

Regression with ARMA errors - daily

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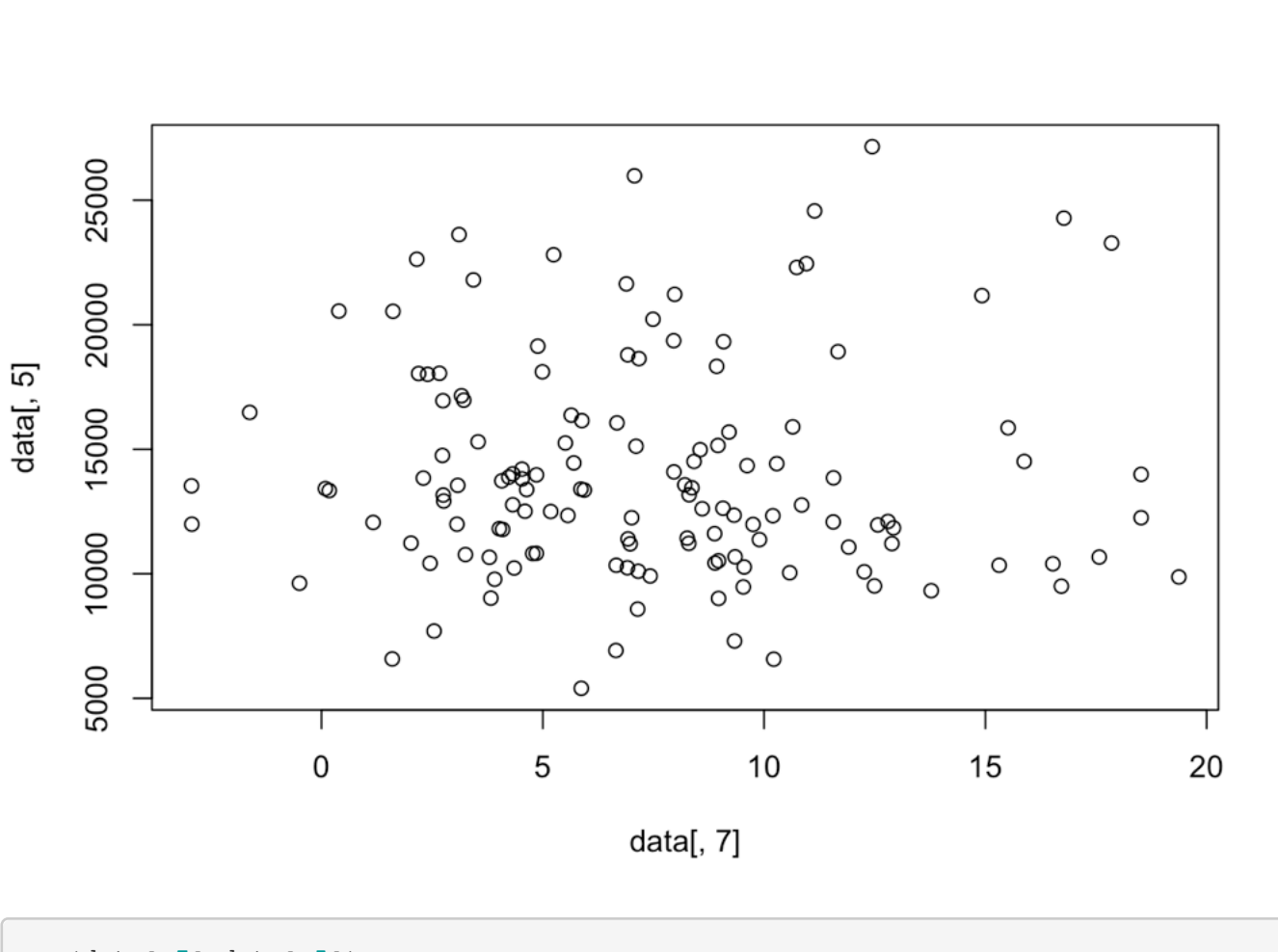
11/21/2020

load data & set up training/testing dataset

```
data = read.csv('daily.csv')
temperature = ts(data[,7], frequency=7)
energy = ts(data[,5], frequency=7)
weekend = ts(data[,4], frequency=7)
temperature_train = ts(data[1:120,7], frequency=7)
temperature_test = ts(data[121:136,7], frequency=7)
energy_train = ts(data[1:120,5], frequency=7)
energy_test = ts(data[121:136,5], frequency=7)
weekend_train = ts(data[1:120,4], frequency=7)
weekend_test = ts(data[121:136,4], frequency=7)
```

plot for energy y against temperature x

```
plot(data[,7],data[,5])
```

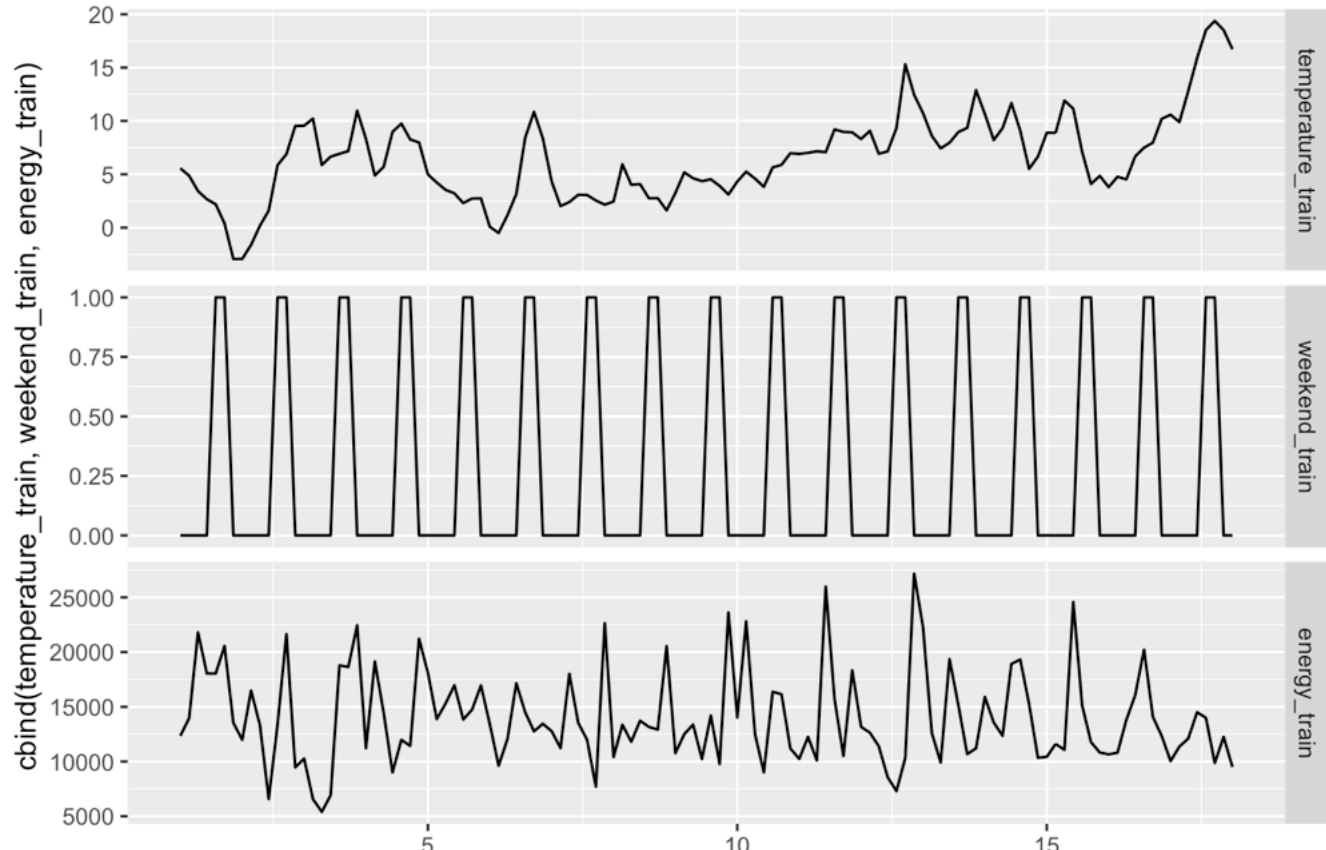


```
cor(data[,7],data[,5])
```

```
## [1] -0.009796044
```

plot the ts training data

```
autoplot(cbind(temperature_train,weekend_train,energy_train),facets=TRUE)
```



```
kps.test(weekend)
```

```
##
## KPSS Test for Level Stationarity
## data: weekend
## KPSS Level = 0.018045, Truncation lag parameter = 4, p-value = 0.1
```

```
kps.test(temperature)
```

```
##
## KPSS Test for Level Stationarity
## data: temperature
## KPSS Level = 1.5637, Truncation lag parameter = 4, p-value = 0.01
```

```
kps.test(energy)
```

```
##
## KPSS Test for Level Stationarity
## data: energy
## KPSS Level = 0.056142, Truncation lag parameter = 4, p-value = 0.1
```

Energy and Weekend ts is stationary; Temperature is not stationary.

```
xreg = cbind(temperature_train,weekend_train)
(fit = auto.arima(energy_train,xreg = xreg))
```

```
## Series: energy_train
## Regression with ARIMA(0,0,1)(1,0,0)[7] errors
##
## Coefficients:
##      mal      sar1  intercept  temperature_train  weekend_train
##    0.1640  0.1761  14637.8437         -96.1714         -10.2921
## s.e.  0.0958  0.0917   946.0709          111.2716         1098.6568
##
## sigma^2 estimated as 18416073: log likelihood=-1171.57
## AIC=2355.13  AICc=2355.88  BIC=2371.86
```

Best fit model: Regression with ARIMA(0,0,1)(1,0,0)[7] errors

```
summary(fit)
```

```
## Series: energy_train
## Regression with ARIMA(0,0,1)(1,0,0)[7] errors
##
## Coefficients:
##      mal      sar1  intercept  temperature_train  weekend_train
##    0.1640  0.1761  14637.8437         -96.1714         -10.2921
## s.e.  0.0958  0.0917   946.0709          111.2716         1098.6568
##
## sigma^2 estimated as 18416073: log likelihood=-1171.57
## AIC=2355.13  AICc=2355.88  BIC=2371.86
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -22.31588 4201.04 3216.003 -9.086014 24.60502 0.7700799
## ACF1
## Training set -0.00870926
```

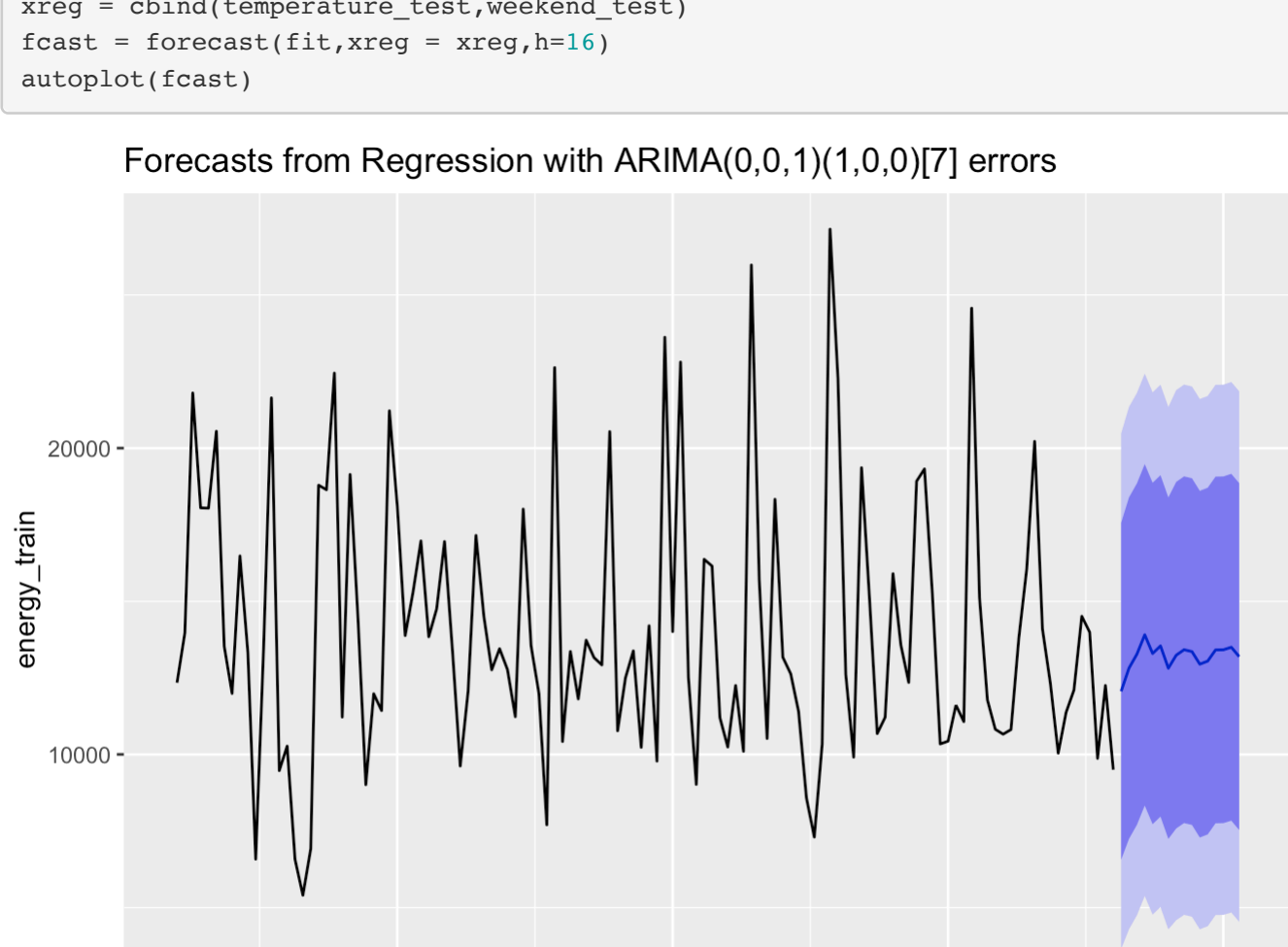
```
checkresiduals(fit)
```



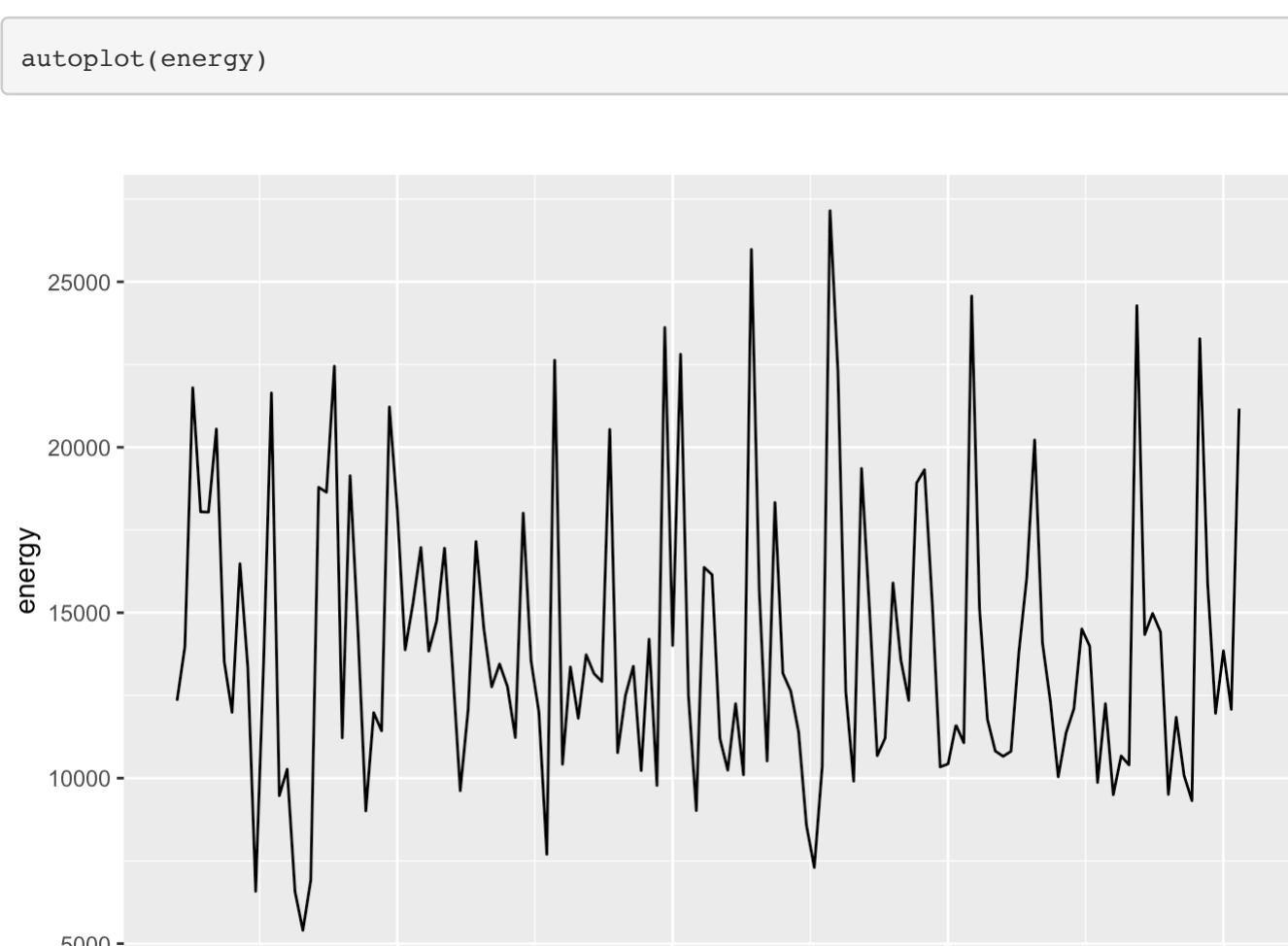
```
##
## Ljung-Box test
##
## data: Residuals from Regression with ARIMA(0,0,1)(1,0,0)[7] errors
## Q* = 14.901, df = 9, p-value = 0.0937
##
## Model df: 5. Total lags used: 14
```

All lags are inside the significant intervals

```
xreg = cbind(temperature_test,weekend_test)
fcast = forecast(fit,xreg = xreg,h=16)
autoplot(fcast)
```

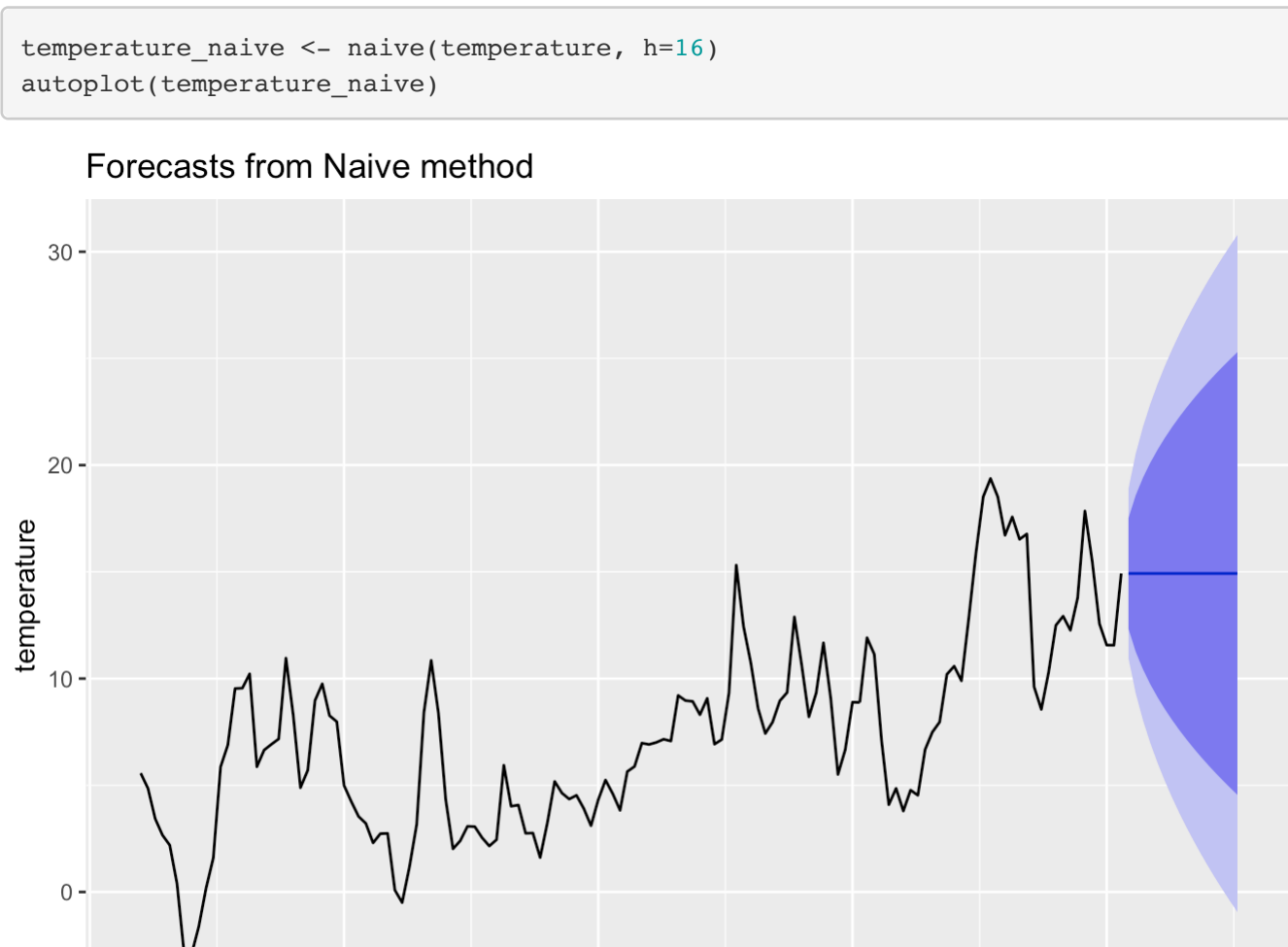


```
autoplot(energy)
```



forecasting

```
temperature_naive <- naive(temperature, h=16)
autoplot(temperature_naive)
```



```
weekend_naive = c(0,1,1,0,0,0,0,0,1,1,0,0,0,0,1)
temperature_naive = rep(14.92361,16)
xreg = cbind(temperature_naive,weekend_naive)
xreg
```

```
##      temperature_naive weekend_naive
## [1,]      14.92361              0
## [2,]      14.92361              1
## [3,]      14.92361              1
## [4,]      14.92361              0
## [5,]      14.92361              0
## [6,]      14.92361              0
## [7,]      14.92361              0
## [8,]      14.92361              0
## [9,]      14.92361              1
## [10,]     14.92361              1
## [11,]     14.92361              0
## [12,]     14.92361              0
## [13,]     14.92361              0
## [14,]     14.92361              0
## [15,]     14.92361              0
## [16,]     14.92361              1
```

```
fcast = forecast(fit,xreg = xreg,h=16)
autoplot(fcast)
```

