

W271 Live Session 9: ARIMA and SARIMA

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Main topics covered in Week 9

- Mixed Autoregressive Moving Average (ARMA) Models
 - Mathematical formulation and derivation of key properties
 - Comparing ARMA models and AR models using simulated series
 - Comparing ARMA models and AR models using an example
- An introduction to non-stationary time series model
- Random walk and integrated processes
- Autoregressive Integrated Moving Average (ARIMA) Models
 - Discuss the steps to build ARIMA time series model: Box-Jenkins' approach
 - Simulation
 - Modeling with simulated data using the Box-Jenkins approach
 - Estimation, model diagnostics, model identification, model selection, assumption testing, and statistical inference / forecasting, backtesting
- Seasonal ARIMA (SARIMA) Models
 - Mathematical formulation
 - An empirical example
- Putting everything together: ARIMA modeling

Readings

CM2009: Paul S.P. Cowpertwait and Andrew V. Metcalfe. *Introductory Time Series with R*. Springer. 2009.

- Ch. 4.3 – 4.7, 6, 7.1 – 7.3

HA: Rob J Hyndman and George Athanasopoulos. *Forecasting: Principles and Practice*: - Ch. 8.5 – 8.9

Agenda for this week's live session:

1. Quiz
2. Roadmap (of the course) revisit
3. ARIMA Modeling Review
4. A Break-out Room Discussion
5. An Extended Example

Recap and overview

1. Last week, we were introduced to autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models. These models are only appropriate for time-series that are weakly stationary (stationary in the mean and the variance).
2. We often are confronted with time-series that is not stationary in the mean and variance (and other forms, such as seasonality and volatility clustering). Luckily, many of the non-stationary series can be simply transformed into stationary series using very simple transformation such as differencing.
3. Here are some common reasons of how/why time-series might not be stationary in the mean:
 - a. The series has a trend
 - b. The series contains seasonal elements
 - c. The series contains time-varying variance
4. We can take care of some of these problems either by detrending the data or by differencing the data. In fact, we did this in our two lectures on time series analysis; we modeled the trend and seasonality directly. In the context of ARIMA modeling, we would apply transformation to “attempt” to convert a non-stationary series into a stationary series. Once the data are transformed into a weakly stationary series, we can model the resulting series with an ARMA model. We call these models ARIMA models if the data do not exhibit any seasonality. If the data are seasonal, then these models are called SARIMA models - an ARIMA model with seasonal components.
5. Remember, here are the steps to building an ARIMA model (assuming that you already have your questions well-defined and data collected and cleansed):
 - i. Conduct an EDA to determine if you need to transform the series in order to make it stationary.
 - ii. Transform the series if needed.
 - iii. Estimate several $ARIMA(p, d, q) \times (P, D, Q)_s$ models, with starting values coming from the examination of time series plot, ACF, and PACF.
 - iv. Evaluate the residuals of models that have the lowest AIC and/or BIC values and models that are more parsimonious. Select the model where the residuals resemble white noise.
 - v. Answer your question / generate forecasts!

EDA, Data transformation, and Discussion

We are going to practice ARIMA modeling with the possibility of using seasonal components if the series warrants it. For the practice, we will use the “relative search activity for the phrase **flight prices**”. This series, contained in a data set with many other variables, is provided by google correlate, and they come in as weekly frequency. For simplicity, we will focus on the series that is year 2010 onward.

Remember that we can express a SARIMA model as: $ARIMA(p, d, q) \times (P, D, Q)_m$.

The following code loads a dataset, select one specific series, convert it to a time-series (**ts**) object, and split the data into training and test sets.

```
# Insert the function to *tidy up* the code when they are printed out
library(knitr)
opts_chunk$set(tidy.opts=list(width.cutoff=60),tidy=TRUE)

# Clean up the workspace before we begin
#rm(list = ls())

# Set working directory
#wd <- "~/Documents/Teach/Cal/w271/_2018.03_Fall/live-session-files/week09"
```

```

#setwd(wd)

# Load libraries
library(forecast)
library(fpp2)

## Loading required package: ggplot2
## Loading required package: fma
## Loading required package: expsmooth
library(astsa)

##
## Attaching package: 'astsa'
## The following object is masked from 'package:fpp2':
##
##     oil
## The following objects are masked from 'package:fma':
##
##     chicken, sales
## The following object is masked from 'package:forecast':
##
##     gas
library(dplyr)

##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##     filter, lag
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
library(Hmisc)

## Loading required package: lattice
## Loading required package: survival
## Loading required package: Formula
##
## Attaching package: 'Hmisc'
## The following objects are masked from 'package:dplyr':
##
##     src, summarize
## The following objects are masked from 'package:base':
##
##     format.pval, units

```

Breakout room sessions - Load the file - Examine the data - Subset the data frame to include only the flight.prices series - Create a R time-series object - Keep data between 2010 and 2014. Leave 2015 data as a hold-out or test data which we will use later - Conduct EDA

```
d <- read.csv("correlate-flight_prices.csv", header=TRUE, sep=',')
```

```
# Examine the data
```

```
head(d)
```

```
##      Date flight.prices the.florida.keys florida.beach.resorts
## 1  1/4/04          5.811           1.810           1.149
## 2 1/11/04          2.901           2.762           1.394
## 3 1/18/04          1.575           2.127           1.901
## 4 1/25/04          0.047           1.351           0.384
## 5  2/1/04          2.800           2.599          -0.212
## 6  2/8/04          1.058           1.822           0.342
## planning.a.trip resorts.florida exercise florida.beach.house key.florida
## 1          2.841           1.446          3.592          3.774          1.915
## 2          0.660           2.170          3.253          1.266          1.762
## 3          0.707           2.768          3.057          2.000          2.370
## 4          0.909           0.636          2.304          1.879          1.739
## 5          0.805           1.062          2.000          2.392          1.087
## 6          0.828           1.672          1.558          -0.813          1.432
## keys.florida hotels.in.florida longboat.key weights cay family.resorts
## 1          1.725           2.249          1.955          1.435 3.243          1.361
## 2          1.541           2.533          1.720          2.189 1.806          1.098
## 3          0.729           2.315          1.929          2.185 1.709          1.026
## 4         -0.031           2.385          1.083          1.753 1.556          0.319
## 5          0.584           1.246          1.499          1.078 1.147          0.510
## 6          0.340           2.359          2.144          1.107 1.178          0.214
## south.beach.miami buying.a.house shore.excursions island.florida
## 1          1.588           1.065           -0.582          1.502
## 2          1.937           1.933           1.128          1.500
## 3          1.687           1.297           1.677          1.666
## 4          1.563           1.584           1.614          1.287
## 5          1.423           1.031           -1.179          0.992
## 6          1.934           0.433           1.692          1.889
## longboat destin.florida.rentals florida.homes.for.sale key.west.florida
## 1          2.265           1.031           2.280          2.925
## 2          2.311           0.968           1.281          2.613
## 3          2.392          -0.180           2.224          2.681
## 4          1.345           0.869           3.544          1.753
## 5          1.498           0.308           2.380          2.036
## 6          2.447           0.399           2.173          1.807
## breakfast.key.west hotels.clearwater suites.orlando vacation.in.florida
## 1          3.970           -0.289          1.058          0.041
## 2          1.507           -0.300          2.700          0.675
## 3          3.257           0.981          1.555          0.261
## 4          2.639           0.876          0.943          0.361
## 5          2.012           1.934          2.215          1.495
## 6          4.907           2.898          2.141          1.050
## axles clearwater.beach.florida st.petersburg.beach resort.packages
## 1 0.604          -0.289          4.090          4.335
## 2 0.738           0.031          0.292          2.318
## 3 0.681           1.230          0.265          2.470
```

## 4	1.730		-0.354		-0.249		1.214
## 5	1.476		-0.456		0.768		2.382
## 6	1.504		0.538		2.056		1.139
##	key.largo marathon.key all.inclusive.aruba family.beach.vacations						
## 1	1.185	2.122		2.163			0.638
## 2	1.661	2.654		3.271			-0.559
## 3	1.885	3.831		2.374			0.839
## 4	1.549	2.301		0.780			1.102
## 5	1.465	2.056		-0.953			0.174
## 6	1.942	3.460		1.929			1.056
##	cruise.prices plan.a marathon.florida bed.and.breakfast.key.west						
## 1	2.887	1.002		3.318			4.069
## 2	3.652	1.144		2.242			1.360
## 3	2.963	0.947		1.597			3.246
## 4	3.877	0.204		2.108			2.266
## 5	1.374	-0.336		1.150			1.406
## 6	1.951	-0.416		3.484			3.502
##	universal.studios.vacation florida.resorts diet lido.key						
## 1		1.360		3.543	5.764	1.088	
## 2		0.714		3.377	4.955	1.397	
## 3		0.456		3.560	4.431	2.595	
## 4		1.066		3.162	3.025	0.933	
## 5		1.698		1.956	1.873	2.860	
## 6		-0.102		3.394	1.761	0.725	
##	beach.houses.for.rent florida.disney stanford.summer us.virgin.islands						
## 1		0.010		2.793		0.881	3.067
## 2		0.115		0.630		0.572	3.329
## 3		1.250		3.106		0.619	3.339
## 4		0.167		1.945		0.812	3.608
## 5		-0.172		0.824		1.081	2.324
## 6		0.237		2.522		1.421	2.254
##	hotels.daytona pine.key florida.for.sale to.do.in.cancun						
## 1	1.383	2.802		1.310		0.430	
## 2	1.722	1.443		1.162		1.703	
## 3	1.900	2.624		0.867		-0.729	
## 4	0.740	1.477		1.443		0.359	
## 5	0.900	1.439		0.290		1.756	
## 6	2.116	2.392		0.481		1.136	
##	vacation.house.rentals florida.cheap cruise.bahamas diet.snacks						
## 1		1.064		2.092		1.412	6.428
## 2		0.592		1.387		2.721	2.385
## 3		1.260		2.188		2.665	3.100
## 4		1.298		-0.754		1.588	2.190
## 5		0.009		1.267		3.490	3.021
## 6		0.307		2.749		2.382	1.750
##	vacation.all.inclusive key.west.beaches house.key homes.for.sale.florida						
## 1		1.852		1.329		1.490	3.899
## 2		2.358		1.338		1.951	1.513
## 3		1.333		3.085		2.031	2.323
## 4		1.832		0.942		1.541	3.198
## 5		-0.072		1.900		0.343	2.427
## 6		-0.584		0.887		0.667	3.103
##	hotels.in.san.juan key.west beach.houses all.inclusive.caribbean						
## 1		2.155	2.936	1.300			1.619

## 2	0.988	3.478	2.421	2.090		
## 3	1.490	3.990	2.361	2.136		
## 4	1.860	2.614	1.455	0.331		
## 5	1.781	1.896	1.364	0.226		
## 6	0.382	2.247	1.184	0.708		
##	high.school.internships las.vegas.flights siesta.keys inclusive.resort					
## 1	3.143	0.493	0.360	0.653		
## 2	0.694	1.153	-0.371	1.453		
## 3	1.292	0.707	0.955	1.850		
## 4	2.640	0.612	0.056	0.720		
## 5	2.766	1.061	0.072	0.328		
## 6	2.443	0.975	0.018	0.386		
##	sirata.beach camping.in.florida passport.renewal low.carb.meals					
## 1	1.620	1.984	1.079	8.675		
## 2	2.193	-0.590	1.024	6.245		
## 3	1.500	1.993	0.695	5.357		
## 4	1.457	-0.523	0.598	4.345		
## 5	1.748	1.917	0.243	4.735		
## 6	3.578	1.929	0.511	3.042		
##	florida.vacation.spots sirata.beach.resort petersburg body.fat					
## 1	0.934	0.944	0.914	2.285		
## 2	2.395	2.248	1.301	2.457		
## 3	1.614	1.571	1.040	1.151		
## 4	0.963	0.916	0.742	0.830		
## 5	2.255	1.377	0.861	0.054		
## 6	1.448	2.857	0.928	0.367		
##	high.school.summer.programs wedding.sandals living.in.florida carb.meals					
## 1	1.828	0.663	3.891	7.867		
## 2	2.302	2.454	0.992	6.054		
## 3	1.150	0.252	3.294	4.606		
## 4	4.233	1.511	2.451	3.655		
## 5	1.411	1.505	2.742	4.123		
## 6	1.905	0.322	4.761	2.509		
##	treasure.island.florida hawaii.packages hawaii.flights					
## 1	1.165	4.355	1.099			
## 2	0.361	2.860	2.338			
## 3	1.056	4.261	0.610			
## 4	0.531	3.160	1.830			
## 5	0.050	2.519	0.319			
## 6	2.472	3.069	0.872			
##	rentals.florida.keys hopper.pass summer.hockey.camps camp.themes					
## 1	4.080	2.513	3.778	0.661		
## 2	1.711	1.632	0.578	0.196		
## 3	1.319	3.350	1.542	-1.843		
## 4	0.855	1.738	0.518	0.614		
## 5	0.679	0.888	1.259	1.591		
## 6	2.830	3.347	2.679	0.900		
##	creatine all.inclusive.resort rosacea banyan big.pine.key hawaiian.inn					
## 1	1.511	0.469	1.468	3.936	2.652	0.711
## 2	1.471	1.160	1.065	3.539	1.523	3.663
## 3	1.676	1.668	0.869	3.466	2.391	0.164
## 4	1.732	0.561	1.687	2.481	1.381	1.440
## 5	1.656	0.289	1.098	1.621	1.183	3.021
## 6	1.571	0.245	0.544	2.842	1.861	1.828

```
##      sugar.alcohol bride.dresses rentals.orlando college.summer.programs
## 1      4.912      -0.064      2.548      1.685
## 2      5.407      0.181      0.790      1.680
## 3      4.664      0.867      0.303      1.653
## 4      4.617      0.523      0.237      0.646
## 5      3.531      0.200      -0.684      1.976
## 6      4.201      0.375      0.459      1.678
##      summer.high duck.key west.florida bavaro miami.beach.hotels
## 1      2.108  0.980      3.564  2.096      4.655
## 2      1.254  1.774      3.326  2.728      3.687
## 3      1.031  2.236      2.934  2.719      3.160
## 4      2.715  2.270      2.676  1.872      2.626
## 5      1.367  1.315      2.179  1.317      2.265
## 6      2.004  2.861      2.354  1.259      3.593
```

```
tail(d)
```

```
##      Date flight.prices the.florida.keys florida.beach.resorts
## 621 11/22/15      -1.430      -0.939      -1.350
## 622 11/29/15      -0.918      -0.918      -1.357
## 623 12/6/15      -0.952      -0.738      -0.871
## 624 12/13/15     -1.224      -0.474      -1.101
## 625 12/20/15     -0.897      0.299      -0.616
## 626 12/27/15      0.462      2.010      0.551
##      planning.a.trip resorts.florida exercise florida.beach.house
## 621      -1.470      0.341  -2.028      -1.000
## 622      -1.201     -0.154  -0.255      -1.224
## 623      -1.029     -0.489  -0.548      -1.091
## 624      -0.886      0.282  -1.308      -1.125
## 625      -0.308      0.833  -2.479      -0.706
## 626      3.128      2.996  -0.312      0.361
##      key.florida keys.florida hotels.in.florida longboat.key weights      cay
## 621     -1.206     -0.885     -1.405     -1.104  -0.374 -1.327
## 622     -1.227     -0.865     -1.296     -1.114  0.233 -0.425
## 623     -1.303     -0.920     -1.164     -1.314  0.402 -0.941
## 624     -0.961     -0.399     -1.028     -0.871  0.163 -0.904
## 625     -0.117      0.599     -0.502      0.295 -0.796 -0.305
## 626      1.179      2.091      0.473      1.819  0.455  0.933
##      family.resorts south.beach.miami buying.a.house shore.excursions
## 621     -1.239     -0.980     -0.689     -1.528
## 622     -1.418     -1.216     -0.207     -1.449
## 623     -1.492     -1.067     -0.115     -1.508
## 624     -1.218     -0.759     -0.172     -1.130
## 625     -0.418      0.305     -0.655     -0.481
## 626      2.104      1.847      1.663      1.206
##      island.florida longboat destin.florida.rentals florida.homes.for.sale
## 621     -1.162  -1.259     -1.201     -0.966
## 622     -1.197  -1.237     -0.974     -1.080
## 623     -1.018  -1.375     -0.966     -0.957
## 624     -0.767  -0.962     -0.915     -0.922
## 625      0.341  0.025     -0.342     -0.174
## 626      2.945  1.406      0.476      1.178
##      key.west.florida breakfast.key.west hotels.clearwater suites.orlando
## 621     -0.785     -1.622     -1.206     -1.581
## 622     -0.702     -1.553     -0.657     -1.068
```

## 623	-0.564	-1.536	-0.263	-1.106
## 624	-0.242	-1.443	-0.555	-0.868
## 625	0.651	-0.435	0.565	-0.587
## 626	1.892	-0.022	2.538	0.730
##	vacation.in.florida axles clearwater.beach.florida			
## 621	-0.803	-0.731	-0.753	
## 622	-0.344	-0.381	-0.737	
## 623	-0.177	-0.344	-0.458	
## 624	-0.402	-0.072	-0.125	
## 625	0.425	-0.336	1.021	
## 626	1.946	0.772	2.136	
##	st.petersburg.beach resort.packages key.largo marathon.key			
## 621	-0.595	-1.288	-0.819	-0.739
## 622	-0.742	-0.702	-1.178	-0.894
## 623	-0.673	-0.751	-1.062	-0.923
## 624	-0.740	-0.852	-0.551	-0.363
## 625	0.008	-0.103	1.145	0.760
## 626	1.588	1.454	2.993	1.936
##	all.inclusive.aruba family.beach.vacations cruise.prices plan.a			
## 621	-1.007	-1.027	0.178	-2.588
## 622	-0.760	-1.046	-0.350	-1.723
## 623	-0.526	-1.080	-0.617	-1.478
## 624	-0.723	-1.038	-0.348	-1.649
## 625	-0.028	-0.352	0.931	-1.603
## 626	2.112	1.439	2.044	1.476
##	marathon.florida bed.and.breakfast.key.west universal.studios.vacation			
## 621	-0.182	-1.905	-1.046	
## 622	-0.255	-1.581	-0.850	
## 623	-0.277	-1.498	-0.909	
## 624	0.274	-1.497	-0.838	
## 625	1.700	-1.040	-0.181	
## 626	3.255	-0.249	1.456	
##	florida.resorts diet lido.key beach.houses.for.rent florida.disney			
## 621	-1.363	-2.220	-0.254	-1.395
## 622	-1.328	-1.566	-0.898	-1.284
## 623	-1.319	-1.636	-0.865	-1.359
## 624	-1.143	-1.962	-0.652	-1.209
## 625	-0.861	-2.013	0.808	-1.090
## 626	0.265	-0.215	2.511	0.337
##	stanford.summer us.virgin.islands hotels.daytona pine.key			
## 621	-0.763	-1.532	-0.762	-0.619
## 622	0.758	-1.432	-1.103	-0.880
## 623	-0.254	-1.439	-1.205	-0.789
## 624	-0.349	-1.318	-0.746	0.000
## 625	-0.336	-0.509	0.043	1.451
## 626	0.021	1.710	1.379	2.756
##	florida.for.sale to.do.in.cancun vacation.house.rentals florida.cheap			
## 621	-0.686	0.247	-1.361	-1.035
## 622	-0.942	0.396	-1.513	-0.941
## 623	-0.865	0.569	-1.306	-0.551
## 624	-0.684	0.846	-1.605	-0.176
## 625	0.353	1.041	-1.109	0.111
## 626	1.910	2.043	0.698	0.764
##	cruise.bahamas diet.snacks vacation.all.inclusive key.west.beaches			

## 621	-0.855	-1.859	-1.005	-0.624
## 622	-0.333	-0.814	0.449	-1.122
## 623	-0.478	-1.212	-1.045	-0.917
## 624	0.198	-1.229	-0.591	-0.603
## 625	0.884	-1.615	-0.573	0.939
## 626	1.841	0.194	1.444	2.243
##	house.key homes.for.sale.florida hotels.in.san.juan key.west			
## 621	-0.755	-0.537	-1.438	-1.186
## 622	-0.816	-0.441	-0.629	-1.258
## 623	-0.874	-0.883	-0.984	-1.263
## 624	-0.825	-0.476	-0.640	-0.929
## 625	0.079	0.053	-0.659	0.470
## 626	1.202	1.620	0.759	1.866
##	beach.houses all.inclusive.caribbean high.school.internships			
## 621	-1.473	-0.964		-0.565
## 622	-1.460	-0.598		0.059
## 623	-1.468	-0.986		0.017
## 624	-1.382	-1.100		-0.089
## 625	-1.157	-0.059		0.262
## 626	-0.041	1.836		0.913
##	las.vegas.flights siesta.keys inclusive.resort sirata.beach			
## 621	-0.779	-0.715	-0.828	-1.157
## 622	-0.198	-0.654	-0.668	-1.071
## 623	0.387	-0.788	-0.791	-0.747
## 624	0.615	-0.465	-0.686	-0.982
## 625	0.796	0.204	0.207	-0.812
## 626	2.192	1.526	2.260	-0.284
##	camping.in.florida passport.renewal low.carb.meals			
## 621	-0.016	-1.085	-0.836	
## 622	-0.186	-0.416	0.013	
## 623	-0.196	-0.570	-0.078	
## 624	0.265	-0.656	-0.227	
## 625	1.526	-0.938	-0.713	
## 626	3.759	1.144	1.605	
##	florida.vacation.spots sirata.beach.resort petersburg body.fat			
## 621	-1.228		-1.099	-1.573
## 622	-0.994		-0.979	-0.731
## 623	-0.969		-0.624	-0.452
## 624	-0.837		-0.906	-0.287
## 625	-0.719		-0.702	0.928
## 626	0.034		-0.130	1.677
##	high.school.summer.programs wedding.sandals living.in.florida			
## 621		-0.787	-0.738	0.102
## 622		-0.527	-1.338	-0.219
## 623		-0.334	-1.230	0.505
## 624		-0.343	-1.133	-0.018
## 625		-0.593	-1.091	0.000
## 626		0.269	0.333	2.046
##	carb.meals treasure.island.florida hawaii.packages hawaii.flights			
## 621	-0.835	-0.582	-0.991	-0.504
## 622	0.083	-0.900	-0.584	0.200
## 623	-0.063	-0.777	-0.535	-0.626
## 624	-0.167	-0.530	-0.465	-0.104
## 625	-0.701	0.420	-0.257	0.599

```
## 626      1.764      1.561      0.588      2.088
##      rentals.florida.keys hopper.pass summer.hockey.camps camp.themes
## 621      -1.448      -1.126      -0.798      -1.289
## 622      -1.201      -1.060      -0.748      -0.836
## 623      -1.052      -1.121      -0.605      -1.189
## 624      -1.217      -1.110      -0.688      -0.834
## 625      -0.572      -0.635      -0.729      -1.245
## 626      0.280      0.297      -0.438      -0.724
##      creatine all.inclusive.resort rosacea banyan big.pine.key hawaiian.inn
## 621     -2.150      -0.815     -0.747     -1.623      -0.588      -0.893
## 622     -1.157      -0.628     -0.328     -0.777      -0.831      -0.974
## 623     -1.279      -0.764     -0.457     -0.777      -0.805      -0.849
## 624     -1.545      -0.661     -0.485     -0.749      -0.025      -0.997
## 625     -2.158      0.252     -0.592     -1.180      1.431      -0.249
## 626     -1.587      2.305      0.911     -0.189      2.616      0.588
##      sugar.alcohol bride.dresses rentals.orlando college.summer.programs
## 621     -0.813      -1.536      -1.749      -0.844
## 622     -0.698      -1.737      -1.016      -0.651
## 623     -0.609      -1.879      -1.260      -0.556
## 624     -0.553      -1.882      -1.192      -0.575
## 625     -0.782      -1.685      -0.660      -0.676
## 626     -0.330      -0.018      0.759      -0.384
##      summer.high duck.key west.florida bavaro miami.beach.hotels
## 621     -0.949     -1.008      -1.524     -1.120      -1.462
## 622     -0.586     -1.327      -1.067     -1.178      -1.239
## 623     -0.598     -1.137      -1.038     -1.171      -1.213
## 624     -0.410     -1.072      -0.809     -1.036      -0.971
## 625     -0.599      0.121      -0.434     -0.920      -0.664
## 626     -0.150      1.054      0.829      0.078      0.378
```

```
str(d)
```

```
## 'data.frame': 626 obs. of 101 variables:
## $ Date : Factor w/ 626 levels "1/1/06","1/1/12",...: 43 4 16 30 211 256 222 23
## $ flight.prices : num 5.811 2.901 1.575 0.047 2.8 ...
## $ the.florida.keys : num 1.81 2.76 2.13 1.35 2.6 ...
## $ florida.beach.resorts : num 1.149 1.394 1.901 0.384 -0.212 ...
## $ planning.a.trip : num 2.841 0.66 0.707 0.909 0.805 ...
## $ resorts.florida : num 1.446 2.17 2.768 0.636 1.062 ...
## $ exercise : num 3.59 3.25 3.06 2.3 2 ...
## $ florida.beach.house : num 3.77 1.27 2 1.88 2.39 ...
## $ key.florida : num 1.92 1.76 2.37 1.74 1.09 ...
## $ keys.florida : num 1.725 1.541 0.729 -0.031 0.584 ...
## $ hotels.in.florida : num 2.25 2.53 2.31 2.38 1.25 ...
## $ longboat.key : num 1.96 1.72 1.93 1.08 1.5 ...
## $ weights : num 1.44 2.19 2.19 1.75 1.08 ...
## $ cay : num 3.24 1.81 1.71 1.56 1.15 ...
## $ family.resorts : num 1.361 1.098 1.026 0.319 0.51 ...
## $ south.beach.miami : num 1.59 1.94 1.69 1.56 1.42 ...
## $ buying.a.house : num 1.06 1.93 1.3 1.58 1.03 ...
## $ shore.excursions : num -0.582 1.128 1.677 1.614 -1.179 ...
## $ island.florida : num 1.502 1.5 1.666 1.287 0.992 ...
## $ longboat : num 2.27 2.31 2.39 1.34 1.5 ...
## $ destin.florida.rentals : num 1.031 0.968 -0.18 0.869 0.308 ...
## $ florida.homes.for.sale : num 2.28 1.28 2.22 3.54 2.38 ...
```

```

## $ key.west.florida      : num  2.92 2.61 2.68 1.75 2.04 ...
## $ breakfast.key.west    : num  3.97 1.51 3.26 2.64 2.01 ...
## $ hotels.clearwater     : num  -0.289 -0.3 0.981 0.876 1.934 ...
## $ suites.orlando        : num   1.058 2.7 1.555 0.943 2.215 ...
## $ vacation.in.florida   : num   0.041 0.675 0.261 0.361 1.495 ...
## $ axles                  : num   0.604 0.738 0.681 1.73 1.476 ...
## $ clearwater.beach.florida : num  -0.289 0.031 1.23 -0.354 -0.456 ...
## $ st.petersburg.beach   : num   4.09 0.292 0.265 -0.249 0.768 ...
## $ resort.packages       : num   4.33 2.32 2.47 1.21 2.38 ...
## $ key.largo              : num   1.19 1.66 1.89 1.55 1.47 ...
## $ marathon.key          : num   2.12 2.65 3.83 2.3 2.06 ...
## $ all.inclusive.aruba    : num   2.163 3.271 2.374 0.78 -0.953 ...
## $ family.beach.vacations : num   0.638 -0.559 0.839 1.102 0.174 ...
## $ cruise.prices         : num   2.89 3.65 2.96 3.88 1.37 ...
## $ plan.a                 : num   1.002 1.144 0.947 0.204 -0.336 ...
## $ marathon.florida      : num   3.32 2.24 1.6 2.11 1.15 ...
## $ bed.and.breakfast.key.west : num  4.07 1.36 3.25 2.27 1.41 ...
## $ universal.studios.vacation : num  1.36 0.714 0.456 1.066 1.698 ...
## $ florida.resorts       : num   3.54 3.38 3.56 3.16 1.96 ...
## $ diet                   : num   5.76 4.96 4.43 3.02 1.87 ...
## $ lido.key               : num   1.088 1.397 2.595 0.933 2.86 ...
## $ beach.houses.for.rent  : num   0.01 0.115 1.25 0.167 -0.172 ...
## $ florida.disney         : num   2.793 0.63 3.106 1.945 0.824 ...
## $ stanford.summer        : num   0.881 0.572 0.619 0.812 1.081 ...
## $ us.virgin.islands      : num   3.07 3.33 3.34 3.61 2.32 ...
## $ hotels.daytona         : num   1.38 1.72 1.9 0.74 0.9 ...
## $ pine.key               : num   2.8 1.44 2.62 1.48 1.44 ...
## $ florida.for.sale       : num   1.31 1.162 0.867 1.443 0.29 ...
## $ to.do.in.cancun        : num   0.43 1.703 -0.729 0.359 1.756 ...
## $ vacation.house.rentals : num   1.064 0.592 1.26 1.298 0.009 ...
## $ florida.cheap         : num   2.092 1.387 2.188 -0.754 1.267 ...
## $ cruise.bahamas        : num   1.41 2.72 2.67 1.59 3.49 ...
## $ diet.snacks            : num   6.43 2.38 3.1 2.19 3.02 ...
## $ vacation.all.inclusive : num   1.852 2.358 1.333 1.832 -0.072 ...
## $ key.west.beaches       : num   1.329 1.338 3.085 0.942 1.9 ...
## $ house.key              : num   1.49 1.951 2.031 1.541 0.343 ...
## $ homes.for.sale.florida : num   3.9 1.51 2.32 3.2 2.43 ...
## $ hotels.in.san.juan     : num   2.155 0.988 1.49 1.86 1.781 ...
## $ key.west               : num   2.94 3.48 3.99 2.61 1.9 ...
## $ beach.houses           : num   1.3 2.42 2.36 1.46 1.36 ...
## $ all.inclusive.caribbean : num   1.619 2.09 2.136 0.331 0.226 ...
## $ high.school.internships : num   3.143 0.694 1.292 2.64 2.766 ...
## $ las.vegas.flights      : num   0.493 1.153 0.707 0.612 1.061 ...
## $ siesta.keys            : num   0.36 -0.371 0.955 0.056 0.072 0.018 0.226 0.234 0.658 0.693 ...
## $ inclusive.resort       : num   0.653 1.453 1.85 0.72 0.328 ...
## $ sirata.beach           : num   1.62 2.19 1.5 1.46 1.75 ...
## $ camping.in.florida     : num   1.984 -0.59 1.993 -0.523 1.917 ...
## $ passport.renewal       : num   1.079 1.024 0.695 0.598 0.243 ...
## $ low.carb.meals         : num   8.68 6.25 5.36 4.34 4.74 ...
## $ florida.vacation.spots  : num   0.934 2.395 1.614 0.963 2.255 ...
## $ sirata.beach.resort    : num   0.944 2.248 1.571 0.916 1.377 ...
## $ petersburg             : num   0.914 1.301 1.04 0.742 0.861 ...
## $ body.fat               : num   2.285 2.457 1.151 0.83 0.054 ...
## $ high.school.summer.programs : num  1.83 2.3 1.15 4.23 1.41 ...

```

```
## $ wedding.sandals      : num  0.663 2.454 0.252 1.511 1.505 ...
## $ living.in.florida    : num  3.891 0.992 3.294 2.451 2.742 ...
## $ carb.meals           : num  7.87 6.05 4.61 3.65 4.12 ...
## $ treasure.island.florida : num  1.165 0.361 1.056 0.531 0.05 ...
## $ hawaii.packages      : num  4.36 2.86 4.26 3.16 2.52 ...
## $ hawaii.flights       : num  1.099 2.338 0.61 1.83 0.319 ...
## $ rentals.florida.keys : num  4.08 1.711 1.319 0.855 0.679 ...
## $ hopper.pass          : num  2.513 1.632 3.35 1.738 0.888 ...
## $ summer.hockey.camps  : num  3.778 0.578 1.542 0.518 1.259 ...
## $ camp.themes          : num  0.661 0.196 -1.843 0.614 1.591 ...
## $ creatine             : num  1.51 1.47 1.68 1.73 1.66 ...
## $ all.inclusive.resort  : num  0.469 1.16 1.668 0.561 0.289 ...
## $ rosacea              : num  1.468 1.065 0.869 1.687 1.098 ...
## $ banyan               : num  3.94 3.54 3.47 2.48 1.62 ...
## $ big.pine.key         : num  2.65 1.52 2.39 1.38 1.18 ...
## $ hawaiian.inn        : num  0.711 3.663 0.164 1.44 3.021 ...
## $ sugar.alcohol        : num  4.91 5.41 4.66 4.62 3.53 ...
## $ bride.dresses       : num  -0.064 0.181 0.867 0.523 0.2 0.375 0.863 0.067 0.597 0.954 ...
## $ rentals.orlando      : num  2.548 0.79 0.303 0.237 -0.684 ...
## $ college.summer.programs : num  1.685 1.68 1.653 0.646 1.976 ...
## $ summer.high         : num  2.11 1.25 1.03 2.71 1.37 ...
## $ duck.key            : num  0.98 1.77 2.24 2.27 1.31 ...
## $ west.florida        : num  3.56 3.33 2.93 2.68 2.18 ...
## [list output truncated]
```

```
# Subset the data frame to include only the flight.prices series
# Lets keep data between 2010 and 2014. Let's hold out 2015 as test data that you can use later.
# Create an R time-series object
```

```
#class(d$Date)
df <- d %>% select(Date, flight.prices)

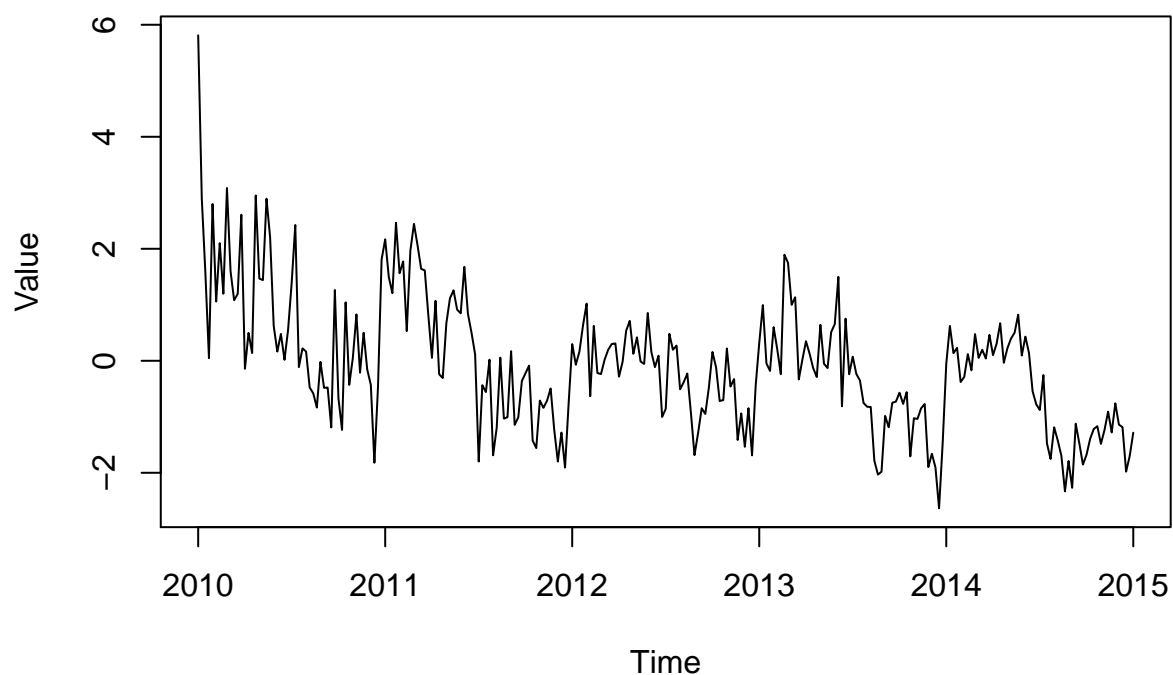
tr_2010_2014 <- ts(d$flight.prices, frequency = 52, start = c(2010,1), end=c(2015, 1))

test.2015 <- ts(d$flight.prices, frequency=52, start=c(2015,1))
```

```
# EDA
```

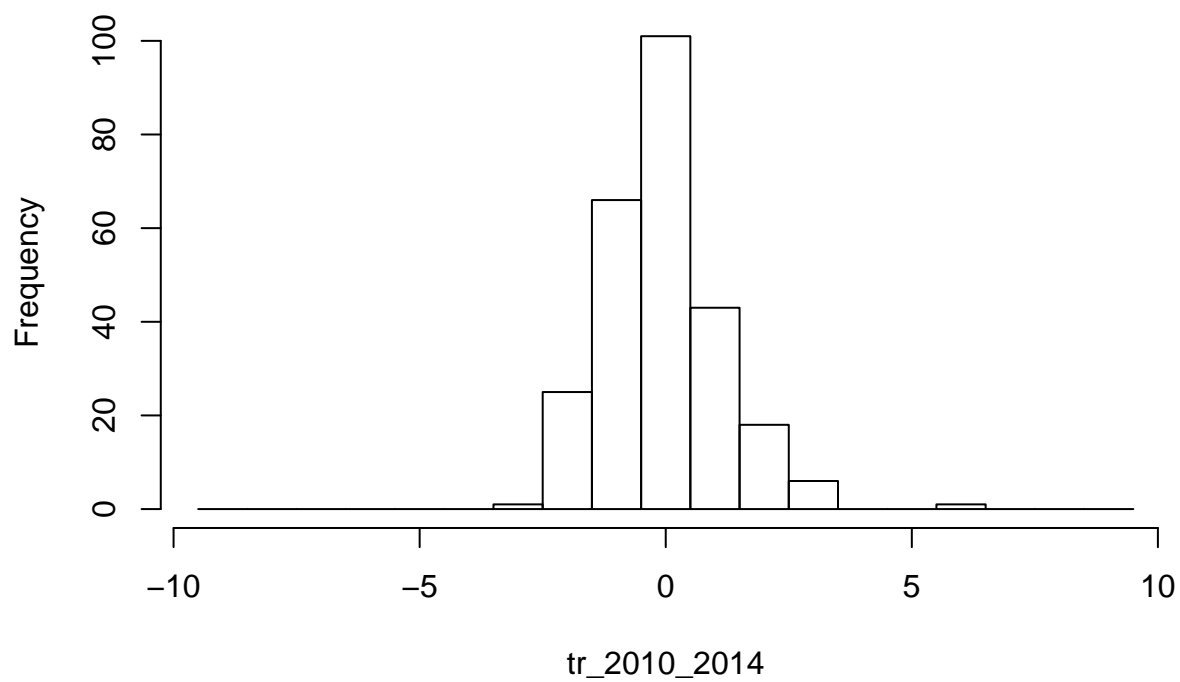
```
#par(mfrow=c(2,2))
plot(tr_2010_2014, main='Flight Prices: 2010 - 2014', ylab='Value')
```

Flight Prices: 2010 – 2014



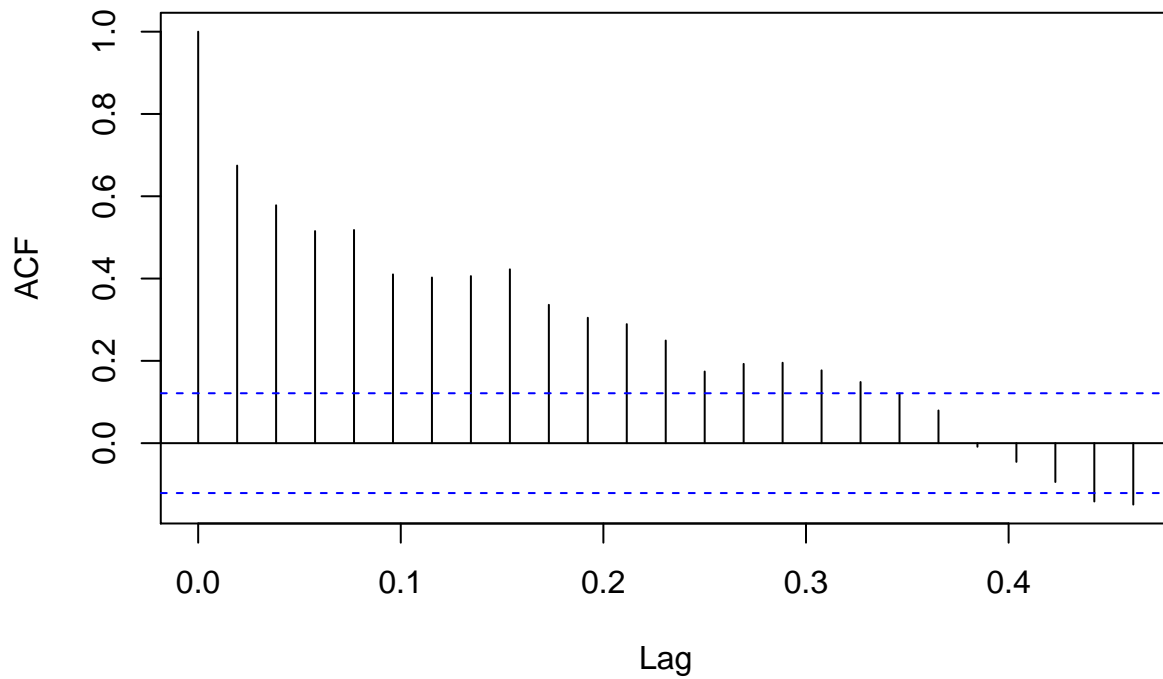
```
hist(tr_2010_2014, breaks=seq(-9.5, 9.5, by=1))
```

Histogram of tr_2010_2014



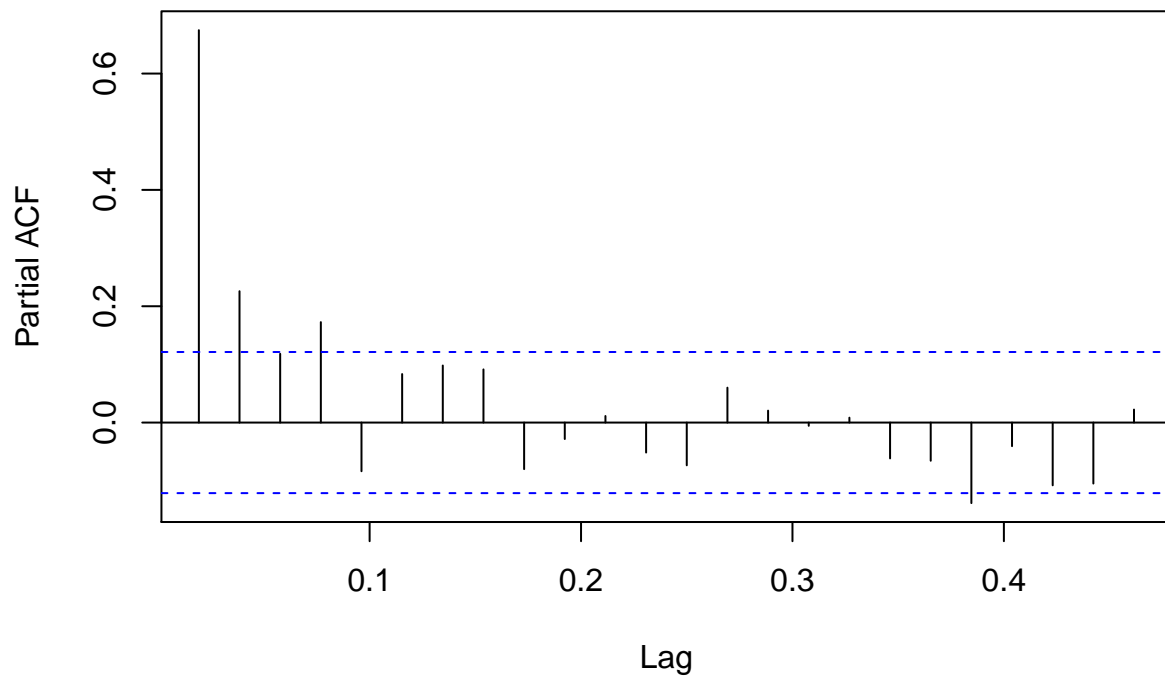
```
acf(tr_2010_2014, main='ACF of Flight Prices')
```

ACF of Flight Prices

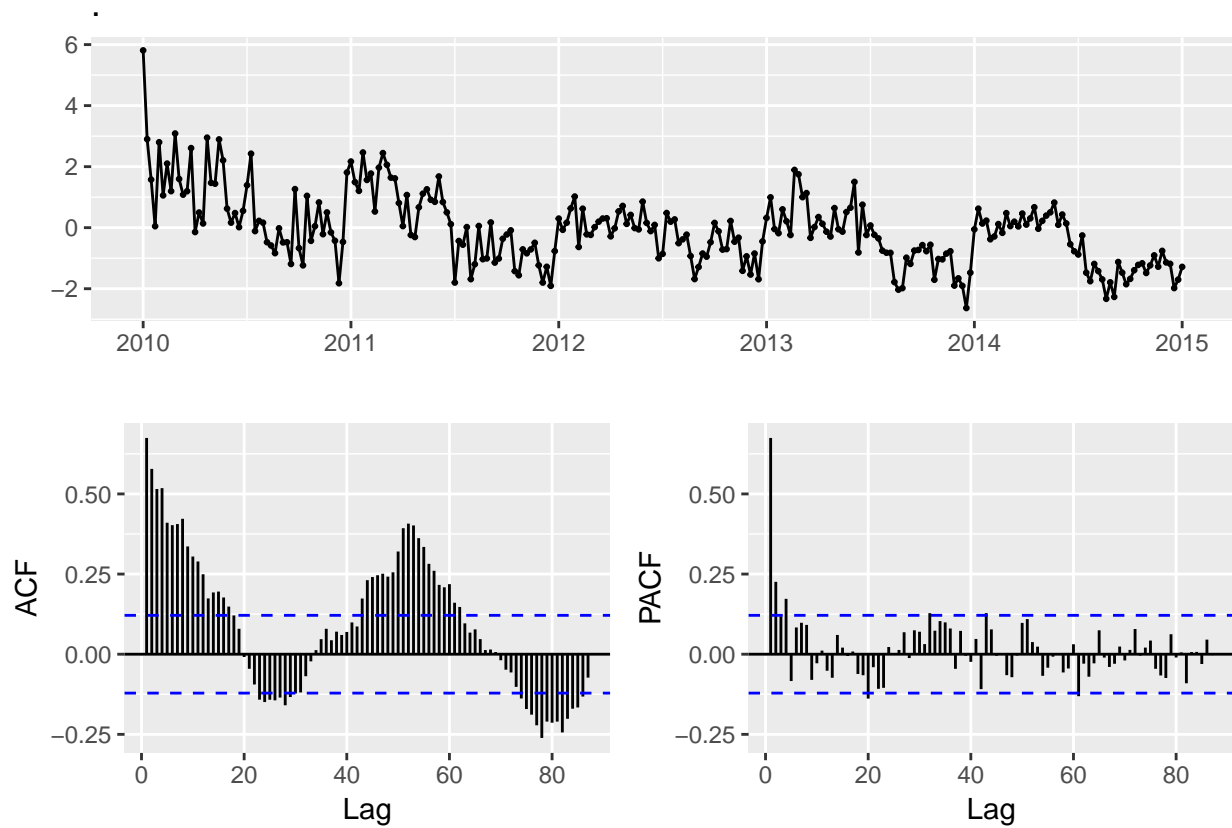


```
pacf(tr_2010_2014, main='PACF of Flight Prices')
```

PACF of Flight Prices

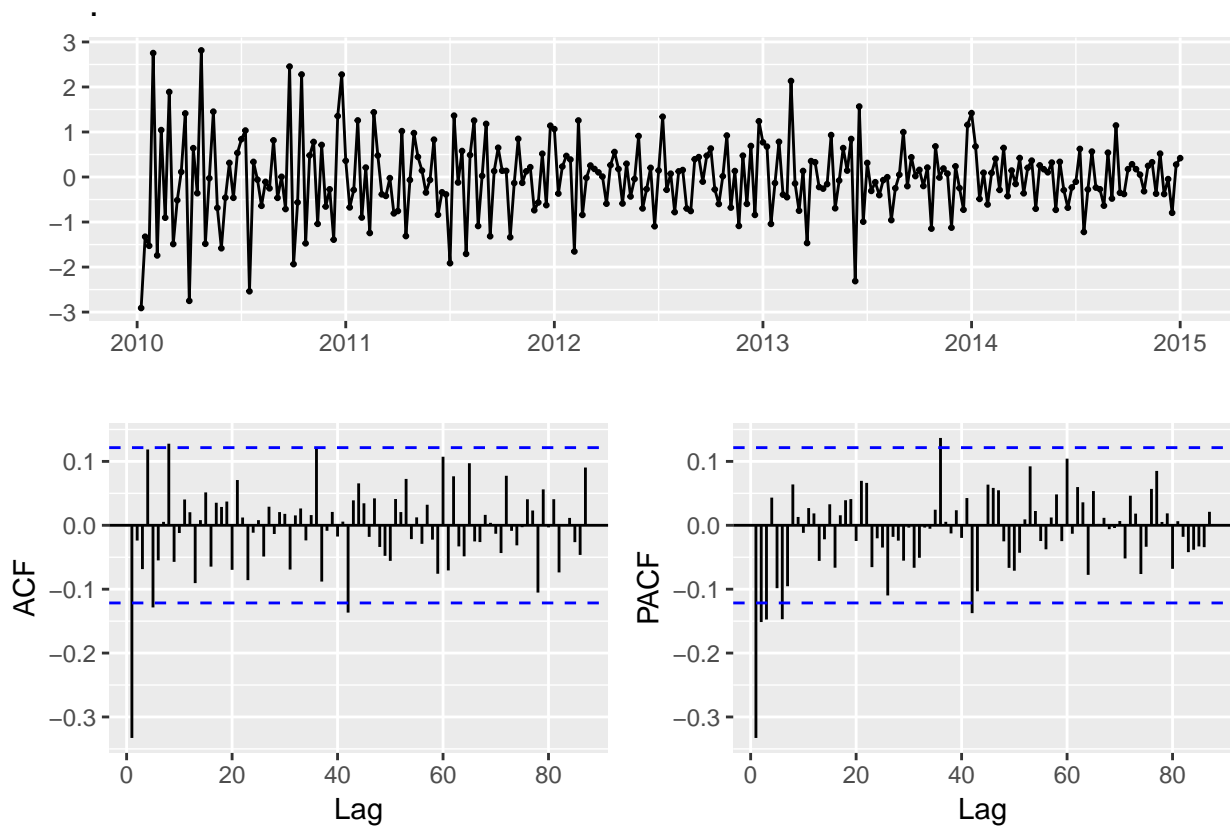


```
tr_2010_2014 %>% ggtsdisplay()
```

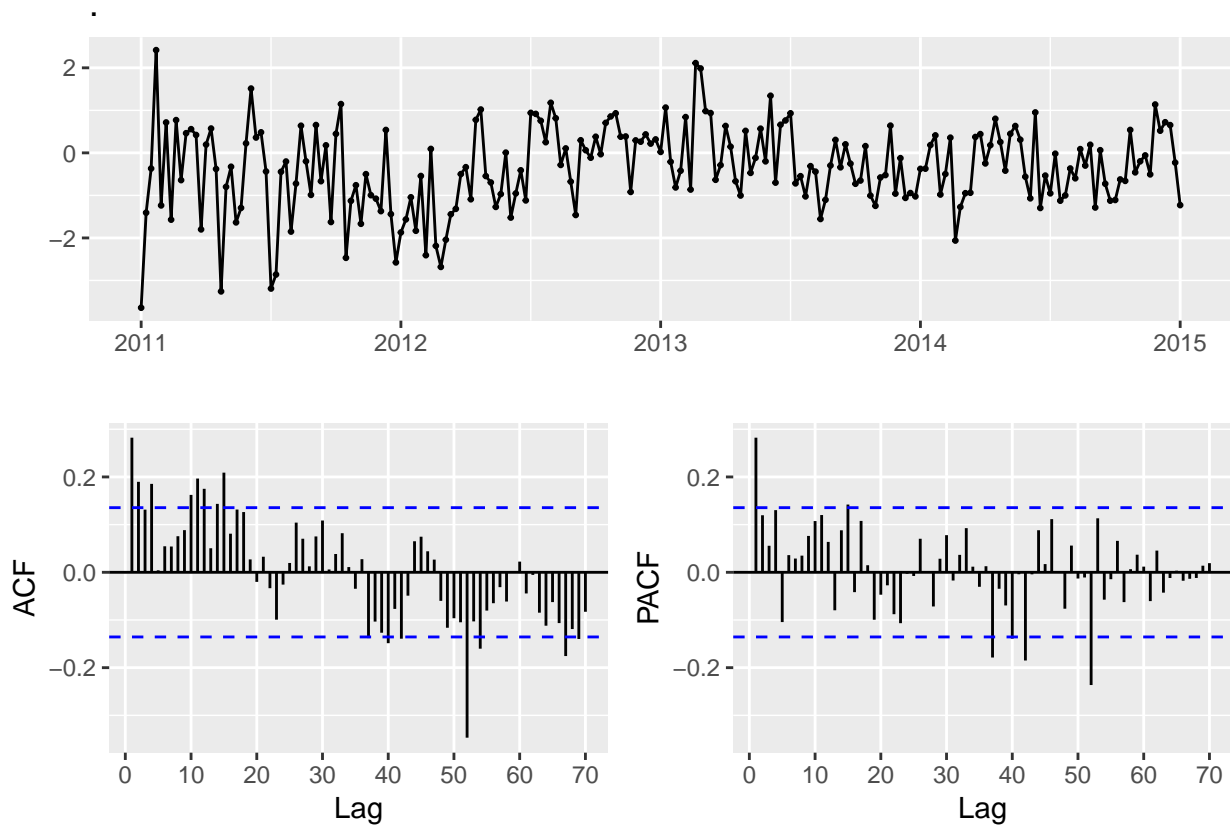


Next, let's examine some differencing-transformation of the series: - seasonal differencing - non-seasonal differencing on top of seasonal differencing

```
tr_2010_2014 %>% diff(1) %>% ggtsdisplay()
```

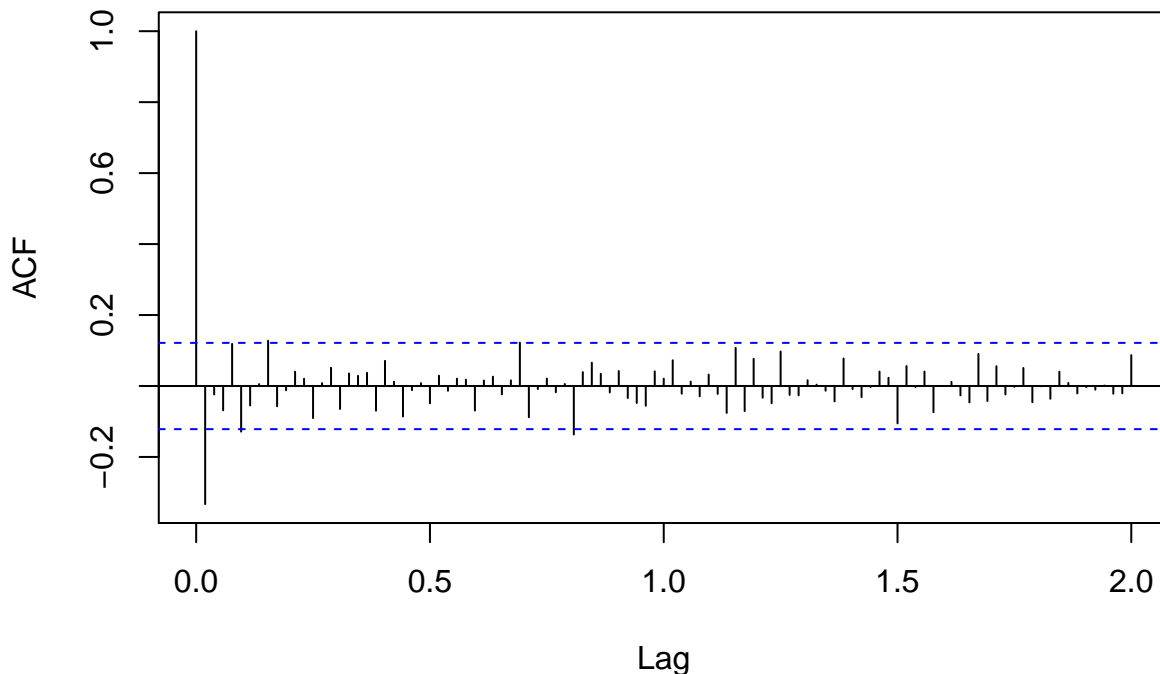


```
tr_2010_2014 %>% diff(52) %>% ggtsdisplay()
```




```
tr_2010_2014 %>% diff() %>% acf(lag=104)
```

Series .



Note that I generally would not model SARIMA like that. However, I just want to illustrate the consequence of ignoring certain patterns of the series.

Modeling the non-seasonal component

First, let's model the non-seasonal component of the raw series. In order to do that, we are going to use the `Arima()` function in the `forecast` package. I am making the extra steps of modeling the non-seasonal component as pure AR and MA processes first, for illustrative purposes. Based on the ACF and PACF charts, I expect that we can model the non-seasonal component with an `ARIMA(0,1,1)` or `ARIMA(0,1,2)`.

Professors Hyndman and Athanasopoulos points out that `arima()` in R can also be used to estimate an ARIMA model, but it does not allow for the constant `c` unless `d=0`, does not return everything required for the `forecast()` function, and does not allow the estimated model to be applied to new data (which is useful for checking forecast accuracy). As such, they recommend using `Arima()` instead.

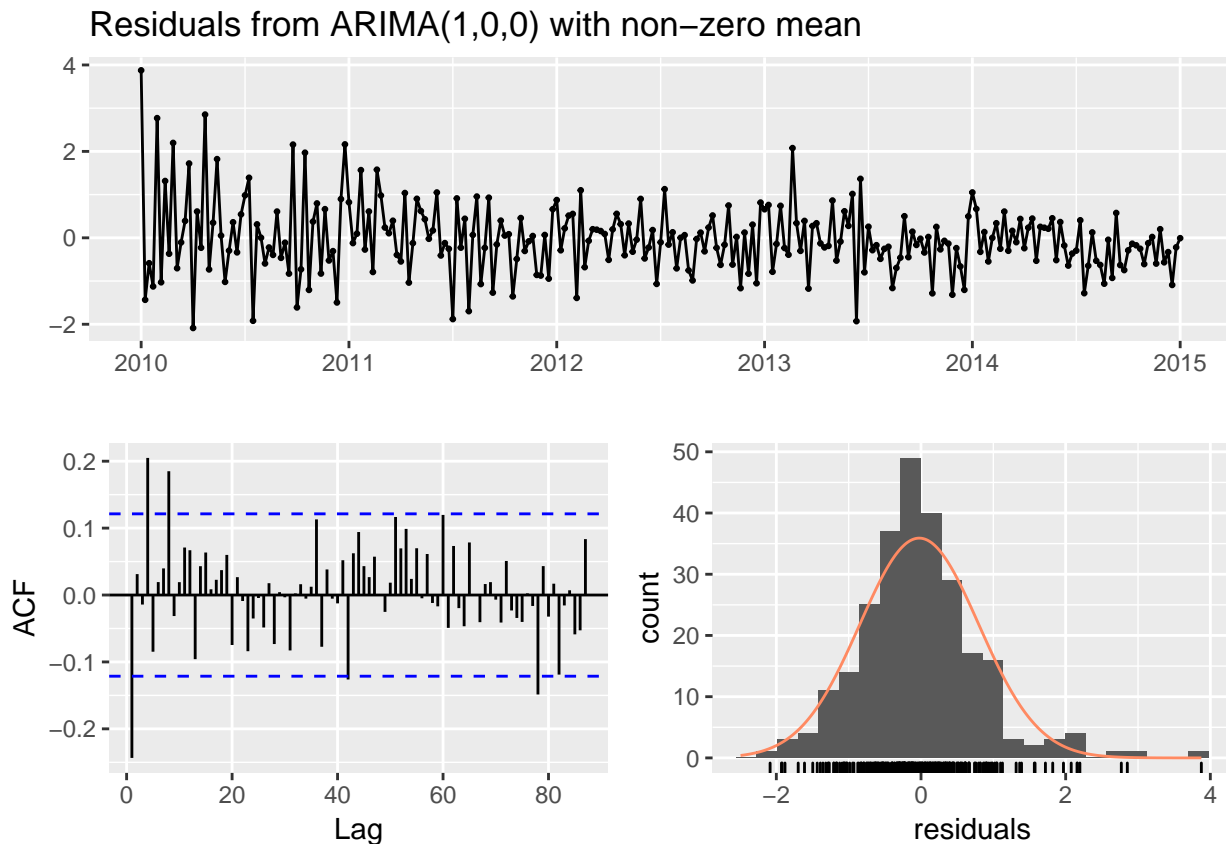
```
# Let's start by modeling it as a pure AR process
```

```
ts.ar <- Arima(tr_2010_2014, order = c(1,0,0))
summary(ts.ar)
```

```
## Series: tr_2010_2014
## ARIMA(1,0,0) with non-zero mean
##
## Coefficients:
##      ar1      mean
##  0.7469  -0.0172
```

```
## s.e. 0.0455 0.1992
##
## sigma^2 estimated as 0.6813: log likelihood=-319.67
## AIC=645.35 AICc=645.44 BIC=656.04
##
## Training set error measures:
##           ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.02414116 0.8222612 0.6043131 65.9152 197.3423 0.7339949
##           ACF1
## Training set -0.2434035
```

```
checkresiduals(ts.ar)
```



```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(1,0,0) with non-zero mean
## Q* = 80.748, df = 50.2, p-value = 0.004029
##
## Model df: 2. Total lags used: 52.2
```

```
# Let's model using a pure MA process
```

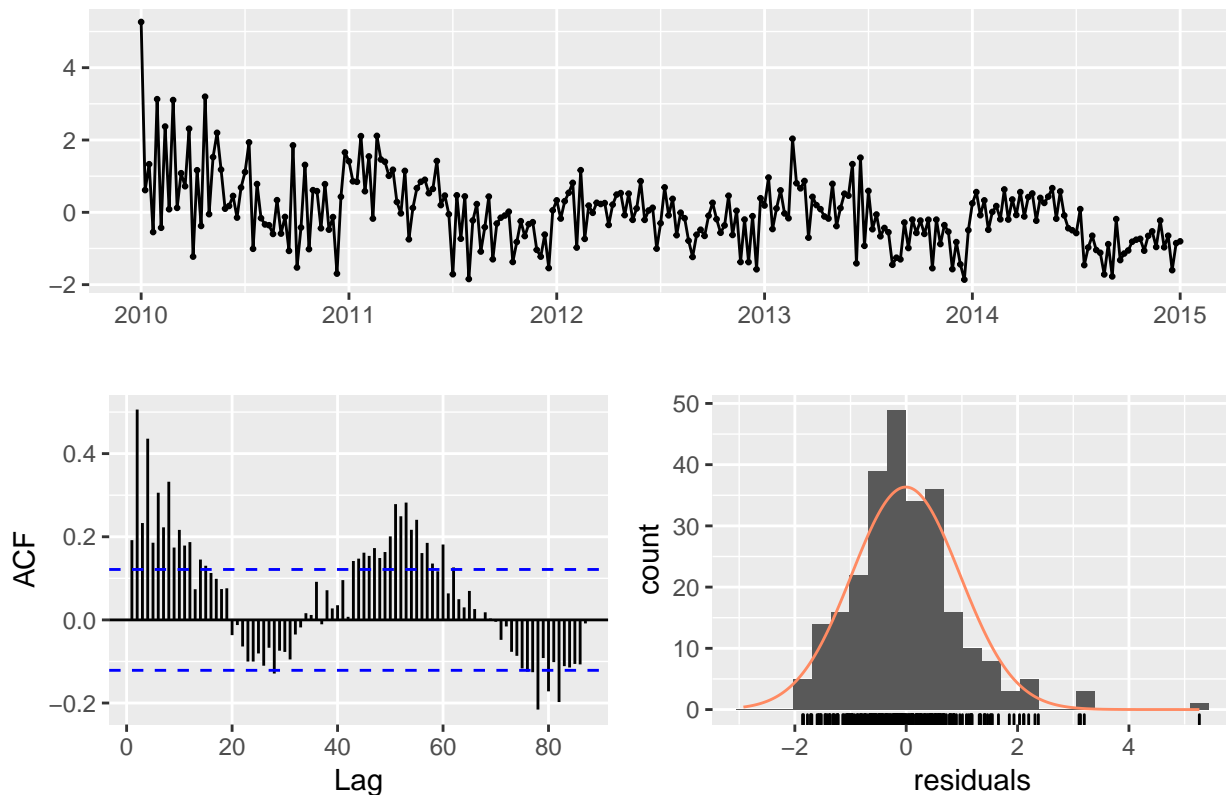
```
ts.ma <- Arima(tr_2010_2014, order=c(0,0,1))
summary(ts.ma)
```

```
## Series: tr_2010_2014
## ARIMA(0,0,1) with non-zero mean
##
```

```
## Coefficients:
##      ma1      mean
##      0.4942 -0.0608
## s.e.  0.0411  0.0896
##
## sigma^2 estimated as 0.9487:  log likelihood=-362.6
## AIC=731.2   AICc=731.3   BIC=741.9
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.007188033 0.970254 0.7225422 92.6743 153.7135 0.8775953
##              ACF1
## Training set 0.1918342
```

```
checkresiduals(ts.ma)
```

Residuals from ARIMA(0,0,1) with non-zero mean



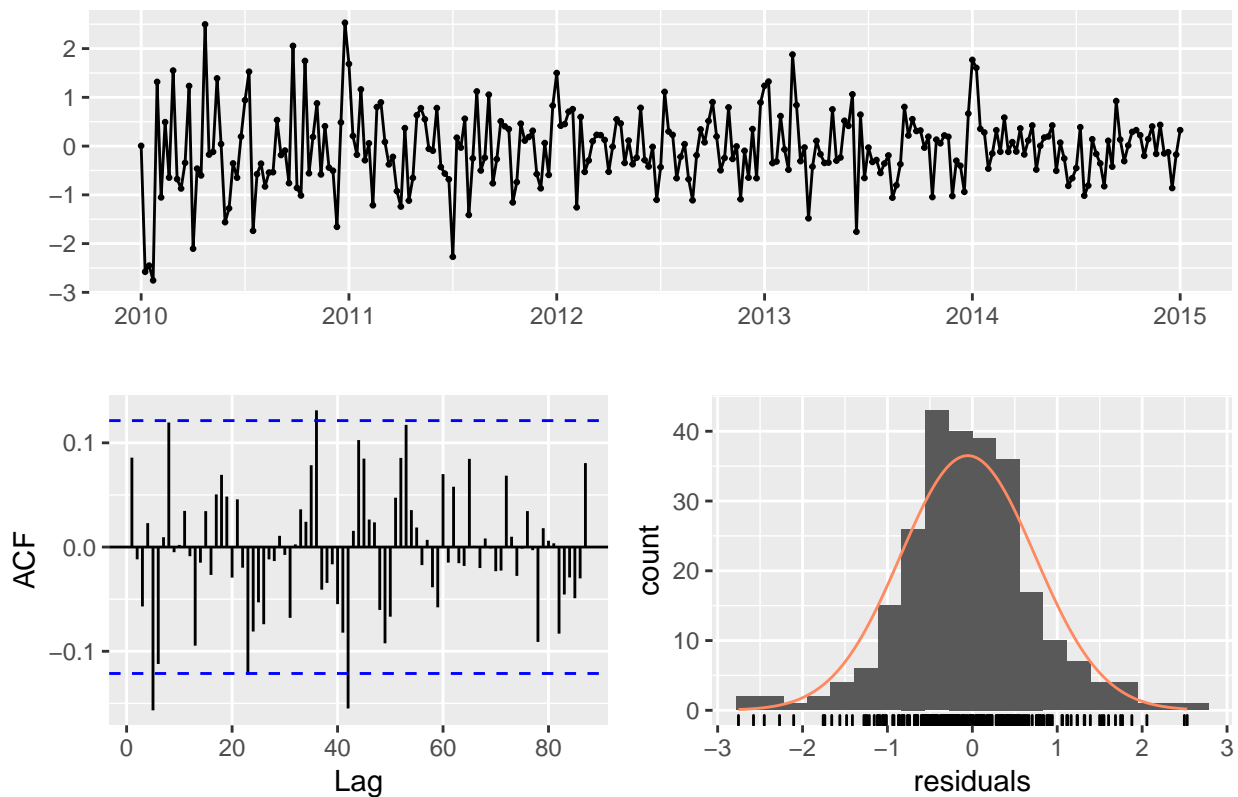
```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(0,0,1) with non-zero mean
## Q* = 428.43, df = 50.2, p-value < 2.2e-16
##
## Model df: 2.    Total lags used: 52.2
# Let's look at some ARIMA models
ts.arima <- Arima(tr_2010_2014, order=c(0,1,1))
summary(ts.arima)
```

```
## Series: tr_2010_2014
```

```
## ARIMA(0,1,1)
##
## Coefficients:
##      ma1
##      -0.5240
## s.e.    0.0699
##
## sigma^2 estimated as 0.635:  log likelihood=-309.55
## AIC=623.1   AICc=623.15   BIC=630.22
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.05344978 0.7938181 0.5949837 6.851986 230.1725 0.7226635
##              ACF1
## Training set 0.08578263
```

```
checkresiduals(ts.arima)
```

Residuals from ARIMA(0,1,1)



```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(0,1,1)
## Q* = 67.992, df = 51.2, p-value = 0.05814
##
## Model df: 1. Total lags used: 52.2
```

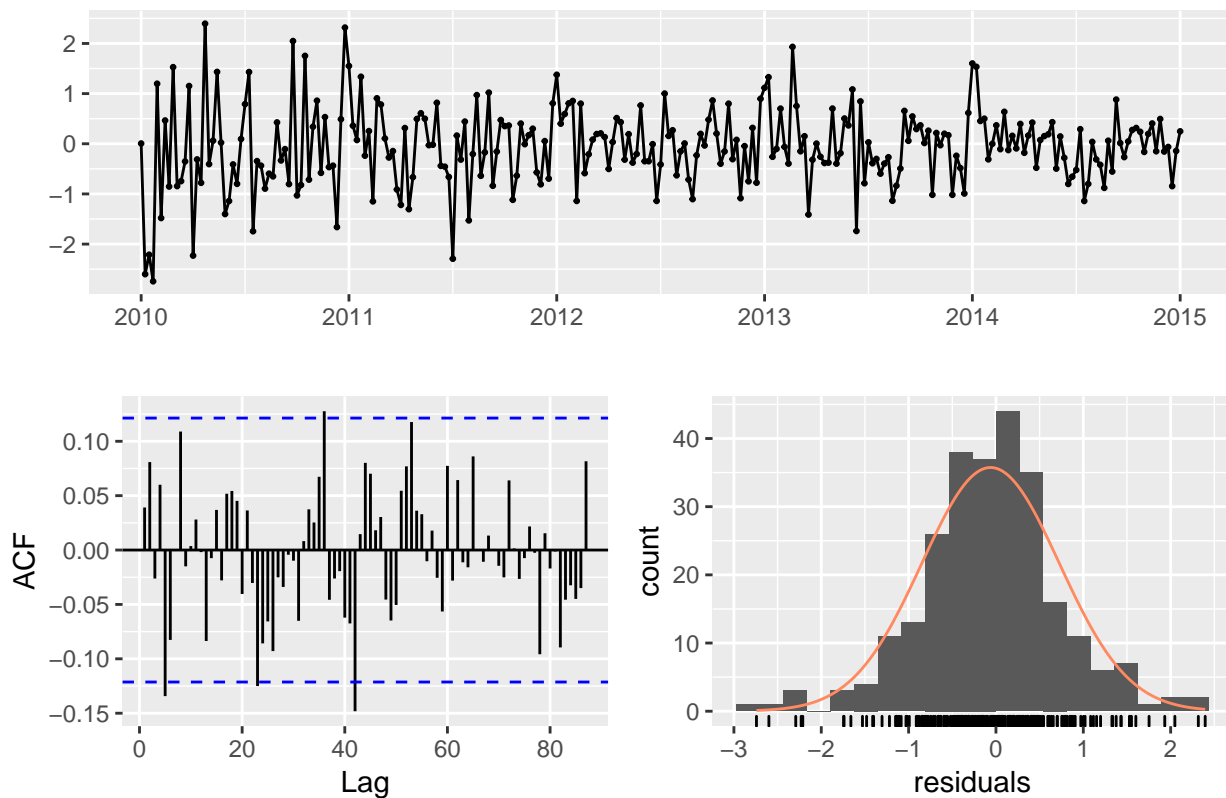
```
# Let's look at some ARIMA models
ts.arima2 <- Arima(tr_2010_2014, order=c(0,1,2))
```

```
summary(ts.arima2)
```

```
## Series: tr_2010_2014
## ARIMA(0,1,2)
##
## Coefficients:
##          ma1          ma2
##      -0.4888  -0.1195
## s.e.   0.0621   0.0625
##
## sigma^2 estimated as 0.629:  log likelihood=-307.84
## AIC=621.69   AICc=621.78   BIC=632.37
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.06159602 0.7885146 0.5924847 7.544857 226.2096 0.7196282
##              ACF1
## Training set 0.03910778
```

```
checkresiduals(ts.arima2)
```

Residuals from ARIMA(0,1,2)



```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(0,1,2)
## Q* = 58.801, df = 50.2, p-value = 0.1896
##
## Model df: 2. Total lags used: 52.2
```

Breakout Session: Modeling the seasonal component

In your group, try to find appropriate values for P and Q. For now, set p,d,q to 0,1,1 respectively, but keep in mind that we might have to change our values for p and q after we add the seasonal component!

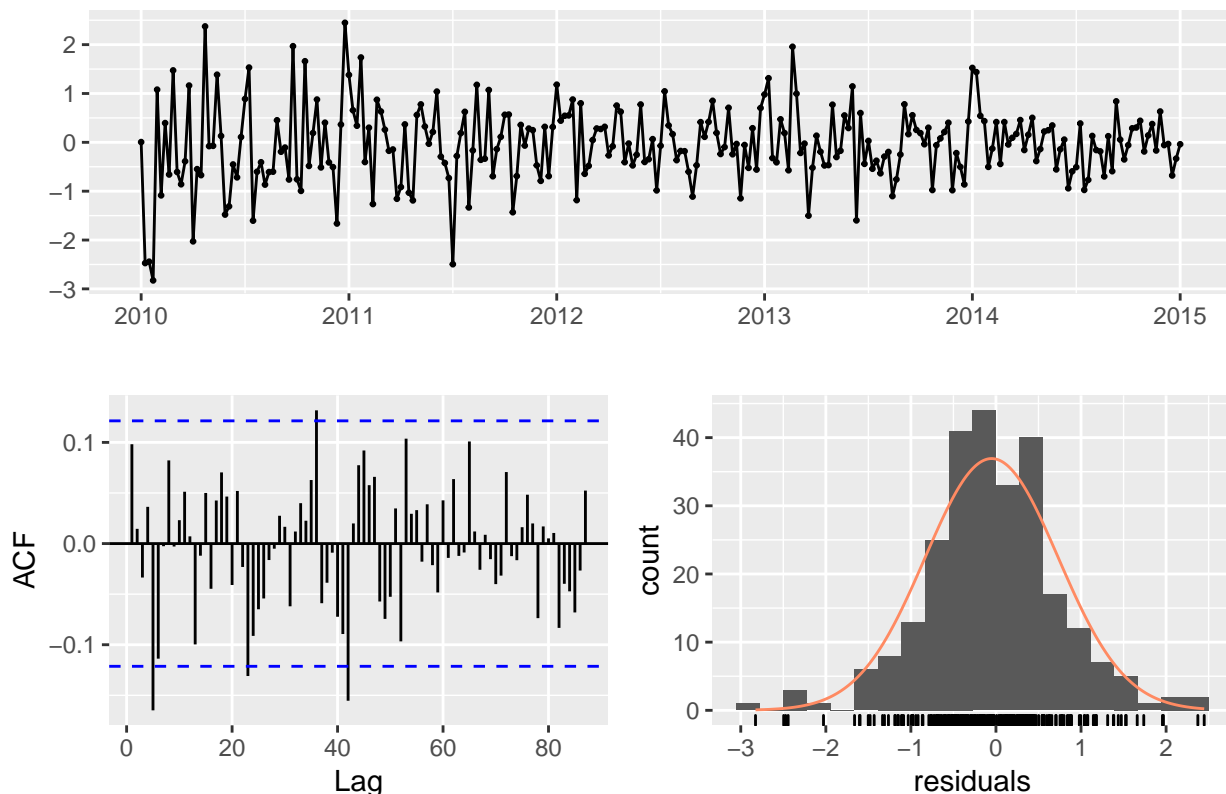
YOUR CODE HERE

```
ts.season <- Arima(tr_2010_2014, order = c(0,1,1), seasonal= c(1,0,0))
summary(ts.season)
```

```
## Series: tr_2010_2014
## ARIMA(0,1,1)(1,0,0)[52]
##
## Coefficients:
##          ma1      sar1
##        -0.5810  0.1861
## s.e.      0.0734  0.0802
##
## sigma^2 estimated as 0.6201:  log likelihood=-306.91
## AIC=619.83   AICc=619.92   BIC=630.51
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.05058931 0.7829077 0.5908358 17.42845 235.3316 0.7176255
##              ACF1
## Training set 0.09818725
```

```
checkresiduals(ts.season)
```

Residuals from ARIMA(0,1,1)(1,0,0)[52]



```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(0,1,1)(1,0,0)[52]
## Q* = 70.48, df = 50.2, p-value = 0.031
##
## Model df: 2. Total lags used: 52.2
```

AIC

```
Arima(tr_2010_2014, order = c(0,2,4), seasonal= c(1,0,1)) = .013 Arima(tr_2010_2014, order =
c(0,2,5), seasonal= c(1,0,1)) = .022 Arima(tr_2010_2014, order = c(0,2,3), seasonal= c(1,0,1)) =
.049 Arima(tr_2010_2014, order = c(0,2,2), seasonal= c(1,0,1)) = .132 Arima(tr_2010_2014, order =
c(0,1,1), seasonal= c(1,0,1)) = .14 Arima(tr_2010_2014, order = c(0,1,1), seasonal= c(1,0,2)) = .15
Arima(tr_2010_2014, order = c(0,1,1), seasonal= c(2,0,2)) = .15
```

```
# YOUR CODE HERE
```

```
ts.season <- Arima(tr_2010_2014, order = c(0,2,4), seasonal= c(1,0,1))
summary(ts.season)
```

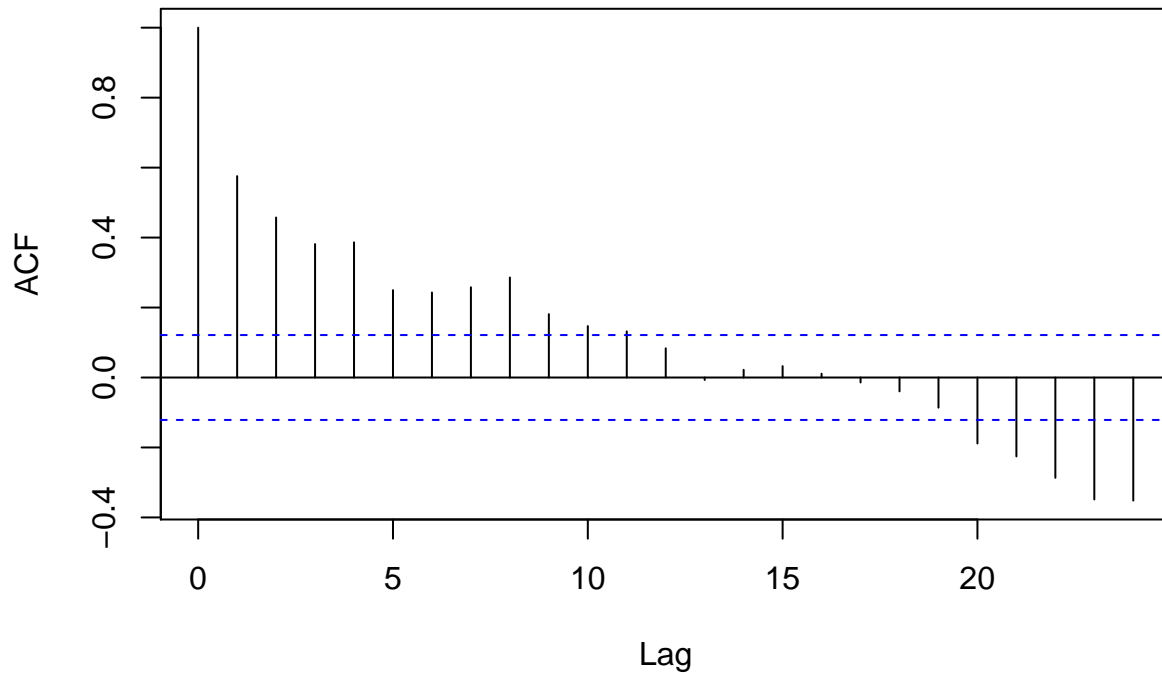
```
## Series: tr_2010_2014
## ARIMA(0,2,4)(1,0,1)[52]
##
## Coefficients:
##          ma1      ma2      ma3      ma4      sar1      sma1
##      -1.5500  0.4441  0.0418  0.0641  0.8448 -0.6795
## s.e.   0.0715  0.1163  0.1002  0.0589  0.1586  0.2188
##
## sigma^2 estimated as 0.5878: log likelihood=-303.83
## AIC=621.67 AICc=622.12 BIC=646.57
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set 0.1167773 0.7548495 0.5541185 70.60335 200.488 0.6730288
##              ACF1
## Training set 0.03554429
```

```
#checkresiduals(ts.season)
```

-write loop for p, d, q and PDQ -go up to 5 for non seasonal - turn off differencing for now - examine residuals for white noise; then look for model w lowest AIC - do forecast for 2015

```
flt.lm <- lm(tr_2010_2014 ~ time(tr_2010_2014))
acf(resid(flt.lm))
```

Series resid(flt.lm)



```
find.best <- c(0,0,0)
best.aic <- Inf
for (i in 0:5) for (j in 0:4) {
  fit.aic <- AIC(arima(resid(flt.lm), order = c(i,0,j)))
  if (fit.aic < best.aic) {
    best.order <- c(i,0,j)
    best.arma <- arima(resid(flt.lm), order = best.order)
    best.aic <- fit.aic
  }
}
```

```
## Warning in arima(resid(flt.lm), order = c(i, 0, j)): possible convergence
## problem: optim gave code = 1
```

```
## Warning in arima(resid(flt.lm), order = best.order): possible convergence
## problem: optim gave code = 1
```

```
## Warning in arima(resid(flt.lm), order = c(i, 0, j)): possible convergence
## problem: optim gave code = 1
```

```
## Warning in arima(resid(flt.lm), order = best.order): possible convergence
## problem: optim gave code = 1
```

```
## Warning in arima(resid(flt.lm), order = c(i, 0, j)): possible convergence
## problem: optim gave code = 1
```

```
## Warning in arima(resid(flt.lm), order = best.order): possible convergence
## problem: optim gave code = 1
```

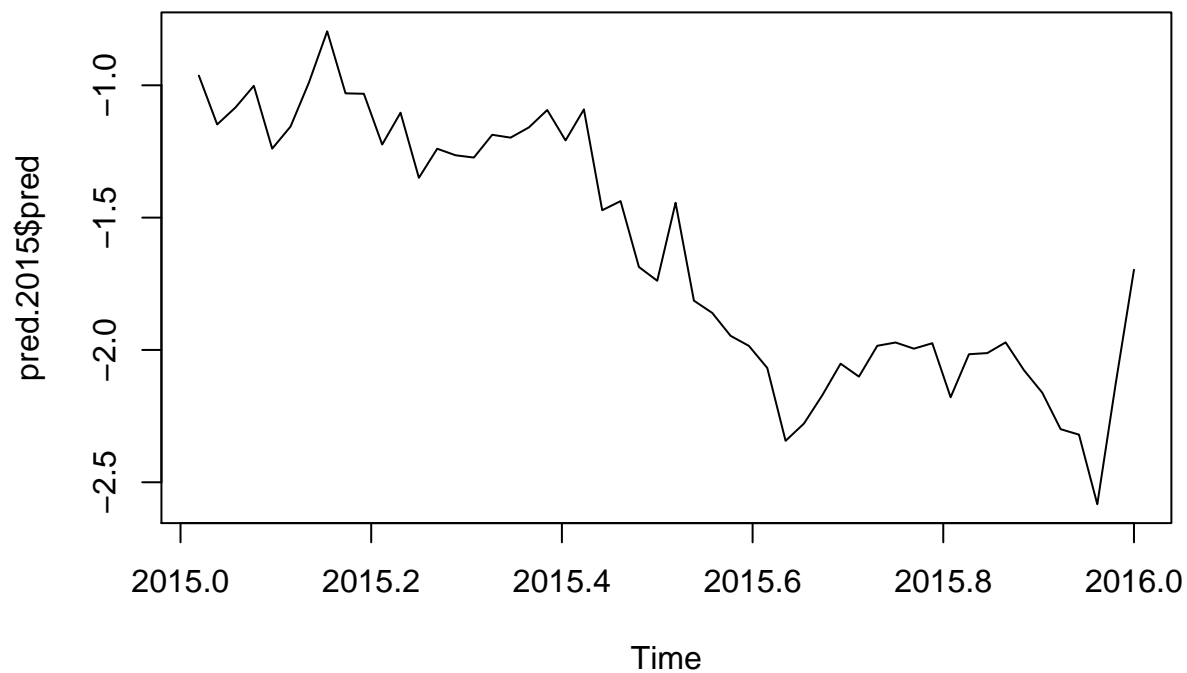
```
best.order
```

```
## [1] 5 0 4
```



```
#ts.season > Arima fitted w season
```

```
pred.2015 <- predict(ts.season, n.ahead = 52)  
plot(pred.2015$pred)
```



```
actual_2010_2015 <- ts(d$flight.prices, frequency = 52, start = c(2010,1), end=c(2015,52))  
plot(actual_2010_2015)
```

