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```
from helpers import *
import_all()
from xgboost import XGBRegressor
%matplotlib inline
import seaborn as sns
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import TimeSeriesSplit
```

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The Data

- This data is an excerpt from a **[Kaggle maintained and regularly update dataset collection]()**
- The dataset reflects the energy consumption as reported by the National Grid ESO, Great Britain's electricity system operator
- Consumption is recorded twice an hour
- The data covers January 1, 2009 to December 31, 2022

Importing Data

```
data = pd.read_csv('uk_power_consumption.csv', parse_dates = ['settlement_date'])
data = data[['settlement_date', 'tsd', 'is_holiday']]
data.columns = ['datetime', 'consumption', 'holiday']
data = data.set_index('datetime', drop=True)
```

```
head_tail_horz(data, 5, "UK Power Consumption Data", intraday = True)
```

UK Power Consumption Data

head(5)

datetime	consumption	holiday
2009-01-01 00:00:00	38,704	1
2009-01-01 00:30:00	38,964	1
2009-01-01 01:00:00	38,651	1
2009-01-01 01:30:00	37,775	1
2009-01-01 02:00:00	37,298	1

tail(5)

datetime	consumption	holiday
2022-12-31 21:30:00	25,634	0
2022-12-31 22:00:00	24,788	0
2022-12-31 22:30:00	24,365	0
2022-12-31 23:00:00	24,766	0
2022-12-31 23:30:00	24,843	0

```
def timeseries_overview(df, main_col):
    index_col = ['number of records', 'number of columns',
                 'missing values', 'columns', 'start date',
                'end date', 'main column min', 'main column max']

    num_records = df.shape[0]
    num_cols = df.shape[1]
    missing_values = df.isna().sum().sum()
    columns = ', '.join(list(df.columns))
    start_date = min(df.index).strftime('%m/%d/%Y')
    end_date = max(df.index).strftime('%m/%d/%Y')
    main_min = min(df[main_col])
    main_max = max(df[main_col])

    values = [num_records, num_cols, missing_values,
              columns, start_date, end_date, main_min, main_max]

    overview = pd.concat([pd.Series(index_col), pd.Series(values)], axis = 1)
    overview.columns = ['aspects', 'information']
    overview.set_index('aspects')

    styling = {'information': [{'selector': '',
                          'props': [('font-size', '15px'),
                                    ('padding-right', '15px'),
                                    ('padding-left', '35px')]}],
               'aspects': [{'selector': '',
                         'props': [('font-weight', 'bold'),
                                   ('font-size', '15px'),
                                   ('padding-right', '15px'),
                                   ('padding-left', '15px')]}]}

    pretty('Initial DataFrame Overview', fontsize=4)

    return overview.style\
```

```
                    .hide(axis='index')\
                    .set_table_styles(styling)\
                    .format(precision=0, thousands=",")
```

```
timeseries_overview(data, 'consumption')
```

Initial DataFrame Overview

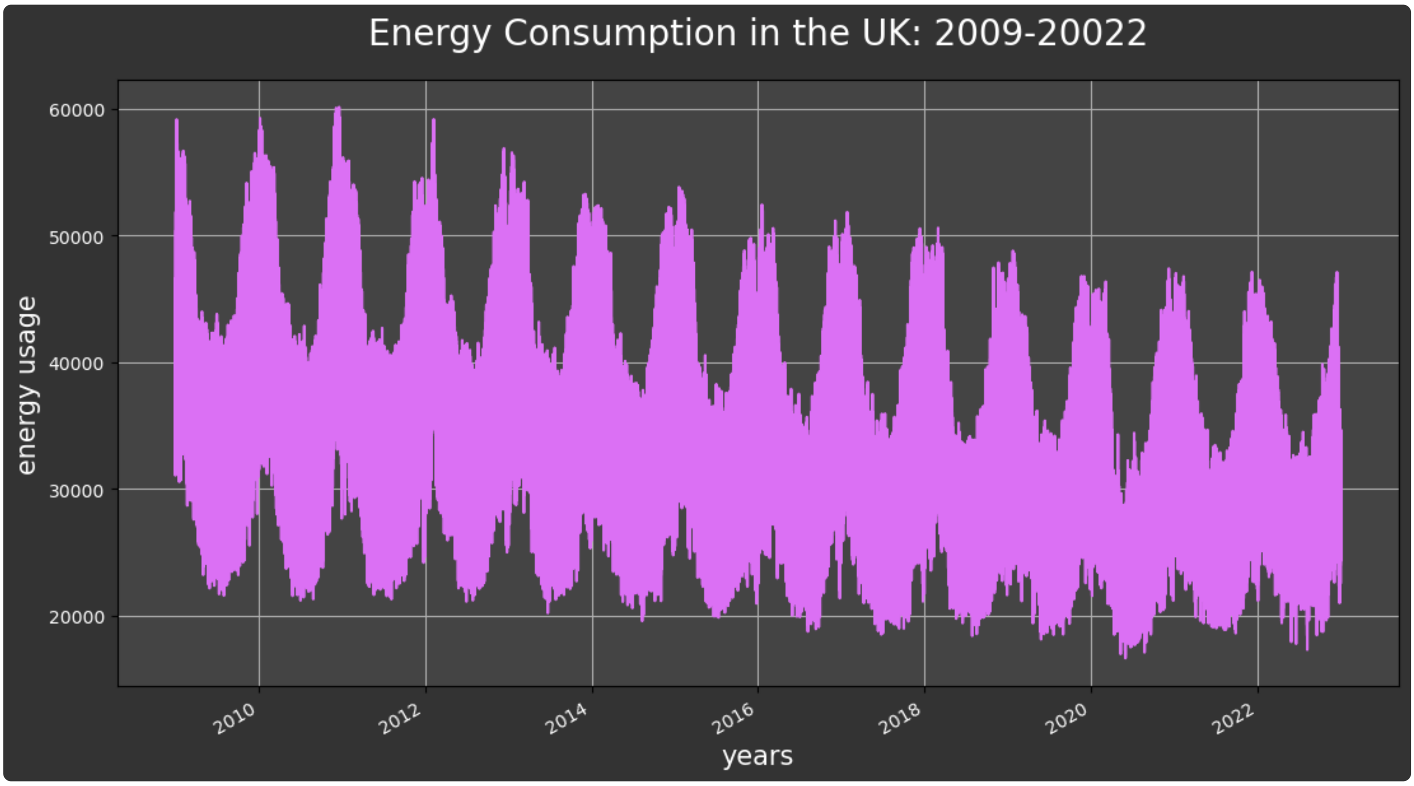
aspects	information
number of records	244,676
number of columns	2
missing values	0
columns	consumption, holiday
start date	01/01/2009
end date	12/31/2022
main column min	16,629
main column max	60,147

Initial Plotting

```
colors = sns.color_palette('husl', 11)
colors
```

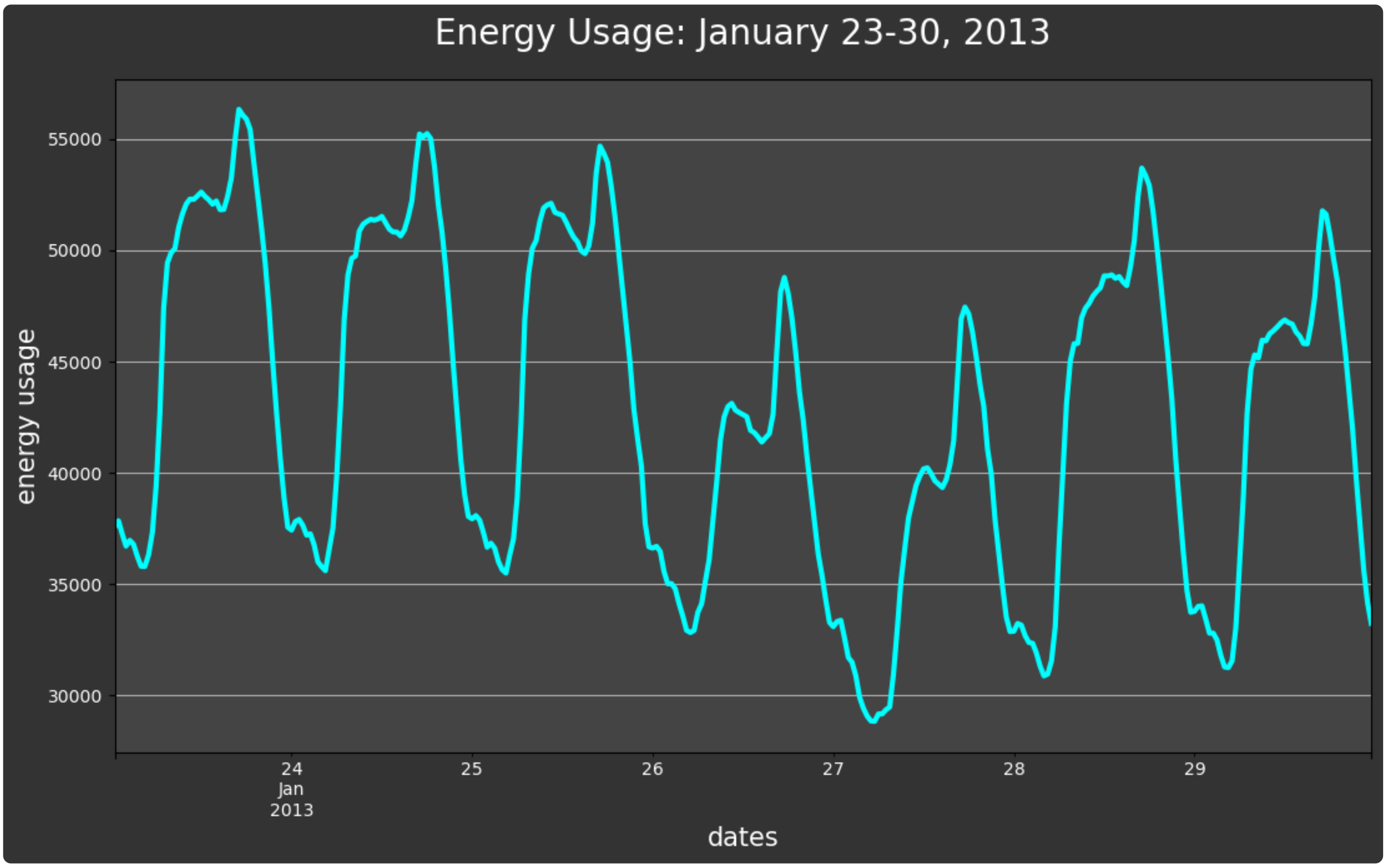
svg

```
fig = plt.figure(facecolor = '#333333', figsize = (13,7));
ax = plt.axes();
ax.set_facecolor('#444444')
data['consumption'].plot(color = colors[9],
          ax = ax);
ax.grid()
plt.xlabel('years', color = 'white', fontsize = 15)
plt.ylabel('energy usage', color = 'white', fontsize = 15)
plt.xticks(color='white'); plt.yticks(color='white');
plt.title('Energy Consumption in the UK: 2009-20022', fontsize = 20,
          pad = 20, color = 'white');
```



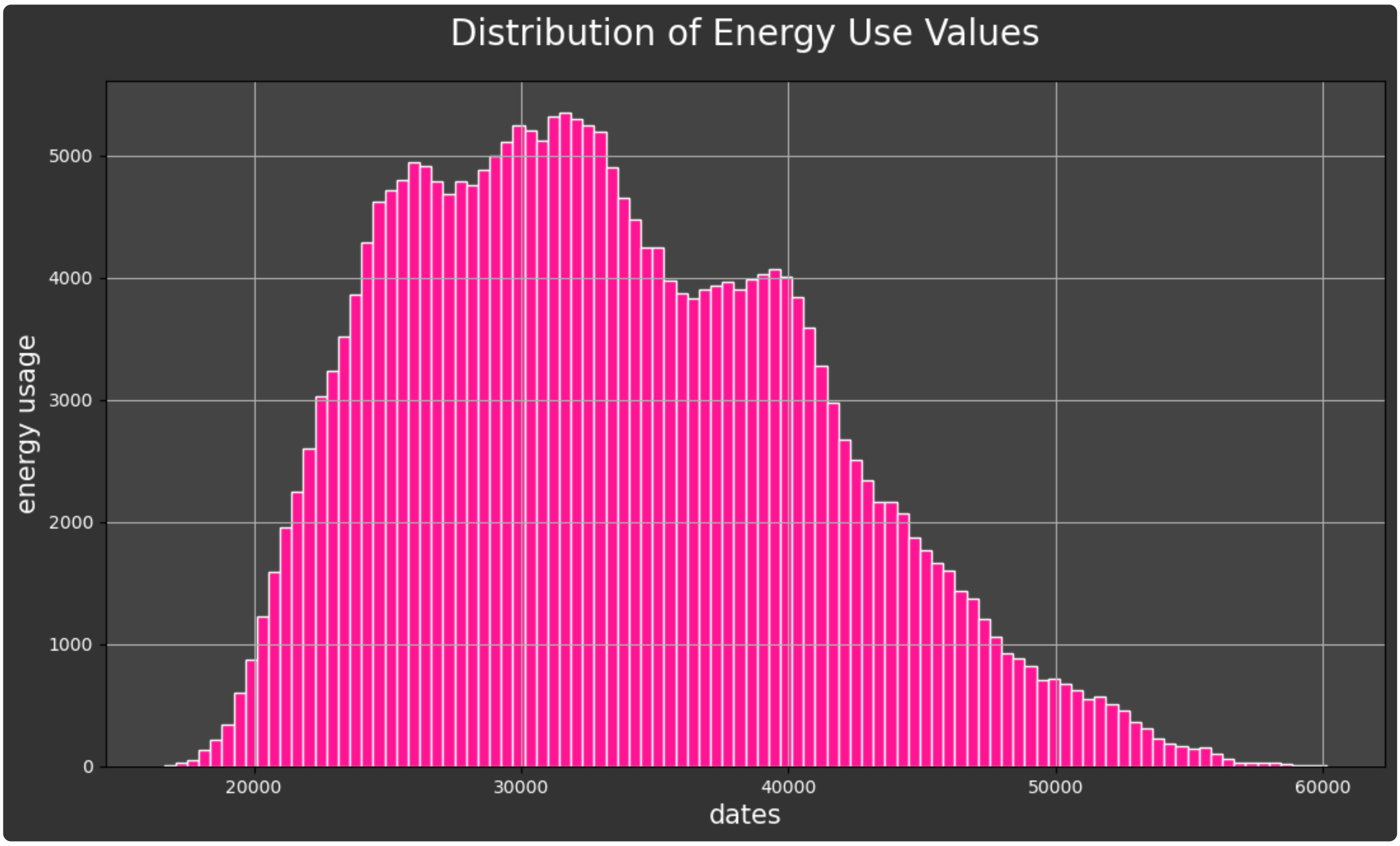
Looking at a Single Week of Data

```
fig, ax = plt.subplots(figsize = (13, 7), facecolor = '#333333')
ax.set_facecolor('#444444')
data['consumption'].iloc[(data.index > '01-23-2013') \
          & (data.index < '01-30-2013')].plot(ax = ax, linewidth = 3, color = 'cyan')
ax.grid()
plt.xlabel('dates', color = 'white', fontsize = 15)
plt.ylabel('energy usage', color = 'white', fontsize = 15)
plt.tick_params(labelcolor = 'white', which = 'both')
plt.title('Energy Usage: January 23-30, 2013', fontsize = 20,
          pad = 20, color = 'white');
plt.legend().remove()
```



Distribution of Energy Use Values

```
fig, ax = plt.subplots(figsize = (13, 7), facecolor = '#333333')
ax.set_facecolor('#444444')
data['consumption'].plot(kind = 'hist', bins = 100,
                  color = 'deeppink', edgecolor = 'white');
ax.grid()
plt.xlabel('dates', color = 'white', fontsize = 15)
plt.ylabel('energy usage', color = 'white', fontsize = 15)
plt.tick_params(labelcolor = 'white', which = 'both')
plt.title('Distribution of Energy Use Values',
          fontsize = 20, pad = 20, color = 'white');
plt.legend().remove()
```



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Feature Engineering

Time Series DateTime Index Feature Creation

```
def featurize_datetime_index(df, daytime = True):
    df = df.copy()

    df['hour'] = df.index.hour
    df['weekday'] = df.index.dayofweek
    df['weekday_name'] = df.index.strftime('%A')
    df['month'] = df.index.month
    df['month_name'] = df.index.strftime('%B')
    df['quarter'] = df.index.quarter
    df['year'] = df.index.year
    df['week_of_year'] = df.index.isocalendar().week
    df['day_of_year'] = df.index.dayofyear

    if daytime:
        # Add column with category for time of day:
        # midnight, early_morning, late_morning, afternoon, evening, night
        def time_of_day(hour):
            if hour >= 0 and hour < 6:
                return 'midnight'
            elif hour >= 6 and hour < 9:
                return 'early_morning'
```

```
        elif hour >= 9 and hour < 12:
            return 'late_morning'
        elif hour >= 12 and hour < 15:
            return 'afternoon'
        elif hour >= 15 and hour < 18:
            return 'evening'
        else:
            return 'night'

    df['time_of_day'] = (df['hour'].apply(time_of_day)).astype('category')

    df['weekday_name'] = df['weekday_name'].astype('category')
    df['month_name'] = df['month_name'].astype('category')

    return df
```

```
df = featurize_datetime_index(data.copy())
```

```
head_tail_horz(df.sample(10), 5, 'DF with Added Datetime Features (Random Samples)', ir
```

DF with Added Datetime Features (Random Samples)

head(5)

datetime	consumption	holiday	hour	weekday	weekday_name	month	month_name	quarter	year	week_of_year	d
2019-03-23 18:00:00	37,097	0	18	5	Saturday	3	March	1	2,019	12	
2021-10-07 21:00:00	30,872	0	21	3	Thursday	10	October	4	2,021	40	
2022-06-20 08:30:00	30,410	0	8	0	Monday	6	June	2	2,022	25	
2010-11-15 23:00:00	36,683	0	23	0	Monday	11	November	4	2,010	46	
2016-11-06 21:00:00	35,070	0	21	6	Sunday	11	November	4	2,016	44	

tail(5)

datetime	consumption	holiday	hour	weekday	weekday_name	month	month_name	quarter	year	week_of_year	d
2014-05-08 14:30:00	39,753	0	14	3	Thursday	5	May	2	2,014	19	
2011-04-05 12:30:00	43,494	0	12	1	Tuesday	4	April	2	2,011	14	
2011-12-01 06:00:00	33,868	0	6	3	Thursday	12	December	4	2,011	48	
2012-04-03 07:30:00	38,705	0	7	1	Tuesday	4	April	2	2,012	14	
2019-05-04 17:00:00	26,747	0	17	5	Saturday	5	May	2	2,019	18	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 244676 entries, 2009-01-01 00:00:00 to 2022-12-31 23:30:00
Data columns (total 12 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   consumption   244676 non-null  int64
 1   holiday       244676 non-null  int64
 2   hour          244676 non-null  int64
 3   weekday       244676 non-null  int64
 4   weekday_name  244676 non-null  category
 5   month         244676 non-null  int64
 6   month_name    244676 non-null  category
 7   quarter       244676 non-null  int64
 8   year          244676 non-null  int64
 9   week_of_year  244676 non-null  UInt32
 10  day_of_year   244676 non-null  int64
 11  time_of_day   244676 non-null  category
dtypes: UInt32(1), category(3), int64(8)
memory usage: 18.7 MB
```

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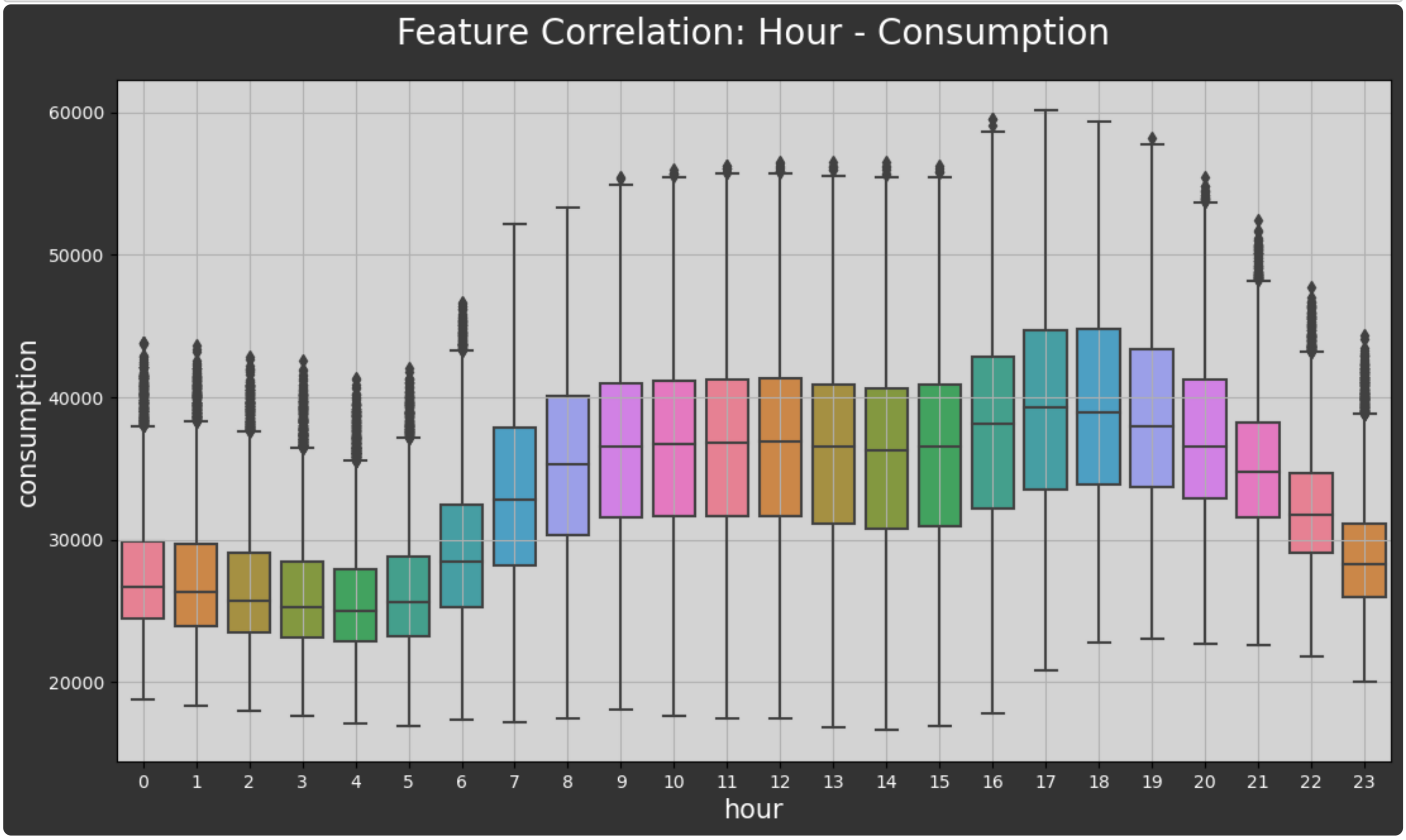
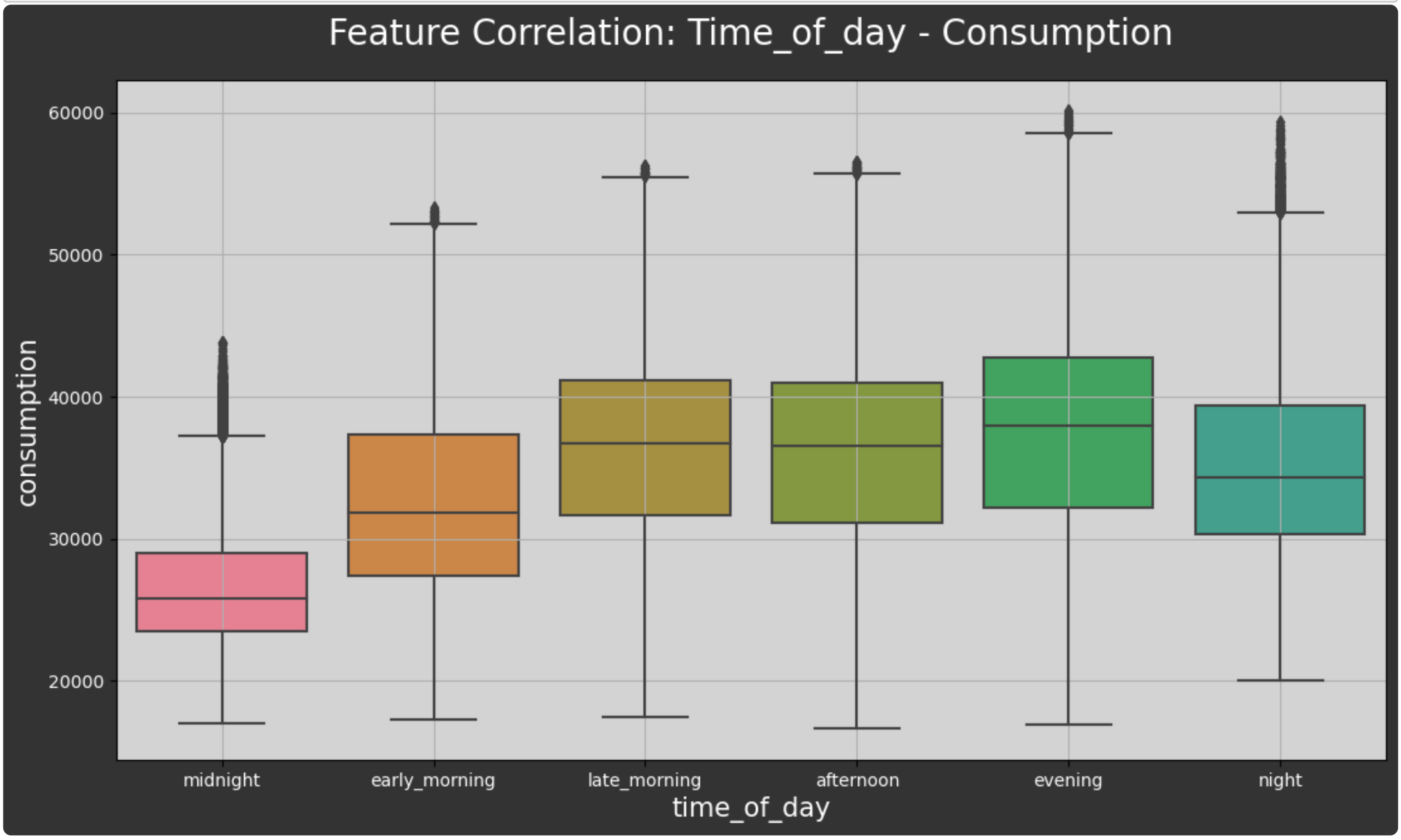
Visualize Correlation Between Features and Target

```
def boxplot_correlation(df, feature_x, feature_y, order = None, palette = None):

    fig, ax = plt.subplots(figsize = (13, 7), facecolor = '#333333')
    ax.set_facecolor('LightGray')

    sns.boxplot(data = df,
                x = feature_x,
                y = feature_y,
                order = order,
                palette = palette)

    x_name = str(df[feature_x].name)
    y_name = str(df[feature_y].name)

    ax.grid()
    plt.xlabel(x_name, color = 'white', fontsize = 15)
    plt.ylabel(y_name, color = 'white', fontsize = 15)
    plt.xticks(color='white'); plt.yticks(color='white');
    plt.title(f'Feature Correlation: {x_name.capitalize()} - {y_name.capitalize()}',
              fontsize = 20, pad = 20, color = 'white');
```

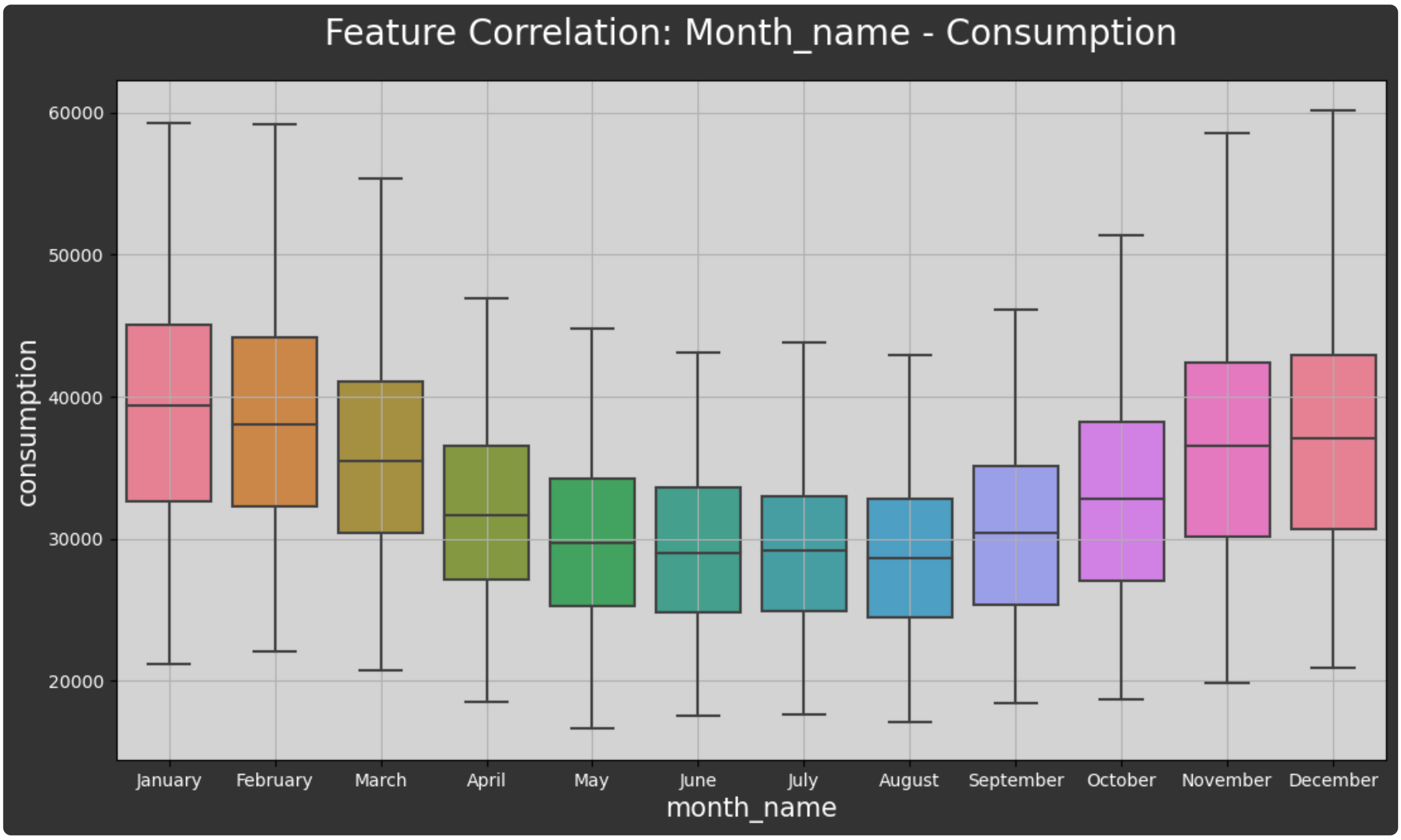
```
boxplot_correlation(df, 'hour', 'consumption',
                    palette = colors)
```



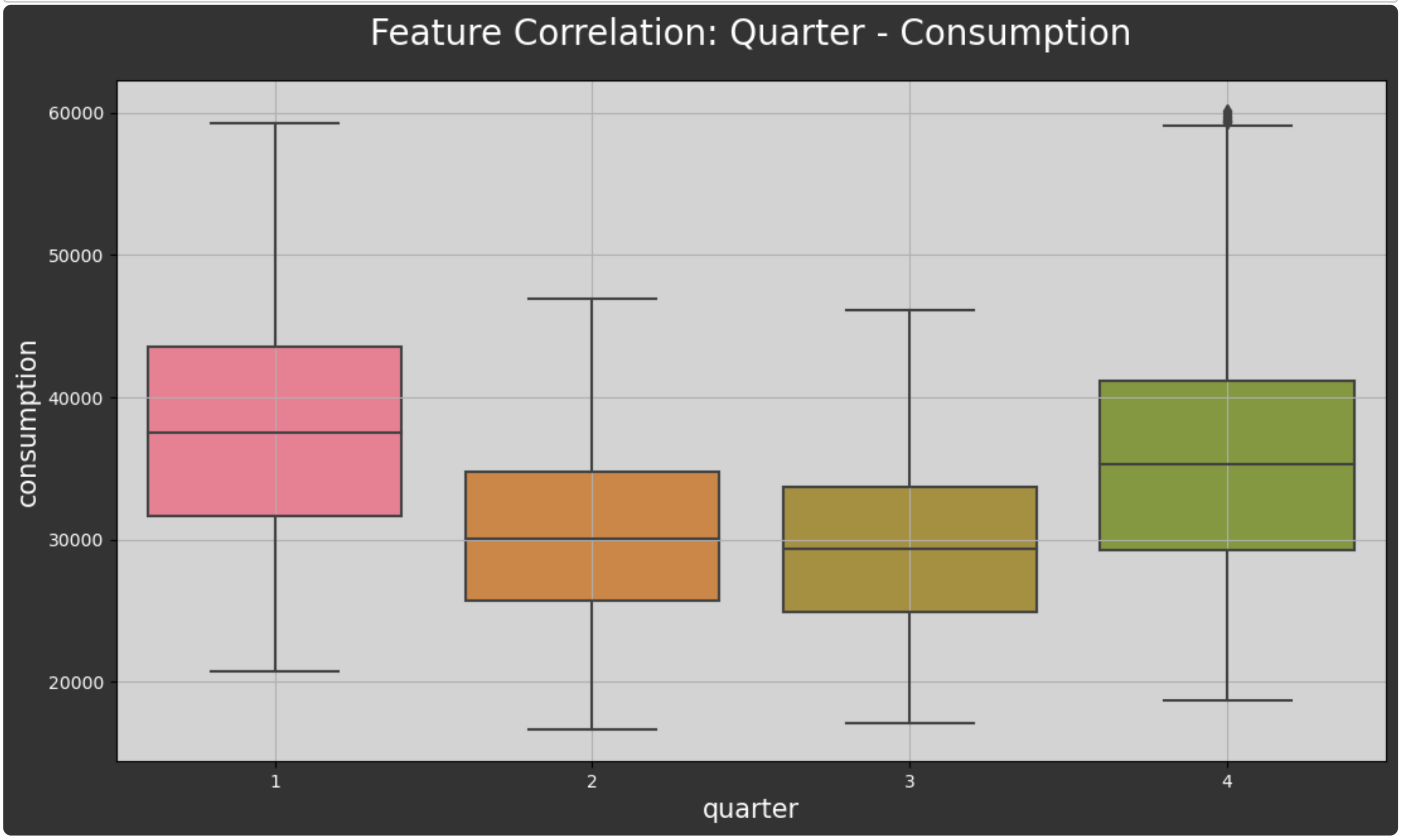
```
daytimes = ['midnight', 'early_morning', 'late_morning', 'afternoon',
            'evening', 'night']

boxplot_correlation(df, 'time_of_day', 'consumption',
                    order = daytimes, palette = colors)
```



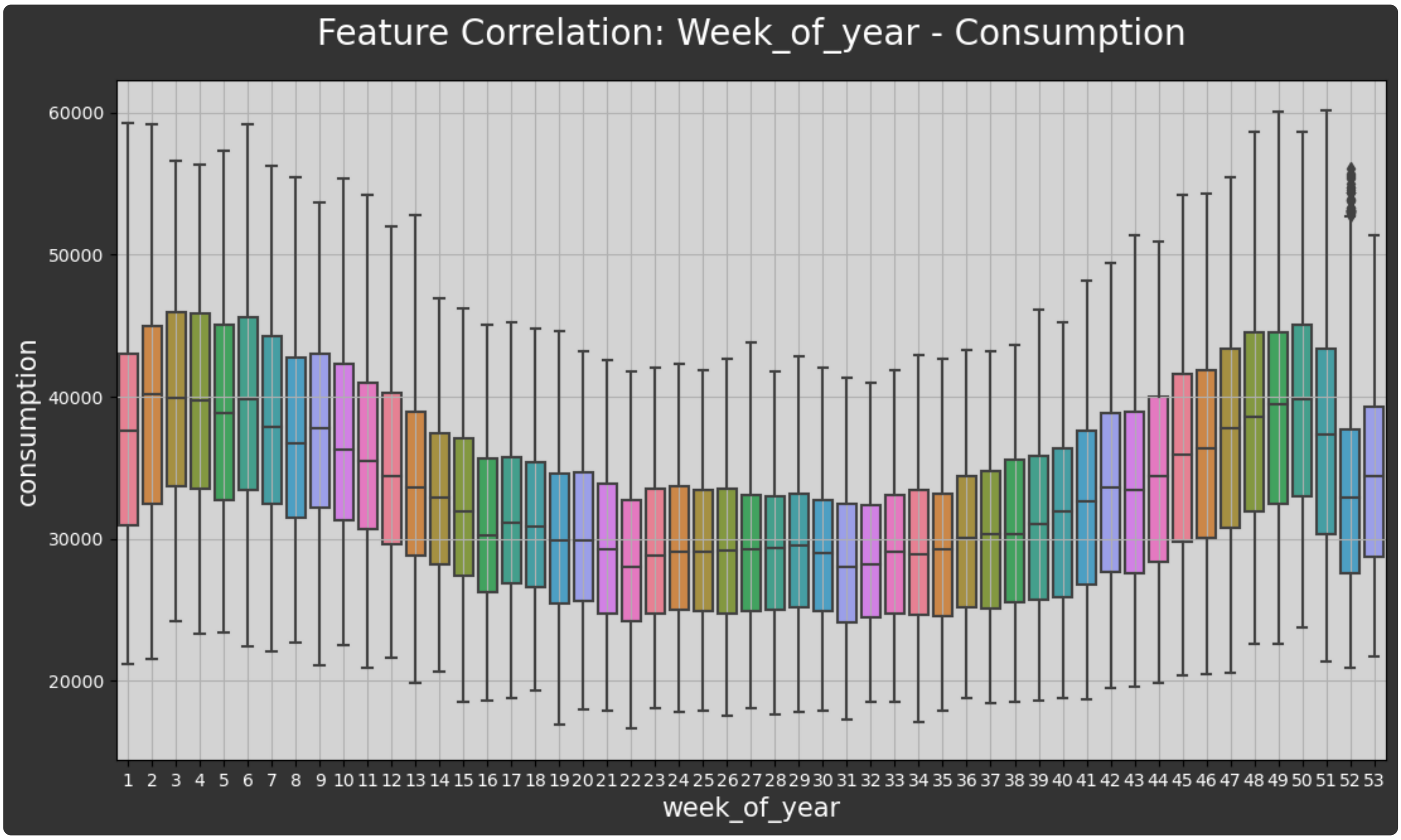

```
months = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
          'August', 'September', 'October', 'November', 'December']

boxplot_correlation(df, 'month_name', 'consumption',
                    order = months, palette = colors)
```




```
boxplot_correlation(df, 'quarter', 'consumption',
                    palette = colors)
```




```
boxplot_correlation(df, 'week_of_year', 'consumption',
                    palette = colors)
```



Converting `week_of_year` to float for model training

```
df['week_of_year'] = df.week_of_year.astype(float)
```

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Lag Features

Forecasting Horizon & Lag Features

- Lag Features: telling the model to look back into the past, and use the target value for that many days back as a new feature fed into the model
- in this case, it is a value from the energy usage column
- we are saving this column as a `dict` called `target_map`
- using 364 as the increment, because it is perfectly divisible by 7 and will line up days of the week
- the forecast horizon cannot extend farther than the shortest lag chosen
- using `map()` to map the values

```
def year_lags(df, target_column, lag_label_list):

    target_map = df[target_column].to_dict()
    inputs = lag_label_list.copy()

    for tup in inputs:
```

```
        df[tup[1]] = (df.index - pd.Timedelta(tup[0])).map(target_map)

    return df
```

```
lag_label_list = [('364 days', 'one_year'),
                  ('728 days', 'two_year'),
                  ('1092 days', 'three_year')]
```

```
df_lags = df.copy()
df_lags = year_lags(df_lags, 'consumption', lag_label_list)
```

```
missing_values(df_lags[['one_year', 'two_year', 'three_year']])
```

Columns and Missing Values

	column name	missing
0	one_year	18098
1	two_year	35380
2	three_year	52854

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Splitting the Data

- Because I noticed that I actually got better results training without the lag features added, I will be running each operation on both the data without lag features and with lag features for comparison.

Traditional Train-Test Split

- training data will the first 75% of the data
- test data will be everything the last 25% of the data

```
split_point = round(len(df) * .75)
```

```
train_data = df[: split_point]
test_data = df[split_point :]
train_data = pd.get_dummies(data=train_data, columns = ['time_of_day'])
test_data = pd.get_dummies(data=test_data, columns = ['time_of_day'])
```

```
train_data_lags = df_lags[: split_point]
test_data_lags = df_lags[split_point :]
train_data_lags = pd.get_dummies(data=train_data_lags, columns = ['time_of_day'])
test_data_lags = pd.get_dummies(data=test_data_lags, columns = ['time_of_day'])
```

Checking the point at which the training and testing divide

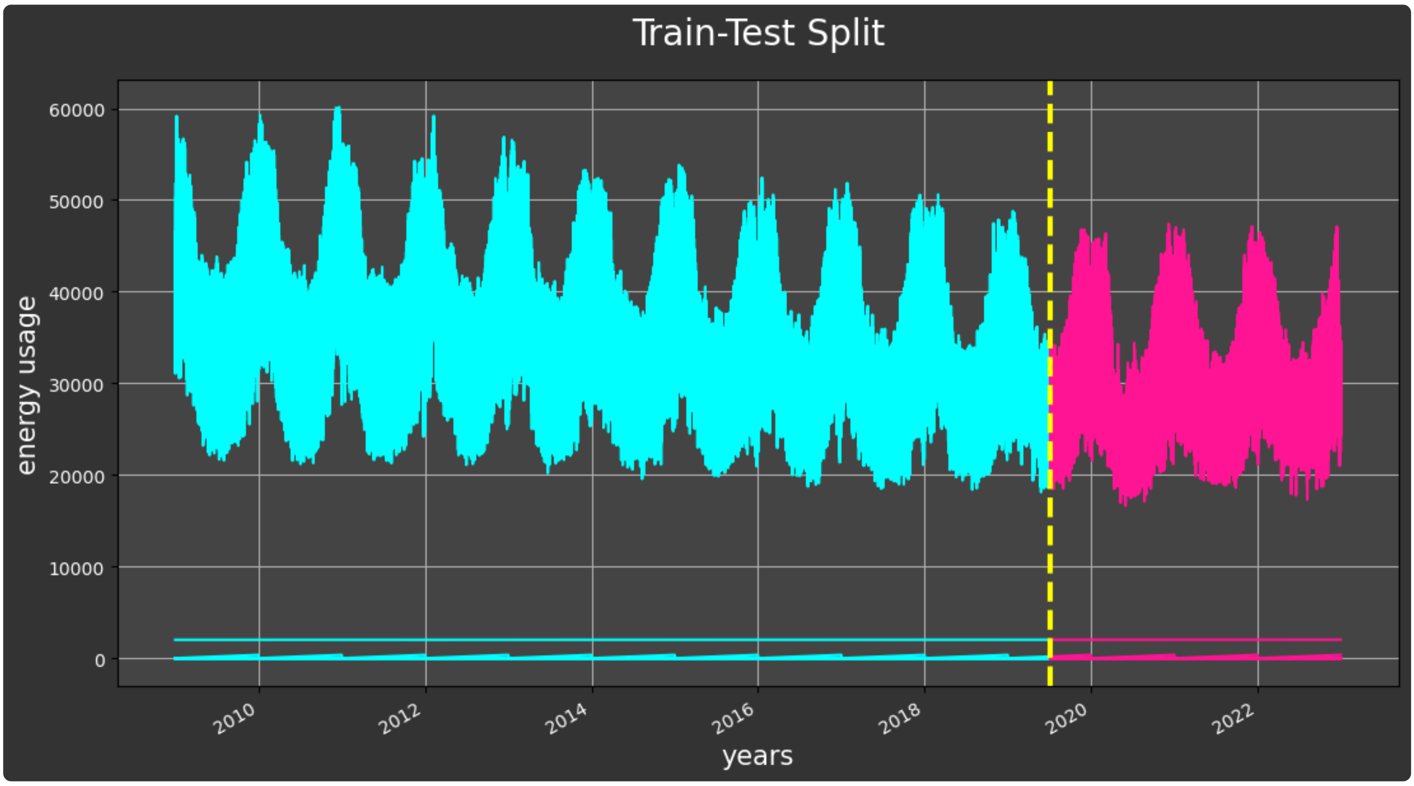
```
d(train_data.tail(1))
d(test_data.head(1))
```

datetime	consumption	holiday	hour	weekday	weekday_name	month	month_name	quarter	year	week_of_year	da
2019-07-06 12:00:00	27249	0	12	5	Saturday	7	July	3	2019	27	

datetime	consumption	holiday	hour	weekday	weekday_name	month	month_name	quarter	year	week_of_year	da
2019-07-06 12:30:00	27055	0	12	5	Saturday	7	July	3	2019	27	

Visualizing the Traditional Train-Test Split

```
fig, ax = plt.subplots(figsize = (13, 7), facecolor = '#333333')
ax.set_facecolor('#444444')
train_data.plot(ax = ax, label = 'Training Data', color = 'cyan');
test_data.plot(ax = ax, label = 'Testing Data', color = 'deeppink');
ax.grid()
ax.axvline('2019-07-06', color = 'yellow', ls = '--', linewidth = 3)
plt.xlabel('years', color = 'white', fontsize = 15)
plt.ylabel('energy usage', color = 'white', fontsize = 15)
plt.xticks(color='white'); plt.yticks(color='white');
plt.title('Train-Test Split', fontsize = 20, pad = 20, color = 'white');
plt.legend().remove()
```



Defining Features & Targets

```
features = ['hour', 'weekday', 'month', 'quarter', 'year',
            'week_of_year', 'day_of_year', 'time_of_day_afternoon',
            'time_of_day_early_morning', 'time_of_day_evening',
            'time_of_day_late_morning', 'time_of_day_midnight',
            'time_of_day_night']

features_lags = ['hour', 'weekday', 'month', 'quarter', 'year',
            'week_of_year', 'day_of_year', 'time_of_day_afternoon',
            'time_of_day_early_morning', 'time_of_day_evening',
            'time_of_day_late_morning', 'time_of_day_midnight',
            'time_of_day_night', 'one_year', 'two_year', 'three_year']

target = "consumption"
```

Defining Training & Testing Data with Features

```
train_in = train_data[features]
train_out = train_data[target]
test_in = test_data[features]
test_out = test_data[target]
```

```
train_in_lags = train_data_lags[features_lags]
train_out_lags = train_data_lags[target]
test_in_lags = test_data_lags[features_lags]
test_out_lags = test_data_lags[target]
```

The XGBoost Regressor Model

Creating the Model (without lags)

```
xgb_regressor = XGBRegressor(n_estimators = 1200,
                             learning_rate = 0.012,
                             early_stopping_rounds = 23)
```

Fitting the Model (without lags)

```
xgb_regressor.fit(train_in, train_out,
                 eval_set = [(train_in, train_out),
                              (test_in, test_out)], verbose = 25)
```

```
[0] validation_0-rmse:35068.46435   validation_1-rmse:29587.12720
[25]    validation_0-rmse:26018.01179   validation_1-rmse:21235.48885
[50]    validation_0-rmse:19337.02538   validation_1-rmse:15148.51055
[75]    validation_0-rmse:14411.06888   validation_1-rmse:10692.43309
[100]   validation_0-rmse:10787.75506   validation_1-rmse:7519.52345
[125]   validation_0-rmse:8131.03112    validation_1-rmse:5323.82623
[150]   validation_0-rmse:6192.47195    validation_1-rmse:3833.85620
[175]   validation_0-rmse:4791.75784    validation_1-rmse:2961.30137
[200]   validation_0-rmse:3789.02170    validation_1-rmse:2547.03297
[225]   validation_0-rmse:3086.91956    validation_1-rmse:2420.27304
[250]   validation_0-rmse:2602.61653    validation_1-rmse:2429.93979
[257]   validation_0-rmse:2496.84033    validation_1-rmse:2442.06684
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
colsample_bylevel=None, colsample_bynode=None,
colsample_bytree=None, early_stopping_rounds=23,
enable_categorical=False, eval_metric=None, feature_types=None,
gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
interaction_constraints=None, learning_rate=0.012, max_bin=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=None,
n_estimators=1200, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
XGBRegressor

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
colsample_bylevel=None, colsample_bynode=None,
colsample_bytree=None, early_stopping_rounds=23,
enable_categorical=False, eval_metric=None, feature_types=None,
gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
interaction_constraints=None, learning_rate=0.012, max_bin=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=None,
n_estimators=1200, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)
```

Fitting the Model (with lags)

```
xgb_regressor_lags = XGBRegressor(n_estimators = 1200,
                                  learning_rate = 0.012,
                                  early_stopping_rounds = 23)
```

```
xgb_regressor_lags.fit(train_in_lags, train_out_lags,
                 eval_set = [(train_in_lags, train_out_lags),
                              (test_in_lags, test_out_lags)],
                  verbose = 25)
```

```
[0] validation_0-rmse:35067.37778   validation_1-rmse:29621.32089
[25]    validation_0-rmse:25992.89494   validation_1-rmse:21982.27167
[50]    validation_0-rmse:19296.64994   validation_1-rmse:16362.81470
[75]    validation_0-rmse:14362.19803   validation_1-rmse:12236.19017
[100]   validation_0-rmse:10732.97496   validation_1-rmse:9220.63188
[125]   validation_0-rmse:8075.19740    validation_1-rmse:7039.05742
[150]   validation_0-rmse:6141.15746    validation_1-rmse:5477.98424
[175]   validation_0-rmse:4744.45133    validation_1-rmse:4392.53113
[200]   validation_0-rmse:3752.23105    validation_1-rmse:3673.74192
[225]   validation_0-rmse:3063.21492    validation_1-rmse:3212.91990
[250]   validation_0-rmse:2594.90743    validation_1-rmse:2925.86404
[275]   validation_0-rmse:2282.94267    validation_1-rmse:2750.60546
[300]   validation_0-rmse:2073.32089    validation_1-rmse:2662.13021
[325]   validation_0-rmse:1937.22774    validation_1-rmse:2611.90552
[350]   validation_0-rmse:1836.60203    validation_1-rmse:2585.33120
[375]   validation_0-rmse:1762.79711    validation_1-rmse:2569.20642
[400]   validation_0-rmse:1706.81078    validation_1-rmse:2561.84587
[425]   validation_0-rmse:1670.78904    validation_1-rmse:2555.93349
[450]   validation_0-rmse:1644.08868    validation_1-rmse:2551.10259
[475]   validation_0-rmse:1621.20190    validation_1-rmse:2548.89837
[500]   validation_0-rmse:1604.13354    validation_1-rmse:2547.76779
```

```
[525]	validation_0-rmse:1587.04879	validation_1-rmse:2549.01441
[531]	validation_0-rmse:1583.52664	validation_1-rmse:2549.17672
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
colsample_bylevel=None, colsample_bynode=None,
colsample_bytree=None, early_stopping_rounds=23,
enable_categorical=False, eval_metric=None, feature_types=None,
gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
interaction_constraints=None, learning_rate=0.012, max_bin=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=None,
n_estimators=1200, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook. On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
XGBRegressor


```
XGBRegressor(base_score=None, booster=None, callbacks=None,
colsample_bylevel=None, colsample_bynode=None,
colsample_bytree=None, early_stopping_rounds=23,
enable_categorical=False, eval_metric=None, feature_types=None,
gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
interaction_constraints=None, learning_rate=0.012, max_bin=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=None,
n_estimators=1200, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)
```


Feature Importance (without lags)

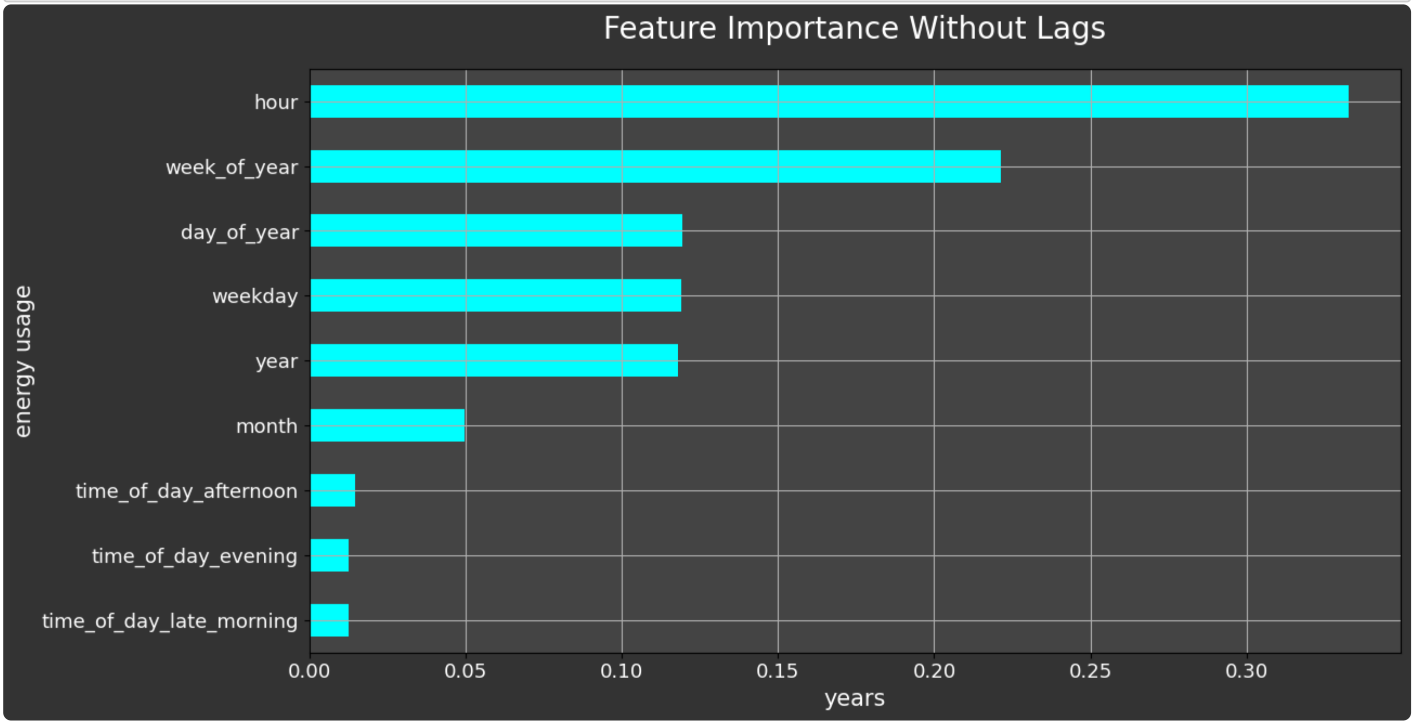
```
feature_importance = pd.DataFrame(data = xgb_regressor.feature_importances_,
                                  index = xgb_regressor.feature_names_in_,
                                  columns = ['importance'])

feature_importance = feature_importance[feature_importance.importance > 0.0005]

multi([(feature_importance.sort_values('importance', ascending = False),
        'Feature Importance (no lags)'),
      (feature_importance_lags.sort_values('importance', ascending = False),
        'Feature Importance (with lags)')], precision = 4)
```

Feature Importance (no lags)	importance
hour	0.3328
week_of_year	0.2212
day_of_year	0.1193
weekday	0.1191
year	0.1179
month	0.0498
time_of_day_afternoon	0.0147
time_of_day_evening	0.0127
time_of_day_late_morning	0.0125

Feature Importance (with lags)	importance
hour	0.3328
week_of_year	0.2212
day_of_year	0.1193
weekday	0.1191
year	0.1179
month	0.0498
time_of_day_afternoon	0.0147
time_of_day_evening	0.0127
time_of_day_late_morning	0.0125

Plotting Feature Importance

```
fig, ax = plt.subplots(figsize = (13, 7), facecolor = '#333333')
ax.set_facecolor('#444444')

feature_importance.sort_values('importance').plot(kind = 'barh',
                                                  color = 'cyan',
                                                  ax = ax)
ax.grid()
plt.xlabel('years', color = 'white', fontsize = 15)
plt.ylabel('energy usage', color = 'white', fontsize = 15)
plt.xticks(color='white', size = 13); plt.yticks(color='white', size = 13);
plt.title('Feature Importance Without Lags', fontsize = 20, pad = 20, color = 'white');
plt.legend().remove()
```



Results with Traditional Train-Test Split

- Because there is no benefit to having the lag data added, for the remainder of the project, I will be working with only the data without lags added.

Predicting with Test Data

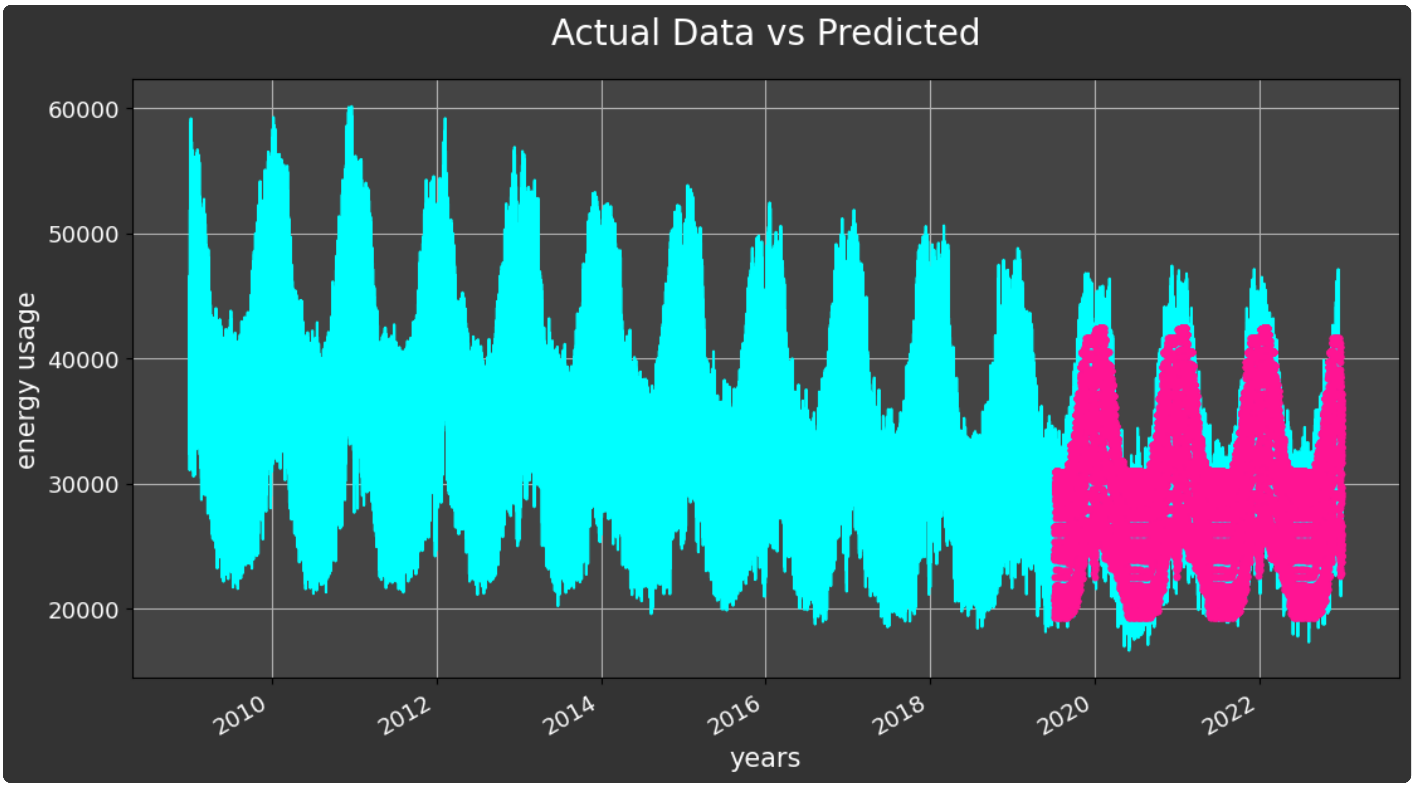
```
test_data['prediction'] = xgb_regressor.predict(test_in)
```

Merging Predictions into Original DF

```
df = df.merge(test_data['prediction'],
              how = 'left',
              left_index = True,
              right_index = True)
```

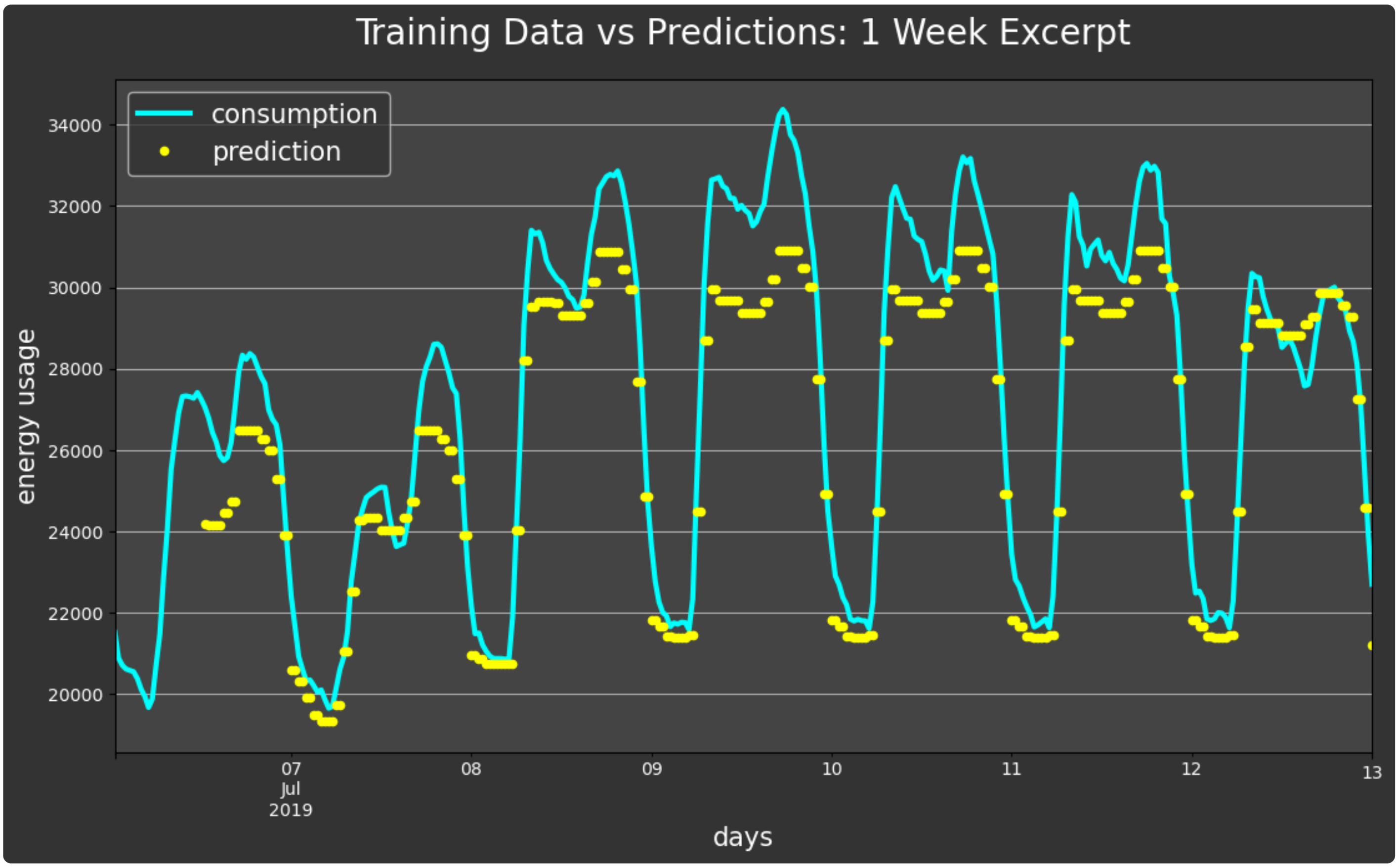
Plotting Predictions vs Original Data

```
plt.figure(facecolor = '#333333');
ax = df['consumption'].plot(figsize = (13, 7), color = 'cyan');
ax.set_facecolor('#444444');
df['prediction'].plot(ax = ax, style = '.', color = 'deeppink');
plt.legend();
ax.grid()
plt.xlabel('years', color = 'white', fontsize = 15)
plt.ylabel('energy usage', color = 'white', fontsize = 15)
plt.xticks(color='white', size = 13); plt.yticks(color='white', size = 13);
plt.title('Train-Test Split', fontsize = 20, pad = 20, color = 'white');
plt.legend().remove()
ax.set_title('Actual Data vs Predicted', color = 'white', size = 20, pad = 20);
```



Predictions vs Targets: One Week Excerpt

```
plt.figure(figsize = (13, 7), facecolor = '#333333')
ax = df.loc[(df.index > '2019-07-06') & (df.index <= '2019-07-13')]\
            ['consumption'].plot(color = 'cyan', linewidth = 3);
df.loc[(df.index > '2019-07-06') & (df.index <= '2019-07-13')]\
            ['prediction'].plot(style = '.', color = 'yellow', markersize = 9);
ax.set_facecolor('#444444')
plt.legend();
ax.grid()
plt.xlabel('days', color = 'white', fontsize = 15)
plt.ylabel('energy usage', color = 'white', fontsize = 15)
plt.tick_params(labelcolor = 'white', which = 'both')
plt.title('Training Data vs Predictions: 1 Week Excerpt', fontsize = 20, pad = 20, colc
plt.legend(fontsize = 15, labelcolor = 'white', facecolor = '#333333');
```



Prediction Accuracy

```
def get_accuracy(df, pred_col, actual_col):
    from sklearn.metrics import mean_squared_error
    df = df.copy()

    df['abs_acc'] = (1 - (abs(df[actual_col] -
                               df[pred_col]) / df[actual_col])) * 100

    range_diff = np.max(df[actual_col]) - np.min(df[actual_col])

    df['rel_acc'] = (1 - (abs(df[actual_col] -
                               df[pred_col]) / range_diff)) * 100

    range_std = np.std(df[actual_col])

    df['sharpe'] = (abs(df[actual_col] -
                               df[pred_col]) / range_std)

    rmse = np.sqrt(mean_squared_error(df[actual_col],
                                      df[pred_col]))

    results = pd.Series([f"{rmse:,.2f}",
                         f"{df['abs_acc'].mean():.2f}%",
                         f"{df['rel_acc'].mean():.2f}%",
                         f"{df['sharpe'].mean():.2f}"],
                        index = ['Average RMSE',
                                 'Average Absolute Accuracy',
                                 'Average Relative Accuracy',
```

```python
                                   'Average Sharpe Ratio'],
                         name = "Resulting Metrics")

    see(results, 'Overall Metrics for Accuracy and Model Performance')

    return df
```

```python
pred_actual = df.loc[df.prediction.notna()]
```

```python
pred_actual = get_accuracy(pred_actual, 'consumption', 'prediction')

head_tail_horz(pred_actual[['consumption', 'prediction', 'abs_acc',
                            'rel_acc', 'sharpe']], 5, 'Predictions vs Actual Targets')
```

Overall Metrics for Accuracy and Model Performance

	Resulting Metrics
Average RMSE	2,414.50
Average Absolute Accuracy	93.58%
Average Relative Accuracy	91.91%
Average Sharpe Ratio	0.33

Predictions vs Actual Targets

head(5)

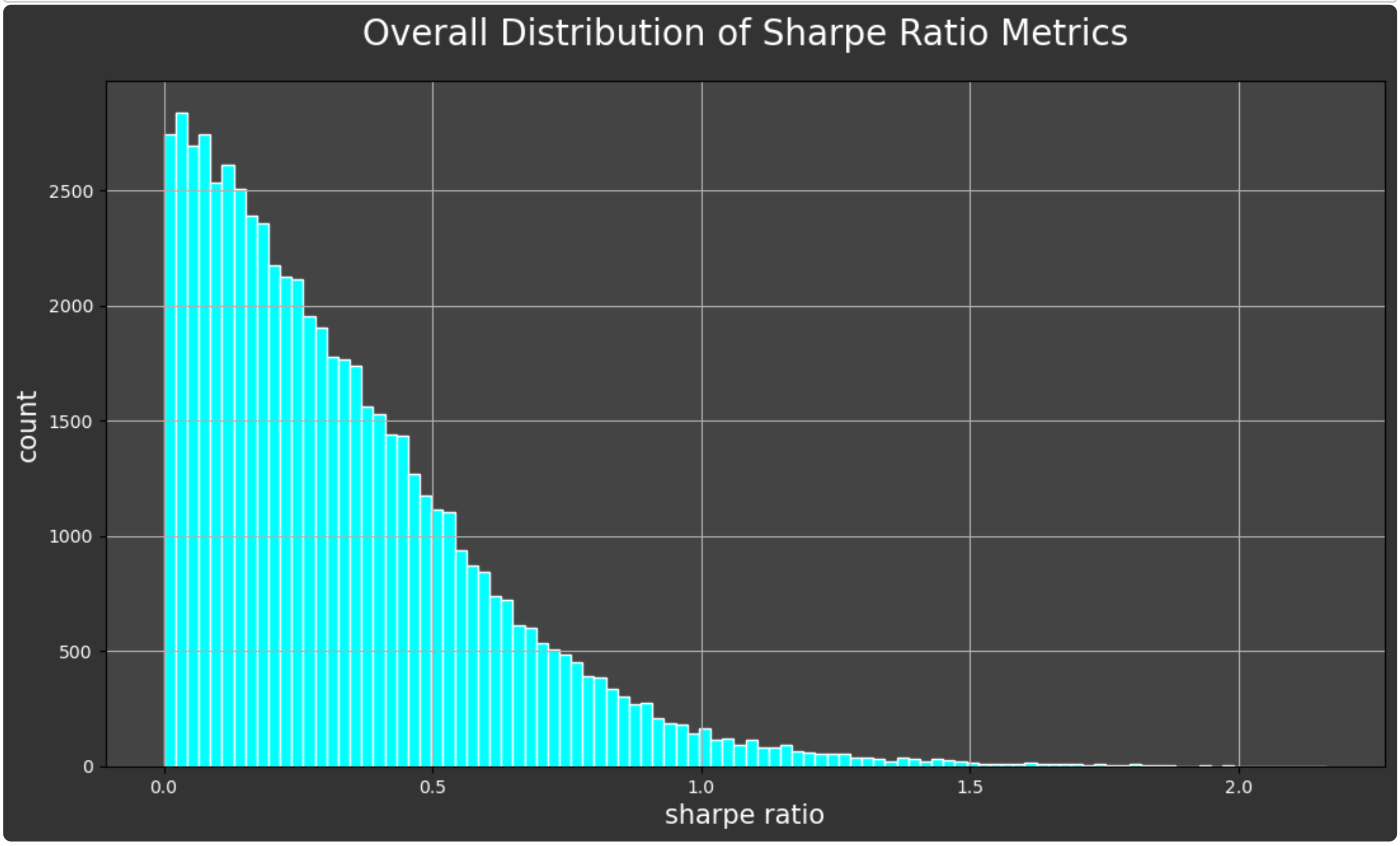
datetime	consumption	prediction	abs_acc	rel_acc	sharpe
2019-07-06	27,055	24,169.05	88.06	87.51	0.51
2019-07-06	26,790	24,147.77	89.06	88.56	0.47
2019-07-06	26,434	24,147.77	90.53	90.10	0.40
2019-07-06	26,204	24,147.77	91.48	91.10	0.36
2019-07-06	25,862	24,147.77	92.90	92.58	0.30

tail(5)

datetime	consumption	prediction	abs_acc	rel_acc	sharpe
2022-12-31	25,634	32,205.60	79.59	71.56	1.16
2022-12-31	24,788	29,192.30	84.91	80.94	0.78
2022-12-31	24,365	29,192.30	83.46	79.11	0.85
2022-12-31	24,766	26,653.43	92.92	91.83	0.33
2022-12-31	24,843	26,653.43	93.21	92.16	0.32

Plotting the Sharpe Ratio

```
plt.figure(figsize = (13, 7), facecolor = '#333333')
ax = plt.axes()
pred_actual.sharpe.plot(kind="hist",
                        bins=100,
                        color = 'cyan',
                        edgecolor = 'white',
                        ax = ax)
ax.set_facecolor('#444444')
plt.legend();
ax.grid()
plt.xlabel('sharpe ratio', color = 'white', fontsize = 15)
plt.ylabel('count', color = 'white', fontsize = 15)
plt.tick_params(labelcolor = 'white', which = 'both')
plt.title('Overall Distribution of Sharpe Ratio Metrics',
          fontsize = 20, pad = 20, color = 'white');
plt.legend().remove()
```



Daily Error - Investigating the Days with the Highest and Lowest Error

```
def get_daily_error(df, actual_col, pred_col, num_examples,
                    ascending = False):

    temp = df[[actual_col, pred_col]].copy()
    temp['date'] = temp.index.strftime('%A, %b %d, %Y')
    temp['error'] = np.abs(df[actual_col] - df[pred_col])

    results = temp.sort_values("error", ascending = ascending)

    error_style = {'error': [{'selector': '',
```

```
                                    'props': [('color', 'red'),
                                              ('font-weight', 'bold'),
                                              ('padding-right', '15px'),
                                              ('padding-left', '15px')]}],
                        'date': [{'selector': 'td',
                                  'props': [('color', 'blue'),
                                            ('font-weight', 'bold'),
                                            ('padding-right', '15px'),
                                            ('padding-left', '15px')]}],
                        'prediction': [{'selector': 'td',
                                  'props': [('padding-right', '25px'),
                                            ('padding-left', '15px')]}]}

    if ascending == True:
        pretty(f'Daily error for the {num_examples} days with the lowest error:',
               fontsize = 4)
    else:
        pretty(f'Daily error for the {num_examples} days with the highest error:',
               fontsize = 4)

    return results[['date',
                    'error',
                    pred_col,
                    actual_col]].head(num_examples).style.hide(axis='index')\
                        .set_table_styles(error_style)\
                        .format(precision=3, thousands=",")
```

```
get_daily_error(pred_actual, 'consumption', 'prediction', 10)
```

Daily error for the 10 days with the highest error:

date	error	prediction	consumption
Monday, Jan 03, 2022	12,227.672	38,637.672	26,410
Sunday, Dec 25, 2022	11,386.129	34,748.129	23,362
Monday, May 25, 2020	11,337.658	29,313.658	17,976
Monday, May 25, 2020	11,248.658	29,313.658	18,065
Monday, Jan 03, 2022	11,133.672	38,637.672	27,504
Sunday, Dec 25, 2022	11,090.129	34,748.129	23,658
Monday, May 25, 2020	10,898.234	29,617.234	18,719
Sunday, Dec 25, 2022	10,891.258	34,945.258	24,054
Monday, Apr 13, 2020	10,769.680	30,451.680	19,682
Monday, Apr 13, 2020	10,671.783	30,159.783	19,488

```
get_daily_error(pred_actual, 'consumption', 'prediction', 10,
               ascending = True)
```

Daily error for the 10 days with the lowest error:

date	error	prediction	consumption

date	error	prediction	consumption
Monday, Oct 14, 2019	0.107	25,882.107	25,882
Saturday, Dec 14, 2019	0.250	26,106.250	26,106
Wednesday, Oct 13, 2021	0.395	32,784.605	32,785
Tuesday, Feb 09, 2021	0.395	40,235.605	40,236
Tuesday, Nov 26, 2019	0.443	26,390.443	26,390
Friday, Aug 27, 2021	0.479	28,798.521	28,799
Saturday, Oct 30, 2021	0.508	23,858.508	23,858
Thursday, Dec 02, 2021	0.557	31,655.443	31,656
Sunday, Jun 27, 2021	0.600	20,580.600	20,580
Monday, Mar 14, 2022	0.686	24,652.314	24,653

Sections: ● Top ● The Data ● Feature Engineering ● Investigating Correlation ● Lag Features ● Splitting ● The Model ● Results with Traditional Split ● Using Cross-Validation ● Making Future Predictions

Training the Model Using Cross Validation

What is Cross Validation?

- using sklearn `TimeSeriesSplit()`
- test size is 1 year of hourly records
- a gap of 24 puts a 1 day gap between the end of a training set and beginning of a test set
- must be sure time series data is sorted so that the time series split will work

```
time_series_split = TimeSeriesSplit(n_splits = 5,
                                    test_size = (24 * 365 * 1),
                                    gap = 24)

df = df.sort_index()
```

This creates a time series split generator object

- this object will be applied across the data
- it will loop over the data for as many splits as are passed

```
time_series_split
```

```
TimeSeriesSplit(gap=24, max_train_size=None, n_splits=5, test_size=8760)
```

Visualizing the `TimeSeriesSplit()` process

- for each fold, the model goes back and tests the testing data in 1 year increments, independently from the rest of the testing data

- this is a very good approach when the dataset has a large number of records

```
for train_index, validation_index in time_series_split.split(df):
    break
pretty(train_index, 'Indices of training data:')
pretty(validation_index, 'Indices of validation data:'); sp()
```

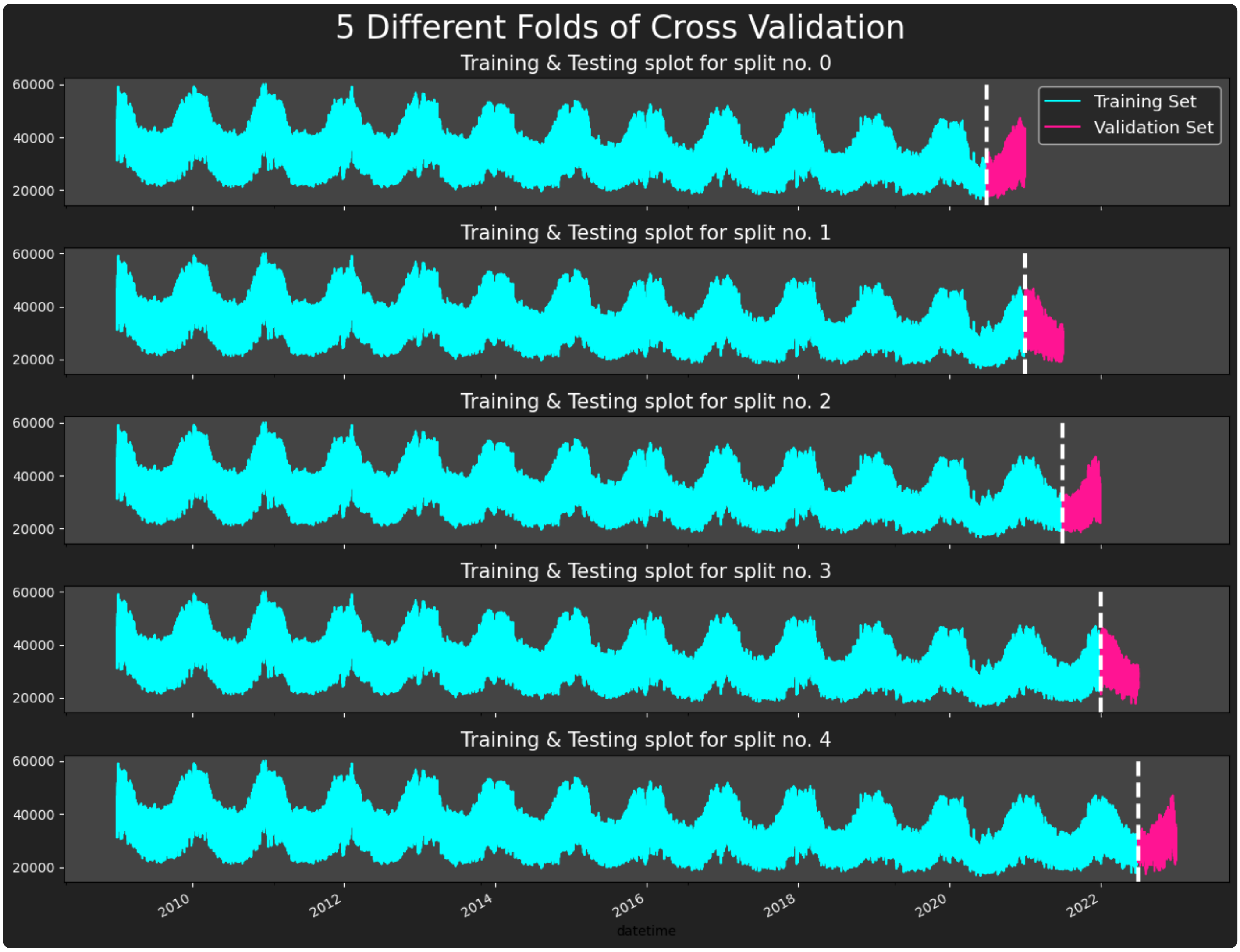
Indices of training data:

[0 1 2 ... 200849 200850 200851]

Indices of validation data:

[200876 200877 200878 ... 209633 209634 209635]

```
fig, axs = plt.subplots(5, 1, figsize = (13, 10),
                       sharex = True, facecolor = "#222222")

split = 0
for train_index, validation_index in time_series_split.split(df):
    training = df.iloc[train_index]
    validation = df.iloc[validation_index]

    ax = axs[split]
    ax.set_facecolor('#444444')
    ax.set_title(f'Training & Testing splot for split no. {split}',
                 fontsize = 15, color = 'white')
    ax.tick_params(color = 'white', labelcolor = 'white')

    training['consumption'].plot(ax = ax,
                                label = 'Training Set',
                                color = 'cyan')
    validation['consumption'].plot(ax = ax,
                                label = 'Validation Set',
                                  color = 'deeppink')

    axs[split].axvline(validation.index.min(),
                      color = 'white', ls = "--", linewidth = 3)

    axs[0].legend(fontsize=13, facecolor = '#222222', labelcolor = 'white')

    split += 1

plt.suptitle('5 Different Folds of Cross Validation', color = 'white', fontsize = 24)
plt.tight_layout()
```



Training with Cross Validation

- this will repeat the steps above in order to now train with cross validation and the `TimeSeriesSplit()` method

```
def cross_validation_train(df, target_column,
                            lags = False, lag_label_list = None,
                            splits = 5, test_size = (24 * 365 * 1),
                            gap = 24, base_score = 0.5, booster = 'gbtree',
                            n_estimators = 1200, early_stopping_rounds = 50,
                            objective = 'reg:squarederror', max_depth = 3,
                            learning_rate = 0.01, verbose = 25):

    from sklearn.metrics import mean_squared_error
    from sklearn.model_selection import TimeSeriesSplit

    # ................ Establishing Features & Targets ................ #

    df = featurize_datetime_index(df)
    target = target_column

    # ................ Lag Features & Feature Cleanup ................. #
```

```python
    if lags:
        df = year_lags(df, target_column, lag_label_list)
        features = list(df.columns)

    else:
        features = list(df.columns)

    features.remove('weekday_name')
    features.remove('month_name')
    features.remove('time_of_day')
    features.remove(target)

    # ................. Correcting Datatypes for Model ................ #

    df['week_of_year'] = df.week_of_year.astype(float)

    # .................. Setting Up Cross-Validation .................. #

    split = 1
    prediction_log = []
    target_log = []
    rmse_log = []

    df = df.sort_index()
    time_series_split = TimeSeriesSplit(n_splits = splits,
                                        test_size = test_size,
                                        gap = gap)

    # ............... Running Cross-Validation Training ............... #

    for train_index, validation_index in time_series_split.split(df):
        pretty(f'Training split:  {split} of {splits}')
        training = df.iloc[train_index]
        validation = df.iloc[validation_index]

        train_in = training[features]
        train_out = training[target]
        test_in = validation[features]
        test_out = validation[target]

        model = XGBRegressor(base_score = base_score,
                             booster = booster,
                             n_estimators = n_estimators,
                             early_stopping_rounds = early_stopping_rounds,
                             objective = objective,
                             max_depth = max_depth,
                             learning_rate = learning_rate)


        model.fit(train_in, train_out,
                  eval_set = [(train_in, train_out),
                              (test_in, test_out)],
```

```
                    verbose = verbose)

        targets = list(test_out)
        target_log += targets

        prediction = model.predict(test_in)
        prediction_log += list(prediction)

        rmse = np.sqrt(mean_squared_error(test_out, prediction))
        rmse_log.append((f'split {split}', rmse))

        split += 1

    # ............. Compiling Training & Testing Results .............. #

    results = pd.DataFrame(pd.concat([pd.Series(prediction_log),
                                      pd.Series(target_log)],
                                     axis = 1))
    results.columns = ['prediction', 'actual']

    pred_actual = get_accuracy(results, 'actual', 'prediction')

    print('')

    head_tail_horz(pred_actual[['actual', 'prediction', 'abs_acc',
                        'rel_acc', 'sharpe']], 5, 'Predictions vs Actual Targets')

    return pred_actual, rmse_log
```

Cross-Validation Results without Lag Features

```
cross_results, rmses = cross_validation_train(df,
                                              target_column = "consumption",
                                              learning_rate = 0.012,
                                              verbose = 500,
                                              splits = 16)
```

Training split: 1 of 16

```
[0] validation_0-rmse:36927.43252    validation_1-rmse:34875.18364
[500]    validation_0-rmse:2056.87214     validation_1-rmse:2423.05766
[1000]   validation_0-rmse:1676.66795     validation_1-rmse:2181.13980
[1199]   validation_0-rmse:1616.77561     validation_1-rmse:2155.05839
```

Training split: 2 of 16

```
[0] validation_0-rmse:36775.76007    validation_1-rmse:32375.93347
[265]    validation_0-rmse:3149.83870     validation_1-rmse:3050.08925
```

Training split: 3 of 16

```
[0] validation_0-rmse:36479.99831    validation_1-rmse:33557.74521
[298]    validation_0-rmse:2863.89178     validation_1-rmse:2735.91368
```

Training split: 4 of 16

```
[0]	validation_0-rmse:36295.33002	validation_1-rmse:32125.01992
[500]	validation_0-rmse:2137.87922	validation_1-rmse:2715.88639
[1000]	validation_0-rmse:1753.45240	validation_1-rmse:2321.19621
[1199]	validation_0-rmse:1693.75240	validation_1-rmse:2266.00976
```

Training split: 5 of 16

```
[0]	validation_0-rmse:36049.16304	validation_1-rmse:32516.82046
[281]	validation_0-rmse:3059.10355	validation_1-rmse:3166.45254
```

Training split: 6 of 16

```
[0]	validation_0-rmse:35853.96617	validation_1-rmse:31558.53324
[500]	validation_0-rmse:2192.45384	validation_1-rmse:2735.75052
[1000]	validation_0-rmse:1807.99360	validation_1-rmse:2231.06479
[1199]	validation_0-rmse:1746.01944	validation_1-rmse:2185.40512
```

Training split: 7 of 16

```
[0]	validation_0-rmse:35629.26492	validation_1-rmse:32723.94519
[500]	validation_0-rmse:2209.88738	validation_1-rmse:2666.12457
[803]	validation_0-rmse:1906.31098	validation_1-rmse:2620.93845
```

Training split: 8 of 16

```
[0]	validation_0-rmse:35484.56719	validation_1-rmse:30590.92882
[500]	validation_0-rmse:2238.18373	validation_1-rmse:2665.97085
[1000]	validation_0-rmse:1874.88304	validation_1-rmse:2380.88144
[1199]	validation_0-rmse:1815.11051	validation_1-rmse:2338.74912
```

Training split: 9 of 16

```
[0]	validation_0-rmse:35256.84386	validation_1-rmse:31274.43857
[291]	validation_0-rmse:3042.73232	validation_1-rmse:3021.40147
```

Training split: 10 of 16

```
[0]	validation_0-rmse:35080.13209	validation_1-rmse:30334.97187
[500]	validation_0-rmse:2293.31344	validation_1-rmse:2368.77382
[1000]	validation_0-rmse:1929.70739	validation_1-rmse:1904.35239
[1199]	validation_0-rmse:1875.09340	validation_1-rmse:1853.25663
```

Training split: 11 of 16

```
[0]	validation_0-rmse:34879.05495	validation_1-rmse:28467.95624
[214]	validation_0-rmse:4217.73427	validation_1-rmse:3978.68606
```

Training split: 12 of 16

```
[0]	validation_0-rmse:34628.76251	validation_1-rmse:28969.99048
[500]	validation_0-rmse:2316.41624	validation_1-rmse:2452.28254
[828]	validation_0-rmse:2030.48465	validation_1-rmse:2354.46986
```

Training split: 13 of 16

```
[0] validation_0-rmse:34410.39062   validation_1-rmse:30310.69798
[407]   validation_0-rmse:2547.65380    validation_1-rmse:2682.01408
```

Training split: 14 of 16

```
[0] validation_0-rmse:34257.96348   validation_1-rmse:29340.27107
[500]   validation_0-rmse:2362.09599    validation_1-rmse:1989.56895
[607]   validation_0-rmse:2223.56214    validation_1-rmse:2001.37904
```

Training split: 15 of 16

```
[0] validation_0-rmse:34081.45769   validation_1-rmse:30150.75685
[460]   validation_0-rmse:2437.94536    validation_1-rmse:2518.15912
```

Training split: 16 of 16

```
[0] validation_0-rmse:33944.73814   validation_1-rmse:29491.10969
[382]   validation_0-rmse:2668.21192    validation_1-rmse:2609.05645
```

Overall Metrics for Accuracy and Model Performance

	Resulting Metrics
Average RMSE	2,582.19
Average Absolute Accuracy	93.57%
Average Relative Accuracy	93.70%
Average Sharpe Ratio	0.33

Predictions vs Actual Targets

head(5)

	actual	prediction	abs_acc	rel_acc	sharpe
0	41,297	44,150.49	93.54	90.99	0.46
1	44,813	44,150.49	98.50	97.91	0.11
2	46,139	45,633.64	98.89	98.40	0.08
3	45,716	45,633.64	99.82	99.74	0.01
4	45,342	45,633.64	99.36	99.08	0.05

tail(5)

	actual	prediction	abs_acc	rel_acc	sharpe
140155	25,634	32,433.49	79.04	78.52	1.11
140156	24,788	29,763.41	83.28	84.29	0.81
140157	24,365	29,763.41	81.86	82.95	0.88
140158	24,766	27,849.91	88.93	90.26	0.50
140159	24,843	27,849.91	89.20	90.50	0.49

Cross-Validation Results with Lag Features

```
cross_results_lags, rmses_lags = cross_validation_train(df,
                                        target_column = "consumption",
                                        lags = True,
                                        lag_label_list = lag_label_list,
                                        learning_rate = 0.012,
                                        verbose = 500,
                                        splits = 16)
```

Training split: 1 of 16

```
[0] validation_0-rmse:36925.12428   validation_1-rmse:34888.08778
[500]   validation_0-rmse:2037.49828    validation_1-rmse:2026.48655
[576]   validation_0-rmse:1964.88895    validation_1-rmse:2029.35903
```

Training split: 2 of 16

```
[0] validation_0-rmse:36773.31063   validation_1-rmse:32394.96397
[335]   validation_0-rmse:2386.18647    validation_1-rmse:1923.99288
```

Training split: 3 of 16

```
[0] validation_0-rmse:36477.26414   validation_1-rmse:33584.40726
[444]   validation_0-rmse:2104.36729    validation_1-rmse:2129.39891
```

Training split: 4 of 16

```
[0] validation_0-rmse:36292.39954   validation_1-rmse:32157.17855
[500]   validation_0-rmse:2046.95073    validation_1-rmse:2450.85211
[902]   validation_0-rmse:1815.59204    validation_1-rmse:2399.96702
```

Training split: 5 of 16

```
[0] validation_0-rmse:36046.01723   validation_1-rmse:32549.80008
[500]   validation_0-rmse:2064.69275    validation_1-rmse:2385.32174
[1000]  validation_0-rmse:1794.49164    validation_1-rmse:2315.57542
[1194]  validation_0-rmse:1740.22213    validation_1-rmse:2305.69089
```

Training split: 6 of 16

```
[0] validation_0-rmse:35850.48363   validation_1-rmse:31592.50643
[500]   validation_0-rmse:2095.36822    validation_1-rmse:2027.17829
[504]   validation_0-rmse:2090.82782    validation_1-rmse:2024.67160
```

Training split: 7 of 16

```
[0] validation_0-rmse:35625.58122   validation_1-rmse:32765.45789
[500]   validation_0-rmse:2089.91556    validation_1-rmse:2825.18626
[548]   validation_0-rmse:2048.50601    validation_1-rmse:2831.43948
```

Training split: 8 of 16

```
[0] validation_0-rmse:35480.78265   validation_1-rmse:30627.60853
[412]   validation_0-rmse:2209.38032    validation_1-rmse:2202.98109
```

Training split: 9 of 16

```
[0] validation_0-rmse:35252.84829   validation_1-rmse:31312.27241
[369]   validation_0-rmse:2293.48245    validation_1-rmse:2485.35647
```

Training split: 10 of 16

```
[0] validation_0-rmse:35075.91026   validation_1-rmse:30377.44317
[500]   validation_0-rmse:2132.74711    validation_1-rmse:1835.06696
[748]   validation_0-rmse:1989.27927    validation_1-rmse:1819.15242
```

Training split: 11 of 16

```
[0] validation_0-rmse:34874.70089   validation_1-rmse:28512.73610
[261]   validation_0-rmse:2895.43167    validation_1-rmse:2931.84616
```

Training split: 12 of 16

```
[0] validation_0-rmse:34623.79921   validation_1-rmse:28973.77077
[400]   validation_0-rmse:2271.53341    validation_1-rmse:2734.28776
```

Training split: 13 of 16

```
[0] validation_0-rmse:34405.31749   validation_1-rmse:30354.22325
[400]   validation_0-rmse:2289.59348    validation_1-rmse:3920.04580
```

Training split: 14 of 16

```
[0] validation_0-rmse:34252.93483   validation_1-rmse:29339.39192
[495]   validation_0-rmse:2193.78422    validation_1-rmse:1936.44759
```

Training split: 15 of 16

```
[0] validation_0-rmse:34076.15009   validation_1-rmse:30173.91135
[500]   validation_0-rmse:2186.48824    validation_1-rmse:2422.19548
[813]   validation_0-rmse:2021.39231    validation_1-rmse:2313.93976
```

Training split: 16 of 16

```
[0] validation_0-rmse:33939.52789   validation_1-rmse:29495.56077
[500]   validation_0-rmse:2189.84373    validation_1-rmse:2304.33924
[977]   validation_0-rmse:1978.42327    validation_1-rmse:2270.01215
```

Overall Metrics for Accuracy and Model Performance

	Resulting Metrics
Average RMSE	2,411.87
Average Absolute Accuracy	93.83%
Average Relative Accuracy	94.32%
Average Sharpe Ratio	0.29

Predictions vs Actual Targets

head(5)

	actual	prediction	abs_acc	rel_acc	sharpe
0	41,297	43,600.54	94.72	92.88	0.36
1	44,813	45,461.97	98.57	98.00	0.10
2	46,139	46,121.54	99.96	99.95	0.00
3	45,716	45,878.23	99.65	99.50	0.03
4	45,342	45,525.46	99.60	99.43	0.03

tail(5)

	actual	prediction	abs_acc	rel_acc	sharpe
140155	25,634	28,081.06	91.29	92.44	0.38
140156	24,788	26,979.71	91.88	93.23	0.34
140157	24,365	26,686.66	91.30	92.83	0.36
140158	24,766	25,165.46	98.41	98.77	0.06
140159	24,843	24,667.06	99.29	99.46	0.03

Predicting into the Future

1. Retrain Model with All Training Data

```
df = data.copy()
```

```
def future_predicting_model(df, target_column,
                            lags = False,
                            lag_label_list = None,
                            base_score = 0.5,
                            booster = 'gbtree',
                            n_estimators = 500,
                            early_stopping_rounds = 50,
                            objective = 'reg:squarederror',
                            max_depth = 3,
                            learning_rate = 0.012,
                            verbose = 250):

    from sklearn.metrics import mean_squared_error
    from sklearn.model_selection import TimeSeriesSplit

    # ................ Establishing Features & Targets ................ #

    df = featurize_datetime_index(df)
    target = target_column

    # ................ Lag Features & Feature Cleanup ................. #

    if lags:
        df = year_lags(df, target_column, lag_label_list)
        features = list(df.columns)
        features.remove('weekday_name')
        features.remove('month_name')
        features.remove('time_of_day')
        features.remove(target)
    else:
        features = list(df.columns)
        features.remove('weekday_name')
        features.remove('month_name')
        features.remove('time_of_day')
        features.remove(target)

    # ................. Correcting Datatypes for Model ................ #

    df['week_of_year'] = df.week_of_year.astype(float)

    input_data = df[features]
```

```
    target_data = df[target_column]

    model = XGBRegressor(base_score = base_score,
                         booster = booster,
                         n_estimators = n_estimators,
                         early_stopping_rounds = early_stopping_rounds,
                         objective = objective,
                         max_depth = max_depth,
                         learning_rate = learning_rate)

    trained_model = model.fit(input_data, target_data,
                              eval_set = [(input_data, target_data)],
                              verbose = verbose)

    return trained_model
```

```
trained_model = future_predicting_model(df,
                                        'consumption',
                                        lags = True,
                                        lag_label_list = lag_label_list)
```

```
[0] validation_0-rmse:33789.62223
[250]   validation_0-rmse:3052.85375
[499]   validation_0-rmse:2203.62563
```

2. Create an empty dataframe for the date range to predict

- Starting from the end of the input data
- Predicting almost 1 year into the future
- Frequency will be 1 hour, just like the input data frequency

```
df.index.max()
```

```
Timestamp('2022-12-31 23:30:00')
```

```
prediction_range = pd.date_range('2023-01-01', '2024-01-01',
                                 freq = '1h')

see(prediction_range[0:6], "First rows of prediction df")
```

First rows of prediction df

	0
2023-01-01 00:00:00	2023-01-01 00:00:00
2023-01-01 01:00:00	2023-01-01 01:00:00
2023-01-01 02:00:00	2023-01-01 02:00:00
2023-01-01 03:00:00	2023-01-01 03:00:00
2023-01-01 04:00:00	2023-01-01 04:00:00

	0
2023-01-01 05:00:00	2023-01-01 05:00:00

```
future_predictions_df = pd.DataFrame(index = prediction_range)
future_predictions_df['in_future'] = True
orig = df.copy()
orig['in_future'] = False
orig_plus_future = pd.concat([orig, future_predictions_df])
```

3. Combining the Past Data with Future

- Adding the datetime and lag features
- Pulling out just the records that need predictions, `future_predictions`
- Removing from features the columns the model cannot or should not work with

```
orig_plus_future = featurize_datetime_index(orig_plus_future)
orig_plus_future = year_lags(orig_plus_future,
                             target_column = "consumption",
                             lag_label_list = lag_label_list)
```

```
features = list(orig_plus_future.columns)
features.remove('weekday_name')
features.remove('month_name')
features.remove('time_of_day')
features.remove('consumption')
features.remove('in_future')
```

```
future_predictions = orig_plus_future.query('in_future').copy()
head_tail_horz(future_predictions, 5, 'DF for Future Predictions')
```

DF for Future Predictions

head(5)

	consumption	holiday	in_future	hour	weekday	weekday_name	month	month_name	quarter	year	week_of_
2023-01-01	nan	nan	True	0	6	Sunday	1	January	1	2,023	
2023-01-01	nan	nan	True	1	6	Sunday	1	January	1	2,023	
2023-01-01	nan	nan	True	2	6	Sunday	1	January	1	2,023	
2023-01-01	nan	nan	True	3	6	Sunday	1	January	1	2,023	
2023-01-01	nan	nan	True	4	6	Sunday	1	January	1	2,023	

tail(5)

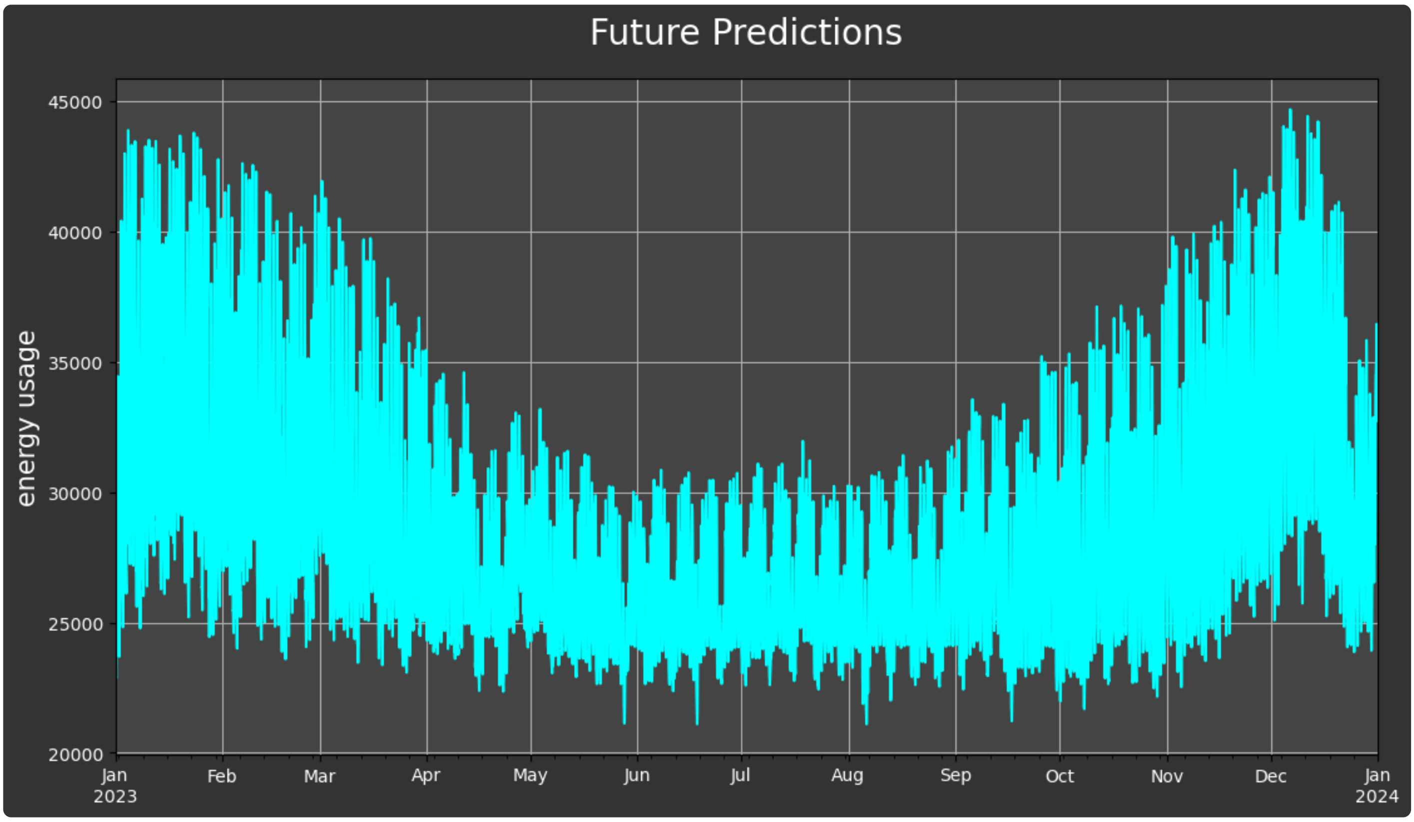
	consumption	holiday	in_future	hour	weekday	weekday_name	month	month_name	quarter	year	week_of_
2023-12-31	nan	nan	True	20	6	Sunday	12	December	4	2,023	
2023-12-31	nan	nan	True	21	6	Sunday	12	December	4	2,023	
2023-12-31	nan	nan	True	22	6	Sunday	12	December	4	2,023	
2023-12-31	nan	nan	True	23	6	Sunday	12	December	4	2,023	
2024-01-01	nan	nan	True	0	0	Monday	1	January	1	2,024	

```
future_predictions = future_predictions[features]
future_predictions['week_of_year'] = future_predictions['week_of_year'].astype(float)
```

```
future_predictions['predictions'] = trained_model.predict(future_predictions[features])
```

4. Plotting the Prediction Results

```
plt.figure(figsize = (13, 7), facecolor = '#333333')
ax = plt.axes()
future_predictions['predictions'].plot(ax = ax, color = 'cyan')
ax.set_facecolor('#444444')
ax.grid()
plt.xlabel('', color = 'white', fontsize = 15)
plt.ylabel('energy usage', color = 'white', fontsize = 15)
plt.tick_params(labelcolor = 'white', which = 'both')
plt.title('Future Predictions',
          fontsize = 20, pad = 20, color = 'white');
plt.legend().remove()
```



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