Tugas 3

Prediksi Konsumsi Daya Listrik Rumah Tangga Menggunakan LSTM *(Long Short-Term Memory)*

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1. Deskripsi

1.1 Prasyarat

- Python 3.7.3
- Pandas
- Numpy
- Matplotlib
- TensorFlow
- Scikit-learn
- Jupyter Notebook (optional)

1.2 Dataset

Dataset yang digunakan adalah **"Individual Household Electric Power Consumption Dataset"** dari **UCI Machine Learning**, yakni dataset *time series* multivariat berisi **2075259** data yang dikumpulkan di sebuah rumah di Sceaux (7km dari Paris, Prancis) antara Desember 2006 dan November 2010.

Memiliki 9 atribut yang dideskripsikan sebagai berikut:

Atribut	Deskripsi
date	Tanggal (dd/mm/yyyy)
time	Waktu (hh:mm:ss)
global_active_power	Total daya aktif yang dikonsumsi (Kilowatt)
global_reactive_power	Total daya reaktif yang dikonsumsi (Kilowatt)
voltage	Tegangan rata-rata (Volt)
global_intensity	Intensitas Arus Rata-Rata (Ampere)
sub_metering_1	Energi aktif untuk dapur, berisi mesin pencuci piring, oven, dan*microwave* (Watt-hour energi aktif)
sub_metering_2	Energi aktif untuk ruang *laundry*, berisi mesin cuci, pengering, kulkas, dan lampu (Watt-hour energi aktif)
sub_metering_3	Energi aktif untuk kontrol iklim, berisi pemanas air dan AC (Watt-hour energi aktif)

2. Langkah-Langkah yang Dilakukan

In [1]:

```
## import library yang diperlukan

# basic python libraries
import os, sys, math

# data handling
import pandas as pd # data processing, CSV file I/O, data manipulation as in SQL
pd.set_option('display.float_format', lambda x: '%.4f' % x)
import numpy as np # linear algebra

# graph plotting
import matplotlib.pyplot as plt
import matplotlib.ticker as tkr
import seaborn as sns
sns.set_context("paper", font_scale=1.3)
sns.set_style('white')
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()
```

```python
# statistics
from scipy import stats
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import pacf

# machine learning
from sklearn.model_selection import train_test_split # to split the data into two parts
from sklearn.preprocessing import MinMaxScaler # for normalization
from sklearn.pipeline import Pipeline # pipeline making
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# deep learning
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.callbacks import EarlyStopping
```

2.1 Import Dataset

In [2]:

```python
# definisikan dataset path
PATH = os.getcwd()
DATASET_DIR_PATH = PATH + '/dataset/'
DATASET_PATH = DATASET_DIR_PATH + 'household_power_consumption.txt'
PREPARED_DATASET_PATH = DATASET_DIR_PATH + 'household_power_consumption.csv'
```

In [3]:

```python
# import dataset dalam format .txt
# merge kolom 'Date' and 'Time' menjadi 'datetime'
# convert 'datetime' menjadi data time series dengan membuat'datetime' menjadi index
df = pd.read_csv(DATASET_PATH, sep=';', header=0, low_memory=False, infer_datetime_format=True,
                parse_dates={'datetime':[0,1]}, index_col=['datetime'])
```

In [4]:

```python
# ambil metadata
print('Jumlah baris :', df.shape[0])
print('Jumlah kolom :', df.shape[1])
print('Atribut :', df.columns.to_list())
print('Time series mulai dari :', df.index.min())
print('Time series berakhir di :', df.index.max())

# lihat data
df.head()
```

```
Jumlah baris : 2075259
Jumlah kolom : 7
Atribut : ['Global_active_power', 'Global_reactive_power', 'Voltage', 'Global_intensity',
'Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3']
Time series mulai dari : 2006-12-16 17:24:00
Time series berakhir di : 2010-11-26 21:02:00
```

Out[4]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
datetime							
2006-12-16 17:24:00	4.216	0.418	234.840	18.400	0.000	1.000	17.0000
2006-12-16 17:25:00	5.360	0.436	233.630	23.000	0.000	1.000	16.0000
2006-12-16 17:26:00	5.374	0.498	233.290	23.000	0.000	2.000	17.0000

datetime	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
2006-12-16 17:27:00	5.388	0.502	233.740	23.000	0.000	1.000	17.0000
2006-12-16 17:28:00	3.666	0.528	235.680	15.800	0.000	1.000	17.0000

In [5]:

```
# lihat data akhir
df.tail()
```

Out[5]:

datetime	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
2010-11-26 20:58:00	0.946	0.000	240.430	4.000	0.000	0.000	0.0000
2010-11-26 20:59:00	0.944	0.000	240.000	4.000	0.000	0.000	0.0000
2010-11-26 21:00:00	0.938	0.000	239.820	3.800	0.000	0.000	0.0000
2010-11-26 21:01:00	0.934	0.000	239.700	3.800	0.000	0.000	0.0000
2010-11-26 21:02:00	0.932	0.000	239.550	3.800	0.000	0.000	0.0000

2.2 Prepare dan Preprocess Data

In [6]:

```
# cek null value
df.isnull().sum()
```

Out[6]:

```
Global_active_power          0
Global_reactive_power        0
Voltage                      0
Global_intensity             0
Sub_metering_1               0
Sub_metering_2               0
Sub_metering_3           25979
dtype: int64
```

Null value didapatkan nol semua. Cek data types:

In [7]:

```
# cek data types
df.dtypes
```

Out[7]:

```
Global_active_power        object
Global_reactive_power      object
Voltage                    object
Global_intensity           object
Sub_metering_1             object
Sub_metering_2             object
Sub_metering_3            float64
dtype: object
```

Ternyata, data types-nya object, sehingga null value tidak terdeteksi.

household_power_consumption.txt

```
30/12/2006;09:55:00;6.900;0.210;235.190;29.200;0.000;73.000;17.000
30/12/2006;09:56:00;6.898;0.266;234.320;29.400;0.000;71.000;17.000
30/12/2006;09:57:00;6.920;0.258;234.600;29.400;0.000;73.000;17.000
30/12/2006;09:58:00;6.940;0.266;235.010;29.400;0.000;72.000;17.000
30/12/2006;09:59:00;6.938;0.262;235.140;29.400;0.000;72.000;17.000
30/12/2006;10:00:00;7.016;0.302;236.000;29.600;0.000;73.000;17.000
30/12/2006;10:01:00;7.070;0.290;236.070;29.800;1.000;73.000;17.000
30/12/2006;10:02:00;8.024;0.276;234.530;34.400;16.000;72.000;17.000
30/12/2006;10:03:00;9.078;0.252;233.690;38.800;38.000;71.000;16.000
30/12/2006;10:04:00;8.176;0.274;234.270;35.200;37.000;58.000;17.000
30/12/2006;10:05:00;7.068;0.284;236.300;29.800;37.000;37.000;17.000
30/12/2006;10:06:00;6.698;0.298;237.010;28.400;38.000;32.000;17.000
30/12/2006;10:07:00;6.218;0.414;237.400;26.200;38.000;19.000;18.000
30/12/2006;10:08:00;?;?;?;?;?;?;
30/12/2006;10:09:00;?;?;?;?;?;?;
30/12/2006;10:10:00;6.816;0.378;236.890;28.800;37.000;28.000;17.000
30/12/2006;10:11:00;7.026;0.384;234.450;30.000;37.000;35.000;17.000
30/12/2006;10:12:00;6.074;0.388;235.130;25.800;38.000;17.000;17.000
30/12/2006;10:13:00;6.962;0.394;234.310;29.800;34.000;36.000;17.000
30/12/2006;10:14:00;4.936;0.482;236.440;21.000;1.000;35.000;17.000
30/12/2006;10:15:00;3.920;0.438;236.630;16.600;1.000;17.000;17.000
30/12/2006;10:16:00;5.188;0.398;235.010;22.200;2.000;34.000;17.000
30/12/2006;10:17:00;7.132;0.360;232.860;30.600;36.000;36.000;17.000
30/12/2006;10:18:00;7.076;0.290;232.300;30.400;37.000;36.000;16.000
30/12/2006;10:19:00;4.840;0.268;234.570;20.800;4.000;34.000;17.000
30/12/2006;10:20:00;3.902;0.290;235.520;16.600;1.000;17.000;17.000
30/12/2006;10:21:00;5.028;0.282;234.090;21.600;3.000;34.000;17.000
30/12/2006;10:22:00;6.916;0.312;232.470;29.800;37.000;21.000;17.000
30/12/2006;10:23:00;7.932;0.276;231.960;34.200;36.000;39.000;16.000
30/12/2006;10:24:00;6.776;0.306;233.640;29.000;37.000;32.000;17.000
```

In [8]:

```
# pada data ini, null value digambarkan dengan string '?' (tanda tanya), sehingga harus diubah ter
lebih dahulu menggunakan null value-nya Numpy
# mengganti missing values
df.replace('?', np.nan, inplace=True)
# mengubah semua tipe data menjadi float32
df = df.astype('float32')
```

In [9]:

```
# cek tipe data
df.dtypes
```

Out[9]:

```
Global_active_power      float32
Global_reactive_power    float32
Voltage                  float32
Global_intensity         float32
Sub_metering_1           float32
Sub_metering_2           float32
Sub_metering_3           float32
dtype: object
```

In [10]:

```
# cek null value
df.isnull().sum()
```

Out[10]:

```
Global_active_power      25979
Global_reactive_power    25979
Voltage                  25979
Global_intensity         25979
Sub_metering_1           25979
Sub_metering_2           25979
Sub_metering_3           25979
dtype: int64
```

Setelah melakukan data preparing dengan mengganti semua string '?' menjadi np.nan dan mengubah tipe datanya menjadi float32, maka didapatkan jumlah missing value sebanyak **25979 x 7**.

In [12]:

```
# metode yang digunakan untuk mengisi missing value adalah dengan mengisinya menggunakan nilai pad
a waktu yang sama pada satu hari yang lalu
def fill_missing_value(values):
    one_day = 60 * 24
    for row in range(values.shape[0]):
        for col in range(values.shape[1]):
            if np.isnan(values[row, col]):
                values[row, col] = values[row - one_day, col]
```

In [13]:

```
# mengisi missing value
fill_missing_value(df.values)
```

In [14]:

```
# cek null value lagi
df.isnull().sum()
```

Out[14]:

```
Global_active_power      0
Global_reactive_power    0
Voltage                  0
Global_intensity         0
Sub_metering_1           0
Sub_metering_2           0
Sub_metering_3           0
dtype: int64
```

2.2.1 Export Prepared Data

In [15]:

```
# export dataset yang telah di prepared dan preprocessed
df.to_csv(PREPARED_DATASET_PATH)
```

2.3 EDA (Exploratory Data Analysis)

2.3.1 Uji Normalitas

Uji Normalitas adalah sebuah uji yang dilakukan dengan tujuan untuk menentukan sebaran data pada sebuah kelompok data atau variabel, apakah sebaran data tersebut terdistribusi normal ataukah tidak.

Dalam hal ini, saya akan menggunakan Tes K-kuadrat **D'Agostino's K-squared Test** menggunakan SciPy:

- p <= alpha: reject H0, tidak normal
- p> alpha: fail to reject H0, normal

In [16]:

```
stat, p = stats.normaltest(df.Global_active_power)
print('Statistics = %.3f, p = %.3f' %(stat, p))
alpha = 0.05
if p > alpha:
    print('Terlihat Gaussian (fail to reject H0)')
else:
    print('Tidak terlihat Gaussian (reject H0)')
```

```
Statistics = 735736.314, p = 0.000
Tidak terlihat Gaussian (reject H0)
```

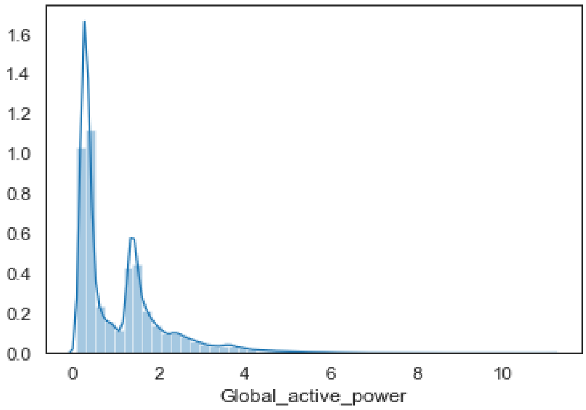
Dari hasil uji tersebut, dapat dilihat bahwa distribusi data ini **tidak normal**.

Kemudian, saya juga menghitung **kurtosis dan skewness** untuk menentukan apakah distribusi data menyimpang dari distribusi normal.

In [14]:

```
sns.distplot(df.Global_active_power);
print( 'Kurtosis of normal distribution: {}'.format(stats.kurtosis(df.Global_active_power)))
print( 'Skewness of normal distribution: {}'.format(stats.skew(df.Global_active_power)))
```

```
Kurtosis of normal distribution: 4.237163146889262
Skewness of normal distribution: 1.7888684272766113
```



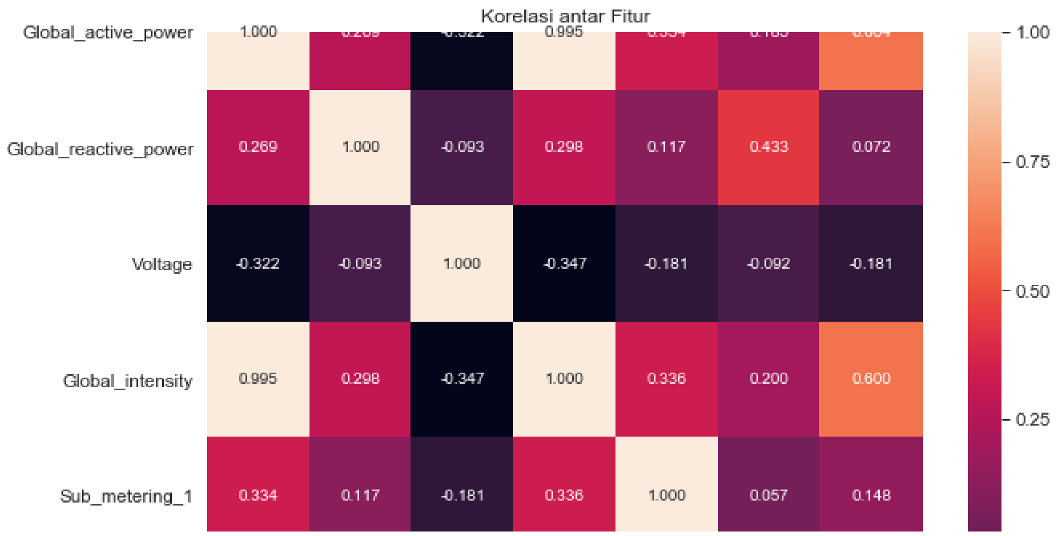
- **KURTOSIS**: Distribusi normal memiliki kurtosis mendekati 0. Jika kurtosis lebih besar dari nol, maka distribusi memiliki ekor yang lebih berat. Jika kurtosisnya kurang dari nol, maka distribusinya adalah ekor ringan. Dan Kurtosis data ini lebih besar dari nol.
- **SKEWNESS**: Jika kemiringannya antara -0,5 dan 0,5, datanya cukup simetris. Jika kemiringannya antara -1 dan - 0,5 atau antara 0,5 dan 1, datanya cenderung miring. Jika kemiringan kurang dari -1 atau lebih besar dari 1, data sangat miring. Dan kemiringan kita lebih besar dari 1.

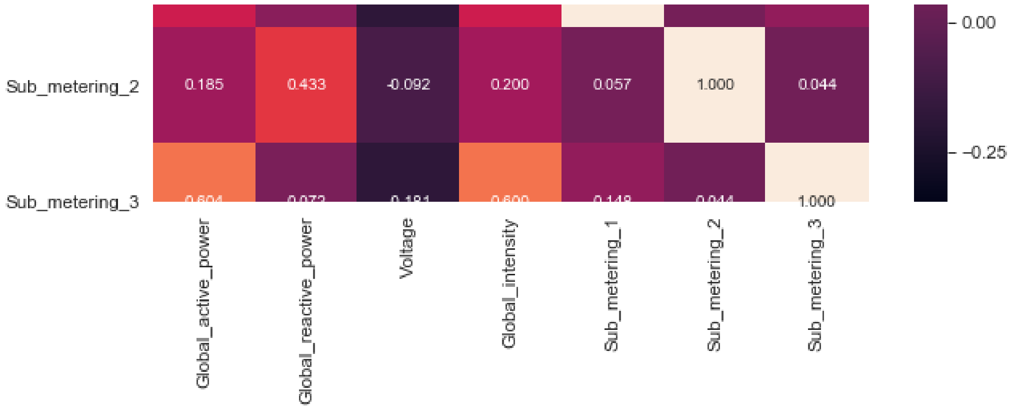
2.3.2 Korelasi antar Fitur

Semakin berkorelasi, maka warnanya semakin terang. Menggunakan metode 'Spearman'.

In [17]:

```
f, ax = plt.subplots(figsize=(10,8))
sns.heatmap(df.corr(method='spearman'), annot=True, fmt='.3f', ax=ax)
ax.set_title('Korelasi antar Fitur')
plt.show()
```





Dari dua plot di atas terlihat bahwa **'Global_intensity' dan 'Global_active_power' berkorelasi**, tetapi **'Tegangan' dan 'Global_active_power' kurang berkorelasi**.

2.3.3 Yearly Global Active Power VS Quarterly Global Active Power

In [18]:

```
# menyiapkan df for analysis
df.reset_index(level=0, inplace=True)
df['year'] = df['datetime'].apply(lambda x: x.year)
df['quarter'] = df['datetime'].apply(lambda x: x.quarter)
df['month'] = df['datetime'].apply(lambda x: x.month)
df['day'] = df['datetime'].apply(lambda x: x.day)

df_compare = df.loc[:,['datetime','Global_active_power', 'year','quarter','month','day']]
df_compare.sort_values('datetime', inplace=True, ascending=True)
df_compare = df_compare.reset_index(drop=True)
df_compare["weekday"] = df_compare.apply(lambda row: row["datetime"].weekday(),axis=1)
df_compare["weekday"] = (df_compare["weekday"] < 5).astype(int)

df = df.drop(['year','quarter','month','day'], axis=1)
df = df.set_index('datetime')
```

In [19]:

```
# ambil metadata
print('Jumlah baris :', df_compare.shape[0])
print('Jumlah kolom :', df_compare.shape[1])
print('Atribut :', df_compare.columns.to_list())
print('Time series mulai dari :', df_compare['datetime'].min())
print('Time series berakhir di :', df_compare['datetime'].max())

# lihat data
df_compare.head()
```

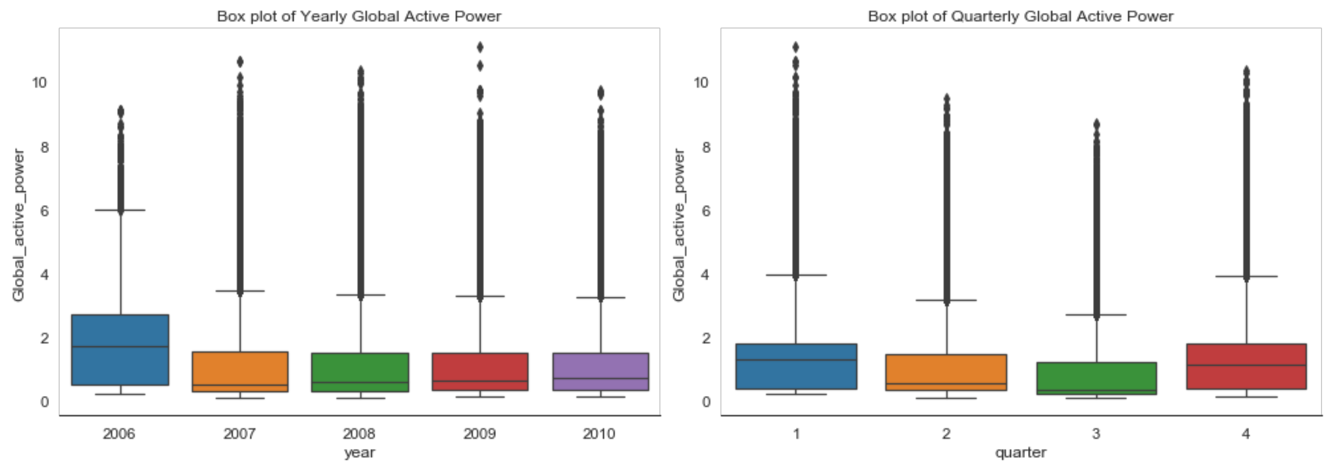
```
Jumlah baris : 2075259
Jumlah kolom : 7
Atribut : ['datetime', 'Global_active_power', 'year', 'quarter', 'month', 'day', 'weekday']
Time series mulai dari : 2006-12-16 17:24:00
Time series berakhir di : 2010-11-26 21:02:00
```

Out[19]:

	datetime	Global_active_power	year	quarter	month	day	weekday
0	2006-12-16 17:24:00	4.2160	2006	4	12	16	0
1	2006-12-16 17:25:00	5.3600	2006	4	12	16	0
2	2006-12-16 17:26:00	5.3740	2006	4	12	16	0
3	2006-12-16 17:27:00	5.3880	2006	4	12	16	0
4	2006-12-16 17:28:00	3.6660	2006	4	12	16	0

In [20]:

```
plt.figure(figsize=(14,5))

plt.subplot(1,2,1)
plt.subplots_adjust(wspace=0.2)
sns.boxplot(x="year", y="Global_active_power", data=df_compare)
plt.xlabel('year')
plt.title('Box plot of Yearly Global Active Power')
sns.despine(left=True)
plt.tight_layout()

plt.subplot(1,2,2)
sns.boxplot(x="quarter", y="Global_active_power", data=df_compare)
plt.xlabel('quarter')
plt.title('Box plot of Quarterly Global Active Power')
sns.despine(left=True)
plt.tight_layout();
```



Analisis : Median pada tahun 2006 jauh lebih tinggi daripada tahun-tahun lainnya. Perlu diingat jika data timeseries ini dimulai pada bulan Desember 2006 (musim dingin), dimana bulan ini merupakan puncak konsumsi listrik. Sedangkan jika di-boxplot berdasarkan musim/kuarter, maka mediannya lebih konsisten: kuarter 1 dan 4 lebih tinggi dibandingkan yang lain karena musim dingin, sedangkan kuarter 3 paling rendah dibandingkan yang lain karena musim panas.

dt.quarter dari Pandas akan membagi kuarter bulan menjadi:

- Month 1 - 3 : quarter 1
- Month 4 - 6 : quarter 2
- Month 7 - 9 : quarter 3
- Month 10 - 12 : quarter 4

Tetapi, 4 Musim di Prancis terjadi pada bulan berikut:

- Spring : 3 - 5 (quarter 1)
- Summer : 6 - 8 (quarter 2)
- Autumn : 9 - 11 (quarter 3)
- Winter : 12 - 2 (quarter 4)

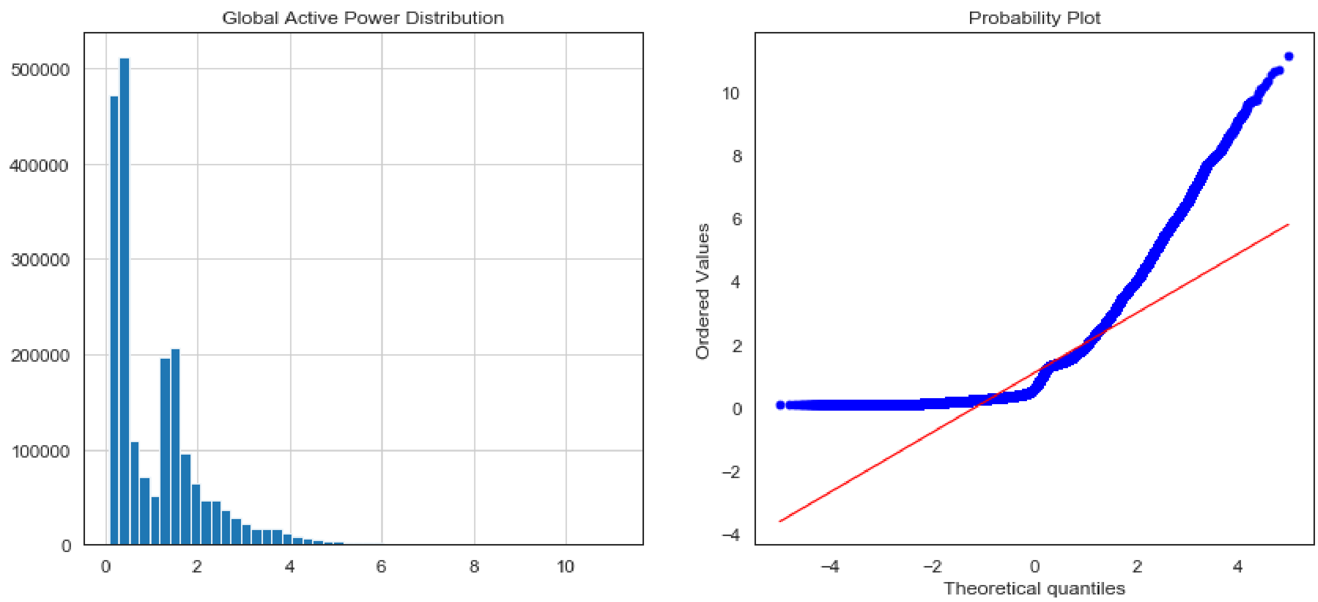
2.3.4 Distribusi Global Active Power

In [21]:

```
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
df['Global_active_power'].hist(bins=50)
plt.title('Global Active Power Distribution')

plt.subplot(1,2,2)
stats.probplot(df['Global_active_power'], plot=plt);
df.describe().T
```

Out[21]:

	count	mean	std	min	25%	50%	75%	max
Global_active_power	2075259.0000	1.0894	1.0547	0.0760	0.3080	0.6020	1.5260	11.1220
Global_reactive_power	2075259.0000	0.1237	0.1126	0.0000	0.0480	0.1000	0.1940	1.3900
Voltage	2075259.0000	240.8364	3.2401	223.2000	238.9900	241.0000	242.8700	254.1500
Global_intensity	2075259.0000	4.6184	4.4332	0.2000	1.4000	2.6000	6.4000	48.4000
Sub_metering_1	2075259.0000	1.1185	6.1415	0.0000	0.0000	0.0000	0.0000	88.0000
Sub_metering_2	2075259.0000	1.2911	5.7969	0.0000	0.0000	0.0000	1.0000	80.0000
Sub_metering_3	2075259.0000	6.4486	8.4336	0.0000	0.0000	1.0000	17.0000	31.0000



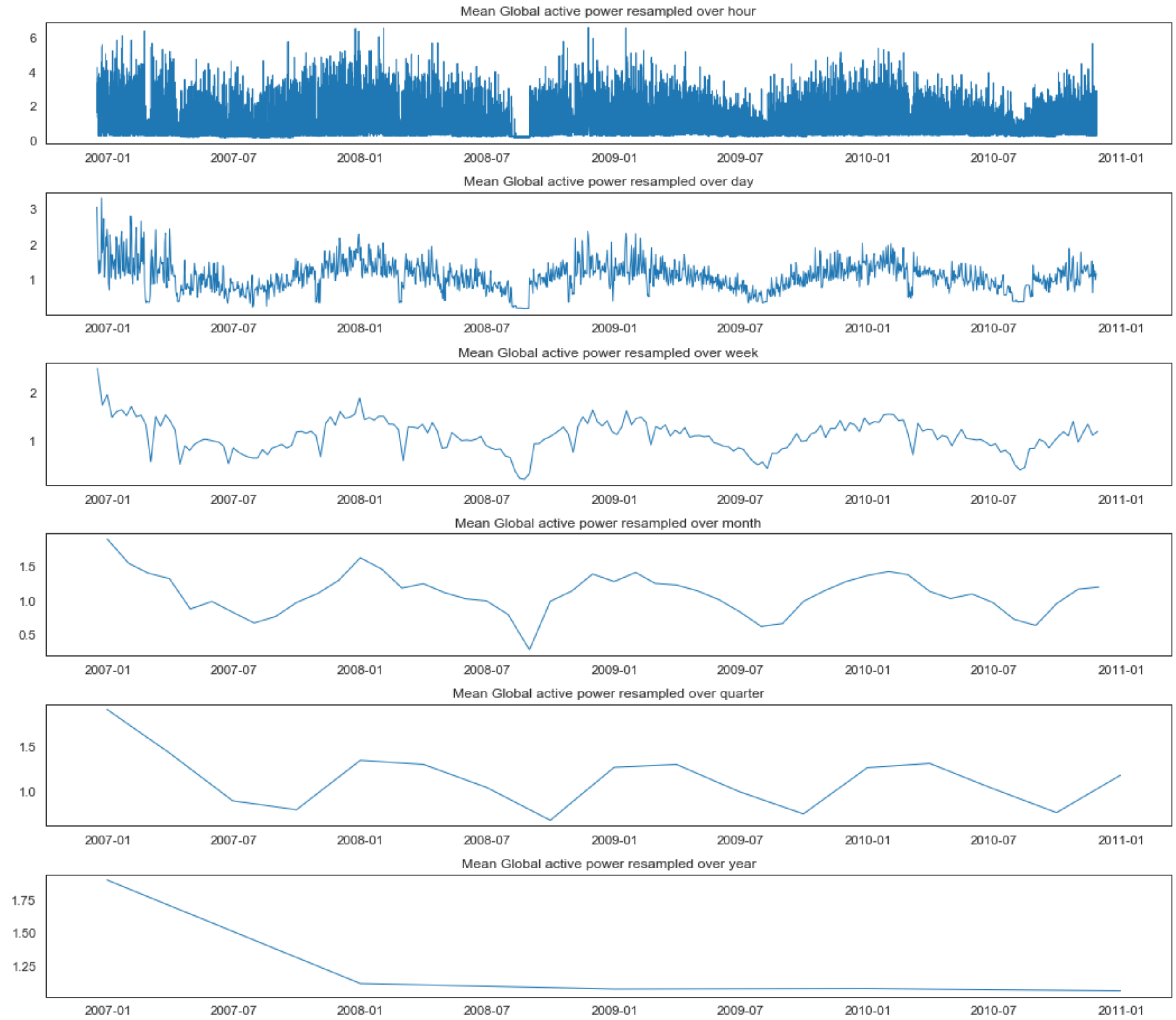
Plot probabilitas juga menunjukkan bahwa data yang digunakan **jauh dari distribusi normal**.

2.3.5 Rata-Rata Global Active Power di-Resample per-Jam, Hari, Minggu, Bulan, Kuarter dan Tahun

In [22]:

```
fig = plt.figure(figsize=(18,16))
fig.subplots_adjust(hspace=.4)

ax0 = fig.add_subplot(6,1,1)
ax0.plot(df['Global_active_power'].resample('h').mean(),linewidth=1)
ax0.set_title('Mean Global active power resampled over hour')
ax0.tick_params(axis='both', which='major')

ax1 = fig.add_subplot(6,1,2, sharex=ax0)
ax1.plot(df['Global_active_power'].resample('D').mean(),linewidth=1)
ax1.set_title('Mean Global active power resampled over day')
ax1.tick_params(axis='both', which='major')

ax2 = fig.add_subplot(6,1,3, sharex=ax0)
ax2.plot(df['Global_active_power'].resample('W').mean(),linewidth=1)
ax2.set_title('Mean Global active power resampled over week')
ax2.tick_params(axis='both', which='major')

ax3 = fig.add_subplot(6,1,4, sharex=ax0)
ax3.plot(df['Global_active_power'].resample('M').mean(),linewidth=1)
ax3.set_title('Mean Global active power resampled over month')
ax3.tick_params(axis='both', which='major')

ax4  = fig.add_subplot(6,1,5, sharex=ax0)
ax4.plot(df['Global_active_power'].resample('Q').mean(),linewidth=1)
ax4.set_title('Mean Global active power resampled over quarter')
ax4.tick_params(axis='both', which='major')

ax5  = fig.add_subplot(6,1,6, sharex=ax0)
ax5.plot(df['Global_active_power'].resample('A').mean(),linewidth=1)
ax5.set_title('Mean Global active power resampled over year')
ax5.tick_params(axis='both', which='major');
```

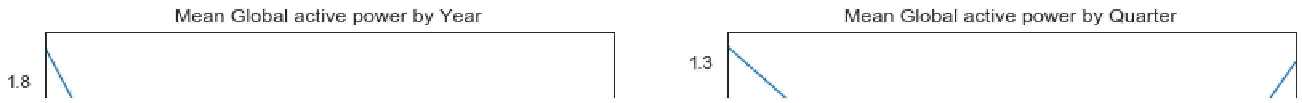
```
ax5.tick_params(axis='both', which='major');
```

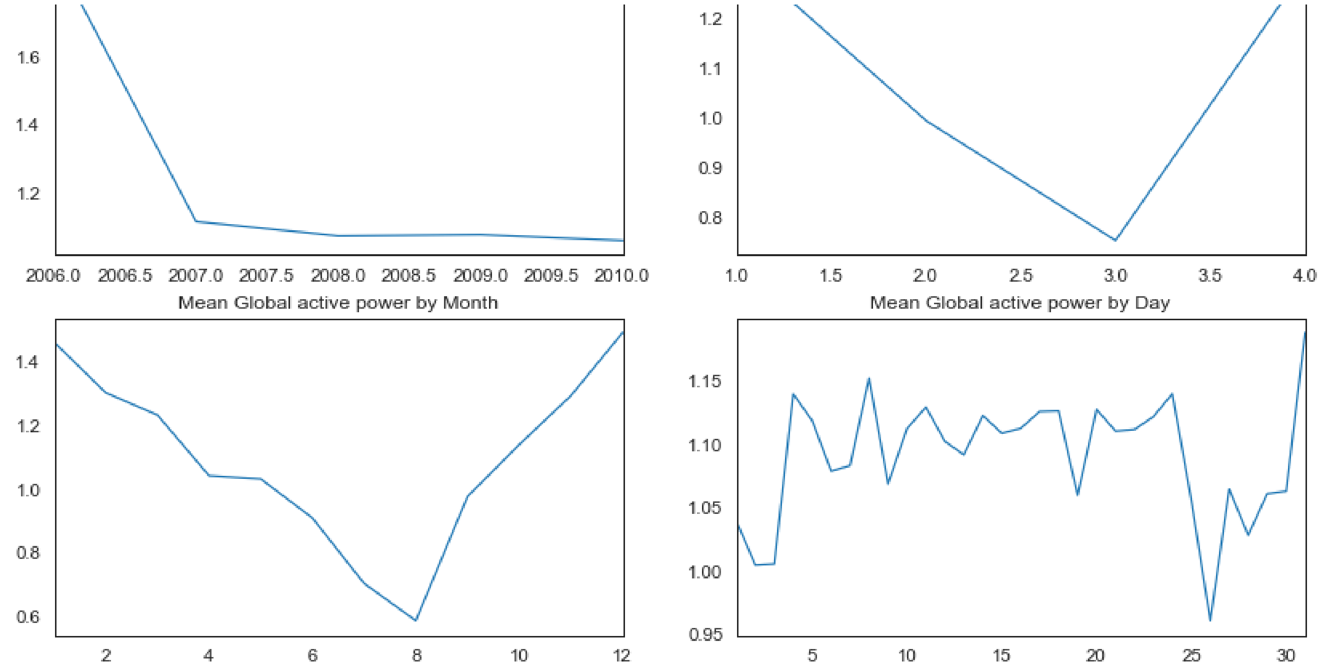


2.3.6 Rata-Rata Global Active Power di Group berdasar Tahun, Kuarter, Bulan, dan Hari

In [23]:

```
plt.figure(figsize=(14,8))
plt.subplot(2,2,1)
df_compare.groupby('year').Global_active_power.agg('mean').plot()
plt.xlabel('')
plt.title('Mean Global active power by Year')

plt.subplot(2,2,2)
df_compare.groupby('quarter').Global_active_power.agg('mean').plot()
plt.xlabel('')
plt.title('Mean Global active power by Quarter')

plt.subplot(2,2,3)
df_compare.groupby('month').Global_active_power.agg('mean').plot()
plt.xlabel('')
plt.title('Mean Global active power by Month')

plt.subplot(2,2,4)
df_compare.groupby('day').Global_active_power.agg('mean').plot()
plt.xlabel('')
plt.title('Mean Global active power by Day');
```





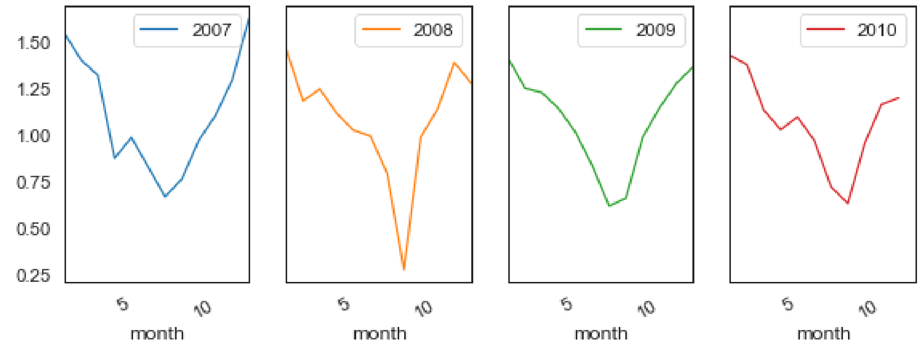
Pada plot berdasar tahun, konsumsi daya rata-rata tertinggi adalah sebelum 2007 dan konsisten setelahnya. Pada plot berdasar kuartal, konsumsi daya rata-rata terendah di kuartal ke-3 (musim panas). Menurut plot berdasar bulan, konsumsi daya rata-rata terendah adalah pada bulan Agustus (musim panas). Pada plot berdasar hari, konsumsi daya rata-rata terendah adalah pada hari ke 26 (tidak tahu mengapa).

2.3.7 Global Active Power Tahunan

Pada tahun 2006 hanya ada bulan Desember, sehingga dihapus saja.

In [24]:

```
pd.pivot_table(df_compare.loc[df_compare['year'] != 2006], values = "Global_active_power",
                    columns = "year", index = "month").plot(subplots = True, figsize=(12, 12), layout=(3,
5), sharey=True);
```

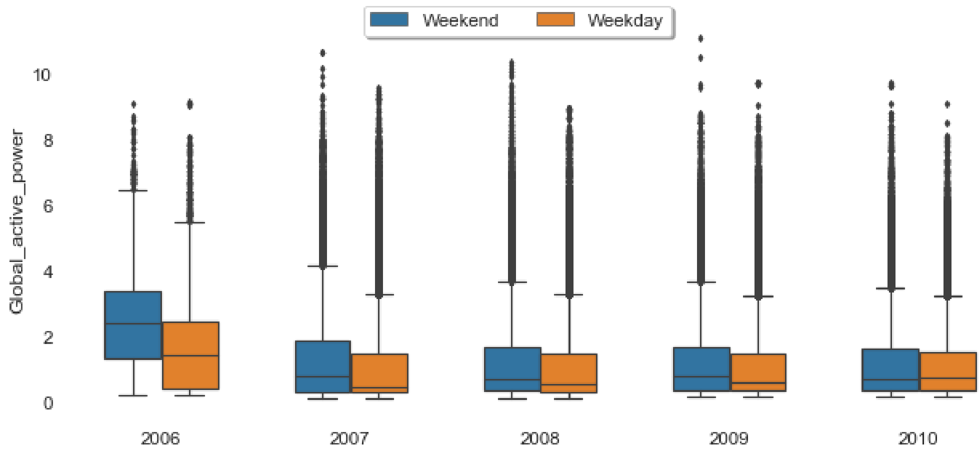


2.3.8 Konsumsi Global Active Power Consumption pada Weekdays vs. Weekends

In [25]:

```
dic = {
    0:'Weekend',
    1:'Weekday'
}
df_compare['Day'] = df_compare.weekday.map(dic)

a = plt.figure(figsize=(9,4))
plt1 = sns.boxplot('year','Global_active_power',hue='Day',width=0.6,fliersize=3,
                    data=df_compare)

a.legend(loc='upper center', bbox_to_anchor=(0.5, 1.00), shadow=True, ncol=2)
sns.despine(left=True, bottom=True)
```

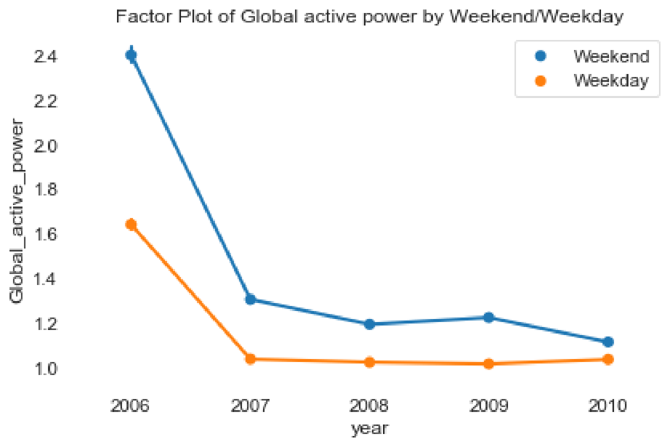
```
plt.xlabel('')
plt.tight_layout()

plt.legend().set_visible(False);
```



In [26]:

```
plt1 = sns.factorplot('year','Global_active_power',hue='Day',
                    data=df_compare, size=4, aspect=1.5, legend=False)

plt.title('Factor Plot of Global active power by Weekend/Weekday')

plt.tight_layout()

sns.despine(left=True, bottom=True)
plt.legend(loc='upper right');
```

```
/usr/local/lib/python3.7/site-packages/seaborn/categorical.py:3666: UserWarning: The `factorplot`
function has been renamed to `catplot`. The original name will be removed in a future release. Ple
ase update your code. Note that the default `kind` in `factorplot` (`'point'`) has changed
`'strip'` in `catplot`.
  warnings.warn(msg)
/usr/local/lib/python3.7/site-packages/seaborn/categorical.py:3672: UserWarning: The `size`
paramter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



2.4 LSTM *(Long Short-Term Memory)*

Pada proses LSTM ini, saya hanya menggunakan 1 fitur saja, yaitu **'Global_active_power'**.

In [27]:

```
df.head()
```

Out[27]:

datetime	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
2006-12-16 17:24:00	4.2160	0.4180	234.8400	18.4000	0.0000	1.0000	17.0000
2006-12-16 17:25:00	5.3600	0.4360	233.6300	23.0000	0.0000	1.0000	16.0000
2006-12-16 17:26:00	5.3740	0.4980	233.2900	23.0000	0.0000	2.0000	17.0000
2006-12-16 17:27:00	5.3880	0.5020	233.7400	23.0000	0.0000	1.0000	17.0000
2006-12-16 17:28:00	3.6660	0.5280	235.6800	15.8000	0.0000	1.0000	17.0000

Karena mengurangi waktu komputasi, saya melakukan resampling data per-jam.

Untuk versi fullnya, saya melakukan komputasi di google colaboration: https://colab.research.google.com/drive/14v_wt4rcl0xW5z6YwQqFH_TtdZatNszh

In [28]:

```
# resample data per-jam
df_resample = df.resample('h').mean()
```

In [29]:

```
# ambil metadata
print('Jumlah baris :', df_resample.shape[0])
print('Jumlah kolom :', df_resample.shape[1])
print('Atribut :', df_resample.columns.to_list())
print('Time series mulai dari :', df_resample.index.min())
print('Time series berakhir di :', df_resample.index.max())

# lihat data
df_resample.head()
```

```
Jumlah baris : 34589
Jumlah kolom : 7
Atribut : ['Global_active_power', 'Global_reactive_power', 'Voltage', 'Global_intensity',
'Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3']
Time series mulai dari : 2006-12-16 17:00:00
Time series berakhir di : 2010-11-26 21:00:00
```

Out[29]:

datetime	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
2006-12-16 17:00:00	4.2229	0.2290	234.6439	18.1000	0.0000	0.5278	16.8611
2006-12-16 18:00:00	3.6322	0.0800	234.5802	15.6000	0.0000	6.7167	16.8667
2006-12-16 19:00:00	3.4002	0.0852	233.2325	14.5033	0.0000	1.4333	16.6833
2006-12-16 20:00:00	3.2686	0.0751	234.0715	13.9167	0.0000	0.0000	16.7833
2006-12-16 21:00:00	3.0565	0.0767	237.1587	13.0467	0.0000	0.4167	17.2167

2.4.1 Normalisasi Data

In [30]:

```
# ambil nilai Global_active_power dalam bentuk array
values = df_resample.Global_active_power.values
values
```

Out[30]:

```
array([4.222889 , 3.6322    , 3.4002333, ..., 1.6593333, 1.1637    ,
       0.9346667], dtype=float32)
```

In [31]:

```
# cek dimensi
values.shape
```

Out[31]:

```
(34589,)
```

In [32]:

```
# reshape dimensi
values = np.reshape(values, (-1, 1))
values.shape
```

Out[32]:

```
(34589, 1)
```

In [33]:

```
# normalisasi fitur jadi 0-1
scaler = MinMaxScaler(feature_range=(0, 1))
values = scaler.fit_transform(values)

values
```

Out[33]:

```
array([[0.6368162 ],
       [0.5450449 ],
       [0.50900584],
       ...,
       [0.23853418],
       [0.16153105],
       [0.12594771]], dtype=float32)
```

2.4.2 Split Data

Split data jadi data training (80%) dan data testing (20%).

In [34]:

```
# determine train and test size
train_size = int(len(values) * 0.80)
test_size = len(values) - train_size
print('Train size: ', train_size)
print('Test size: ', test_size)
```

```
Train size:  27671
Test size:  6918
```

In [35]:

```
# split data
train, test = values[0:train_size,:], values[train_size:len(values),:]
```

In [37]:

```
# cek data train
pd.DataFrame(train).head()
```

Out[37]:

	0
0	0.6368
1	0.5450
2	0.5090
3	0.4885
4	0.4556

In [38]:

```
# cek data test
pd.DataFrame(test).head()
```

Out[38]:

	0
0	0.0550
1	0.0825
2	0.2039
3	0.3412
4	0.3163

In [39]:

```
# ubah array menjadi matrix
def create_dataset(dataset, look_back=1):
    X, Y = [], []
    for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        X.append(a)
        Y.append(dataset[i + look_back, 0])
    return np.array(X), np.array(Y)
```

In [40]:

```
# reshape jadi X=t and Y=t+1
# 30 jam ke belakang
look_back = 30
X_train, Y_train = create_dataset(train, look_back)
X_test, Y_test = create_dataset(test, look_back)
```

In [41]:

```
# cek dimensi X_train
X_train.shape
```

Out[41]:

```
(27640, 30)
```

In [42]:

```
pd.DataFrame(X_train).head()
```

Out[42]:

	0	1	2	3	4	5	6	7	8	9	...	20	21	22	23	24	25
0	0.6368	0.5450	0.5090	0.4885	0.4556	0.3226	0.3010	0.2732	0.5011	0.2273	...	0.2388	0.3059	0.4446	0.4975	0.5100	0.5551
1	0.5450	0.5090	0.4885	0.4556	0.3226	0.3010	0.2732	0.5011	0.2273	0.2390	...	0.3059	0.4446	0.4975	0.5100	0.5551	0.4326
2	0.5090	0.4885	0.4556	0.3226	0.3010	0.2732	0.5011	0.2273	0.2390	0.3250	...	0.4446	0.4975	0.5100	0.5551	0.4326	0.5030

	0	1	2	3	4	5	6	7	8	9	...	20	21	22	23	24	25
3	0.4880	0.4556	0.3226	0.3010	0.2732	0.5011	0.2273	0.2390	0.3250	0.2910	...	0.4920	0.5100	0.5551	0.4326	0.5030	0.4532
4	0.4556	0.3226	0.3010	0.2732	0.5011	0.2273	0.2390	0.3250	0.2910	0.1832	...	0.5100	0.5551	0.4326	0.5030	0.4532	0.2166

5 rows × 30 columns

In [43]:

```
# cek dimensi Y_train
Y_train.shape
```

Out[43]:

```
(27640,)
```

In [44]:

```
pd.DataFrame(Y_train).head()
```

Out[44]:

	0
0	0.0487
1	0.0237
2	0.0294
3	0.0249
4	0.0289

In [45]:

```
# reshape input menjadi 3D array : [samples, time steps, features]
X_train = np.reshape(X_train, (X_train.shape[0], 1, X_train.shape[1]))
X_test = np.reshape(X_test, (X_test.shape[0], 1, X_test.shape[1]))
```

In [46]:

```
# cek dimensi X_train
X_train.shape
```

Out[46]:

```
(27640, 1, 30)
```

2.4.3 Arsitektur Model

- LSTM dengan 100 neurons di layer pertama
- Dropout 20%
- 1 neuron di layer output untuk memprediksi Global_active_power
- Model di fit untuk training epochs = 20 dengan batch size = 70

In [47]:

```
# membuat model
model = Sequential()
model.add(LSTM(100, input_shape=(X_train.shape[1], X_train.shape[2])))
model.add(Dropout(0.2))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
```

```
WARNING: Logging before flag parsing goes to stderr.
W1101 11:08:29.121592 4494579136 deprecation.py:506] From /usr/local/lib/python3.7/site-packages/tensorflow/python/ops/init_ops.py:1251: calling VarianceScaling.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be removed in a future version.
Instructions for updating:
```

```
Call initializer instance with the dtype argument instead of passing it to the constructor
```

In [48]:

```
# fit jaringan
history = model.fit(X_train, Y_train, epochs=20, batch_size=70, validation_data=(X_test, Y_test),
                    callbacks=[EarlyStopping(monitor='val_loss', patience=10)], verbose=1, shuffle=
False)
```

```
Train on 27640 samples, validate on 6887 samples
```

```
W1101 11:08:38.824702 4494579136 deprecation.py:323] From /usr/local/lib/python3.7/site-
packages/tensorflow/python/ops/math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

```
Epoch 1/20
27640/27640 [==============================] - 3s 109us/sample - loss: 0.0126 - val_loss: 0.0072
Epoch 2/20
27640/27640 [==============================] - 2s 71us/sample - loss: 0.0093 - val_loss: 0.0069
Epoch 3/20
27640/27640 [==============================] - 2s 76us/sample - loss: 0.0091 - val_loss: 0.0069
Epoch 4/20
27640/27640 [==============================] - 3s 113us/sample - loss: 0.0090 - val_loss: 0.0070
Epoch 5/20
27640/27640 [==============================] - 2s 83us/sample - loss: 0.0090 - val_loss: 0.0072
Epoch 6/20
27640/27640 [==============================] - 2s 70us/sample - loss: 0.0089 - val_loss: 0.0073
Epoch 7/20
27640/27640 [==============================] - 2s 67us/sample - loss: 0.0088 - val_loss: 0.0073
Epoch 8/20
27640/27640 [==============================] - 2s 66us/sample - loss: 0.0088 - val_loss: 0.0073
Epoch 9/20
27640/27640 [==============================] - 2s 78us/sample - loss: 0.0088 - val_loss: 0.0074
Epoch 10/20
27640/27640 [==============================] - 2s 74us/sample - loss: 0.0087 - val_loss: 0.0073
Epoch 11/20
27640/27640 [==============================] - 2s 71us/sample - loss: 0.0087 - val_loss: 0.0074
Epoch 12/20
27640/27640 [==============================] - 2s 70us/sample - loss: 0.0086 - val_loss: 0.0073
```

In [49]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 100)               52400
_________________________________________________________________
dropout (Dropout)            (None, 100)               0
_________________________________________________________________
dense (Dense)                (None, 1)                 101
=================================================================
Total params: 52,501
Trainable params: 52,501
Non-trainable params: 0
_________________________________________________________________
```

In [50]:

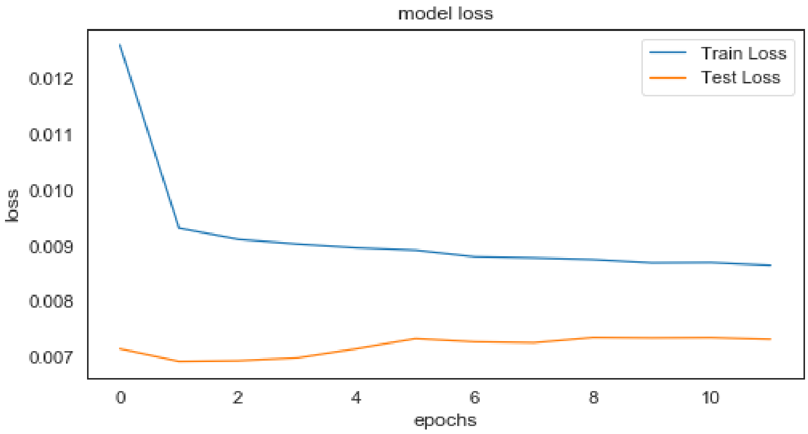
```
# bikin prediksi
train_predict = model.predict(X_train)
test_predict = model.predict(X_test)
# invert prediksi
train_predict = scaler.inverse_transform(train_predict)
Y_train = scaler.inverse_transform([Y_train])

test_predict = scaler.inverse_transform(test_predict)
Y_test = scaler.inverse_transform([Y_test])
```

```
print('Train Mean Absolute Error:', mean_absolute_error(Y_train[0], train_predict[:,0]))
print('Train Root Mean Squared Error:',np.sqrt(mean_squared_error(Y_train[0],
train_predict[:,0])))
print('Test Mean Absolute Error:', mean_absolute_error(Y_test[0], test_predict[:,0]))
print('Test Root Mean Squared Error:',np.sqrt(mean_squared_error(Y_test[0], test_predict[:,0])))
```

```
Train Mean Absolute Error: 0.46800867405353697
Train Root Mean Squared Error: 0.6211122146015357
Test Mean Absolute Error: 0.42692339793598466
Test Root Mean Squared Error: 0.5507995415932379
```

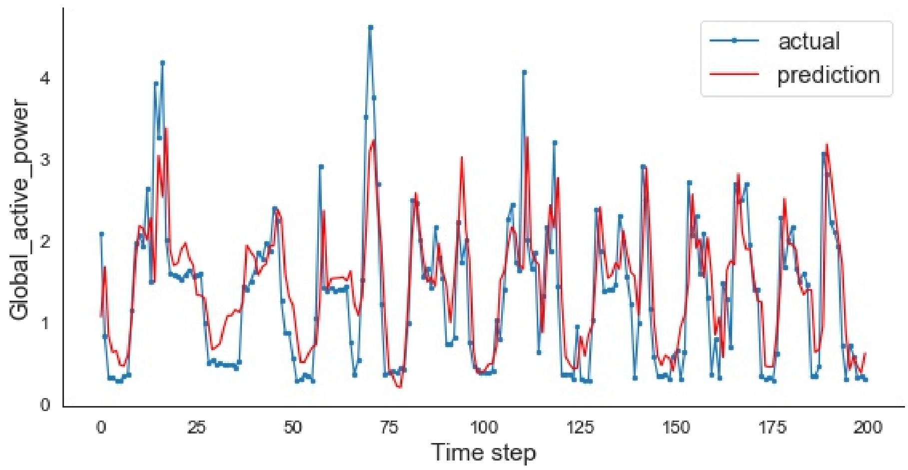
In [51]:

```
plt.figure(figsize=(8,4))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epochs')
plt.legend(loc='upper right')
plt.show();
```



In [52]:

```
aa = [x for x in range(200)]
plt.figure(figsize=(8,4))
plt.plot(aa, Y_test[0][:200], marker='.', label="actual")
plt.plot(aa, test_predict[:,0][:200], 'r', label="prediction")
# plt.tick_params(left=False, labelleft=True) #remove ticks
plt.tight_layout()
sns.despine(top=True)
plt.subplots_adjust(left=0.07)
plt.ylabel('Global_active_power', size=15)
plt.xlabel('Time step', size=15)
plt.legend(fontsize=15)
plt.show();
```



3. Referensi

- T.-Y. Kim and S.-B. Cho, "Predicting Residential Energy Consumption Using CNN-LSTM Neural Networks," Energy, vol. 182, pp. 72-81, 2019.
- https://github.com/susanli2016/Machine-Learning-with-Python/blob/master/LSTM%20Time%20Series%20Power%20Consumption.ipynb
- “How to Develop Multi-Step LSTM Time Series Forecasting Models for Power Usage,” *Machine Learning Mastery*, 10-Oct-2018. [Online]. Available: https://machinelearningmastery.com/how-to-develop-lstm-models-for-multi-step-time-series-forecasting-of-household-power-consumption/. [Accessed: 12-Oct-2019].