

## Today

1. Exploratory Data Analysis
2. Data cleaning

# Motivating Examples

## STAT3022 Applied Linear Models Lecture 21

2020/02/18



## The Avocado Lover's job problem

Dear statistician,

I work in an Avocado company that has many offices in US. My boss asked me to analyse the US market for the price and sales trends and factors that drive these trends. I am able to obtain a data set to analyse but I need your help to advise me how to conduct this research.

Personally, I am also an avocado lover and eat avocado toast nearly every day. My boss told me that he will send me to an US office in July 2019 to get some trainings and let me choose which office to work in. My salary is not too high so I need to make sure that avocado is least expensive there. I like organic avocado but if it's too costly, I'm willing to settle for non-organic avocado. Please help me decide where I should go!

Kind regards,  
Avocado Lover

### What is the aim?

# The Avocado Lover's job problem

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I work in an Avocado company that has many offices in US. My boss asked me to analyse the US market for the **price and sales trends and factors that drive these trends**. I am able to obtain a data set to analyse but I need your help to advise me how to conduct this research.

Personally, I am also an avocado lover and eat avocado toast nearly every day. My boss told me that he will send me to an US office in **July 2019** to get some trainings and let me choose which office to work in. My salary is not too high so I need to make sure that **avocado is least expensive** there. I **like organic avocado** but if it's too costly, I'm willing to **settle for non-organic avocado**. Please help me decide **which state** I should go!

Kind regards,

Avocado Lover

First identify what the client wants.

- Price and sales trends and their driving factors.
- Personally, the price in **July 2019**.
- Recommendation of which **state** to go. More beneficial is to identify city in which her workplace has an office.
- The client cares moderately for **organic** avocados. How much is she willing to pay extra for it?
- The client may also care about cost of living other than avocados (rent, electricity, water bills, etc), lifestyle, etc.

3 / 38

## Do you have the data to answer the question?

- In real world, the questions are often not clearly defined.
- Keep in mind that the client may find it hard to pinpoint exactly what they want.
- It is your job as a statistician to work together with the client to frame the problems numerically/statistically.
- Even after you form the questions analytically, you may have insufficient data to answer the questions.
- You may need to make the best out of data, acknowledging the potential flaws in the analysis.
- In some cases, you just simply cannot gain any information out of data.
- "If you torture the data long enough, it will confess." -Ronald H. Coase

4 / 38

# Understand avocado prices and sales volume in US

```
skimr::skim(dat)
```

## Skim summary statistics

```
n obs: 18249
n variables: 13
```

### Variable type:character

variable	missing	complete	n	min	max	empty	n_unique
Date	0	18249	18249	6	8	0	169
region	0	18249	18249	4	19	0	54
type	0	18249	18249	7	12	0	2

### Variable type:numeric

variable	missing	mean	sd	p0	p50	p100	hist
4046	0	293008.42	1264989.08	0	8645.3	2.3e+07	
4225	0	3e+05	1204120.4	0	29061.02	2e+07	
4770	0	22839.74	107464.07	0	184.99	2546439.11	
AveragePrice	0	1.41	0.4	0.44	1.37	3.25	
Large Bags	0	54338.09	243965.96	0	2647.71	5719096.61	
Small Bags	0	182194.69	746178.51	0	26362.82	1.3e+07	
Total Bags	0	239639.2	986242.4	0	39743.83	1.9e+07	
Total Volume	0	850644.01	3453545.36	84.56	107376.76	6.3e+07	
XLarge Bags	0	3106.43	17692.89	0	0	551693.65	
year	0	2016.15	0.94	2015	2016	2018	

5 / 38

## Get data summary

### What does each variable mean?

```
dat <- dat %>%
  mutate(Date=as.Date(Date, format="%d/%m/%y")) %>%
  janitor::clean_names() # better names for analysis
str(dat)
```

```
tibble [18,249 x 13] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
 $ date      : Date [1:18249], format: "2015-12-27" "2015-12-20"
 $ average_price: num [1:18249] 1.33 1.35 0.93 1.08 1.28 1.26 0.9
 $ total_volume : num [1:18249] 64237 54877 118220 78992 51040 .
 $ x4046       : num [1:18249] 1037 674 795 1132 941 ...
 $ x4225       : num [1:18249] 54455 44639 109150 71976 43838 .
 $ x4770       : num [1:18249] 48.2 58.3 130.5 72.6 75.8 ...
 $ total_bags  : num [1:18249] 8697 9506 8145 5811 6184 ...
 $ small_bags  : num [1:18249] 8604 9408 8042 5677 5986 ...
 $ large_bags  : num [1:18249] 93.2 97.5 103.1 133.8 197.7 ...
 $ x_large_bags : num [1:18249] 0 0 0 0 0 0 0 0 0 0 ...
 $ type        : chr [1:18249] "conventional" "conventional" "c
 $ year        : num [1:18249] 2015 2015 2015 2015 2015 ...
 $ region      : chr [1:18249] "Albany" "Albany" "Albany" "Alba
```

### Given description

- date - the date of the observation
- average\_price - the average price of a single avocado
- type - conventional or organic
- year - the year
- region - the city or region of the observation
- total\_volume - Total number of avocados sold
- x4046 - total number of avocados with PLU 4046 - small/medium Hass avocado (about 3-5oz avocado) - sold
- x4225 - total number of avocados with PLU 4225 - large Hass avocado (about 8-10oz avocado) - sold
- x4770 - total number of avocados with PLU 4770 - extra large Hass avocado (about 10-15oz avocado) - sold

The PLU or Price Look-Up code is a 4- or 5-digit number that is primarily used on fresh produce items.

6 / 38

# Do your research of avocado market!

Original data source:

<http://www.hassavocadoboard.com/retail/volume-and-price-data>

## Regions:

IRI Retail Sales Regions



Markets

CALIFORNIA Los Angeles Sacramento San Diego San Francisco	WEST Denver Phoenix Portland Salt Lake City Seattle West Texas/New Mexico	PLAINS St. Louis	SOUTH CENTRAL Dallas Houston New Orleans
GREAT LAKES Chicago Cincinnati Columbus Detroit Grand Rapids Indianapolis	MIDSOUTH Baltimore Charlotte Louisville Nashville Raleigh Richmond Roanoke	SOUTHEAST Atlanta Jacksonville Miami Orlando South Carolina Tampa	NORTHEAST Albany Boston Buffalo Harrisburg/Scranton Hartford/Springfield New England New York Philadelphia Pittsburgh Syracuse

7 / 38

## Understand regions

unique(dat\$region)

```
[1] "Albany"
[5] "Boston"
[9] "Chicago"
[13] "Denver"
[17] "HarrisburgScranton"
[21] "Jacksonville"
[25] "MiamiFtLauderdale"
[29] "NewYork"
[33] "Philadelphia"
[37] "Portland"
[41] "Sacramento"
[45] "SouthCarolina"
[49] "StLouis"
[53] "West"

"Atlanta"
"BuffaloRochester"
"CincinnatiDayton"
"Detroit"
"HartfordSpringfield"
"LasVegas"
"MidSouth"
"Northeast"
"PhoenixTucson"
"RaleighGreensboro"
"SanDiego"
"SouthCentral"
"Syracuse"
"WestTexNewMexico"

"BaltimoreWashington"
"California"
"Columbus"
"GrandRapids"
"Houston"
"LosAngeles"
"Nashville"
"NorthernNewEngland"
"Pittsburgh"
"RichmondNorfolk"
"SanFrancisco"
"Southeast"
"Tampa"

"Boise"
"Charlotte"
"DallasFtWorth"
"GreatLakes"
"Indianapolis"
"Louisville"
"NewOrleansMobile"
"Orlando"
"Plains"
"Roanoke"
"Seattle"
"Spokane"
"TotalUS"
```

- Some regions are unclear:
  - Albany in OR, GA and NY
  - Columbus in IN and OH
  - Jacksonville in FL
  - Portland in ME and OR
- Some regions seem to be a combination, e.g. BuffaloRochester, CincinnatiDayton, etc.
- How do we verify where it is?
- Is it possible?

8 / 38

# Information on US cities

Below omits the

```
ggrepel::geom_label_repel.
```

```
library(maps)
states <- map_data("state")
ggplot(states) +
  geom_polygon(aes(long, lat,
    group = group), color = "white",
    fill="black") + coord_fixed(1.3) +
  theme_void() + guides(fill=FALSE)
```

```
us.cities %>%
  select(name, pop, lat, long) %>%
  head()
```

	name	pop	lat	long
1	Abilene TX	113888	32.45	-99.74
2	Akron OH	206634	41.08	-81.52
3	Alameda CA	70069	37.77	-122.26
4	Albany GA	75510	31.58	-84.18
5	Albany NY	93576	42.67	-73.80
6	Albany OR	45535	44.62	-123.09

9 / 38

# Duplicate city names

```
us.cities %>%
  filter(grepl("Albany", name) |
    grepl("Columbus", name) |
    grepl("Jacksonville", name) |
    grepl("Portland", name)) %>%
  select(name, pop, lat, long)
```

	name	pop	lat	long
1	Albany GA	75510	31.58	-84.18
2	Albany NY	93576	42.67	-73.80
3	Albany OR	45535	44.62	-123.09
4	Columbus GA	184900	32.51	-84.87
5	Columbus IN	39453	39.21	-85.91
6	Columbus OH	741677	39.99	-82.99
7	Jacksonville FL	809874	30.33	-81.66
8	Jacksonville NC	68201	34.76	-77.40
9	Portland ME	62882	43.66	-70.28
10	Portland OR	542751	45.54	-122.66

- Albany should be in NY
- Portland should be in OR
- Columbus should be in IN or OH (GA far away)
- Jacksonville should be in FL or NC

10 / 38

# How to choose Columbus? Use US City Information

Getting key variables to merge with original data.

```
USkey <- us.cities %>% mutate(region=substr(name, 1, nchar(name) - 3)) %>%
  rename(state=country.etc) %>%
  mutate(region=gsub(" ", "", region)) %>%
  select(region, pop, lat, long, state) %>%
  rbind(tribble(~region, ~pop, ~lat, ~long, ~state,
    "BaltimoreWashington", 602658 + 548359, (39.30 + 38.91)/2, (-76.61 -77.02)/2, "MD+DC",
    "BuffaloRochester", 276762 + 209587, (42.89 + 43.17)/2, (-78.86-77.62)/2, "NY+NY",
    "California", 26729306, 35.42923, -119.3301, "CA",
    "CincinnatiDayton", 301561+157607, (39.14 + 39.78)/2, (-84.51-84.20)/2, "OH+OH",
    "DallasFtWorth", 1216543+633849, (32.79+32.75)/2, (-96.77-97.34)/2, "TX+TX",
    "district of columbia", 548359, 38.91, -77.02, "DC",
    "GreatLakes", 15182052, 41.8975, -86.31265, "WI+IA+IL+MI+OH",
    "HarrisburgScranton", 47576 + 72516, (40.28+41.40)/2, (-76.88-75.67)/2, "PA+PA",
    "HartfordSpringfield", 123836 + 152095, (41.77 + 42.12)/2, (-72.68-72.54)/2, "CT+MA",
    "MiamiFtLauderdale", 173597 + 386740, (26.14+25.78)/2, (-80.14-80.21)/2, "FL+FL",
    "MidSouth", 10669181, 37.51253, -79.53505, "KY+WV+TN+VA+NC+WV+MD+DE+DC",
    "NewOrleansMobile", 188467+454207, (30.68+30.07)/2, (-88.09-89.93)/2, "AL+LA",
    "Northeast", 21530612, 41.54582, -73.37044, "NJ+PA+NY+CT+RI+MA+VT+NH+ME",
    "NorthernNewEngland", 372834, 43.39, -71.14, "ME+NH+VT", # guess
    "PhoenixTucson", 1450884+525268, (33.54+32.20)/2, (-112.07-110.89)/2, "AZ+AZ",
    "Plains", 6719966, 41.87682, -94.22152, "ND+SD+NE+KS+MN+IA+MO",
    "RaleighGreensboro", 233342+350822, (36.08+35.82)/2, (-79.83-78.66)/2, "NC+NC",
    "RichmondNorfolk", 248182+189498, (36.92+37.53)/2, (-76.24-77.47)/2, "VA+VA",
    "SouthCarolina", 526667, 33.75429, -80.65286, "SC",
    "SouthCentral", 16433060, 31.9431, -96.3638, "TX+OK+LA+AR",
    "Southeast", 11204354, 29.29783, -82.32278, "MS+AL+GA+SC+FL",
    "StLouis", 315546, 38.64, -90.24, "MO",
    "TotalUS", 126175816, 37.49531, -95.10346, "AL+AK+AZ+AR+CA+CO+CT+DE+FL+GA+HI+ID+IL+IN+IA+KS+
    "West", 15735863, 40.74418, -113.9845, "WA+OR+NV+ID+MT+WY+UT+CO+NM+AZ",
    "WestTexNewMexico", 13721930, 31.44962, -98.13192, "TX+NM" # includes east Texas too
```

How to choose?

IN or OH differ in pop size!

- Use total volume to predict pop size.
- Add pop size information.
- Some regions encompasses a large region.
- Some regions are subset of other region.
- Some coded here involve guess work and may have room for error.

# Is there a relationship with volume and population?

```
us.cities %>%
  filter(grepl("Columbus", name)) %>% # IN or OH
  select(name, pop, lat, long)

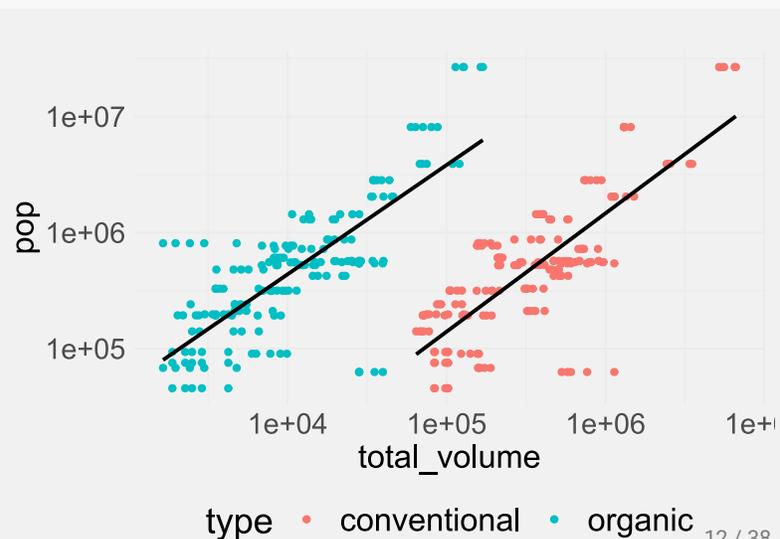
  name    pop    lat    long
1 Columbus GA 184900 32.51 -84.87
2 Columbus IN  39453 39.21 -85.91
3 Columbus OH 741677 39.99 -82.99

dat2 <- dat %>% left_join(USkey, by="region") %>%
  # leave these out for now
  filter(region!="Columbus") %>%
  filter(!grepl("+", state, fixed=T)) #drop comb

dim(dat2) #dat 18429,13 drop columbus & comb

[1] 12168    17
```

```
library(lubridate)
dat3 <- dat2 %>% filter(year==2017 & month(date)==7)
ggplot(dat3, aes(total_volume, pop,
  color=type, group=type)) +
  geom_point() + scale_x_log10() + scale_y_log10() +
  geom_smooth(method="lm", se=FALSE, color="black") +
  theme(legend.position = "bottom")
```



# Predict the population of Columbus

```
predat <- dat %>%
  filter(grepl("Columbus", region)) %>%
  filter(year==2017 & month(date)==7) %>%
  group_by(region, type) %>%
  summarise(total_volume=mean(total_volume)) %>%
  ungroup()
predat #use tot vol at 7-2017 to pred pop size
```

```
# A tibble: 2 x 3
  region type      total_volume
  <chr>   <chr>         <dbl>
1 Columbus conventional 195168.
2 Columbus organic      9886.
```

```
M0 <- lm(log10(pop)~type+log10(total_volume),dat3)
10^predict(M0,newdata=predat,
  interval="prediction") %>%
cbind(predat)
```

```
      fit      lwr      upr region      type tot.
1 282664.3 51813.66 1542047 Columbus conventional 1'
2 430889.5 79026.84 2349401 Columbus organic
```

- Since the predicted population size is large, Columbus appears to be in OH.
- Let's modify our key:

```
USkey_ncr <- USkey %>%
  filter(!(region=="Columbus" & state!="OH") &
    region %in% dat$region)
dat_ncr<-dat %>% left_join(USkey_ncr,by="region") %>%
  filter(!grepl("+", state, fixed=T)) #no comb region
dat_cr <- dat %>% left_join(USkey_ncr, by="region")
```

```
dim(dat_ncr)
```

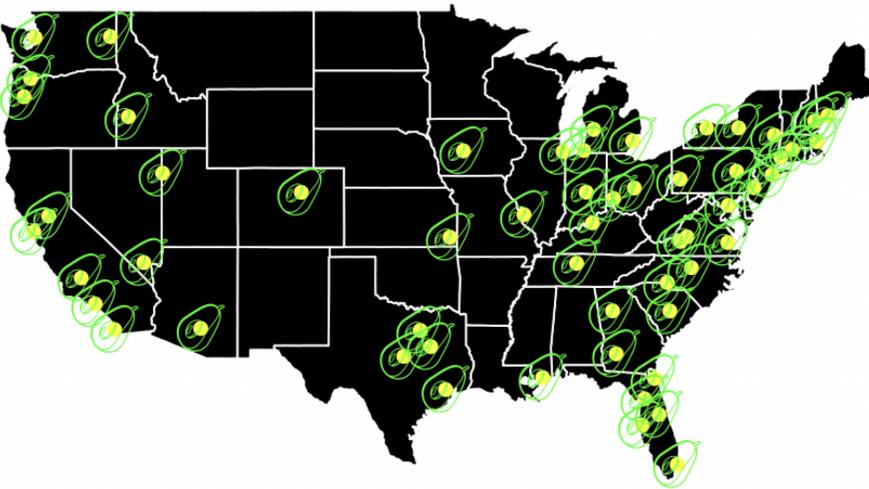
```
[1] 12506 17
```

```
dim(dat_cr)
```

```
[1] 19601 17
```

13 / 38

# Data coverage for her company offices?



- Some states are not well covered.

```
strsplit(dat_cr$state, "+", fixed=T) %>%
  unlist() %>%
  unique()
```

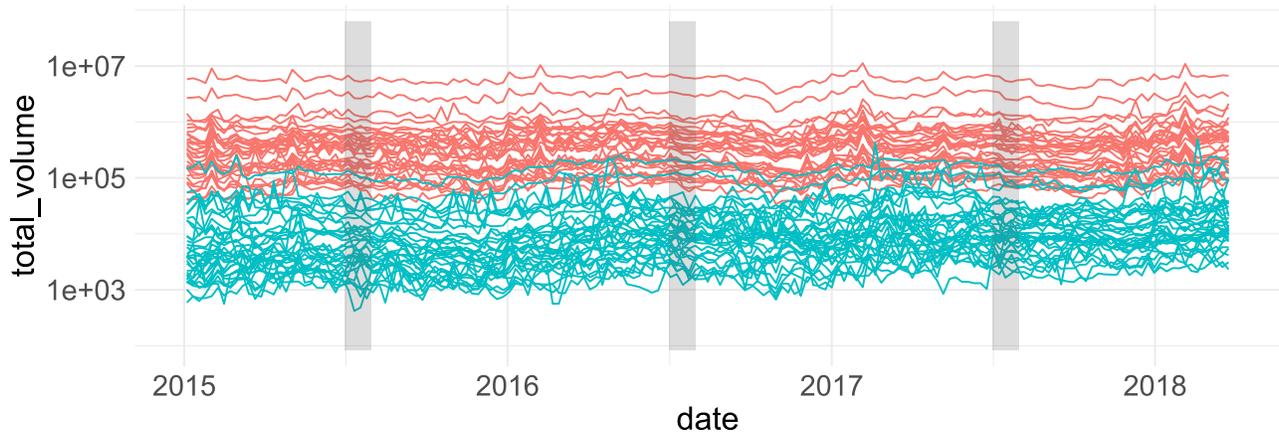
```
[1] "GA" "NY" "OR" "MD" "DC" "ID" "MA"
[8] "CA" "NC" "IL" "OH" "TX" "CO" "MI"
[15] "WI" "IA" "PA" "CT" "IN" "FL" "NV"
[22] "KY" "WV" "TN" "VA" "DE" "AL" "LA"
[29] "NJ" "RI" "VT" "NH" "ME" "AZ" "ND"
[36] "SD" "NE" "KS" "MN" "MO" "WA" "SC"
[43] "OK" "AR" "MS" "AK" "HI" "MT" "NM"
[50] "UT" "WY"
```

14 / 38

# Boss's question: does sales (total) volume change?

```
julyperiod <- data.frame(xmin=as.Date(c("01/07/15", "01/07/16", "01/07/17"), format="%d/%m/%y"),
                        xmax=as.Date(c("31/07/15", "31/07/16", "31/07/17"), format="%d/%m/%y"),
                        ymin=min(dat$total_volume), ymax=max(dat$total_volume))

ggplot(dat_ncr) +
  geom_line(aes(date, total_volume, group=interaction(region,type), color=type)) + scale_y_log10() +
  geom_rect(data=julyperiod,
           mapping=aes(xmin=xmin, xmax=xmax, ymin=ymin, ymax=ymin), alpha=0.2) + guides(color=FALSE)
```



15 / 38

# Is the change of total volume over time significant?

```
M1<-lm(total_volume~region:type+date,data=dat_ncr)
summary(M1) #date has associated numerical value
```

```
Call:
lm(formula = total_volume ~ region:type + date, data = dat_ncr)
```

```
Residuals:
    Min       1Q   Median       3Q      Max
-2800515  -14931   -1542    9843  5270823
```

```
Coefficients: (1 not defined because of singularities)
            Estimate
(Intercept) -4.171e+05
date         2.475e+01
regionAlbany:typeconventional 8.866e+04
regionAtlanta:typeconventional 5.086e+05
```

```
[1] "2015-12-27" "2015-05-10"
```

```
[1] 16796 16565
```

```
M2 <- lm(total_volume ~ region:type, data=dat_ncr)
anova(M2, M1)
```

Analysis of Variance Table

```
Model 1: total_volume ~ region:type
Model 2: total_volume ~ region:type + date
  Res.Df    RSS Df Sum of Sq
1  12440 3.7261e+14
2  12439 3.7172e+14  1  8.9302e+11
      F      Pr(>F)
```

```
1
2 29.884 4.676e-08 ***
---
```

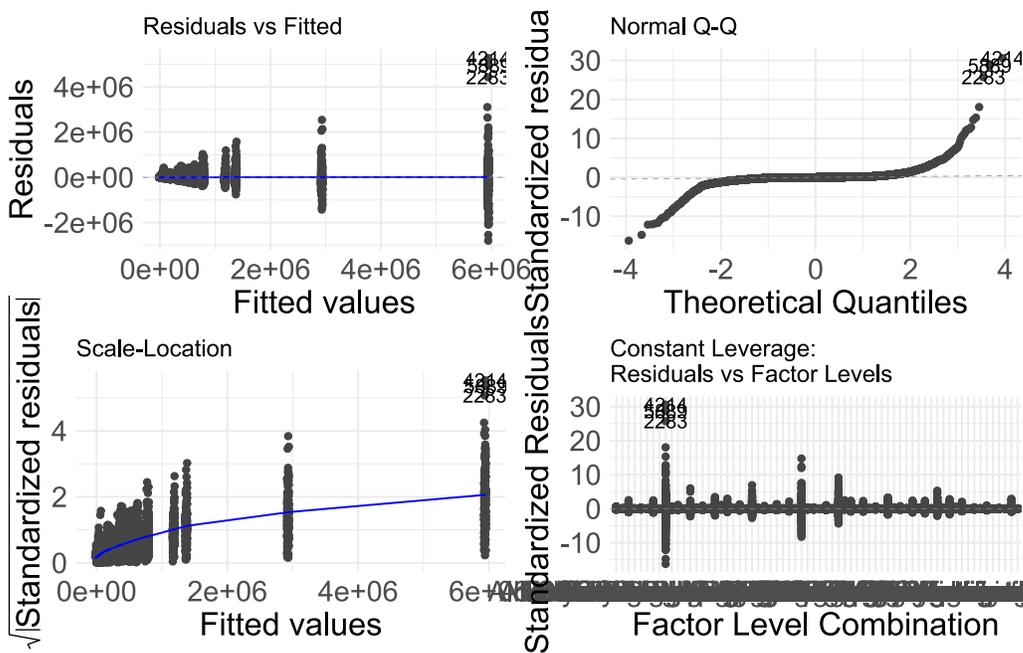
```
Signif. codes:
  0 '***' 0.001 '**' 0.01 '*' 0.05
  '.' 0.1 ' ' 1
```

- The overall date effect is significant partly due to the large sample size.
- Since the date coefficient is +ve, total\_volume increases over time in general.

16 / 38

# Model diagnostics?

```
library(ggfortify)
autoplot(M1)
```

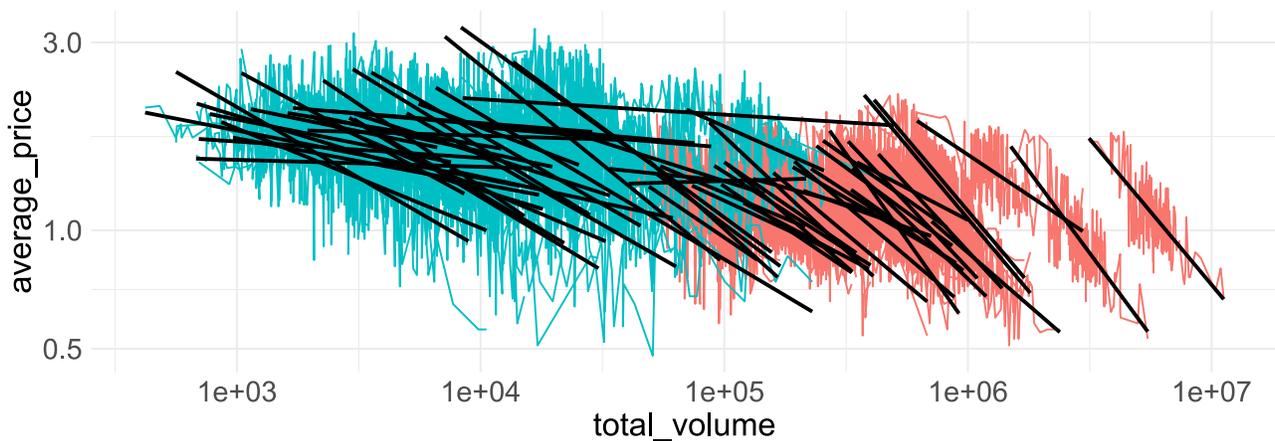


- The reality is that the model diagnostics are not satisfied and thus inferences may not be reliable.
- However outliers often present in large data set.
- It is common to see an increasing trend of variance for a time series.

17 / 38

# Boss's question: Does price change with supply?

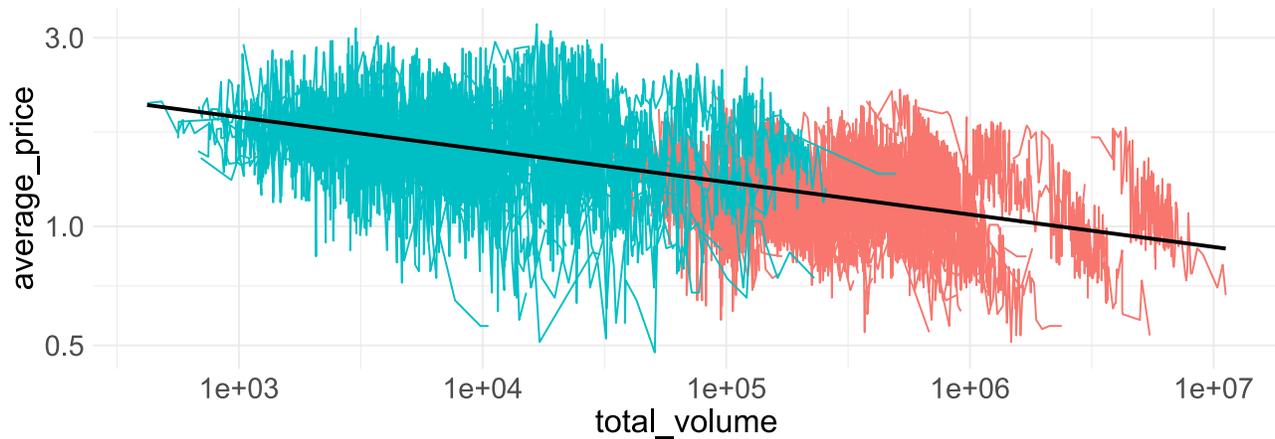
```
ggplot(dat_ncr) +
  geom_line(aes(total_volume, average_price, group=interaction(region,type), color=type)) +
  scale_y_log10() + scale_x_log10() + guides(color=FALSE) +
  geom_smooth(method="lm", se=FALSE, aes(total_volume, average_price,
  group=interaction(region,type)), color="black") #no overall line
```



18 / 38

# Does price change with supply? Overall trend?

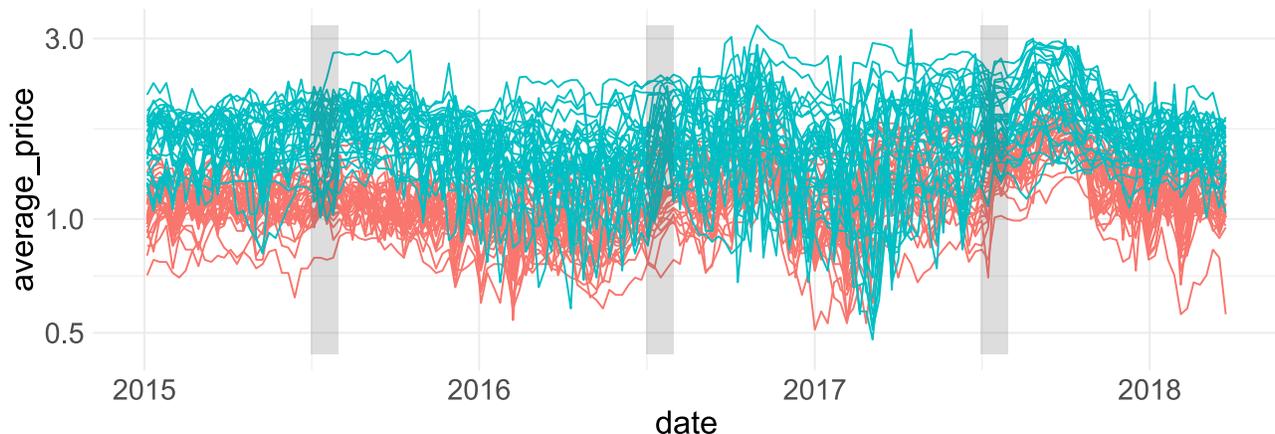
```
ggplot(dat_ncr) +  
  geom_line(aes(total_volume, average_price, group=interaction(region,type), color=type)) +  
  scale_y_log10() + scale_x_log10() + guides(color=FALSE) +  
  geom_smooth(method="lm", se=FALSE, aes(total_volume, average_price), color="black") #drop lines of each reg
```



19 / 38

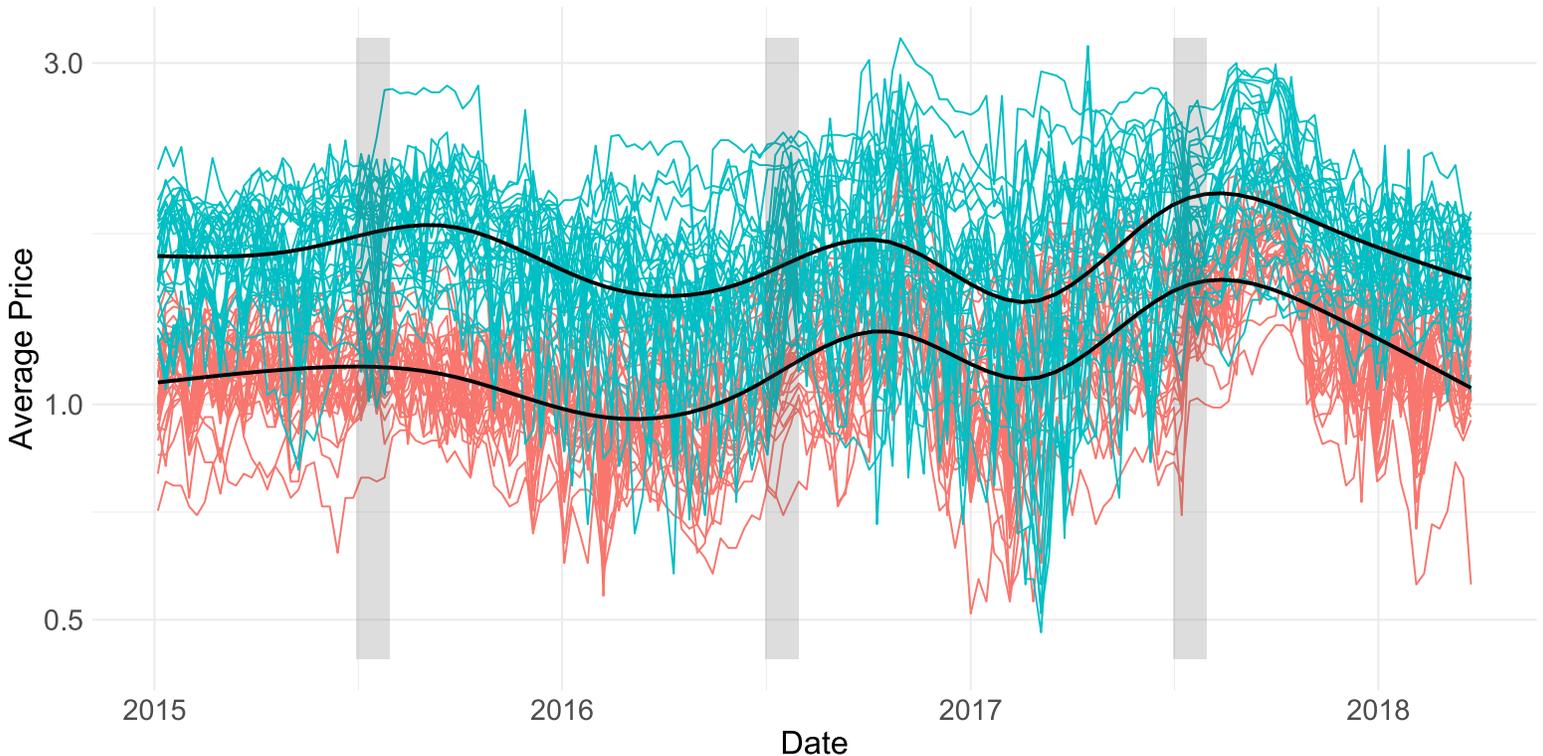
# Boss's question: Does price change over time?

```
julyperiod <- data.frame(xmin=as.Date(c("01/07/15", "01/07/16", "01/07/17"), format="%d/%m/%y"),  
  xmax=as.Date(c("31/07/15", "31/07/16", "31/07/17"), format="%d/%m/%y"),  
  ymin=min(dat$average_price), ymax=max(dat$average_price)) #July highlight  
ggplot(dat_ncr) +  
  geom_line(aes(date, average_price, group=interaction(region,type), color=type)) + scale_y_log10() +  
  geom_rect(data=julyperiod,  
  mapping=aes(xmin=xmin,xmax=xmax,ymin=ymin,ymax=ymax), alpha=0.2) + guides(color=FALSE) #log scale
```

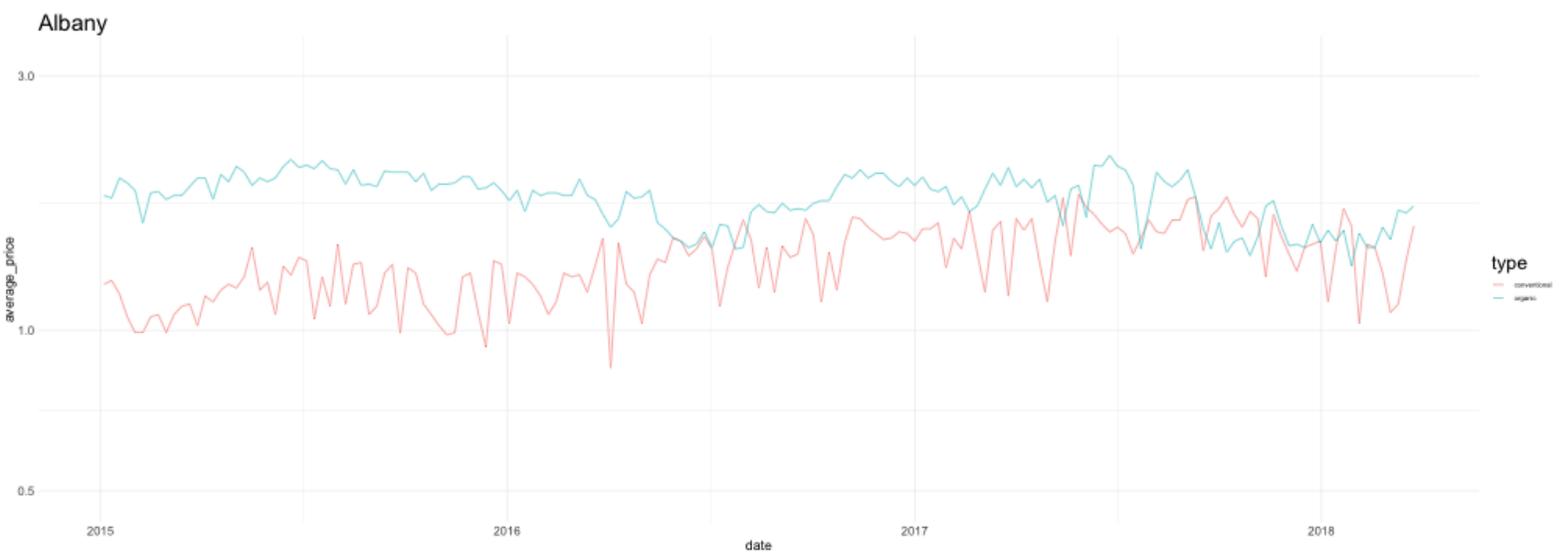


20 / 38

# Does price over time by region and type?

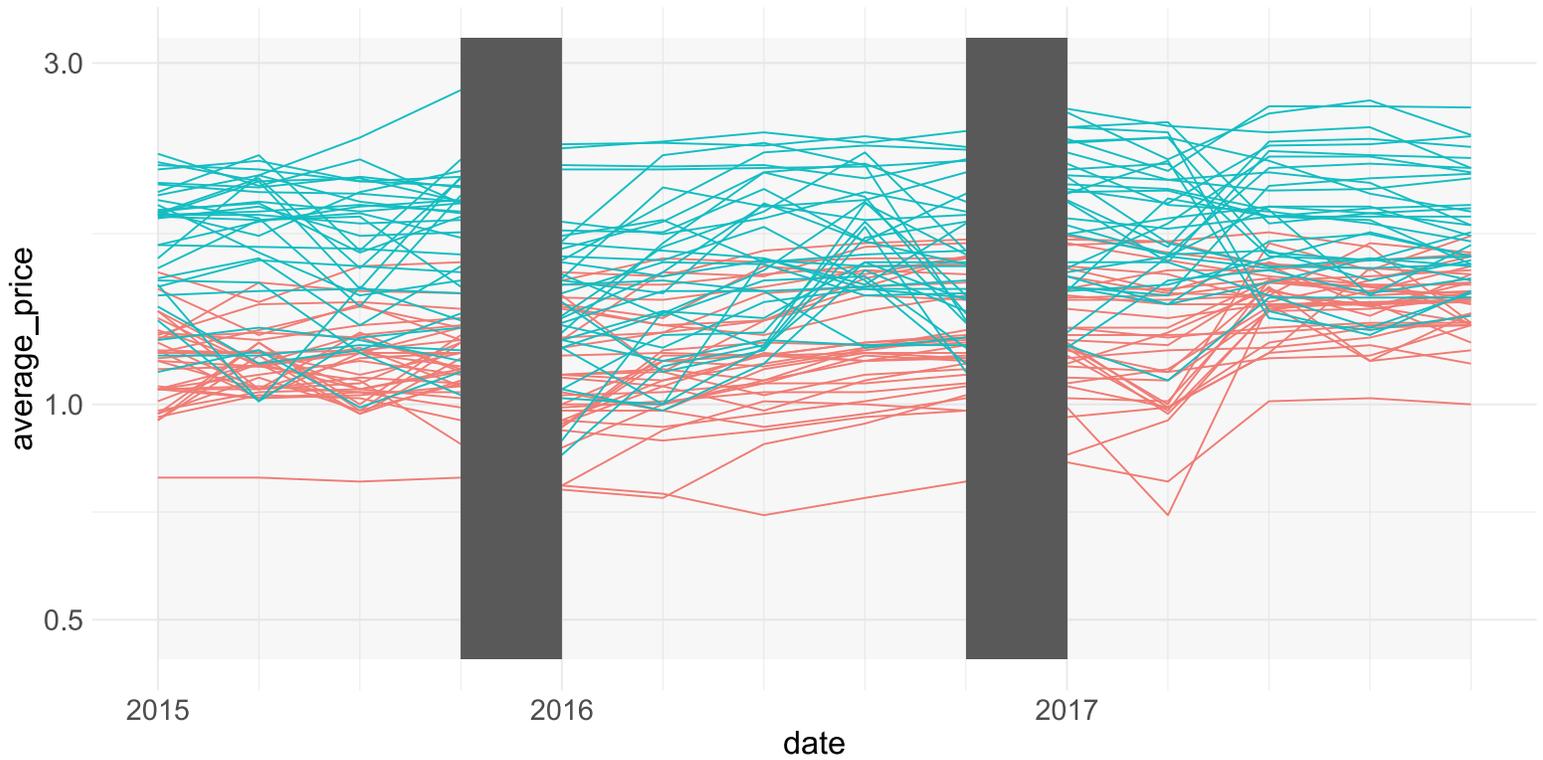


# Does price change over time by region and type?

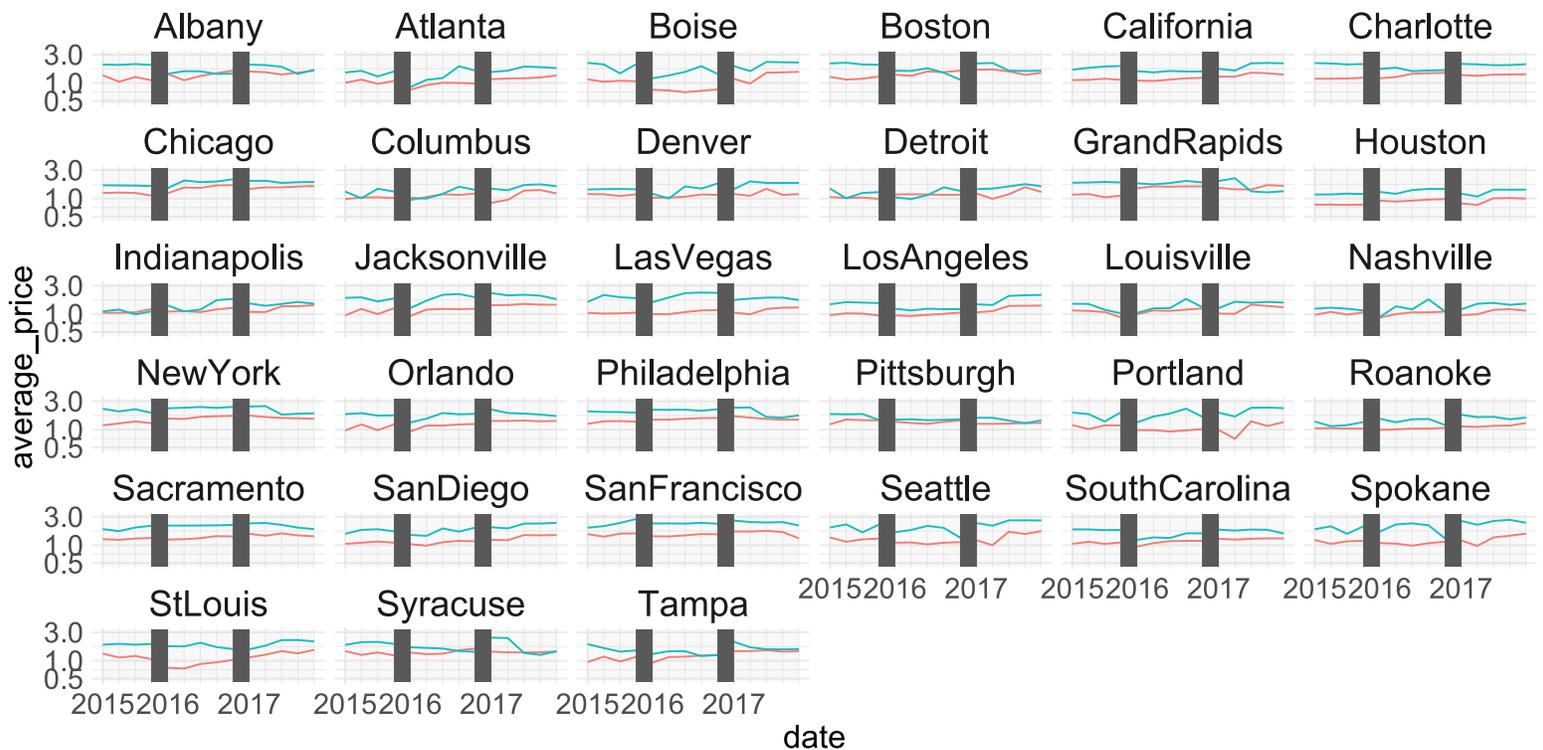


Do we need data for other days beside July?

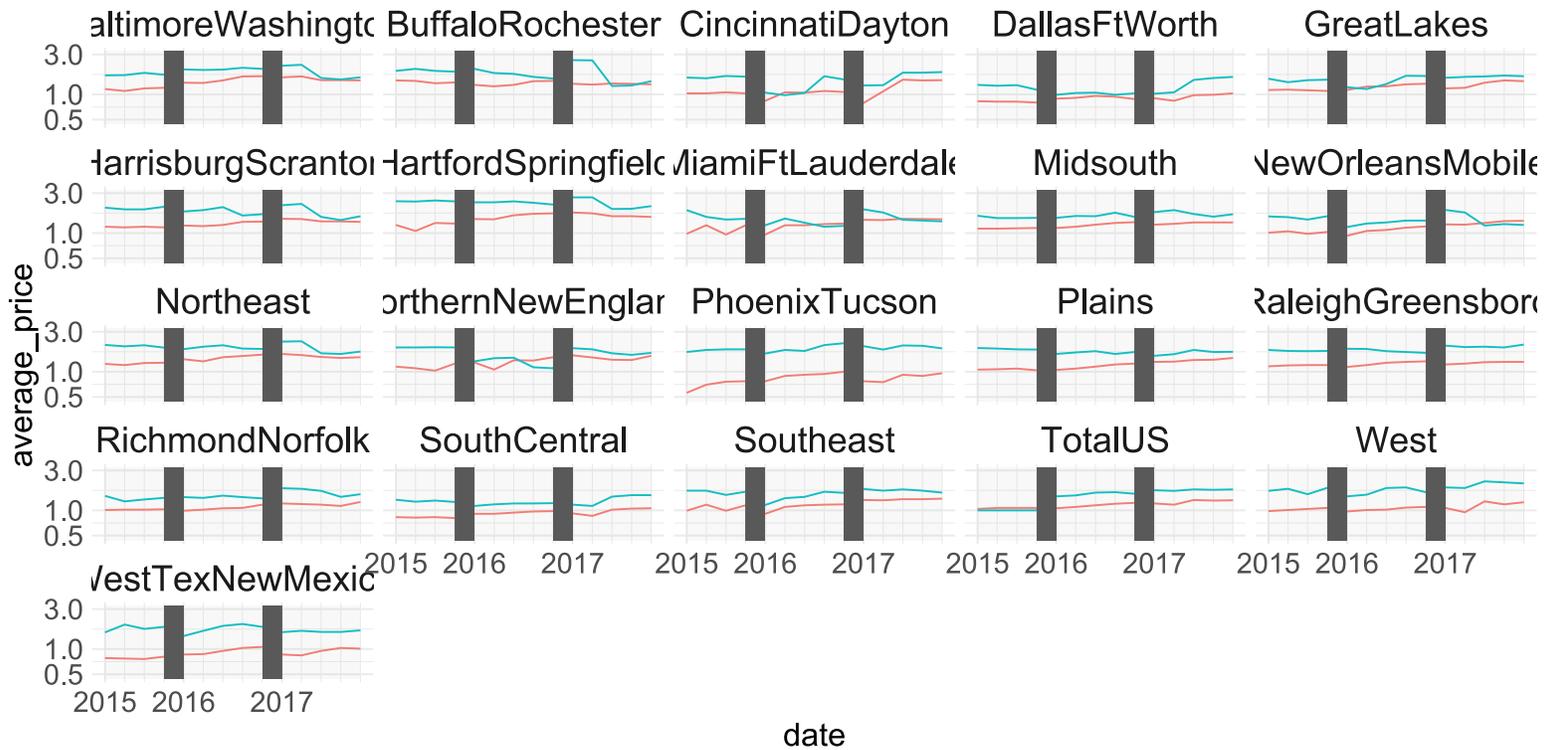
# Price in cities across July weeks each year



# Price for each city across July weeks each year



# Price for each combined region across July weeks



# Mean price for region by type by year via modelling

Show  entries

Search:

Region	Conventional			Organic		
	2015	2016	2017	2015	2016	2017
Albany	1.1925	1.382	1.514	2.035	1.486	1.798
Atlanta	1.05	0.936	1.226	1.4875	1.344	1.732
Boise	1.09	0.748	1.338	1.94	1.484	2.04
Boston	1.2175	1.478	1.554	2.0975	1.52	1.822
California	1.14	1.148	1.378	1.8225	1.56	1.96

Showing 1 to 5 of 33 entries

Previous  2 3  
4 5 6 7

```
julydat_ncr <- julydat_ncr %>%
  mutate(year=factor(year))
M0 <- lm(average_price ~
region:type:year-1,data=julydat_ncr)
outM0 <- broom::tidy(M0) %>%
  arrange(estimate) %>%
  select(term, estimate) %>%
  separate(term,
    c("region", "type", "year")) %>%
  mutate(region=gsub("region", "", region),
    type=gsub("type", "", type),
    year=gsub("year", "", year)) %>%
  mutate(tyear=
    paste0(substring(type, 1, 1), year)) %>%
  select(region, tyear, estimate) %>%
  spread(tyear, estimate)
outM0
```

```
# A tibble: 33 x 7
  region c2015 c2016 c2017 o2015 o2016
<chr> <dbl> <dbl> <dbl> <dbl> <dbl>
1 Albany 1.19 1.38 1.51 2.03 1.49
2 Atlanta 1.05 0.936 1.23 1.49 1.34
3 Boise 1.09 0.748 1.34 1.94 1.48
4 Boston 1.22 1.48 1.55 2.10 1.52
```

# Mean price for region by type by year via means

Show 5 entries

Search:

Region	Conventional			Organic		
	2015	2016	2017	2015	2016	2017
Albany	1.1925	1.382	1.514	2.035	1.486	1.798
Atlanta	1.05	0.936	1.226	1.4875	1.344	1.732
Boise	1.09	0.748	1.338	1.94	1.484	2.04
Boston	1.2175	1.478	1.554	2.0975	1.52	1.822
California	1.14	1.148	1.378	1.8225	1.56	1.96

Showing 1 to 5 of 33 entries

Previous

1

2

3

4

5

6

7

Next

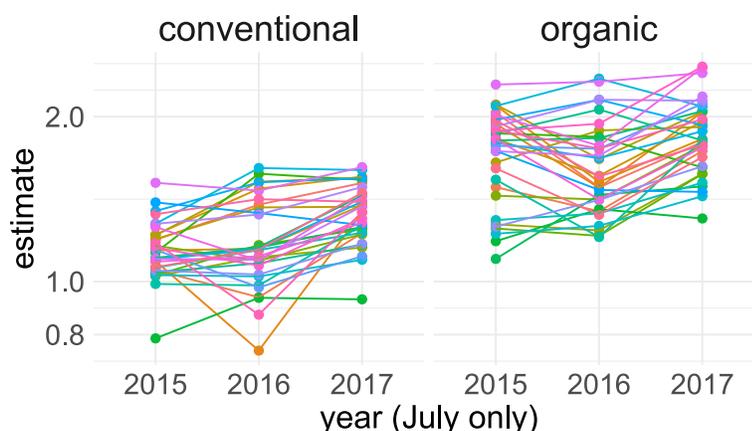
```
outsum <- julydat_ncr %>%
  group_by(region, type, year) %>%
  summarise(estimate=mean(average_price))%>%
  ungroup() %>%
  mutate(tyear=
    paste0(substring(type, 1, 1), year)) %>%
  select(region, tyear, estimate) %>%
  spread(tyear, estimate)
outsum
```

```
# A tibble: 33 x 7
  region c2015 c2016 c2017 o2015 o2016
  <chr> <dbl> <dbl> <dbl> <dbl> <dbl>
1 Albany 1.19 1.38 1.51 2.04 1.49
2 Atlanta 1.05 0.936 1.23 1.49 1.34
3 Boise 1.09 0.748 1.34 1.94 1.48
4 Boston 1.22 1.48 1.55 2.10 1.52
5 Califo~ 1.14 1.15 1.38 1.82 1.56
6 Charlo~ 1.19 1.37 1.37 2.10 1.67
7 Chicago 1.22 1.52 1.55 1.65 1.89
8 Columb~ 1.02 1.11 1.15 1.27 1.24
9 Denver 1.16 1.09 1.22 1.44 1.41
10 Detroit 1.03 1.17 1.25 1.25 1.21
# ... with 23 more rows, and 1 more
# variable: o2017 <dbl>
```

27 / 38

# Factors for price trend: Interaction effects for July

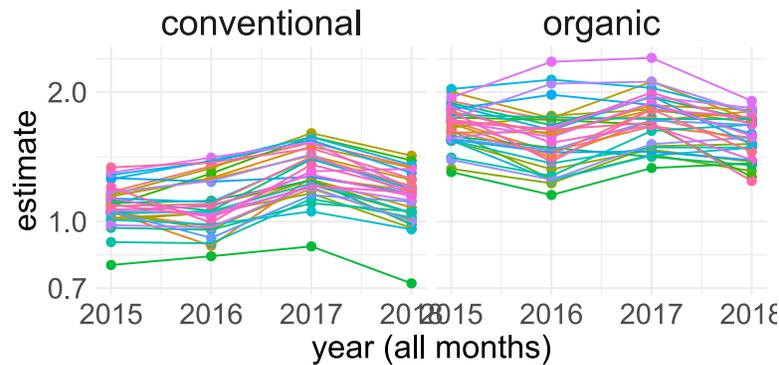
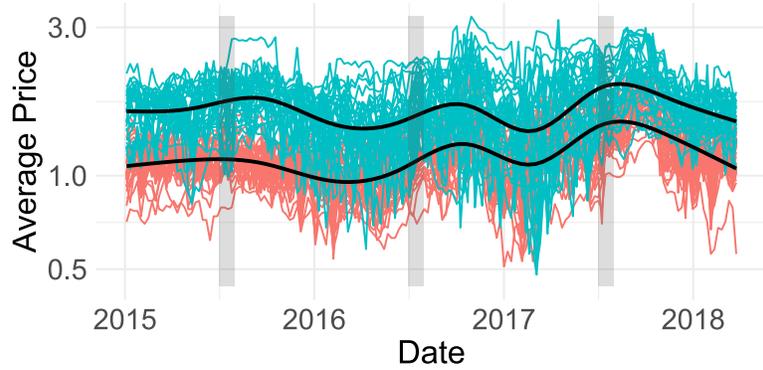
```
gather(outsum, "typeyear", "estimate", -region) %>%
  mutate(type=case_when(
    substring(typeyear, 1, 1)=="c" ~ "conventional",
    substring(typeyear, 1, 1)=="o" ~ "organic"),
    year=substring(typeyear, 2, nchar(typeyear))) %>%
  ggplot(aes(year, estimate, group=region, color=region)) +
  facet_wrap(~type) + geom_point(size=2) + geom_line() +
  guides(color=FALSE) + scale_y_log10() + labs(x="year (July only)")
```



- We already know that type is an important factor for determining the average\_price.
- Is year or date important?
- Is year:region important?
- Is year:type important?
- Is year:type:region?
- What about date:region:type?

28 / 38

# Interaction effects



- Is year or date important?
  - Yes! Early-year price appears to dip across all region and type.
- Is year:region important?
  - This can be thought of as average of year by region combination. At specific dates, it seemed to behave differently but averaged over year may be not much.
- Is year:type important? Maybe.
- Is year:type:region? Maybe.
- What about date:type:region?

# Testing for interaction effects

- Start with testing higher order interaction term year:region:type.
- If a higher order interaction term is included, you cannot drop main effects (year, region, type) or lower order interaction term (e.g. year:region, year:type, region:type).
- Because of the large data size, all terms including the higher order interaction are significant.

```
M1 <- lm(average_price~year*region*type,data=dat_ncr)
anova(M1)
```

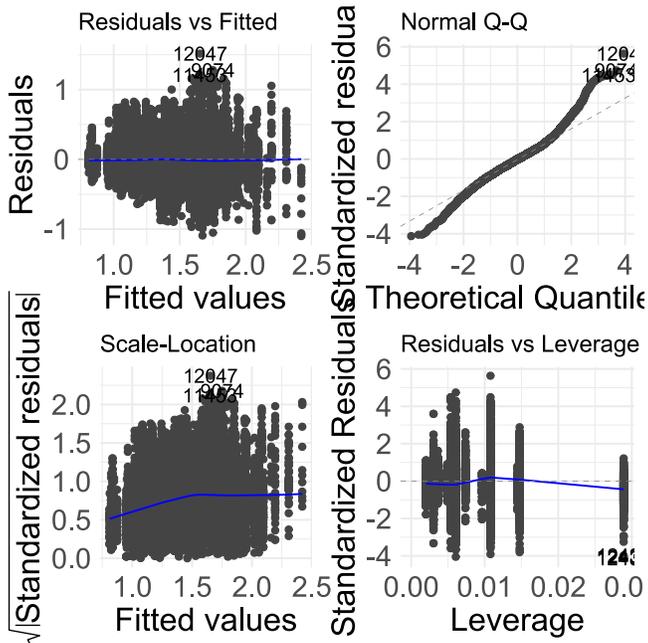
## Analysis of Variance Table

Response: average\_price

	Df	Sum Sq	Mean Sq
year	1	18.33	18.33
region	32	305.62	9.55
type	1	754.51	754.51
year:region	32	16.67	0.52
year:type	1	12.66	12.66
region:type	32	62.57	1.96
year:region:type	32	19.35	0.60
Residuals	12374	905.67	0.07
		F value	Pr(>F)
year		250.4643	< 2.2e-16
region		130.4870	< 2.2e-16
type		10308.7792	< 2.2e-16
year:region		7.1172	< 2.2e-16
year:type		172.9561	< 2.2e-16
region:type		26.7147	< 2.2e-16
year:region:type		8.2626	< 2.2e-16
Residuals			

# Model diagnostic

autoplot(M1)



- Model diagnostics are difficult for large data as seen here.
- For large sample size,  $p$ -values tend to be all significant.
- Thus it is more effective to check the effect size instead.

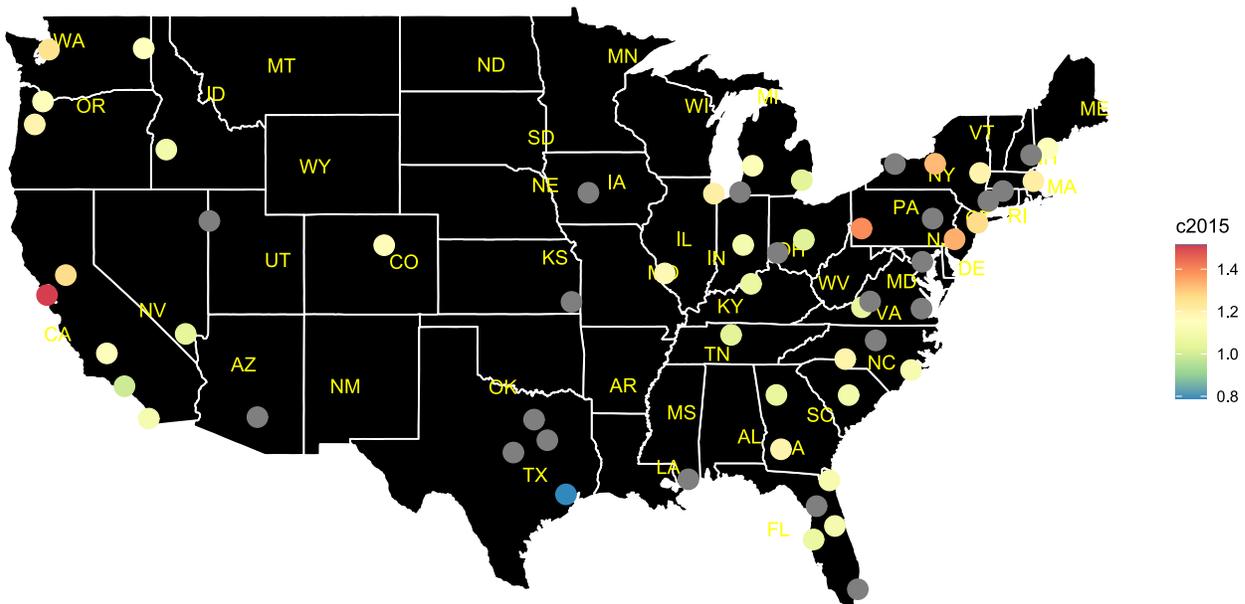
```
#print(broom::tidy(M1), n=Inf)  
print(summary(M1))
```

```
Call:  
lm(formula = average_price ~ year * region * type, data = data)
```

```
Residuals:  
      Min       1Q   Median       3Q      Max
```

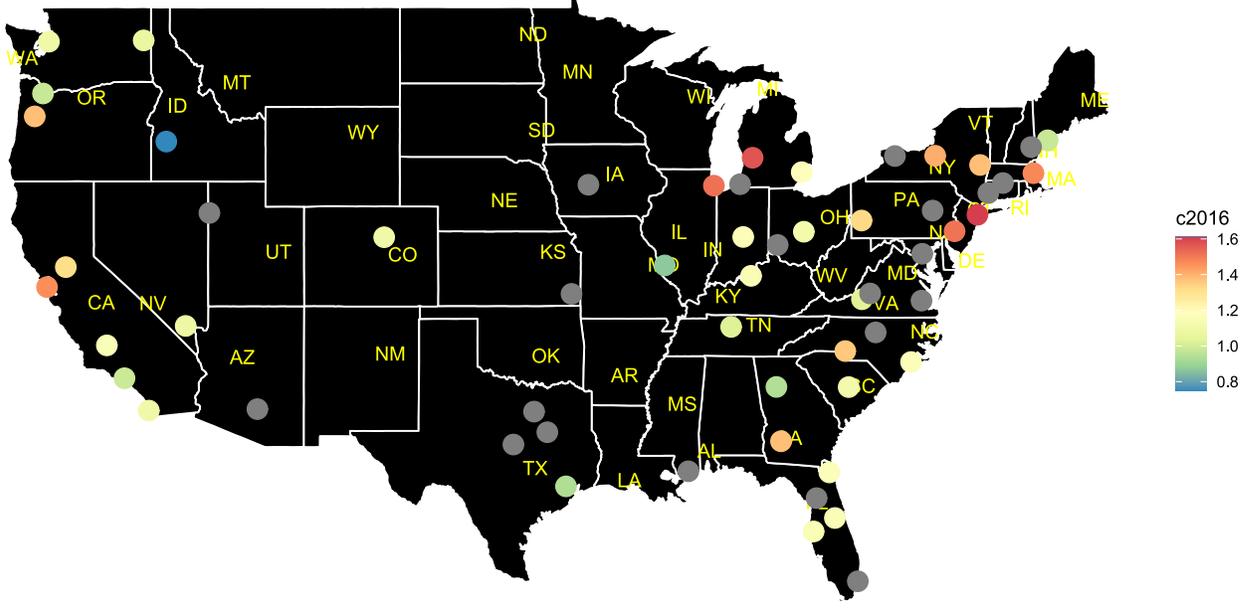
31 / 38

# Estimate for Conventional Avocado Price in 2015 July

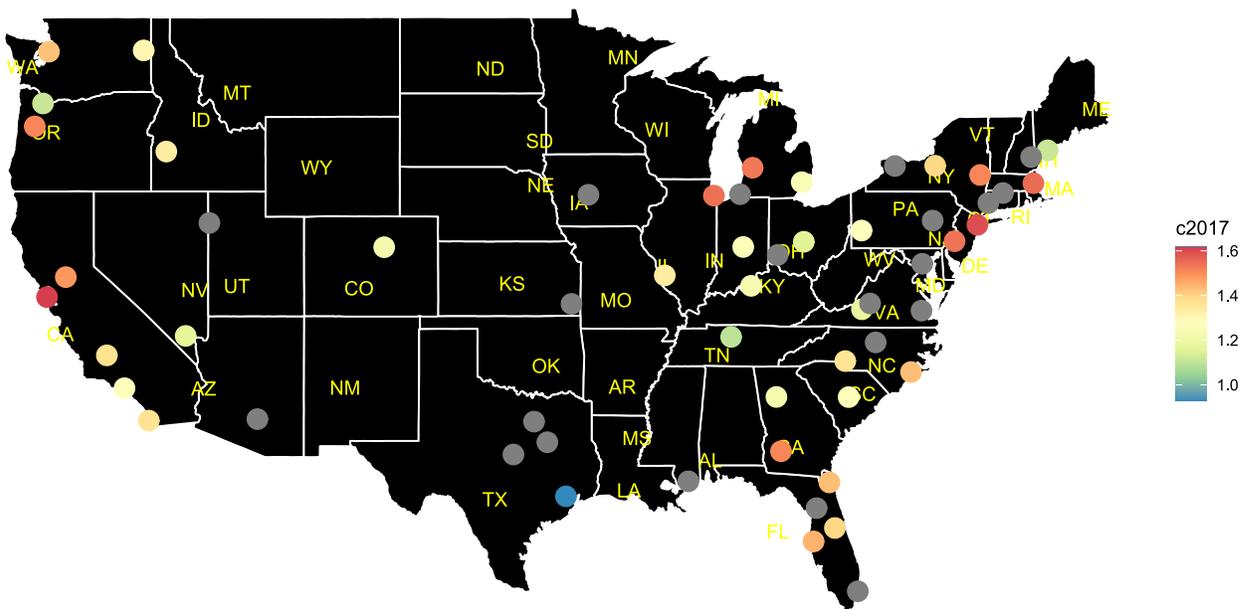


32 / 38

# Estimate for Conventional Avocado Price in 2016 July

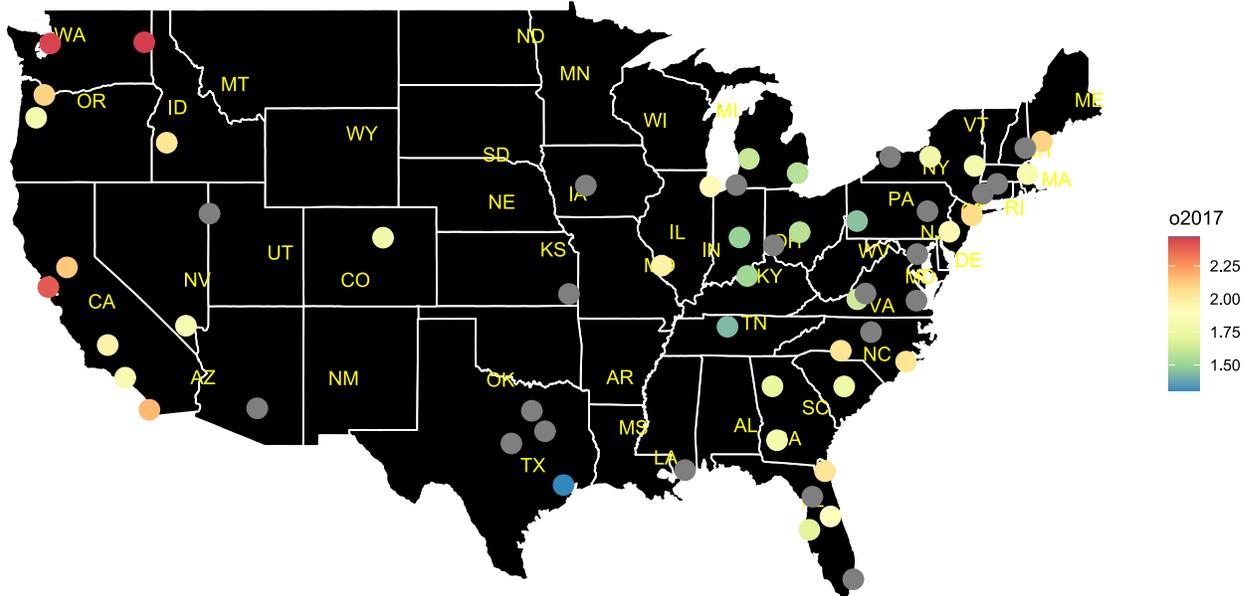


# Estimate for Conventional Avocado Price in 2017 July





# Estimate for Organic Avocado Price in 2017 July



37 / 38

## Wait...

- What about the different PLU, Price Look-Up code?
- What about different total volumes etc?
- You can try to predict these values for July 2019.
- Some models have simplifying assumptions that the volume is constant across year or all regions are increasing their volume by the same amount.

38 / 38