

R Notebook

```
#install.packages("dplyr")
#install.packages("tidyverse")
#install.packages("astsa")
#install.packages("forecast")
```

```
library(dplyr)
library(tidyverse)
library(astsa)
library(forecast)
```

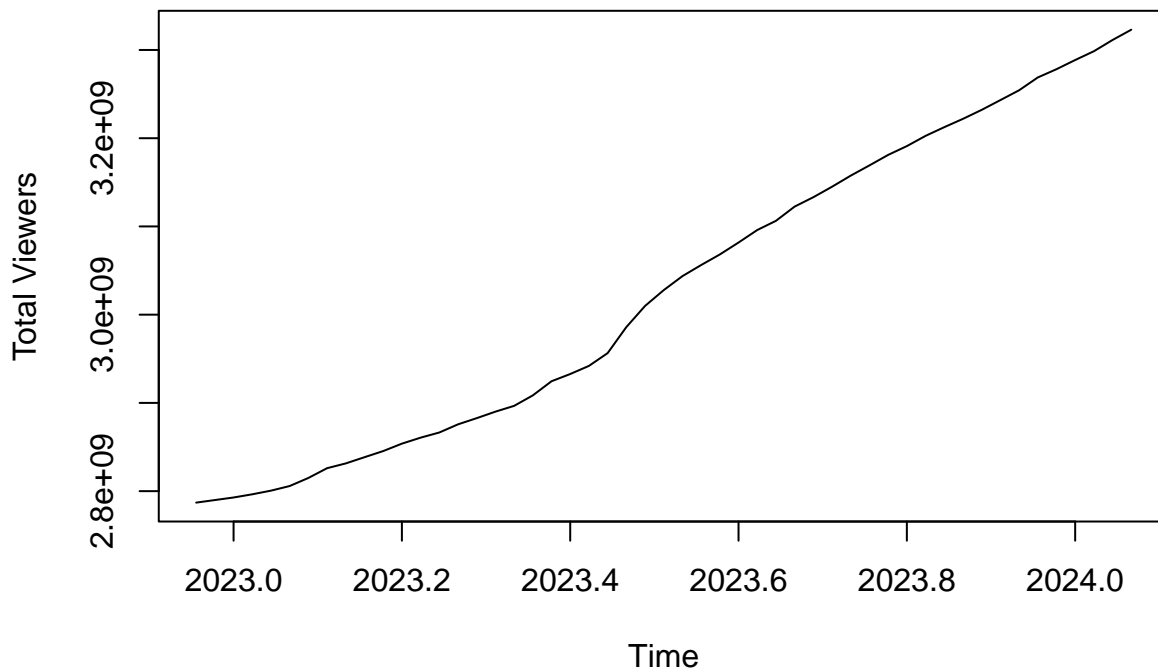
```
PATH <- ""
smosh <- read.csv(paste(PATH, "smosh_market.csv", sep = ""))
head(smosh)
```

```
##   Day      Month Year Total.Viewers
## 1  25 December 2022    2787011608
## 2   2  January 2023    2789909808
## 3  10  January 2023    2792792592
## 4  18  January 2023    2796442297
## 5  26  January 2023    2800576231
## 6   3 February 2023    2805812495
##
##                                     Video.1
## 1 Try Not To Laugh Challenge #110 - Gauntlet w/ Our Crew! (Dec. 20 2022; 1699048, 24:05)
## 2                                     Eat It Or Yeet It: Cast vs. Crew! (Dec. 27 2022; 896884, 25:49)
## 3                                     Try Not To Laugh 2022 Marathon (Jan. 3 2023; 804787, 8:23:46)
## 4                                     How Much Do We Know About Spongebob? (Jan. 12 2023; 692537, 21:11)
## 5                                     Short Kings Rank Short Kings (Jan. 19 2023; 684072, 36:59)
## 6                                     Try Not To Laugh Challenge #112 (Jan. 31 2023; 1457075, 19:58)
##
##                                     Video.2
## 1                                     These Memes Destroyed Us (Who Meme'd It) (Dec. 22, 2022; 1422918, 28:13)
## 2                                     Beopardy 2022 Marathon (Dec. 29 2022; 789801, 04:57:38)
## 3                                     Reading Unhinged Reddit Stories w/ MacDoesIt (Jan. 5 2023; 2515511, 45:47)
## 4                                     Try Not To Laugh Challenge #111 (Jan. 17 2023; 2693844, 26:05)
## 5                                     Filipino Food Taste Test (Eat It or Yeet It) (Jan. 24 2023; 1970618, 25:04)
## 6 We Try The TikTok Candle Challenge... and MORE! | The Challenge Pit (Feb. 2 2023; 818879, 22:07)
##
##                                     Video.3 Video.4
## 1                                     ; 0,      ; 0,
## 2                                     ; 0,      ; 0,
## 3 Eat It Or Yeet It 2022 Marathon (Jan. 10 2023; 548572, 7:10:39)      ; 0,
## 4                                     ; 0,      ; 0,
## 5                                     Can I Work A Real Job? (Jan. 26 2023; 864940, 30:33)      ; 0,
## 6                                     ; 0,      ; 0,
##   Total.Views.of.Videos.Posted.that.Week X..Videos.Posted
## 1                                     3121966      2
## 2                                     1686685      2
## 3                                     3868870      3
## 4                                     3386381      2
```

```
## 5          3519630          3
## 6          2275954          2
##   Avg..Views.of.Videos.Posted.That.Week
## 1          1560983
## 2          843343
## 3          1289623
## 4          1693191
## 5          1173210
## 6          1137977
##   Total.Duration.of.Videos.Posted.That.Week
## 1          NA
## 2          NA
## 3          NA
## 4          NA
## 5          NA
## 6          NA
```

```
smosh <- smosh %>% rename("Total Viewers" = "Total.Viewers")
sm <- ts(smosh["Total Viewers"], start = c(2022, 44), frequency = 45)
plot(sm, main = "Smosh Pit Total Weekly Total Views")
```

Smosh Pit Total Weekly Total Views



- Non-stationary in mean
- Dataframe only about a year, likely won't track seasonality (if any) and unlikely due to nature of channel
- Mild viewership jump around June 2023 (steeper slope after jump?)

```
growth <- diff(sm)
which.max(growth)
```

```
## [1] 23
```

```
growth[23]
```

```
## [1] 29457404
```

```
which.min(growth)
```

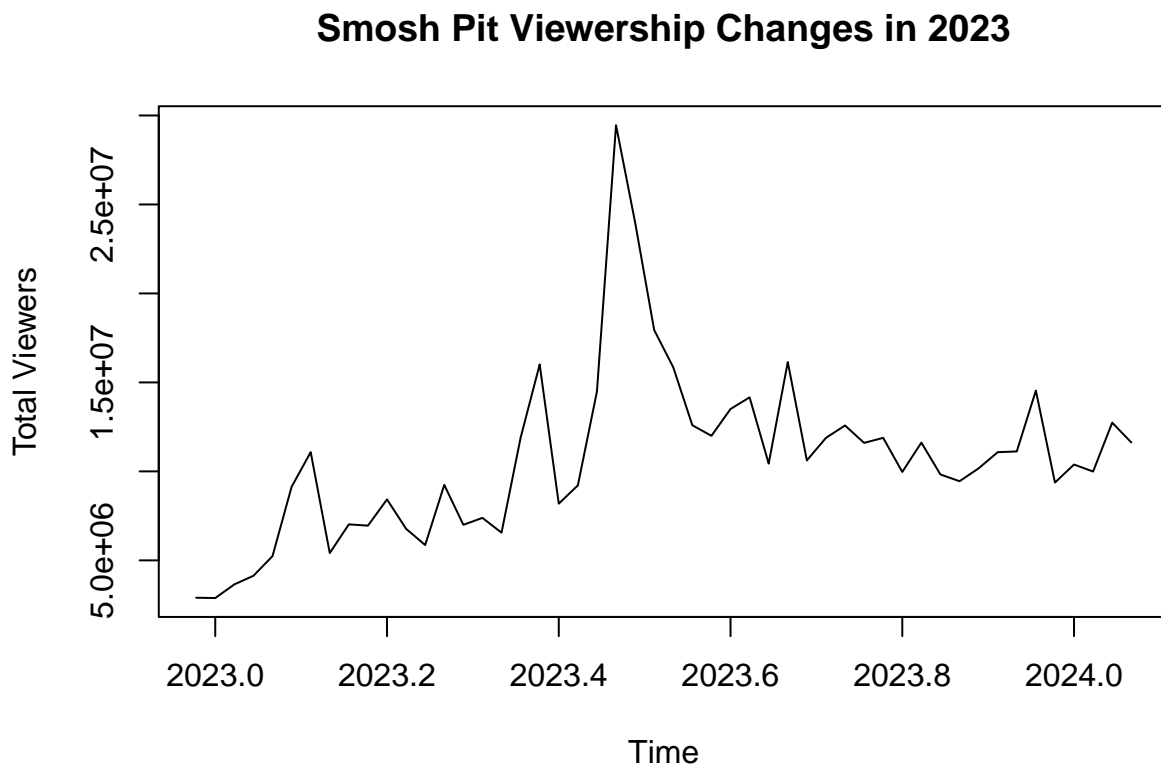
```
## [1] 2
```

```
growth[2]
```

```
## [1] 2882784
```

```
# 24 and 25 (now 23 and 24) have most significant increases in viewership  
# (Anthony returns - 24th Anthony specific videos (in title))
```

```
plot(growth, type = "l", main = "Smosh Pit Viewership Changes in 2023")
```



```
# 5 noticeable peaks (7, 18/19, 23/24, 32, 45)
```

```
# post big peak - different mean, variance pretty constant aside from peaks
```

- Mean more stationary... how significant is difference after massive peak
- Variance changes: some kind of seasonality or caused by outside events (like major peak)?? - appear about equidistant of each other

```
# roa = return of Anthony
```

```
pre_roa <- growth[1:22]
```

```
post_roa <- growth[24:50]
```

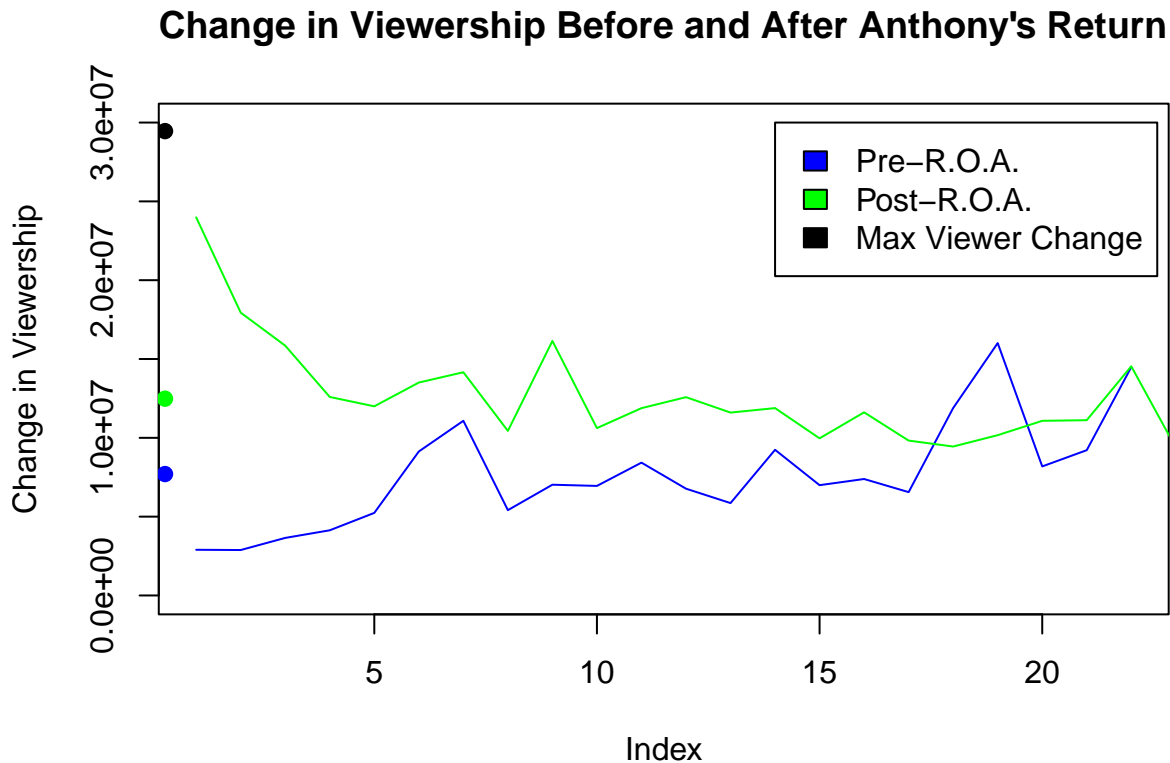
```
mean(pre_roa)
```

```
## [1] 7701073
```

```
mean(post_roa)
```

```
## [1] 12483718
```

```
plot(pre_roa, type = "l", col = "blue", ylim = c(0, 30000000), ylab = "Change in Viewership", main = "Change in Viewership Before and After Anthony's Return")
lines(post_roa, type = "l", col = "green")
points(x = c(0.3, 0.3, 0.3), c(mean(pre_roa), mean(post_roa), max(growth)), col = c("blue", "green", "black"))
legend(14, 30000000, legend = c("Pre-R.O.A.", "Post-R.O.A.", "Max Viewer Change"), fill = c("blue", "green", "black"))
```



Post return of Anthony has a sustained increase in viewership. Jump at end of pre-ROA period and dip at end of post-ROA period - is time series stabilizing around specific mean or residual effect of week 19 peak?

No apparent trend before or after Anthony's return. Potential seasonality? Effect of intervention mimicking autocorrelation?

```
video1_len <- strcapture(".*, ([0-9]*):([0-9]*):([0-9]*)", smosh$Video.1,
  list(hour_1 = "", minute_1 = "", second_1 = ""))
video2_len <- strcapture(".*, ([0-9]*):([0-9]*):([0-9]*)", smosh$Video.2,
  list(hour_2 = "", minute_2 = "", second_2 = ""))
video3_len <- strcapture(".*, ([0-9]*):([0-9]*):([0-9]*)", smosh$Video.3,
  list(hour_3 = "", minute_3 = "", second_3 = ""))
video4_len <- strcapture(".*, ([0-9]*):([0-9]*):([0-9]*)", smosh$Video.4,
  list(hour_4 = "", minute_4 = "", second_4 = ""))

video_lengths <- cbind(video1_len, video2_len, video3_len, video4_len)
video_lengths
```

Finish formatting dataframe

```
## hour_1 minute_1 second_1 hour_2 minute_2 second_2 hour_3 minute_3 second_3
```

## 1		24	05		28	13	<NA>	<NA>	<NA>
## 2		25	49	04:	57	38	<NA>	<NA>	<NA>
## 3	8:	23	46		45	47	7:	10	39
## 4		21	11		26	05	<NA>	<NA>	<NA>
## 5		36	59		25	04		30	33
## 6		19	58		22	07	<NA>	<NA>	<NA>
## 7		21	26		50	40	<NA>	<NA>	<NA>
## 8		18	12		30	07	<NA>	<NA>	<NA>
## 9		20	10		24	35		0	54
## 10		26	46		24	25	1:	13	45
## 11		21	46		21	15		20	53
## 12		30	20	1:	14	41		18	13
## 13		17	11		20	08		17	24
## 14	1:	16	19		24	52		27	44
## 15		17	10		20	34	1:	05	10
## 16		24	41		39	04		29	37
## 17		17	05		20	54	1:	14	29
## 18		42	30	1:	03	53		20	17
## 19		30	33	1:	16	59		19	05
## 20		38	44		14	44		28	45
## 21	1:	15	45		18	08		18	06
## 22		24	18		21	55	1:	09	57
## 23		18	28		40	10	1:	14	30
## 24		26	03		39	30	1:	10	16
## 25		21	31	1:	14	26		19	43
## 26		24	08	1:	08	15		31	49
## 27	1:	10	33		18	55		24	23
## 28	1:	13	10		25	47		26	41
## 29		25	36		36	22	1:	08	02
## 30		24	47		23	07	1:	10	43
## 31		22	10		45	19	1:	17	35
## 32		28	26	1:	14	05		26	33
## 33		49	07	1:	09	39		27	36
## 34	1:	15	59		22	32		28	34
## 35		26	55		30	31	1:	10	32
## 36		23	28		42	37	1:	16	39
## 37		22	22		26	34	1:	22	38
## 38		17	27		37	43	1:	08	02
## 39		22	28	1:	15	04		22	20
## 40		48	09	1:	22	43		26	01
## 41	1:	05	11		19	19		36	03
## 42	1:	07	41		30	42		48	29
## 43		25	01		48	12		55	32
## 44		27	09	1:	15	57	<NA>	<NA>	<NA>
## 45		19	31		34	56	1:	10	02
## 46		35	02	1:	08	20		27	19
## 47	1:	15	24	1:	20	00		31	38
## 48	1:	18	32	8:	34	13	4:	44	32
## 49	6:	28	27	9:	06	33		33	57
## 50		14	50		29	31	1:	21	26
## 51		51	29		33	31	1:	13	23
##	hour_4 minute_4 second_4								
## 1	<NA>	<NA>	<NA>						
## 2	<NA>	<NA>	<NA>						

```

## 3    <NA>    <NA>    <NA>
## 4    <NA>    <NA>    <NA>
## 5    <NA>    <NA>    <NA>
## 6    <NA>    <NA>    <NA>
## 7    <NA>    <NA>    <NA>
## 8    <NA>    <NA>    <NA>
## 9    <NA>    <NA>    <NA>
## 10   21     12
## 11   <NA>    <NA>    <NA>
## 12   21     37
## 13   <NA>    <NA>    <NA>
## 14   29     15
## 15   <NA>    <NA>    <NA>
## 16   <NA>    <NA>    <NA>
## 17   17     47
## 18   <NA>    <NA>    <NA>
## 19   26     48
## 20   <NA>    <NA>    <NA>
## 21   1:     02     45
## 22   <NA>    <NA>    <NA>
## 23   <NA>    <NA>    <NA>
## 24   18     57
## 25   <NA>    <NA>    <NA>
## 26   44     54
## 27   <NA>    <NA>    <NA>
## 28   55     19
## 29   <NA>    <NA>    <NA>
## 30   <NA>    <NA>    <NA>
## 31   26     14
## 32   <NA>    <NA>    <NA>
## 33   23     30
## 34   <NA>    <NA>    <NA>
## 35   <NA>    <NA>    <NA>
## 36   <NA>    <NA>    <NA>
## 37   <NA>    <NA>    <NA>
## 38   28     10
## 39   <NA>    <NA>    <NA>
## 40   43     15
## 41   <NA>    <NA>    <NA>
## 42   58     31
## 43   <NA>    <NA>    <NA>
## 44   <NA>    <NA>    <NA>
## 45   26     58
## 46   <NA>    <NA>    <NA>
## 47   39     41
## 48   <NA>    <NA>    <NA>
## 49   54     26
## 50   <NA>    <NA>    <NA>
## 51   <NA>    <NA>    <NA>

```

```

video_lengths <-
  video_lengths %>%
  mutate(hour_1 = str_replace_all(hour_1, ":", ""),
         hour_2 = str_replace_all(hour_2, ":", ""))

```

```

    hour_3 = str_replace_all(hour_3, ":", ""),
    hour_4 = str_replace_all(hour_4, ":", ""))

video_lengths <- data.frame(sapply(video_lengths, as.integer))

h <- c("hour_1", "hour_2", "hour_3", "hour_4")
m <- c("minute_1", "minute_2", "minute_3", "minute_4")
s <- c("second_1", "second_2", "second_3", "second_4")

video_lengths <-
  video_lengths %>%
  rowwise() %>%
  mutate(hours = sum(c_across(any_of(h)), na.rm = TRUE),
         minutes = sum(c_across(any_of(m)), na.rm = TRUE),
         seconds = sum(c_across(any_of(s)), na.rm = TRUE)) %>%
  ungroup() %>% select("hours", "minutes", "seconds")

channel_growth <- smosh %>% select(!(starts_with(("Video"))))
channel_growth["Total.Duration.of.Videos.Posted.That.Week"] <-
  video_lengths %>%
  mutate(minutes = floor(hours*60 + minutes + seconds/60)) %>% select(minutes)

channel_growth <- channel_growth[-c(1), ]
channel_growth["Viewer Growth"] <- as.numeric(growth[, 1])

channel_growth <- channel_growth %>%
  relocate("Viewer Growth", .after = "Total Viewers") %>% rename(
    "Total Views of Videos Posted that Week" = Total.Views.of.Videos.Posted.that.Week,
    "Number Videos Posted" = X..Videos.Posted,
    "Avg. Views of Videos Posted that Week" = Avg..Views.of.Videos.Posted.That.Week,
    "Total Duration of Videos Posted that Week" = Total.Duration.of.Videos.Posted.That.Week
  )

rownames(channel_growth) <- NULL
channel_growth

```

##	Day	Month	Year	Total Viewers	Viewer Growth
## 1	2	January	2023	2789909808	2898200
## 2	10	January	2023	2792792592	2882784
## 3	18	January	2023	2796442297	3649705
## 4	26	January	2023	2800576231	4133934
## 5	3	February	2023	2805812495	5236264
## 6	11	February	2023	2814945755	9133260
## 7	19	February	2023	2826026147	11080392
## 8	27	February	2023	2831436611	5410464
## 9	7	March	2023	2838461335	7024724
## 10	15	March	2023	2845410880	6949545
## 11	23	March	2023	2853837066	8426186
## 12	31	March	2023	2860609759	6772693
## 13	8	April	2023	2866469219	5859460
## 14	16	April	2023	2875708845	9239626
## 15	24	April	2023	2882705793	6996948
## 16	2	May	2023	2890092808	7387015
## 17	10	May	2023	2896647971	6555163

## 18	18	May 2023	2908538438	11890467	
## 19	26	May 2023	2924547732	16009294	
## 20	3	June 2023	2932733429	8185697	
## 21	11	June 2023	2941948662	9215233	
## 22	19	June 2023	2956435224	14486562	
## 23	27	June 2023	2985892628	29457404	
## 24	5	July 2023	3009881599	23988971	
## 25	13	July 2023	3027823781	17942182	
## 26	21	July 2023	3043670914	15847133	
## 27	29	July 2023	3056263820	12592906	
## 28	6	August 2023	3068262616	11998796	
## 29	14	August 2023	3081768900	13506284	
## 30	22	August 2023	3095929026	14160126	
## 31	30	August 2023	3106367373	10438347	
## 32	7	September 2023	3122512475	16145102	
## 33	15	September 2023	3133129472	10616997	
## 34	23	September 2023	3145011950	11882478	
## 35	1	October 2023	3157591416	12579466	
## 36	9	October 2023	3169191993	11600577	
## 37	17	October 2023	3181076729	11884736	
## 38	25	October 2023	3191044070	9967341	
## 39	2	November 2023	3202661578	11617508	
## 40	10	November 2023	3212486353	9824775	
## 41	18	November 2023	3221934010	9447657	
## 42	26	November 2023	3232103226	10169216	
## 43	4	December 2023	3243182015	11078789	
## 44	12	December 2023	3254301659	11119644	
## 45	20	December 2023	3268840215	14538556	
## 46	28	December 2023	3278211346	9371131	
## 47	5	January 2024	3288597261	10385915	
## 48	13	January 2024	3298588679	9991418	
## 49	21	January 2024	3311328516	12739837	
## 50	29	January 2024	3322953024	11624508	
##	Total Views of Videos Posted that Week				Number Videos Posted
## 1			1686685		2
## 2			3868870		3
## 3			3386381		2
## 4			3519630		3
## 5			2275954		2
## 6			3436121		2
## 7			1441645		2
## 8			2620191		3
## 9			6481835		4
## 10			3035189		3
## 11			4855481		4
## 12			1994275		3
## 13			4410841		4
## 14			4880999		3
## 15			2890042		3
## 16			6271837		4
## 17			3870685		3
## 18			7269584		4
## 19			2325618		3
## 20			5556022		4

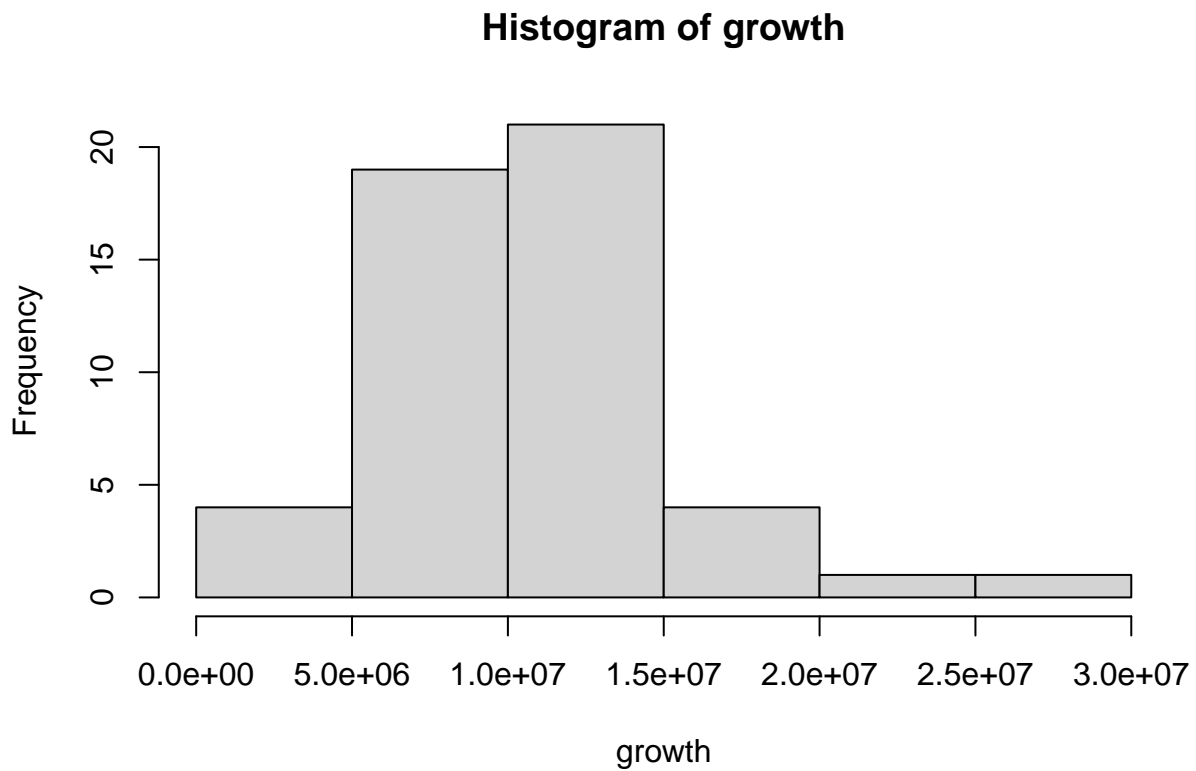
## 21	4252415	3
## 22	5484814	3
## 23	13882853	4
## 24	4452081	3
## 25	6999184	4
## 26	3831462	3
## 27	6313003	4
## 28	4638467	3
## 29	3403611	3
## 30	6380212	4
## 31	4726224	3
## 32	7210340	4
## 33	3661877	3
## 34	5134042	3
## 35	3129607	3
## 36	4002739	3
## 37	5739373	4
## 38	2977481	3
## 39	3629886	4
## 40	2590855	3
## 41	5377169	4
## 42	2015374	3
## 43	2186709	2
## 44	3527577	4
## 45	3100627	3
## 46	3477939	4
## 47	2102020	3
## 48	2291395	4
## 49	2913832	3
## 50	2194338	3
##	Avg. Views of Videos Posted that Week	
## 1	843343	
## 2	1289623	
## 3	1693191	
## 4	1173210	
## 5	1137977	
## 6	1718061	
## 7	720823	
## 8	873397	
## 9	1620459	
## 10	1011730	
## 11	1213870	
## 12	664758	
## 13	1102710	
## 14	1627000	
## 15	963347	
## 16	1567959	
## 17	1290228	
## 18	1817396	
## 19	775206	
## 20	1389006	
## 21	1417472	
## 22	1828271	
## 23	3470713	

## 24	1484027
## 25	1749796
## 26	1277154
## 27	1578251
## 28	1546156
## 29	1134537
## 30	1595053
## 31	1575408
## 32	1802585
## 33	1220626
## 34	1711347
## 35	1043202
## 36	1334246
## 37	1434843
## 38	992494
## 39	907472
## 40	863618
## 41	1344292
## 42	671791
## 43	1093355
## 44	881894
## 45	1033542
## 46	869485
## 47	700673
## 48	572849
## 49	971277
## 50	731446
##	Total Duration of Videos Posted that Week
## 1	323
## 2	980
## 3	47
## 4	92
## 5	42
## 6	72
## 7	48
## 8	45
## 9	146
## 10	63
## 11	144
## 12	54
## 13	158
## 14	102
## 15	93
## 16	130
## 17	126
## 18	153
## 19	82
## 20	174
## 21	116
## 22	133
## 23	154
## 24	115
## 25	169
## 26	113

## 27	180
## 28	130
## 29	118
## 30	171
## 31	129
## 32	169
## 33	127
## 34	127
## 35	142
## 36	131
## 37	151
## 38	119
## 39	200
## 40	120
## 41	205
## 42	128
## 43	103
## 44	151
## 45	130
## 46	226
## 47	877
## 48	1023
## 49	125
## 50	158

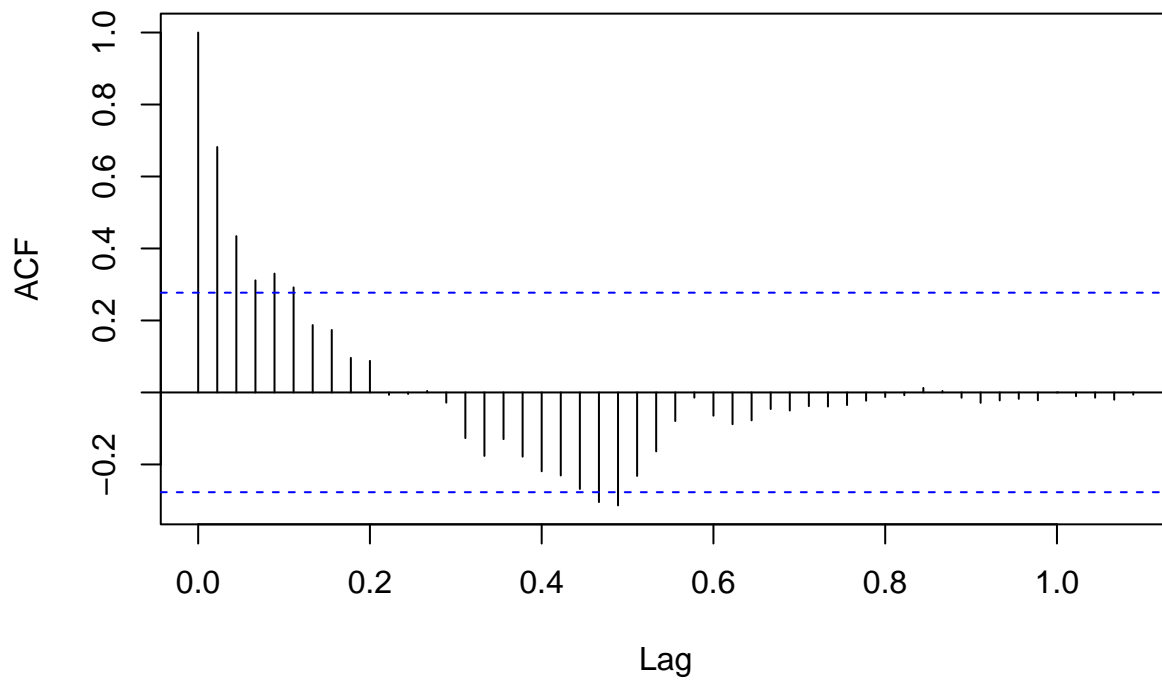
First focus on viewership only

```
hist(growth)
```



```
acf(growth, lag.max = 50)
```

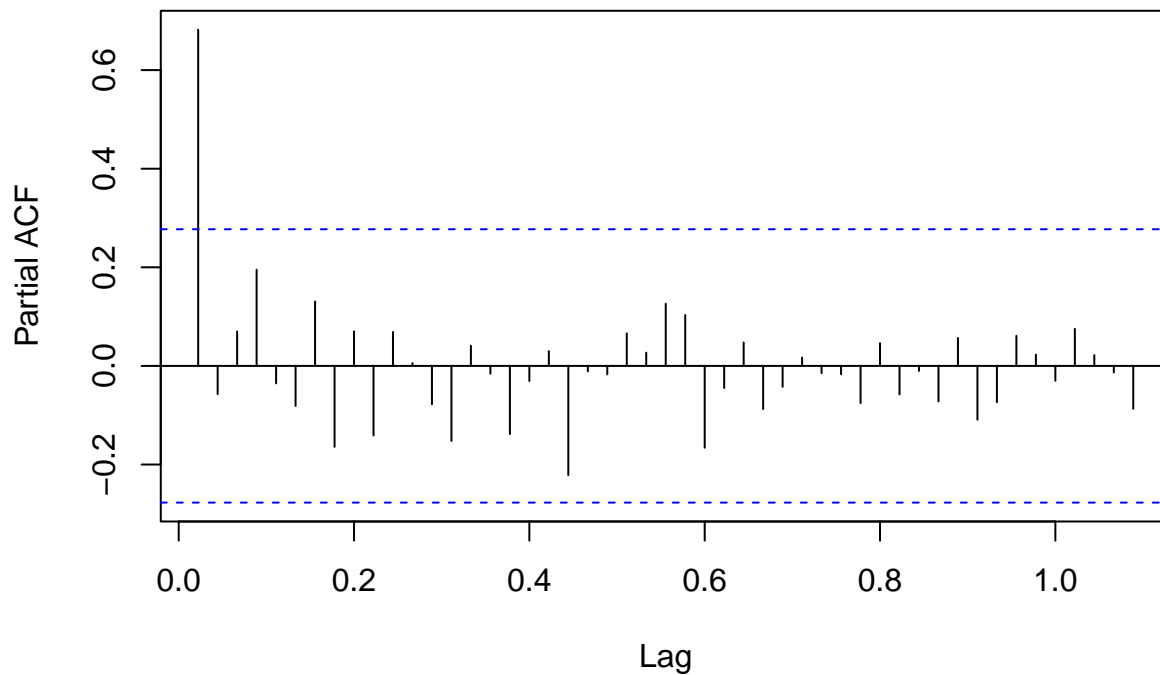
Total Viewers



```
# MA(2)?
```

```
pacf(growth, lag.max = 50)
```

Series growth



#only significant at lag 1 (AR(1))

Forecasting growth without intervention

```
# train - test split
train_pre <- pre_roa[1:17]
test_pre <- pre_roa[18:22]

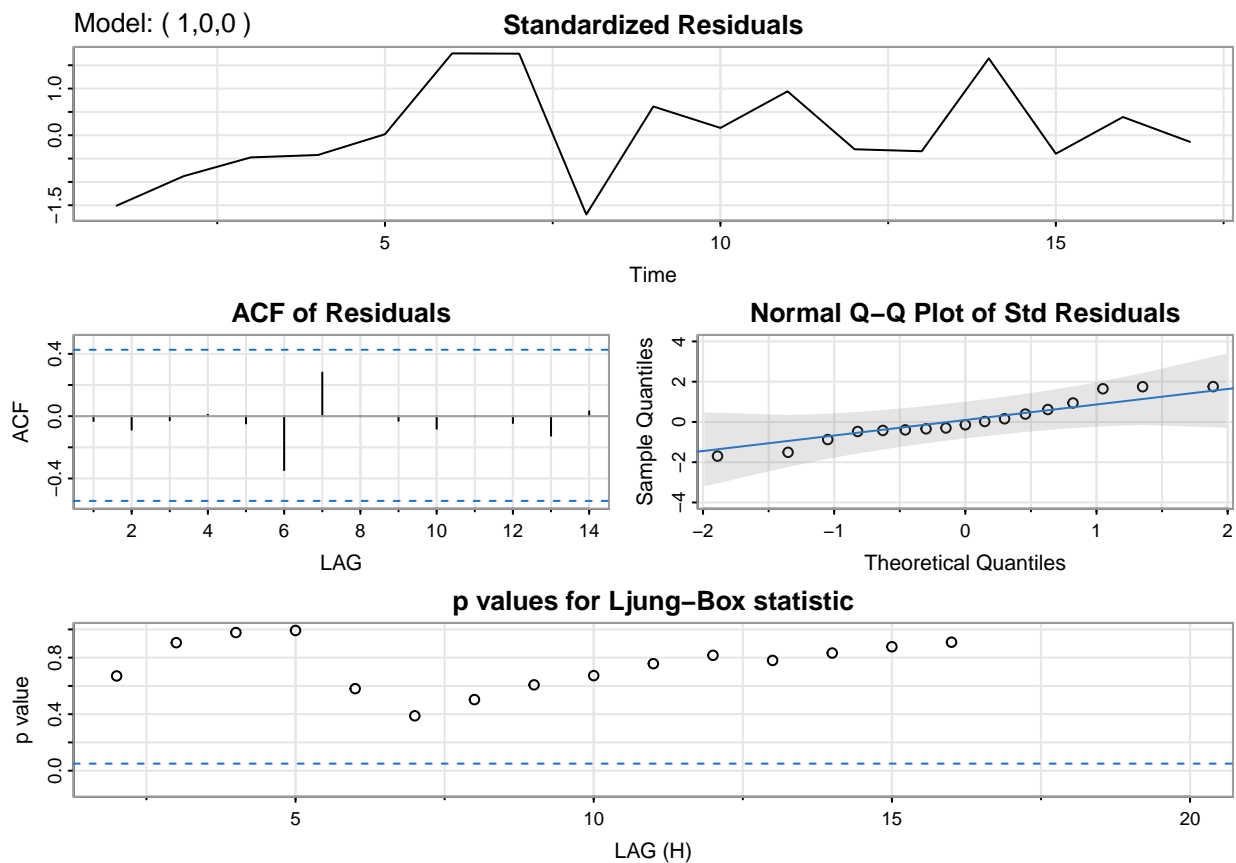
# AR(1) model

#t <- 1:length(train_pre)
#noint_model <- lm(formula = pre_roa ~ t)

ar1 <- sarima(train_pre, 1, 0, 0, P = 0, D = 0, Q = 0)
```

```
## initial value 14.560831
## iter 2 value 14.454468
## iter 3 value 14.441005
## iter 4 value 14.415382
## iter 5 value 14.414876
## iter 6 value 14.414655
## iter 6 value 14.414655
## final value 14.414655
## converged
## initial value 14.496742
## iter 2 value 14.485651
## iter 3 value 14.481763
## iter 4 value 14.481496
## iter 5 value 14.481484
## iter 5 value 14.481484
```

```
## iter    5 value 14.481484
## final   value 14.481484
## converged
## <><><><><><><><><><><><><>
##
## Coefficients:
##           Estimate      SE t.value p.value
## ar1          0.5026    0.2171  2.3152  0.0352
## xmean 6266169.1357 900995.8430  6.9547  0.0000
##
## sigma^2 estimated as 3.724061e+12 on 15 degrees of freedom
##
## AIC = 32.15379  AICc = 32.20421  BIC = 32.30082
##
```



```
# ARMA(1, 2)
ar1_ma2 <- sarima(train_pre, 1, 0, 2, P = 0, D = 0, Q = 0)
```

```
## initial value 14.560831
## iter    2 value 14.549241
## iter    3 value 14.451523
## iter    4 value 14.419840
## iter    5 value 14.397602
## iter    6 value 14.280453
## iter    7 value 14.270940
## iter    8 value 14.240431
## iter    9 value 14.178564
```

```
## iter 10 value 14.164847
## iter 11 value 14.151673
## iter 12 value 14.110410
## iter 13 value 14.104645
## iter 14 value 14.082963
## iter 15 value 14.073591
## iter 16 value 14.069513
## iter 17 value 14.062022
## iter 18 value 14.057450
## iter 19 value 14.055355
## iter 20 value 14.053263
## iter 21 value 14.035690
## iter 22 value 14.025868
## iter 22 value 14.025868
## iter 23 value 14.025360
## iter 24 value 14.025280
## iter 25 value 14.025130
## iter 26 value 14.025016
## iter 27 value 14.024916
## iter 28 value 14.024796
## iter 29 value 14.024704
## iter 30 value 14.024584
## iter 31 value 14.024493
## iter 32 value 14.024374
## iter 33 value 14.024282
## iter 34 value 14.024164
## iter 35 value 14.024072
## iter 36 value 14.023955
## iter 37 value 14.023862
## iter 38 value 14.023746
## iter 39 value 14.023652
## iter 40 value 14.023538
## iter 41 value 14.023442
## iter 42 value 14.023330
## iter 43 value 14.023233
## iter 44 value 14.023122
## iter 45 value 14.023025
## iter 46 value 14.022915
## iter 47 value 14.022816
## iter 48 value 14.022708
## iter 49 value 14.022608
## iter 50 value 14.022501
## iter 51 value 14.022401
## iter 52 value 14.022295
## iter 53 value 14.022193
## iter 54 value 14.022089
## iter 55 value 14.021986
## iter 56 value 14.021883
## iter 57 value 14.021780
## iter 58 value 14.021678
## iter 59 value 14.021573
## iter 60 value 14.021473
## iter 61 value 14.021368
## iter 62 value 14.021268
```

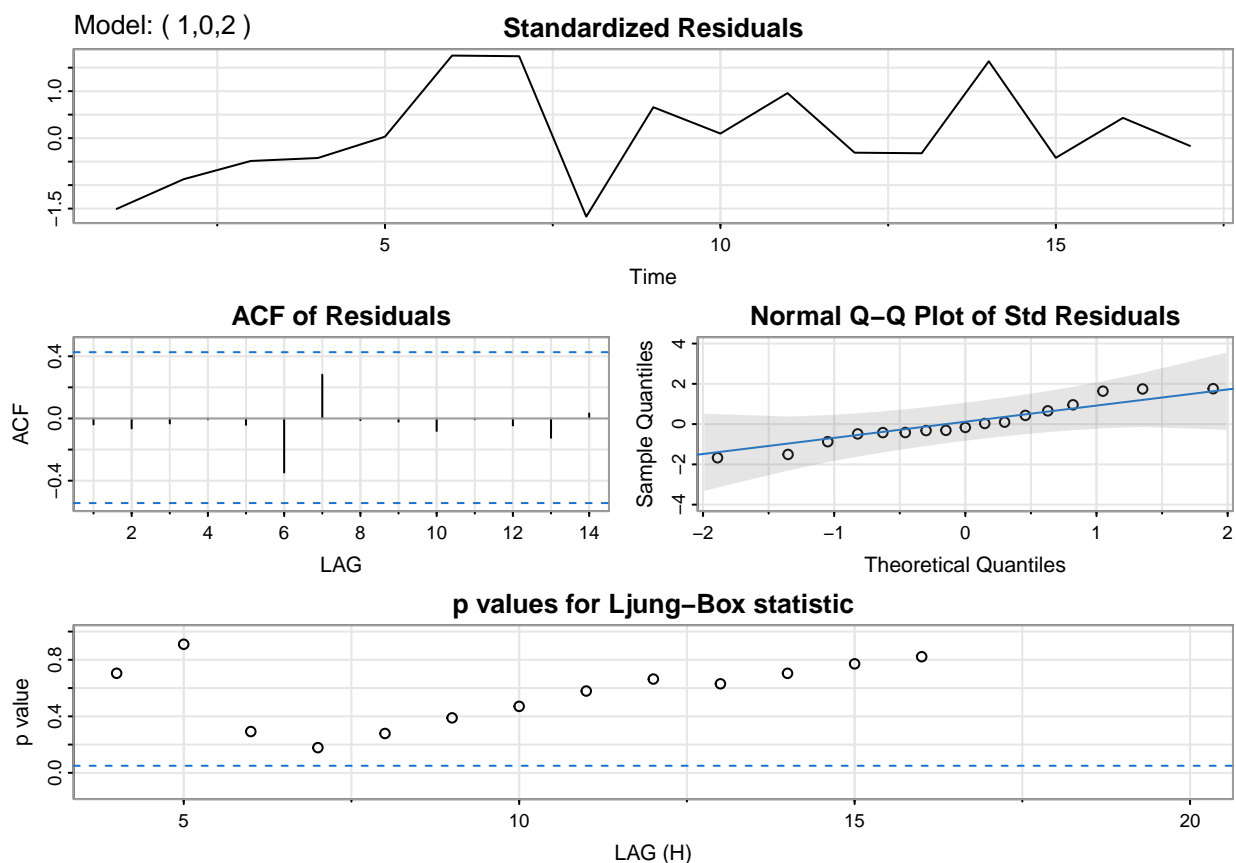
```
## iter 63 value 14.021162
## iter 64 value 14.021064
## iter 65 value 14.020957
## iter 66 value 14.020860
## iter 67 value 14.020752
## iter 68 value 14.020657
## iter 69 value 14.020548
## iter 70 value 14.020453
## iter 71 value 14.020343
## iter 72 value 14.020251
## iter 73 value 14.020140
## iter 74 value 14.020048
## iter 75 value 14.019936
## iter 76 value 14.019846
## iter 77 value 14.019733
## iter 78 value 14.019644
## iter 79 value 14.019531
## iter 80 value 14.019443
## iter 81 value 14.019328
## iter 82 value 14.019242
## iter 83 value 14.019126
## iter 84 value 14.019042
## iter 85 value 14.018925
## iter 86 value 14.018841
## iter 87 value 14.018724
## iter 88 value 14.018641
## iter 89 value 14.018523
## iter 90 value 14.018442
## iter 91 value 14.018323
## iter 92 value 14.018243
## iter 93 value 14.018123
## iter 94 value 14.018044
## iter 95 value 14.017923
## iter 96 value 14.017846
## iter 97 value 14.017724
## iter 98 value 14.017648
## iter 99 value 14.017525
## iter 100 value 14.017450
## final value 14.017450
## stopped after 100 iterations
## initial value 14.612216
## iter 2 value 14.550963
## iter 3 value 14.487569
## iter 4 value 14.485066
## iter 5 value 14.483358
## iter 6 value 14.483209
## iter 7 value 14.483077
## iter 8 value 14.483011
## iter 9 value 14.482547
## iter 10 value 14.482000
## iter 11 value 14.481448
## iter 12 value 14.481219
## iter 13 value 14.481209
## iter 14 value 14.481167
```



```

## iter 15 value 14.481119
## iter 16 value 14.481089
## iter 17 value 14.481084
## iter 18 value 14.481083
## iter 18 value 14.481083
## iter 18 value 14.481083
## final value 14.481083
## converged
## <><><><><><><><><><><>
##
## Coefficients:
##           Estimate      SE t.value p.value
## ar1         0.5352    0.7279  0.7353  0.4752
## ma1        -0.0235    0.7456 -0.0316  0.9753
## ma2        -0.0378    0.3833 -0.0985  0.9230
## xmean 6262476.1788 931110.8309  6.7258  0.0000
##
## sigma^2 estimated as 3.720567e+12 on 13 degrees of freedom
##
## AIC = 32.38828  AICc = 32.58436  BIC = 32.63334
##

```



```

# ARMA(1, 1)
ar1_ma1 <- sarima(train_pre, 1, 0, 1, P = 0, D = 0, Q = 0)

```

```

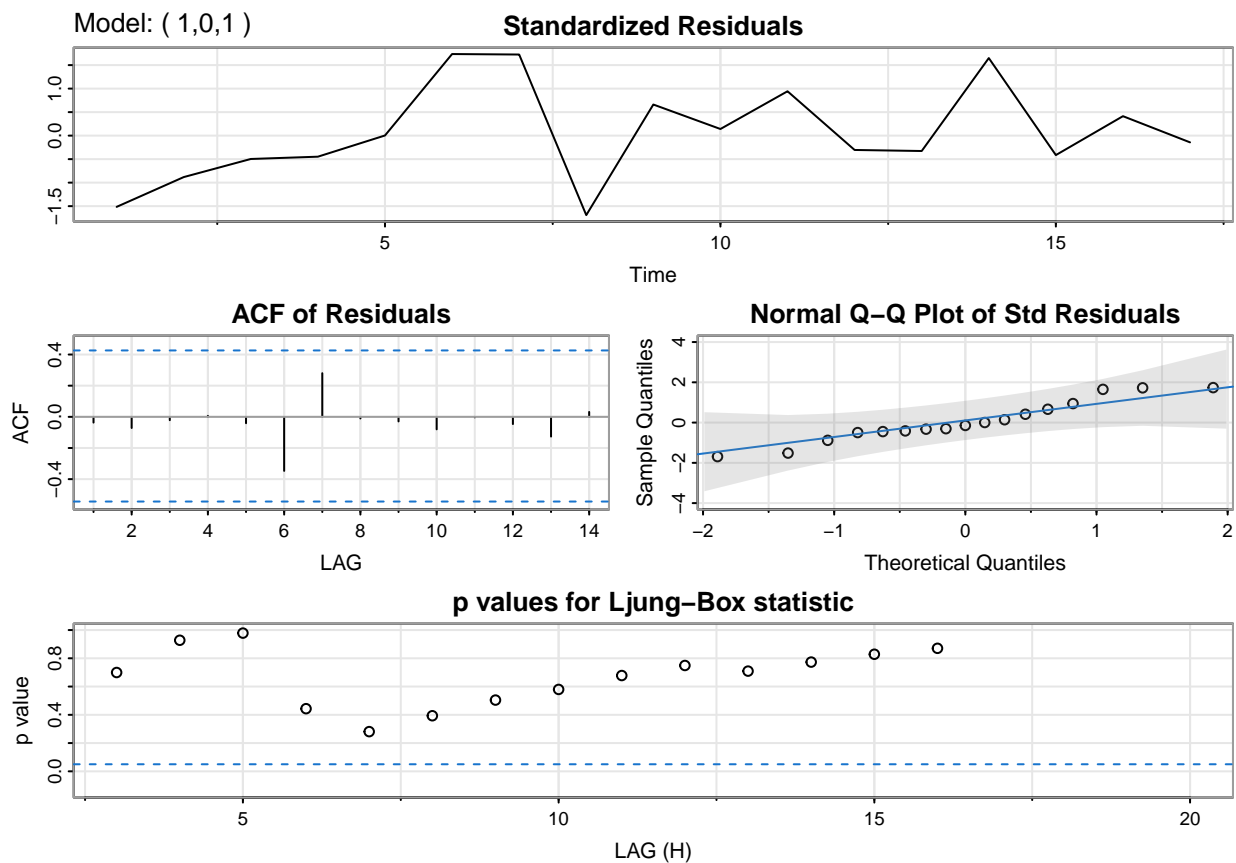
## initial value 14.560831
## iter 2 value 14.550320

```

```
## iter    3 value 14.443753
## iter    4 value 14.419103
## iter    5 value 14.404919
## iter    6 value 14.363494
## iter    7 value 14.353003
## iter    8 value 14.232056
## iter    9 value 14.220365
## iter   10 value 14.202507
## iter   11 value 14.193284
## iter   12 value 14.184163
## iter   13 value 14.183098
## iter   14 value 14.170050
## iter   15 value 14.163938
## iter   16 value 14.157764
## iter   17 value 14.147669
## iter   18 value 14.132436
## iter   19 value 14.117223
## iter   20 value 14.117007
## iter   21 value 14.107178
## iter   22 value 14.060340
## iter   23 value 14.059482
## iter   24 value 14.057704
## iter   25 value 14.056848
## iter   26 value 14.011620
## iter   26 value 14.011620
## iter   27 value 14.011006
## iter   27 value 14.011006
## iter   28 value 14.010965
## iter   29 value 14.010965
## iter   30 value 14.010916
## iter   31 value 14.010913
## iter   32 value 14.010866
## iter   33 value 14.010864
## iter   34 value 14.010817
## iter   35 value 14.010815
## iter   36 value 14.010768
## iter   37 value 14.010765
## iter   38 value 14.010718
## iter   39 value 14.010716
## iter   40 value 14.010669
## iter   41 value 14.010667
## iter   42 value 14.010620
## iter   43 value 14.010618
## iter   44 value 14.010571
## iter   45 value 14.010569
## iter   46 value 14.010522
## iter   47 value 14.010520
## iter   48 value 14.010473
## iter   49 value 14.010471
## iter   50 value 14.010424
## iter   51 value 14.010422
## iter   52 value 14.010375
## iter   53 value 14.010373
## iter   54 value 14.010327
```

```
## iter 55 value 14.010325
## iter 56 value 14.010278
## iter 57 value 14.010276
## iter 58 value 14.010230
## iter 59 value 14.010228
## iter 60 value 14.010181
## iter 61 value 14.010179
## iter 62 value 14.010133
## iter 63 value 14.010131
## iter 64 value 14.010085
## iter 65 value 14.010083
## iter 66 value 14.010036
## iter 67 value 14.010034
## iter 68 value 14.009988
## iter 69 value 14.009986
## iter 70 value 14.009940
## iter 71 value 14.009938
## iter 72 value 14.009892
## iter 73 value 14.009890
## iter 74 value 14.009844
## iter 75 value 14.009842
## iter 76 value 14.009796
## iter 77 value 14.009795
## iter 78 value 14.009749
## iter 79 value 14.009747
## iter 80 value 14.009701
## iter 81 value 14.009699
## iter 82 value 14.009653
## iter 83 value 14.009652
## iter 84 value 14.009606
## iter 85 value 14.009604
## iter 86 value 14.009558
## iter 87 value 14.009557
## iter 88 value 14.009511
## iter 89 value 14.009509
## iter 90 value 14.009464
## iter 91 value 14.009462
## iter 92 value 14.009416
## iter 93 value 14.009415
## iter 94 value 14.009369
## iter 95 value 14.009368
## iter 96 value 14.009322
## iter 97 value 14.009321
## iter 98 value 14.009275
## iter 99 value 14.009274
## iter 100 value 14.009228
## final value 14.009228
## stopped after 100 iterations
## initial value 14.612216
## iter 2 value 14.560760
## iter 3 value 14.484787
## iter 4 value 14.484389
## iter 5 value 14.483217
## iter 6 value 14.481384
```

```
## iter    7 value 14.481354
## iter    7 value 14.481353
## iter    7 value 14.481353
## final   value 14.481353
## converged
## <><><><><><><><><><><><><>
##
## Coefficients:
##           Estimate      SE t.value p.value
## ar1          0.4734    0.4967  0.9532  0.3567
## ma1          0.0365    0.5478  0.0666  0.9478
## xmean 6277441.4932 898531.8875  6.9863  0.0000
##
## sigma^2 estimated as 3.723499e+12 on 14 degrees of freedom
##
## AIC = 32.27117  AICc = 32.37977  BIC = 32.46722
##
```



```
# models virtually indistinguishable from eachother (AR(1) slightly
# lower AIC and BIC and has less parameters)
print(ar1$ICs)
```

```
##      AIC      AICc      BIC
## 32.15379 32.20421 32.30082
```

```
print(ar1_ma2$ICs)
```

```
##      AIC      AICc      BIC
```

```
## 32.38828 32.58436 32.63334
```

```
print(ar1_ma1$ICs)
```

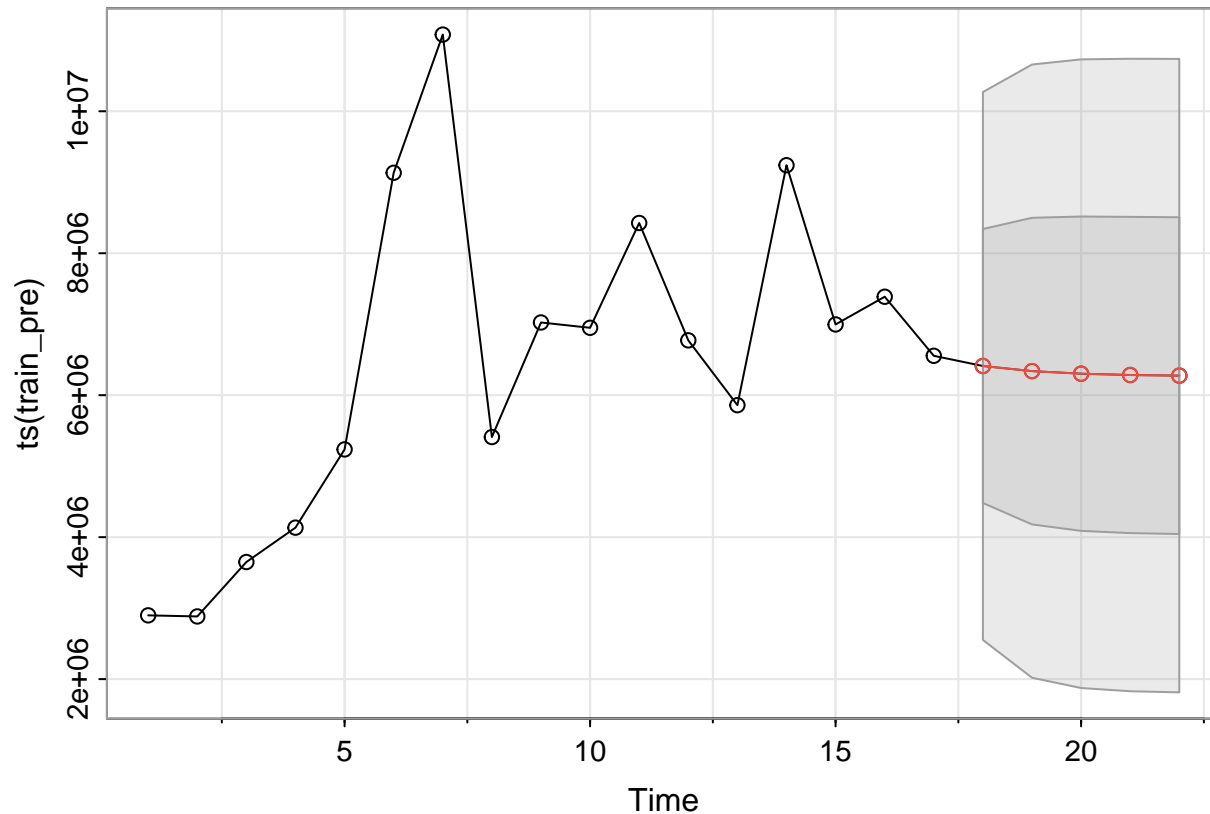
```
##      AIC      AICc      BIC
## 32.27117 32.37977 32.46722
```

```
# no pattern in residuals (no autocorrelation)
# standardized residuals over time still show some
```

```
# test model on test data
```

```
#ar1_forecast <- forecast(train_pre, h = 5)
```

```
ar1_forecast <- sarima.for(ts(train_pre), n.ahead = 5, 1, 0, 0)
```



```
ar1_pred <- ar1_forecast$pred
ar1_pred
```

```
## Time Series:
## Start = 18
## End = 22
## Frequency = 1
## [1] 6411432 6339185 6302871 6284617 6275442
```

```
#unlist(list(pre_roa, noint_pred))
```

```
# predictions for test_pre
```

```
mape <- function(actual, prediction){
  return(mean(abs((actual - prediction)/actual)) * 100)
}
```

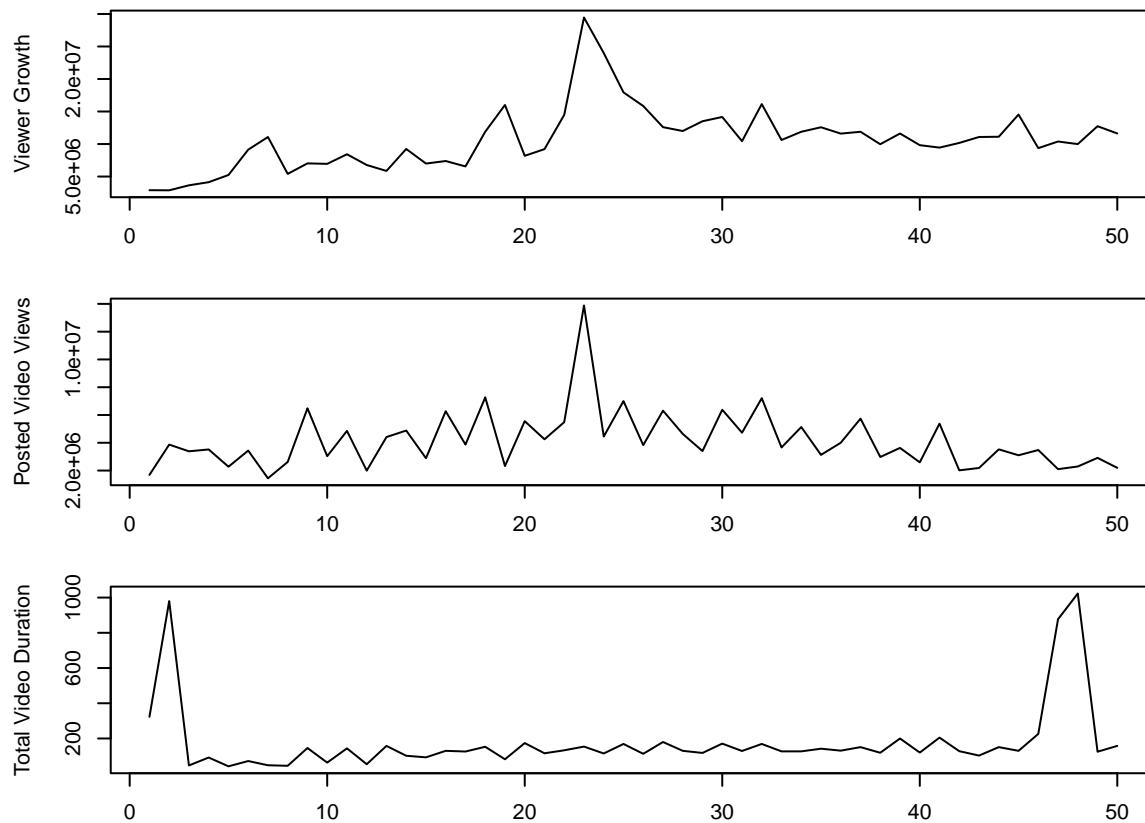
```
mape(test_pre, ar1_pred)
```

```
## [1] 43.59331
```

```
# high mape makes sense - peak right after train set ends
```

Multivariate analysis

```
par(mfrow = c(3, 1), mar = c(2, 6, 2, 2))
ts.plot(channel_growth["Viewer Growth"], xlab = "Time",
        ylab = "Viewer Growth")
ts.plot(channel_growth["Total Views of Videos Posted that Week"],
        xlab = "Time", ylab = "Posted Video Views")
ts.plot(channel_growth["Total Duration of Videos Posted that Week"],
        xlab = "Time", ylab = "Total Video Duration")
```



Sometimes, peaks in viewership do not coincide with that weeks video views and vice versa. Videos that may have performed well at the time may not have performed well in comparison to other weeks.

Videos posted during Anthony's return have maintained the highest overall views at the time and going forward.

Video duration consistent aside from December and January when they posted 4-9 hour themed compilations of videos from that year.

Notes:

Viewers instead of subscribers - Smosh channels old and contained many kinds of content and cast members (don't have accurate data for those)

- Viewership based on number of new channel views in 8 day period

- Viewership from the time it was measured, but average video views recorded second week of January, so they include all views from video posted until January 2024.

8 day period instead of 7/1 week - this was based on the way videos were posted on the channel

- 45 8 day blocks (7 days inclusive)

Use viewership changes vs total views - total views don't capture changes in viewership well (ie. 200,000 is a big jump over 8 days, but very small compared to 3mil)

- no way to know who watched what videos (and different series/video types have different audiences)

Anthony usually makes appearances on Smosh main channel and Smosh Pit.

- Pit felt more interesting to follow overtime since all the cast appears there