In [1]:
```
import pandas as pd
import datetime
```

In [2]:
```
# Task 1
# Examine the data, parse the time fields wherever necessary.
# Take the sum of the energy usage (use[kW]) to get per day usage and merge i

energy_df = pd.read_csv('energy_data.csv')
weather_df = pd.read_csv('weather_data.csv')

energy_df.head()
```

Out[2]:

	Date & Time	use [kW]	gen [kW]	Grid [kW]	AC [kW]	Furnace [kW]	Cellar Lights [kW]	Washer [kW]	First Floor lights [kW]	Utility Rm + Basement Bath [kW]
0	2014-01-01 00:00:00	0.304439	0.0	0.304439	0.000058	0.009531	0.005336	0.000126	0.011175	0.003836
1	2014-01-01 00:30:00	0.656771	0.0	0.656771	0.001534	0.364338	0.005522	0.000043	0.003514	0.003512
2	2014-01-01 01:00:00	0.612895	0.0	0.612895	0.001847	0.417989	0.005504	0.000044	0.003528	0.003484
3	2014-01-01 01:30:00	0.683979	0.0	0.683979	0.001744	0.410653	0.005556	0.000059	0.003499	0.003476
4	2014-01-01 02:00:00	0.197809	0.0	0.197809	0.000030	0.017152	0.005302	0.000119	0.003694	0.003865

In [3]:
```
weather_df.head()
```

Out[3]:

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	tim
0	34.98	partly-cloudy-night	0.64	10.00	Partly Cloudy	1017.69	7.75	0.29	138853440
1	16.49	clear-night	0.62	10.00	Clear	1022.76	2.71	0.06	138853800
2	14.63	clear-night	0.68	10.00	Clear	1022.32	4.84	0.03	138854160
3	13.31	clear-night	0.71	10.00	Clear	1021.64	4.00	0.14	138854520
4	13.57	clear-night	0.71	9.93	Clear	1020.73	3.67	0.04	138854880

In [4]:
```
# parse time of weather
weather_df['time'] = pd.to_datetime(weather_df['time'], unit="s")
weather_df.head()
```

Out[4]:

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	time
0	34.98	partly-cloudy-night	0.64	10.00	Partly Cloudy	1017.69	7.75	0.29	2014-01-01 00:00:00
1	16.49	clear-night	0.62	10.00	Clear	1022.76	2.71	0.06	2014-01-01 01:00:00
2	14.63	clear-night	0.68	10.00	Clear	1022.32	4.84	0.03	2014-01-01 02:00:00
3	13.31	clear-night	0.71	10.00	Clear	1021.64	4.00	0.14	2014-01-01 03:00:00
4	13.57	clear-night	0.71	9.93	Clear	1020.73	3.67	0.04	2014-01-01 04:00:00

In [5]:
```
# split up energy date and time into two columns

weather_df['Date'] = pd.to_datetime(weather_df['time']).dt.date
weather_df['Time'] = pd.to_datetime(weather_df['time']).dt.time
weather_df.rename(columns= {'time': 'Date & Time'}, inplace=True)

energy_df['Date'] = pd.to_datetime(energy_df['Date & Time']).dt.date
energy_df['Time'] = pd.to_datetime(energy_df['Date & Time']).dt.time

weather_df.head()
```

Out[5]:

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	Date & Time
0	34.98	partly-cloudy-night	0.64	10.00	Partly Cloudy	1017.69	7.75	0.29	2014-01-01 00:00:00
1	16.49	clear-night	0.62	10.00	Clear	1022.76	2.71	0.06	2014-01-01 01:00:00
2	14.63	clear-night	0.68	10.00	Clear	1022.32	4.84	0.03	2014-01-01 02:00:00
3	13.31	clear-night	0.71	10.00	Clear	1021.64	4.00	0.14	2014-01-01 03:00:00
4	13.57	clear-night	0.71	9.93	Clear	1020.73	3.67	0.04	2014-01-01 04:00:00

In [6]:
```
energy_df.head()
```

Out[6]:

	Date & Time	use [kW]	gen [kW]	Grid [kW]	AC [kW]	Furnace [kW]	Cellar Lights [kW]	Washer [kW]	First Floor lights [kW]	Utility Rm + Basement Bath [kW]
0	2014-01-01 00:00:00	0.304439	0.0	0.304439	0.000058	0.009531	0.005336	0.000126	0.011175	0.003836
1	2014-01-01 00:30:00	0.656771	0.0	0.656771	0.001534	0.364338	0.005522	0.000043	0.003514	0.003512

	Date & Time	use [kW]	gen [kW]	Grid [kW]	AC [kW]	Furnace [kW]	Cellar Lights [kW]	Washer [kW]	First Floor lights [kW]	Utility Rm + Basement Bath [kW]
2	2014-01-01 01:00:00	0.612895	0.0	0.612895	0.001847	0.417989	0.005504	0.000044	0.003528	0.003484

In [7]:
```
# Take the sum of the energy usage (use[kW]) to get per day usage and merge i
usage_df = energy_df.groupby('Date')[['use [kW]']].sum()
usage_df
```

Out[7]:

Date	use [kW]
2014-01-01	65.013592
2014-01-02	32.305336
2014-01-03	31.164468
2014-01-04	45.287782
2014-01-05	36.316643
...	...
2014-12-27	35.046127
2014-12-28	37.695824
2014-12-29	28.675929
2014-12-30	31.514313
2014-12-31	28.674498

365 rows × 1 columns

In [8]:
```
# have one weather row per day
# average of the number values per day
# exclude "icon" and "summary"
daily_df = weather_df.groupby('Date')[['temperature', 'humidity', 'visibility
```

In [9]:
```
daily_df
```

Out[9]:

Date	temperature	humidity	visibility	pressure	windSpeed	cloudCover	windBearing	pr
2014-01-01	20.110833	0.556667	9.970000	1025.395000	6.820417	0.031304	252.291667	
2014-01-02	16.382500	0.784583	3.834583	1023.465833	7.433750	0.354444	53.458333	
2014-01-03	6.256667	0.680833	4.509167	1014.428750	12.828333	0.186364	207.333333	
2014-01-04	2.711667	0.617083	9.822917	1030.096250	5.248333	0.001667	240.166667	
2014-01-05	17.654167	0.682083	9.134583	1025.275000	3.417083	0.010952	208.958333	

Date	temperature	humidity	visibility	pressure	windSpeed	cloudCover	windBearing	pr
...	...	...	...	...	...	...	...	
2014-12-27	35.487083	0.756250	9.246250	1022.081667	3.677083	0.030417	243.791667	
2014-12-28	41.892917	0.763750	9.332917	1013.549167	6.587917	0.245909	224.458333	
2014-12-29	34.728333	0.592083	9.997083	1018.870833	8.129583	0.119167	281.833333	
2014-12-30	24.846667	0.488750	9.998333	1026.102083	7.566667	0.031250	312.041667	
2014-12-31	19.522917	0.552917	9.986250	1025.940833	5.943750	0.117917	260.083333	

In [10]:
```
df = pd.merge(daily_df, usage_df, on="Date")
df
```

Out[10]:

Date	temperature	humidity	visibility	pressure	windSpeed	cloudCover	windBearing	pr
2014-01-01	20.110833	0.556667	9.970000	1025.395000	6.820417	0.031304	252.291667	
2014-01-02	16.382500	0.784583	3.834583	1023.465833	7.433750	0.354444	53.458333	
2014-01-03	6.256667	0.680833	4.509167	1014.428750	12.828333	0.186364	207.333333	
2014-01-04	2.711667	0.617083	9.822917	1030.096250	5.248333	0.001667	240.166667	
2014-01-05	17.654167	0.682083	9.134583	1025.275000	3.417083	0.010952	208.958333	
...	...	...	...	...	...	...	...	
2014-12-27	35.487083	0.756250	9.246250	1022.081667	3.677083	0.030417	243.791667	
2014-12-28	41.892917	0.763750	9.332917	1013.549167	6.587917	0.245909	224.458333	
2014-12-29	34.728333	0.592083	9.997083	1018.870833	8.129583	0.119167	281.833333	
2014-12-30	24.846667	0.488750	9.998333	1026.102083	7.566667	0.031250	312.041667	
2014-12-31	19.522917	0.552917	9.986250	1025.940833	5.943750	0.117917	260.083333	

365 rows × 11 columns

In [11]:
```
# Task 2
# Split the data obtained from step 1, into training and testing sets. The ai
# for each day in the month of December using the weather data, so split acco
# as per devices should be dropped, only the "use [kW]" column is to be used

# training set (days before December)
# splitting dataframe by row index
december = datetime.date(2014, 12, 1)
train_x = df[df.index < december] # df.iloc[:334]
train_y = train_x['use [kW]']
train_x = train_x.drop(['use [kW]'], axis=1)

# testing set (all days in December)
test_x = df[df.index >= december] # df.iloc[334:]
test_y = test_x['use [kW]']
test_x = test_x.drop(['use [kW]'], axis=1)
```

In [12]:
```
train_x
```

Out[12]:

Date	temperature	humidity	visibility	pressure	windSpeed	cloudCover	windBearing	pr
2014-01-01	20.110833	0.556667	9.970000	1025.395000	6.820417	0.031304	252.291667	
2014-01-02	16.382500	0.784583	3.834583	1023.465833	7.433750	0.354444	53.458333	
2014-01-03	6.256667	0.680833	4.509167	1014.428750	12.828333	0.186364	207.333333	
2014-01-04	2.711667	0.617083	9.822917	1030.096250	5.248333	0.001667	240.166667	
2014-01-05	17.654167	0.682083	9.134583	1025.275000	3.417083	0.010952	208.958333	
...	...	...	...	...	...	...	...	
2014-11-26	36.385000	0.778333	6.551667	1019.266250	6.445833	0.171333	185.375000	
2014-11-27	31.992500	0.847083	7.394583	1012.272917	7.599167	0.420769	316.833333	
2014-11-28	29.126250	0.763750	8.919167	1018.359583	6.599167	0.268947	316.416667	
2014-11-29	22.344583	0.706667	9.793750	1025.543750	4.299167	0.049167	230.375000	
2014-11-30	36.430000	0.730000	9.826250	1021.495000	5.782917	0.202667	185.750000	

334 rows × 10 columns

In [13]:
```
train_y
```

Out[13]:
```
Date
2014-01-01    65.013592
2014-01-02    32.305336
2014-01-03    31.164468
2014-01-04    45.287782
2014-01-05    36.316643
                ...
2014-11-26    27.712850
2014-11-27    30.114004
2014-11-28    26.348404
2014-11-29    20.241298
2014-11-30    32.239043
```

```
Name: use [kW], Length: 334, dtype: float64
```

In [14]:
```
test_x.head()
```

Out[14]:

Date	temperature	humidity	visibility	pressure	windSpeed	cloudCover	windBearing	pr
2014-12-01	45.276250	0.722083	9.656667	1018.805417	6.397083	0.263333	226.958333	
2014-12-02	34.177917	0.582917	9.839583	1034.805833	7.527083	0.121818	166.625000	
2014-12-03	36.345833	0.911250	4.939167	1022.247500	5.691250	0.862000	119.333333	
2014-12-04	36.216250	0.584167	9.976667	1024.064583	9.129583	0.130000	286.125000	
2014-12-05	27.463750	0.698750	9.847083	1035.654167	3.421667	0.069130	63.833333	

In [15]:
```
test_y.head()
```

Out[15]:
```
Date
2014-12-01    30.550010
2014-12-02    31.748857
2014-12-03    28.773233
2014-12-04    39.484491
2014-12-05    33.342503
Name: use [kW], dtype: float64
```

In [16]:
```
# Task 3
# Linear Regression - Predicting Energy Usage:

# Set up a simple linear regression model to train, and then predict energy u
# the month of December using features from weather data (Note that you need
# [kW]" column in the test set first). How well/badly does the model work? (E
# Calculate the Root Mean Squared error of your model
# Finally generate a csv dump of the predicted values.
# Format of csv: Two columns, first should be the date and second should be t

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

X = train_x
y = train_y
reg = LinearRegression().fit(X, y)
predicted = reg.predict(test_x)

mean_squared_error(test_y, predicted, squared=False)
```

Out[16]:
```
8.740566311138375
```

In [17]:
```
# Finally generate a csv dump of the predicted values.
# Format of csv: Two columns, first should be the date and second should be t

dates_list = [datetime.datetime.strftime(date, "%Y/%m/%d") for date in test_x

csv_dump = pd.DataFrame(data=predicted, index=dates_list, columns=["Predicted
csv_dump.index.name = "Date"
csv_dump.to_csv('cse351_hw2_Lee_Cynthia_111737790_linear_regression.csv')
```

In [18]:
```
# How well/badly does the model work?

# The root mean squared error is 8.740566311138375. A great model would have
# A lower RMSE means a better model.
# This model was not that good.
```

In [19]:
```
# Task 4

# Logistic Regression - Temperature classification:

# Using only weather data we want to classify if the temperature is high or l
# temperature greater than or equal to 60 is 'high' and below 60 is 'low'. Se
# regression model to classify the temperature for each day in the month of D
# Finally generate a csv dump of the classification (1 for high, 0 for low)
# Format: Two columns, first should be the date and second should be the clas

# treshold changed to 35

temp_df = daily_df.copy()
temp_df.loc[temp_df['temperature'] >= 35, 'temp'] = 1 # high
temp_df.loc[temp_df['temperature'] < 35, 'temp'] = 0 # low
temp_df.drop(['temperature'], axis=1)
```

Out[19]:

Date	humidity	visibility	pressure	windSpeed	cloudCover	windBearing	precipIntensity
2014-01-01	0.556667	9.970000	1025.395000	6.820417	0.031304	252.291667	0.000000
2014-01-02	0.784583	3.834583	1023.465833	7.433750	0.354444	53.458333	0.002004
2014-01-03	0.680833	4.509167	1014.428750	12.828333	0.186364	207.333333	0.002029
2014-01-04	0.617083	9.822917	1030.096250	5.248333	0.001667	240.166667	0.000000
2014-01-05	0.682083	9.134583	1025.275000	3.417083	0.010952	208.958333	0.000033
...	...	...	...	...	...	...	...
2014-12-27	0.756250	9.246250	1022.081667	3.677083	0.030417	243.791667	0.000000
2014-12-28	0.763750	9.332917	1013.549167	6.587917	0.245909	224.458333	0.003996
2014-12-29	0.592083	9.997083	1018.870833	8.129583	0.119167	281.833333	0.000000
2014-12-30	0.488750	9.998333	1026.102083	7.566667	0.031250	312.041667	0.000000
2014-12-31	0.552917	9.986250	1025.940833	5.943750	0.117917	260.083333	0.000000

365 rows × 10 columns

In [20]:
```
# splitting the data

# training set (days before December)
# splitting dataframe by row index
december = datetime.date(2014, 12, 1)
train_x = temp_df[temp_df.index < december]
train_y = train_x['temp']
train_x = train_x.drop(['temp'], axis=1)

# testing set (all days in December)
test_x = temp_df[temp_df.index >= december]
test_y = test_x['temp']
test_x = test_x.drop(['temp'], axis=1)
```

In [21]:
```
train_x
```

Out[21]:

Date	temperature	humidity	visibility	pressure	windSpeed	cloudCover	windBearing	pr
2014-01-01	20.110833	0.556667	9.970000	1025.395000	6.820417	0.031304	252.291667	
2014-01-02	16.382500	0.784583	3.834583	1023.465833	7.433750	0.354444	53.458333	
2014-01-03	6.256667	0.680833	4.509167	1014.428750	12.828333	0.186364	207.333333	
2014-01-04	2.711667	0.617083	9.822917	1030.096250	5.248333	0.001667	240.166667	
2014-01-05	17.654167	0.682083	9.134583	1025.275000	3.417083	0.010952	208.958333	
...	...	...	...	...	...	...	...	
2014-11-26	36.385000	0.778333	6.551667	1019.266250	6.445833	0.171333	185.375000	
2014-11-27	31.992500	0.847083	7.394583	1012.272917	7.599167	0.420769	316.833333	
2014-11-28	29.126250	0.763750	8.919167	1018.359583	6.599167	0.268947	316.416667	
2014-11-29	22.344583	0.706667	9.793750	1025.543750	4.299167	0.049167	230.375000	
2014-11-30	36.430000	0.730000	9.826250	1021.495000	5.782917	0.202667	185.750000	

334 rows × 10 columns

In [22]:
```
# logistic regression

from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import f1_score

# scale data
scaler = StandardScaler().fit(train_x)
s_train_x = scaler.transform(train_x)
s_test_x = scaler.transform(test_x)

X = s_train_x
y = train_y
reg = LogisticRegression().fit(X, y)
predicted = reg.predict(s_test_x)

f1_score(test_y, predicted)
```

Out[22]: 0.8125000000000001

In [23]:
```
# Finally generate a csv dump of the classification (1 for high, 0 for low)
# Format: Two columns, first should be the date and second should be the clas

dates_list = [datetime.datetime.strftime(date, "%Y/%m/%d") for date in test_x

csv_dump = pd.DataFrame(data=predicted, index=dates_list, columns=["Classifica
csv_dump.index.name = "Date"
csv_dump.to_csv('cse351_hw2_Lee_Cynthia_111737790_logistic_regression.csv')
```

In [24]:
```
# Task 5

# Energy usage data Analysis:

# We want to analyze how different devices are being used in different times
# - Is the washer being used only during the day?
# - During what time of the day is AC used most?
# There are a number of questions that can be asked.
# For simplicity, let's divide a day in two parts:
# - Day : 6AM - 7PM
# - Night: 7PM - 6AM
# Analyze the usage of any two devices of your choice during the 'day' and 'n
# trends. Explain your findings.

energy_df.head()
```

Out[24]:

	Date & Time	use [kW]	gen [kW]	Grid [kW]	AC [kW]	Furnace [kW]	Cellar Lights [kW]	Washer [kW]	First Floor lights [kW]	Utility Rm + Basement Bath [kW]
0	2014-01-01 00:00:00	0.304439	0.0	0.304439	0.000058	0.009531	0.005336	0.000126	0.011175	0.003836
1	2014-01-01 00:30:00	0.656771	0.0	0.656771	0.001534	0.364338	0.005522	0.000043	0.003514	0.003512

	Date & Time	use [kW]	gen [kW]	Grid [kW]	AC [kW]	Furnace [kW]	Cellar Lights [kW]	Washer [kW]	First Floor lights [kW]	Utility Rm + Basement Bath [kW]
2	2014-01-01	0.612895	0.0	0.612895	0.001847	0.417989	0.005504	0.000044	0.003528	0.003484

In [25]:
```
# assign day into to parts
day_energy_df = energy_df.copy()

start = datetime.time(6,0)
end = datetime.time(19,0)
time = day_energy_df['Time']
day_energy_df.loc[((start <= time) | (time < end)), 'Day'] = 1 # day

start = datetime.time(19,0)
end = datetime.time(6,0)
day_energy_df.loc[((start <= time) | (time < end)), 'Day'] = 0 # night

day_energy_df = day_energy_df.drop(['Time', 'Date & Time'], axis=1)
day_energy_df
```

Out[25]:

	use [kW]	gen [kW]	Grid [kW]	AC [kW]	Furnace [kW]	Cellar Lights [kW]	Washer [kW]	First Floor lights [kW]	Utility Rm + Basement Bath [kW]	Garag outle [kW
0	0.304439	0.0	0.304439	0.000058	0.009531	0.005336	0.000126	0.011175	0.003836	0.0048
1	0.656771	0.0	0.656771	0.001534	0.364338	0.005522	0.000043	0.003514	0.003512	0.0048
2	0.612895	0.0	0.612895	0.001847	0.417989	0.005504	0.000044	0.003528	0.003484	0.0049
3	0.683979	0.0	0.683979	0.001744	0.410653	0.005556	0.000059	0.003499	0.003476	0.0049
4	0.197809	0.0	0.197809	0.000030	0.017152	0.005302	0.000119	0.003694	0.003865	0.0048
...	...	...	...	...	...	...	...	...	...	
17515	1.560890	0.0	1.560890	0.003226	0.392996	0.006342	0.000872	0.030453	0.002248	0.0048
17516	0.958447	0.0	0.958447	0.000827	0.027369	0.006326	0.000811	0.030391	0.002543	0.0047
17517	0.834462	0.0	0.834462	0.001438	0.170561	0.020708	0.000636	0.012631	0.002372	0.0047
17518	0.543863	0.0	0.543863	0.001164	0.153533	0.008423	0.000553	0.003832	0.002353	0.0047
17519	0.414441	0.0	0.414441	0.000276	0.009223	0.006619	0.000526	0.003818	0.002424	0.0046

17520 rows × 19 columns

In [26]:
```
# Analyze the usage of any two devices of your choice during the 'day' and 'n
# Plot these trends. Explain your findings.

# Choosen devices: Furnace, Washer

devices_df = day_energy_df.filter(['Washer [kW]','Furnace [kW]','Date','Day'],
devices_df
```

Out[26]:

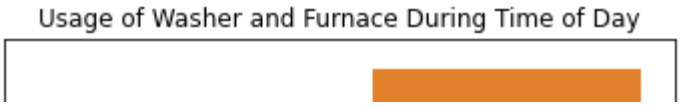
	Washer [kW]	Furnace [kW]	Date	Day
0	0.000126	0.009531	2014-01-01	0.0
1	0.000043	0.364338	2014-01-01	0.0
2	0.000044	0.417989	2014-01-01	0.0
3	0.000059	0.410653	2014-01-01	0.0
4	0.000119	0.017152	2014-01-01	0.0
...	...	...	...	...
17515	0.000872	0.392996	2014-12-31	0.0
17516	0.000811	0.027369	2014-12-31	0.0
17517	0.000636	0.170561	2014-12-31	0.0
17518	0.000553	0.153533	2014-12-31	0.0
17519	0.000526	0.009223	2014-12-31	0.0

17520 rows × 4 columns

In [27]:
```
washer_df = day_energy_df.filter(['Washer [kW]','Date','Day'], axis=1)
furnace_df = day_energy_df.filter(['Furnace [kW]','Date','Day'], axis=1)
```

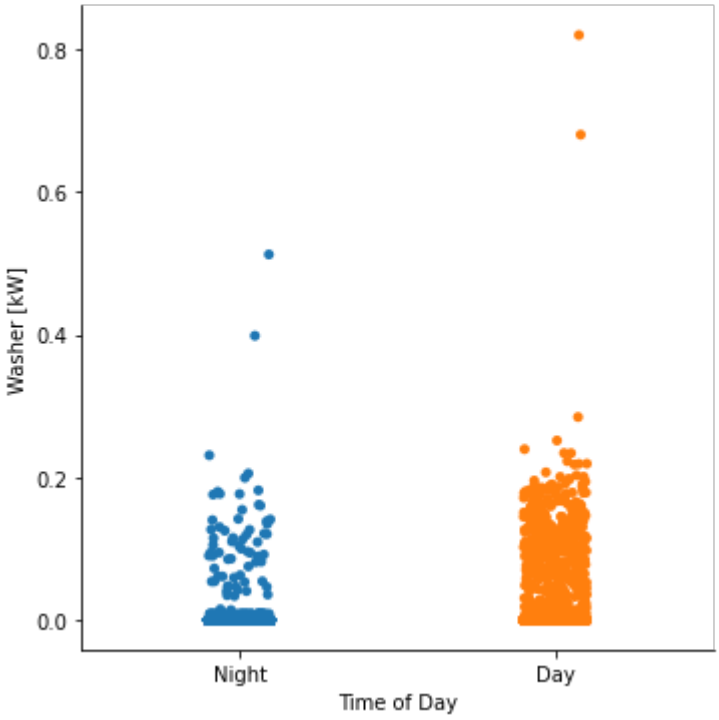
In [28]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(6, 6))
plot = sns.countplot(x="Day", data=devices_df)
plot.set_title("Usage of Washer and Furnace During Time of Day")
plot.set_xticklabels(["Night", "Day"])
plot.set_xlabel("Time of Day")
```

Out[28]:
```
Text(0.5, 0, 'Time of Day')
```



In [29]:
```
# Is the washer only being used during the day? No
# Used most during the day

plot = sns.catplot(data=washer_df, x="Day", y="Washer [kW]")
plot.set_titles("Usage of Washer and Furnace During Time of Day")
plot.set_xticklabels(["Night", "Day"])
plot.set_xlabels("Time of Day")
```

Out[29]: <seaborn.axisgrid.FacetGrid at 0x27e94ae3a60>

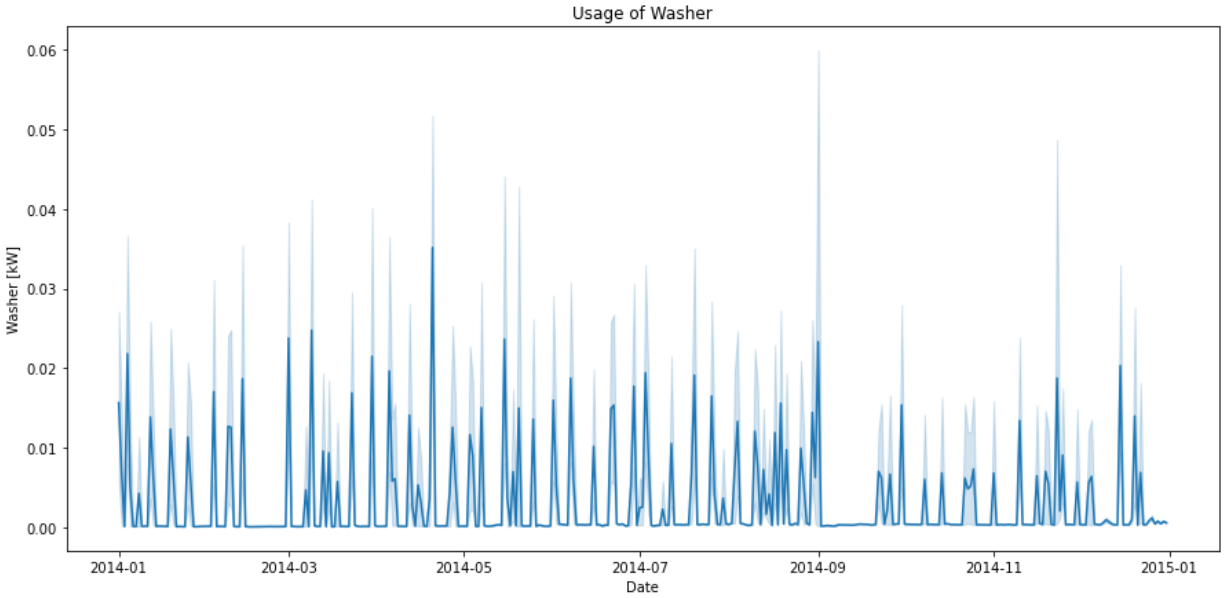


In [30]:
```
# The furnace is used both day and night

plot = sns.catplot(data=furnace_df, x="Day", y="Furnace [kW]")
plot.set_titles("Usage of Washer and Furnace During Time of Day")
plot.set_xticklabels(["Night", "Day"])
plot.set_xlabels("Time of Day")
```

Out[30]: <seaborn.axisgrid.FacetGrid at 0x27e94bc6460>

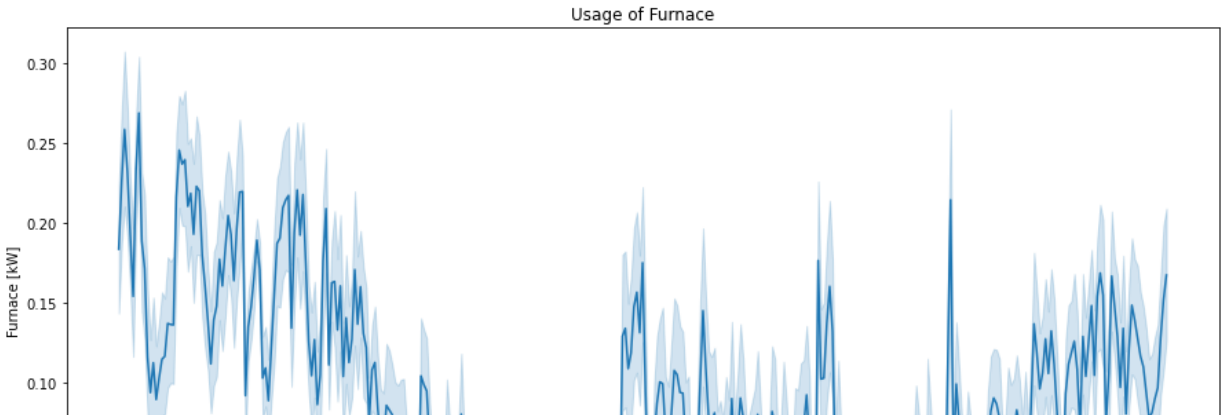
In [31]:
```
plt.figure(figsize=(15, 7))
sns.lineplot(data=washer_df, x="Date", y="Washer [kW]").set_title("Usage of Wa

# Washer has a lot of small periods of not being used
# there is a pattern of not being used and then a spike and then not being use
# perhaps this household does laundry every 1 or 2 weeks which explains this p
# during the spikes, laundry is done throughout the year as shown with the wa
```

Out[31]:
```
Text(0.5, 1.0, 'Usage of Washer')
```



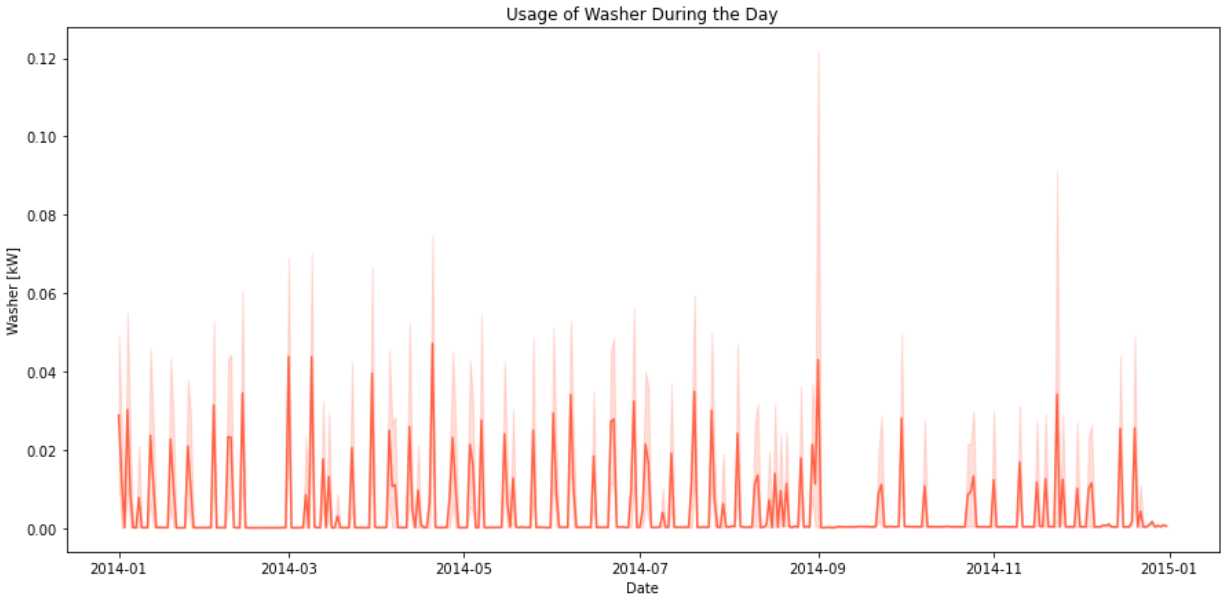
In [32]:
```
plt.figure(figsize=(15, 7))
sns.lineplot(data=furnace_df, x="Date", y="Furnace [kW]").set_title("Usage of

# Furnace hasn't had much usage at all during some time periods after 2014-5 a
# also during the time period around the end of 2014-9
# perhaps this household has taken a vacation during the summer months and le
# during the vacation they did not use their kitchen/furnace

# Furnace usage kW is higher during the months of 1-3 (January to March) compa
# perhaps bigger and warmer meals are cooked furing the winter time compared t
# bigger and warmer meals would require more furnace usage
```

Out[32]:
```
Text(0.5, 1.0, 'Usage of Furnace')
```



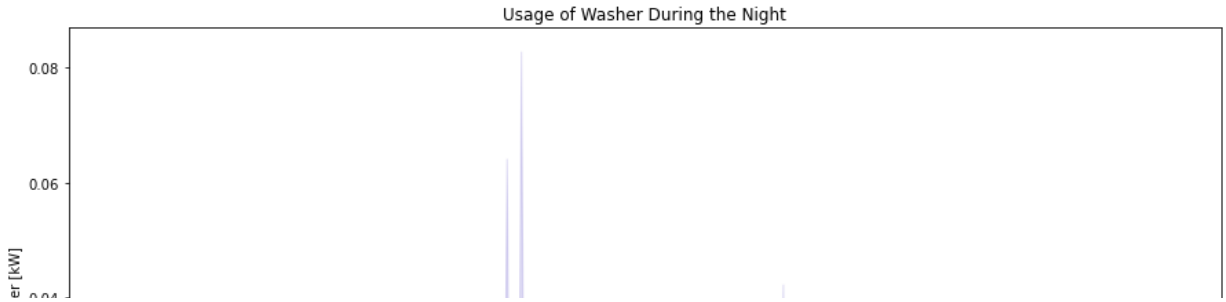
In [33]:
```
washer_day_df = washer_df.loc[washer_df['Day'] == 1]
washer_night_df = washer_df.loc[washer_df['Day'] == 0]

plt.figure(figsize=(15, 7))
sns.lineplot(data=washer_day_df, x="Date", y="Washer [kW]", color="tomato").se
```

Out[33]: Text(0.5, 1.0, 'Usage of Washer During the Day')



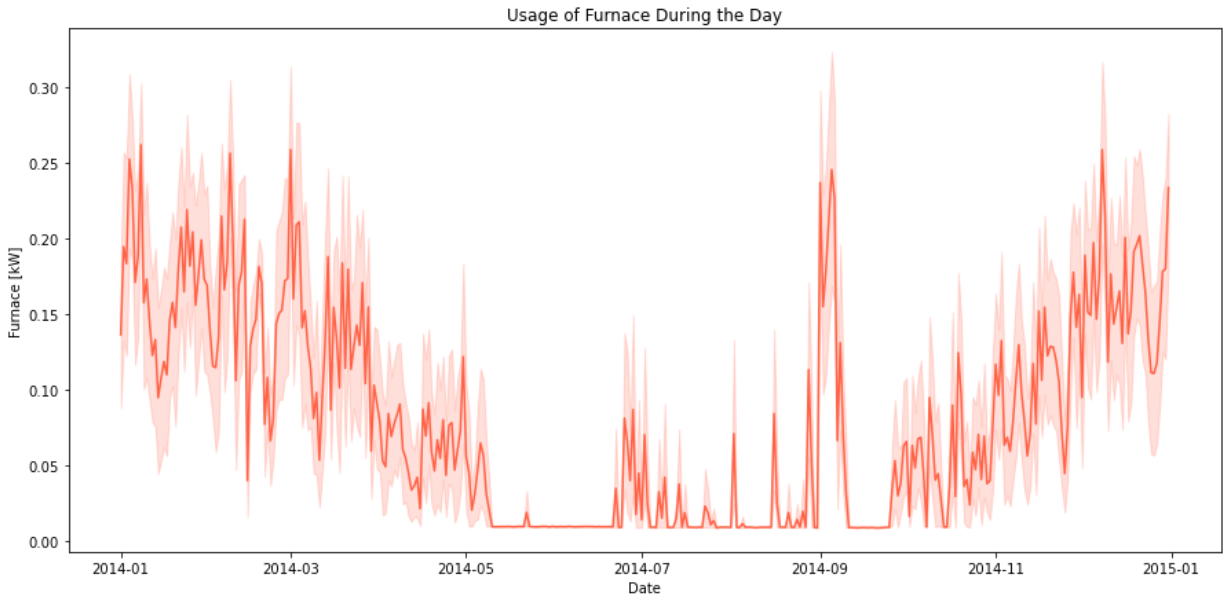
In [34]:
```
plt.figure(figsize=(15, 7))
sns.lineplot(data=washer_night_df, x="Date", y="Washer [kW]", color="slateblue

# washer is used less frequently during the night
# perhaps washing clothes is easier to deal during the day if some delicate c
# or perhaps this household prefers to do laundry during the day
```

Out[34]: Text(0.5, 1.0, 'Usage of Washer During the Night')



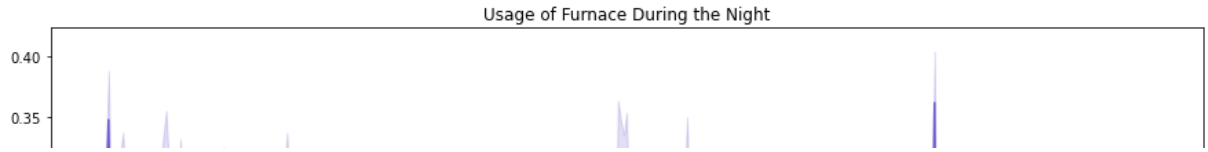
In [35]:
```
furnace_day_df = furnace_df.loc[furnace_df['Day'] == 1]
furnace_night_df = furnace_df.loc[furnace_df['Day'] == 0]

plt.figure(figsize=(15, 7))
sns.lineplot(data=furnace_day_df, x="Date", y="Furnace [kW]", color="tomato")
```

Out[35]: Text(0.5, 1.0, 'Usage of Furnace During the Day')



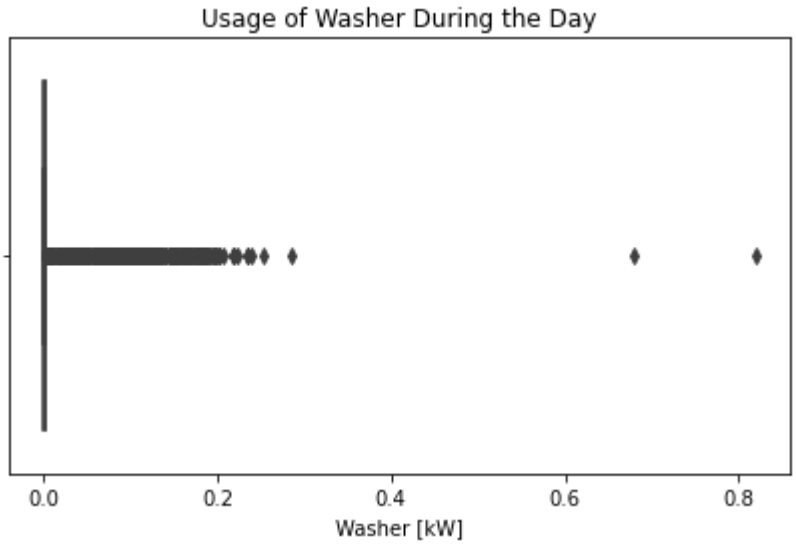
In [36]:
```
plt.figure(figsize=(15, 7))
sns.lineplot(data=furnace_night_df, x="Date", y="Furnace [kW]", color="slateb

# furnace usage used both during the day and night, probably because of cooki
# ex. breakfast during the day, lunch, dinner during the night
```

Out[36]: Text(0.5, 1.0, 'Usage of Furnace During the Night')



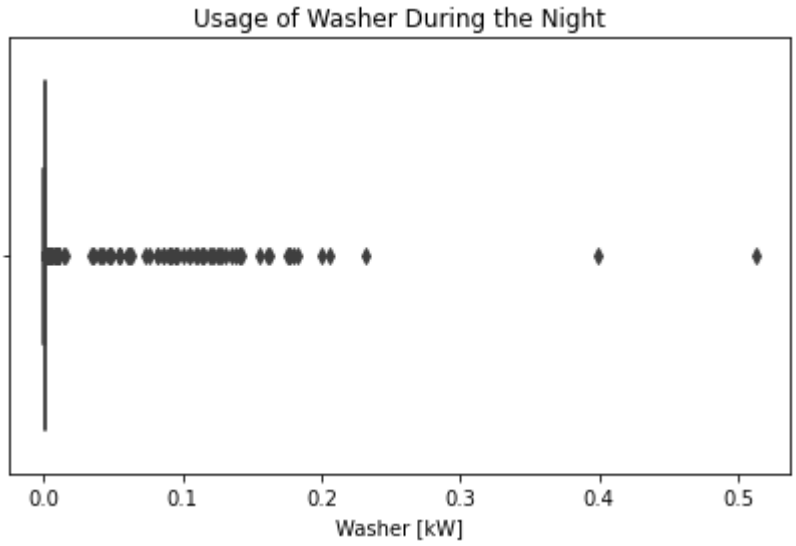
In [37]:
```
plt.figure(figsize=(7, 4))
sns.boxplot(x="Washer [kW]", data=washer_day_df).set_title("Usage of Washer Du
```

Out[37]: Text(0.5, 1.0, 'Usage of Washer During the Day')



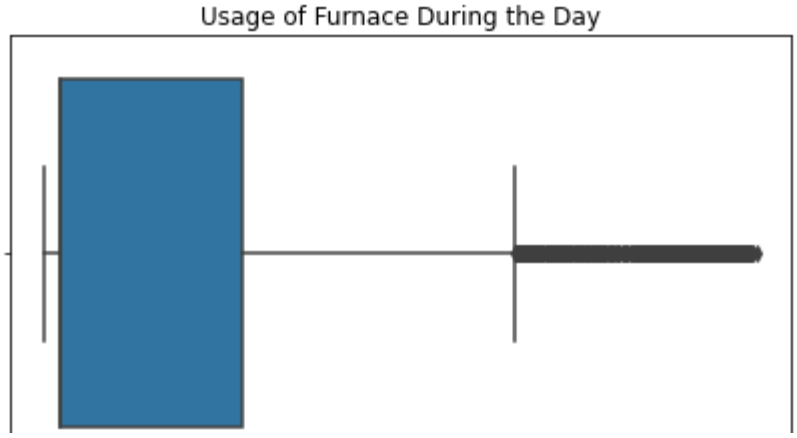
In [38]:
```
plt.figure(figsize=(7, 4))
sns.boxplot(x="Washer [kW]", data=washer_night_df).set_title("Usage of Washer
```

Out[38]: Text(0.5, 1.0, 'Usage of Washer During the Night')



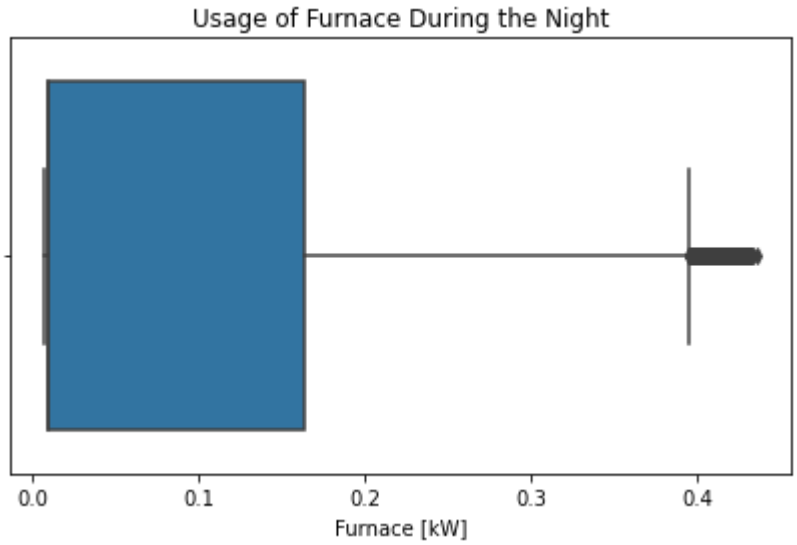
In [39]:
```
plt.figure(figsize=(7, 4))
sns.boxplot(x="Furnace [kW]", data=furnace_day_df).set_title("Usage of Furnace
```

Out[39]: Text(0.5, 1.0, 'Usage of Furnace During the Day')



In [40]:
```
plt.figure(figsize=(7, 4))
sns.boxplot(x="Furnace [kW]", data=furnace_night_df).set_title("Usage of Furna
# furnace usage during the night has an average of more datapoints with highe
# perhaps dinner requires more furnace usage than breakfast
# as dinner meals tend to be more hearty and bigger than breakfast meals
```

Out[40]: Text(0.5, 1.0, 'Usage of Furnace During the Night')



In [ ]: