02-01
                        118
           1949-03-01
                        132
           1949-04-01
                        129
           1949-05-01
                        121
        timegpt.plot(df, time col="timestamp", target col="value")
Out[ ]:
```

## Important requirements of the data

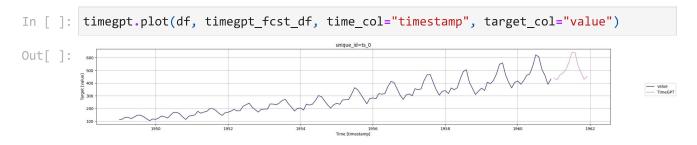
- Make sure the target variable column does not have missing or non-numeric values.
- Do not include gaps/jumps in the datestamps (for the given frequency) between the first and late datestamps. The forecast function will not impute missing dates.
- The format of the datestamp column should be readable by Pandas (see this link for more details).

Next, forecast the next 12 months using the SDK forecast method. Set the following parameters:

- df: A pandas dataframe containing the time series data.
- h: The number of steps ahead to forecast.
- freq: The frequency of the time series in Pandas format. See pandas' available frequencies.
- time\_col : Column that identifies the datestamp column.
- target\_col : The variable that we want to forecast.

Out[ ]:		timestamp	TimeGPT
	0	1961-01-01	437.837921
	1	1961-02-01	426.062714
	2	1961-03-01	463.116547
	3	1961-04-01	478.244507
	4	1961-05-01	505.646484

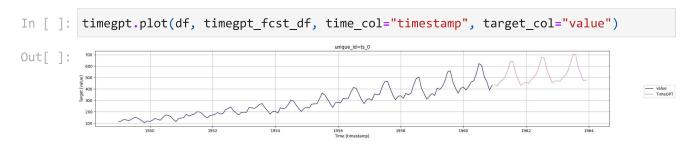
BEFORE: 2 API Calls | 146400 Tokens | 245.28 Spent AFTER: 3 API Calls | 146556 Tokens | 245.49 Spent **USAGE: 1 API Call | 156 Tokens | 0.21 Spent** 



You can also produce a longer forecasts increasing the horizon parameter. For example, let's forecast the next 36 months:

Out[ ]:		timestamp	TimeGPT
	0	1961-01-01	437.837921
	1	1961-02-01	426.062714
	2	1961-03-01	463.116547
	3	1961-04-01	478.244507
	4	1961-05-01	505.646484

BEFORE: 3 API Calls | 146556 Tokens | 245.49 Spent AFTER: 4 API Calls | 146736 Tokens | 245.78 Spent USAGE: 1 API Call | 180 Tokens | 0.29 Spent



Or a shorter one:

BEFORE: 4 API Calls | 146736 Tokens | 245.78 Spent AFTER: 5 API Calls | 146886 Tokens | 245.97 Spent USAGE: 1 API Call | 150 Tokens | 0.19 Spent

TimeGPT-1 is currently optimized for short horizon forecasting. While the forecast method will allow any positive and large horizon, the accuracy of the forecasts might degrade. We are currently working to improve the accuracy on longer forecasts.

## Using DateTime index to infer frequency

The freq parameter, which indicates the time unit between consecutive data points, is particularly critical. Fortunately, you can pass a DataFrame with a DateTime index to the forecasting method, ensuring that your time series data is equipped with necessary temporal features. By assigning a suitable freq parameter to the DateTime index of a DataFrame, you inform the model about the consistent interval between observations — be it days ('D'), months ('M'), or another suitable frequency.

```
In []: df_time_index = df.set_index("timestamp")
    df_time_index.index = pd.DatetimeIndex(df_time_index.index, freq="MS")
    timegpt.forecast(df=df, h=36, time_col="timestamp", target_col="value").head()

INFO:nixtlats.timegpt:Validating inputs...
    INFO:nixtlats.timegpt:Preprocessing dataframes...
    INFO:nixtlats.timegpt:Inferred freq: MS
    WARNING:nixtlats.timegpt:The specified horizon "h" exceeds the model horizon. This m ay lead to less accurate forecasts. Please consider using a smaller horizon.
    INFO:nixtlats.timegpt:Calling Forecast Endpoint...
```

Out[ ]:		timestamp	TimeGPT
	0	1961-01-01	437.837921
	1	1961-02-01	426.062714
	2	1961-03-01	463.116547
	3	1961-04-01	478.244507
	4	1961-05-01	505.646484

BEFORE: 5 API Calls | 146886 Tokens | 245.97 Spent AFTER: 6 API Calls | 147066 Tokens | 246.26 Spent **USAGE: 1 API Call | 180 Tokens | 0.29 Spent**