Holidays and Special Dates

Calendar variables and special dates are one of the most common types of exogenous variables used in forecasting applications. They provide additional context on the current state of the time series, especially for window-based models such as TimeGPT-1. These variables often include adding information on each observation's month, week, day, or hour. For example, in high-frequency hourly data, providing the current month of the year provides more context than the limited history available in the input window to improve the forecasts. In this tutorial we will show how to add calendar variables automatically to a dataset using the `date_features` function.

In [ ]:
```
# | hide
from fastcore.test import test_eq, test_fail, test_warns
from dotenv import load_dotenv
```

In [ ]:
```
# | hide
load_dotenv()
```

Out[ ]:
```
True
```

In [ ]:
```
import pandas as pd
from nixtlats import TimeGPT
import os
```

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
```

Given the predominance usage of calendar variables, we included an automatic creation of common calendar variables to the forecast method as a pre-processing step. To automatically add calendar variables, use the `date_features` argument.

In [ ]:
```
pltr_df = pd.read_csv(
    "https://raw.githubusercontent.com/Nixtla/transfer-learning-time-series/main/da
)
```

In [ ]:
```
fcst_pltr_calendar_df = timegpt.forecast(
    df=pltr_df.tail(2 * 14),
    h=14,
    freq="B",
    time_col="date",
    target_col="Close",
    date_features=["month", "weekday"],
)
fcst_pltr_calendar_df.head()
```

```
INFO:nixtlats.timegpt:Validating inputs...
INFO:nixtlats.timegpt:Preprocessing dataframes...
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:Using the following exogenous variables: month_8, month_9, mon
th_10, weekday_0, weekday_1, weekday_2, weekday_3, weekday_4
INFO:nixtlats.timegpt:Calling Forecast Endpoint...
```

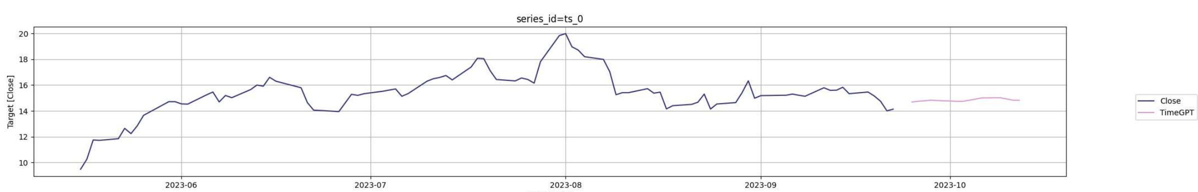
Out[ ]:

	date	TimeGPT
0	2023-09-25	14.688427
1	2023-09-26	14.742798
2	2023-09-27	14.781240
3	2023-09-28	14.824156
4	2023-09-29	14.795214

> BEFORE: *7 API Calls | 377307 Tokens | 594.40 Spent*
>
> AFTER: *8 API Calls | 377694 Tokens | 594.89 Spent*
>
> **USAGE: 1 API Call | 387 Tokens | 0.49 Spent**

In [ ]:
```
timegpt.plot(
    pltr_df,
    fcst_pltr_calendar_df,
    id_col="series_id",
    time_col="date",
    target_col="Close",
    max_insample_length=90,
)
```

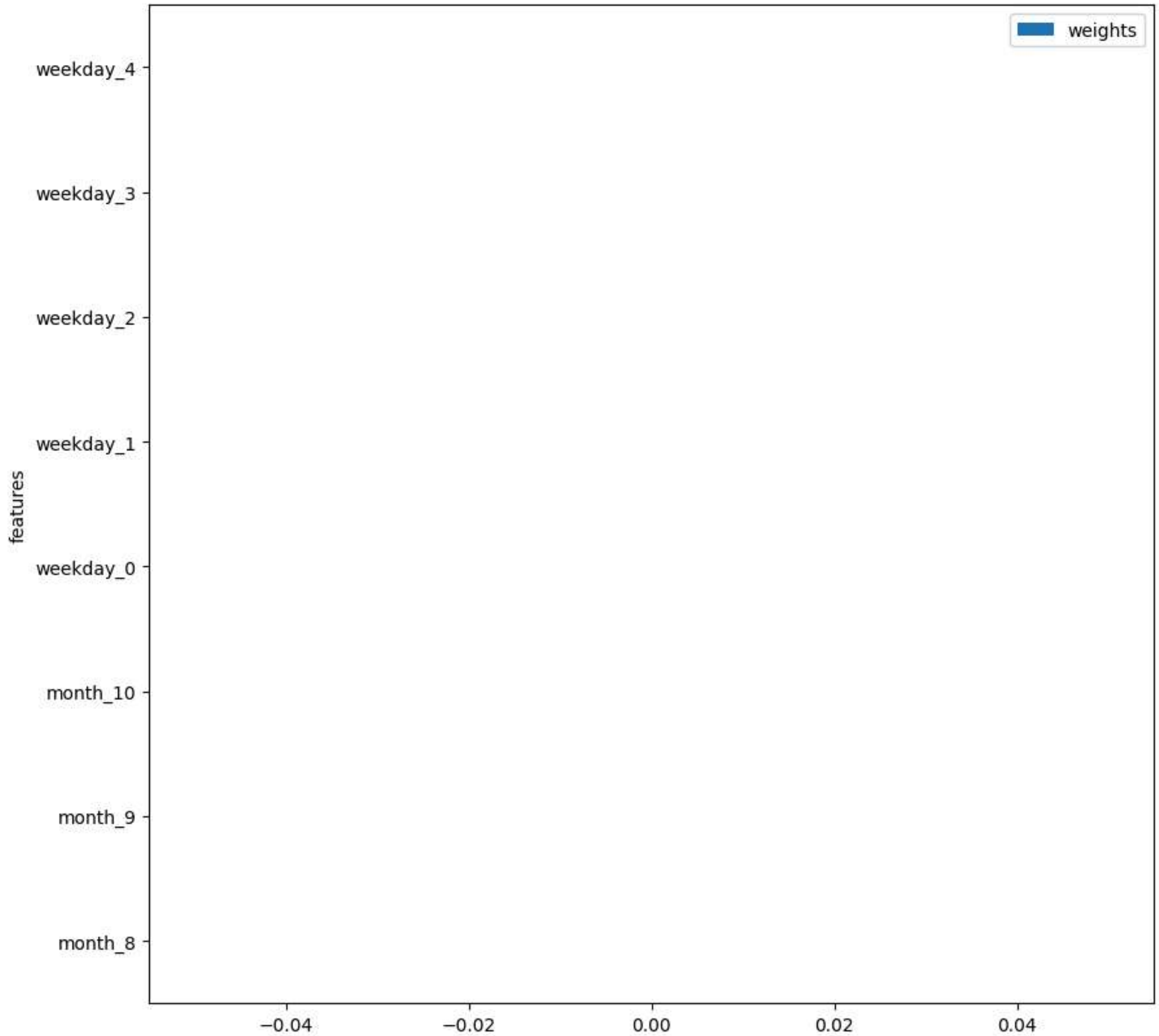
Out[ ]:



We can also plot the importance of each of the date features:

In [ ]:
```
timegpt.weights_x.plot.barh(x="features", y="weights", figsize=(10, 10))
```

Out[ ]: <Axes: ylabel='features'>



> BEFORE: *8 API Calls | 377694 Tokens | 594.89 Spent*
> AFTER: *8 API Calls | 377694 Tokens | 594.89 Spent*
> **USAGE: DID NOT IMPACT**

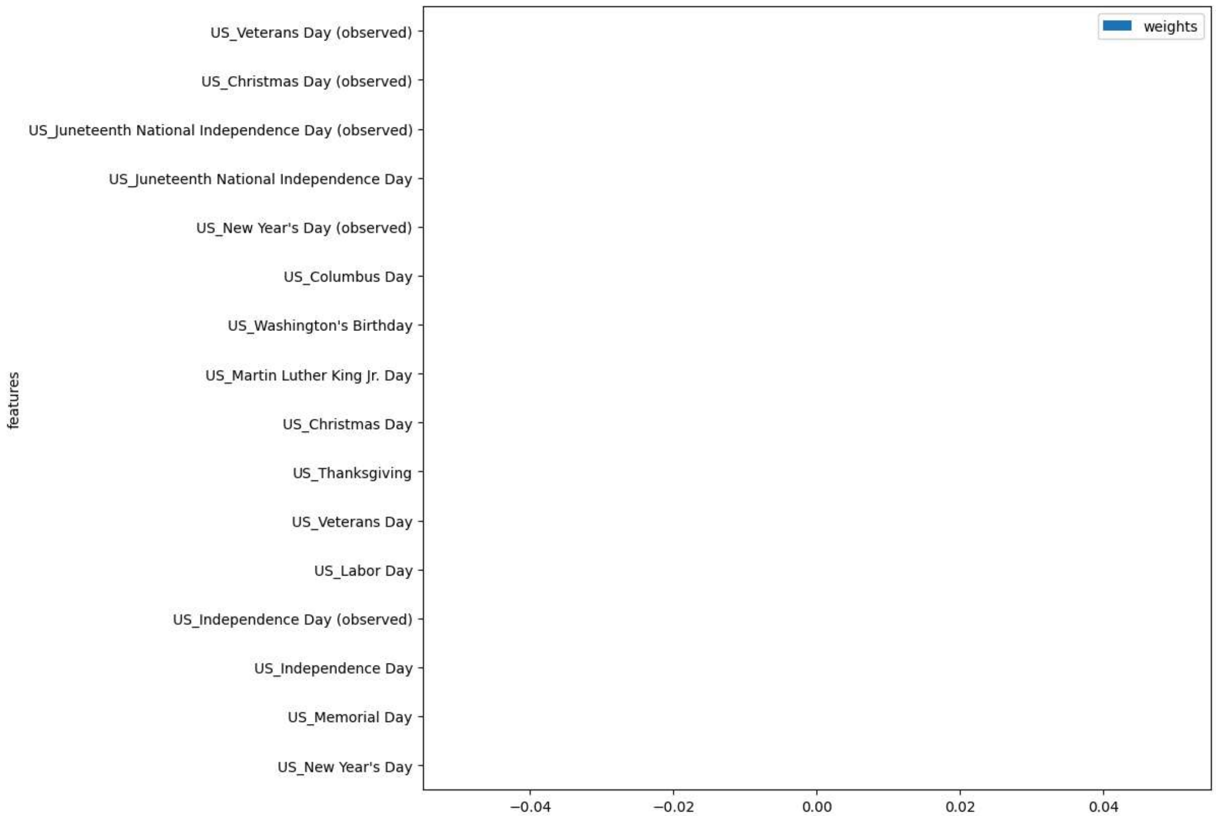
You can also add country holidays using the `CountryHolidays` class.

In [ ]:
```
from nixtlats.date_features import CountryHolidays
```

In [ ]:
```
fcst_pltr_calendar_df = timegpt.forecast(
    df=pltr_df,
    h=14,
    freq="B",
    time_col="date",
    target_col="Close",
    date_features=[CountryHolidays(["US"])],
)
timegpt.weights_x.plot.barh(x="features", y="weights", figsize=(10, 10))
```

```
INFO:nixtlats.timegpt:Validating inputs...
INFO:nixtlats.timegpt:Preprocessing dataframes...
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:Using the following exogenous variables: US_New Year's Day, US
_Memorial Day, US_Independence Day, US_Independence Day (observed), US_Labor Day, US
_Veterans Day, US_Thanksgiving, US_Christmas Day, US_Martin Luther King Jr. Day, US_
Washington's Birthday, US_Columbus Day, US_New Year's Day (observed), US_Juneteenth
National Independence Day, US_Juneteenth National Independence Day (observed), US_Ch
ristmas Day (observed), US_Veterans Day (observed)
INFO:nixtlats.timegpt:Calling Forecast Endpoint...
```

Out[ ]: `<Axes: ylabel='features'>`



> BEFORE: *8 API Calls | 377694 Tokens | 594.89 Spent*
> AFTER: *9 API Calls | 391158 Tokens | 611.07 Spent*
> **USAGE: 1 API Call | 13464 Tokens | 16.18 Spent**

Here's a breakdown of how the `date_features` parameter works:

- `date_features` **(bool or list of str or callable)**: This parameter specifies which date attributes to consider.
  - If set to `True`, the model will automatically add the most common date features related to the frequency of the given dataframe (`df`). For a daily frequency, this could include features like day of the week, month, and year.
  - If provided a list of strings, it will consider those specific date attributes. For example, `date_features=['weekday', 'month']` will only add the day of the

week and month as features.
    - If provided a callable, it should be a function that takes dates as input and returns the desired feature. This gives flexibility in computing custom date features.
- `date_features_to_one_hot` **(bool or list of str)**: After determining the date features, one might want to one-hot encode them, especially if they are categorical in nature (like weekdays). One-hot encoding transforms these categorical features into a binary matrix, making them more suitable for many machine learning algorithms.
    - If `date_features=True`, then by default, all computed date features will be one-hot encoded.
    - If provided a list of strings, only those specific date features will be one-hot encoded.

By leveraging the `date_features` and `date_features_to_one_hot` parameters, one can efficiently incorporate the temporal effects of date attributes into their forecasting model, potentially enhancing its accuracy and interpretability.