Weather and Electric Load Forecasting
... (from scratch) with Python Data Science Tools

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PyData Part II - Electric Load Forecasting

Outline:

Python data science tools

Weather forecasting

- Datasets (NOAA)
- Visualization & description
- Features, models, seasonality (yearly); model evaluation

Electric load forecasting

- Datasets (GEFCON2012 Load)
- Visualization & analysis
- Features and models, seasonality (yearly, daily); model evaluation

Conclusion

- Other models and further work

Data source and references

GEFCON2012 & Dr. Tao Hong, UNC Charlotte, NC

- http://www.gefcom.org (http://www.gefcom.org) @DrHongTao (https://twitter.com/DrHongTao)

Global Energy Forecasting Competition 2012 (GEFCom2012)

- IEEE Power Engineering Society, General Meeting 2013, Vancouver, Canada
- Kaggle competition: two months, 8/31/2012 - 10/31/2012,

References

Hong, T., Pinson, P., & Fan, S. (2014). Global energy forecasting competition 2012. *International Journal of Forecasting*, 30(2), 357-363.

GEFCom2012: Global Energy Forecasting Competition 2012, Tao Hong, Pierre Pinson, Shu Fan, HSC/13/16.

IEEE GEFCOM2012 Data Files

Hierarchical load forecasting track

Forecast hourly loads (in kW) for a US utility with 20 zones at both the zonal (20 series) and system (sum of the 20 zonal level series) levels, with a total of 21 series.

NOTE: GEFCOM2012 included a separate *Wind power forecasting* track, not considered here.

Data

- 20 zonal load zones (20 series)
- 1 system zone (sum of the 20 zonal level series)
- 4.5 years of hourly load and temperature history data; eight non-consecutive weeks of load data removed.

Task

- Predict the loads for the week immediately after the 4.5 years of history, without the actual temperatures or temperature forecasts being given.

In [2]:

```
# imports
import numpy as np
import pandas as pd
from datetime import datetime

%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
```

In [3]:
```
# Read Load solution data: load_solution_df.csv
load_history_df = pd.read_csv("GEFCOM2012_ieee/Load/Load_history.csv", sep=',')
print("load_history_df.shape:", load_history_df.shape)
print("load_history_df.columns:", load_history_df.columns)
load_history_df.head(3)
```

```
load_history_df.shape: (33000, 28)
load_history_df.columns: Index(['zone_id', 'year', 'month', 'day', 'h1', 'h2',
'h3', 'h4', 'h5', 'h6',
       'h7', 'h8', 'h9', 'h10', 'h11', 'h12', 'h13', 'h14', 'h15', 'h16',
       'h17', 'h18', 'h19', 'h20', 'h21', 'h22', 'h23', 'h24'],
      dtype='object')
```

Out[3]:

	zone_id	year	month	day	h1	h2	h3	h4	h5	
0	1	2004	1	1	16,853	16,450	16,517	16,873	17,064	1
1	1	2004	1	2	14,155	14,038	14,019	14,489	14,920	1
2	1	2004	1	3	14,439	14,272	14,109	14,081	14,775	1

3 rows × 28 columns

Load history data wrangling

- File `Load_history.csv` has load numbers as strings; convert to int64
- File `Load_history.csv` has 9 missing weeks of data, for backcasting and for forecasting.
- Load for hourly data appears in columns `h1` to `h24`; unpivot (pandas.melt()) to create time series index.
- Load for 21 zones appears as individual records, per `zone_id`; pivot on `zone_id`.

In [4]:

```
# Convert h1-h24 load number strings to int64 (remove format commas, NAs, etc)
load_history_df = load_history_df.replace(regex=r',', value='')
load_history_df = load_history_df.dropna()
load_history_df = load_history_df.astype('int64')
print("load_history_df.shape:", load_history_df.shape)
load_history_df.head(3)
```

```
load_history_df.shape: (31720, 28)
```

Out[4]:

	zone_id	year	month	day	h1	h2	h3	h4	h5	
0	1	2004	1	1	16853	16450	16517	16873	17064	17
1	1	2004	1	2	14155	14038	14019	14489	14920	16
2	1	2004	1	3	14439	14272	14109	14081	14775	15

3 rows × 28 columns

In [5]:
```
# Load history hourly - Unpivot h1-h24 columns (pandas.melt())
load_hours = ['h1', 'h2', 'h3', 'h4', 'h5', 'h6', 'h7', 'h8', 'h9', 'h10', 'h11',
'h12',
        'h13', 'h14', 'h15', 'h16', 'h17', 'h18', 'h19', 'h20', 'h21', 'h22', 'h2
3', 'h24']
load_history_vars = ['zone_id', 'year', 'month', 'day']
load_history_df_hourly = load_history_df.melt(id_vars=load_history_vars,
                                value_vars=load_hours, var_name='hour', value_name
='load')

# Convert h1-h24 'hour' values to 0-23 int values
load_history_df_hourly['hour'] = load_history_df_hourly['hour'].str.replace('h',
'').astype('int64') - 1

print("load_history_df_hourly.shape:", load_history_df_hourly.shape)
print("load_history_df_hourly.columns:", load_history_df_hourly.columns)
```

```
load_history_df_hourly.shape: (761280, 6)
load_history_df_hourly.columns: Index(['zone_id', 'year', 'month', 'day', 'hou
r', 'load'], dtype='object')
```

Hourly time series: Pivot `zone_id` and reindex load history

Convert hierarchical time series index to Datetime

- year, month, day, hour
- load_history_df_data

In [6]:

```
# Pivot zone_id and reindex with date_index
date_index = ['year', 'month', 'day', 'hour']
load_history_df_data = load_history_df_hourly.pivot_table(index=date_index,
                              columns='zone_id', values='load', aggfunc='sum', fi
ll_value=0)

print("load_history_df_data.shape:", load_history_df_data.shape)
print("load_history_df_data.columns:", load_history_df_data.columns)
load_history_df_data.head(3)
```

```
load_history_df_data.shape: (38064, 20)
load_history_df_data.columns: Int64Index([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 1
2, 13, 14, 15, 16, 17, 18, 19,
            20],
           dtype='int64', name='zone_id')
```

Out[6]:

			zone_id	1	2	3	4	5	6
year	month	day	hour						
2004	1	1	0	16853	126259	136233	484	6829	133088
			1	16450	123313	133055	457	6596	129909
			2	16517	119192	128608	450	6525	125717

In [7]:

```
print("load_history_df_data.index len:", len(load_history_df_data.index))
print("load_history_df_data.index.nlevels:", load_history_df_data.index.nlevels)

# Reindex load_history_df_data with hierarchical index (year, month, day, hour)
# to time series with datetime index
load_history_df_index_dt = [datetime(y,m,d,h) for (y,m,d,h) in load_history_df_dat
a.index]
load_history_df_data.index = load_history_df_index_dt
load_history_df_data[[1,2,3,20]].head(3)
```

```
load_history_df_data.index len: 38064
load_history_df_data.index.nlevels: 4
```

Out[7]:

zone_id	1	2	3	20
2004-01-01 00:00:00	16853	126259	136233	79830
2004-01-01 01:00:00	16450	123313	133055	77429
2004-01-01 02:00:00	16517	119192	128608	75558

In [8]:

```
# Add aggregate system zone 21 to load history
load_history_df_data[21] = load_history_df_data.sum(axis=1)
load_history_df_data[[1,2,20,21]].describe()
```

Out[8]:

zone_id	1	2	20	21
count	38064.000000	38064.000000	38064.000000	3.806400e+04
mean	18641.241488	173748.222730	88649.680223	1.647167e+06
std	5796.667521	34996.374374	18654.775828	3.746085e+05
min	7319.000000	82672.000000	46291.000000	8.369000e+05
25%	14415.000000	149160.500000	75384.000000	1.383689e+06
50%	17349.500000	170451.500000	86771.000000	1.586182e+06
75%	22024.250000	196107.750000	100715.000000	1.885652e+06
max	45547.000000	321509.000000	176705.000000	3.280423e+06

Load history per zone

- Aggregate system load: zone 21, 1.58 GW mean
- Largest zone load: zone 18, 205 MW mean, 540 MW peak
- Smallest zone load: zone 4, 480 kW mean, 1.1 MW peak

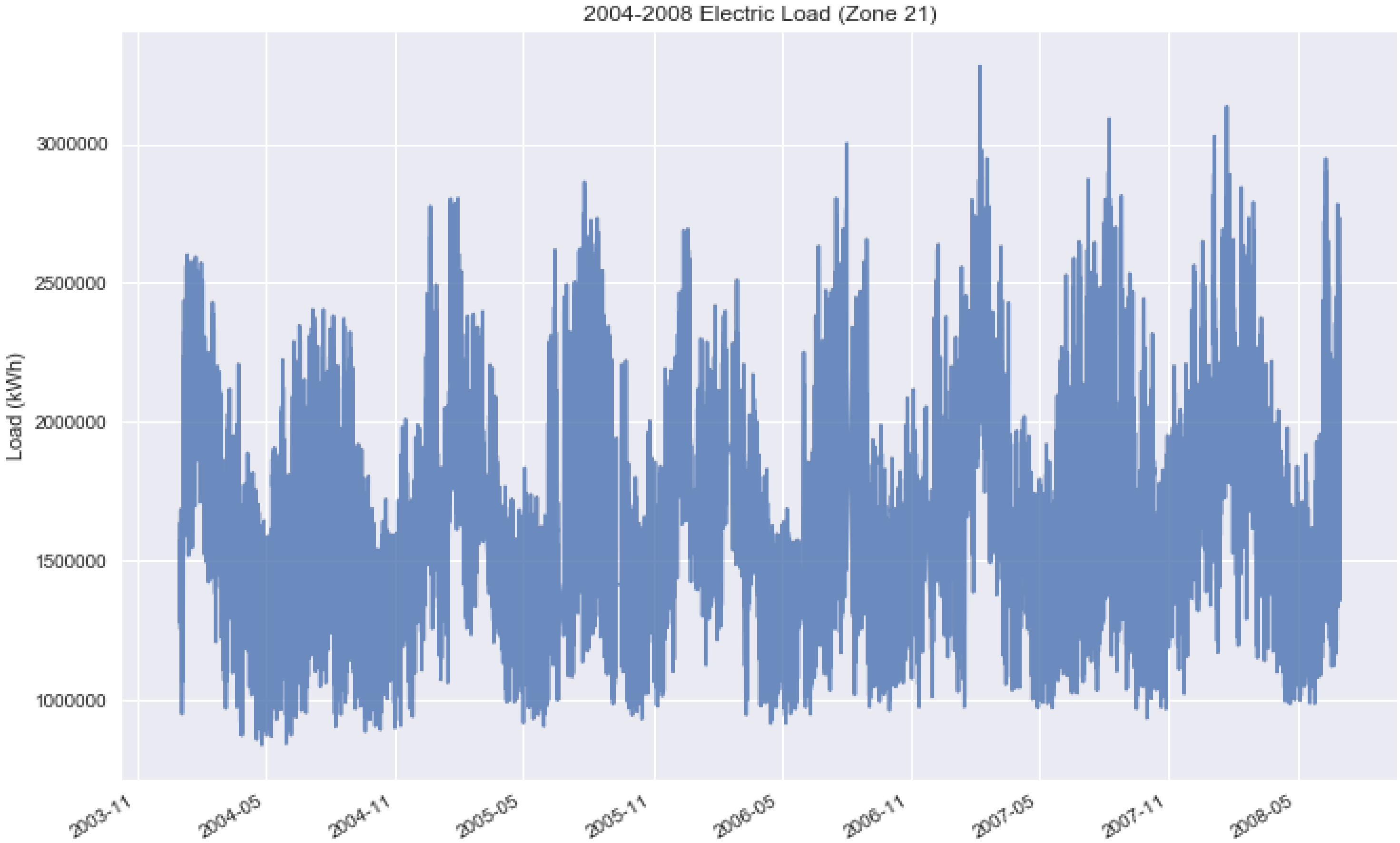
Visualization: Load history, 4.5 years, aggregate system (zone 21)

Electric load of 20 different zones (zone_ids 1-20), plus aggregate total zone_id 21

- 4.5 years of data: date range 01/01/2004 (00:00AM) to 06/30/2008 (06:00 AM)
- 224 Weeks; 9 deleted weeks 1-8 backcast; 1 week forecast

In [9]:

```
# Visualize: load_history_df_data, Total zone_id 21; 224 weeks
title = '2004-2008 Electric Load (Zone 21)'
load_history_df_data[:][21].plot(alpha=0.8, title=title, figsize=(12,8));
plt.ylabel('Load (kWh)');
```



Aggregate system load (zone 21)

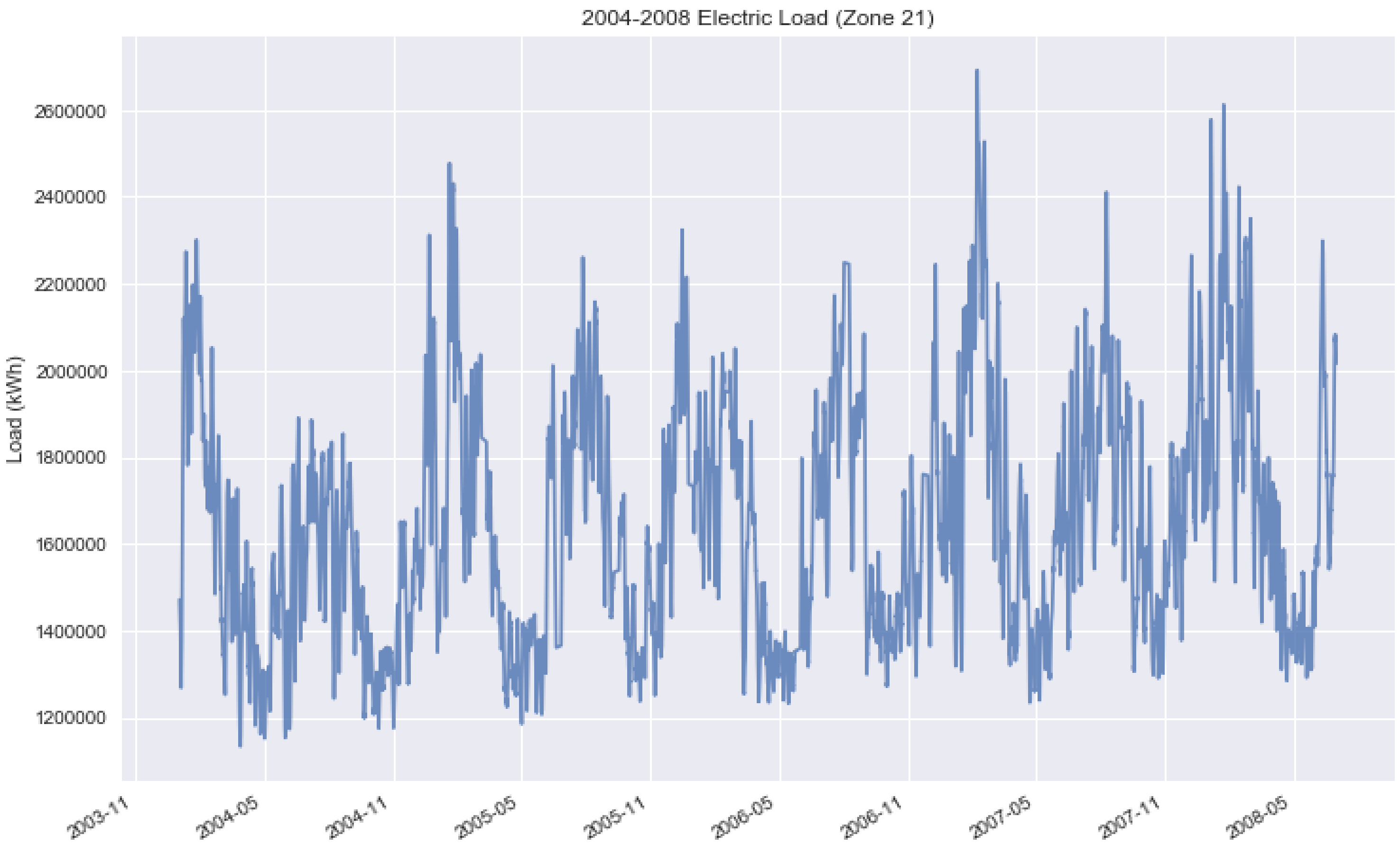
Yearly seasonal pattern clearly visible, with load lows in [April, October] and load highs in [January, July].

- Hypothesis: load lows after equinox times of Spring and Fall.
- Hypothesis: load peaks in Summer and Winter.

High daily load variation

- Filter out with moving average (MA) - e.g., 2 day

In [10]:
```
# Visualize: 48 hour moving average (MA) - filter out daily variation
load_history_df_data[:][21].rolling(48).mean().plot(alpha=0.8, title=title, figsiz
e=(12,8));
plt.ylabel('Load (kWh)');
```

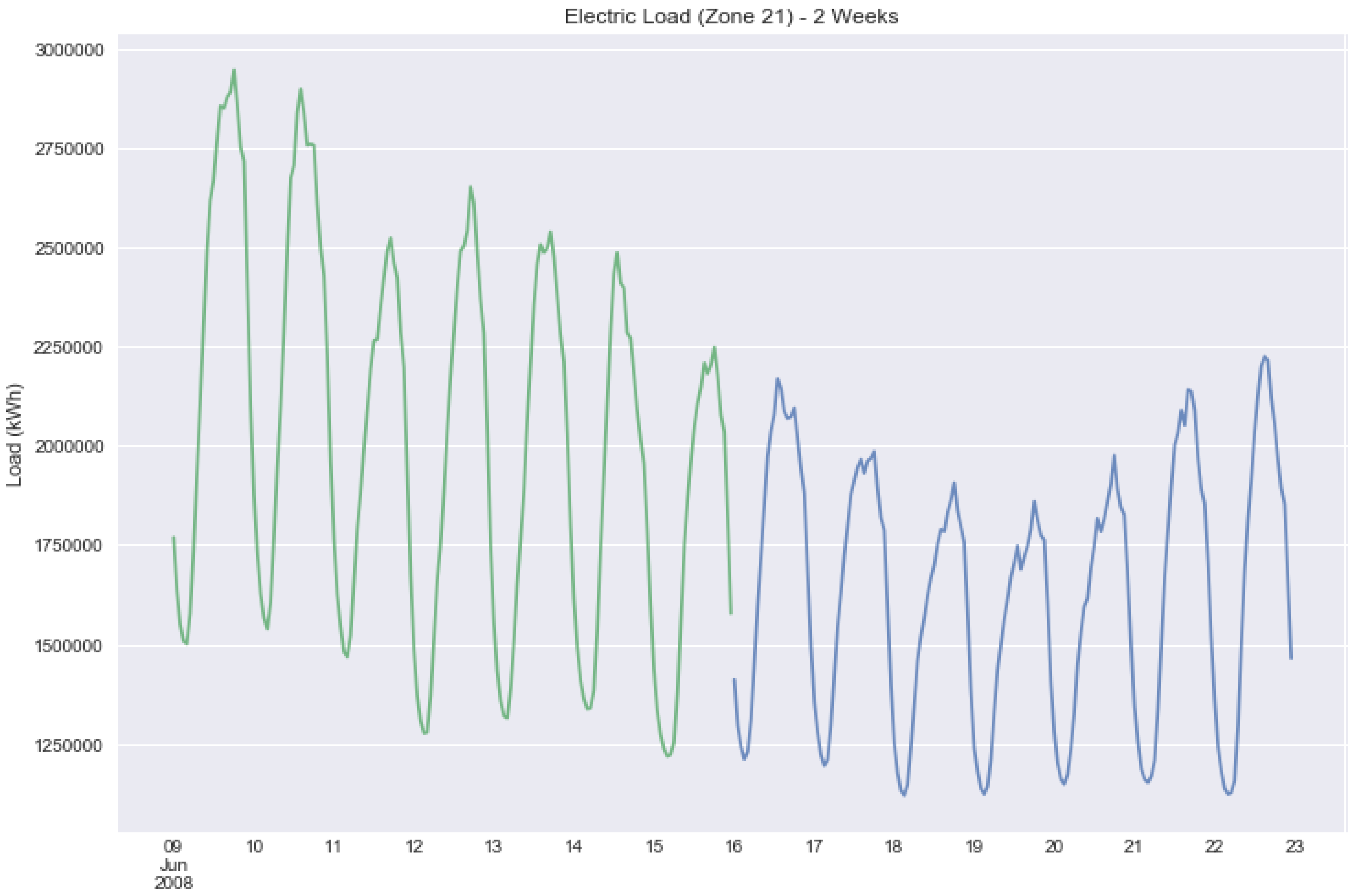


Load history, weekly view, aggregate system load (21)

- Last two weeks of load history period (06/17-30/2008)
- First week of load history period

In [11]:

```
# Visualize: load_history_df_data, Total zone_id 21; 2 weeks
title = 'Electric Load (Zone 21) - 2 Weeks'
load_history_df_data[-168*2:-168][21].plot(alpha=0.8, title=title, figsize=(12,8
));
load_history_df_data[-168*3:-168*2][21].plot(alpha=0.8, title=title, figsize=(12,8
));
plt.ylabel('Load (kWh)');
```



Load history, weekly view, aggregate system load (21)

Intra-day hourly pattern clearly visible, with load lows around 1AM and highs around 12N.

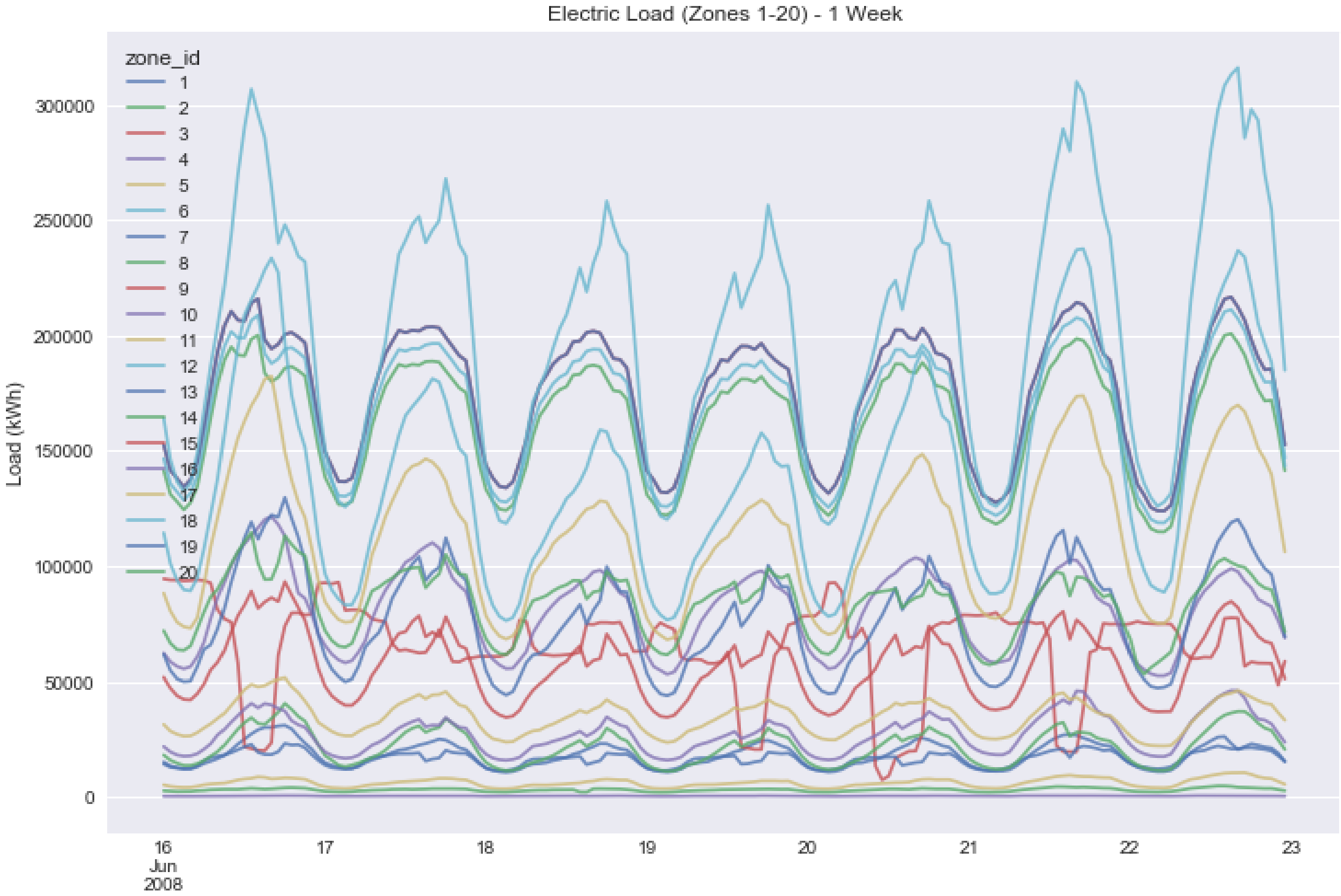
- Peak daily load ~ 2.5 GWh
- Low daily load ~ 1.2 GWh
- Last day of history period is 06/30/2008

Load history, weekly view, zones 1-20

- Last two weeks of load history period (06/17-30/2008)

In [28]:

```
# Visualize: load_history_df_data, Total load zone_ids 1-20; 1 week
# Zone 4 has 500 kWh; zone 18 reaches 400,000 kWh
local_zones = np.arange(1,21)
title='Electric Load (Zones 1-20) - 1 Week'
load_history_df_data[-168*2:-168][local_zones].plot(alpha=0.8, title=title, figsiz
e=(12,8));
plt.ylabel('Load (kWh)');
```



Load history, weekly view, individual zones 1-20

Intra-day hourly pattern clearly visible, with load lows around 1AM and highs around 12N.

- Peak daily load: zone 18, 205 kW mean, 540 kW peak
- Low daily load: zone 4, 0.48 kW mean, 1.1 kW peak
- Zone 9 is an industrial zone; has inverted load demand phase w.r.t. other zones

Electric Load Forecasting - Data Model

We consider here a baseline Linear Regression model, with time series seasonality features.

sklearn.linear_models.LinearRegression()

- Year seasonality (twice year frequency), sin(182.625 days)
- Hour seasonality, sin(24 hours)
- Day of the week (SMTWTFS), weekly seasonality
- Calendar holidays, yearly seasonality, holidays()

Model input features

- Temperature prediction as a function of time (DATE) and previous temperature only
- train on historical data (e.g., past 10, 30, 50, 70 years)

Length of forecast period (length of test period)

- multi-year test period
- 1-10 day test period

In [13]:

```
# imports
import numpy as np
import pandas as pd

%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()

from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
```

In [14]:

```
# models
model_load = LinearRegression(fit_intercept=True)
model_load_polynomial = make_pipeline(PolynomialFeatures(3), LinearRegression())
```

Linear Prediction Model, Yearly and daily seasonality

- Training data: 2004-01-01 to 2008-06-30 (4.5 years)
- Test data: 2008-07-01 to 2008-07-07 (1 week)

Seasonality features

- Yearly seasonality feature, one year period, with phase delay
- Daily seasonality feature, one day period, with phase delay
- Model input features: data index 'DATE', 'SEASON', 'DAY'

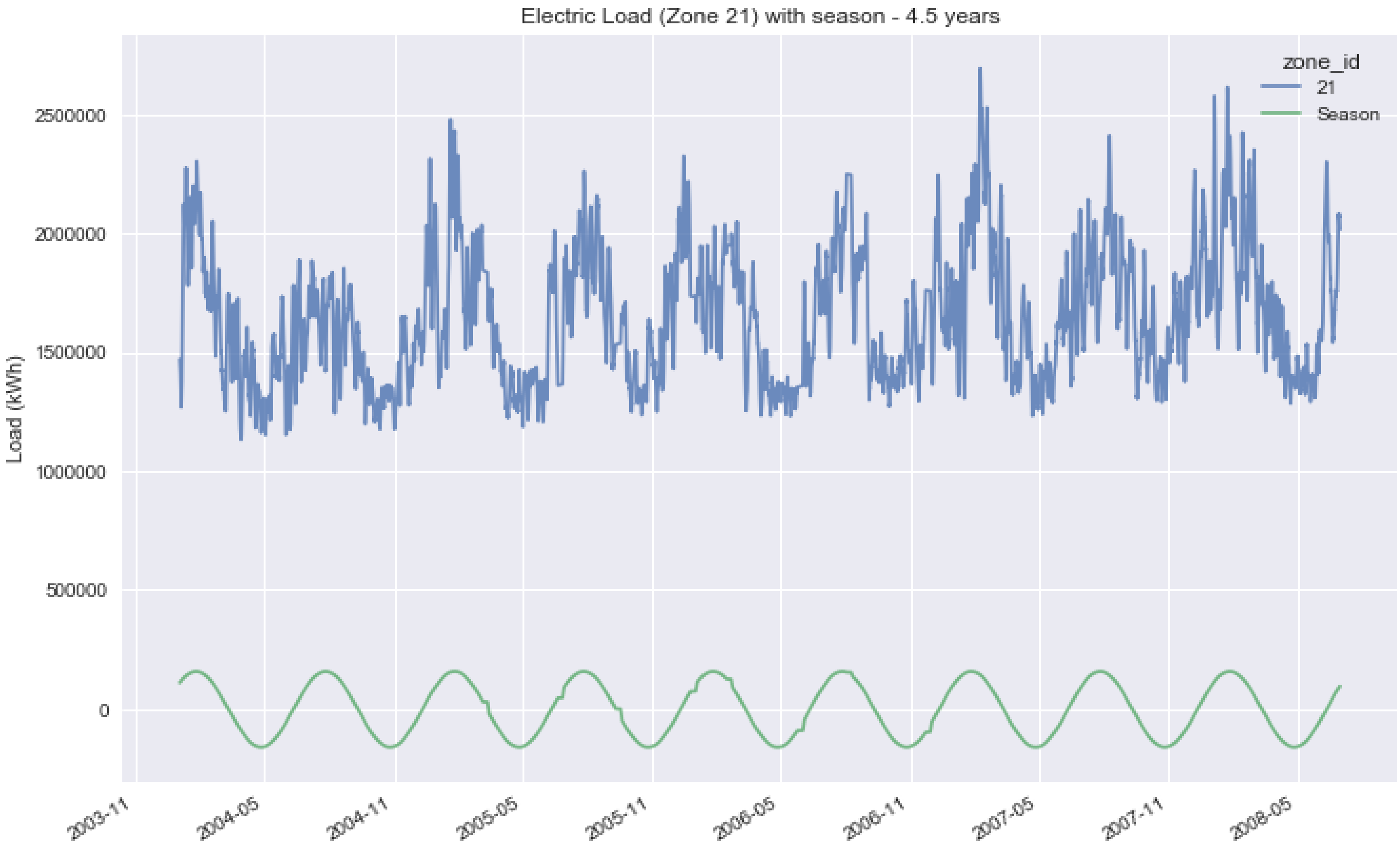
In [15]:

```python
# Make yearly season signal: yearly season variation, with phase delay
def season_year(date):
    """Compute yearly season signal for input date"""
    period = 182.625  # period in days
    phase_lag = -125   # lag in days
    days = (date - pd.datetime(1900, 12, 21)).days
    m = np.cos((days + phase_lag) * 2 * np.pi / period)
    return 0.0 + 5e5 * np.degrees(-m) / 180.

load_history_season = load_history_df_data.copy()
load_history_season['Season'] = list(map(season_year, load_history_season.index))
load_history_season[[21, 'Season']].head(3)
```

Out[15]:

zone_id	21	Season
2004-01-01 00:00:00	1397668	110155.537334
2004-01-01 01:00:00	1351507	110155.537334
2004-01-01 02:00:00	1315742	110155.537334

In [26]:
```
# Visualize system load (21)
title = 'Electric Load (Zone 21) with season - 4.5 years'
load_history_season[[21,'Season']].rolling(48).mean().plot(
                        alpha=0.8, title=title, figsize=(12,8))
plt.ylabel('Load (kWh)');
```



In [17]:

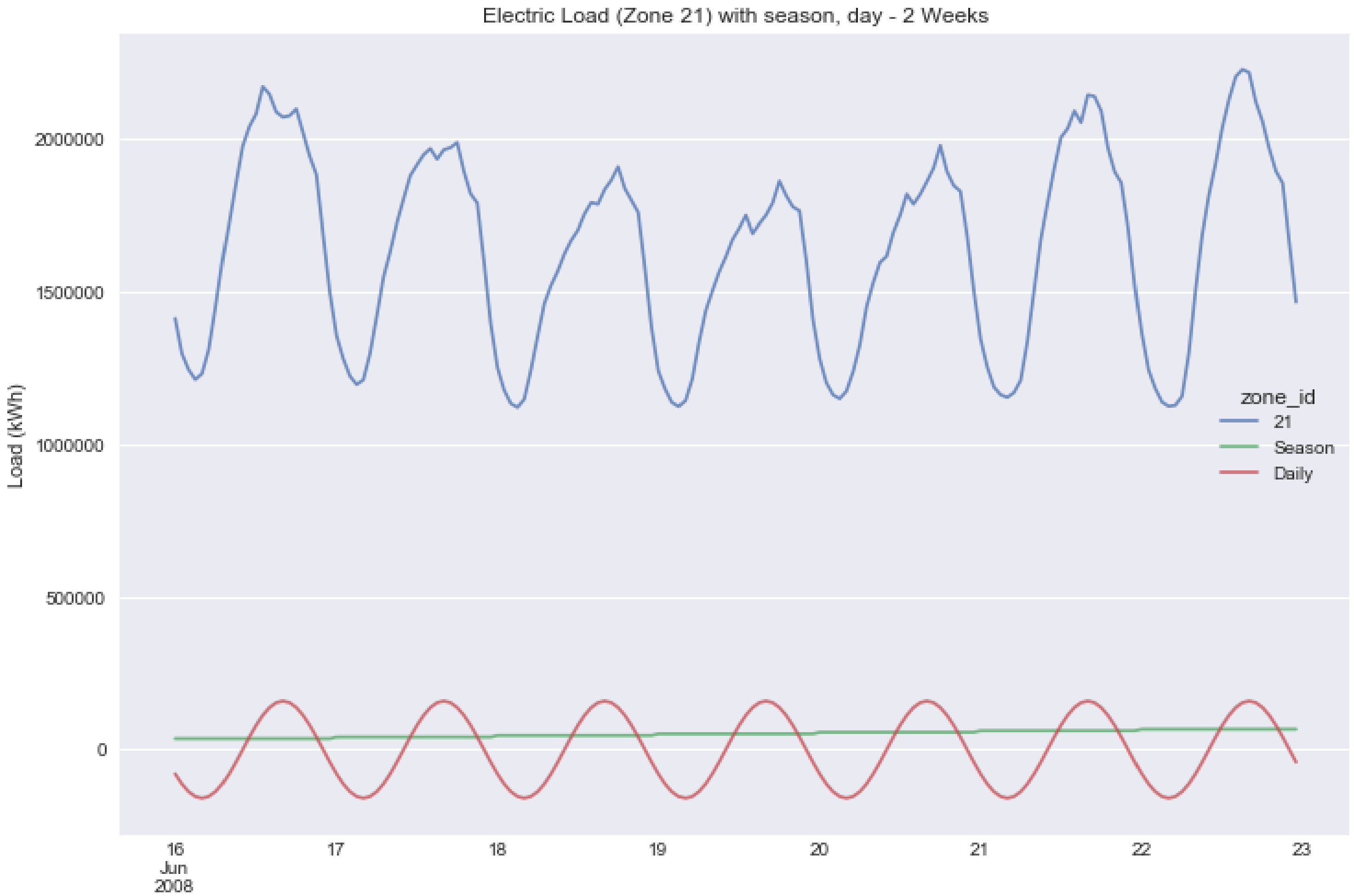
```python
# Make daily seasonality signal: daily variation date.hour, with phase delay
def season_day(date):
    """Compute season signal for input date"""
    period = 24  # period in hours
    phase_lag = -4   # lag in hours
    m = np.cos((date.hour + phase_lag) * 2 * np.pi / period)
    return 0.0 + 5e5 * np.degrees(-m) / 180.

load_history_season['Daily'] = list(map(season_day, load_history_season.index))
load_history_season[[21, 'Season', 'Daily']].head(3)
```

Out[17]:

zone_id	21	Season	Daily
2004-01-01 00:00:00	1397668	110155.537334	-79577.471546
2004-01-01 01:00:00	1351507	110155.537334	-112539.539520
2004-01-01 02:00:00	1315742	110155.537334	-137832.223855

In [18]:

```
# Visualize system load (21)
title = 'Electric Load (Zone 21) with season, day - 2 Weeks'
load_history_season[-168*2:-168][[21,'Season','Daily']].plot(alpha=0.8, title=titl
e, figsize=(12,8))
plt.ylabel('Load (kWh)');
```



In [19]:

```
# Load data with yearly and daily season signal
start_date = '2004-01-01'
end_date = '2008-06-30'
score_dates = load_history_season[start_date:end_date].index
# pd.date_range(start_date, end_date)

X_train = pd.DataFrame(index=score_dates)
# X_train = pd.DataFrame(index=load_history_season[start_date:end_date].index)
X_train['date'] = score_dates[:, np.newaxis].astype('float64') * 1e-17
X_train['season'] = list(map(season_year, score_dates))
X_train['day'] = list(map(season_day, score_dates))

y_train = load_history_season[start_date:end_date][[21]]
X_train.head(3)
```

Out[19]:

	date	season	day
2004-01-01 00:00:00	10.729152	110155.537334	-79577.471546
2004-01-01 01:00:00	10.729188	110155.537334	-112539.539520
2004-01-01 02:00:00	10.729224	110155.537334	-137832.223855

In [21]:

```
# Train models (linear only)
X_train_float64 = X_train.astype('float64')
model_load.fit(X_train_float64, y_train)

# Model score and coefficients: X as training date_range()
print("model_load.coef_:", model_load.coef_, "model_load.intercept_:", model_load.
intercept_)
print("model_load.score:", model_load.score(X_train, y_train))
```

```
model_load.coef_: [[1.47084734e+05 1.72658062e+00 1.18971696e+00]] model_load.
intercept_: [-33366.60552771]
model_load.score: 0.4165223085070894

/Users/nelson/Dev/anaconda3/lib/python3.6/site-packages/scipy/linalg/basic.py:
884: RuntimeWarning: internal gelsd driver lwork query error, required iwork d
imension not returned. This is likely the result of LAPACK bug 0038, fixed in
LAPACK 3.2.2 (released July 21, 2010). Falling back to 'gelss' driver.
  warnings.warn(mesg, RuntimeWarning)
```

In [22]:

```
# Run model on training data
load_predict = load_history_season[start_date:end_date]
load_predict['p21'] = model_load.predict(X_train_float64)[:,0]
load_predict[['Season', 'Daily', 21, 'p21']].head(3)
```

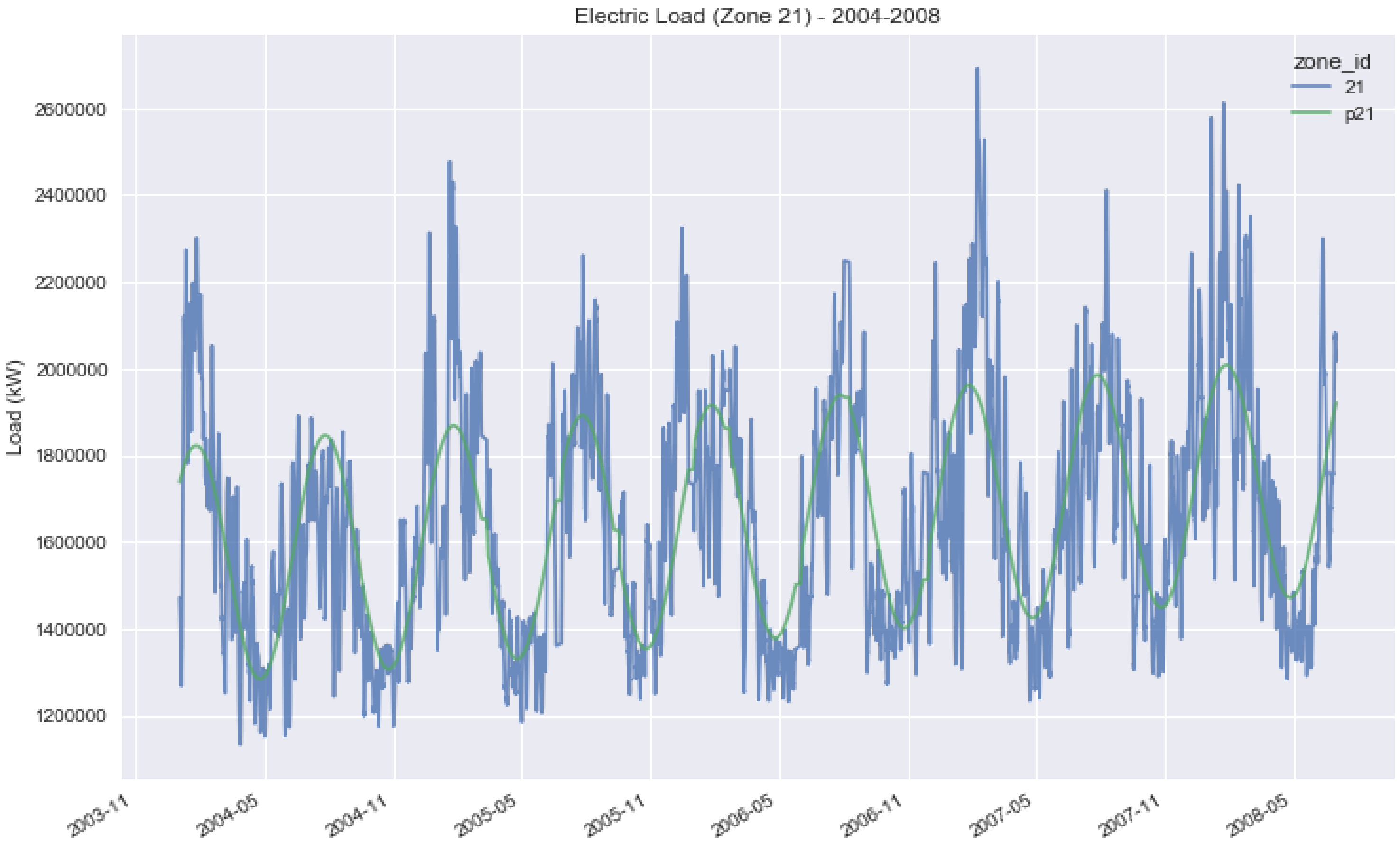
```
/Users/nelson/Dev/anaconda3/lib/python3.6/site-packages/ipykernel/__main__.py:
3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/sta
ble/indexing.html#indexing-view-versus-copy
  app.launch_new_instance()
```

Out[22]:

zone_id	Season	Daily	21	p21
2004-01-01 00:00:00	110155.537334	-79577.471546	1397668	1.640246e+06
2004-01-01 01:00:00	110155.537334	-112539.539520	1351507	1.601035e+06
2004-01-01 02:00:00	110155.537334	-137832.223855	1315742	1.570950e+06

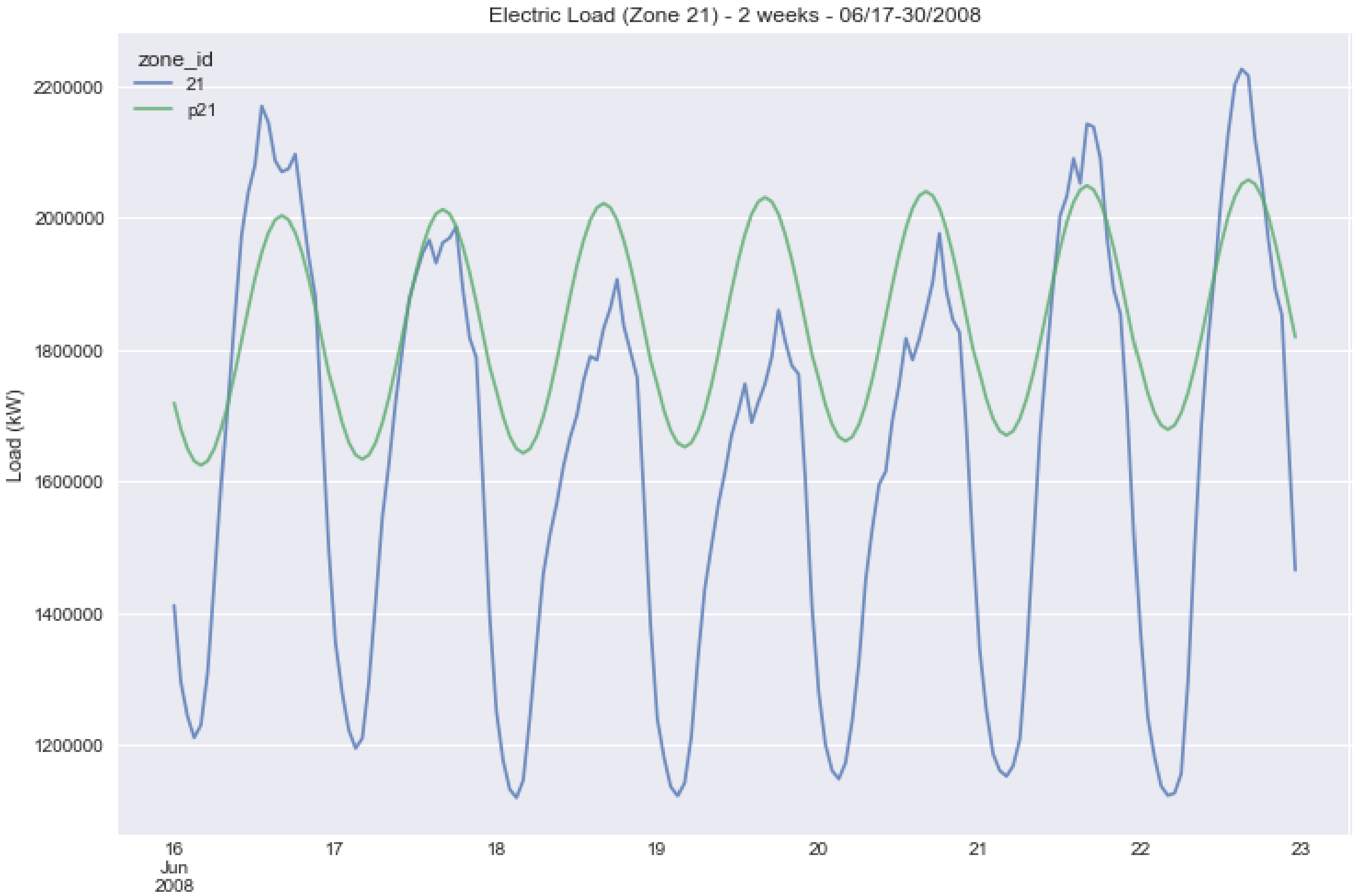
In [27]:

```
# Plot load_predict on training data
title='Electric Load (Zone 21) - 2004-2008'
load_predict[[21,'p21']].rolling(48).mean().plot(alpha=0.8,figsize=(12,8),title=ti
tle);
plt.ylabel('Load (kW)');
```



In [24]:

```
# Plot load_predict on training data
title='Electric Load (Zone 21) - 2 weeks - 06/17-30/2008'
load_predict[-168*2:-168][[21,'p21']].plot(alpha=0.8,figsize=(12,8),title=title);
plt.ylabel('Load (kW)');
```



In [25]:

```python
# Define prediction error (MSE, RMSE)
def prediction_error(y1, y2):
    """prediction_error(y1, y2): returns MSE and RMSE"""
    if len(y1) != len(y2):
        return (-1, -1)
    mse = (1/len(y1))*np.sum((y1-y2)**2)
    return (mse, np.sqrt(mse))

# Compute prediction error, load Zone 21
_, rmse_load = prediction_error(load_predict[21], load_predict['p21'])
print("rmse_load (kW):", rmse_load)
```

```
rmse_load (kW): 286143.5713603093
```

Electric load forecasting - *Weekly seasonality and other trends?*

The above linear regression model with yearly and daily seasonality signals has a high electric load prediction error (RMSE).

In addition to yearly and daily seasonality, electric load demand data also exhibits weekly seasonality and other seasonality and demand trends that should be accounted for.

We leave as an exercise:

- Add day-of-the-week as weekly indicator variables ('MON' to 'SUN')
- Add holidays of the year as a yearly indicator variable ('HOLIDAY')

Include weekly indicator variables to the prediction model.

We also leave for another exercise prediction of individual load zones (1-20).

Summary: Electric Load Prediction

Model score and error measure (with seasonality)

- model_load.score: 0.2195
- rmse_zone_21: 419 MW, on peak load of ~ 2.5 GW

Other models/toolkits to explore and further work

We built time-series models with seasonality (yearly and daily) from scratch. Follow up to this intial work on forecasting include applying traditional models for time-series analysis: exponential smoothing, autoregressive integrated moving average (ARIMA), and seasonal ARIMA models.

Other recent methods include time-series analysis with recurrent neural networks (RNN nd LSTM), autoregressive RNNs, and other recent toolkits for forecasting and time-series analysis.

Exponential and autoregressive models

- Exponential smoothing models:
  - https://www.statsmodels.org/dev/generated/statsmodels.tsa..holtwinters.Exponent
    (https://www.statsmodels.org/dev/generated/statsmodels.tsa..holtwinters.Exponen
- Autoregressive Integrated Moving Average (ARIMA) models:
  - https://www.statsmodels.org/dev/generated/statsmodels.tsa.arima_model.ARIMA.h
    (https://www.statsmodels.org/dev/generated/statsmodels.tsa.arima_model.ARIMA.
- Seasonal AutoRegressive Integrated Moving Average (SARIMA) models:
  - https://www.statsmodels.org/dev/generated/statsmodels.tsa.statespace.sarimax.SA
    (https://www.statsmodels.org/dev/generated/statsmodels.tsa.statespace.sarimax.S/

Neural network models

- Bandara et al, Forecasting Across Time Series Databases using Recurrent Neural Networks on Groups of Similar Series: A Clustering Approach. Kasun Bandara, Christoph Bergmeir, Slawek Smyl. https://arxiv.org/abs/1710.03222 (https://arxiv.org/abs/1710.03222)

- García-Ascanio et al, Electric power demand forecasting using interval time series: A comparison between VAR and iMLP. Carolina García-Ascanio, Carlos Maté. In Energy Policy, Volume 38, Issue 2, February 2010, Pages 715-725.

Facebook Prophet - open source forecasting tool

- Facebook Research - Prophet: forecasting at scale (2017)
  - https://research.fb.com/prophet-forecasting-at-scale/ (https://research.fb.com/prophet-forecasting-at-scale/)

Conclusion

We have presented baseline linear weather and electric load prediction models with seasonality.

We have outlined more powerful and recent forecasting models for future work.

Github Jupyter notebooks

- https://github.com/nelscorrea/PyDataMiami2019/ (https://github.com/nelscorrea/PyDataMiami2019/)
